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**Origines microscopiques de la séparation xénon/krypton  
dans les matériaux nanoporeux**

Screening of the microscopic origins of Xe/Kr separation in  
nanoporous materials

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# GENERAL INTRODUCTION

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Industrial gas separation processes is widely used to supply purified reactants and inert gases for the chemical, the health, the agricultural and the food industries. It can also be used to mitigate negative environmental impact of some industrial activities: in concrete or steel production factories, the highly problematic CO<sub>2</sub> emissions could be separated from other atmospheric gases and captured; in nuclear treatment plants, volatile radioactive compounds (e.g., <sup>85</sup>Kr) can also be captured through an effective separation. Different small molecules are usually considered in these processes such as nitrogen, oxygen, carbon dioxide, hydrogen, methane, nitrous oxide or the noble gases. The xenon/krypton separation studied in this thesis is usually performed to extract xenon and krypton from the atmosphere,<sup>1</sup> but the nuclear industry constitutes a more abundant source of noble gases.<sup>2</sup>

In the industry, Xe/Kr separation is usually based on the cryogenic distillation of liquified atmospheric air, which requires a lot of energy, heavy infrastructures and a thorough hazard management. The hazardousness of the process resonates with the recent industrial accidents (1997) that occurred due to the reaction of non-filtered hydrocarbons with purified liquid oxygen.<sup>3,4</sup> To avoid security problems and to reduce the installation and the running cost of the gas separation process, a promising technology based on the competitive adsorption on a nanoporous material is now being actively researched. Nanoporous materials are constituted by nanoscale pores that offers a large surface area on which molecules can interact and adhere on. Industrial adsorption separation usually utilizes pressure swing adsorptions (PSA) – the pores are loaded with a given gas mixture at high pressure and then the gas is released by applying a lower pressure. If the material preferentially load one type of molecule, the composition of the released gas would have a much higher content of this molecule, hence achieving a gradual separation. In this thesis, xenon being chemically similar to krypton, the most challenging step of the purification of xenon remains the xenon/krypton separation. For instance, some prototypes involving beds of nanoporous materials have been developed for xenon/krypton separation.<sup>5</sup>

For the process to be viable, materials need to perform even better and many studies focus on synthesizing ever more selective materials by leveraging all chemical intuitions around noble gas adsorption properties.<sup>6–8</sup> In order to speed the discovery process of novel materials with key properties, computational screening can identify factors explaining the performance and pre-select candidates for further experimental studies. As recently conceptualized by Lyu et al., a synergistic workflow combining computational discovery and experimental validation can push material discovery to the next stage.<sup>9,10</sup> But to efficiently guide experimental discoveries, computational chemists are facing two major challenges: generating reliably more structures

and evaluating them with fast and accurate models. My work will focus on the second aspect on tool development.

The number of nanoporous materials is potentially unlimited; for the metal–organic frameworks (MOFs) alone, over 90,000 structures have been synthesized<sup>11</sup> and 500,000 digitally constructed.<sup>12–14</sup> To deal with this ever-increasing quantity of structures, researchers are developing screening strategies to efficiently identify the best materials, while building a chemical intuition on the characteristics favorable to a high separation performance. Some studies focus on a multistep screening strategy,<sup>12,15,16</sup> while others use machine learning algorithms to speed up their screening procedures.<sup>17–19</sup> The current screening strategies are usually based on computational tools that are more adapted to single-structure studies rather than high-throughput screenings. Moreover, in the industrial process of PSA introduced earlier and other similar technologies, many variables are required to draw a complete picture of the performance: the selectivity, the working capacity, the kinetics and thermodynamics behind the regeneration of the material (i.e., unloading the pores for another cycle).<sup>20</sup> This thesis aims at answering both these challenges by designing more efficient tools for high-throughput screening of not only the most studied selectivity performance metric, but also of transport properties and others.



This manuscript starts with a literature review on the screening methodologies that are applied to very different applications of nanoporous materials. It was an opportunity to explore the different techniques that are used in a variety of research fields to inspire the current work.<sup>21</sup> For instance, the research focus will be oriented toward the screening of the separation process by breaking down the selectivity metric into thermodynamic quantities such as the enthalpy, the free energy and the entropy. This study based on time-consuming calculations revealed the effects of pressure, the thermodynamic nature of the selectivity and some structure–property relationships.<sup>22</sup> To further improve the selectivity screening for Xe/Kr separation, different simulation tools were introduced to evaluate the adsorption performance of a nanoporous material.<sup>23</sup> This opened up new opportunities for the development of computationally cheaper and more accurate energy descriptors for the ML prediction of Xe/Kr selectivity at ambient pressure.<sup>24</sup> Through this work, faster and accurate evaluation tools of the Xe/Kr separation have been developed, which potentially enables the improvement of the physical description of the system.

As previously mentioned, the gas capacity of the nanoporous materials and the transport properties inside them are also very important metrics to evaluate the industrial separation process. The gas capacity can be obtained by GCMC calculations, and alternative methodologies were not thoroughly studied in this thesis. The fifth chapter of this thesis rather focuses on the determination of transport properties and alternative methods of evaluating it. Finally, some perspectives on the physical description of the system (flexibility and polarizability) are provided in the final chapter.







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# HIGH-THROUGHPUT COMPUTATIONAL SCREENING OF NANOPOROUS MATERIALS

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## 1.1 NANOPOROUS MATERIALS

Before exploring the screening methodologies of screening, the first section aims to introduce key concepts related to the system of interest, specifically nanoporous materials. These concepts will be referred consistently throughout the text, as the structural characteristics of these materials are intricately linked to their performance in targeted applications.

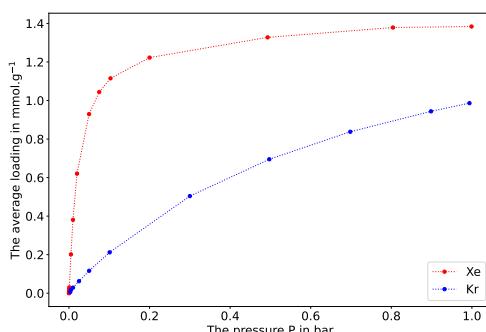
### 1.1.1 The main characteristics of nanoporous materials

Nanoporous materials are characterized by their nanoscale structure constituted by pores and cavities, some of which are connected by a network of channels. These pores can be empty or filled with a variety of substances called adsorbates. By attaching molecules from either a liquid or a gas phase onto the internal surface of the material, we can use it in a wide range of applications such as gas separation and purification,<sup>25,26</sup> energy storage and conversion,<sup>27,28</sup>

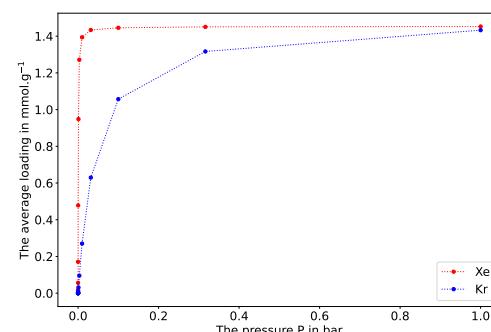
heterogeneous catalysis<sup>29–31</sup> drug delivery,<sup>32,33</sup> or sensing.<sup>34</sup> By designing the chemical nature, size, shape and distribution of the pores, we can tailor the physicochemical properties to the targeted application.<sup>35</sup>

### ADSORPTION ISOTHERMS AND GEOMETRICAL DESCRIPTORS

The process of particles or molecules adhering on a surface is called adsorption. Adsorption occurs due to attractive forces between adsorbates and the adsorbent surface, such as van der Waals forces, hydrogen bonding, and electrostatic interactions. The adsorption performance depends on the chemical nature of the interface, its exposed surface area and the shape of the pores. The characterization of adsorption properties of an adsorbate compound typically involves measuring the quantity of adsorbed molecules as a function of its pressure at a given temperature, which is referred to as adsorption isotherm. Figure 1.1 illustrates examples of adsorption isotherms that can be used, along other techniques, to determine the distribution of pore sizes, the accessible surface area and the pore volume.<sup>36</sup> These isotherms can also be utilized, through fitting models, to characterize the maximum adsorption uptake, among other adsorption descriptors.<sup>37</sup> By using a set of experimental isotherms at similar but distinct temperatures, we can also retrieve information on the isosteric heat of adsorption  $q_{st}$  (the negative differential of the excess enthalpy of adsorption with respect to the excess adsorption).<sup>38</sup> This heat of adsorption (related to the enthalpy of adsorption) can also be directly determined using calorimetry.<sup>39</sup> Additionally, measurements at infinite dilution enable the establishment of a relationship between the adsorbed quantity and the pressure, as defined by the Henry's law. The Henry adsorption constant, representing the slope of this linear regime,<sup>40</sup> serves as another key adsorption descriptor. Although these thermodynamic quantities alone do not provide a complete picture of the adsorption process as an adsorption isotherm would, they are most valuable for comparing experimental data with computational models to rapidly characterize the materials suitable for a target gas adsorption process.



(a) Experimental



(b) Theoretical calculation

Figure 1.1: Illustration of monocomponent adsorption isotherms of Xe and Kr obtained experimentally (a) and through GCMC calculations (b). The experimental data are made available<sup>1</sup> by the authors of the Ref. [41].

Most of the materials studied in my thesis have pores with sizes around the nanometer scale, therefore called “nanopores”. The International Union of Pure Applied Chemistry (IUPAC) classifies these pores into three categories according to their size: micropores ( $\leq 2$  nm), mesopores

<sup>1</sup> Available on Github at <https://github.com/CorySimon/XeKrMOFAdsorptionSurv>

(2 nm–50 nm) and macropores (>50 nm).<sup>42</sup> Here, a single terminology – nanopore – will be used to encompass all pores that are a few nanometers or less in size. A good characterization of the nanopores of these materials is key to fine-tuning the adsorption properties.<sup>35</sup> The pore size distribution (PSD) can be computationally determined if the structure of the nanoporous material has already been resolved using X-ray diffraction on crystallized porous solids. This method provides the most accurate determination of the PSD, assuming the structure is perfectly rigid and crystalline, allowing for a single set of structural data to characterize it. Other experimental methods rely on assumptions, model systems (e.g., cylindrical) or adsorption characteristics. For instance, stereological analyses based on plane sections cut through a porous material can be used to evaluate the PSD.<sup>43</sup> Another approach is the Horvath-Kawazoe (HK) method is a semi-empirical analytic model of adsorption isotherm that can extract information about the PSD. Small angle X-ray and neutron scattering methods are non-destructive methods of pore characterization.<sup>44</sup> My thesis will primarily rely on computationally analyzing experimental structures to deduce pore sizes and other geometric characteristics.

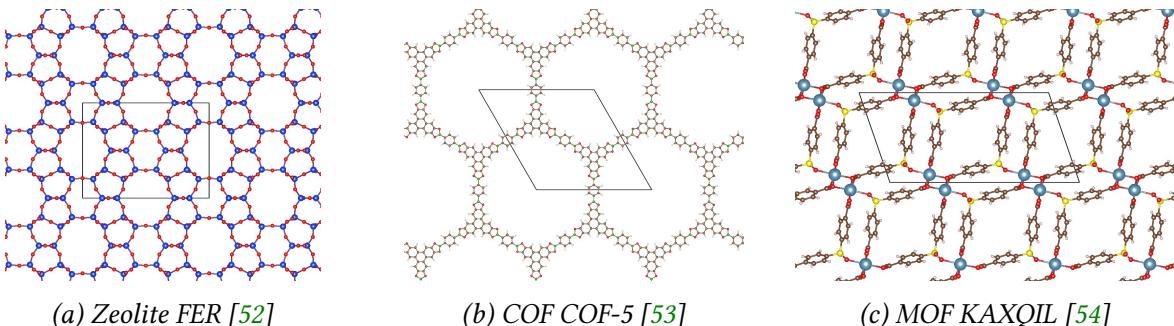
The pore volume of nanoporous materials represents the combined volume of both “closed” and “open” pores. However, the measured quantity can vary depending on the method used. Some pores are not accessible to a specific adsorbate, resulting in different calculated volumes depending on the size of the probe used. Methods that do not rely on adsorption like scattering or stereology techniques can only measure the total pore volume. The porosity or void fraction is defined as the ratio between the pore volume and the apparent framework volume. The specific method used determines whether we can retrieve total porosity, porosity open or closed to a given probe or adsorbate.

The cavities within nanoporous materials provide an exceptionally large adsorbable surface area, which is extremely useful for increasing the number of molecules within a given volume or mass of material, several thousands of square meters can be found in a gram of some nanoporous materials.<sup>45</sup> A higher surface area of nanoporous materials allows for a greater number of molecules to be adsorbed for applications such as storage, separation or reactions. Therefore, accurate measurement of surface area using both experimental and computational methods is of utmost importance. The Brunauer–Emmett–Teller (BET) theory is the most widely used method for experimental determination of surface areas based on adsorption isotherms.<sup>46</sup> Most BET areas are calculated using the N<sub>2</sub> isotherm at its boiling temperature (77 K). While alternative probe adsorbates can be considered, they are not standardized.<sup>47</sup> However, it is important to note that the definition of surface area is highly dependent on the measurement conditions and the fitting methodology employed. In a statistical experiment involving 61 laboratories, a set of twelve isotherms was provided for BET area calculation, revealing significant disparities in calculation results.<sup>48</sup>

Beyond the experimental techniques, there are softwares such as Zeo++ or PoreBlazer that specialize in computing pore size distributions, surface areas and void fractions based on well-defined structure files.<sup>49,50</sup> The definition of these values also depends on the probe size chosen to model a given adsorbate, the size of the framework atoms and the quality of the input structure. The computational values utilize more comprehensive structural data rather than relying on adsorption models or isotherm data like the BET area calculation. However, the determination of these values heavily relies on a well-designed definition of the volume, the surface and the pore size we aim to evaluate. Moreover, these values also highly depend on the

radii of the framework atoms and the adsorbate we consider.<sup>51</sup> In this thesis, we will rely on these computational methods to define geometrical descriptors of nanoporous materials.

### CLASSES OF NANOPOROUS MATERIALS



*Figure 1.2: Illustration of a zeolite, a covalent organic framework (COF) and a metal–organic framework (MOF). Color code: brown for C, white for H, red for O, blue for Si, cyan for Ca, yellow for S and green for B. The structure visualizations were generated using the VESTA software.<sup>55</sup>*

Nanoporous materials exhibit varying degrees of crystallinity, ranging from perfectly crystalline structures to completely amorphous ones. Computational studies primarily focus on crystalline structures, as atoms are well described within a periodic framework, enabling faster simulations. However, these simulations often neglect the presence of defects, which can explain some discrepancies between simulations and experimental observations. Amorphous materials are described by thousands of atomic positions to capture their inherent non-periodicity.<sup>56</sup> Activated carbons, a well-known class of amorphous material, find extensive industry applications for gas purification purposes. However, characterizing their adsorption properties in a rational manner poses challenges. In general, crystalline nanoporous materials can be categorized into three main classes: inorganic materials such as zeolites (aluminosilicates or aluminophosphates), organic materials like porous polymer networks (PPNs) or covalent organic frameworks (COFs), and metal–organic frameworks (MOFs).

Zeolites are naturally occurring nanoporous aluminosilicate materials that are commonly synthesized to be used in the industry as a commercial adsorbent and heterogeneous catalyst.<sup>57,58</sup> They are considered as one of the most mature nanoporous material technologies at our disposal. This class of material offers ample opportunities for innovation as different Al/Si ratios within a specific zeolite type pan out a wide range of structures. Furthermore, zeolite materials have inspired the synthesis of zeolitic frameworks harboring different atoms such as the aluminophosphates or the zeolitic imidazolate frameworks.<sup>59,60</sup>

Porous polymer networks (PPNs) are porous materials based on the well-established polymer material technology.<sup>37,61,62</sup> However, one of the major drawbacks of this type of material is the formation of irreversible covalent bonds, which make the synthesis kinetically controlled and poses challenges in crystallizing PPNs.<sup>63</sup> To overcome this limitation and create crystalline porous materials, Cote et al. developed a strategy using boron-based organic compounds to form reversible bounds, leading to thermodynamically stable materials COF-1 and COF-5.<sup>53</sup> This initiative was led by the group of Yaghi, who has made significant contributions to another very promising and well-known class of materials. A decade earlier, they had pioneered a hydrothermal synthesis of a metal–organic framework presenting broad rectangular channels.<sup>64</sup>

Metal–organic frameworks (MOFs) are a class of nanoporous materials formed by metallic centers connected with organic linkers, resulting in a stable crystalline solid. Although the first synthesis of MOFs dates back to the early 90s,<sup>65</sup> and brought about a sparking interest in the scientific community a couple of decades later.<sup>66,67</sup> The vast number of possible combinations of linkers and metals allows for the theoretical design of an infinite variety of MOFs. Their structure can be tuned to meet our specific requirements and enhance their performance in targeted applications.<sup>68</sup> This diversity of nanoporous materials offer a wide range of potential candidates that can be evaluated for any targeted application.

### 1.1.2 Databases of nanoporous materials

All the previously described materials have been either synthesized and resolved using X-ray crystallography or computationally constructed. By combining almost all possible nanoporous materials, nearly a million structures have been considered for applications in separation or storage.<sup>18,69,70</sup> This extended database can be broken down into synthesized materials and hypothetical ones for all the above-mentioned classes of material.

The International Zeolite Association (IZA) has provided a standardized set of 244 zeolites (in their idealized all-silica form) that can be used for screening purposes. To generate a dataset of structures, existing experimental databases such as the Cambridge Structural Database can be leveraged. However, the raw structures determined experimentally via X-ray cannot be directly used as they are. To obtain a computation-ready dataset, Chung et al. used algorithmic cleaning procedures, resulting in the creation of the publicly available Computation-Ready Experimental MOF (CoRE MOF) database.<sup>71,72</sup> CoRE MOF 2019 contains about 14,000 MOF structures, making it the largest experimental database available. Similar approach has been applied to organic frameworks leading to the generation of a set of 187 COFs with disorder-free and solvent-free structures.<sup>73,74</sup>

These experiment-based databases can provide valuable information on targeted applications using computational screenings, but they have limitations since unknown structures are yet to be discovered. To overcome these limitations and biases of experimental synthesis, the use of artificial methods for generating nanoporous material datasets has proven to be extremely efficient. The first *in silico* generated database of approximately 130,000 MOFs used a recursion-based assembly (or Tinkertoy-like) algorithm to combine 102 building blocks.<sup>12</sup> Martin and Haranczyk then proposed a topology-specific structure assembly algorithm that leverages the topological information of the structures.<sup>75</sup> This algorithm served as inspiration for the development of topology-based databases emerged a few years later with the set of 13,000 MOF structures generated using the Topologically Based Crystal Constructor (ToBaCCo) algorithm by Colon, Gómez-Gualdrón and Snurr.<sup>14</sup> Later, Boyd and Woo introduced another topology-based algorithm using a graph theoretical approach and generated a 300,000-structure database (BW-DB) based on 46 different network topologies.<sup>13</sup> Similar approaches have been used for other classes of materials. For instance, Deem and co-workers presented a dataset comprising approximately 2.6 million hypothetical zeolite structures.<sup>76–78</sup> However, an important consideration arises regarding the synthesizability and the stability of these hypothetical structures under various operational conditions (e.g., thermal, mechanical, radioactive constraints). To discuss their synthetic likelihood, Anderson and Gómez-Gualdrón computed the free energies of 8,500 hypothetical structures and compared them with experimentally observed

MOF structures.<sup>79</sup> Later, Nandy et al. performed a meta-analysis of thousands of articles associated to the CoRE MOF 2019 database to extract their experimental solvent-removal stability and thermal decomposition temperature.<sup>80</sup> These data are then leveraged in the training of multiple ML models to predict stability properties. Such predictions can prove very useful for gauging the relative stability of each material and to only consider stable structures. Other types of materials have been explored. For instance, Turcani et al. published 60,000 organic cage structures and used machine learning to predict their stability based on the shape persistence metric.<sup>81</sup>

The Materials Genome Initiative, 100 million dollar effort initiated by the White House that aims to “discover, develop, and deploy new materials twice as fast”, led to the creation of the “Materials Project”, a centralized database encompassing all the above-mentioned structures.<sup>82–84</sup> The fast development of this nanoporous materials genome has motivated Boyd et al. to write a comprehensive review on all the initiatives focused on generating new data for computational analysis.<sup>85</sup>

Yet, simply increasing the size of the databases is not sufficient. It is essential to add diversity to obtain more comprehensive knowledge on the maximum performance and the explanatory features contributing to that performance. Moreover, the diversity of structures ensures the quality of predictions for identifying the best materials for specific applications. To qualitatively or quantitatively assess the diversity of a database, innovative methodologies have been developed. For instance, Martin, Smit and Haranczyk proposed a Voronoi hologram representation as a way of measuring similarities between structures to generate geometrically diverse subsets of a database.<sup>86</sup> Moosavi et al. conducted a comparative study of the diversity of three well-known databases CoRE MOF 2019,<sup>72</sup> BW-DB<sup>13</sup> and ToBaCCo<sup>14,87</sup> – using geometric and chemical descriptors to design a theoretical strategy for generating the most diverse set of materials.<sup>88</sup> Another approach consists in searching for similarities instead of differences between materials by studying topological patterns in the data.<sup>89</sup> These investigations into data structures provide a solid ground for the development of novel materials by objectively defining similarity, diversity and novelty. Based on the analyses conducted thus far, a radical shift in approach is necessary to achieve significant improvements in the diversity of current databases. This requires proposing materials featuring new chemistry, topology or mechanisms (e.g., flexibility).

### 1.1.3 Exploring the chemical and structural space

With the development of ever-increasing nanoporous material databases, computational chemists have proposed increasingly innovative methods for evaluating and screening thousands of structures. However, new challenges have emerged, including the need to design more efficient screening methods that surpass the brute force screening and effectively analyze big data. Two research groups in Northwestern University, led by R. Snurr and J. Hupp, began to address these challenges by using a “funnel-like” approach to efficiently screen approximately 130,000 hypothetical MOF structures.<sup>12</sup> To achieve this, they performed a first screening that involved fewer steps of simulation on the entire dataset. They then extracted a subset of top-performing structures to subject them to a second round of simulations, which involved more steps. This procedure was repeated until a few materials were selected through a final round of simulations with reasonable accuracy. Similar “funnel-like” procedures have then been adopted

in other fields of applications as described on Figure 1.3. This screening method optimizes computation time by striking a balance between the complexity of calculations and the amount of data to be screened. It ensures that only the most demanding simulations or experiments are applied to the few most promising structures. While this method efficiently identifies top candidates, it has limitations in drawing quantitative structure-property relationships (QSPR) and faces scalability issues beyond a critical dataset size.

To overcome these new challenges, researchers are increasingly turning to transferable models trained by a machine learning (ML) algorithm on diverse and size-limited subsamples. Ideally, such models are transferable to potentially millions of structures and can provide valuable QSPR. For instance, Fernandez et al.<sup>17</sup> used multiple linear regression analysis, decision tree regression, and nonlinear support-vector machine models to extract QSPR and establish design principles for high-performing MOFs in methane storage applications, while also identifying promising structures. In their initial work, they only used geometrical descriptors to describe methane storage.<sup>17</sup> However, realizing the importance of chemical descriptors, they proposed the atomic property weighted radial distribution function as a powerful descriptor to predict CO<sub>2</sub> uptakes.<sup>90</sup> More importantly, they proved that ML can be used as a pre-screening tool to avoid running time-costly simulations by accurately identifying around 95 % of the top 1000 best-performing materials. Recently, the same group used similar techniques to predict CO<sub>2</sub> working capacity as well as CO<sub>2</sub>/H<sub>2</sub> selectivity in MOFs for pre-combustion carbon capture.<sup>91</sup>

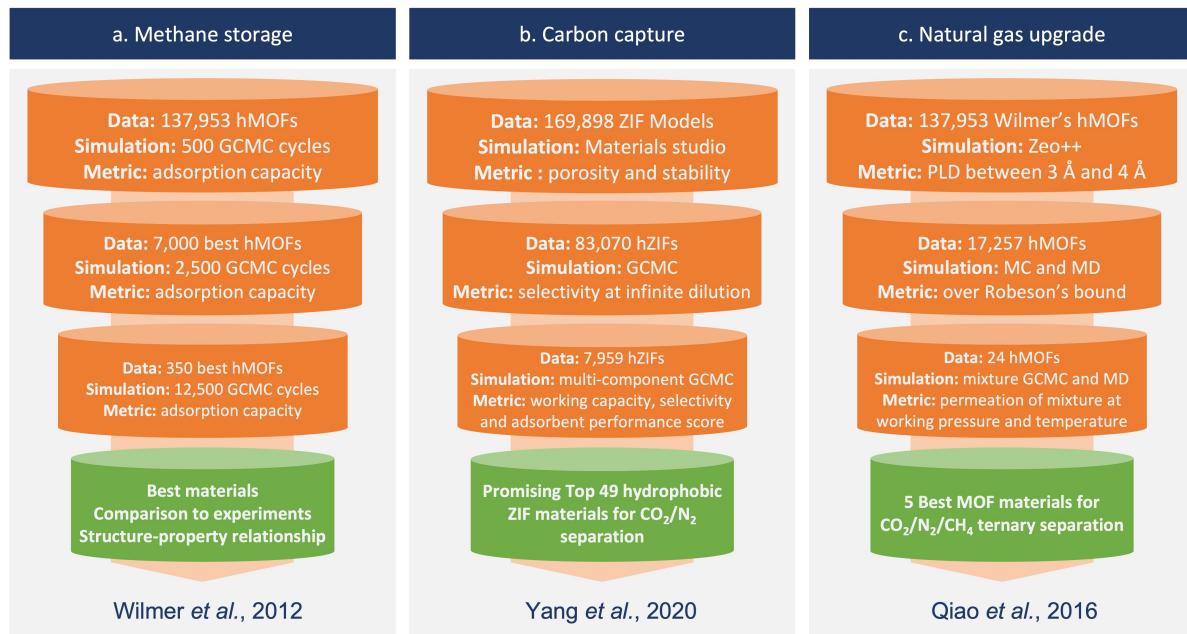
## 1.2 REVIEW OF SCREENING METHODOLOGIES

Now that the main concepts around nanoporous materials and their computational representations have been covered, we can introduce the methods used to extract meaningful information from this data. These methods enable us to screen, i.e. evaluate systematically all the structures from a database. Given the scaling issue of such an enterprise, it is essential to employ speed-up strategies in these screenings.

The following review aims to provide an exhaustive overview of different screening methodologies used for evaluating nanoporous materials across very different applications. This state-of-the-art review, originally published in Digital Discoveries Ref. [21], has been adapted for the purpose of this manuscript.

### 1.2.1 Non-adsorption properties

Due to their high internal surface area, adsorption applications were a natural outlet for nanoporous materials. However, these materials can be used in a wide range of other applications. This section focuses on the physical and chemical properties that are not directly related to adsorption processes inside nanoporous materials, such as catalytic activity,<sup>92–94</sup> mechanical properties,<sup>95,96</sup> or thermal properties.<sup>97–99</sup> These properties require a more refined description of atomic interactions within the material. To accurately capture these properties, DFT simulations are typically performed. However, the computational cost required for DFT simulations is significantly higher, multiplying the computational time by several orders of magnitude compared to classical simulations. The size of the datasets screened is therefore much smaller (a few hundreds maximum), and the use of ML can potentially speed up the



*Figure 1.3: Simplified representation of typical funnel-type screening procedures, exemplified on three different applications from the published literature. (a) Wilmer et al.<sup>12</sup> used a series of bi-component Grand Canonical Monte Carlo (GCMC) calculations at different levels of complexity to screen a large dataset of hypothetical MOFs for methane storage application. (b) Yang et al.<sup>16</sup> used simulations at infinite dilution to prescreen the dataset before using computationally demanding simulations and multiple metrics to find the most promising ZIFs for carbon capture. (c) In Qiao et al.,<sup>15</sup> transport properties were screened along standard adsorption properties to find the best materials for the targeted CO<sub>2</sub>/N<sub>2</sub>/CH<sub>4</sub> ternary separation; similarly, cheaper calculations at infinite dilution were carried out in a first step, before using more expensive calculations at working pressure and temperature.*

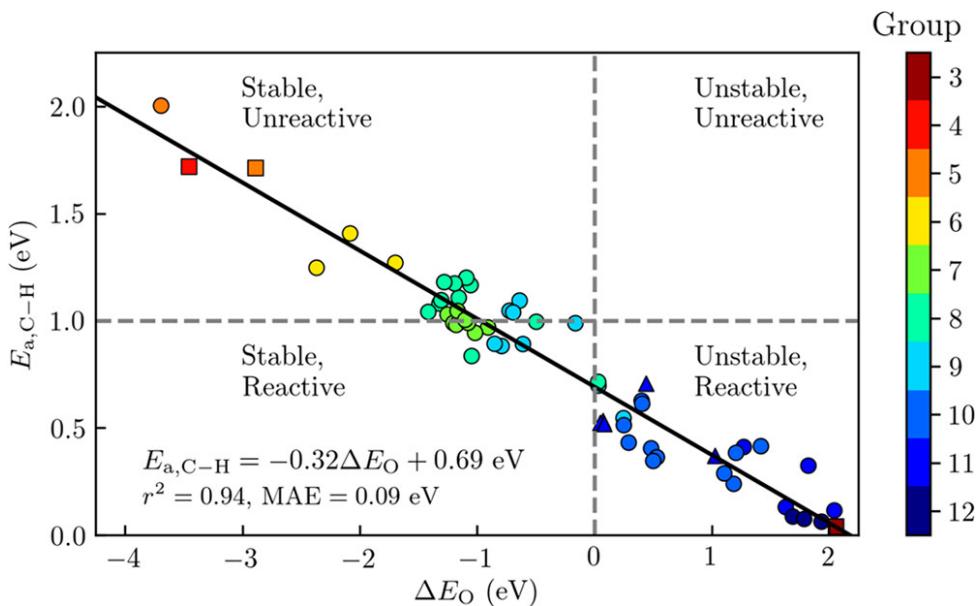
whole process. ML is based on lower-cost descriptors,<sup>100,101</sup> or can be used in ML potentials for molecular simulations.<sup>102,103</sup>

### CATALYTIC ACTIVITY

Beyond adsorption properties, screening procedures have been applied to chemical properties, such as catalytic activities. While heterogeneous catalysis is generally performed using metallic nonporous structures, the use of nanoporous materials can significantly increase the active surface area and catalytic activity. In this regard, MOFs have demonstrated promising catalytic properties for several chemical reactions, including hydrogenation, hydrolysis, oxidation among others, as explicitly covered by McCarver et al. in their review.<sup>104</sup> Considering the sheer number of possible materials, computational studies are potentially more effective than experimental ones. Therefore, computational screenings have evolved over the past decade to study larger datasets.

Although the vast majority of computational screenings have been conducted on small series, there have been a few notable attempts to conduct systematic screenings on larger datasets. The scarcity of the latter can be attributed to the high level of computational cost required. Here, we show some examples of such attempts, particularly in the context of C–H bond activation for the conversion of alkanes into alcohols in the presence of nitrous oxide.

Inspired by enzymatic catalysis of the reaction of small alkanes with N<sub>2</sub>O into alcohols, Vogiatzis et al. identified seven iron-containing MOF structures out of 5,000 structures from the CoRE MOF database.<sup>105</sup> They found two descriptors that govern the catalytic activity: (i) the N–O dissociation energy of N<sub>2</sub>O on the adsorption site and (ii) the energy difference between two spin states of the intermediate. By screening these descriptors, the authors identified three promising structures for further experimental studies. The best structure has been computationally demonstrated to catalytically and selectively oxidize ethane to ethanol in presence of N<sub>2</sub>O. Moreover, the authors found that defects played a major role in the observed catalytic activity.



*Figure 1.4: Analysis of a diverse set of experimentally derived metal–organic frameworks (MOFs) with accessible metal sites for the oxidative activation of methane. The graph shows the predicted barrier for the C–H bond activation of methane,  $E_a$ , as a function of the metal-oxo formation energy,  $\Delta E_O$ . For each material, the symbol color refers to the group number of the metal in the periodic table. The best-fit line has been plotted in black, and has a mean absolute error (MAE) of 0.09 eV. MOFs with  $E_a < 1$  eV are classified as being reactive towards C–H bond activation and MOFs with  $\Delta E_O < 0$  as having thermodynamically favored active sites when using O<sub>2</sub> as the reference state. Reprinted with permission from Ref. [106]. Copyright © 2019 American Chemical Society.*

Later, Rosen et al. enlarged the scope of materials screened to other metals.<sup>106</sup> From an 838 DFT-optimized MOFs subset of CoRE MOF 2014, the authors selected 168 MOFs that were likely to have open metal sites and pore-limiting diameters enabling reactant diffusion. They then used a fully automated workflow to place the reactants in the adsorption site and performed periodic DFT calculations to relax the system. As shown on Figure 1.4, they used the bond activation energy  $E_{a,C-H}$  and the metal-oxo formation energy  $\Delta E_O$  as key parameters to classify materials according to their relative stability and reactivity and find the best materials for the application. These energies were then analyzed using physicochemical descriptors such as spin density on oxygen and metal–oxygen distance.

As this brute force screening approach can quickly become cumbersome, researchers in the field are striving to find essential structure-activity relationships to accelerate future computational

screenings. Several descriptors have been developed for high-throughput screenings. For instance, Butler et al. used electron removal energies to explain photocatalytic behaviors of MOFs,<sup>107</sup> while Rosen et al. showed that the energy required to form the metal oxide intermediate was a major descriptor of the thermal catalysis of alkane oxidation by N<sub>2</sub>O.<sup>108</sup> Fumanal et al. presented a screening protocol based on two energy-based descriptors to predict the photocatalytic properties of MOFs.<sup>109</sup> Rosen et al. recently conducted screenings of thousands of MOF structures to compare different DFT functionals and leveraged the calculated data to train machine learning models capable of rapidly predicting MOF band gaps.<sup>110</sup>

The development of ML methods is also critical in the field,<sup>19</sup> although the lack of centralized database with high precision descriptors poses a challenge for the future of these methods. The influence of defects, the different ways of modeling MOFs as periodic structures or clusters, the diversity of structures and the stability of such structures remain open problems. However, these challenges do not undermine the major role of high-throughput screenings in the early design process of nanoporous materials for catalysis. In conclusion, for a more comprehensive understanding of this topic, readers are encouraged to refer to a more exhaustive presentation in Ref..<sup>111</sup>

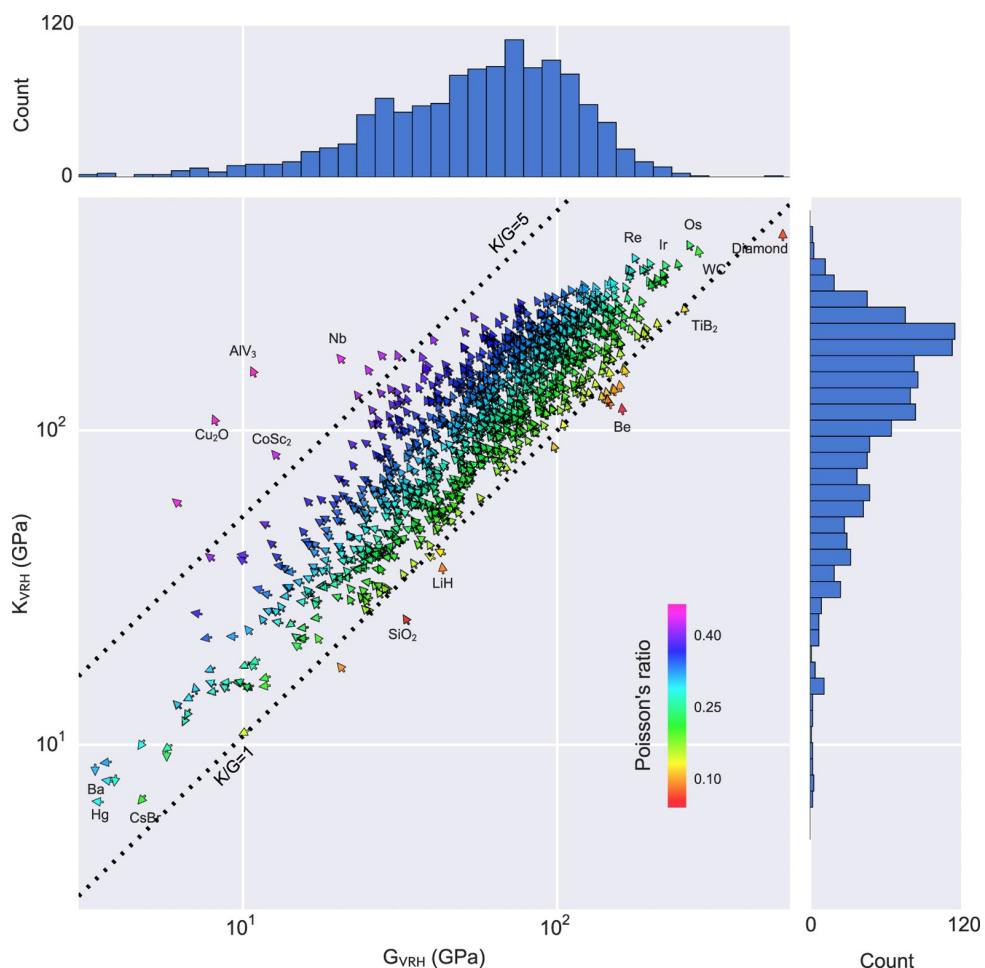
### MECHANICAL PROPERTIES

In the past decade, there has been a growing interest in the systematic study of physical properties of various classes of materials, including inorganic and framework materials. Among these physical properties, mechanical properties have garnered significant interest due to their fundamental importance and relevance to numerous applications. The ability to compute these properties using relatively standard methodologies has further fueled this interest. In particular, is it possible to calculate linear elastic constants (the second-order elastic tensor) in the zero-Kelvin limit by strain/stress or strain/energy approaches, performing a series of DFT calculations of strained structures and calculating the elastic constants. From these constants, all other mechanical properties can be evaluated through tensorial analysis,<sup>112</sup> including the bulk modulus, Young's modulus, shear modulus, Poisson's ratio, etc. This type of calculation can be coupled with any available quantum chemistry code,<sup>113</sup> and is even integrated in some packages like CRYSTAL17.<sup>114</sup>

A notable early study that investigated systematically the elastic properties of a specific material family was conducted in 2013 on all-silica zeolites,<sup>115</sup> i.e., crystalline and porous SiO<sub>2</sub> polymorphs. While this study focused on only 121 zeolitic frameworks out of the 244 known structures, it demonstrated that systematic studies at the DFT level were computationally tractable and provided physical insights into the link between microscopic structure and macroscopic physical properties. This study also showed, among other things, that a few zeolites presented large negative linear compressibility (NLC), which could be linked to the wine-rack motif of their frameworks.

Beyond the specific case of zeolites, other groups have applied DFT calculations to determine elastic constants in a high-throughput manner. For example, de Jong et al. leveraged the structures of the Materials Project<sup>83,84</sup> to chart the diversity of elastic properties across the whole space of inorganic crystalline compounds.<sup>116</sup> As shown on Figure 1.5, they provided a database containing the full elastic information of 1,181 inorganic compounds initially. Since then, the database has grown steadily and currently encompasses nearly 14,000 records.<sup>117</sup> This dataset has been used in two different ways by researchers in the field.

Firstly, researchers have employed tensorial analysis to quantitatively investigate the occurrence of certain “anomalous” or rare mechanical behavior within the database of elastic properties. These behaviors include negative linear compressibility, very high anisotropy, or negative Poisson’s ratio (also called *auxeticity*). Indeed, such properties are considered rare and usually sought after – the materials exhibiting these anomalous behaviors are mechanical metamaterials.<sup>118</sup> In addition to their fundamental significance, such materials find applications in materials engineering areas, such as energy dissipation (as shock absorbers and for bulletproofing), energy storage, as well as acoustics.<sup>119</sup> However, quantifying exactly “how rare” these behaviors have been challenging until now. Chibani et al. performed a systematic exploration of available mechanical properties of crystalline materials and demonstrated that the general mechanical trends, which hold for isotropic (noncrystalline) materials at the macroscopic scale, also apply, on average, to crystals. Moreover, they could quantify the presence of materials with rare anomalous mechanical properties: 3% of the crystals exhibited negative linear compressibility, and only 0.3% displayed complete auxeticity (negative Poisson’s ratio in all directions of space).



*Figure 1.5: Statistical analysis of the calculated volume per atom, Poisson’s ratio, bulk modulus  $K_{VRH}$  and shear modulus  $G_{VRH}$  of 1,181 compounds in the Materials Project database. In the vector field-plot, arrows pointing at 12 o’clock correspond to minimum volume-per-atom and move anti-clockwise in the direction of maximum volume-per-atom, which is located at 6 o’clock.*

*Reprinted from Ref. [116] under CC-BY license. Copyright © 2015 de Jong et al.*

Secondly, the datasets of mechanical properties were used as a basis to accelerate the discovery of novel materials with targeted behavior. Dagdelen et al. used search algorithms to identify 38 candidate materials exhibiting features correlating with auxetic behavior, from more than 67,000 materials in the Materials Project database.<sup>120</sup> Performing DFT calculations on these 38 structures, they could identify 7 new auxetic compounds. In a more complex setup, Gaillac et al.<sup>96</sup> have used a multiscale modeling strategy for the fast exploration and identification of novel auxetic materials. They combined classical force fields MD simulations with DFT calculations on candidate materials, and then used this reference DFT data to train an ML algorithm. They found that the accuracy of this multiscale method exceeds the current low-computational-cost approaches for screening. In a similar work, Moghadam et al. used molecular simulation to train an artificial neural network (ANN) for the prediction of the bulk modulus of metal-organic frameworks.<sup>121</sup> This shows the potential of such methodologies to treat very different (chemically as well as structurally) classes of materials.

### Thermal Properties

While mechanical properties (in the elastic regime) have been by far the most studied physical property in nanoporous materials, others have also been occasionally screened. We can cite, in particular, the systematic study of piezoelectric tensors by de Jong et al., on almost a thousand crystalline compounds, by first-principle calculations based on density functional perturbation theory.<sup>122</sup> We can also cite efforts to calculate thermal properties in a high-throughput setup, using the quasi-harmonic approximation (QHA).<sup>123</sup> This method requires the calculation of each structure's phonon modes at various volumes, and can be coupled to any electronic structure program.<sup>124</sup> It is, however, quite computationally intensive, and sensitive to the parameters of the QHA methodology (range of volume, range of temperature, precision of the frequency calculation, etc.). Therefore, it has been limited so far to modest numbers of structures: a dataset of 75 inorganic structures by Toher et al.,<sup>97</sup> and more recently a dataset of 134 pure SiO<sub>2</sub> zeolites by Ducamp et al.<sup>99</sup> Very recent work in our group on the prediction of thermal properties through machine learning based on structural features alone indicates that thermal behavior is more difficult than mechanical behavior to predict, and might require the use of a wider set of structural descriptors or more advanced ML models.<sup>101</sup>

### 1.2.2 Transport adsorption properties

The thermodynamic properties, we will be presenting in the next section, only describes the state of equilibrium of the adsorption process. But sometimes the transient state can last long before reaching the equilibrium, which makes the process more time-consuming. Thus, the transport properties complete the thermodynamic description of the adsorption process inside a nanoporous material. For example, a low diffusion rate would mean for storage applications more time and energy needed to fill-up the tanks, or for separation applications a less selective process than expected. In more extreme cases of molecular sieves for fluid separation, the transport properties become predominant to assess the performance. One can leverage the difference of the molecules' diffusion coefficients to selectively filter gas mixtures through a nanoporous membrane.<sup>125</sup> Here, the main subject becomes the transient state and not the equilibrium. This section is thus dedicated to the kinetics of the adsorption process to better model the time required to reach the equilibrium or to study out-of-equilibrium processes such as molecular sieving by nanoporous membranes.

## KINETIC PROPERTIES

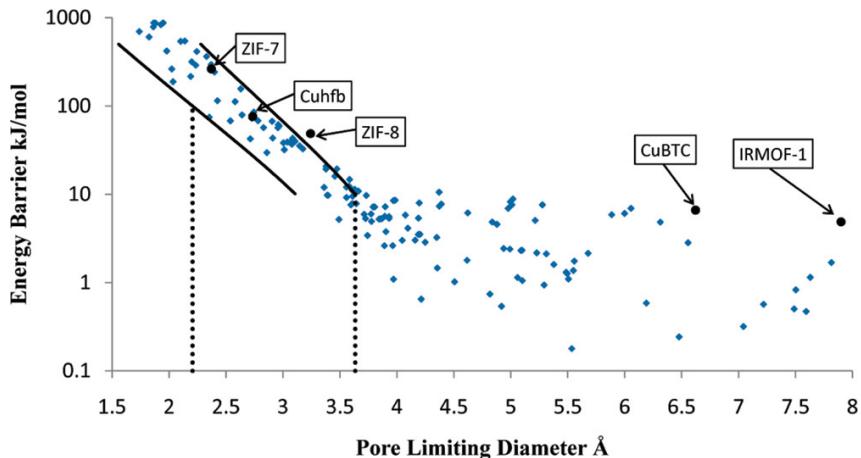
In most computational screenings, the diffusion coefficient considered is the self-diffusion coefficient that describes an infinite-dilution case. Other multi-component diffusion coefficients could be considered, but for simplicity and clarity they won't be mentioned in this review. The calculation of the self-diffusion coefficient gives a first estimation of the kinetics in a storage or a separation process in the limit of low adsorption loading.

There are two approaches to estimate the diffusion inside a porous material: the first one relies on molecular dynamics (MD) and the second one on transition state theories. In the first approach, one can analyze the mean squared displacement of the adsorbed molecule moving in the material. In the second, one identifies minimum energy path along the material to identify transition states (TS) to calculate diffusion energy barriers. The MD-based method requires fewer assumptions and is therefore more reliable than the TS-based method, but the latter is computationally more efficient in the case of low diffusion rate (diffusivity lower than  $10^{-11} \text{ m}^2 \text{ s}^{-1}$ ).

State-of-the-art MD simulations could calculate rather accurate diffusion coefficients, but the computational cost scales quickly with the number of structures. To use this method on a large dataset without spending too much computation time, Watanabe and Sholl prescreened the pore sizes of 1,163 MOFs to select only the structures within a certain range of PLD (pore limiting diameters).<sup>126</sup> A restricted list of 359 MOFs was then used to carry out MD simulations to calculate diffusion coefficients. The results of this final screening are then used to extract the most promising structures for further experimental or computational investigation. Similarly, Qiao et al. used a multistage screening to find the best membrane material within about 130,000 hypothetical MOFs for a CO<sub>2</sub>/N<sub>2</sub>/CH<sub>4</sub> separation.<sup>15</sup> They started to select materials based on pore geometry analysis; then they calculated Henry's coefficient and diffusion coefficients at infinite dilution; finally, they compared the binary permselectivities to extract 24 promising MOFs for ternary adsorption and diffusion calculation at the desired pressure and temperature conditions.

Another approach replaces MD simulations with more computationally efficient TS-based methods to determine diffusion coefficients. Haldoupis et al. developed an algorithm to identify diffusion paths by exploiting an energy grid with a clustering algorithm. The diffusion paths are then analyzed to identify the pores and the channels, and to calculate key geometric (the PLD or the largest cavity diameter) and energetic (Henry's constant, diffusion activation energy) features.<sup>127</sup> As illustrated on Figure 1.6, they found a clear dependence of the diffusion energy barrier to the PLD. As one of the first TS-based screenings, it is still subject to many development perspectives. For instance, the approach is limited to spherical adsorbates and rigid frameworks. Moreover, the diffusion coefficients are approximated using a simplistic hopping model for a qualitative analysis. This method is highly efficient, but the accumulation of approximations makes a quantitative systematic analysis of diffusion coefficients out of reach.

Later, Kim et al. introduced a flood fill algorithm to obtain all the points within a given energy.<sup>128</sup> These points are then identified as channels or blocked regions. Along the channels, local minimums of energy are defined as lattice sites and transition states are defined perpendicular to the diffusion direction. A random walk is then computed along the lattice sites with hopping



*Figure 1.6: Calculated energy barrier for the diffusion of CH<sub>4</sub> in 216 metal–organic frameworks (MOFs), shown as a function of the pore-limiting diameter. The solid lines represent statistical upper and lower bounds on the energy barrier, in a transition state theory approach. Reprinted with permission from Ref. [127]. Copyright © 2010 American Chemical Society.*

rates defined according to the activation energy. A diffusion coefficient is then calculated in each three directions of the space and an average diffusion coefficient is finally determined. A comparison with the MD method on the IZA zeolite structures shows good agreement, but there are still some discrepancies explained by correlated hops in the case of rapid diffusion or by the presence of complicated channel profiles. Inspired by this work, Mace et al. developed a similar method that progressively fill the energy grid to detect transition states, hence removing the previous restriction to orthogonal cells only.<sup>129</sup> The diffusion coefficient is now computed using a kinetic Monte Carlo simulation allowing the adsorbate to jump freely in all directions instead of restricting it in a single dimension. This new method, called TuTraSt, handles very complex diffusion paths (like in the AEI zeolite). This new approach seems to be promising as it is in good agreement with MD simulations, while being 2-3 orders of magnitude faster. However, the time performance could improve tremendously by translating it from Matlab to C++ and by implementing parallelization procedures.

Very recently a massively parallel GPU-accelerated string method has been implemented and shared publicly to compute very efficiently diffusion coefficients based on the transition state theory.<sup>130</sup> The recent developments in the prediction of diffusion coefficients in nanoporous materials point towards a promising future for the screening of transport properties applied to even larger databases. Going further, Bukowski et al. reviewed thoroughly diffusion in nanoporous solids as an attempt to connect theory to experiments.<sup>131</sup>

## MEMBRANE MATERIALS

In separation application, the study of the transport properties can evaluate the feasibility of the thermodynamic equilibrium, crucial for any bed separation process. If this separation is not feasible, kinetic separation or partial molecular sieving are to be considered. Some notable examples are air separation in zeolites using pressure swing adsorption,<sup>132</sup> N<sub>2</sub>/O<sub>2</sub> separation in carbon molecular sieves,<sup>133</sup> or N<sub>2</sub> removal from natural gas.<sup>134</sup> In kinetic separation, the valuable metric is not the selectivity anymore, but the permselectivity, i.e. the product of the selectivity and the permeability (ratio of diffusion coefficients). Therefore, the screening of diffusion coefficients gives complementary information to the thermodynamic selectivity

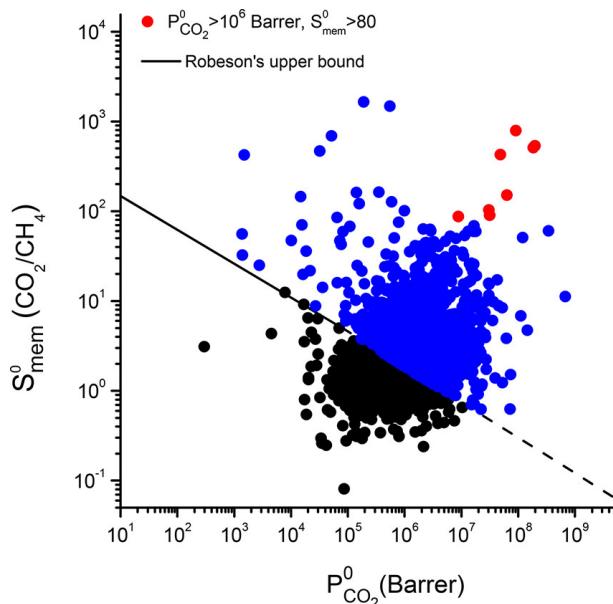
screenings. Here, we give some examples of such screening and the main descriptors that partially explain the computed figures of merit.

To give an overview on the potential of computational screenings to predict transport properties, we are now going to focus on the membrane separation applied to natural gas upgrading. The separation of CH<sub>4</sub> from N<sub>2</sub> and CO<sub>2</sub> is a crucial step of this upgrading process. In 2016, a large-scale high-throughput screening (see Figure 1.3 for the approach) of hypothetical MOF membranes for upgrading natural gas has been performed using MD simulations.<sup>135</sup> Qiao et al. confirmed the existence of MOF materials beyond the upper bound for N<sub>2</sub>/CH<sub>4</sub> and CO<sub>2</sub>/CH<sub>4</sub> separations determined by Robeson on a large set of polymeric membranes.<sup>135</sup> This Robeson's upper bound is systematically crossed by MOF materials in computational screenings, see as an example Figure 1.7. This can be explained by the fact that MOFs perform better than polymeric frameworks and the simulations at this level of theory. They also identified 24 MOFs suitable for the ternary CO<sub>2</sub>/N<sub>2</sub>/CH<sub>4</sub> separation using a multistage screening described in the previous section.

Two years later, Qiao et al. used the same approach to study this ternary separation on a database of synthesized structures.<sup>136</sup> Applying machine learning techniques to their data, they performed a QSPR analysis. Using a principal component analysis, they notably found that the permeability is higher when materials have high PLD and void fraction coupled with low density and percentage of pores within a characteristic range. The opposite was found to be true for high membrane selectivity for the CO<sub>2</sub>/CH<sub>4</sub> separation. Using decision tree algorithms, they gave objective procedures of selecting the best separation membranes based on some key descriptors. Finally, they studied in detail some top performing materials found by a support vector machine algorithm.

Altintas and Keskin later performed a screening on the same database for CO<sub>2</sub>/CH<sub>4</sub> membrane separation to identify the best performing materials and perform more computationally demanding simulations.<sup>137</sup> The simulations in rigid structures at infinite dilution show numerous structures above the Robeson's upper bound as shown on Figure 1.7, this crossing of the upper-bound can be explained by either a better performance of MOF membranes compared to the polymeric membranes used by Robeson, or an overestimation due to oversimplified assumptions (infinite dilution, rigidity). But when higher pressures and flexibility are considered, the selectivity values are dropping down closer to the upper boundary, hence confirming the overestimation of the performance in screenings based on rigid approximations at infinite dilution. But the best performing materials are still above the Robeson's upper bound and can therefore be used in mixed matrix membranes with polymeric membranes. Budhathoki et al. developed a screening methodology for MOFs in mixed matrix membranes for carbon capture applications by estimating permeation values in these composite materials using a Maxwell model.<sup>138</sup> The authors even proposed a pricing for each material compared to their relative performance. Similar studies have been carried out on different materials, Yan et al. showed the influence of decorating COFs with different chemical compounds on the membrane selectivity.<sup>139</sup>

The transport properties screening is based on the calculation of diffusion coefficients at infinite dilution and in rigid molecules. There are different methods to calculate them (mainly MD and TS-based methods). Flexibility and pressure dependence are very hard to incorporate directly in



*Figure 1.7: Selectivity and permeability of metal–organic framework (MOF) membranes for  $CO_2/CH_4$  separation computed at infinite dilution by combining Grand Canonical Monte Carlo and molecular dynamics simulations.<sup>137</sup> The black solid line represents the Robeson’s upper bound.<sup>135,140</sup> MOFs that can exceed the bound are shown in blue, and the 8 top-performing MOF membranes are shown with red symbols. Reprinted with permission from Ref. [137]. Copyright © 2018 American Chemical Society.*

the screening procedures. Researchers usually consider these factors at the end of the screening on the most promising structures because of the computational complexity of the corresponding simulations. To take account of pressure dependence, we need an MD simulation of several adsorbates that takes much more time than running single component simulations,<sup>141,142</sup> which makes it harder to include in a high-throughput screening. Flexibility could be taken account by calculating snapshots and running multiple MD simulations, or by using flexible force fields, which means in both cases an increase in computational run-time. Some faster methods of quantitatively predicting the impact of flexibility on diffusion are being investigated in ZIFs and could give an interesting alternative to these expensive methodologies.<sup>143</sup>

### 1.2.3 Thermodynamic adsorption properties

In its early development, computational screening was mainly used to predict thermodynamic properties in adsorption processes. Three main applications have been identified in the associated literature: gas storage (for energy or medical applications), gas separation (noble gas, hydrocarbons, carbon dioxide, etc.) and post-combustion  $CO_2$  capture. These applications are closely linked to urgent environmental and energy issues that are yet to be solved. Screening can guide the development of better performing materials by shedding light upon unknown structure-property relationship, probes possible theoretical limitations (unreachable targets) and identifies potential candidates that need to be experimentally tested.

#### GAS STORAGE

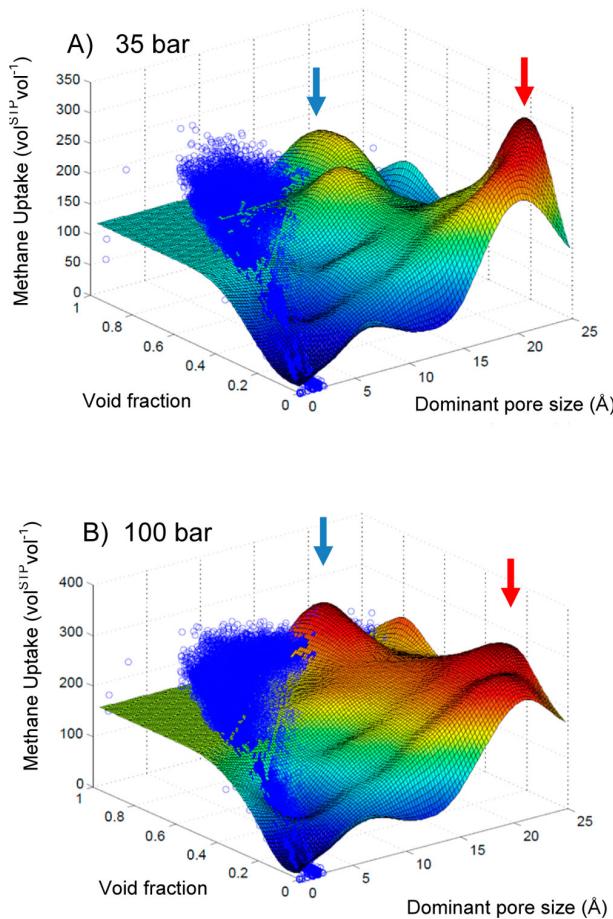
One can leverage the high surface density of the nanoporous materials, especially the MOFs, to stock in very low-density gas. In the field of energy storage or transportation, natural gas (mainly methane) and hydrogen are considered plausible alternative fuels to replace conven-

tional ones for transport. The US Department of Energy (US DOE) recently financed research programs and set targets for methane and hydrogen storage. Nanoporous materials could reduce energy, infrastructure and security cost due to the required compression and cooling. In this section, we are focusing on high-throughput screening for methane storage in nanoporous materials, before broadening the scope hydrogen and other perspectives.

One of the pioneering works in computational screening was published in 2012 by Wilmer et al.<sup>12</sup> They performed a large-scale screening of 137,953 hypothetical MOF structures to estimate the methane storage capacity of each MOF at 35 bar and 298 K based on the US DOE standards. Back then, the US DOE set a target methane capacity value of  $180 \text{ vol}^{\text{STP}}\text{vol}^{-1}$  (which has since been achieved by several materials reported in the literature). In their large-scale analysis, Wilmer et al. found over 300 hypothetical MOFs that meet the targeted requirements and the best one can store up to  $267 \text{ vol}^{\text{STP}}\text{vol}^{-1}$ , surpassing the state-of-the-art of the time. From their large dataset, a preliminary structure-property relationship analysis revealed that void fraction values of approximately 0.8 and gravimetric surface areas in a range  $2500\text{--}3000 \text{ m}^2 \text{ cm}^{-3}$  resulted in the highest methane capacities. Optimal pore size is also shown to be around the size of one or two methane molecule(s). Maximization of gravimetric surface area was a common strategy in the MOF design for storage applications, but this study showed the existence of an optimal range of surface area values. Computational screenings can draw clear relationships between structural descriptors and performance. Later, a more quantitative relationship was drawn by Fernandez et al. using ML models as illustrated on Figure 1.8. Beware not to over-interpret the relation given by the response surface, since the identified maxima do not always have a physical reality, especially where there is no training data in the area pointed by the red arrows. However, it highlights promising unexplored feature space and shows potential research directions.

Since then new materials above the target have been found and the US DOE decided to set a higher target of  $315 \text{ vol}^{\text{STP}}\text{vol}^{-1}$ . Until now, this new target is not yet reached. This is why the recent developments have focused on assessing the feasibility of such a target by accelerating the screening methods so that more data can be screened, and by interpreting the QSPR models to extract important knowledge for the design of novel materials. For instance, Gómez-Gualdrón et al. showed that even by artificially quadrupling the Lennard-Jones interaction factor  $\epsilon$  and by increasing the delivery temperature by 100 K, the newly set target is only reached by a handful of MOFs.<sup>144</sup> This study suggests the impossibility to reach the DOE target using a preconceived (experimentally or theoretically) material to store methane. However, this theoretical limitation can be overcome by increasing the surface density of sites with high affinity with methane and by increasing the delivery temperature.

Later, a larger-scale screening on methane storage was carried out by Simon et al. on 650,000 experimental and hypothetical structures of zeolites, MOFs, and PPNs. This study confirmed that the classes of materials currently being investigated were unlikely to meet the new target. The authors suggested that it wasn't surprising since the target was based on economic arguments, while the screening is based on thermodynamic arguments.<sup>69</sup> This example illustrates the power of large-scale screening to settle questions of physical feasibility (if simulations are accurate) and hence avoiding experimental efforts spent on impossible tasks.



*Figure 1.8: Two-dimensional response surfaces of the support vector machine (SVM) models trained by Fernandez et al. for methane storage at (A) 35 bar and (B) 100 bar using void fraction and dominant pore size. The blue dots represent the GCMC simulated uptake values. The color of the surface represents the methane storage value, from blue (the lowest values) to red (the highest values). Blue and red arrows indicate maxima on the response surface. Reprinted with permission from Ref. [17]. Copyright © 2013 American Chemical Society.*

More recently, a dataset containing trillions of hypothetical MOFs have been screened for methane storage.<sup>145</sup> Lee et al. developed a methodology using machine learning combined with genetic algorithm to perform the largest screening until now. In addition to confirming most of the results (theoretical limits and QSPR) found by previous screenings, 96 MOFs were found to outperform the current world record. This study shows the scaling potential of ML-assisted screenings in handling “Big data”.

Similarly, computational high-throughput screenings have been applied to other storage applications such as hydrogen storage. Computational screenings showed that cryogenic storage of hydrogen can meet the DOE target of  $50 \text{ g L}^{-1}$ .<sup>70,87,146</sup> Anderson et al. performed a large-scale screening based on neural networks to test out multiple pressure/temperature swing conditions to find that the maximal deliverable capacity cannot exceed  $62 \text{ g L}^{-1}$ .<sup>147</sup> Compared to the density of liquid hydrogen ( $72 \text{ g L}^{-1}$ ), this upper limit seems reasonable since the adsorbent material takes at least 10-20% of the tank. Here, we only showed some flagship results of the field. For a more detailed meta-analysis, Bobbitt and Snurr wrote a very complete review on computational high-throughput screening of MOFs for hydrogen storage.<sup>148</sup>

### 1.2.4 Gas separation

As a representative example of what could be done in the field of gas separation, we are going to focus on Xe/Kr separation. Nanoporous materials can be used as a safer, cheaper and less energy-intensive option for this gas separation. However, experimental design of top-performing materials can be cumbersome. Computational screenings is an ideal tool to kick-start the development of this new technology by identifying rapidly the best candidates.

#### SMALL-SCALE SCREENINGS

Metal–organic frameworks, and later other supramolecular porous materials like covalent organic frameworks (COFs), have been proposed for applications in separation of noble gases for a decade. With no aim of being exhaustive, we highlight some milestones in that area, both from experimental and computational point of view.

In 2012, Liu et al.<sup>149</sup> published an experimental study of two MOFs, HKUST-1 and Ni/DOBDC, for adsorption of Xe and Kr at ppm (part-per-million) levels in air. The target application was the removal of Xe and Kr from nuclear fuel reprocessing plants. The same group later proposed a two-column method for the separation of Kr and Xe from processed off-gases,<sup>150</sup> based on MOF materials. At about the same time, Bae et al.<sup>151</sup> combined a computational Grand Canonical Monte Carlo (GCMC) study with experimental breakthrough measurements of the separation of a Xe/Kr mixture on MOF-505 and HKUST-1.

Parkes et al.<sup>152</sup> studied sixteen different MOF materials for Kr, Ar, and N<sub>2</sub> adsorption and separation, through GCMC simulations. They concluded on the potential of MOFs for separation, and a general correlation between the Henry's constant and the isosteric heat of adsorption for the three gases studied. A year later, in 2014, Chen et al.<sup>6</sup> demonstrated, again through a combined computational and experimental study, the potential of porous organic cages for selective binding of xenon over krypton.

Later experimental work expanded these early separation studies to different types of MOF materials. Xiong et al.<sup>153</sup> studied a flexible zinc tetrazolate framework for xenon selective adsorption over krypton, argon and nitrogen. Thermodynamic analysis of the adsorption isotherms at various temperatures confirmed the occurrence of a “breathing” structural transition upon Xe uptake, contributing to a high working capacity for a pressure swing adsorption (PSA) cycle. Lee et al.<sup>154</sup> compared the selective adsorption properties for Xe/Kr mixtures on three highly studied MOFs, namely UiO-66(Zr), MIL-100(Fe) and MIL-101(Cr), and confirmed a high potential of UiO-66(Zr) for separations under dynamic flow conditions. These authors also assessed the hydrothermal and radioactive stability of the material, a test seldom performed in the existing literature, and found it to be good. In a further study,<sup>155</sup> they demonstrated that Xe/Kr selectivity could be further improved by ligand substitution.

In parallel, computational studies were published to provide insight at the microscopic level into the mechanisms behind good (and bad) separation properties. Wang et al.<sup>156</sup> studied 6 MOFs and COFs for adsorption of Xe and Xe/N<sub>2</sub> separation, through GCMC simulations looking at the impact of pressure (and therefore pore filling) on selectivity. Anderson et al.<sup>157</sup> combined GCMC and biased MD simulations to elucidate the nature of adsorption- and diffusion-based Kr/Xe separation mechanisms in four archetypal nanoporous materials: SAPO-34, ZIF-8, UiO-66, and IRMOF-1. These authors draw a couple of general conclusions, including the fact that diffusion selectivity for krypton dominates membrane separation selectivity, and large

pore cages and stiff pore windows are desirable — however the scope of these conclusions is inherently limited by the small number of materials actually studied.

In a different family of materials, Tong et al.<sup>73</sup> have surveyed the structure–property relationships of covalent organic frameworks (COFs) for noble gas separation, by GCMC simulations of 187 different materials for Kr/Ar, Xe/Kr and Rn/Xe separations. These authors included in their calculations some adsorption figures of merit (AFM), representative of the conditions of industrial vacuum (VSA) and pressure swing adsorption (PSA) processes.

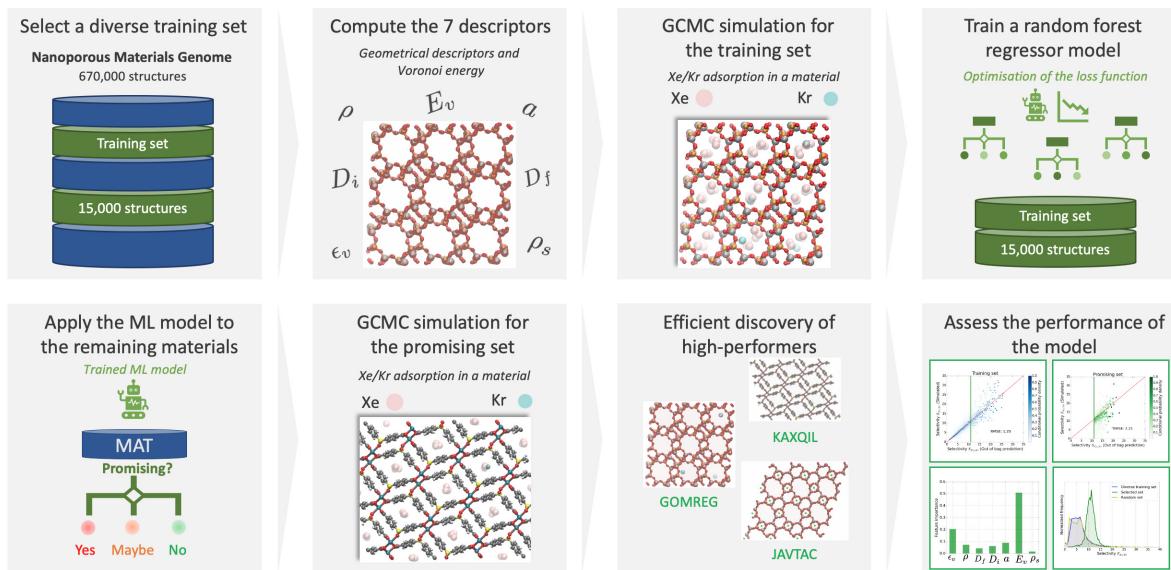
One area that has been particularly explored is the tuning and improvement of separation properties through the presence and nature of coordinatively unsaturated sites (or open metal sites) in MOFs. In 2016, Vazhappilly et al.<sup>158</sup> used density functional theory (DFT) calculations of host–guest binding energies to probe the impact of the metal atoms in a specific framework (MOF-74) on Xe and Kr adsorption. Later, Zarabadi-Poor et al.<sup>159</sup> investigated — again through computational methods — a series of metal–BTC MOFs for recovering xenon from exhaled anesthetic gas, i.e., mixtures of CO<sub>2</sub>, O<sub>2</sub>, and N<sub>2</sub>.

#### LARGE-SCALE COMPUTATIONAL SCREENING

In its early stage, computational screening has been used on a small series of nanoporous materials to generate specific knowledge on some subclasses of materials. These small-scale screenings combined with experiments helped faster identification of good performing candidates, but they failed to establish general rules of design or to explore the unknown. Larger-scale screenings overcame these limitations by trying to exhaustively cover the whole spectrum of nanoporous materials.

The first large-scale computational screening on Xe/Kr adsorption-based was performed by Sikora et al. based on the same approach previously developed for methane storage by their group at the Northwestern University.<sup>160</sup> This study was based on the same 137,000 structures of hypothetical MOFs.<sup>12</sup> They calculated the Xe/Kr selectivity using Monte Carlo molecular simulations on the whole database by iteratively increasing the number of steps and selecting the best materials similar to the approach on Figure 1.3. By analyzing the relationships between pore sizes and selectivity, they confirmed a hypothesis from a smaller scale study that the pores should be between the size of 1 to 2 xenon molecules.<sup>161</sup> Tube-like channel was also found to favor better selectivity. Moreover, they found that top performing materials could have a selectivity around 500; but we can only conclude on the order of magnitude of the theoretical limitation of the Xe/Kr selectivity, considering the statistical uncertainty of the simulation.

Seizing the opportunity of a formidable expansion of the nanoporous materials database triggered by the Materials Genome Initiative, Simon et al. screened 670,000 experimental and hypothetical nanoporous material structures for Xe/Kr separation (see Figure 1.9).<sup>18</sup> It is one of the largest-scale screenings performed in this area. Inspired by the work of Fernandez and co-workers,<sup>17</sup> they used ML algorithms to train a model on a diverse subset of 15,000 structures. This method allowed them to run time-consuming molecular simulations only on this training set, before applying the ML model to predict the selectivity values on the larger set of structures. On top of analyzing the links between pore descriptors and selectivity, they rationalized it using theoretical pore models of spherical and cylindrical geometries to confirm the findings of Snurr and co-workers.<sup>160,161</sup> By comparing the structural descriptors of good-performing



*Figure 1.9: Schematic representation of large-scale screening of nanoporous materials for Xe/Kr adsorption-based separation by Simon et al.,<sup>18</sup> based on a combination of Grand Canonical Monte Carlo simulations and machine learning algorithm (Random Forest Regressor). The main goal of this screening is to find high-performing materials in a large dataset of both experimental and hypothetical materials. Adapted with permission from Ref. [18]. Copyright © 2015 American Chemical Society.*

and bad-performing structures, they concluded that geometrical descriptors wasn't enough to explain the performance. The analysis of a few top candidates suggests that different chemical insights could explain their good performance. For SBMOF-1 or KAXQIL,<sup>54</sup> an experimental MOF, its higher performance was explained by the tubelike 1D channel with a very favorable binding site formed by carbon aromatic rings. This nanoporous material was later tested using breakthrough experiments and proved to be one of the most promising candidates.<sup>41</sup> This close collaboration between computation and experimentation is a testimony of the potential of computational screenings to find nanoporous materials for any targeted application.

The experimental work on Xe/Kr separation on SBMOF-1 revealed discrepancies between the selectivity values obtained experimentally and computationally.<sup>41</sup> The assumption of rigid crystal structures in the molecular simulations could partially explain the difference observed. Witman et al. proposed that the flexibility of the materials that weren't considered in the screening of Simon et al. could explain the lower selectivity observed experimentally.<sup>162</sup> In this study, they screened the Henry regime separation of about 4,000 MOF structures of the CORE MOF 2014 database,<sup>71</sup> and found that intrinsic flexibility, i.e. the thermal vibration of the material, can make the pore size derive from the ideal value for the separation and hence lower the selectivity. This study further confirms the importance of the pore size by highlighting the effect of its evolution over time.

In 2019, Chung et al. screened the most extensive simulation-ready and experimentally synthesized MOF structures for Xe/Kr separation.<sup>72</sup> This study pointed out the potential of coordinated solvent molecules to fine-tune the selectivity for any separation application, since their presence can enhance selectivity in some cases. The results of their screening confirm the potential

of structures such as SBMOF-1 found by Simon et al., but they also described a few structures with similar selectivity but with better xenon uptake. The authors emphasize the importance of considering other figures of merit such as the adsorption capacity. Other factors should be taken into account to find the best trade-off between all the relevant figures of merit; we could think of the kinetics of such a separation, the effect of flexibility on the performance, the stability of the materials (especially in radioactive environment), the financial aspects, and more.

After this quick overview of the different screening studies in the field of xenon/krypton separation, we are now going to detail its industrial context, the foreseen top materials that could fulfill the industrial separation and the further studies needed to better understand the process while discovering new materials.

### 1.3 SEPARATION OF XENON FROM KRYPTON

This section will be dedicated on how the above-mentioned screening methodologies can help us understand the origins of the Xe/Kr separation and identify promising materials for industrial applications.

#### 1.3.1 Industrial applications

The industrial interest for noble gases lies first in the many applications attached to them. For instance, xenon has multiple applications in the medical (e.g., anesthesia, painkiller, imaging),<sup>163–165</sup> aeronautical,<sup>166,167</sup> lithographic,<sup>168</sup> microelectronic<sup>169</sup> or lighting sectors,<sup>170,171</sup> just to cite a few. To meet the demand for these noble gases, one should consider all available sources, the most obvious one being the air we breathe. Xenon and krypton have both very low atmospheric concentrations; out of a thousand liters of air, we would extract at most one tenth of a milliliter of xenon and one of krypton.<sup>1</sup> Nevertheless, direct extraction from the air remains the main production mean for xenon and krypton along with chemical plant off-gases that contains a higher concentration of inert gas (e.g., ammonia purge gas). In these cases, the industry more commonly uses cryogenic distillation to extract xenon and krypton, which requires a compression and cooling of the gas mixture at very low temperatures. The separation process can be broken down into three steps: first the condensation of all gas with a boiling point higher than the oxygen, then the purification of oxygen resulting in a 20-80 xenon/krypton mixture, and finally the separation of xenon from krypton. In 1997, several cases of explosion of separation units were caused by the reaction of non-filtered dangerous hydrocarbons with purified liquid oxygen produced in the second step of this long process.<sup>3,4</sup> The extreme chemical and physical conditions required for cryogenic distillation support the need for less energy-intensive and safer alternatives.

The role of a dispatchable source of low-carbon energy can only be fulfilled by batteries charged by renewable energies (wind or solar) or by nuclear plants. However, one of the major criticisms of this source of energy concerns the management of the radioactive waste. As promising technologies in gas separation emerge, there is an increasing need for a solution for the release of very small amount of radioactive off-gases like Kr<sub>85</sub> from nuclear spent fuels.<sup>176</sup> Furthermore, stable xenon isotopes are also produced in these spent nuclear fuels, which can be used in all the above-mentioned applications. In the context of a regained interest in nuclear energy, the

Industrial source	Xe/Kr composition
Extraction from ambient air <sup>1</sup>	100 ppm/400 ppm
Uranium 235 fission <sup>172</sup>	85/15
Spent nuclear fuel <sup>173</sup>	90/10
Molten salt reactor <sup>174,175</sup>	unknown

Table 1.1: Composition of the Xe/Kr mixture coming from different industrial sources of production. The Xe/Kr composition can change over time depending on the radioactive decay of Xe and Kr isotopes. The composition out of a molten salt reactor is unknown (no industrial installation exists) and depend on the fissile element, if it is a majority of  $^{235}\text{U}$ , then the composition would be very close to the one indicated by the Ref. [172].

fourth generation nuclear plants are projected to be built on other technologies such as the light water or the molten salt technologies.<sup>177</sup> Molten salt reactors would continuously produce xenon and radioactive krypton in the electricity generation process.<sup>175</sup> The development of gas separation units in these facilities would represent a promising source for xenon production. Yet, we can laboriously imagine deploying standard cryogenic distillation units in a nuclear facility for obvious security reasons. Consequently, nanoporous materials are considered as the alternative technology for xenon/krypton separation. Zeolites are already used as a pre-purification system,<sup>1</sup> and they are now projected to be used as a standalone separation system.

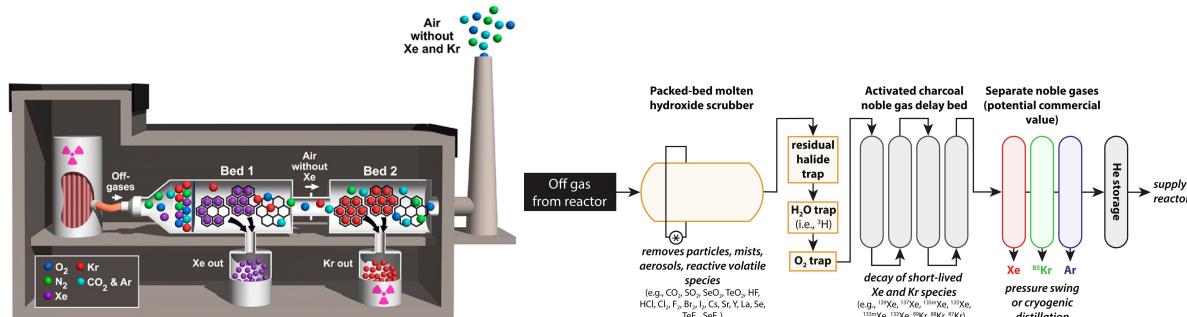


Figure 1.10: Representation of xenon/krypton separation process using porous materials in a nuclear fuel reprocessing plant and in a molten salt reactor. Reprinted with permission from Ref. [2] copyright © 2014 American Chemical Society and Ref. [175] copyright © 2019 Elsevier.

Banerjee et al. proposed a two-bed system with a first bed filled with MOFs designed for xenon separation and then a second one for radioactive krypton capture.<sup>2</sup> The authors proposed some examples of material that could be used for this separation unit; more research is needed to find out what the best materials for these separations are. In the following section, we will review the most promising materials for this separation and the structural explaining their high performance.

### 1.3.2 Promising materials for the separation

Several experimental reports used the strategy outlined by computational screenings to improve separation properties, as well as tuning the chemical nature of the organic linkers. The main criteria outlined by the different studies on xenon/krypton separation call for pore size tailor-

made for xenon and also for maximized interactions with the framework atoms obtained either through the chemical nature or the shape of the cavities.

In the early phase of the experimental design of materials for the xenon/krypton separation, Wang et al. synthesized a cobalt MOF  $\text{Co}_3(\text{HCOO})_6$  with a selectivity of 12 that present rather narrow pores (around 5 Å) connected by zig-zag segments.<sup>178</sup> Later, Chen et al. synthesized a selective porous cage material by not only focusing on the pore size but more importantly on the shape of the cavity, the selectivity of around 20 was considered record high at that time. For instance, the cage windows are open for small noble gases such as krypton, whereas they close around the xenon hence maximizing the interaction.<sup>6</sup> Mohamed et al. also designed a material with a similar selectivity, CROFOUR-1-Ni. However the performance was now explained by the chemical nature of the chromium oxide ligands that interact more strongly with the more polarizable xenon than the krypton molecules.<sup>179</sup> Finally, Banerjee et al. tested a previously synthesized<sup>54</sup> MOF after it was identified through high-throughput screening<sup>18</sup> for its outstanding theoretical selectivity around 70. However, experimental measurements showed that its selectivity was not exceeding the one of the previous top materials. Similar emphases were made on the ideal pore size coupled with highly attractive framework atoms.<sup>41</sup>

More recently, Li et al. proposed a rigid squarate-based MOF with “perfect pore size” (comparable with the kinetic diameter of Xe), and an internal pore surface decorated with very polar hydroxyl groups. This material experimentally demonstrated record-high Xe/Kr selectivity of 60.6 at low pressure (0.2 bar) and ambient temperature.<sup>7</sup> Later, Pei et al. discovered even better performing materials with Xe/Kr selectivity of 74.1 and 103.4 in the same conditions 0.2 bar and 298 K. In addition to the perfectly tailored pore size, the structure features two oppositely adjacent open metal sites that strongly clamp the adsorbed xenon molecule.<sup>8</sup> These studies clearly show the potential of polar sites that preferentially interact with the more polarizable xenon over the krypton, hence explaining these record-breaking separation performances.

### 1.3.3 From the computer to the test tube

To connect back this work to computational screenings, one of the rare cases of direct contribution of high-throughput screenings to the lab testing of a material will be presented here. In 2015, Simon et al.<sup>18</sup> analyzed the Nanoporous Materials Genome,<sup>69,85</sup> a database of about 670,000 experimental and hypothetical porous material structures, including MOFs, zeolites, PPNs, ZIFs, and COFs, for candidate adsorbents for xenon/krypton separations. This study led to the rediscovery of SBMOF-1, a promising nanoporous material that was presented one year later.<sup>41</sup>

It is possibly the largest-scale study performed in this area, both by the sheer number of frameworks involved and by the diversity of their nature. Because such a set is too big for brute-force screening with GCMC simulations, they proposed a multiscale modeling strategy combining machine learning algorithms (trained on a diverse subset of 15,000 materials) with molecular simulations (used both to generate the ML training data, and to refine the separation properties for the top performers obtained by the ML predictor). Without going into details (see Fig. 1.9 for more details), the ML model they trained was mainly based on geometric structural descriptors, with the addition of a single energy-based descriptor: the Voronoi energy (i.e., the average energy of a xenon atom at the accessible nodes in the Voronoi partition of space). In addition to identifying and describing some top performing materials, the authors also

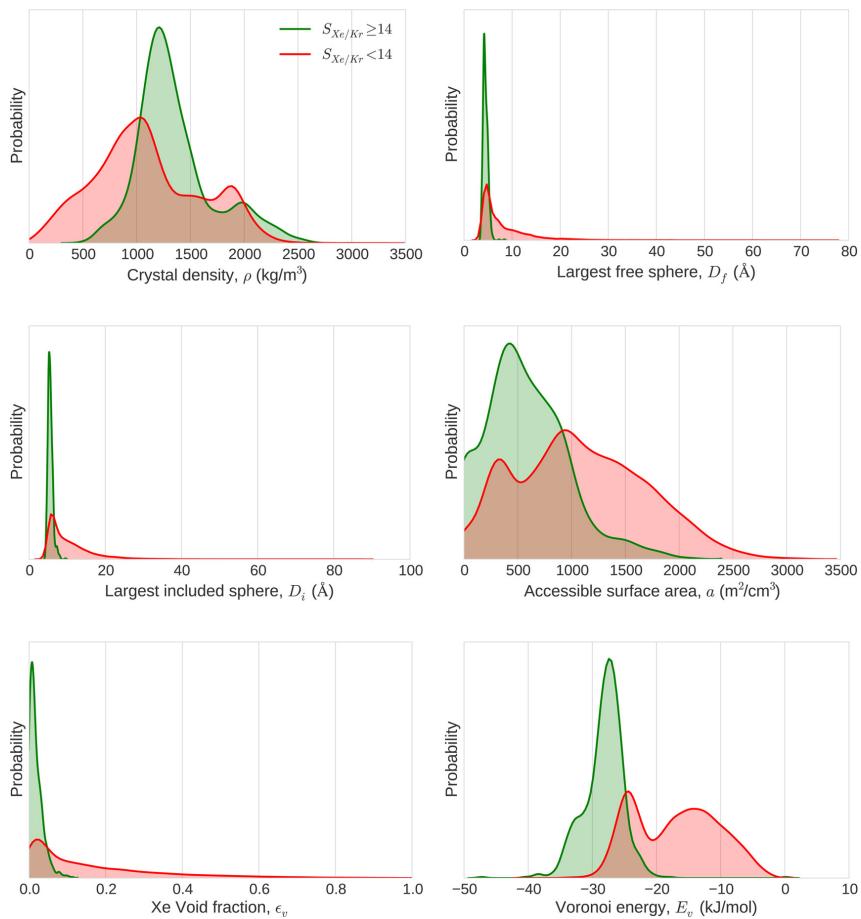
analyzed the correlations between high Xe/Kr selectivity and the geometric properties of the frameworks, in order to “rationalize the strong link between pore size and selectivity”. In particular, by developing theoretical pore models of spherical and cylindrical geometries, they could highlight the general geometrical trends observed, but also the fact that there is a wide diversity of performance beyond the geometrical features of the frameworks, which suggests the key role of the chemical nature of the cavities.

By looking at the distribution of the most selective materials ( $s \geq 14$ ) compared to the less selective ones ( $s < 14$ ) on Figure 1.11, Simon et al. established a first profile of the selective materials. These materials have pore sizes of a specific diameter very close to the kinetic diameter of xenon around  $4.4\text{ \AA}$  depending on how it is defined. They have rather low surface areas and porosities (void fractions), unlike what we would normally expect since the adsorbable surface is a key reason for using nanoporous materials in adsorption applications. This behavior can be rationalized by the fact that small pores of the order of a few  $\text{\AA}$  immediately imply smaller pore volumes and surface areas since the framework atoms occupy much more space. The crystal density is therefore also a bit higher for these reasons. Moreover, the pore’s shape is also a crucial factor since a shape closer to a sphere would interact with the xenon with more atoms, hence increasing its affinity and the selectivity. Finally, last but not least, the Voronoi energy described the physical nature of the binding between the xenon and the pore atoms, the more negative it is and the more selective the material will be. To wrap up, the ideal materials have a pseudo-spherical shape (a complete sphere would stop the diffusion of the adsorbates) with a size close to the diameter of a xenon which is rather dense and not very porous.

The chemical nature of the cavities was best described using the Voronoi energy descriptor they developed. This descriptor gives an idea of the xenon adsorption isosteric heat of the material. Given these results, more studies should focus on describing the adsorption thermodynamic quantities such as the adsorption enthalpy but also the Henry adsorption constants. This study finally leads to the synthesis and testing of one of the top performing materials in the field. However, we cannot stop but wondering why there is a discrepancy between the theoretical selectivity of around 70 of SBMOF-1 and its actual experimental selectivity of 16. In the final chapter of this thesis, we will try to give an explanation for this. In the future, such close collaboration between experimental and computational teams are crucial even if they are still too rare. A recent paper suggests that these collaborations are rare across all nanoporous fields and a lot of improvements are needed to foster cooperation between the labs.<sup>180</sup>

### 1.3.4 The future of screening

Despite the progress made, important drawbacks of the current methodologies remain. High-throughput screenings rely too much on oversimplified assumptions such as the rigidity of the framework, the absence of defects, the use of Lennard-Jones potentials and inaccurate charges. For instance, the rigidity of the framework only takes into account one conformation of the framework. Yet, thermal agitation induces a “breathing” movement of the framework with an amplitude dependent on its intrinsic flexibility. The pores of the framework can change depending on the number of adsorbates to interact more optimally with them, which can be induced by a change in pressure. The issue of flexibility is rarely tackled, and when considered, it is only on the few most selective structures given by an inaccurate screening based on the rigid crystal approximation. One can wonder about the results obtained if it is applied to larger



*Figure 1.11: Statistical analysis of the adsorption separation of xenon/krypton mixtures by nanoporous materials. The graphs represent the distributions of structural descriptors explored by highly selective (green) and poorly selective (red) materials separately. Reprinted with permission from Ref. [18]. Copyright © 2015 American Chemical Society.*

sets of structures. Witman et al. found that flexibility applied to top performing materials can decrease the selectivity, because the pore does not have an optimal size anymore.<sup>162</sup> In some cases, the selectivity of a well-performing material can even increase to become a top performing one. Computational screenings can be closer to predict experimental values of selectivity, diffusivity, and other key performance metrics.

Many open problems remain for the design of efficient high-throughput computational screenings. The connection between different properties for a given application is not systematically integrated in the screening procedures. For example, in methane storage, the working capacity of the material is the main property to optimize, but the kinetics of the adsorption/desorption or the mechanical resistance to compaction among others also need to be considered. Designing a nanoporous material is in fact a multivariate optimization problem with tacit constraints (e.g., synthesizability) – a material for industrial xenon/krypton separation we need not only to optimize the selectivity but also the regenerability (how much gas can be retrieved at each cycle) and the capacity and so on, and a key constraint is to know if it is synthesizable or the robustness within the industrial conditions. For instance, although the transport properties of the adsorbates in the material are not key in explaining the separation performance, they are, however, very important in the breakthrough experiments and eventually in the indus-

trial separation process in pressure or temperature swing adsorption beds. For this reason, studying transport properties along with uptake capacities and thermodynamic selectivity of the xenon/krypton separation can give a more complete picture of the industrial process we ultimately want to model.

Moreover, the transferability of the methodology to a broad range of materials is often achieved at the expense of accuracy in specific cases. And one can rightly question the universality of depending on faster but less elaborated models, which boils down to a trade-off problem between prediction accuracy and computational cost (or complexity). For instance, classical forcefields are broadly used in rigid materials for adsorption properties, but the switch to more costly *ab initio* methods or the addition of flexibility can result in a more accurate description at the expense of computational resources. The addition of polarization could be very promising since several top performing materials harbor open metal sites and highly polar sites that explain the acute affinity to xenon adsorbates.

The development of ML-assisted screenings is paired with the advances in data science techniques and algorithms. Recent advances in deep learning have enabled the development of transformer-based (the technology at the foundation of ChatGPT) machine learning models to predict adsorption properties.<sup>181,182</sup> More importantly, the construction of descriptors tailored to the many possible applications is also an ongoing work. This construction work cannot be dissociated from the physical and chemical intuition of the scientists. Topological, chemical, electronic and other descriptors have been developed on top of the more common geometrical and thermodynamic descriptors, which displays the importance of strong physical chemistry knowledge. Recently Shi et al. highlighted the key role of energy histograms in predicting adsorption properties.<sup>183</sup> The discovery of novel relevant descriptors remains the main lever for increased performance of the ML models and is closely related to a rigorous theoretical work. For these reasons, this thesis focuses on more accurate and faster ways of calculating these interaction energies to extract valuable energy/thermodynamic descriptors.

The development of databases is another key aspect in the promotion of data science in the field of materials science in general, and nanoporous materials chemistry in particular. The diversity of materials, the inclusion of experimental data (successful or failed), the addition of understudied classes of materials (e.g., amorphous) are all key aspects to upgrade the existing database. Even if existing attempts to create a centralized database have been initiated by the materials project,<sup>117</sup> this database does not contain all the existing information on each material. Furthermore, this high amount of data will need to be efficiently explored, and non-supervised deep learning algorithms have been developed to do so.<sup>184</sup> Coupled with synthesis robot, these methods can navigate through the unexplored databases to find the few most interesting candidates for a given targeted application.

In the future, computational high-throughput screening could be integrated more tightly into the design process of nanoporous materials, hence further improving its efficiency. The computational prescreening can be coupled with automated screenings of the most promising materials to finally identify candidates for further studies. This automated design process is described by Lyu et al. in their paper on “Digital Reticular Chemistry” and set out promising perspectives for computational screenings in the field.<sup>9</sup> Some studies are already pioneering this new research area by combining high-throughput characterizations, active learning algorithms

and robotic synthesis.<sup>185,186</sup> Another step towards faster industrialization would integrate process modeling to enrich the purely atomistic approach.

This chapter introduced different studies on the screening of nanoporous material properties coming from a large set of research fields from adsorption to transport properties and exploring the more eclectic mechanical, thermal and catalytic properties. Considering all the different approaches gathered from the literature, the next chapter will aim at better describing the microscopic origins of the xenon/krypton separation in nanoporous materials through a thermodynamics-driven screening. This study will include the study of relationships between the separation performance and geometrical characteristics of the structures, the identification of the thermodynamic nature of the separation. By doing so, some interesting effects were unraveled and we expect to use them at our advantage to accelerate the evaluation of the selectivity at any pressure values.





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# THERMODYNAMIC EXPLORATION OF XENON/KRYPTON SEPARATION

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## 2.1 CHARACTERIZATION OF ADSORPTION EQUILIBRIUM PROPERTIES

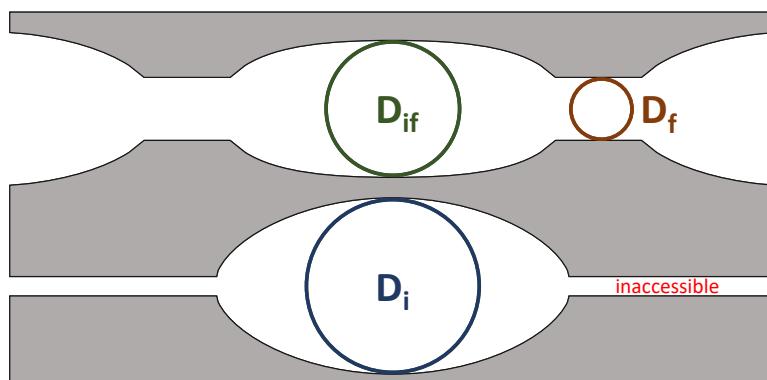
Before exploring the thermodynamic properties of the adsorption-based xenon/krypton separation, this first section aims at defining some key concepts that will be referenced throughout this manuscript. These concepts include the computational definition of the geometrical descriptors mentioned in the previous chapter, as well as the molecular simulations used to assess the separation performance of each material. In addition, the definition of these thermodynamic quantities will be elucidated to ensure a better understanding of the work presented in the following sections.

### 2.1.1 Geometrical descriptors

Before delving into the details of adsorption properties, it is important to introduce the different simulation techniques used to characterize the internal pore structure of the material. These properties play an essential role in interpreting the adsorption properties obtained using more complex molecular simulations. In this thesis, the Zeo++ software was utilized to calculate all the geometrical descriptors used.<sup>49</sup> While other tools exist,<sup>50,187</sup> the use of Voronoi decomposition of the volume offers computational efficiency advantages (efficiency gain mainly on volume calculation),<sup>188</sup> making Zeo++ the preferred tool in this study.

#### PORE SIZE

Different definitions of pore sizes can be defined depending on the point where we measure it. These diverse pore sizes collectively form what is known as a pore size distribution. However, some pore size values are uniquely defined and can be used to characterize the internal structure. For instance, the diameter of the largest sphere that can freely diffuse in the structure is referred to as  $D_f$ . The diameter  $D_{if}$  corresponds to the diameter of the largest included sphere along a free diffusion path. The diameter of the largest included sphere (not necessarily in a free diffusion path) is denoted  $D_i$ . The Figure 2.1 illustrates the difference between these pore sizes. In thermodynamic studies, the term “largest cavity diameter” (LCD) will be frequently employed instead of the largest included sphere  $D_i$ . Moreover, the term “pore limiting diameter” will be used instead of  $D_f$ , especially when studying the transport effects within the nanopores.



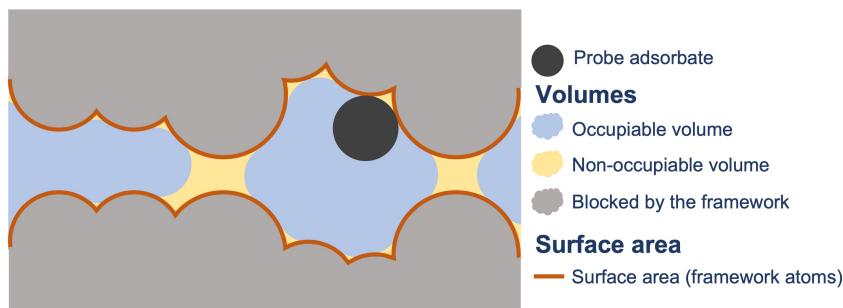
*Figure 2.1: Illustration of the different pore sizes  $D_f$ ,  $D_i$  and  $D_{if}$ . Note that in some materials  $D_{if}$  is equal to  $D_i$ , when the largest included sphere is also accessible through a free diffusion path.*

To define these pore sizes, it is necessary to first determine the radii of the framework atoms that shape the surrounding pores. These radii can be defined using different methods, with the default mode utilizing the Cambridge Crystallographic Data Centre’s (CCDC) radii. This method is widely used in the literature. Additionally, this section introduces another set of radii based on the universal forcefield,<sup>189</sup> which is used for all types of molecular simulations throughout this thesis. The determination of these radii are inspired by an approach developed by Hung et al.<sup>51</sup> The atomic radii correspond to the distance at which the LJ potential reaches  $3k_B T/2$ , for  $T = 298$  K. This definition enables easier comparison with the quantities obtained from molecular simulations. In case of ambiguity, different indices will be used to differentiate between the two methods. For instance, LCD<sub>CCDC</sub> corresponds to the standard definition of the LCD that utilizes the CCDC radii when running the Zeo++ software, while the LCD<sub>UFF</sub> is defined based on the atomic radii that is dependent on the UFF forcefield. In this chapter, I will

mainly use the forcefield-based definition – the largest cavity diameter denoted  $LCD_{UFF}$  will be predominantly used, and the studies on void fraction and surface areas will also be defined using this set of radii.

### SURFACE AREA

The surface areas are calculated using a random sampling technique across the surface of the different atom surfaces. The algorithm counts only the points that do not overlap with another atom. This allows for the calculation of an adsorbable surface for each atom. Ultimately, the surface area can be obtained by summing up all these surfaces. This algorithm, known as the “rolling ball” algorithm, was initially developed by Shrake and Rupley in 1973.<sup>190</sup> The Voronoi tessellation determines the accessible and non-accessible areas of the structure by using a probe. Depending on the location of the surfaces, they are categorized as either accessible or non-accessible surface areas. In this chapter, the accessible surface area is defined using a probe of 1.2 Å. This value is computationally equivalent to the experimental N<sub>2</sub> BET surface area.



*Figure 2.2: Illustration of the pore surface area and volume in a nanoporous material. As illustrated, there are different definitions of the pore volume: we can either consider the whole volume of the pores (occupiable+non-occupiable) or only the volume occupiable by a probe. People usually use the first definition, but the second definition has recently been proposed. Studies have shown that occupiable volume has a better accordance with experimental data.<sup>191</sup> The surface area also changes depending on the definition. [à discuter]*

### PORE VOLUME AND POROSITY

The pore volume is calculated by randomly sampling the accessible and inaccessible Voronoi cells. Similarly, other algorithms performs a random sampling over a regular mesh. If the probe used for sampling does not overlap with a framework atom, then it is counted in the number of accessible points N in the volume. The ratio of this number N and the total number of points sampled gives the fraction of the pore volume, also known as the void fraction or porosity. By using the Voronoi decomposition, it is also possible to define the accessible and non-accessible Voronoi cells to reduce the space that needs to be sampled in a Monte Carlo simulation for the surface area and the void fraction calculations.

#### 2.1.2 Intermolecular interactions

In most of the studies in this thesis, rigid structures interacting with guest adsorbates are considered. The intramolecular interactions will not play any significant role in the simulations, as the ionic, chemical, or metallic bonds between the atoms of a molecule are predefined at a specific set of distances and remain unchanged throughout the simulations. As discussed in the final chapter, this approximation can generate discrepancies between the theoretical model

and the experimental observations. However, considering the goal of achieving screening approaches, such as the ones introduced in the first chapter, adding flexibility in intramolecular interactions would significantly reduce the size of the database that can be screened. For these reasons, the term “interaction energy” will mainly refer to the guest–host and guest–guest intermolecular interactions – host–host interactions would compromise the assumption of framework rigidity.

In classical theory of molecular physics, the intermolecular interactions can be categorized into three different types based on their strength: (i) the ion–dipole and ion–induced dipole interactions ( $40\text{--}600 \text{ kJ mol}^{-1}$ ), (ii) the hydrogen bonding ( $10\text{--}50 \text{ kJ mol}^{-1}$ ), and (iii) the van der Waals interactions ( $1\text{--}10 \text{ kJ mol}^{-1}$ ). It is important to note that these energy values are only indicative and the interaction depends on the nature of the molecules. However, they provide a ranking of the different forces according to their strength. Moreover, the ionic and covalent bonding is always stronger than any intermolecular interactions (over  $100 \text{ kJ mol}^{-1}$ ). The generic term “van der Waals interactions” actually encompasses three different concepts known as the Keesom, Debye and London interactions. The Keesom interaction focuses on the electrostatic interaction between permanent multipoles (representing the electronic density around the molecules),<sup>192</sup> while the Debye induction force corresponds to the interaction between a multipole of a molecule and an induced multipole of another one.<sup>193</sup> The London dispersion interaction occurs between instantaneous multipoles created by natural fluctuations in the electron density around polarizable atoms.<sup>194,195</sup> To quantify these interactions, it is possible to consider dipole interactions since they have the most influence in the multipole expansion of the electron density. The Keesom interaction potential  $U_K$  can therefore be reduced to the dipole–dipole interaction, which depends on the inverse third power of the distance for fixed dipoles. However, in fluid phases, the average over all angles is better described by the inverse sixth power, as shown in the equation 2.1 below:

$$U_K = -\frac{\mu_1^2 \mu_2^2}{(4\pi\epsilon_0\epsilon_r)^2 r^6} \times \frac{2}{3k_B T} \quad (2.1)$$

where  $\mu_1$  and  $\mu_2$  are the dipole moments of the molecules 1 and 2,  $\epsilon_0$  the vacuum dielectric permittivity and  $\epsilon_r$  relative permittivity of the surrounding material,  $k_B$  the Boltzmann constant,  $T$  the temperature and  $r$  the intermolecular distance. The Debye interaction potential  $U_D$  being reduced to the permanent dipole–induced dipole interactions can now be expressed using the electric polarizability  $\alpha_1$  and  $\alpha_2$  of the molecule 2 as shown in equation 2.2.

$$U_D = -\frac{\mu_1^2 \alpha_2 + \mu_2^2 \alpha_1}{(4\pi\epsilon_0\epsilon_r)^2 r^6} \times \frac{1}{k_B T} \quad (2.2)$$

Finally, the London dispersion interaction potential  $U_L$  is now the fluctuating dipole–induced dipole interaction and can be expressed as follows:

$$U_L = -\frac{\alpha_1 \alpha_2}{(4\pi\epsilon_0\epsilon_r)^2 r^6} \times \frac{3}{2} \times \frac{I_1 I_2}{I_1 + I_2} \quad (2.3)$$

where  $I_1$  and  $I_2$  are the first ionization energies. Note that the van der Waals potentials are all negative (attractive interaction) and depend on the inverse sixth power of the distance – considering only the dipole moments. Before delving into the computational modelization of

these long-distance intermolecular forces, it is necessary to specify the repulsive force that occurs at very short distances. This force can be explained by the Pauli exclusion principle, which states that electrons in both atoms cannot occupy the same quantum space.

For the system of interest, the adsorption of noble gases in nanoporous materials, the guest–guest and guest–host interactions can be described by the induction and dispersion interactions only. I will use a simple model, the Lennard-Jones (LJ) potential  $U^{\text{LJ}}$ ,<sup>196</sup> that relies on a repulsive term for the Pauli exclusion principle and an attractive term to model the attractive van der Waals component of the interaction, as shown below:

$$U^{\text{LJ}} = 4\epsilon \left( \left( \frac{\sigma}{r} \right)^{12} - \left( \frac{\sigma}{r} \right)^6 \right) \quad (2.4)$$

where  $\epsilon$  is the depth of the well (minimal attractive energy) and  $\sigma$  is the distance at which the potential is zero. The forcefield defines the LJ parameters  $\epsilon$  and  $\sigma$  for either all atom pairs or only for the same type of atoms. For the commonly used universal forcefield (UFF),<sup>189</sup> only the parameters for atoms of the same nature are defined and the parameters of the pair atoms can be induced using combining rules. In this thesis, I will use the UFF forcefield (as it performs well compared with *ab initio* forcefields for CO<sub>2</sub> and CH<sub>4</sub> uptake values<sup>197</sup>) and the Lorentz-Berthelot mixing rules to combine the LJ parameters – it makes an arithmetic average of the  $\sigma$  values (Lorentz rule) and a geometric one of the  $\epsilon$  values (Berthelot rule). Finally, to reduce the computation time, one usually set a cutoff distance at which the LJ potential can be considered negligible. At this cutoff distance, one can apply a shift so that the energy equals zero at the cutoffs (discontinuity of energy), just truncate (discontinuity of the force), or use a tail switching function to make the tail converge smoothly to zero near the cutoff. In most of the simulations in my screening studies, I adopted a shifting strategy combined with a cutoff of 12 Å.

In adsorption simulations of other gas molecules with partial charges, it is usually necessary to calculate the Coulomb interaction between the partial charges of the host framework and those of the adsorbate – in periodic systems, an Ewald summation is typically employed to account for this interaction. However, in the case of noble gases, such ion–dipole and dipole–dipole interactions do not exist due to the perfect neutrality of the molecules. Nevertheless, it can be argued that the ion–induced dipole can be adequately described by a simple LJ potential. To provide a comprehensive representation of the intermolecular interactions, the energy induced by the charges of the surrounding framework atoms should be added to the adsorbate. Several approaches have been developed in the literature to enhance the description of the intermolecular interactions by coupling LJ potentials with an induction potential,<sup>198,199</sup> which are not used in my work.

To summarize this section on the modelization of the intermolecular interactions in the adsorption simulations, it is essential to highlight the main assumptions in the modelization that may impact the accuracy of the method. Firstly, the framework remains rigid throughout the simulation, which eliminates the need for molecular dynamics simulations of the framework to save time, but it also hides the effects of a known phenomenon.<sup>162</sup> Secondly, the polarizability of the adsorbate is only partially considered, as the interaction with the charges of the framework is not taken into account. The difference in polarizability between xenon and krypton can be further exploited to enhance the selectivity, as suggested by experimental studies emphasizing

the key role of polar groups and open metal sites.<sup>7,8,200</sup> Lastly, the complex induction and dispersion interactions are described using a two-parameter model. Although this model does not capture all the nuances of differences between the same atom in different environments, it is possible to fine-tune these parameters for very specific cases. However, in a screening strategy, some accuracy on specific cases can be sacrificed to improve the generalization error, as demonstrated by the good performance of the UFF forcefield on a large dataset.<sup>197</sup> These assumptions have been made to strike a balance between the computational speed and a detailed description of the physical phenomena at stake. Moreover, the focus this thesis is on the development of screening methodologies rather than molecular interaction modeling.

### 2.1.3 Mixture adsorption: Grand Canonical Monte Carlo

As previously discussed, adsorption can be viewed as a gas–solid or liquid–solid interfacial phenomenon. The adsorbate phase fills the accessible pore volumes depending on the physical conditions of the material. Predicting how adsorbates would interact with the pore surface, the maximum number of molecules that can fit, the most stable configuration, etc., is challenging and cannot be achieved through a simple model. To address these questions, it is necessary to evaluate all possible adsorption configurations each with a different number of adsorbate molecules, and then select the most thermodynamically plausible ones. This evaluation requires these configurations to follow a pre-defined probability distribution from statistical physics, such as the grand canonical ensemble probability, as it allows for the variation of the number of molecules (adsorbate molecules) and the total energy. By using a Monte Carlo simulation, it is possible to vary the energy and the loading inside the pores so that the distribution of configurations  $c$  follows the probability law below:

$$P_c = \frac{1}{\Xi} e^{-\beta(E_c - \mu N_c)} \quad (2.5)$$

where  $E_c$  and  $N_c$  are respectively the energy and the number of adsorbate particles in the configuration  $c$ . Normally the energy and the number of molecules of all particles should be considered, but for now, since the whole system is considered rigid, I will only focus on the adsorbate molecules. The chemical potential  $\mu$  and the temperature  $T$  ( $\beta = 1/k_B T$ ) correspond to the ones of the gas phase in equilibrium with the adsorbent material. And the pressure and volume  $V$  are considered fixed under the rigidity assumption. The grand canonical partition function  $\Xi(\mu, V, T)$  will then be the following sum over all possible configurations:

$$\Xi(\mu, V, T) = \sum_c e^{-\beta(E_c - \mu N_c)} \quad (2.6)$$

This multiplicative constant does not need to be known in the Monte Carlo simulation I will describe now.

Beyond these theoretical considerations, the grand canonical Monte Carlo simulation which refers to a Metropolis-Hastings Monte Carlo algorithm in the context of the grand canonical thermodynamic ensemble, requires several key characteristics to fulfill the above-mentioned probability distribution of the configurations. Monte Carlo (MC) refers to the randomness inherent to gambling games at the eponymous casino on the azure coast of Monaco. In MC simulations, are therefore relying on randomly generating atomic configurations; but it is necessary to remain in the physically possible atomic space to the greatest extent, while exhaustively exploring all possible chemical configurations. Starting from an initial configuration

$c_0$ , the algorithm has different rational moves to change the configuration with a controlled degree of randomness. Some of these moves are illustrated on Figure 2.3. The second key algorithmic step (acceptance or rejection condition), introduced by Metropolis and co-workers, allows the reproduction of any distribution with an unknown multiplicative prefactor.<sup>201</sup> The configuration  $c_1$  resulting from the random move is evaluated by calculating the transition probability (like in a Markov chain) or acceptance rate  $acc(c_0 \rightarrow c_1)$ :

$$acc(c_0 \rightarrow c_1) = \min \left( 1, e^{-\beta(E_{c_1} - E_{c_0} - \mu(N_{c_1} - N_{c_0}))} \right) \quad (2.7)$$

The configuration  $c_1$  is accepted, if a number randomly drawn from the  $[0, 1]$  interval is higher than the acceptance rate  $acc(c_0 \rightarrow c_1)$ . For an acceptance rate of 1, when  $c_1$  is more stable than  $c_0$  ( $E_{c_1} - \mu N_{c_1} \leq E_{c_0} - \mu N_{c_0}$ ), the move is automatically accepted since by construction this randomly drawn number would be lower than 1. On the other hand, if the move is rejected, then we generate another configuration  $c_1$  using another random move, and the acceptance/rejection process restarts until a move is accepted. At the end of the  $n$  cycles of the MC simulation, only the accepted configurations  $\{c_0, \dots, c_n\}$  form a Markov chain, and this sequence describes the probability distribution of the grand canonical ensemble described in equation 2.5. The multiplicative prefactor does not influence the algorithm since the acceptance rate corresponds to ratios of probabilities  $P_c$ , so that no prior knowledge of the chemical space are needed, which is a valuable simplification.

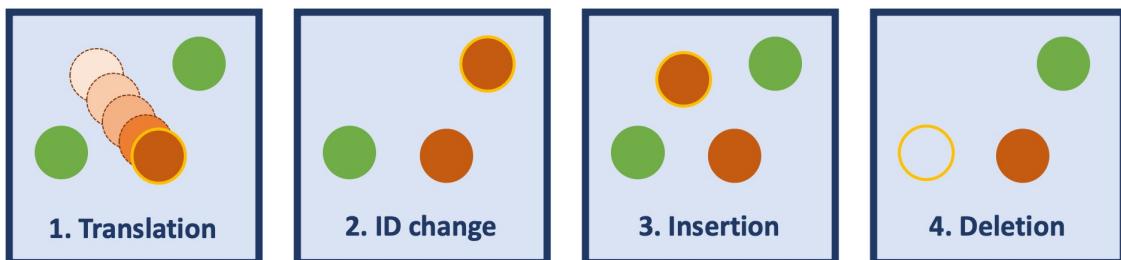


Figure 2.3: MC moves in a system of two types of monoatomic atoms (green and orange). The modification on the first box is highlighted by the yellow circle and the dragging pattern is represented by a set of dashed circles. The boxes 2 to 4 represent the moves going from the initial state represented in box 1, the corresponding move is highlighted by a yellow outer circle. All these moves are used in the GCMC calculations performed using the RASPA2 software.

To complete the description of the grand canonical Monte Carlo (GCMC) simulation, let us now consider the different MC moves used to generate a configuration from another. The probabilities of occurrence of these moves vary depending on the chosen parameterization. For monoatomic molecules, there are only four relevant moves (see Figure 2.3): (i) translation of a randomly selected molecule with a displacement randomly chosen within a specific radius, (ii) conversion of the identity of a randomly chosen molecule to another one, (iii) insertion of an adsorbate molecule, and (iv) deletion of an adsorbate molecule. Rotations of the adsorbate are deliberately omitted due to the spherical symmetry of noble gases, and the change of volume is also dismissed since the flexibility of the material framework is not considered. In the GCMC screenings performed in this thesis, the probabilities of translation (i), of identity change (ii), of particle reinsertion ((iii) and (iv)) and of particle swap ((iii) or (iv)) are respectively 1/6, 1/3, 1/6 and 1/3. To clarify the terms used here, for a particle reinsertion, a particle is selected and

moved randomly to another location; and for a particle swap, there is the same equal chances to insert a new molecule or to delete one.

By using a GCMC algorithm, it is possible to generate a set of configurations according to their corresponding probability of occurrence. Since the probability law is directly derived from equation 2.5, the series of configurations describe the thermodynamic equilibrium state of a nanoporous material in contact with a reservoir containing a xenon-krypton mixture at a given composition, pressure and temperature. Ensemble averaging enables the derivation of different thermodynamic quantities, such as the averaging loading or uptake at a given pressure (several pressures yield the isotherm) and the isosteric heat of adsorption for each adsorbate (Xe and Kr). The ratio of the uptakes  $q$  informs on the selectivity  $s$  of the thermodynamic separation process:

$$s = \frac{q^{\text{Xe}}}{q^{\text{Kr}}} \times \frac{y^{\text{Kr}}}{y^{\text{Xe}}} \quad (2.8)$$

where  $y^{\text{Xe}}$  and  $y^{\text{Kr}}$  designate respectively the mole fractions of Xe and Kr in the gas phase reservoir.

To characterize a separation process, it is theoretically sufficient to perform a GCMC calculation at every pressure, temperature and composition conditions. However, such simulations can be very time-consuming due to the need to extensively test insertion/deletion moves to accurately estimate the number of adsorbed molecules and the composition of the mixture. As a result, faster methods (machine learning) have been developed to estimate the selectivity at different physico-chemical conditions.<sup>18,181</sup> For the case of infinite dilution, faster methods are already available. One such method that will be introduced in the following subsection is the Widom insertion, which enables the estimation of adsorption performances at infinite dilution by estimating the Henry adsorption constant.

#### 2.1.4 Infinite dilution adsorption: Widom insertion

In 1963, B. Widom introduced a simple method for calculating thermodynamic properties in materials or fluid mixtures.<sup>202</sup> This method typically allows accessing to the difference of internal energy before and after the insertion of a test particle while keeping all other particles fixed, thereby comparing the N-particle and (N+1)-particle states. This energy difference  $\Delta\Phi$  can then be used to deduce the excess free energy associated with the insertion  $\Delta F_{\text{exc}} = -k_B T \ln (\langle \exp(-\beta\Delta\Phi) \rangle)$  by averaging the Boltzmann factors, which corresponds to the excess chemical potential induced by the addition of a particle. More precisely, the average is theoretically performed for all possible positions of the inserted particle; in practice, the tridimensional space is uniformly and randomly sampled until convergence of the value of  $\Delta F_{\text{exc}}$ . In the domain of fluid phase equilibrium, Widom insertion is the most straightforward method to calculate chemical potential values. However, it has limitations in liquid-like phases where the insertable space is very narrow, and no relaxation is implemented to account for the reorganization of surrounding particles.<sup>203</sup>

This thesis will only focus on the insertion from 0 to 1 particle, where no issues of overlap between adsorbate particles occur. In this low-loading limit, Widom insertion is simply a random insertion of an adsorbate into an empty nanoporous framework. By randomly sampling the void space, a distribution of interaction energies  $\mathcal{E}_{\text{int}}$  can be obtained. The average of the

Boltzmann weights associated with these energies is directly proportional to the adsorption free energy  $\Delta G_{\text{ads}}$  and the Henry adsorption constant  $K_H$ . By taking the Boltzmann average of the interaction energies, the adsorption enthalpy  $\Delta H_{\text{ads}}$  can also be computed. It should be noted that these quantities remain valid only at infinite dilution, and for higher quantities of adsorbates, the previously described GCMC technique should be used. If the sampling is thorough enough, it is possible to derive the following definitions of  $\Delta G_{\text{ads}}$  (equation 2.9),  $K_H$  (equation 2.14) and  $\Delta H_{\text{ads}}$  (equation 2.22) based on a complete sampling of the interaction energies  $\mathcal{E}_{\text{int}}$  in all points of the space.

### ADSORPTION GIBBS FREE ENERGY

The adsorption Gibbs free energy  $\Delta G_{\text{ads}}$  is equal to the excess free energy previously calculated in a Widom insertion as the structure is rigid and  $PV$  does not fluctuate ( $G = F + PV$ ).

$$\boxed{\Delta G_{\text{ads}} = -RT \ln (\langle \exp(-\mathcal{E}_{\text{int}}/RT) \rangle)} \quad (2.9)$$

### HENRY CONSTANT

To derive the Henry constant  $K_H$ , let us consider an ideal gas in the bulk phase. The number of adsorbed molecules  $n_{\text{ads}}$  can then be expressed using the bulk density of the adsorbate molecule  $\rho_{\text{ads,bulk}}$  and the volume of the pores  $V_{\text{pore}}$ :

$$n_{\text{ads}} = \rho_{\text{ads,bulk}} \times V_{\text{pore}} \quad (2.10)$$

The pore volume can be seen as the continuous sum of each voxel times the Boltzmann probability of presence, which is represented by the following integral of the Boltzmann factors. This integral can then be changed to the average of the Boltzmann factors:

$$V_{\text{pore}} = \int_V \exp(-\mathcal{E}_{\text{int}}(\mathbf{r})/RT) d\mathbf{r} = V \langle \exp(-\mathcal{E}_{\text{int}}/RT) \rangle \quad (2.11)$$

Let us apply equation 2.11 and the perfect gas equation of state  $P = \rho_{\text{ads,bulk}} RT$  on the bulk gas in equilibrium. The equation 2.10 can be simplified as

$$\frac{n_{\text{ads}}}{V} = \frac{P}{RT} \langle \exp(-\mathcal{E}_{\text{int}}/RT) \rangle \quad (2.12)$$

By considering the gravimetric loading  $L_{\text{ads}}$  (in  $\text{mmol g}^{-1}$ ) instead of absolute value, we need to divide the equation by the mass density of the framework  $\rho_f$ :

$$L_{\text{ads}} = \frac{n_{\text{ads}}}{V\rho_f} = \frac{\langle \exp(-\mathcal{E}_{\text{int}}/RT) \rangle P}{\rho_f RT} \quad (2.13)$$

Since the Henry's law is described by  $L_{\text{ads}} = K_H \times P$ , we have the final relationship between the Henry adsorption constant and interaction energy distribution. If we consider a mixture, the pressure should be replaced by partial pressures.

$$K_H = \frac{\langle \exp(-\mathcal{E}_{int}/RT) \rangle}{\rho_f RT} = \frac{1}{\rho_f RT} \exp\left(-\frac{\Delta G_{ads}}{RT}\right) \quad (2.14)$$

Note that the  $\rho_f$  factor comes from the use of a gravimetric loading expressed in mmol g<sup>-1</sup> and is not always present in the different derivations of the literature.<sup>50</sup> The RT factor derives from the perfect gas assumption made in equation 2.10, which is a good approximation in the case of noble gas.

#### ADSORPTION ENTHALPY OR HEAT OF ADSORPTION

Finally, if we consider an adsorption equilibrium (e.g., Xe<sub>(g)</sub> ⇌ Xe<sub>(ads)</sub>), we can define an equilibrium constant  $K_{ads}$  based on the thermodynamic activities (partial pressure for a gas and volumetric loading for an adsorption phase) of the adsorbate in the different phases:

$$K_{ads} = \frac{l_{ads} P^o}{y_{gas} P c^o} \quad (2.15)$$

where  $l_{ads} = n_{ads}/V$  is the volumetric loading in the adsorbed phase (similar to a molar concentration) and  $y_{gas}$  the mole fraction in the gas phase for a given compound (e.g., Xe), and  $P^o$  is the standard pressure. And, here we assume the gas ideal by taking a fugacity coefficient of 1. For a gas at infinite dilution, the Henry's law can then be applied to derive the following relation:

$$K_{ads} = \frac{n_{ads} P^o}{y_{gas} P V c^o} = \frac{K_H y_{gas} P \rho_f V P^o}{y_{gas} P V c^o} = \frac{K_H \rho_f P^o}{c^o} = \frac{\langle \exp(-\mathcal{E}_{int}/RT) \rangle}{c^o RT / P^o} \quad (2.16)$$

As a sanity check, we can verify that  $c^o/P^o$  has a unit homogeneous with a molar energy, which is consistent with  $K_{ads}$  being unitless.

Now by applying the Van't Hoff equation to this infinite-dilution adsorption equilibrium constant  $K_{ads}$ , we can derive an expression of the adsorption enthalpy at infinite dilution:

$$\Delta H_{ads} = -R \frac{d \ln(K_{ads}(T))}{d(1/T)} \quad (2.17)$$

Then by decomposing the logarithm on the fraction of equation 2.16,

$$\Delta H_{ads} = \frac{d \ln(c^o R / P^o)}{d(1/T)} - R \frac{d \ln(\langle \exp(-\mathcal{E}_{int}/RT) \rangle)}{d(1/T)} - R \frac{d \ln(1/T)}{d(1/T)} \quad (2.18)$$

Then, as  $c^o R / P^o$  is constant for the variable T, the expression can be simplified to two terms, the first one being the logarithmic derivative of itself (1/T) and the second term is the logarithmic derivative of the sum of the exponential terms.

$$\Delta H_{ads} = 0 - R \frac{d \ln(\langle \exp(-\mathcal{E}_{int}/RT) \rangle)}{d(1/T)} - RT \quad (2.19)$$

Using the property that the logarithmic derivative of a function  $f$  is obtained by the formula  $\frac{d \ln(f)}{dx} = f'/f$ , we can calculate the derivative of the average of the Boltzmann factors  $\langle \exp(-\mathcal{E}_{\text{int}}/RT) \rangle$ :

$$\Delta H_{\text{ads}} = -R \frac{1}{N} \sum e^{-\frac{\mathcal{E}_{\text{int}}}{RT}} \frac{1}{N} \sum \frac{d \exp(-\mathcal{E}_{\text{int}}/RT)}{d(1/T)} - RT \quad (2.20)$$

where  $N$  corresponds to the number of points where the Widom particle has been inserted. The exponential derivative makes the energy factors come out, and we obtain the following expression:

$$\Delta H_{\text{ads}} = -R \frac{1}{\sum e^{-\frac{\mathcal{E}_{\text{int}}}{RT}}} \sum -\frac{\mathcal{E}_{\text{int}}}{R} e^{-\frac{\mathcal{E}_{\text{int}}}{RT}} - RT \quad (2.21)$$

With some simplification, the adsorption enthalpy  $\Delta H_{\text{ads}}$  can be expressed as the Boltzmann average of the interaction energies minus a term  $RT$  that corresponds to the internal energy in the bulk phase under the ideal gas assumption (perfect gas equation of state).

$$\Delta H_{\text{ads}} = \frac{\sum \mathcal{E}_{\text{int}} e^{-\frac{\mathcal{E}_{\text{int}}}{RT}}}{\sum e^{-\frac{\mathcal{E}_{\text{int}}}{RT}}} - RT \quad (2.22)$$

The isosteric heat of adsorption  $q_{\text{st}}$  is then simply the opposite of the adsorption enthalpy, at infinite dilution.

### ADSORPTION ENTROPY

From the values of the adsorption free energy and enthalpy, we can now deduce the adsorption entropy  $\Delta S_{\text{ads}}$  using the definition of the Gibbs free energy ( $G = H - TS$ ):

$$\Delta S_{\text{ads}} = \frac{1}{T} (\Delta H_{\text{ads}} - \Delta G_{\text{ads}}) \quad (2.23)$$

### SELECTIVITY

The selectivity, defined in the thesis as the ratio of the proportion of Xe/Kr in the adsorption phase to the proportion in the gas phase in equation 2.8. At infinite dilution, the selectivity can be rewritten using the Henry's law ( $q^i = V\rho_f K_H^i y^i P / n_{\text{tot}}$ ) and simplifying the constant term  $PV\rho_f / n_{\text{tot}}$ :

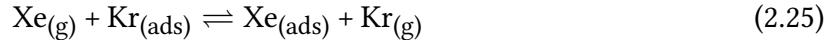
$$s = \frac{K_H^{\text{Xe}} y^{\text{Xe}}}{K_H^{\text{Kr}} y^{\text{Kr}}} \times \frac{y^{\text{Kr}}}{y^{\text{Xe}}} = \frac{K_H^{\text{Xe}}}{K_H^{\text{Kr}}} \quad (2.24)$$

By extrapolating at the zero loading regime, the Xe/Kr selectivity can be simply expressed as the ratio of the Henry adsorption constants of xenon and krypton.

This section has simple thermodynamic quantities such as the adsorption Gibbs free energy, enthalpy and entropy from the study of a simple adsorption equilibrium equation. The following section will explore a thermodynamic characterization of the adsorption-based separation process by using another equilibrium.

### 2.1.5 The thermodynamics behind adsorption-based separation

Now that the main simulation tools used to describe the competing adsorption of Xe/Kr binary mixtures have been introduced, let us rationalize the separation process by modeling the process within a hypothetical “exchange” equilibrium that corresponds to the exchange of gas phase Xe and Kr on a model adsorption site representing all the most attractive sites for a given pressure condition:



At any pressure and for a given composition, the equilibrium constant associated with equation 2.25 is simply the selectivity  $s$ , defined in equation 2.8, as the gas phase activities of  $\text{Xe}_{(\text{g})}$  and  $\text{Kr}_{(\text{g})}$  correspond to the partial pressures  $y^{\text{Xe}}$  and  $y^{\text{Kr}}$ , while the adsorption phase activities of  $\text{Xe}_{(\text{ads})}$  and  $\text{Kr}_{(\text{ads})}$  correspond to their mole fractions  $q^{\text{Xe}}$  and  $q^{\text{Kr}}$ .

#### EXCHANGE GIBBS FREE ENERGY

The Gibbs free energy at equilibrium can be directly defined using the equilibrium constant. Applying this relation to the exchange equilibrium, it is possible to define an exchange Gibbs free energy  $\Delta_{\text{exc}}G$ :

$$\boxed{\Delta_{\text{exc}}G = -RT \ln(s)} \quad (2.26)$$

#### EXCHANGE ENTHALPY

This exchange equilibrium can be viewed as the subtraction between the adsorption equilibria of xenon and krypton. Applying Hess’s law of constant heat summation, we can derive an expression for the exchange enthalpy as the difference of the adsorption enthalpies between xenon and krypton within the mixture.

$$\boxed{\Delta_{\text{exc}}H^{\text{Xe/Kr}} = \Delta_{\text{ads}}H^{\text{Xe}} - \Delta_{\text{ads}}H^{\text{Kr}}} \quad (2.27)$$

Moreover, the adsorption enthalpy  $\Delta_{\text{ads}}H$  is generally defined by comparing the average energy difference between systems differing by one adsorbate:

$$\Delta_{\text{ads}}H = \langle E \rangle (\langle N \rangle + 1) - \langle E \rangle (\langle N \rangle) - RT \quad (2.28)$$

In a GCMC calculation, we do not use the previous equation as it is, but we use a formula derived from the fluctuation theorem in statistical mechanics (see a complete derivation in this online article<sup>204</sup>):

$$\Delta_{\text{ads}}H^{\text{Xe}} \simeq \frac{\partial \langle E \rangle}{\partial \langle N \rangle} - RT = \frac{\partial \langle E \rangle}{\partial \langle \beta \mu \rangle} / \frac{\partial \langle N \rangle}{\partial \langle \beta \mu \rangle} - RT = \frac{\langle EN \rangle - \langle E \rangle \langle N \rangle}{\langle N^2 \rangle - \langle N \rangle^2} - RT \quad (2.29)$$

where  $E$  corresponds to the total energy of the adsorption system and  $N$  the total number of adsorbates at every step of the simulation. Note that this equation remains only valid for  $N \gg 1$ , as the first step of the derivation is based on a first order Taylor expansion  $\langle E \rangle (\langle N \rangle + 1) - \langle E \rangle (\langle N \rangle) \simeq \frac{\partial \langle E \rangle}{\partial \langle N \rangle}$ .

On the other hand, at infinite dilution, we can derive back the equation 2.22 using equation 2.28, where for  $N \rightarrow 0$  we now have  $\Delta H_{\text{ads}} = \langle E \rangle(1) - \langle E \rangle(0) - RT$ . The average energy with one

adsorbate minus the average energy without adsorbate corresponds to the average over the whole space of the guest–host interaction energies for one adsorbate particle (the host–host energy being encompassed in  $\langle E \rangle(0)$ ). This expression of the adsorption enthalpy echoes with the one derived in equation 2.22.

### EXCHANGE ENTROPY

Now that the exchange Gibbs free energy and an exchange enthalpy have been defined at any pressure, the same approach can be applied as in equation 2.23 to derive the exchange entropy:

$$\Delta_{\text{exc}}S = \frac{1}{T} (\Delta_{\text{exc}}H - \Delta_{\text{exc}}G) = \frac{1}{T} \Delta_{\text{exc}}H + R \ln(s) \quad (2.30)$$

### CONCLUSION

Before concluding this methodological section, it is important to note that the thermodynamic quantities associated with the newly defined adsorption exchange equilibrium can be defined at different pressure, temperature and chemical composition conditions. Moreover, various methodologies can be used to calculate them. At infinite dilution, Widom insertions and the adsorption free energies and enthalpies are typically used to deduce the adsorption free energies and enthalpies and the exchange quantities associated with them. At higher pressures, GCMC calculations are necessary to define the free energy (via the loading values) and the isosteric adsorption heat. The following study will focus solely on two characteristic pressures: the ambient pressure (at 1 atm) and the limit of zero loading (infinite dilution). At 1 atm, the previously defined quantities will be denoted with an index 1 to distinguish them from the infinite dilution case where an index 0 will be used. For example,  $\Delta_{\text{ads}}H_1^{\text{Xe/Kr}}$ ,  $\Delta_{\text{exc}}G_1^{\text{Xe/Kr}}$  or  $s_1^{\text{Xe/Kr}}$  at 1 atm, and  $\Delta_{\text{ads}}H_0^{\text{Xe/Kr}}$ ,  $\Delta_{\text{exc}}G_0^{\text{Xe/Kr}}$  or  $s_0^{\text{Xe/Kr}}$  at the low-pressure limit.

As for the simulations details, it is worth mentioning that for the GCMC calculations and Widom insertions, the RASPA2 software, developed by Dubbeldam et al.,<sup>205</sup> was used. The intermolecular van der Waals interactions were described by a Lennard-Jones (LJ) potential with a cutoff distance of 12 Å. The LJ parameters of the framework atoms were obtained from the universal force field (UFF),<sup>189</sup> while the LJ parameters for the guest atoms (xenon and krypton) were taken from a previous screening study.<sup>161</sup> All the MOFs described in this study were taken from the CoRE MOF 2019 database.<sup>72</sup>

## 2.2 PRELIMINARY ANALYSES OF THE SEPARATION

### PERFORMANCE

The previous chapters showed how the computational screening of the nanoporous materials – both existing frameworks and hypothetical structures – for targeted adsorption properties has been a subject of extensive research. Several high-throughput screening studies have particularly focused on noble gas separation, and Xe/Kr separation. In addition to the testing and validation of methodological developments, large-scale studies have generally aimed to achieve one of three main objectives: (i) identify top performing materials for synthesis and/or characterization; (ii) better understand the limits of possible performance, and the relationships and trade-offs between various metrics of performance (selectivity, uptake, etc.); (iii) identify structure–property relationships by analyzing correlations between separation performance

and structural properties of the materials, which provides chemical intuitions on designing better-performing materials. In this initial screening study of the thermodynamic quantities, I performed a screening of approximately 9 700 tridimensional structures of a preprocessed version of the CoRE MOF 2019-ASR (all solvent removed) database that are publicly available — only the non-disordered structures and the structures with a cell volume smaller than  $20\text{ nm}^3$  (to limit the overall calculation time) were considered. The focus of this study is to explore different relationships between Xe/Kr selectivity and structural descriptors based on geometrical analyses, as well as different thermodynamic descriptors (free energy, enthalpy, entropy). Some results have already been published in a scientific article [22].

### 2.2.1 Structure–selectivity relationships

An adsorption separation process is primarily characterized by a pivotal performance metric, known as the selectivity, as defined in equations 2.8 and 2.24. To characterize materials that are likely to exhibit selectivity for a 20:80 Xe/Kr mixture separation (to compare with most literature screenings on a mixture extracted from the air), this selectivity was compared to geometrical descriptors calculated by the Zeo++ software.<sup>49</sup> Three structural descriptors have been computed: the accessible surface area of a N<sub>2</sub>-sized probe of 1.2 Å, the void fraction occupiable by a 2.0 Å radius probe (roughly the size of a xenon),<sup>191</sup> and the diameter of the largest included sphere ( $D_i$ ) using specially designed atom radii. Inspired by a recent work on the comparison of pore limiting diameters and self-diffusion coefficients,<sup>51</sup> a list of van der Waals radii was defined to be used in the Zeo++ software<sup>1</sup>. In all Zeo++ calculations, an atomic radius was chosen based on the distance where the LJ potential reaches  $3k_{\text{B}}T/2$ , for T = 298 K.

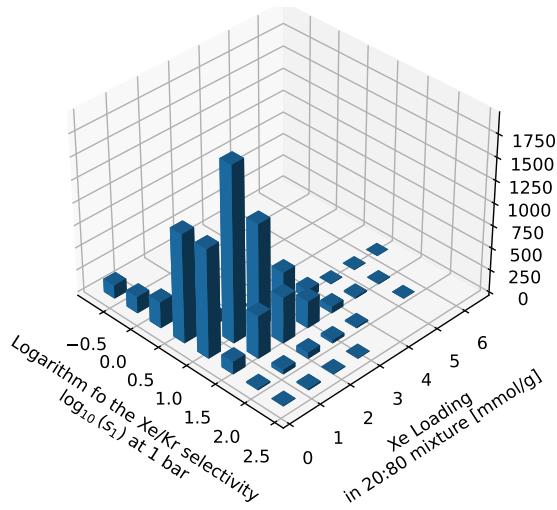
#### XENON UPTAKE AND SELECTIVITY

Before delving deeper into the structure–selectivity relationship, the relation between the xenon uptake (the number of adsorbed xenon in the GCMC simulation) and the selectivity at 1 atm will be described. For instance, the xenon uptake is a crucial factor in the separation process, as it defines the working capacity of xenon produced through adsorption/desorption cycles. Figure 2.4 reveals the possibility to have materials with a very high xenon uptake and a moderately high selectivity, or with very high selectivity but associated lower uptakes. Materials can exhibit selectivity values exceeding 100 with Xe uptake around 3 mmol g<sup>-1</sup>, whereas an uptake exceeding 6 mmol g<sup>-1</sup> can only be obtained for selectivity values between 10 and 20. It becomes evident that maximizing both uptake and selectivity metrics simultaneously is challenging, and a trade-off must be made when designing nanoporous materials for xenon/krypton separation.<sup>206</sup> Various strategies, such as the adsorbent performance score (APS),<sup>207</sup> have been implemented to optimize both metrics using mixed metrics. This trade-off can be rationalized by using the different structural descriptors (pore size, surface area and volume) introduced earlier.

Furthermore, in the optimization of either xenon uptake or Xe/Kr selectivity, it is important to note that the best materials for each of these metrics are very rare within a given diverse dataset. The histogram shown on Figure 2.4 demonstrates this scarcity, with a very low number of highly selective materials and high-capacity materials. The most frequently observed materials typically have selectivity values ranging from 1 to 10 and uptakes below 3 mmol g<sup>-1</sup>. These

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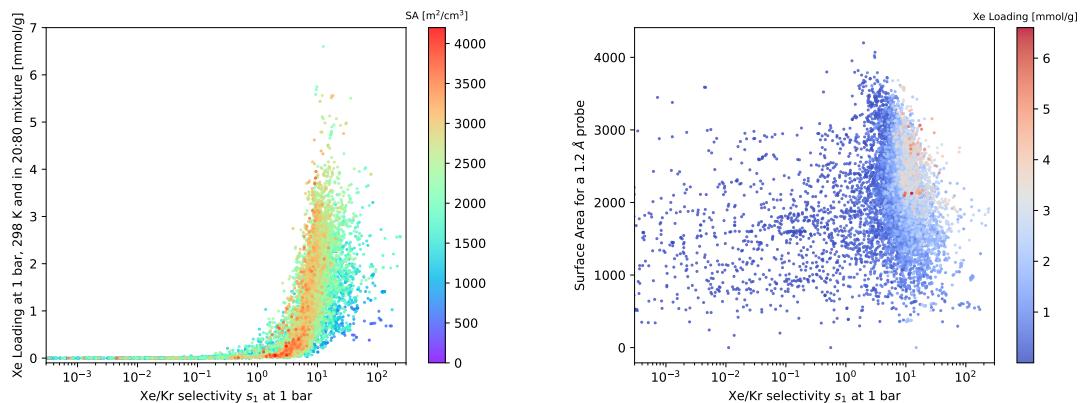
<sup>1</sup>A code can be found at [https://github.com/eren125/zeopp\\_radtable](https://github.com/eren125/zeopp_radtable)



*Figure 2.4:* 3D histograms of in a bidimensional space formed by the Xe/Kr selectivity and the xenon uptake. The z-axis represents the number of structures with characteristics close to the one specified in x and y-axis. A base-10 logarithm has been applied to the selectivity values.

values can be considered as standard values for nanoporous material used in Xe/Kr separation, serving as reference values for comparing various performance metrics and building a chemical intuition. Therefore, a selectivity exceeding 20 is considered relatively high (even though top-performing materials have a much higher selectivity<sup>8</sup>) and a xenon uptake exceeding 4 mmol g<sup>-1</sup> indicates a significant adsorption capacity. The scarcity of these top-performing materials gives rise to the analogy of searching for a needle in a haystack, prompting some computational studies to design algorithms that focus on identifying the best materials rather than equally describing all materials.<sup>208,209</sup>

#### SURFACE AREA AND SELECTIVITY

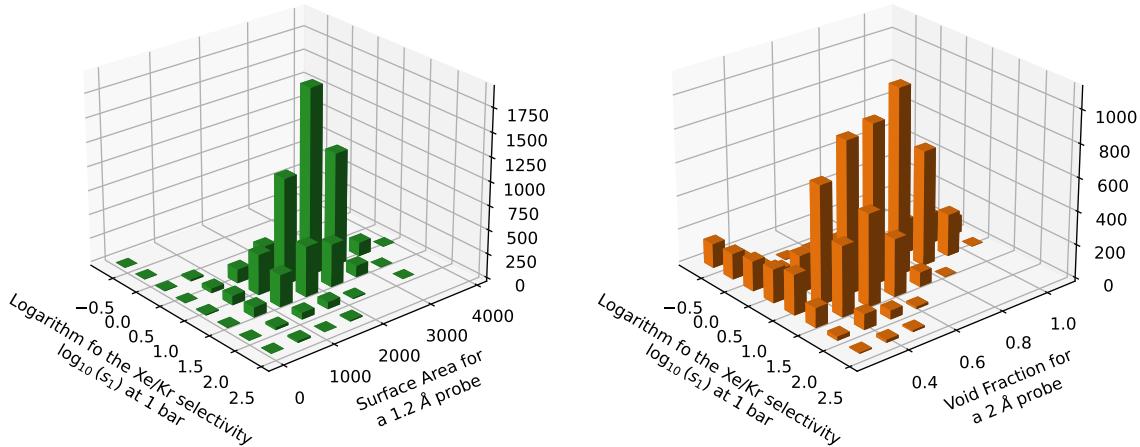


*Figure 2.5:* On the left: scatterplot of the xenon uptake as a function of the selectivity and labeled by the values of the surface area. On the right: scatterplot of the selectivity and the surface area labeled by the quantity of xenon adsorbed. The selectivity and uptake are calculated by a GCMC simulation of a 20:80 Xe/Kr mixture.

Studies on methane storage applications, conducted by Wilmer et al.<sup>12</sup> and by Fernandez et al.,<sup>17</sup> have shown that methane uptake reaches its maximum within a specific optimal range of surface area values (2500-3000 m<sup>2</sup> cm<sup>-3</sup>). Increasing the surface area beyond the range does

not lead to higher values of methane uptake. This limitation is also observed for the Xe/Kr selectivity, as shown in the right plot of the Figure 2.5. Materials with a selectivity around 5 tend to have surface areas ranging from 0 to  $4000 \text{ m}^2 \text{ cm}^3$ , while those with a selectivity above 40 tend to have a surface area below  $2500 \text{ m}^2 \text{ cm}^3$ . On the other hand, the optimal surface area for xenon uptake falls between  $2000$  and  $3000 \text{ m}^2 \text{ cm}^3$ . It is evident that the relationship between selectivity and surface area is highly complex, and a precise range of surface areas does not guarantee high selectivity. Other structural descriptors need to be considered in conjunction with this descriptor to fully characterize selectivity.

The 3D histogram on Figure 2.6 provides a visual representation of the surface area distribution for different selectivity categories. For selectivity values higher than 92, the surface areas are mostly below  $2000 \text{ m}^2 \text{ cm}^3$ . In the range of 92 to 35 selectivity, there distribution extends slightly wider, reaching up to  $2500 \text{ m}^2 \text{ cm}^3$ . For selectivity values between 35 and 13, the interval spans a larger range, up to  $3500 \text{ m}^2 \text{ cm}^3$ , but remains centered predominantly between  $1000$  and  $2500 \text{ m}^2 \text{ cm}^3$ . This split view of the distributions provides a better understanding of the characteristics of the best materials. However, it is important to note that surface area is not a deterministic variable as it is not possible to deduce selectivity based on surface area alone. A surface area between  $500$  and  $1000 \text{ m}^2 \text{ cm}^3$  may have a relatively high chance of exhibiting selectivity, but it encompasses a large number of materials and is even more likely to have selectivity values between 5 and 35 rather than values higher than that.

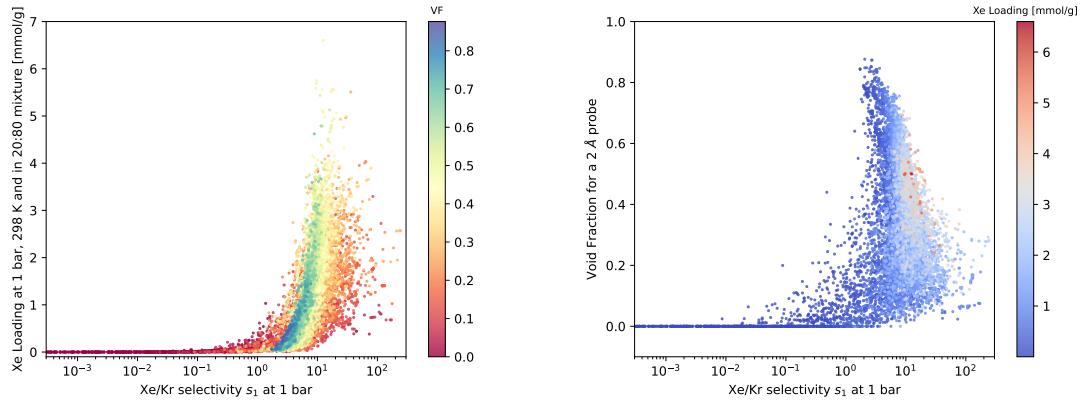


*Figure 2.6: 3D histograms of in a bidimensional space formed by the Xe/Kr selectivity and the surface areas (on the left) and formed by the Xe/Kr selectivity and the pore void fractions (on the right). A base 10 logarithm has been applied to the selectivity values. Bin size increased by 2.4 (on log scale) for the selectivity, by about  $500 \text{ m}^2 \text{ cm}^3$  for the surface areas and by 0.125 for the void fraction.*

#### VOID FRACTION AND SELECTIVITY

A similar analysis for void fraction was also conducted by Wilmer et al. for methane storage applications (Figure 5 of Ref. [12]) and they found an optimal void fraction value of approximately 0.8. As shown by the plots in Figure 2.7, materials with the highest value of Xe uptake tend to have void fraction values around 0.5, whereas those with the highest selectivity value exhibit much lower void fractions around 0.1. The optimal range of void fraction for maximizing uptake lies between 0.2 and 0.6, while for selectivity, the optimal range is completely

dissociated and falls below 0.2. Utilizing the void fraction as a descriptor allows for a more refined characterization of selectivity compared to the use of surface area, even though both descriptors yield very similar results. It becomes evident that both descriptors describe a relatively dense material with “microporosity”, in accordance with the IUPAC definition,<sup>42</sup> indicating materials with medium-low pore volume and surface area.



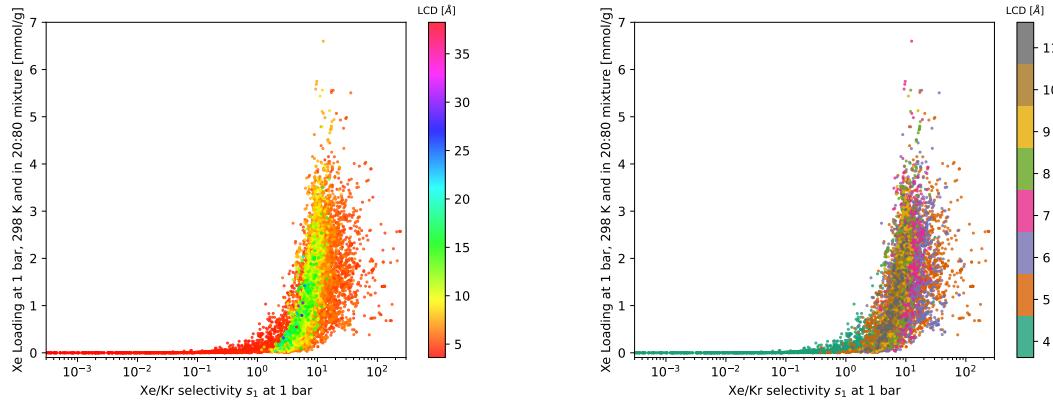
*Figure 2.7: On the left: scatterplot of the xenon uptake as a function of the selectivity and labeled by the values of the void fraction. On the right: scatterplot of the selectivity and the void fraction labeled by the quantity of xenon adsorbed. The selectivity and uptake are calculated by a GCMC simulation of a 20:80 Xe/Kr mixture.*

By conducting a similar analysis to that performed for surface areas, but this time focusing on the void fraction using Figure 2.6 (right), it is possible to identify different intervals of void fractions that correspond to highly selective materials. For instance, selectivity values above 92 correspond to materials with a porosity ranging from 0% to 37.5% (with a higher peak between 12.5% and 25%). Selectivity values between 92 and 35 can be found in materials with a void fraction ranging from 0% to 50.0% and more frequently concentrated between 12.5% and 37.5%. Selectivity values between 35 and 13 can be observed in materials with a void fraction ranging from 0% to 75.0%, with a bell-shaped distribution centered around 31%. As selectivity values decrease, the peak of the distribution shifts toward higher void fraction values, indicating a preference for lower porosity (below 25%) in terms of selectivity performance. However, similar to surface areas, the void fraction is not a deterministic variable — the void fraction alone does not determine the material’s performance. Therefore, it is necessary to investigate whether adding another variable, such as pore size, as a joint variable, can provide a better characterization of the material’s performance. As a temporary conclusion, the most selective materials seem to be little porous with void fraction not exceeding 0.5 and with an internal surface not exceeding  $2500 \text{ m}^2 \text{ cm}^{-3}$ . These materials have pores that are specialized for xenon adsorption, which will be confirmed by the following discussion.

#### PORE SIZE AND SELECTIVITY

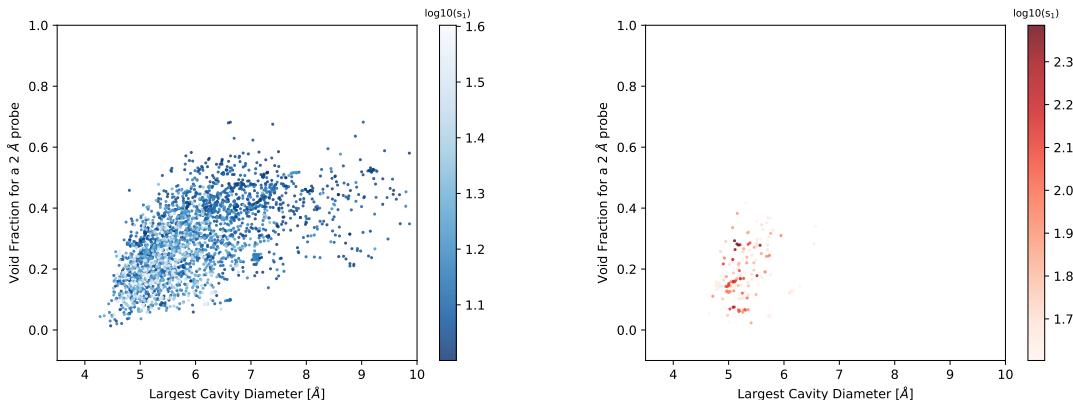
The optimal pore size for xenon/krypton separation can be deduced from Figure 2.8. As shown on the right plot, the most selective materials have a pore size close to 5 Å. However, it is challenging to distinguish between materials with very low selectivity that have a similar label color. To better visualize the differences, different colors were used to represent structures with  $D_i$  values ranging from 3.6 to 11.6 Å. It becomes evident that the pore size should be around

5 Å, but if it is too small (near 4.5 Å), the selectivity significantly decreases. Therefore, there exists a sweet spot of pore size values that enable the attainment of very high selectivity.



*Figure 2.8: Scatterplot of the xenon uptake as a function of the selectivity (20:80) and labeled by the values of  $LCD_{UFF}$  (left). The same scatterplot restricted to values of  $D_i$  between (3.6 and 11.6 Å) and labeled using a different color code to distinguish the most selective materials from the least selective ones. The most selective materials are colored in orange corresponding to a pore size adapted for xenon adsorption (around 5 Å). The least selective ones are in green, with a pore lower than the size of a xenon hence preventing its adsorption.*

The joint effects of void fraction and largest cavity diameter ( $D_i$ ) on selectivity reveal a distinct region in the bidimensional descriptor space where the most selective materials are located. On Figure 2.9, structures with a selectivity above 10 are highly likely to have a void fraction below 0.4 with a relatively wider range of  $D_i$ . However, as shown on the filtered version of the plot (on the right), the most selective materials (over 40) exist within a very narrow range of  $D_i$  values, approximately between 4.8 and 6 Å. This can be attributed to the xenon atom size, which closely matches these  $D_i$  values, which allows a maximal stabilization of xenon. On the other hand, krypton, being slightly smaller, exhibits less favorable interaction with the pores, resulting in higher observed selectivity.



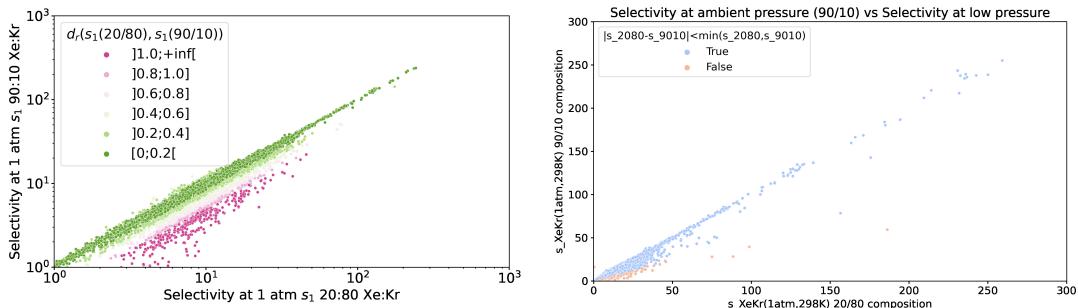
*Figure 2.9: Scatterplots of the void fraction as a function of the  $LCD_{UFF}$  and labeled by the  $\log_{10}$  of the selectivity values. On the left, only the materials with a selectivity between 10 and 40 are considered; and on the right, selectivity values over 40.*

As presented in the previous chapter, Simon et al. found that the most selective materials have a pseudo-spherical shape with a size close to the diameter of a xenon. These materials tend to have a dense structure with limited porosity. In this slightly different approach specific intervals of cavity diameter and pore volume have been associated with high selectivity, thus confirming the size requirement already identified by other studies. However, this structure–property relationship serves as a description tool for identifying selective materials, and it does not enable accurate predictions based solely on structural descriptors.

### EFFECT OF THE COMPOSITION

The previous analyses focused on a specific type of mixture composition (20:80) associated with the extraction of xenon and krypton from air through cryogenic distillation (see section 1.3.1). In the following section, the effects of composition will be investigated by considering the case of xenon/krypton separation in spent nuclear fuel off-gases. In nuclear applications, the mixture has a higher xenon content than in the previous one, with a typical 90:10 Xe/Kr ratio. For this reason, the quantity of xenon adsorbed in the materials will mechanically be higher compared to the previous scenario. However, the second quotient in the formula of selectivity in equation 2.8 compensates for the inherently higher first quotient. The objective of this analysis is to evaluate these two effects and determine whether they offset each other or if different trends emerge depending on the composition value.

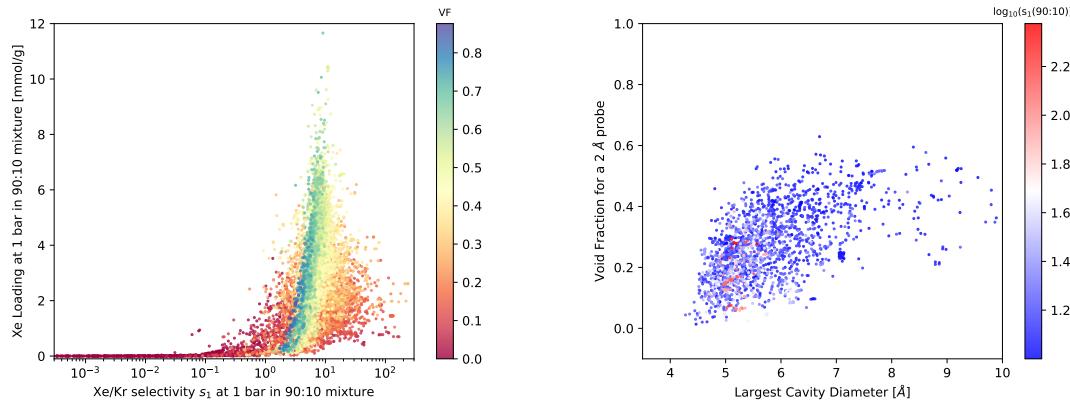
As depicted on Figure 2.10, the selectivity values of both compositions are relatively similar. However, a slight decrease in performance can be observed when increasing the proportion of xenon in the mixture, particularly for materials with moderate selectivity ( $s$  between 2 and 50). This decline in performance can be attributed to variations pores displayed by the material, which possess different affinities for xenon. When the xenon proportion is lower, Xe adsorbates preferentially access the most favorable pores, resulting in a concentration of the small quantity xenon in these sites. However, as the xenon content increases, these most favorable sites become saturated, and xenon needs to compete with krypton for less favorable sites, thereby slightly decreasing the selectivity.



*Figure 2.10: Illustration (scatterplot) of the difference of selectivity ( $s_1(20 : 80)$  and  $s_1(90 : 10)$ ) for two different Xe/Kr mixture compositions 20:80 (x-axis) and 90:10 (y-axis) at 1 atm and 298 K. On the left, the axis is in log scale and the relative difference of selectivity between the two compositions is particularly high for the points labeled in purple. On the right, the axis is in linear scale and the points are labeled only to differentiate the materials with relative difference under and over 1.*

The effect of the composition on the different analyses of the different structural descriptors will be discussed here. Notably, when considering a mixture with a higher xenon content, the xenon uptake values experience significant change. The nanopores of selective materials ( $1 < s_1 \leq 50$ )

are much more saturated with Xe, resulting in a substantially higher maximum xenon uptake. Comparing the Figures 2.7 and 2.11, the maximum uptake increases from  $6.6 \text{ mmol g}^{-1}$  (for the 20:80 composition) to  $11.7 \text{ mmol g}^{-1}$ . In the case of moderately selective materials at the 20:80 composition, the xenon competes with krypton primarily in the most selective nanopores. However, with a higher xenon content, xenon has to compete with krypton in much less favorable sites due to saturation of the most preferable sites. It is worth noting the previous conclusion regarding the maximum uptake of xenon for the most selective materials ( $s_1 > 50$ ) remains valid. The maximum xenon uptake reaches up to  $4.0 \text{ mmol g}^{-1}$ , and it increases slightly to  $4.2 \text{ mmol g}^{-1}$  for the composition with a higher xenon content. Despite the change in composition, the nature of the adsorbed state remains unchanged due to the extremely high selectivity, resulting in similar quantities of xenon being present in the pores. Consequently, the higher xenon content does not significantly influence the performance of the most selective materials, but it can alter selectivity and greatly increase the xenon uptake for some moderately selective materials.



*Figure 2.11: Illustration of the effect of the composition by representing the same figures as in 2.7 and 2.9 but for a 90:10 composition. On the left: scatterplot of the xenon uptake as a function of the selectivity ( $s_1(90 : 10)$ ) and labeled by the values of the void fraction. On the right: scatterplots of the void fraction as a function of the LCD<sub>UFF</sub> and labeled by the selectivity ( $s_1(90 : 10)$ ) values superior to 10 in log-scale.*

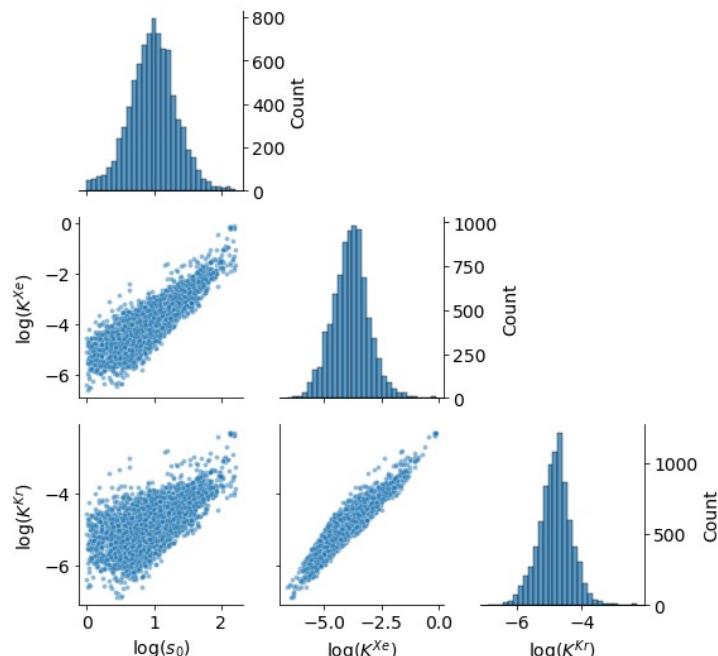
As a conclusion, the composition does not seem to affect the previously determined structural characteristics required for high selectivity. As depicted in the right plot of the Figure 2.11 (right), the most selective materials still exhibit a pore size of approximately  $5 \text{ \AA}$  and a porosity below 40%. This structural domain serves as necessary conditions for achieving selectivity, but they are not sufficient as less selective materials can also display these characteristics. Having established the geometric conditions necessary for obtaining good selectivity, the focus now shifts towards understanding the thermodynamic origins of selectivity by examining energy-based quantities and the various correlations among them.

## 2.2.2 Thermodynamic quantities correlations at infinite dilution

In this section, my goal is to map out the details of the thermodynamic features of Xe/Kr adsorption and separation in nanoporous materials, rather than to directly address the structure–property relationships. The high-throughput screening methodology was used to map out the space of thermodynamic properties, surpassing the conventional metrics of selectivity and

uptake. The specific emphasis was placed on investigating the role of adsorption enthalpy and entropy, differentiating between Xe and Kr adsorption thermodynamics, and analyzing the variations in selectivity at both low and high pressures. The discussion below is based on a work published<sup>1</sup> in the Faraday Discussions Ref. [22].

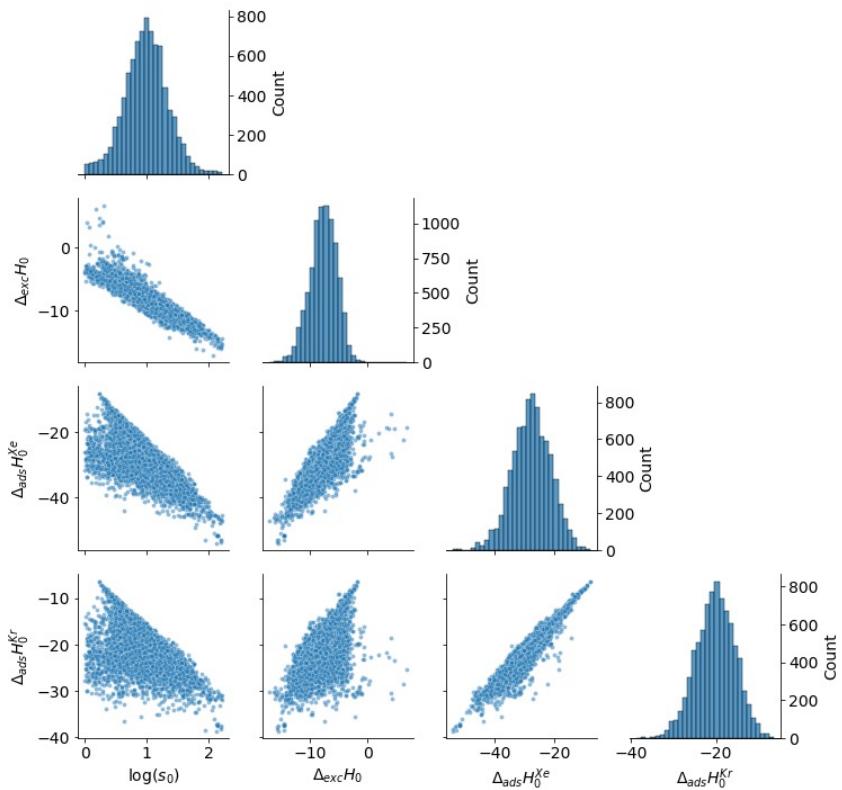
To assess the performance of a given nanoporous material for separation in the low loading (or low pressure) limit, Henry constants are commonly calculated by linearly fitting low-pressure adsorption isotherm data – both experimentally and computationally. In this section, the thermodynamics of Xe and Kr adsorption at low pressure are investigated. Specifically, the low-pressure adsorption properties are obtained using the Widom insertion method<sup>202,210</sup> on a dataset of 9 668 selected structures. This method provides higher accuracy compared to fitting isotherms, where it can be challenging to determine the extent of the linear adsorption regime. Through these simulations, Henry constants K and adsorption enthalpies  $\Delta_{\text{ads}}H_0$  (at the zero loading limit) are calculated for both xenon and krypton. The Xe/Kr thermodynamic selectivity  $s_0$  in the low-pressure limit is then determined by the ratio  $s_0 = K^{\text{Xe}}/K^{\text{Kr}}$  of the Henry constants for the two gases. In the following discussion, the statistical relationships among the thermodynamic quantities at low pressure, namely  $s_0$ ,  $K^{\text{Xe}}$ ,  $K^{\text{Kr}}$ ,  $\Delta_{\text{ads}}H_0^{\text{Xe}}$ ,  $\Delta_{\text{ads}}H_0^{\text{Kr}}$  and  $\Delta_{\text{exc}}H_0$ , will be examined.



*Figure 2.12: For 8 401 MOFs with favorable thermodynamic Xe/Kr selectivity ( $s_0 > 1$ ), pair plots of  $\log_{10}(s_0)$ ,  $\log_{10}(K^{\text{Xe}})$  and  $\log_{10}(K^{\text{Kr}})$  (the Henry constants are in  $\text{mmol g}^{-1} \text{Pa}^{-1}$ ) in the off-diagonal subplots (note that the y-axis is displayed on the right side) and the distribution of each quantity are on the diagonal (note that the y-axis displayed on the right side corresponds to the count and the x-axis is correctly labeled below each subplot).*

The distribution of thermodynamic properties of materials with favorable thermodynamic Xe/Kr selectivity ( $s_0 > 1$ ) is depicted in Figure 2.12. It is important to note that the plots focus on selectivity values above 1, as these are the materials of interest for separation. This selection

<sup>1</sup>The related data can be found at [https://github.com/fxcoudert/citable-data/tree/master/132-Ren\\_FaradayDiscuss\\_2021](https://github.com/fxcoudert/citable-data/tree/master/132-Ren_FaradayDiscuss_2021)



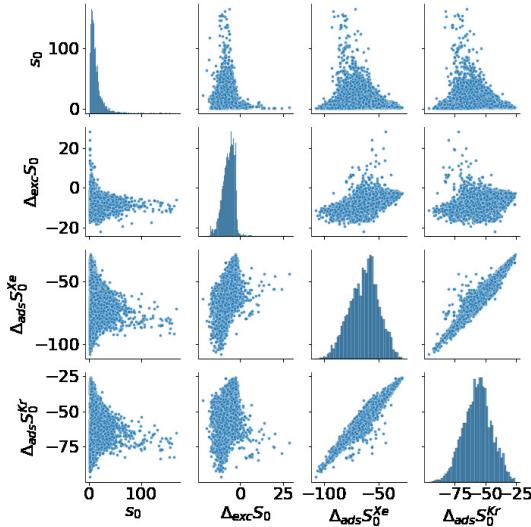
*Figure 2.13: For 8 401 MOFs with favorable thermodynamic Xe/Kr selectivity ( $s_0 > 1$ ), pair plots of  $\log(s_0)$ ,  $\Delta_{exc}H_0$ ,  $\Delta_{ads}H_0^{Xe}$  and  $\Delta_{ads}H_0^{Kr}$  (the enthalpies are in  $\text{kJ mol}^{-1}$ ) in the off-diagonal subplots and the distribution of each quantity is on the diagonal.*

eliminates certain outliers with specific geometries or binding sites (without significantly altering the overall conclusions). The plots reveal that while the logarithm of Xe Henry constant  $K^{Xe}$  exhibits a weak correlation with the logarithm of selectivity  $s_0$ , this correlation is stronger for highly selective materials. Therefore, in a multistep screening study aimed at identifying the most selective materials, it could be possible to utilize as a “first filter” criterion based purely on Xe adsorption, by excluding materials below a certain threshold (e.g., the materials with  $s_0 \geq 30$  can be found in the subset with  $K^{Xe} \geq 2.7 \cdot 10^{-1} \text{ mmol g}^{-1} \text{ Pa}^{-1}$ ). On the other hand, the correlation between  $K^{Kr}$  and  $s_0$  is relatively weaker. These results suggest that a high affinity with xenon measured by the Henry constant is a determining factor of high selectivity for the most selective materials.

In terms of Henry constants, a diverse range of behaviors is observed, with  $K^{Xe}$  ranging from  $2.6 \cdot 10^{-7}$  to  $7.9 \cdot 10^{-1} \text{ mmol g}^{-1} \text{ Pa}^{-1}$ , and  $K^{Kr}$  ranging from  $1.3 \cdot 10^{-7}$  to  $5.1 \cdot 10^{-3} \text{ mmol g}^{-1} \text{ Pa}^{-1}$ . Additionally, there is a statistical trend indicating that a high affinity for xenon typically translates into a relatively high affinity for krypton. This general trend is observed for noble gases, where the adsorption sites lack strong specificity. To delve deeper into the thermodynamic aspects underlying this wide diversity in behavior, the enthalpies involved were plotted on Figure 2.13.

The low-loading adsorption enthalpy of xenon ( $\Delta_{ads}H_0^{Xe}$ ) is strongly correlated with that of krypton ( $\Delta_{ads}H_0^{Kr}$ ), which aligns with the correlation observed between their respective Henry constants. This suggests the involvement of a rather generic physisorption mechanism in

the majority of materials, where the host–adsorbate affinities are primarily determined by the enthalpy. The selectivity of Xe/Kr selectivity is not driven significantly by the xenon or krypton adsorption enthalpy alone (both exhibit weak correlation with selectivity), but rather by their difference,  $\Delta_{\text{exc}}H_0$ , which shows a strong correlation with  $\log(s_0)$ . This finding is further supported by the lack of correlation between selectivity and adsorption entropies (*cf.* Figure 2.14), indicating that the separation is predominantly enthalpic in nature, and any dispersion in the correlation between selectivity  $\log(s_0)$  and  $\Delta_{\text{exc}}H_0$  is influenced by entropy.



*Figure 2.14:* For 8 401 MOFs with favorable thermodynamic Xe/Kr selectivity ( $s_0 > 1$ ), pair plots of  $s_0$ ,  $\Delta_{\text{exc}}S_0$ ,  $\Delta_{\text{ads}}S_0^{\text{Xe}}$  and  $\Delta_{\text{ads}}S_0^{\text{Kr}}$  in the off-diagonal subplots and the distribution of each quantity are on the diagonal.

Upon closer analysis of the Figure 2.14, it is observed that the adsorption entropy of xenon and krypton shows a noticeable correlation. However, their difference (the exchange entropy), which represents the exchange entropy, does not exhibit significant varions (see Figure 2.15) compared to the enthalpy. This suggests that the thermodynamic quantity plays a minor role in the selectivity performance of the materials. However, it is noted that although the most selective materials do not have any exchange entropy values, they are centered around a value of approximately  $-10 \text{ kJ mol}^{-1} \text{ K}^{-1}$ . While this correlation is not straightforward, it indicates that possessing an exchange entropy within this range is a necessary attribute for achieving selectivity in materials.

To further emphasize the enthalpic nature of the separation process, the base-10 logarithm of the Henry constant (proportional to the adsorption free energy) is compared to the adsorption enthalpy for both xenon and krypton. As shown in Figure 2.16, the free energy can be predominantly explained by the enthalpy, which confirms the secondary role played by entropy in accounting for the dispersion in this relationship. The effect of entropy weakens the correlation for materials with less favorable adsorption, but as the adsorption enthalpies become increasingly negative, the correlation becomes increasingly stronger. The most selective materials have an almost negligible entropic contribution to the final free energy value ( $G = H - TS$ ).

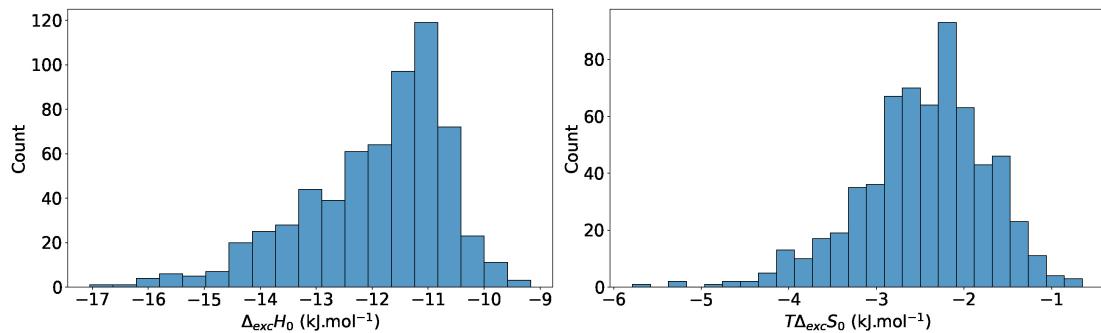


Figure 2.15: Distribution of the enthalpy  $\Delta_{exc}H_0$  and entropy  $T\Delta_{exc}S_0$  of exchange at low pressure on the 630 most selective structures

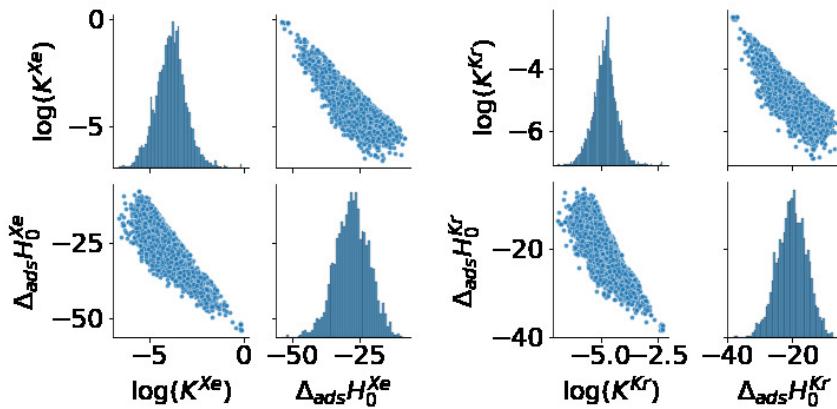


Figure 2.16: For 8 401 MOFs with favorable thermodynamic Xe/Kr selectivity ( $s_0 > 1$ ), pair plots of  $\log(K_H^i)$  and  $\Delta_{ads}H_0^i$  in the off-diagonal subplots for both  $i=Xe$  and  $i=Kr$  and the distribution of each quantity are on the diagonal.

Upon further analysis of Figure 2.17, it becomes apparent that the entropic effect is influenced by the pore size. Specifically, larger pore sizes tend to yield more positive entropic terms (the entropic term refers to  $-T\Delta_{ads}S$ ). This observation elucidates the weaker correlation observed for less attractive materials observed throughout the pairplot of Figures 2.13 and 2.12.

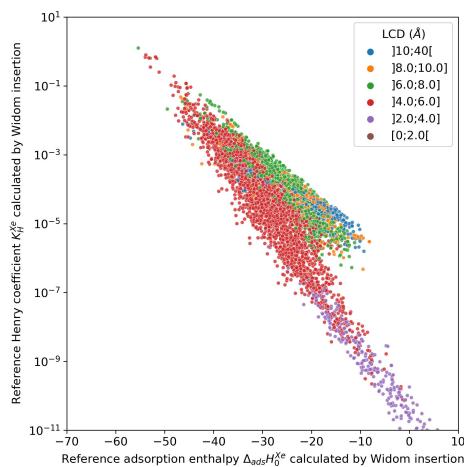
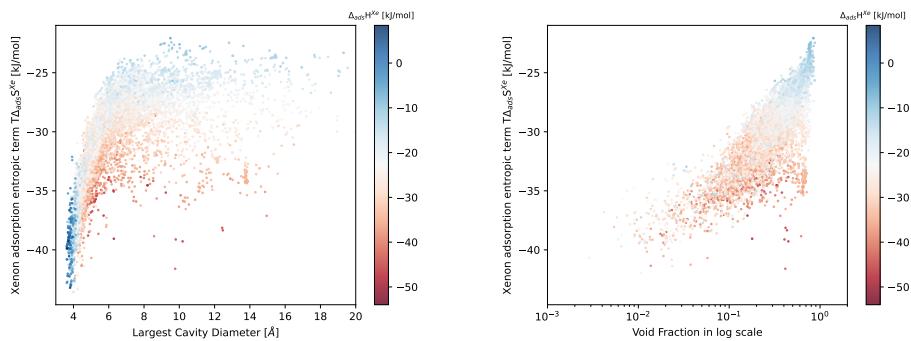


Figure 2.17: Comparison between the Xe Henry constant and Xe adsorption enthalpy labeled by categories of  $LCD_{UFF}$  values for the CoRE MOF structures.

In the analysis of the influence of the pore size and void fraction on the entropic term  $T\Delta_{ads}S_0^{Xe}$  (see Figure 2.18), a clear relationship between entropy and pore size, represented by the LCDUFF<sup>1</sup>, is observed. Larger pores tend to exhibit higher entropy, likely due to the confinement effect of the pore — a small pore limits the available adsorption positions for xenon, while a larger pore provides more sites for adsorption. A similar trend is observed for pore volume, represented by the void fraction here. A weak linear correlation exists between the void fraction (in log-scale) and the adsorption entropic term of xenon. However, it is important to note that these simple geometric descriptors may not capture the entire complexity of the entropic behavior, particularly for larger pore sizes. Other effects that can contribute to the entropic effects include the shape of the channel and cavities (e.g., tortuosity) or the overall distribution of pore sizes that cannot be adequately captured by the LCDUFF.



*Figure 2.18: Comparison plots of the entropic term  $T\Delta_{ads}S_0^{Xe}$  at infinite dilution and two geometric descriptors: the LCDUFF (left) and the void fraction (right).*

Cross-referencing these findings with the previous results obtained on the influence of geometric descriptors in the section 2.2.1, it becomes evident that the entropic effect aligns with the enthalpic term in explaining selectivity when the pore size approaches that of xenon. The confinement of xenon within the pores leads to lower entropy in the adsorbed phase compared to the gas phase, especially for pores tailored to xenon's size. Furthermore, the optimal interaction between xenon and the surrounding framework atoms reduces the enthalpic term. Both factors work in concert, elucidating the optimal selectivity observed for this particular pore size value (around 5 Å).

The key takeaways from this section revolve around two relationships. Firstly, there is a correlation between the Henry constant of xenon and selectivity, allowing for rough estimation of Xe/Kr selectivity — the most selective materials exhibit a strong affinity for xenon. Secondly, the selectivity process is primarily driven by enthalpy — the separation process has an enthalpic nature as a first-order approximation, which is particularly true for the most selective materials. Analyzing the energy interactions within the material provides crucial insights into its performance. While the focus here has been on thermodynamic properties at infinite dilution, the subsequent section will delve into the impact of pressure on selectivity, specifically examining a 20:80 Xe/Kr mixture at 1 atm and 298 K.

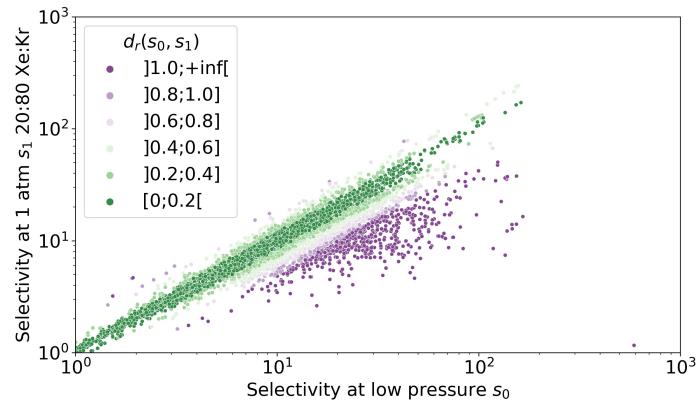
<sup>1</sup>This corresponds to the diameter of the largest included sphere defined by UFF-based atom radii

## 2.3 SELECTIVITY DROP BETWEEN TWO PRESSURE REGIMES

As the previous section has established the relationship between selectivity and some geometrical and thermodynamic descriptors, this section focuses on examining the relationship between selectivity values at infinite dilution and selectivity values at ambient pressure using a thermodynamics-based approach. The aim is to gain a better understanding of the underlying mechanisms driving the observed changes in selectivity as previously discussed in Figure 2.10. It is worth noting that the findings presented in this section have already been published in Ref. ??

### 2.3.1 Thermodynamic origins

After delving into the thermodynamics of the infinite dilution case, the focus now shifts to examining the impact of changes in working pressure on adsorption selectivity and analyzing its underlying thermodynamic mechanisms. Understanding the impact of pressure on selectivity is crucial for accurately assessing adsorption thermodynamics under different working conditions, particularly in specific industrial processes. Insights into the pressure-dependent selectivity may allow for faster screening of materials limited to specific thermodynamic conditions.

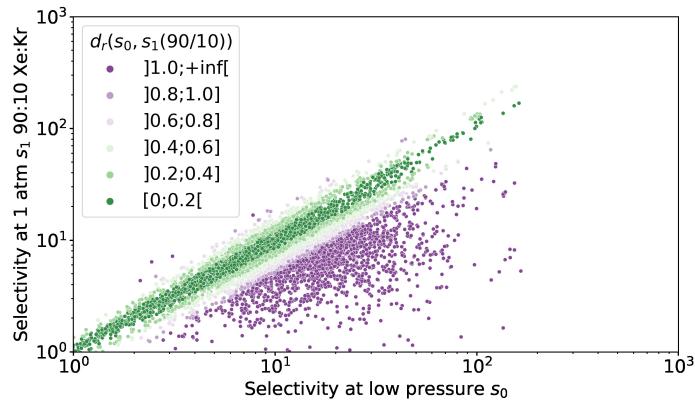


*Figure 2.19: Difference of selectivity between low pressure and at a 1013 hPa pressure for a 20:80 xenon/krypton composition. The relative difference between the low-pressure selectivity and the ambient pressure is particularly high for the points labeled in purple.*

The selectivity  $s_1$  was calculated at a pressure of 1 atm and ambient temperature using GCMC calculations on the entire dataset, with Xe/Kr mixture composition of 20:80 (found in a byproduct stream from air separation<sup>1</sup>), and 90:10 (found in the off-gas streams from nuclear waste<sup>173</sup>). It was observed that for high-selectivity materials, the composition had a minimal impact, as shown in (*cf.* Figure 2.10). In the following analysis, the focus is primarily on the selectivity for the 20:80 mixture, which is the most commonly studied composition in the literature. To quantify the difference in selectivity between low and ambient pressures, a relative difference  $d_r(s_0, s_1)$  is considered, as defined in equation 2.31.

$$d_r(s_0, s_1) = \frac{|s_0 - s_1|}{\min(s_0, s_1)} \quad (2.31)$$

Figure 2.19 presents the selectivity at ambient pressure  $s_1$ , plotted against its low-pressure counterpart  $s_0$  (for materials where  $s_0 > 1$ , as before). The points on the plot are color-coded

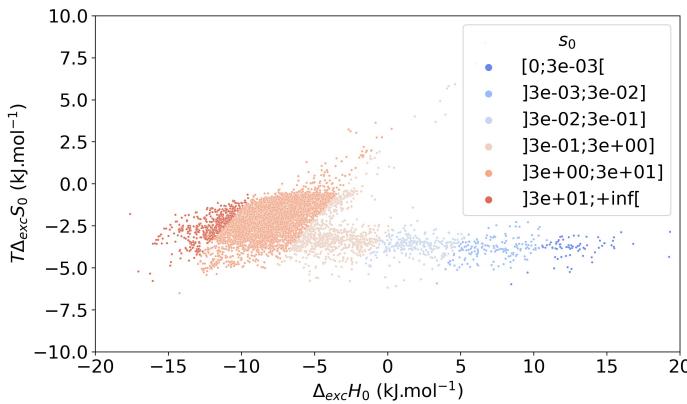


*Figure 2.20: Difference of selectivity between low pressure and at a 1013 hPa pressure for a 90:10 xenon/krypton composition. The relative difference between the low-pressure selectivity and the ambient pressure is particularly high for the points labeled in purple.*

according to the values of  $d_r(s_0, s_1)$ , which are divided into 6 discrete categories for clarity. A broad correlation is observed, particularly near the diagonal line where approximately 61.5% of the materials exhibit a difference below 20% (close to the  $s_0 = s_1$  line). However, it is notable that there are considerably more points, approximately (74.3% of the materials with  $d_r(s_0, s_1) \geq 0.2$ ) below the first bisector ( $s_1 < s_0$ ), indicating that for these materials, the selectivity  $s_1$  at 1 atm is significantly lower than the selectivity  $s_0$  at low pressure.

This drop in selectivity primarily affects materials with a relatively high selectivity  $s_0 > 10$  (see Figure 2.19). It highlights the potential pitfalls of relying solely on pure-component Henry's constant (i.e., zero-pressure selectivity) for materials screening. While calculating low-pressure selectivity is simpler and faster, it can lead to overestimated selectivity by more than 100% in a significant number of materials (646 out of 9,668 in our dataset). To understand the underlying reasons for these shifts in selectivity, a thermodynamic approach will be employed.

Before delving deeper in the analyses of the thermodynamic origins of this pressure-induced selectivity drop, this paragraph will open a small aside on the 90:10 mixture composition. When examining the 90:10 composition, it becomes apparent that the drop in selectivity is even more pronounced. The selectivity for the higher xenon proportion was already found to be higher than that for the 20:80 composition (see Figure 2.11). This drop can be attributed to the presence of more or less favorable adsorption sites. In some materials (labeled in purple), at low xenon content composition, xenon and krypton primarily compete for the most favorable sites until these sites become saturated, leaving no xenon to compete in the less selective sites. As the Xe/Kr ratio increases, these less selective nanopores contribute to an overall decrease in selectivity. When combined with the effect of increased pressure, certain materials undergo both phenomena, resulting in a more pronounced drop in selectivity compared to the selectivity at low pressure. These explanations are backed up by the following analyses on the pressure effect, which highlights similar effects of the total pressure (instead of partial pressure) on selectivity — a higher xenon content is actually equivalent to increasing the partial pressure of xenon. Now that the effect of higher xenon content has been characterized, the following analyses will be based on the 20:80 Xe/Kr composition.



*Figure 2.21: The energetic equivalent of exchange entropy  $T\Delta_{\text{exc}}S_0$  and enthalpy  $\Delta_{\text{exc}}H_0$  at low pressure labeled using the selectivity  $s_0$  at low pressure (for any xenon/krypton composition). The limit between labels follows an affine function of slope  $1/T$  and of intercept  $-R \ln(s_0^{\lim})$  where  $s_0^{\lim}$  is the limit selectivity value (cf. equation (2.30)). In other words, the iso-selectivity lines are all parallel lines of equation  $y = f(x)$  where  $f$  is the affine function described previously.*

To quantitatively assess the thermodynamic effects involved in the competitive adsorption under different regimes (for the 20:80 composition), thermodynamic properties of the “exchange equilibrium” predefined in equation 2.25 are considered. Figure 2.21 displays a scatterplot of the exchange entropy at low pressure, represented as  $T\Delta_{\text{exc}}S_0$ , plotted against the exchange enthalpy  $\Delta_{\text{exc}}H_0$ . The points on the plot are color-coded according to the selectivity  $s_0$  (with discrete categories for clarity), which is related to the enthalpy and entropy through Equation 2.30 – indicating iso-selectivity lines correspond to parallel straight lines in this scatterplot.

Figure 2.15 presents the distributions of the exchange enthalpy and entropy at low pressure. Among the 630 most selective materials ( $s_0 > 30$ ), the distribution of the exchange enthalpy  $\Delta_{\text{exc}}H_0$  is centered around  $-12.0 \text{ kJ mol}^{-1}$  with a standard deviation of  $1.3 \text{ kJ mol}^{-1}$ . On the other hand, the distribution of the exchange entropy (represented as  $T\Delta_{\text{exc}}S_0$ ) is centered around  $-2.5 \text{ kJ mol}^{-1}$ , with a standard deviation of  $0.7 \text{ kJ mol}^{-1}$ . These figures, along with the overall distribution plotted in Figure 2.21, provides further evidence of the relatively modest role of entropy in determining the selectivity at low pressure, which corresponds, on average, to approximately 20% of the exchange enthalpy.

Examining Figure 2.22 for the selectivity at ambient pressure, similar conclusions can be drawn regarding the limited influence of entropy on selectivity values. The distribution of the entropic term  $T\Delta_{\text{exc}}S_1$  is centered around  $-3 \text{ kJ mol}^{-1}$ , which remains relatively small compared to the values of  $\Delta_{\text{exc}}H_1$ . For the most selective materials, the entropic term represents approximately 19% of the exchange enthalpy  $\Delta_{\text{exc}}H_1$  at ambient pressure.

Figure 2.23 represents a scatterplot of the exchange entropy at  $P = 1 \text{ atm}$   $\Delta_{\text{exc}}S_1$  against the exchange enthalpy at ambient pressure  $\Delta_{\text{exc}}H_1$ . The points are color-coded according to the low-pressure selectivity  $s_0$  to compare it with the Fig. 2.21. In comparison to the iso-selectivity  $s_1$  straight parallel lines (cf. Figure 2.24), it can be observed that many materials with high  $s_0$  have lower  $s_1$ , as indicated by a migration of points to the right of the plot. This shift is thus mainly due to a higher (less favorable) exchange enthalpy, implying that enthalpy plays a crucial role in determining selectivity at higher pressures.

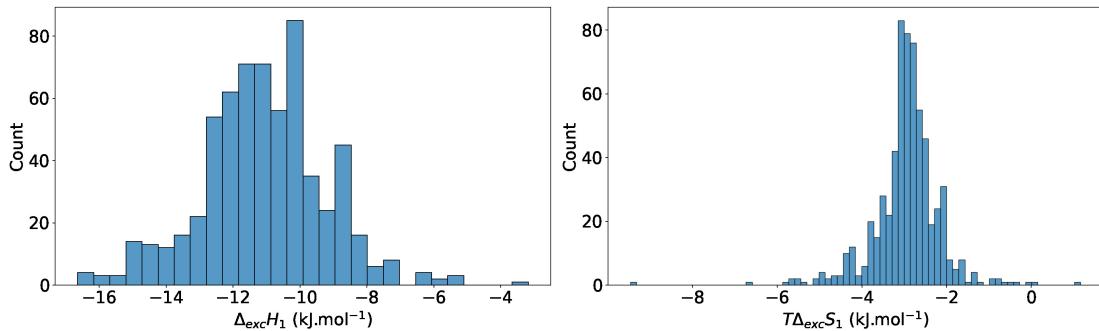


Figure 2.22: Distribution of the enthalpy  $\Delta_{\text{exc}}H_1$  and entropic term  $T\Delta_{\text{exc}}S_1$  of exchange at ambient pressure on the 630 most selective structures.

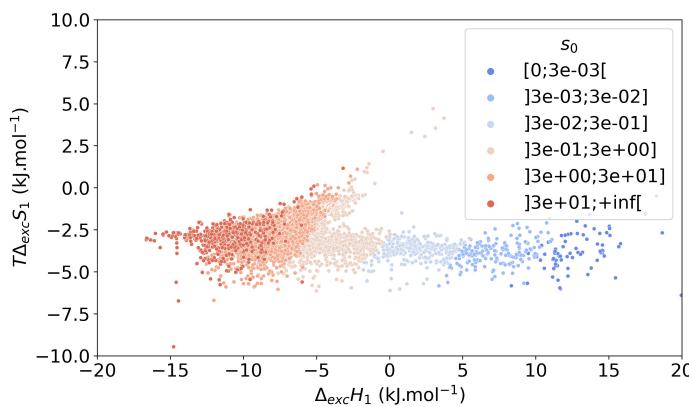
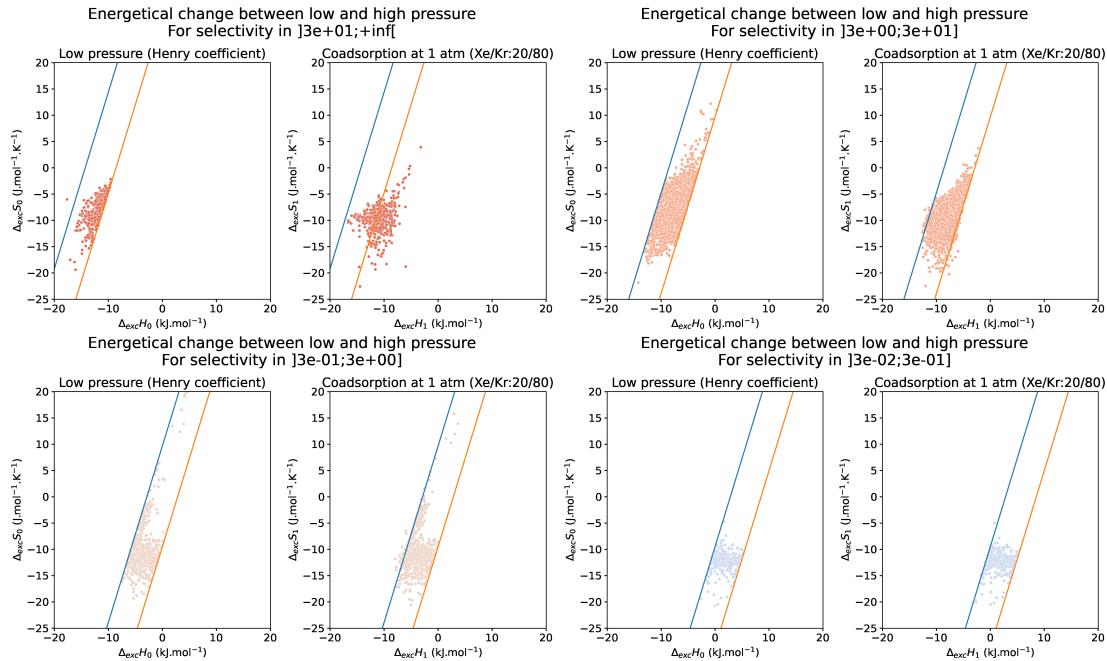


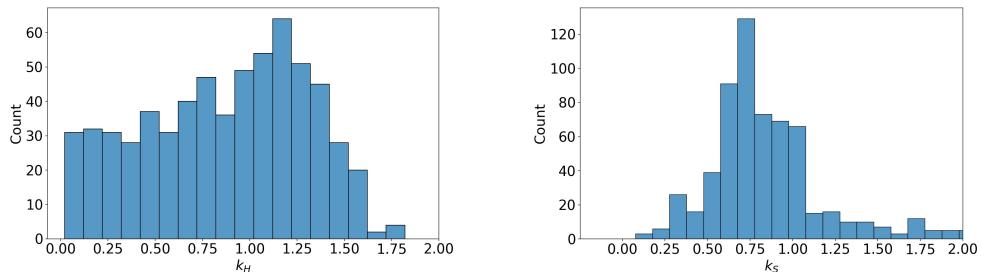
Figure 2.23: The energetic equivalent of exchange entropy  $T\Delta_{\text{exc}}S_1$  and enthalpy  $\Delta_{\text{exc}}H_1$  at ambient pressure (for a 20:80 xenon/krypton composition) labeled using the selectivity  $s_0$  at low pressure. The points are layered so that the points with higher  $s_0$  are always above. To see a split version of this plot, please refer to Figure 2.24.

To quantify this change, the distributions of the exchange enthalpy  $\Delta_{\text{exc}}H_1$  and the energetic equivalent of the exchange entropy  $T\Delta_{\text{exc}}S_1$  at ambient pressure (Figure 2.22) are considered. The enthalpy distribution  $\Delta_{\text{exc}}H_1$  is now centered at  $-11.1 \text{ kJ mol}^{-1}$  with a standard deviation of  $1.9 \text{ kJ mol}^{-1}$ . In comparison to the zero-pressure values, the enthalpy distribution exhibits greater dispersion, suggesting significant changes in individual values and an overall increase in average enthalpy. Most materials display lower selectivity at ambient pressure due to enthalpic effects, which can be attributed to the general increase in adsorption enthalpy with increasing gas phase loading, which is linked to the presence of more adsorbed molecules. The correlations shown in Figure 2.12 suggest that highly selective materials have a high affinity for xenon, resulting in substantial uptake at 1 atm. The large Xe loading means the saturation of the most favorable adsorption sites and the subsequent adsorption of weaker host–guest interactions contribute to an overall increase in average adsorption enthalpy at non-zero loading.

The entropic term  $T\Delta_{\text{exc}}S_1$  is now centered at  $-2.9 \text{ kJ mol}^{-1}$ , with a standard deviation of  $0.8 \text{ kJ mol}^{-1}$  (almost unchanged from low-pressure). The average entropy is lower, indicating a less favorable separation overall due to entropic effects. This evolution of the entropic term suggests the possibility of a reorganization of adsorbed molecules within each material. However, the difference in enthalpy distribution has a greater impact on high-pressure selectivity



*Figure 2.24:* Split view of Figure 2.21 and 2.23. The iso-selectivity lines for the limit considered are represented with blue and orange lines. It seems that the shift in exchange enthalpy for the structures with a selectivity higher than 30.

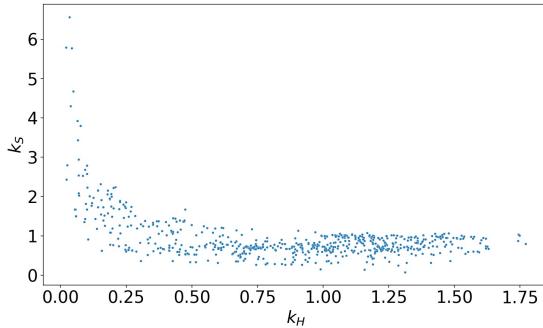


*Figure 2.25:* Distribution of the enthalpic  $k_H$  and entropic  $k_S$  contributions to the change of selectivity from low to ambient pressure for the 630 materials with  $s_0 > 30$ .  $k_H$  has a rather broad and uniform distribution, whereas  $k_S$  has a bell-like distribution.

compared to the distribution of entropy. Thus, the overall contribution of enthalpy appears to be more decisive than the role of entropy in determining selectivity changes, even at ambient pressure. This finding is significant for screening studies, as evaluating adsorption enthalpy computationally is generally faster than determining adsorption free energy (or entropy).

To further investigate the thermodynamics of the selectivity change, I quantify in this section the contributions of enthalpy and entropy. The ratio  $s_1/s_0$  is equal to the product  $k_H \times k_S$  where  $k_H$  and  $k_S$  are the enthalpic and entropic contributions to the selectivity change defined as:

$$\begin{aligned} k_H &= \exp\left(-\frac{\Delta_{\text{exc}}H_1 - \Delta_{\text{exc}}H_0}{RT}\right) \\ k_S &= \exp\left(\frac{\Delta_{\text{exc}}S_1 - \Delta_{\text{exc}}S_0}{R}\right) \end{aligned} \quad (2.32)$$



*Figure 2.26: Scatterplot of the enthalpic contribution  $k_H$  and entropic contribution  $k_S$  for the 630 materials with  $s_0 > 30$ . The entropic compensation occurs when the enthalpic contribution is around 0.1, else its value is around 1 and has little effect on the selectivity change.*

As depicted in Figure 2.25, the entropic contribution  $k_S$  has a bell-shaped distribution, with a mean of 0.9 and a standard deviation of 0.6. This confirms that  $k_S$  is close to 1, indicating that it has only a marginal effect on the selectivity change. In contrast, the enthalpic contribution  $k_H$  has a more uniform distribution ranging from 0.1 to 1.5, which means that enthalpy plays a crucial role in the observed selectivity change. Notably, there exists a significant number of materials with  $k_H$  close to zero, corresponding to the same materials highlighted on Figure 2.19.

Furthermore, the scatterplot of  $k_H$  and  $k_S$  (shown on Figure 2.26) confirms the relatively moderate effect of entropy. For most materials with  $0.25 \leq k_H \leq 1.75$ ,  $k_S$  is close to 1. The most significant entropic contributions are observed for materials where  $k_H$  is close to zero (typically below 0.25). Examining the 29 materials with  $k_S > 2$  in more detail, it appears that the entropic contribution  $k_S$  moderately compensates for the enthalpic contribution, resulting in an average ratio of  $s_1/s_0$  around 0.25. In such cases, entropy is non-negligible and can partially offset the enthalpic contribution to the selectivity change. However, the overall trend is still dictated by enthalpy, as the overall selectivity decreases as a result.

### 2.3.2 Detailed investigation

This section will examine the most selective materials identified at low pressure, as listed in Table 2.1, and provide a detailed investigation of the thermodynamic effects underlying their behavior. These materials can be divided into three main categories: materials exhibiting a slight increase in selectivity or little change in selectivity ( $s_0/s_1 > 0.8$ ), materials with a slight decrease in selectivity ( $0.5 \leq s_0/s_1 \leq 0.8$ ) and materials with a significant decrease in selectivity ( $s_0/s_1 < 0.5$ ). In this section, the origins of these different behaviors will be investigated, with reference to the CSD refcodes of the materials.

Before delving into the different archetypal structures that undergo different selectivity changes, it is necessary to introduce the fundamental concept of adsorption isotherms. The latter can be understood as a plot of the adsorbed quantity as a function of pressure for different components at a given temperature. The following discussion will only focus on the case of pure-component isotherms at 298 K. Various models have been developed to interpret these plots,<sup>222</sup> but for the purpose of this study, the Langmuir model will be used exclusively. the Langmuir model is the most well-established local adsorption model that describes the filling of a monolayer by non-interacting adsorbates. Depending on the pore distribution and shape, the isotherms

can be effectively modeled by either a 1-site Langmuir or a 2-site Langmuir model, for the most simple cases. At a given temperature, At given temperature, certain single site materials' isotherm can accurately be described by the following equation:

$$q(P) = N_{\max} \frac{KP}{1 + KP} \quad (2.33)$$

where  $q$  is the adsorbed quantity of a mono-component gas,  $K$  is the adsorption equilibrium constant and  $P$  is the pressure. When the material has 2 adsorption sites, the isotherm can be described by the following equation:

$$q(P) = N_{\max} \left( (1 - \alpha_2) \frac{K_1 P}{1 + K_1 P} + \alpha_2 \frac{K_2 P}{1 + K_2 P} \right) \quad (2.34)$$

CSD Refcode	Ref.	$s_0$	$s_1$	$s_1/s_0$	$k_H$	$k_S$	$D_i$	$D_f$
VOKJIQ	[211]	157.17	242.73	1.54	1.46	1.06	5.2	3.2
KAXQIL	[54]	103.78	132.57	1.28	1.32	0.96	5.2	4.1
JUFBIX	[212]	106.11	114.83	1.08	1.08	1.00	5.3	3.0
FALQOA	[213]	162.20	171.10	1.05	1.09	0.96	5.1	3.5
GOMREG	[214]	114.14	73.83	0.65	1.01	0.64	5.8	4.0
JAVTAC	[215]	117.38	66.93	0.57	0.77	0.74	5.5	4.3
GOMRAC	[214]	124.11	47.34	0.38	0.58	0.66	5.7	3.7
MISQIQ	[216]	138.94	37.32	0.27	0.51	0.53	4.6	4.4
BAEDTA01	[217]	154.10	37.74	0.24	0.12	1.97	5.7	4.6
VIWMOF	[218]	81.13	13.24	0.16	0.04	4.30	10.2	5.3
LUDLAZ	[219]	165.68	16.42	0.10	0.16	0.63	6.7	4.2
WOJJOV	[220]	146.32	13.94	0.10	0.06	1.68	8.2	6.8
VAPBIZ	[221]	146.73	12.76	0.09	0.06	1.50	6.3	3.7

Table 2.1: Enthalpic ( $k_H$ ) and entropic ( $k_S$ ) contributions to the selectivity change ( $s_1/s_0$ ) between low and ambient pressures for some archetypal structures selected for their high  $s_0$  selectivity at infinite dilution. Every structure is identified using a CSD Refcode and a reference the first article that mentions it. The pore size is also characterized using the diameters  $D_i$  and  $D_f$  in Å.

CSD Refcode	Ref.	$s_0$	$K^{Xe}$	$K^{Kr}$	$\Delta_{ads}H_0^{Xe}$	$\Delta_{ads}H_0^{Kr}$	$s_1$	$q_1^{Xe}$	$q_1^{Kr}$	$\Delta_{ads}H_1^{Xe}$	$\Delta_{ads}H_1^{Xe}$
VOKJIQ	[211]	157	$7.92 \cdot 10^{-1}$	$5.04 \cdot 10^{-3}$	-53.9	-38.2	243	2.57	0.04	-61.1	-44.5
KAXQIL	[54]	104	$3.01 \cdot 10^{-2}$	$2.90 \cdot 10^{-4}$	-44.6	-30.5	133	1.41	0.04	-41.5	-26.8
JUFBIX	[212]	106	$1.59 \cdot 10^{-2}$	$1.50 \cdot 10^{-4}$	-45.6	-31.4	115	0.80	0.03	-45.7	-31.3
FALQOA	[213]	162	$2.23 \cdot 10^{-2}$	$1.38 \cdot 10^{-4}$	-47.3	-32.0	171	0.68	0.02	-48.6	-33.1
GOMREG	[214]	114	$9.16 \cdot 10^{-2}$	$8.03 \cdot 10^{-4}$	-44.7	-31.1	74	2.59	0.14	-47.5	-33.8
JAVTAC	[215]	117	$1.24 \cdot 10^{-1}$	$1.06 \cdot 10^{-3}$	-47.7	-33.5	67	1.50	0.09	-48.5	-34.9
GOMRAC	[214]	124	$1.17 \cdot 10^{-1}$	$9.45 \cdot 10^{-4}$	-45.6	-31.8	47	2.51	0.21	-47.3	-34.8
MISQIQ	[216]	139	$6.87 \cdot 10^{-1}$	$4.94 \cdot 10^{-3}$	-51.9	-37.4	37	2.30	0.25	-45.6	-32.8
BAEDTA01	[217]	154	$1.39 \cdot 10^{-2}$	$9.04 \cdot 10^{-5}$	-47.7	-31.7	38	1.05	11	-34.0	-23.1
VIWMOF	[218]	81	$7.87 \cdot 10^{-3}$	$9.70 \cdot 10^{-5}$	-46.3	-30.1	13	2.99	0.90	-26.0	-17.8
LUDLAZ	[219]	166	$9.04 \cdot 10^{-2}$	$5.46 \cdot 10^{-4}$	-45.4	-30.9	16	1.59	0.39	-38.3	-28.3
WOJJOV	[220]	146	$4.19 \cdot 10^{-2}$	$2.86 \cdot 10^{-4}$	-46.4	-30.7	14	2.82	0.81	-33.0	-24.4
VAPBIZ	[221]	147	$3.54 \cdot 10^{-2}$	$2.41 \cdot 10^{-4}$	-46.4	-30.5	13	2.50	0.78	-34.1	-25.3

Table 2.2: Thermodynamic quantities associated for a few archetypal structures. Henry constant  $K^{Xe}$ ,  $K^{Kr}$  are in  $\text{mmol g}^{-1} \text{Pa}^{-1}$ , loadings  $q_1^{Xe}$  and  $q_1^{Kr}$  are in  $\text{mmol g}^{-1}$ , enthalpies  $\Delta_{ads}H_0^{Xe}$ ,  $\Delta_{ads}H_0^{Xe}$ ,  $\Delta_{ads}H_1^{Xe}$  and  $\Delta_{ads}H_1^{Xe}$  are in  $\text{kJ mol}^{-1}$

where  $q$  is the total loading of a given mono-component gas,  $K_1$  and  $K_2$  are the adsorption equilibrium constants in the respective sites,  $\alpha_2$  is the proportion of secondary sites, and  $P$  is the pressure.

This section will study a few examples of the category of materials where ambient-pressure selectivity is close to (or even higher than) the low-pressure value. For the material VOKJIQ,<sup>211</sup> an open-framework aluminophosphate,  $[\text{Al}_3\text{P}_3\text{O}_{13}]\cdot\text{C}_3\text{NH}_{10}$ , the selectivity increases by a factor of 1.5 between low and ambient pressure. Upon closer examination, it is observed that the adsorption enthalpy of xenon  $\Delta_{\text{ads}}H^{\text{Xe}}$  decreases from  $-53.9 \text{ kJ mol}^{-1}$  to  $-61.1 \text{ kJ mol}^{-1}$ , whereas the adsorption enthalpy for krypton  $\Delta_{\text{ads}}H^{\text{Kr}}$  decreases from  $-38.2 \text{ kJ mol}^{-1}$  to  $-44.5 \text{ kJ mol}^{-1}$  (*cf.* Table 2.2).

This phenomenon of increased stability of the adsorption sites upon loading is not commonly observed in nanoporous materials for rare gas adsorption. It can be attributed to a cooperative effect between the adsorbed molecules, where the interaction between the adsorbed xenon molecules is more favorable than that between the adsorbed krypton molecules. This preference stems from the stabilization due to the interatomic distance within the pores, which closely matches the energy well for favorable Lennard-Jones potential for xenon-xenon interactions, unlike the case for krypton-krypton interactions (where the distance exceeds 4.2 Å; see Figure 2.27).

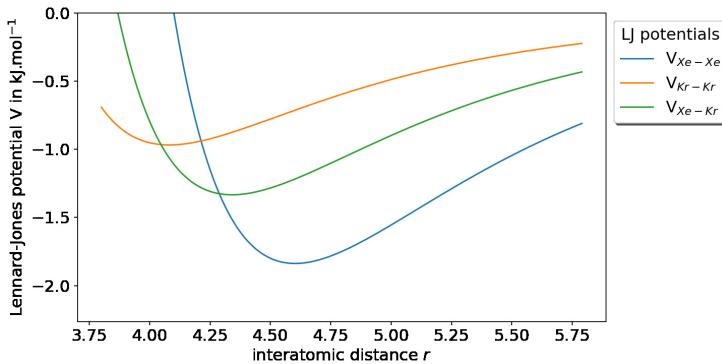


Figure 2.27: The LJ potentials for xenon and krypton interactions. The xenon-xenon interaction is more stabilizing than the krypton-krypton interaction for interatomic distance higher than 4.2 Å.

In the case of KAXQIL, the material features one-dimensional tubes as channels (see Figure 2.28), with a distance between two adsorption sites that is approximately the unit cell parameter along the tube direction (5.6 Å). The selectivity of this material increases with pore filling, primarily driven by enthalpic considerations, which can be explained through a relatively straightforward rationale. By estimating the Lennard-Jones potentials  $U^{\text{LJ}}$  for all species at a distance of 5.6 Å:  $U_{\text{Xe}-\text{Xe}}^{\text{LJ}} = -1.0 \text{ kJ mol}^{-1}$ ,  $U_{\text{Kr}-\text{Kr}}^{\text{LJ}} = -0.3 \text{ kJ mol}^{-1}$  and  $U_{\text{Xe}-\text{Kr}}^{\text{LJ}} = -0.5 \text{ kJ mol}^{-1}$ . In a simplified model where all adsorbed molecules are assumed to be 5.6 Å apart, the cooperative effect between two xenon molecules is more significant, which accounts for the increased selectivity at high uptake. Further analysis of the adsorption enthalpies of xenon and krypton (*cf.* Table 2.2) reveals that both values increase. This can be attributed to the guest molecules deviating from the “ideal” adsorption sites, resulting in guest-guest interactions that do not fully compensate. Consequently, the selectivity change observed in this material is a consequence of the rearrangement of adsorbate positions within the nanopores, driven by guest-guest interactions.

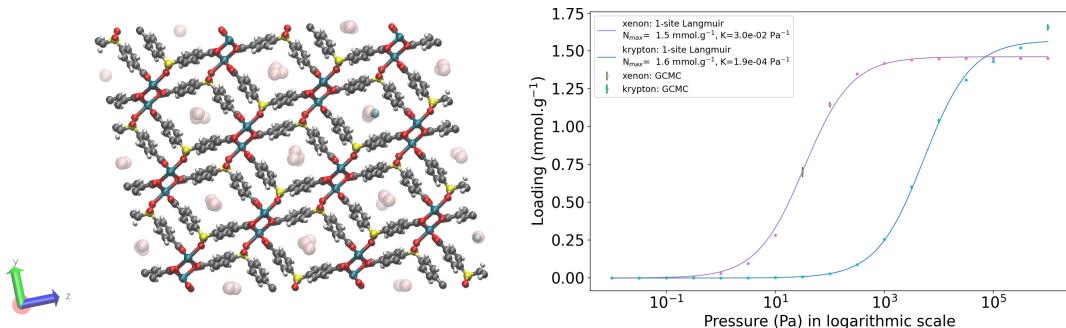


Figure 2.28: KAXQIL: On the left side, an illustration of a clean version (all solvent removed) of the calcium coordination framework  $[\text{Ca}(\text{SDB})]\cdot\text{H}_2\text{O}$ , where  $\text{SDB} = 4,4'$ -sulfonyldibenzoate loaded with xenon and krypton obtained by GCMC calculations. Color code: Ca in dark cyan, C in gray, O in red, H in white, S in yellow; Xe in transparent pink and Kr in cyan for the adsorbates. The mono-component isotherms fitted with a 1-site Langmuir model (equation 2.33) for both xenon and krypton at 298 K is represented on the right side.

To further validate the role of the guest–guest interactions, another material with one-dimensional tubelike channels is considered: JUFBIX, a cobalt(II) coordination polymer based on carboxylic acid linkers (see Figure 2.29).<sup>212</sup> The periodicity along the tube direction is significantly larger at 7.2 Å. The pair interaction energies corresponding to the LJ potentials at this distance are determined as  $U_{\text{Xe-Xe}}^{\text{LJ}} = -0.24 \text{ kJ mol}^{-1}$ ,  $U_{\text{Kr-Kr}}^{\text{LJ}} = -0.06 \text{ kJ mol}^{-1}$  and  $U_{\text{Xe-Kr}}^{\text{LJ}} = -0.13 \text{ kJ mol}^{-1}$ . Upon analyzing the adsorption enthalpies (Table 2.1), it is observed that these values are too small to affect the positioning of the adsorbed molecules. When the loading is high, resulting in a significant distance between the adsorbed molecules, each adsorption site becomes independent of others. Consequently, the ambient-pressure selectivity  $s_1$  remains equal to the low-pressure selectivity  $s_0$  since the guest–guest interactions become negligible. This finding substantiates the critical role played by cooperative effects among guest molecules when considering a saturated material.

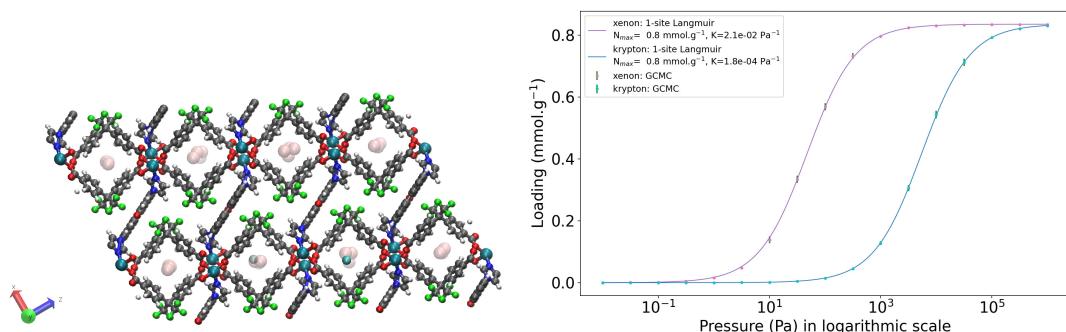
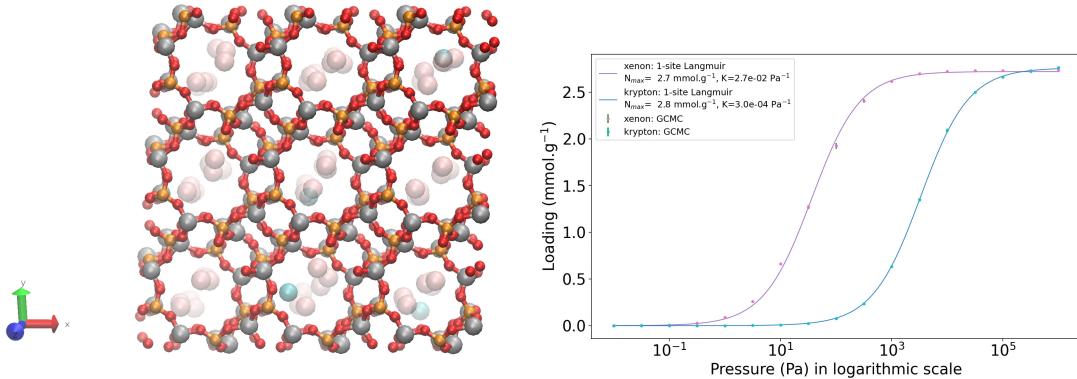


Figure 2.29: JUFBIX: Representation of a clean version (all solvent removed) of the cobalt(II) coordination framework  $[\text{Co}_2(\text{L})(\text{ppda})_2]_2\cdot\text{H}_2\text{O}$ , where the ligand L is 2,8-di(1H-imidazol-1-yl)dibenzofuran and the carboxylic acid ligand  $\text{H}_2\text{ppda}$  is 4,4'-(*perfluoropropene-2,2-diyl*)dibenzoic acid loaded with xenon and krypton obtained by GCMC calculations. Color code: Co in dark cyan, C in gray, O in red, H in white, N in blue, F in green; Xe in transparent pink and Kr in cyan for the adsorbates. The mono-component isotherms fitted with a 1-site Langmuir model (equation 2.33) for both xenon and krypton at 298 K is represented on the right side.

GOMREG and JAVTAC are two frameworks categorized as materials with a moderate decrease in selectivity from low to ambient pressure. In the case of GOMREG, the channels consist of one-dimensional tubes that are larger compared to KAXQIL or JUFBIX (refer to Figure 2.30 and Table 2.1). The adsorption sites alternate from left to right inside the channels, resulting in an organized “zigzag” pattern of adsorbed molecules. Analyzing the adsorption enthalpies, it is observed that both xenon and krypton exhibit lower enthalpies by a similar margin, indicating an equivalent stabilization for both atoms. Consequently, the enthalpic contribution to the selectivity change is close to 1. Due to its smaller size and weaker interaction with the adsorption site, Krypton has more available space within the pore structure. This leads to an entropic advantage for Kr, as reflected by the entropic contribution  $k_S$  of 0.64 in Table 2.1. These findings suggest that while enthalpic considerations primarily account for the observed changes at a statistical level, as discussed in previous sections, entropic considerations can play a significant role in pressure-dependent selectivity for specific cases.

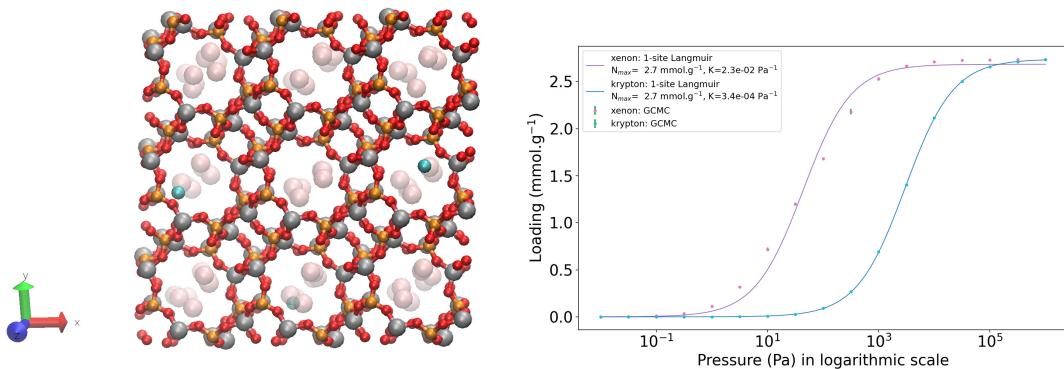


*Figure 2.30: GOMREG: Representation of a clean version (all solvent removed) of this aluminophosphate  $\text{AlPO}_4\text{-}n$  that has a zeotype LAU topology with one-dimensional 10-ring channels loaded with xenon and krypton obtained by GCMC calculations. Color code: Al in silver, P in orange, O in red ; Xe in transparent pink and Kr in cyan for the adsorbates. The mono-component isotherms fitted with a 1-site Langmuir model (equation 2.33) for both xenon and krypton at 298 K is represented on the right side.*

The remaining materials discussed in this third category exhibit a significant decrease in selectivity from low to ambient pressure. To investigate the factors contributing to this decrease, several phenomena that are relevant for screening studies have been examined, as they can impose limitations on the working performance of materials that initially appear to be “top performer” based on zero-pressure screening.

For example, GOMRAC has a similar structure compared to GOMREG (see Figure 2.31), with the distinction of having smaller pores and channels are smaller (see the values of the  $D_i$ , and the  $D_f$ , in Table 2.1). Consequently, the distances between adsorbed molecules— in their ideal sites — are smaller. At such close distances, it is reasonable to assume that the interactions between adsorbates favor krypton over xenon molecules in GOMRAC (see LJ potentials at distance lower than 4.2 Å on Figure 2.27). This enhanced stabilization of krypton relative to xenon results in an enthalpic contribution  $k_H$  of 0.58. Moreover, this finding is consistent with the equivalent guest–guest interactions observed in GOMREG, as discussed earlier. It explains why the difference in adsorption enthalpies becomes smaller for GOMRAC, while it remains unchanged for GOMREG (between low and ambient pressure). This further validates the

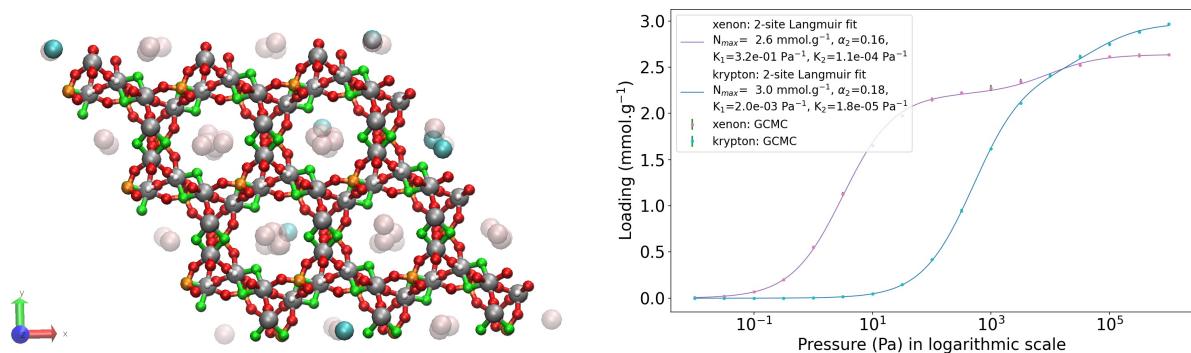
critical role of interactions between adsorbed molecules and their dependence on guest-guest distances, particularly under high loading conditions.



*Figure 2.31: GOMRAC: Representation of a clean version (all solvent removed) of this aluminophosphate AlPO<sub>4</sub>-n that has a zeotype LAU topology with one-dimensional 10-ring channels loaded with xenon and krypton obtained by GCMC calculations. Color code: Al in silver, P in orange, O in red; Xe in transparent pink and Kr in cyan for the adsorbates. The mono-component isotherms fitted with a 1-site Langmuir model (equation 2.33) for both xenon and krypton at 298 K is represented on the right side. It seems that this aluminophosphate is just a smaller version of GOMREG.*

In the case of MISQIQ, the pure-component Xe isotherm depicted in Figure 2.32 does not conform to a single-site Langmuir isotherm, but rather aligns well with a two-site Langmuir model (see Figure 2.32). Upon visual examination of the adsorbed density at various loadings, it becomes evident that the second step in the isotherm (representing about 20% of the uptake at full loading) corresponds to a reorganization of the adsorbate molecules accompanied by a contraction of interatomic distances. It is important to note that this reorganization does not involve the occupation of a distinct and separate adsorption site at high loading. In this case, the change in selectivity can be attributed to the potential for adsorbate reorganization within the nanopores of the material. This reorganization, which can be detected through the xenon isotherm alone, plays a significant role in determining the material's selectivity at ambient pressure. The repacking of the adsorbed phase during this reorganization process is associated with a strong entropic effect and also influences the enthalpic contribution to selectivity.

The materials BAEDTA01, VIWMOF, LUDLAZ, WOJJOV, and VAPBIZ fall into the category of having more than one available adsorption site, resulting in a significant drop in selectivity from low to ambient pressure. The pure-component isotherms and the representation of the materials loaded in xenon and krypton molecules (presented in the supporting information of the Ref. [22] Figures S19-23) confirm the existence of at least two distinct adsorption sites in each material. The preferential filling of the most selective sites (i.e., the most favorable for Xe) occurs at low loading, while the less selective sites are populated as the pressure increases. Consequently, a net decrease in selectivity at ambient pressure is observed for these materials. The existence of different types of adsorption sites and their impact on Xe/Kr selectivity (at non-zero pressure) suggests the inclusion of this factor in the screening of pure-component isotherms without the need for explicit multi-component GCMC simulations.



*Figure 2.32:* Representation of a chiral open-framework fluoroaluminophosphate  $[C_4N_3H_{16}]\cdot[Al_6P_3O_{12}F_6(OH)_6]$  denoted AlPO-JU89 (referenced MISQIQ in the Cambridge structural database), which has been loaded with xenon and krypton in a GCMC simulation, on the left side.<sup>216</sup> Color code: Al in silver, P in orange, O in red, H in white and F in green for the framework; Xe in transparent pink and Kr in cyan for the adsorbates. The pure-component isotherms fitted with a 2-site Langmuir model (equation 2.34) for both xenon and krypton at 298 K on the right side.

## 2.4 TOWARD THE DEVELOPMENT OF NEW SCREENING TOOLS

In the current state of the art on Xe/Kr separation by adsorption in nanoporous materials, many studies have focused on establishing structure/property relationships, determining theoretical performance limits, and identifying top-performing materials, for both existing experimental structures and novel hypothetical structures yet to be synthesized. To provide a better understanding of the thermodynamics underlying Xe/Kr separation and the microscopic origins of selectivity at low and ambient pressure, a high-throughput screening of Xe, Kr was conducted as well as Xe/Kr mixtures in 12 020 experimental open-framework materials. In addition to structural descriptors such as pore sizes, volume, and surface area, thermodynamic quantities were considered to gain insights into the key factors yielding a high selectivity.

The statistical correlation found between Henry's constant for Xe and Xe/Kr selectivity showed that the most selective materials are those with the highest affinity for xenon. To some degree of accuracy, it can be concluded that a direct screening of Kr or xenon adsorption free energy may not be essential for a coarse-grained evaluation of the selectivity of nanoporous frameworks. This finding could facilitate the development of more efficient screening methodologies. For instance, a multistage approach could be employed, starting with a preliminary selection on Henry's constant, which is computationally inexpensive. Subsequently, more computationally intensive grand canonical Monte Carlo (GCMC) simulations can be performed on the selected materials (a gain that can be between 5 and 10-fold in our setup). Furthermore, inspection of the correlations between enthalpy and entropy contributions at low pressure showed that the adsorption-based separation process in the open frameworks studied is mainly enthalpic in nature. It is possible to extend the study in the future to other classes of nanoporous materials beyond MOFs, including covalent organic frameworks, porous aromatic frameworks, purely inorganic porous frameworks such as zeolites, but also amorphous porous materials such as porous polymer membranes.

In the context of xenon-krypton separation using nanoporous materials, pressure swing adsorption (PSA) processes have been widely used, making pressure a crucial thermodynamic variable in the separation cycle. This study has focused on the selectivity difference between a system under very low pressure (at the zero loading limit, which is calculated at relatively low computational cost) and ambient pressure (closer to working conditions but requiring higher simulation cost). The results demonstrated that selectivity can be highly dependent on pressure, with certain materials maintaining high selectivity at both low and ambient pressures, while others experience a significant drop in selectivity. It was found that high ambient-pressure selectivity requires high low-pressure selectivity, but the reverse is not necessarily true.

By using a thermodynamic approach to describe the separation selectivity, the differences in selectivity were elucidated between different pressures (and therefore different loading regimes of the frameworks), primarily attributed to the variations in adsorption enthalpies for Xe and Kr. By delving into specific examples, the microscopic origins of these selectivity changes were uncovered and linked to the relative contributions of host–guest and guest–guest interactions. The population of different adsorption sites or repacking of the adsorbed phase at higher loadings can lead to significant alterations in overall selectivity. The underlying mechanisms of selectivity at high pressure are complex and unique to each framework, requiring a good understanding of the interactions between guest molecules constrained in the nanopores. Nevertheless, this proposed classification of the interactions at play can guide the future design of more efficient high-throughput screening procedures.

For instance, the essentially enthalpic nature of the xenon/krypton separation process underscores the importance of developing more efficient methods for sampling interaction energies and utilizing them as cost-effective descriptors for analyzing an increasing number of structures. In the subsequent chapter, different approaches for evaluating adsorption enthalpy will be explored, considering the computation time required and the accuracy of each method. Additionally, the influence of partial pressure, manifested through changes in composition or pressure, raises questions about the potential use of infinite dilution thermodynamic quantities to predict selectivity at any pressure (GCMC). Numerous studies have focused on predicting GCMC simulations.<sup>18,181,183,223</sup> The thermodynamics-based approach combined with characterizing pore diversity holds the potential to yield improved results in predicting GCMC values of selectivity, contributing to a more comprehensive understanding of adsorption processes in nanoporous materials.





# 3

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## ADSORPTION ENERGIES SAMPLING

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This chapter will introduce three distinct energy sampling techniques that can be used to determine an adsorption enthalpy, and, in some cases, deduce Henry constant values.

### 3.1 VORONOI SAMPLING

The first technique to be discussed has been previously studied for calculating geometric descriptors and, more recently, for deriving energy-based descriptors.<sup>18</sup> This sampling method is relatively biased as it relies on a sparse sampling approach based on Voronoi decomposition, which is limited in terms of incorporating prior physical knowledge. A more detailed explanation of this method will be provided in the subsequent discussion. A detailed explanation of this method will follow.

### 3.1.1 Theoretical considerations

In mathematics, a tessellation of a given space refers to the partitioning of this space into non-overlapping subspaces. In the Voronoi tessellation, named after Georgy Feodosevich Voronoy, a set of points (seeds) corresponds to a tessellation of regions (Voronoi cells). These cells are designed such that each seed possesses a cell wherein all points are closer to that seed than any other seeds.<sup>188</sup> When applied to materials science, the Voronoi cells attributed to each atom of the framework can be leveraged to determine key geometric descriptors (void volume, accessible surface area, pore sizes). This decomposition can also be used to sample adsorption energies, as introduced by Simon et al. — an average of the interaction energies was calculated on the accessible vertices of each Voronoi cell.<sup>18</sup>

#### **EQUAL RADII**

In a tridimensional space, consider the positions  $(\mathbf{x}_k)_{k \in \{1, \dots, n\}}$  of the  $n$  points in a box B that could be periodically propagated in the whole space. For each  $k \in \{1, \dots, n\}$ , a subspace  $S_k$  (also called Voronoi cell) can be defined around the atom  $k$ , encompassing all points  $\mathbf{x}$  within this subspace that are closer to the position  $\mathbf{x}_k$  than to any other points  $\mathbf{x}_l$  ( $l \neq k$ ).

$$S_k = \{\mathbf{x} \in B \mid \forall l \neq k, \|\mathbf{x} - \mathbf{x}_k\|_2 \leq \|\mathbf{x} - \mathbf{x}_l\|_2\} \quad (3.1)$$

The set of all these 3D polyhedral subspaces  $S_k$  is termed the Voronoi partition of the space B. The edges and vertices of these polyhedra offer valuable information regarding the void space between adjacent the Voronoi cells associated with them. By leveraging this information, it becomes feasible to determine the accessible and inaccessible points within the void space. For instance, a vertex  $\mathbf{v}$  of  $p$  subspaces  $\{V_{i_1}, \dots, V_{i_p}\}$  is the point closest to the atomic positions  $\mathbf{x}_{i_1}, \dots, \mathbf{x}_{i_p}$  — this can be easily demonstrated by combining different conditions outlined in the equation 3.1. The same assessment can be performed for any point located on an edge adjacent to certain subspaces, as it will be closer to the atoms associated with these subspaces than to any other atoms.

This regular Voronoi tessellation is suitable only for separating space among equally sized atoms, as it sets the boundaries at equidistance from all the surrounding atoms, as shown in Figure 3.1. For atoms with unequal sizes, this type of definition may not be desirable, as the boundary could be closer to the surface of an atom compared to another. The initial rationale behind using a Voronoi decomposition is to delimit a region for each atom that is closer to that specific atom than any other. The ambiguity of this definition arises from the definition of “closeness”. In this regular Voronoi decomposition, closeness is determined based on the distance between the center of mass of different atoms, which poses challenge for unequally distributed radii.

#### **UNEQUAL RADII**

To address this limitation, an alternative approach called the Apollonian Voronoi diagram can be implemented to model the atomic radii. The definition of the Voronoi decomposition, as previously discussed, is limited to equal-sized atoms, as the closest region to an atom is also the closest to its center of mass. This limitation does not apply to the complex atomic structures found in nanoporous frameworks. To overcome this, the Apollonian Voronoi diagram<sup>224</sup> can



*Figure 3.1: Bidimensional illustrations of a Voronoi decomposition using three types of algorithm: (i) for equally sized circles using the equation 3.1 ([www.shadertoy.com/view/Ms1GD8](http://www.shadertoy.com/view/Ms1GD8)) (ii) for unequally sized circles using the Apollonian Voronoi decomposition condition 3.2 ([www.shadertoy.com/view/4sd3D7](http://www.shadertoy.com/view/4sd3D7)) and (iii) another algorithm for unequally sized circles using the radical Voronoi condition 3.3 ([www.shadertoy.com/view/4tV3z3](http://www.shadertoy.com/view/4tV3z3)). Note that the second picture shows the curved boundaries between the Voronoi cells, while the switch to the radical Voronoi decomposition gives straight line boundaries.*

be utilized to model the atomic radii  $r_1, \dots, r_n$  of points  $\mathbf{x}_1, \dots, \mathbf{x}_n$  within the same box  $B$ . For every  $k \in \{1, \dots, n\}$ , the new subspaces  $A_k$  are defined as follows:

$$A_k = \left\{ \mathbf{x} \in B \mid \forall l \neq k, \|\mathbf{x} - \mathbf{x}_k\|_2 - r_k \leq \|\mathbf{x} - \mathbf{x}_l\|_2 - r_l \right\} \quad (3.2)$$

This new definition of the Voronoi diagram, takes into account the intuitive property of closeness to the atom's surface rather than its center of mass. This adjustment allows for an unequal distribution of atomic radii, as the diagram now depends on these radii. However, as illustrated in Figure 3.1, the initial implementation presents a convenient definition at the cost of curved edges, which introduces computational challenges.

To overcome these challenges and enhance computational efficiency, a less intuitive but more commonly used implementation known as the radical Voronoi tessellation, power diagram or Laguerre-Voronoi diagram<sup>225</sup> is preferred. As depicted in Figure 3.1, this method yields subspaces that are convex polygons with straight edges. Although the condition defining these subspaces is less intuitive, it avoids reliance on a simple definition. The subspaces  $V_k$  are now defined based on the following condition:

$$V_k = \left\{ \mathbf{x} \in B \mid \forall l \neq k, \|\mathbf{x} - \mathbf{x}_k\|_2^2 - r_k^2 \leq \|\mathbf{x} - \mathbf{x}_l\|_2^2 - r_l^2 \right\} \quad (3.3)$$

In addition to the polyhedral form of the Voronoi cells, this new implementation presents interesting properties for porosity calculations in frameworks composed of unequal spheres, such as MOFs of zeolites.<sup>226</sup> First, the boundary between two overlapping spheres corresponds simply to the intersection between the spheres themselves. Secondly, the boundary between non-overlapping spheres always lies within the void space separating them. This assertion can easily be demonstrated by considering a point  $\mathbf{x}$  in  $V_k$  and  $\|\mathbf{x} - \mathbf{x}_k\|_2 \geq r_k$  outside the sphere,

which implies  $\forall l \neq k, \|\mathbf{x} - \mathbf{x}_k\|_2 \geq r_k$ . The point  $\mathbf{x}$  does not overlap with any other atom and resides within the framework's void space.

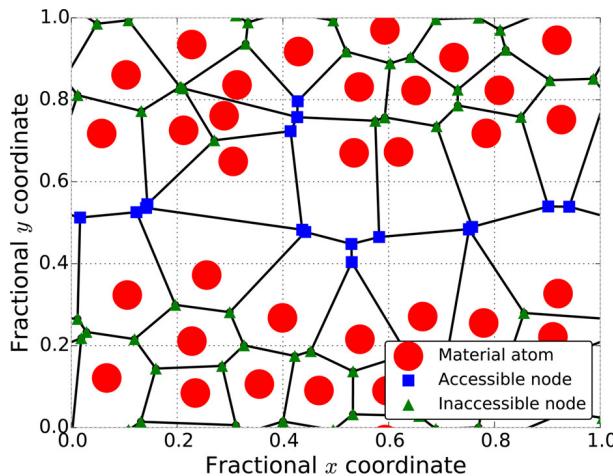
When considering a point  $\mathbf{v}$  on a boundary between  $p$  Voronoi cells, denoted as  $\{\mathbf{V}_{i_1}, \dots, \mathbf{V}_{i_p}\}$ , this point satisfies the conditions  $\|\mathbf{x} - \mathbf{x}_{i_1}\|_2^2 - r_{i_1}^2 = \dots = \|\mathbf{x} - \mathbf{x}_{i_p}\|_2^2 - r_{i_p}^2 = C$ . It is possible to find the minimum distance to the center of mass of neighboring atoms and test possible overlapping. Specifically, in the Zeo++ software,<sup>49</sup> the Voronoi diagram is characterized by storing the minimum distance to the closest atoms and the corresponding atom indices for each vertex and edge (In cases where edges connect two different periodic images, a periodic displacement vector is also stored). Leveraging this information enables the acceleration of void fraction calculations by bypassing volume calculations in non-adsorbable Voronoi cells. Additionally, it provides a swift approach to determine accessible and non-accessible surface areas and volumes.<sup>49</sup> It is important to note that when employing a probe with a radius  $r_{\text{probe}}$ , the sphere radii considered are adjusted accordingly as  $r_k = r_{\text{atom}} + r_{\text{probe}}$ .

### 3.1.2 Implementation in a screening

The use of the Voronoi decomposition of the pore space of materials for their geometric characterization has been widely employed in computational studies in the last decade,<sup>227</sup> especially since it was made easily available as part of the Zeo++ software package.<sup>228</sup> Its use was extended recently to implement a novel sampling scheme, in a study that introduces the ML-assisted screening of nanoporous materials for xenon/krypton separation. In this article, Simon et al.<sup>18</sup> relied on a Voronoi tessellation of the nanoporous materials and assigned the potential adsorption sites (i.e., the sampling points) at the nodes of this decomposition. The Voronoi tessellation identifies the vertices of polyhedra that correspond to the closest regions of each atom of the structure. These vertices (or *Voronoi nodes*) are the points equidistant to at least four atoms of the structure, and they can be associated with adsorption sites since they are positioned near the center of the pores.

The definition of accessibility defined by the Zeo++ software was used in a screening to find the best materials for Xe/Kr separation.<sup>18</sup> The interaction energies of xenon were calculated only on the accessible nodes as schemed on Figure 3.2. The average of the energies at the accessible Voronoi nodes gives an approximation of the adsorption enthalpy. However, this sampling assumes that the nodes are close to the real, most favorable, adsorption sites. Or to put it differently, the adsorption sites need to be at the center of the pores, which is only true for structures with pore sizes close to adsorbate size. This newly defined adsorption energy descriptor was found to be one of the most influential descriptors for the ML model developed to predict the ambient-pressure selectivity.

Starting from the initial idea of Voronoi sampling, I want to question the relevance of using a direct average of the interaction energies instead of a Boltzmann averaging in describing the adsorption enthalpy. To better understand the strengths and weaknesses of this methodology, I compared different ways of approximating adsorption enthalpies using the Voronoi sampling with more accurate infinite dilution and ambient-pressure xenon adsorption enthalpies using Widom insertions and GCMC for a 20:80 Xe/Kr mixture at 1 atm and 298 K.



*Figure 3.2: Voronoi network model of void space (2D caricature). The unit cell of a toy material is shown. Red circles represent atoms of the material; accessible and inaccessible Voronoi nodes are blue squares and green triangles, respectively. The black lines are the edges in the periodic Voronoi graph that model the void space. Reprinted with permission from Ref. [18]. Copyright 2015 American Chemical Society.*

### 3.1.3 Comparative study of the Voronoi sampling

I introduced in the previous chapter, the definition of the xenon adsorption enthalpy at infinite dilution (Widom insertion section 2.1.4) and at ambient pressure (GCMC sections 2.1.3 and 2.1.5). These methods can be considered accurate methods to calculate the adsorption enthalpy which has been proven to be strongly correlated to the logarithm of the selectivity in our previous study on the thermodynamic exploration of the xenon/krypton separation using a high-throughput screening.

#### INTRODUCTION OF THE MAIN CONCEPTS

The Voronoi energy as initially conceptualized by Simon et al. is based on the average of the xenon interaction energies at the accessible Voronoi nodes. But because I will compare to thermodynamic simulations without blocking pockets, I will not consider the accessible Voronoi nodes but the adsorbable ones since it is closer to the simulation I want to approximate. For simplicity, I define the set of the adsorbable Voronoi nodes  $A$  as the Voronoi nodes with a negative energy value, I also apply a condition on the minimum distance (about the radius of a xenon 2 Å) to reduce the number of points to be calculated. This average on the adsorbable Voronoi nodes  $E_{\text{voro-}A}^{Xe}$  can be written:

$$E_{\text{voro-}A}^{Xe} = \sum_{i \in A} E_i \quad (3.4)$$

Another interesting energy descriptor could simply be the minimum of the interaction energies among the Voronoi nodes  $V$  with a minimum distance to the nearest atom is higher than 2 Å. This minimum Voronoi energy  $E_{\text{voro-}M}^{Xe}$  can be written:

$$E_{\text{voro-}M}^{Xe} = \min_{i \in V} E_i \quad (3.5)$$

Finally, to get closer to the definition of the heat of adsorption defined in the previous chapter, we can build an energy descriptor using a Boltzmann averaging. This Boltzmann average of the xenon interaction energies at the Voronoi nodes V written  $E_{\text{voro-B}}^{Xe}$  can be expressed as follows:

$$E_{\text{voro-B}}^{Xe} = \frac{\sum_{i \in V} E_i e^{-\beta E_i}}{\sum_{i \in V} e^{-\beta E_i}} - RT \quad (3.6)$$

Note that the  $-RT$  term is to make the expression comparable to the one of adsorption enthalpy.

Intuitively, the Boltzmann averaging being closer to the definition of the adsorption enthalpy it would be a better candidate as an energy descriptor, hence improving the screening methodology. To test these different methodologies, I will now compare the different energy descriptors to more accurate evaluation of the adsorption heat.

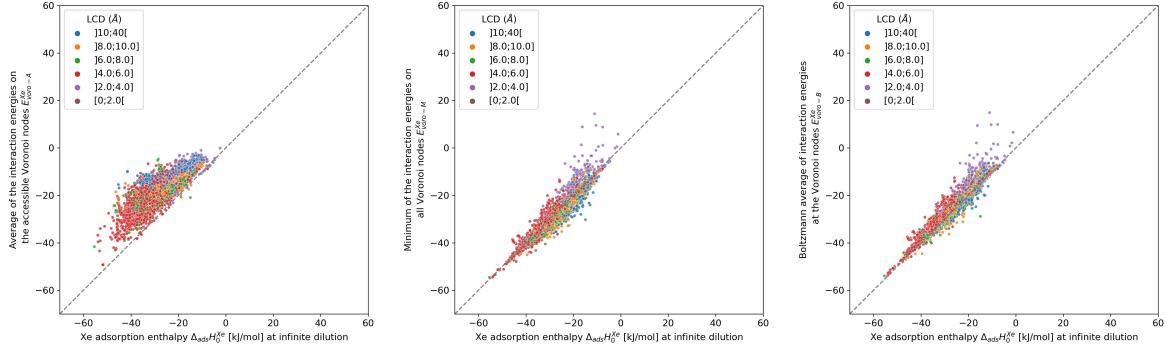
#### LOW-PRESSURE COMPARISON

The Widom insertion is typically used to calculate the infinite dilution adsorption properties such as the adsorption enthalpy, the Henry constant and the selectivity. The evaluation of the interaction energies of xenon at the different Voronoi nodes correspond to a low-pressure averaging and is more comparable to a Widom insertion method. It is, however, biased by the inhomogeneous sampling of the space, which can explain some of the discrepancies observed.

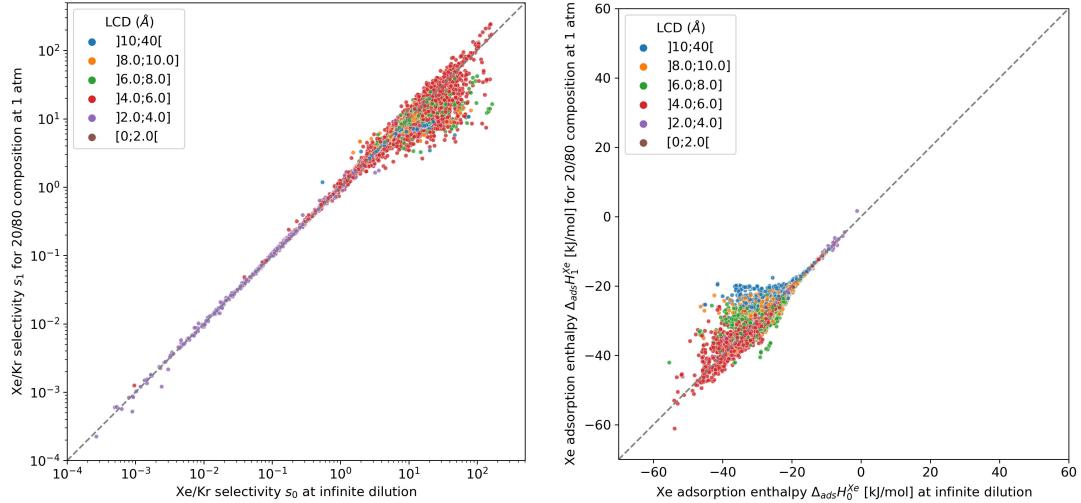
Note that in this chapter, I will mainly use the standard pore size definition found in the literature that is based on the atom radii defined by the Cambridge Crystallographic Data Centre (CCDC). This pore size will only serve a labeling purpose and will help us classify the structures according to their relative size. It has qualitative role mainly, which justifies the fact that I am not using a much more accurate definition based on the forcefield like in the previous chapter.

As shown on Figure 3.3, the average of the energies is not performing very well and is clearly less correlated to the adsorption enthalpy than the minimum interaction energy or the Boltzmann average of the interaction energies. This is because in a normal average, the high-energy values have a much higher weight than in a Boltzmann average, which makes the average much more important than expected. The Voronoi average descriptor  $E_{\text{voro-A}}^{Xe}$  is always higher than the infinite dilution adsorption enthalpy  $\Delta_{\text{ads}}H_0^{Xe}$ .

The Pearson correlation coefficients corroborate our initial observation. The correlation coefficient between  $E_{\text{voro-A}}^{Xe}$  and  $\Delta_{\text{ads}}H_0^{Xe}$  is equal to 0.81, whereas for the minimum  $E_{\text{voro-M}}^{Xe}$  it is 0.95 and for the Boltzmann average  $E_{\text{voro-B}}^{Xe}$  it is 0.97. For this reason, to evaluate the relevance of a Voronoi energy sampling, I should consider a Boltzmann average. As shown in the previous chapter, the selectivity is correlated to the difference of adsorption enthalpies of xenon and krypton. Better describing the enthalpy is a first step toward a better description of the selectivity. However, I only looked at the selectivity values at low pressure. What would happen for selectivity at higher pressure?



*Figure 3.3: Scatterplots of the energy descriptors  $E_{\text{voro}-A}^{\text{Xe}}$ ,  $E_{\text{voro}-M}^{\text{Xe}}$  and  $E_{\text{voro}-B}^{\text{Xe}}$  calculated by a Voronoi sampling compared to the enthalpies calculated by a 100k-step Widom insertion simulation of xenon in structures of CoRE MOF 2019. The points are labeled according to the largest cavity diameter ( $LCD_{CCDC}$ ) belonging to one of the intervals.*

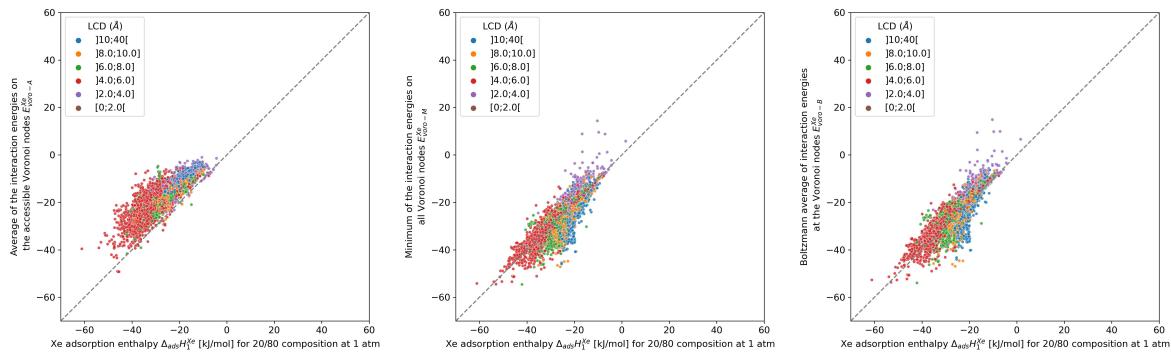


*Figure 3.4: Comparison of the ambient-pressure and low-pressure case through two thermodynamic quantities: the Xe/Kr selectivity (left) and the xenon adsorption enthalpy (right).*

As shown on Figure 3.4, the selectivity drop between the low-pressure case and the ambient-pressure one also impacts the enthalpy values of xenon. There is a reduction of the xenon affinity as the pressure goes up. Since the study of Simon et al. focused on the ambient-pressure selectivity prediction, I want to see if the energy descriptor they developed could, however, be used to describe the adsorption enthalpy at high pressure.

#### AMBIENT-PRESSURE XENON/KRYPTON SEPARATION

Looking at Figure 3.5, it is not so clear which descriptor is better to describe the enthalpy at ambient pressure. The correlation shown by the different scatterplots seems to be equally poor, and this could justify the use of a regular average rather than a Boltzmann average. The correlation coefficient for the average  $E_{\text{voro}-A}^{\text{Xe}}$  is now equal to 0.86, which is equivalent to the one of the minimum  $E_{\text{voro}-M}^{\text{Xe}}$  and slightly lower than the 0.87 for the Boltzmann average  $E_{\text{voro}-B}^{\text{Xe}}$ .



*Figure 3.5: Scatterplots of the energy descriptors  $E_{\text{voro}-A}^{\text{Xe}}$ ,  $E_{\text{voro}-M}^{\text{Xe}}$  and  $E_{\text{voro}-B}^{\text{Xe}}$  calculated by a Voronoi sampling compared to the enthalpies calculated by a 100k-step GCMC simulation of xenon in structures of CoRE MOF 2019. The points are labeled according to the largest cavity diameter ( $\text{LCD}_{\text{CCDC}}$  or  $D_i$ ) belonging to one of the intervals.*

At higher pressure, the adsorption enthalpy has higher values, which degrades the correlation with the Boltzmann average and the minimum of the interaction energies evaluated at the Voronoi nodes. For the averaging, the over-evaluation of the energy values make it closer to the values at higher pressure. Following this idea, I later come up with another idea of averaging with bigger weights on the higher values, a Boltzmann average with a higher temperature value that will be tested in the next chapter.

### 3.1.4 Performance of a Voronoi energy sampling

I will now focus on some performance metrics associated to the Boltzmann average at the Voronoi nodes and compare it to our reference sampling, the Widom insertion with 100,000 cycles. The right plot of Figure 3.3 compares the enthalpy computed in the Voronoi sampling with the reference adsorption enthalpy (ground truth) – showing at the same time the largest cavity diameter for each porous framework. The correlation between the values of enthalpy is very good only for a restricted number of structures with enthalpy around  $-50 \text{ kJ mol}^{-1}$ . For structures with higher enthalpy, the correlation starts to degrade, and becomes very poor for small-pore structures. For the points in purple, the largest cavity diameter is lower than the kinetic diameter of a xenon, the sampling of the Voronoi nodes is clearly insufficient. In addition, the accuracy loss on the other points (larger pores) can be explained by the fact that the pores are slightly bigger and the center of the pore is not a good approximation of adsorption site position anymore: the adsorption sites are effectively closer to the pore surface than to the center of the pore. This conclusion is what prompted us to propose a new sampling scheme based on the molecular surface of the pore space, which I will detail in the next sections.

The root mean squared error (RMSE) and the mean absolute error (MAE) for Voronoi sampling are respectively  $6.78 \text{ kJ mol}^{-1}$  and  $2.01 \text{ kJ mol}^{-1}$ , if we consider all structures in our set, which seems too high to be useful for screening purposes. However, the non-porous materials would be screened out *a priori* in any high-throughput workflow, as they would not be of interest. We can only consider the structures with large enough cavities, higher than  $3.7 \text{ \AA}$  (a bit lower than  $3.96 \text{ \AA}$  Xe kinetic diameter). Thereby, the RMSE and MAE drop respectively to  $2.11 \text{ kJ mol}^{-1}$  and  $1.55 \text{ kJ mol}^{-1}$ , which can be considered acceptable for a quick estimation of the guest–host affinity, but not for accurate adsorption enthalpy calculation.

This is reinforced by the very low computational cost of the method. The Voronoi tessellation done by the Zeo++ software is extremely quick and can output the positions of the Voronoi nodes in 0.28 s (measured as an average over all the structures of the CoRE MOF 2019 database), on a typical workstation (a single Intel Xeon Platinum 8168 core at 2.7 GHz). While a simple Python for the energy calculation took around 27 s per structure, I benchmarked that a C++ optimized implementation can perform the Voronoi sampling in around 0.4 s. This method takes a few hundred milliseconds per structure, while a Widom insertion needs approximately hundreds of seconds per structure. Voronoi sampling is therefore 2 to 3 orders of magnitude quicker than a full sampling of the pore space.

This preliminary study identified a fast method for adsorption enthalpy calculation that can be widely used in screening procedures, but has limited accuracy for quantitative prediction — this sampling technique assumes that the nodes are close to the real, most favorable, adsorption sites, which is not always true. Or to put it differently, the adsorption sites need to be at the center of the pores, which is only true for structures with pore sizes close to adsorbate size. It raised important questions on the importance of selecting sampling points within the pore space of materials, and I wanted to develop an intermediate technique that is both fast and accurate for the prediction of adsorption enthalpy. For this purpose, I developed and optimized a new sampling technique that focuses the sampling on the surface of the material, which is expected to make up for the main flaws of the Voronoi sampling.

## 3.2 RAPID ADSORPTION ENTHALPY SURFACE SAMPLING (RAESS)

In this section, I will describe the development of our surface sampling algorithm, with the goal of being more accurate than Voronoi sampling and faster than Widom insertion. Our initial idea is based on a series of theoretical considerations: (i) the strong adsorption sites are near the surface of the material; (ii) by changing the problem from 3D to 2D sampling we can reduce the complexity; and (iii) the algorithm can scale with the number of unique atoms in the structure (and not with the size of the unit cell), which is efficient because many porous frameworks have high symmetry. The first physical intuition ensures that this method will be more accurate than a Voronoi sampling, whereas the last two enable a more efficient sampling, which means a faster sampling for a well-optimized code. To confirm these hypotheses, I will analyze both the accuracy and the speed of this new algorithm and compare them to existing methods. The study below has already been published in the Chemical Science journal [21].

### 3.2.1 Initial implementation

Here, I present the initial implementation of the surface sampling algorithm and its principles. This first implementation is a relatively basic one and already performs well compared to the other methods. In the next sections, I refine it with two additional features that will improve its accuracy and its speed.

This initial implementation speeds up the calculation of adsorption enthalpy in nanoporous materials by sampling interaction energies only near the surface. It is illustrated on Figure 3.6. For this purpose, a loop over all unique atoms (as defined by crystalline symmetry) is performed. And for each atom, a sphere around its position is sampled using a uniform distribution around

it, these points will be called sampling points, and we can change the number of sampling points. The default radius chosen for the sampling spheres is the distance  $r_{\min} = 2^{1/6}\sigma_{ij}$  to the minimum of the LJ potential between atoms of type  $i$  (belonging to the framework) and  $j$  (the guest), corresponding to the strongest possible pair interaction (although the neighboring atoms will, of course, have an influence). After calculating the interaction energy at each of the sampled points, a Boltzmann average of these energies corresponds to a biased adsorption enthalpy, as described by the equation 2.22.

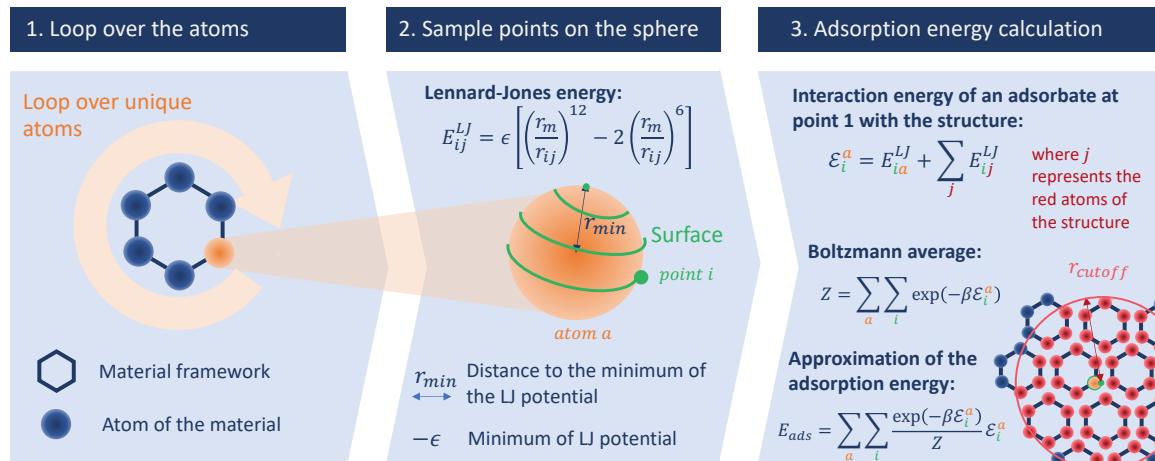
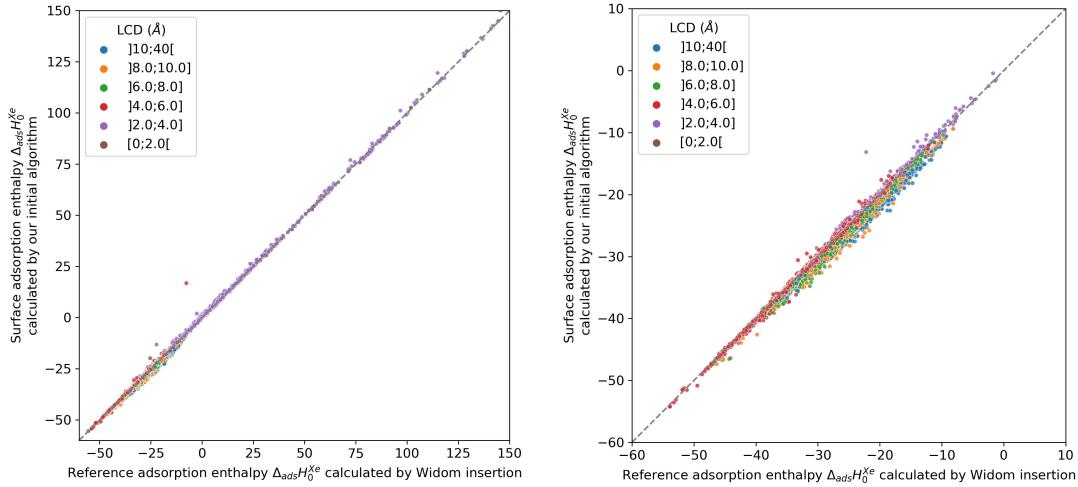


Figure 3.6: Schematic description of the surface sampling based on the three main steps of the algorithm: the loop over the unique atoms, the spiral sampling around each atom, and the energy averaging. The adsorbate is represented by the point  $i$  and is moved across all the points around the unique atoms of the structure.

In order to validate the accuracy of the approximation made using this sampling, I applied this algorithm with 300,000 sampling points per unique atom. The results are illustrated by Figure 3.12. There is a good numerical agreement with the reference calculations, the RMSE and MAE are only around  $0.90 \text{ kJ mol}^{-1}$  and  $0.66 \text{ kJ mol}^{-1}$  considering all the structures from the database. Moreover, there is no noticeable difference of RMSE when considering the structures with a pore size above  $3.7 \text{ \AA}$  (as determined by the LCD<sub>CCDC</sub>). Unlike Voronoi sampling, this method gives a consistent accuracy across all the structures of the database with a lower error. An RMSE value below  $1 \text{ kJ mol}^{-1}$  validates the intuition that this new sampling technique balances the accuracy and efficiency of the previously introduced methods (Voronoi and Widom).

After proving the good accuracy of the method, I am now exploring the computation time required. As shown on Figure 3.8 that the method reaches an RMSE below  $1.0 \text{ kJ mol}^{-1}$  very quickly for an average CPU time of  $1.2 \text{ s}$ , corresponding to 2,000 sampling points per atom. This is far less than the  $150 \text{ s}$  required for a Widom insertion to be near its plateau value (converges to zero), for an RMSE of  $0.10 \text{ kJ mol}^{-1}$  with 12,000 cycles. Moreover, the Widom insertion needs around  $14 \text{ s}$  to reach a similar RMSE of  $1.0 \text{ kJ mol}^{-1}$ , which is still slower than the surface sampling. This initial implementation of the surface sampling is faster than a standard Widom insertion, with a good accuracy.

These results on the convergence speed and the limit values of the error can be simply rationalized by the nature of each sampling. In a surface sampling, the sampled points are biased toward the most attractive points of adsorption for the xenon, which explains the fact that the



*Figure 3.7: Scatterplots of the xenon surface adsorption enthalpy calculated by an initial implementation of the RAESS algorithm as a function of the xenon adsorption enthalpy calculated by a 100k-step Widom insertion simulation using two value windows. The second plot zooms on the negative values corresponding to the most selective materials.*

value converges very quickly because the most influential terms of the Boltzmann average are quickly gathered. However, in a Widom insertion every point of the space has equal chances of being sampled, which is extremely close to the definition of the enthalpy but requires much more time to randomly sample a very attractive adsorption site. The surface sampling by its biased nature, however, will inherently be less accurate since not all points are considered equally and sometimes the most optimal adsorption site could be missed, because it could in some cases be further from the sampled surface.

However, this initial implementation of the method is slower than a Voronoi sampling that only needs to sample around 1,600 points on average, instead of 13,000 sampled points on average (if we multiply by the average number of unique atoms). The sampling part would take approximately 0.15 s and the Voronoi nodes generation 0.28 s, so the surface sampling algorithm remains 2 to 3 times slower (implemented in an identical compiled language, in this case C++). In order to improve the accuracy and performance, I have further tweaked the surface sampling method, adjusting the size of the sampling sphere and adopting a fast rejection criterion. The rejection of high-energy points with little contribution to the final enthalpy value can reduce the simulation time, whereas the size of the sampling sphere can improve the accuracy. The initially chosen sphere size is only taking account of the interaction with the closest atom, I therefore chose to set it at the minimum of Lennard-Jones potential. However, the interaction with the neighboring atoms can further stabilize the adsorbate, sampling further from this minimum could in consequence increase the accuracy of the surface sampling method.

### 3.2.2 Performance improvement of the algorithm

#### SIZE OF THE SAMPLING SPHERE

The validity of the initial algorithm is based on the assumption that the adsorption site is at the minimum of the Lennard-Jones potential. It will only perform well if the closest atom contributes to almost all the interaction, but in real frameworks other neighboring atoms

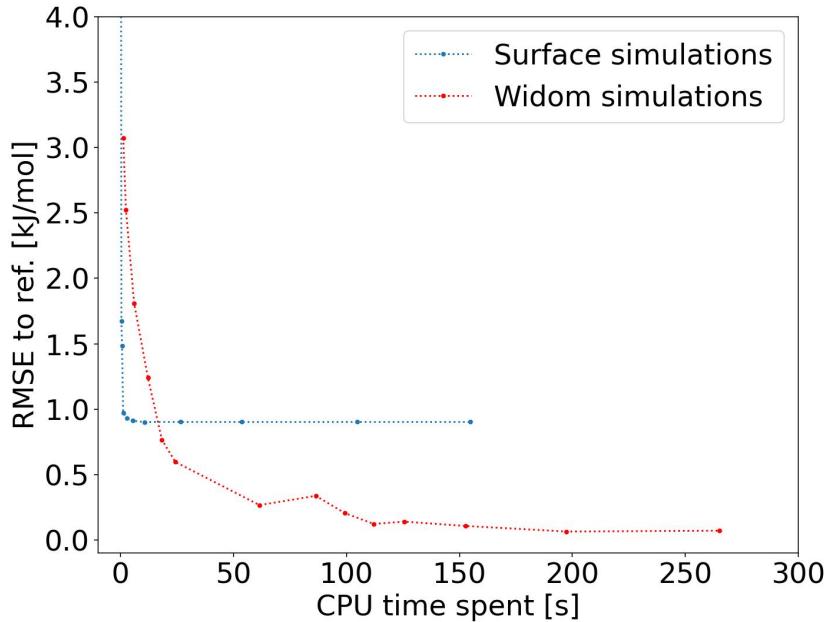


Figure 3.8: Convergence plot of the RMSE on the adsorption enthalpy for the RAESS algorithm (blue) compared to a 100k-step Widom insertion simulation (red) for xenon adsorption in all structures of the CoRE MOF 2019 database.

contribute to the host/guest interaction as well. I found that in the vast majority of materials, the adsorption sites are located farther apart compared to the LJ potential minimum, in order to maximize the contribution of all atoms – and because of the dissymmetry of the interaction potential well. In order to see if this could be introduced in the RAESS algorithm, I implemented a parameter  $\lambda$ , and the sampling sphere radius is now defined by  $R_\lambda = \lambda\sigma$ , where  $\sigma$  is the distance at which the LJ potential is zero. If  $\lambda = 2^{1/6}$ , we fall back to the initial definition of the sampling sphere, and the adsorbent is at the minimum of the LJ potential of the atom. If  $\lambda = 1$ , the sampling sphere is at the zero of the LJ potential, and by increasing this parameter, I can verify my intuition.

Because no analytical model could predict the optimal value of the sampling sphere, I followed a statistical approach. I studied the influence of the  $\lambda$  parameter on both the accuracy and the computation time, and the results are represented on Figure 3.9. The RMSE turns out to be relatively high around  $0.90 \text{ kJ mol}^{-1}$  for radius sphere lower than the  $r_{\min}$ , it then decreases for larger values of radius to reach a plateau around  $0.35 \text{ kJ mol}^{-1}$ . I confirm that by increasing the sampling sphere radius I can improve the accuracy of the algorithm, and find that for values of  $\lambda$  higher than 1.6, the accuracy is stabilized. I also find that increasing the sphere radius negatively impacts the computational efficiency, since it increases the number of neighbors considered in the energy calculation.

By choosing an optimal sampling sphere, we can more than halve the error, while increasing the computation time by around 20 percent, when comparing the case  $\lambda = 1.6$  with  $\lambda = 1.1$  (close to  $r_{\min}$ ). In most cases, it will be an acceptable trade-off. However, in a case where the computation time is crucial, like in a rapid screening, the optimal choice might not be to increase the sampling sphere at  $\lambda = 1.6$  but to have it lower at  $\lambda = 1.4$  or  $\lambda = 1.2$ , and have

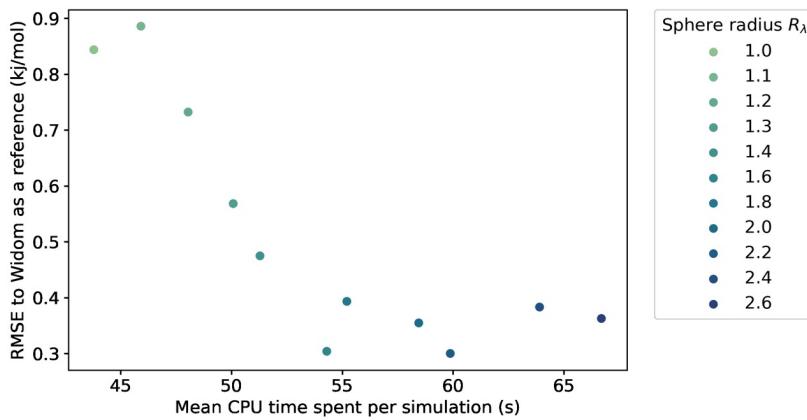


Figure 3.9: Influence of the sampling sphere radius  $R_\lambda$  on the average CPU time required for a simulation of 100k sampling points and the RMSE, compared to the reference adsorption enthalpy. The averaging is done only on the structures with the largest cavity diameter ( $LCD_{CCDC}$ ) higher than 3.7 Å.

an RMSE around 0.5 kJ mol<sup>-1</sup> – still quite acceptable. The new scale parameter introduced in this section can therefore be tweaked to serve the users' purpose, whether it is to focus on the accuracy or to optimize the computation speed. If one wants to use it on a completely different database in very different conditions, then one can either choose a default value that works fine (e.g.  $\lambda = 1.4$ ) or one can optimize the parameter on a small diverse sample of the unseen data.

#### REJECTION CONDITION

As shown above, the RAESS algorithm has better accuracy than Voronoi sampling, but its initial implementation was several times slower, which could be unsuitable for screening applications in high-throughput workflows, where the number of structures to be screened can reach one million or more. To reduce the computational expense, I implemented the rejection of the points with little contribution to the final enthalpy, i.e., the largely positive interaction energies that would vanish in the exponential of the Boltzmann average.

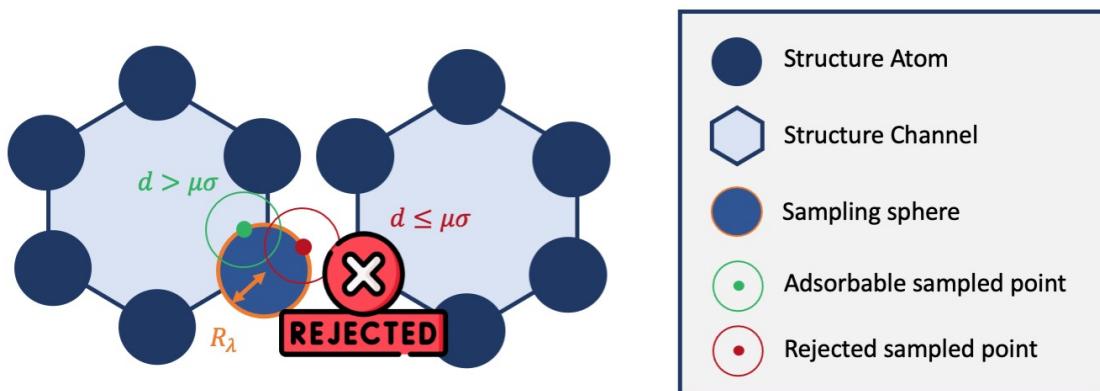


Figure 3.10: Simplified representation of the principle of rejection condition and the concept of sampling sphere inside 2D channels of a nanoporous material.

Inspired by typical methods for accessible surface calculation, I implemented a hard sphere rejection condition based on the distance to neighbors. If the adsorbate is too close to another atom of the structure, the sampling point is rejected, i.e., its energy is not calculated (or considered to be infinite). This distance threshold is based on the  $\sigma_{ij}$  parameter of the Lennard-Jones potential. To determine the optimal threshold, I introduced a factor  $\mu$  with real values between 0 and 1, that changes the size of the hard sphere rejection condition. If the guest–host distance is lower than  $d_\mu = \mu \times \sigma$ , then the point is rejected. If  $\mu = 0$ , then there is no rejection condition. And if  $\mu = 1$ , I reject all points with a positive energy interaction to at least one atom of the structure. This condition could be a bit strong and points with non-negligible contribution would end up rejected. This rejection condition is schematically represented on Figure 3.10.

This rejection condition is expected to speed up the calculation, since the energy calculation is avoided for the rejected sampling points. The energy calculation accounts for the largest portion of the CPU time spent in the surface sampling. For the structure KAXQIL,<sup>229</sup> the Lennard-Jones potential calculation represents up to 90% of the calculation time for 100,000 sampling points per sphere (with the initial algorithm). The higher the factor  $\mu$ , the more rejections there would be. But, if too many points are rejected, the accuracy would drop. Here again, I used a statistical analysis to determine the optimal value of  $\mu$ , making the sampling faster without compromising the accuracy of the enthalpy calculation. The results are displayed on Figure 3.11.

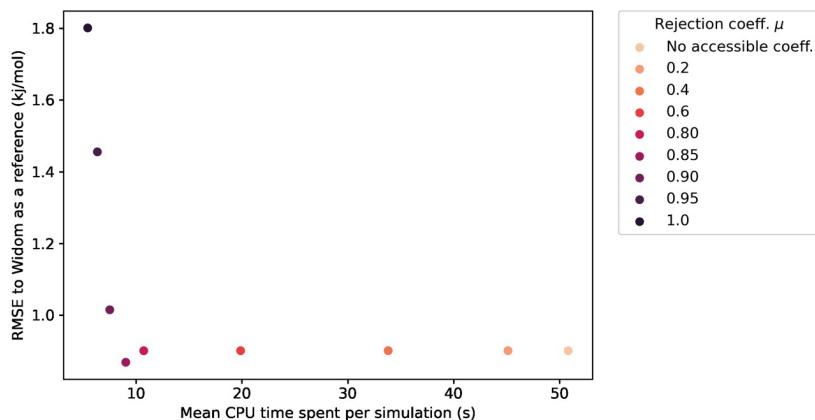


Figure 3.11: Influence of the rejection coefficient  $\mu$  on the average CPU time required for a simulation of 100k sampling points and the RMSE compared to the reference adsorption enthalpy. The averaging is done only on the structures with the largest cavity diameter ( $LCD_{CCDC}$ ) superior to 3.7 Å.

The values of RMSE and time on Figure 3.11 are averaged only on the most interesting structures for xenon adsorption ( $LCD_{CCDC} \geq 3.7$  Å). For  $\mu \leq 0.85$ , increasing the value of  $\mu$  improves the speed of the calculation without changing the RMSE.<sup>1</sup> For high values of  $\mu$ , the rejection condition is too strong and we reject points with non-negligible contribution to the overall enthalpy. The RMSE increases as a consequence. If we want to keep the accuracy unchanged, the optimal value is therefore  $\mu \simeq 0.85$ , because it gives the lowest computation time with a

<sup>1</sup>In fact, what is observed is a deterioration of the accuracy for structures with small pores because the probability of rejection in a confined space is really high and all sampled points end up rejected. But these points are not considered when applying a filter on the cavity size ( $LCD_{CCDC} \geq 3.7$  Å).

similar RMSE. It would be possible, in specific cases, to explore higher values of  $\mu$  that trade a bit more accuracy in exchange for further speed gains.

For the simulations considered on Figure 3.11, the use of a rejection condition  $\mu = 0.85$  make the simulation four times faster than the standard algorithm. In the next section, the combination of optimal values for the  $\lambda$  and  $\mu$  parameters generates an algorithm with very interesting performance compared to Voronoi sampling or Widom insertion.

### 3.2.3 Final surface sampling implementation

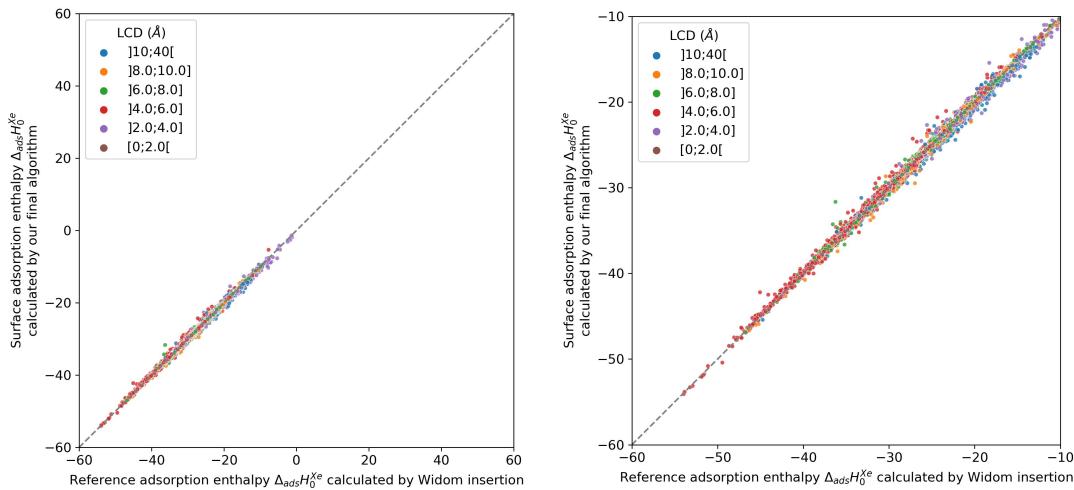
#### PERFORMANCE COMPARISON

For the calculation of adsorption enthalpy, the proposed surface sampling method is a good compromise between the accuracy of Widom insertion (full sampling of the porous space) and the speed of a less accurate method such as Voronoi sampling. The performance of the algorithm, including the two new features (sampling sphere scaling and rejection criterion) is illustrated on Figure 3.13, where we can see the improvement brought by each feature and how it compares to reference simulations. All CPU times are calculated using the smallest possible number of sampling points so that the respective algorithms reach convergence. With the implementation of a rejection condition, I find that surface sampling is even quicker than Voronoi sampling. Moreover, the increase of the size of the sampling sphere makes the surface sampling much more accurate, reaching an RMSE of  $0.33 \text{ kJ mol}^{-1}$  and an MAE of  $0.21 \text{ kJ mol}^{-1}$ . The ideal set of parameters, determined for porous materials from the CoRE MOF 2019 database, is ( $\lambda = 1.6$ ,  $\mu = 0.85$ ) in order to combine the lowest error and smallest computational cost. By combining both of these new features to the algorithm, the final surface sampling method has an RMSE of only  $0.33 \text{ kJ mol}^{-1}$  and an average computation time of 0.34 s per structure. According to the data represented on Figure 3.13, it is about 6 times more accurate and 26% faster than Voronoi sampling, and it is also about 430 times faster than a Widom insertion with 12k cycles.

Finally, the values of the parameters optimized in this work might need adjustment when applied to other adsorption systems. The optimal  $\mu$  parameter depends on the size of the adsorbent, and it should be tweaked differently when considering another adsorbent. For instance, the set of structures used for the optimization of  $\mu$  depends on the size of their cavities, and the  $3.7 \text{ \AA}$  threshold chosen here would need to be changed according to the kinetic diameter of the adsorbate. Furthermore, as aforementioned in the section on the rejection condition, it is possible to trade off a bit of accuracy for faster simulations especially in high-throughput screenings where speed is extremely important. Similarly, in the case of xenon, the cost of increasing the sphere size is around 10 to 20%. On very large databases, one could consider that this increase on the required computational time is not worth the accuracy improvement, and one could decide to keep a smaller sampling sphere. If this method is transposed to different molecular systems, its parameters should be tested on the specific database and adsorbate of interest.

#### CALCULATION OF HENRY CONSTANT AND SURFACE AREA

The main goal of the sampling algorithm is to calculate adsorption enthalpy in the zero-loading limit. But the method can also calculate at the same time the Henry constant and surface area of the materials, without significant additional computational cost. The Henry constant is a key metric for assessing the affinity of an adsorbate to a nanoporous structure. The Xe/Kr

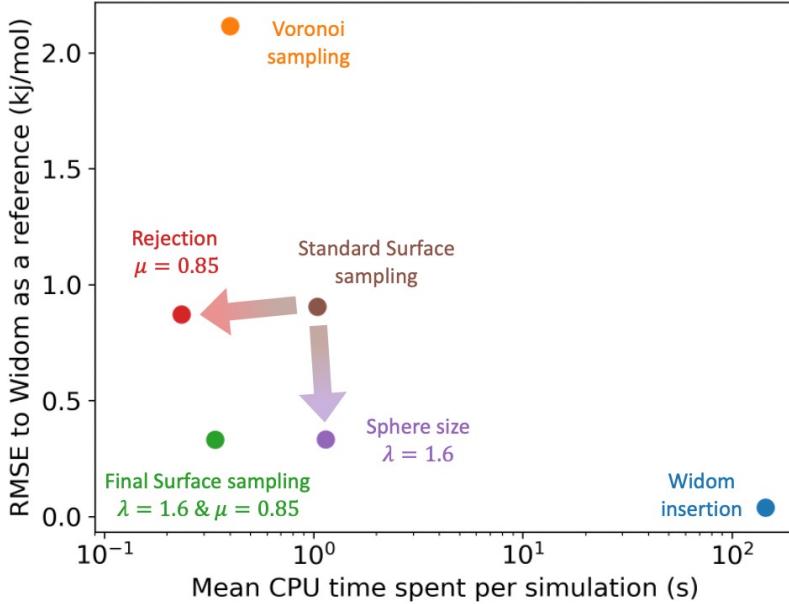


*Figure 3.12: Scatterplots of the xenon surface adsorption enthalpy calculated by the final RAESS algorithm ( $\lambda = 1.6$  and  $\mu = 0.85$ ) as a function of the xenon adsorption enthalpy calculated by a 100k-step Widom insertion simulation using two value windows, in structures of CoRE MOF 2019 with  $LCD_{CCDC} \geq 3.7 \text{ \AA}$  at 298 K. The second plot zooms on the negative values corresponding to the most selective materials.*

gas selectivity at low pressure is defined as a ratio of Henry constants of Xe and Kr. This important property can be calculated using Equation 2.16 in a Widom insertion calculation. Instead of using the interaction energies at the Widom inserted points, we can now use the surface sampled points to get an approximate value for the Henry constant.

Using the optimized set of parameters for surface sampling, I assessed the performance of the algorithm on the values of Henry constant by comparing them to ground truth obtained by 100,000 cycles of Widom insertion. Since the Henry constant corresponds to the exponential of an adsorption free energy, and I am more interested in the precision on the free energy, I will use a log-scale evaluation metric. For surface sampling, the log-RMSE of  $K_H$  is equal to 0.2, which means that the order of magnitude of the values are well predicted as shown on Figure 3.15. If I consider the derived free energy  $\Delta F_{ads} = -RT \log(\rho_f RT K_H)$ , the RMSE is of the order of  $1.1 \text{ kJ mol}^{-1}$  and is reached in about 1 s (Figure 3.15). Whereas for Widom insertion, this level of error is also reached in a similar amount of time and  $0.1 \text{ kJ mol}^{-1}$  of RMSE is reached in about 86 s (Figure 3.15). For free energy calculation, surface sampling is still 86 times faster to converge. If consider that the main target is the adsorption enthalpy, the Henry constant is calculated with little additional computational cost and with reasonable accuracy: we get two thermodynamic properties of interest for the price of one.

The same goes for the determination of the surface area. We can adapt the algorithm to count the number of points of the sampling spheres that have a negative energy. These represent the points were a guest molecule can favorably interact, therefore when dividing it by the number of sampled points, we obtain a proportion of adsorbable area of the sphere. Summing



*Figure 3.13: Comparison of the RMSE to the reference Widom insertion and the average computation time for different types of enthalpy calculation methods. The surface sampling calculation was all done with 2k sampling points on each sphere and the Widom simulations were done using 12k cycles. These values correspond to the value at the convergence identified using Figure 3.8.*

this over all atoms, we obtain a total surface area. This implementation is summed up in equation 3.7:

$$SA = \frac{1}{V} \sum_{a \in \text{cell}} \frac{N_{\text{accessible}}(a)}{N_{\text{total}}} 4\pi r(a)^2 \quad (3.7)$$

where  $V$  volume of the cell;  $a$  atoms of the cell;  $N_{\text{accessible}}(a)$  accessible points around the atom  $a$ ;  $N_{\text{total}}$  sampling points;  $r(a)$  radius of the sampling sphere around the atom  $a$ . When we set  $\lambda = 1$ , we are sampling spheres that have a radius  $\sigma$ , and it is equivalent as considering hard spheres all defined by  $\sigma$  (convention used by RASPA2 to calculate surface areas). If we compare simulation with  $\lambda = 1$ , we obtain surface areas that are very close to the one obtained by RASPA2 (see Figure 3.16 in SI). However, when we consider  $\lambda = 1.6$ , we lose the perfect accordance previously obtained and the points weakly correlated in log-scale (see Figure 3.16 in SI). The difference can be explained by the fact that the sphere size is larger, but the proportion of adsorbable points also changes. The relationship between these two adsorption surface areas is not trivial at all. Since the calculation of surface areas is quite cheap, this implementation would not be very useful, except for having a rough idea of the surface area.

### 3.2.4 Surface sampling application use cases

After introducing the performance of our surface energy sampling algorithm for xenon and on specific materials from CoRE MOF 2019 at 298 K, I will explore other conditions to test the transferability of the methodology. First, I will use the algorithm to assess the xenon/krypton selectivity at infinite dilution compared to the standard Widom insertion. Then, I want to compare the influence of the temperature on the performance since it most likely would be

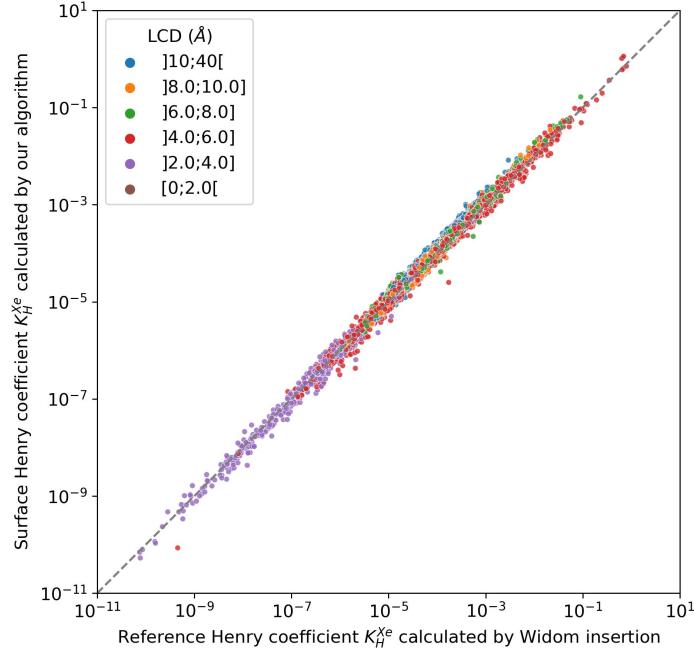


Figure 3.14: Scatterplots of the xenon Henry constants calculated by the RAESS algorithm compared to the ones calculated by a 100k-step Widom insertion simulation using two value windows.

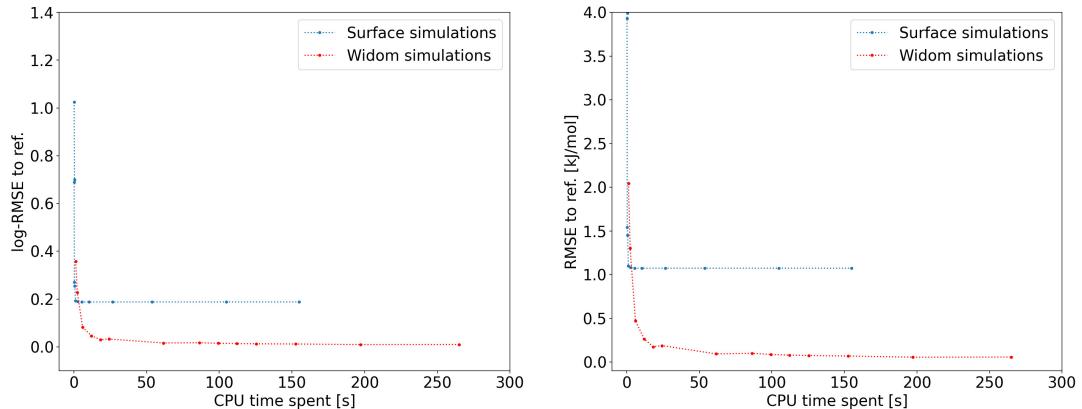
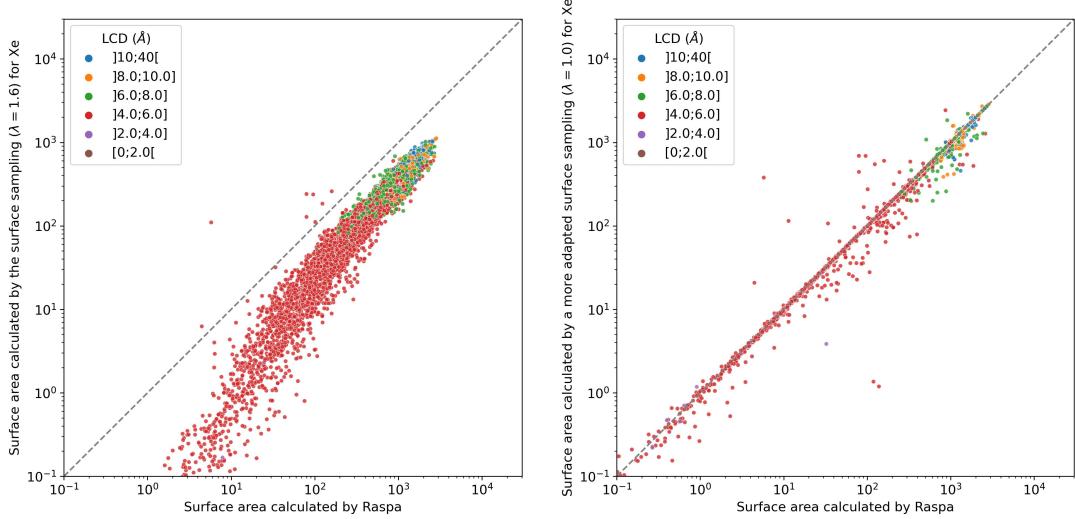


Figure 3.15: Left: convergence plot of the log-RMSE on the xenon Henry constants for both the surface sampling and the Widom insertion. Right: convergence plot of the RMSE on the xenon adsorption Gibbs free energy for the final implementation of the surface sampling and the Widom insertion.

much less ideal since the Boltzmann weights are less concentrated on the less attractive points. Finally, I tested the RAESS algorithm on databases of different materials.

### SELECTIVITY CALCULATIONS

The selectivity value is the most important metric in evaluating the Xe/Kr separation performance of a nanoporous material. I want to see if a surface sampling technique can accurately evaluate this metric while being limited by all the approximations inherent to the technique.



*Figure 3.16: Scatterplots of the surface areas calculated by the RAESS algorithm with two different parameterizations compared to the surface area given by a RASPA2 surface area calculation. The left plot corresponds to the surface sampling described in the section 3.2.3 with  $\lambda = 1.6$  and  $\mu = 0.85$ , while the right plot uses a sampling sphere near  $\sigma$  with  $\lambda = 1.0$ . The second parameterization is much closer to what a RASPA2 sampling based on the  $\sigma$  parameter of a LJ potential does, hence explaining the much better accordance.*

A few precautions should be considered before blindly using the algorithm for selectivity prediction. When investigating the calculation of the selectivity, I noted that the rejection condition on xenon can be high since I am more interested in the most favorable materials for xenon adsorption. But for krypton, I want to accurately describe very low Henry constants, because a selective material would also be a material unfavorable to krypton. For these reasons, the parameter  $\mu$  needs to be chosen wisely and needs to be low enough to have accurate Kr Henry constant and then selectivity values.

As shown in Table 3.1, the error on the selectivity highly depends on the  $\mu$  value that excludes the points at  $\mu\sigma$  of a framework atom center. Logically, a low parameter  $\mu$  enables the sampling of higher energy values that goes in the Boltzmann averaging. Another reason is that when dividing by small values any small error on the values can be amplified in the quotient, and this effect can be reduced as the number of sampled points increases.

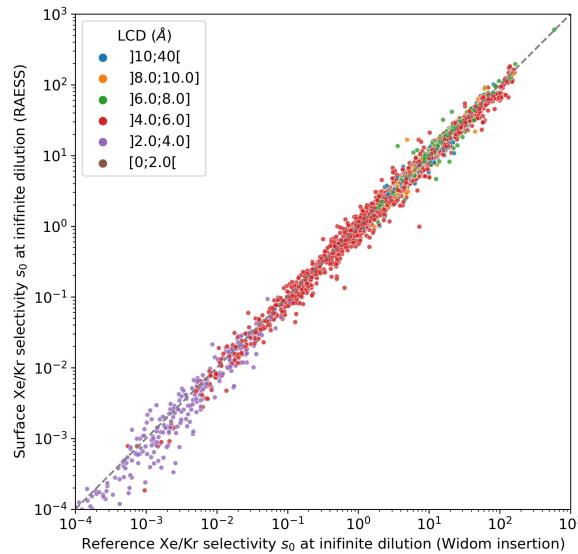
rejection parameter $\mu$	log10-RMSE to 100k-Widom	log10-MAE to 100k-step Widom
0.85	0.107	0.077
<b>0.50</b>	<b>0.0635</b>	<b>0.0402</b>
0.20	0.0637	0.0403

*Table 3.1: Influence of the rejection condition in the krypton surface simulation on the accuracy of the Xe/Kr selectivity calculation. The lower the parameter  $\mu$  the more accurate the simulations are for the final selectivity calculation.*

According to the quick study here, the optimal value is  $\mu = 0.5$  since it gives the best accuracy for a minimal amount of time. This value will be used for krypton to make a comprehensive study of the performance on the Xe/Kr selectivity for materials from CoRE MOF 2019. To sum

up, in the following study, I will use the RAEss algorithm with  $\lambda = 1.6$  and  $\mu = 0.85$  for xenon and  $\lambda = 1.6$  and  $\mu = 0.5$  for krypton.

The selectivity can be compared directly using a log-scale plot and log-scale metric. If I apply the  $\log_{10}$  to the selectivity values, the RMSE is about 0.064 and the MAE 0.04. This means that we have an error of about 0.06 when we compare the orders of magnitude of the selectivity. For example, if a selectivity is predicted to be  $s = 10^{-7}$ , then  $s$  would be in the interval  $[10^{-7.06}, 10^{-6.94}]$ .



*Figure 3.17: Scatterplot comparison of the Xe/Kr selectivity calculated by RAEss algorithm and the one calculated by the Widom insertion (in log scale) and labeled by the cavity size.*

To be able to give a thermodynamic interpretation, we can use the exchange Gibbs free energy associated  $\Delta_{\text{exch}}G_0^{\text{Xe/Kr}}$  to this selectivity defined in the previous chapter (equation 2.26). Using this exchange Gibbs free energy, we can assess much more easily the performance of the approach. The RMSE is about  $0.36 \text{ kJ mol}^{-1}$ . We cannot compare it to the adsorption enthalpy errors, since the ranges and interpretation are very different. Here, the selective materials have a negative  $\Delta_{\text{exch}}G_0^{\text{Xe/Kr}}$ , and it goes to a maximum value of about  $-12.7 \text{ kJ mol}^{-1}$ . The relative error is, of course, higher on the Gibbs free energy. This is due to a higher uncertainty on the Henry constant and to the denominator term brought by the krypton.

To know how well the RAEss algorithm would work in real situations, I tried to compare the top 100 most selective materials given by RAEss and a Widom simulation (RASPA2). I found that 83 structures of the top 100 given by RAEss are in the top 100 given by Widom insertion. As the correlation is not perfect, it is inevitable that there is a change in the order of the top 100 given by these two methods. This number of 83% proves that the difference is quite narrow. If I enlarge to the top 150 of the Widom simulation, 94 are present in the top 100 of the surface simulation. I can therefore say that a vast majority of the best candidates given by the Widom insertion simulation are found by the RAEss algorithm.

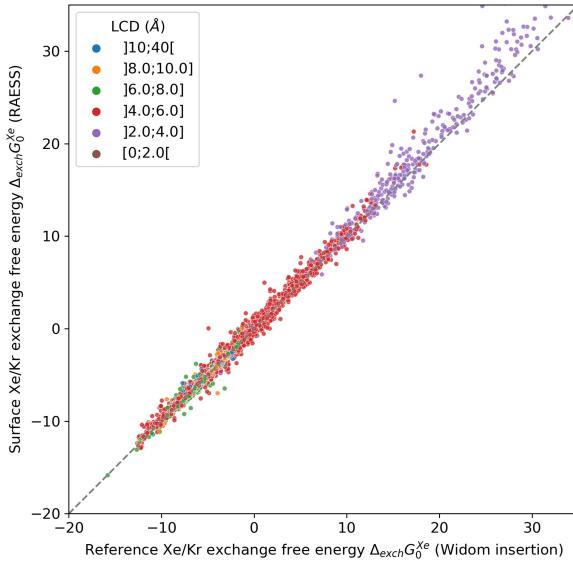


Figure 3.18: Scatterplot comparison of the exchange Gibbs free energy  $\Delta_{\text{exch}}G_0^{\text{Xe/Kr}}$  calculated by the Widom insertion compared to the final implementation of RAESS (RMSE=0.36 kJ mol<sup>-1</sup> and MAE=0.23 kJ mol<sup>-1</sup>).

### A HIGHER TEMPERATURE

The RAESS method relies on the higher weight of the strong sites close to the surface of the pores. If I increase the temperature, the less attractive sites would play an increasing role and the accuracy of the method would drop. To grasp this limitation of the RAESS algorithm at higher temperature, I compared the results of a screening over the CoREMOF 2019 database.

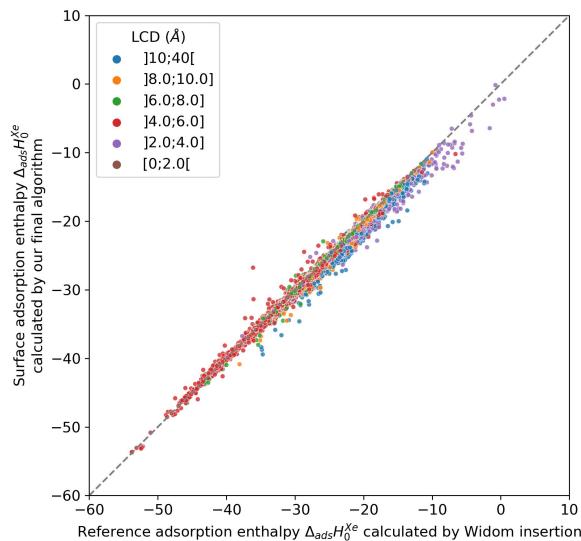


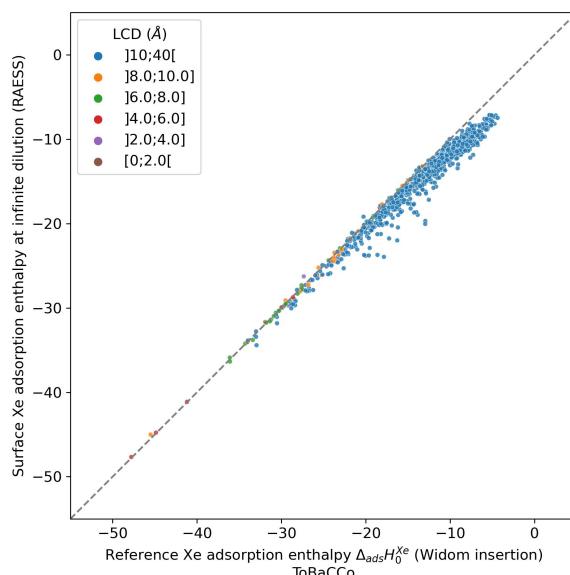
Figure 3.19: Scatterplot of the enthalpies calculated by our final algorithm ( $\lambda = 1.6$  and  $\mu = 0.85$ ) compared to the enthalpies calculated by a 12k step Widom insertion simulation of xenon in structures of CoRE MOF 2019 with  $LCD_{CCDC} \geq 3.7 \text{ \AA}$  at 600 K.

As expected, the surface sampling method is less accurate for a higher temperature Boltzmann averaging, but it still gives an acceptable correlation on the performance, with an RMSE of  $0.70 \text{ kJ mol}^{-1}$  and an MAE of  $0.41 \text{ kJ mol}^{-1}$ . The errors have almost doubled when increasing the temperature from 298 K to 600 K. However, these limitations of the method are not crippling since adsorption processes are usually not performed at very high temperature. High temperatures are commonly used in temperature swing adsorption (TSA) to desorb the adsorbates rather than to adsorb them.

## OTHER DATABASES

### ToBaCCo

I randomly selected 1,000 structures from the 13,511 porous frameworks of the ToBaCCo database to test the robustness of the RAESS method on a database other than CoreMOF. Since ToBaCCo contains structures with larger pores as suggested by a Moosavi et al., these materials are more unfavorable for adsorption of small molecules (such as Xe). The correlation is therefore found to be weaker than in the CoRE MOF 2019 database. This lower accuracy should be nuanced by the lack of suitability of these materials for Xe/Kr separation. Moreover, I can note that the points with weaker correlations correspond to the ones with the LCD<sub>CCDC</sub> greater than  $10 \text{ \AA}$ , which is not ideal to separate Xe from Kr.



*Figure 3.20: Scatterplot comparison of the xenon adsorption enthalpy calculated by the RAESS algorithm and the Widom insertion (RASPA2) on the ToBaCCo database. RMSE =  $1.79 \text{ kJ mol}^{-1}$  and MAE =  $1.48 \text{ kJ mol}^{-1}$ . 915 structures have the LCD<sub>CCDC</sub> greater than  $10 \text{ \AA}$ .*

The algorithm performs very well on the most adsorptive materials with xenon adsorption enthalpy values lower than  $-30 \text{ kJ mol}^{-1}$ , because the adsorption sites are located near the surface. For broader pore sizes, it is interesting to note some limitations of the methodology we should be aware of. For determining the most attractive materials, this shortcoming does not influence the final results. Moreover, this limitation is not that damaging since the correlation is weakened but did not disappear.

## Amorphous materials

To further extend the possible uses cases of the RAESS algorithm, I tested the RAESS algorithm on the amorphous database.<sup>56</sup> The algorithm found results for 176 structures out of 196. The RASPA2 software was not able to run on these amorphous structures with our computers, running out of memory due to the large system size: therefore, there is no comparison point with a Widom simulation. However, I used another simulation that is closer to the ground truth since it samples a homogeneously distributed grid using an optimized algorithm I will present in the next section. This grid sampling managed to compute the adsorption energies of 175 structures.

Table 3.2 gives the values of the adsorption enthalpies and the Henry constants of a few amorphous materials as well as the time they took to be computed. The sheer number of atoms in each structure makes the CPU time required much higher than for the crystalline structures of CoRE MOF 2019. The time required are, however, quite manageable in a hypothetical screening procedure. If I consider all the 175 structures that could be calculated by our methods, the average time required is about 75 s per structure. The detailed data is available in csv format

Structure Name	$\Delta_{\text{ads}}H_0^{\text{Xe}}$ (kJ mol <sup>-1</sup> )	$K_{\text{H}}^{\text{Xe}}$ (mol kg <sup>-1</sup> Pa <sup>-1</sup> )	CPU time (s)
aCarbon-Marks-id035	-63.55	6.98e-01	285.45
HCP-Colina-id016	-30.61	8.85e-05	3.88
Kerogen-Coasne-id010	-44.38	8.02e-03	61.2
PIM-Colina-id012	-26.39	7.00e-05	8.86

Table 3.2: Some amorphous materials' performance according to the RAESS algorithm. The results on the whole amorphous database is given in CSV format on the Github: [github.com/fxcoudert/citable-data/tree/master/154-Ren\\_ChemSci\\_2023](https://github.com/fxcoudert/citable-data/tree/master/154-Ren_ChemSci_2023).

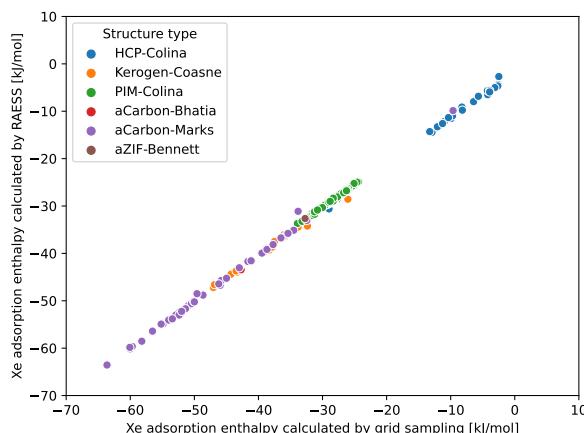


Figure 3.21: Scatterplot comparison of the xenon adsorption enthalpy calculated by the RAESS algorithm and the one calculated by a grid sampling (presented in the next section) on a database of porous rigid amorphous materials.<sup>56</sup> RASPA2 simulation could not be run on this database. Only the 175 structures computed by both methods are presented here.

As shown on Figure 3.21, the accuracy of the surface sampling is rather high since by comparing it to an unbiased grid-based sampling, I obtain very similar results. The RMSE is about 0.83 kJ mol<sup>-1</sup>, which is higher than the one for CoRE MOF structures. This method could very likely be used to evaluate amorphous materials as a fast screening tool especially since the

computation time required by the optimized grid sampling is about 623 s. The dimension reduction inherent to the surface sampling makes it one order of magnitude faster than conventional techniques.

### 3.2.5 Perspectives of surface sampling

I described a novel algorithm for the high-speed calculation of adsorption enthalpy in nanoporous materials,<sup>1</sup> that takes a unique approach to reduce the sampling necessary. This new algorithm is based on the core principle of dimensional reduction, from a volume problem to a surface one. The algorithm is proven to be significantly faster than the reference Widom insertion (random sampling of porous space). Moreover, the error associated is found to be of the order of 0.4 kJ mol<sup>-1</sup>, tested throughout the entire CoRE MOF 2019 database, for xenon adsorption. Even when compared to existing very fast sampling techniques such as the Voronoi sampling, this surface sampling technique requires similar CPU time, combined with a better accuracy.<sup>1</sup>

Based on these results, this algorithm has important potential for applications in the current computational analysis workflows of material databases, such as high-throughput screening studies. For instance, this algorithm can be used to get a fast approximation of the low-loading adsorption enthalpy of a molecule inside nanoporous materials. This cheap evaluation of the enthalpy can be used to screen out the structures with little affinity with the targeted adsorbate molecule. It can also be used as a thermodynamic descriptor for selectivity prediction in a machine learning model, as done by Simon et al.<sup>18</sup> The computational speedup brought by this novel methodology can also enable the screening of materials databases at larger scale in the future.

I note, moreover, that the speed of our method resides in the sampling technique itself, rather than in the actual energy calculation. While I have benchmarked it in this work for a simple Lennard-Jones interaction potential, this sampling technique could equally be used to speed up samplings of space based on more expensive modeling strategies, including polarizable force fields or density functional theory (DFT) calculations. In the literature, the need for cheap *ab initio* grade thermodynamic properties is usually fulfilled by using an importance sampling method based on a classical force field.<sup>230</sup> In our method, the description of surface sampling is independent of any force field, and the sampling spheres can be defined according to kinetic radius, van der Waals radius or any other physically relevant distance. Consequently, given a definition of atomic radii, it is possible to define a surface on which to carry out other types of simulations such as neural network potential, DFT or any other force fields. Although the accuracy or relevance of such a sampling remains an open question, the approach will undeniably speed up the simulations. This could even be applied to calculate adsorption enthalpies while considering intrinsic structure flexibility,<sup>162</sup> a task whose main drawback is the high computation time required. Since surface sampling is hundreds of times faster than standard methodologies, I could use hundreds of snapshots in a flexibility-aware calculation.

Finally, although the algorithm in its present form can already be applied in a wide range of applications, additional development work could allow us to generalize it to polyatomic

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<sup>1</sup>The code is made available on the group's GitHub ([github.com/coudertlab/RAESS](https://github.com/coudertlab/RAESS)), where further development will be released.

<sup>1</sup>All data shown in this section is available at [https://github.com/fxcoudert/citable-data/tree/master/154-Ren\\_ChemSci\\_2023](https://github.com/fxcoudert/citable-data/tree/master/154-Ren_ChemSci_2023)

adsorbates. For instance, I would need to work on a definition of the molecular radius for non-spherical adsorbates as well as working all the orientation conformation of the adsorbent. I could imagine making the distance to the surface depend on the orientation of the adsorbate or sample a band volume on the surface. Although the best implementation of the surface sampling for polyatomic adsorbates remains an open question, in theory it should be possible to apply it to more complex adsorbates than the spherical noble gas. This would add more complexity to the algorithm but would not change the fundamental speedup due to surface sampling, since these orientation moves are also performed in other standard methodologies. To improve even more the accuracy, we could test hybrid samplings with multiple sampling spheres, or a combination of Voronoi nodes and sampling spheres. Another idea could be to have fractions of spheres that are oriented toward the center of the pore given by the Voronoi node. In theory, having a wider variety of sampling points can only improve the sampling. There are therefore multiple possible sampling techniques that could be built around the method introduced herein.

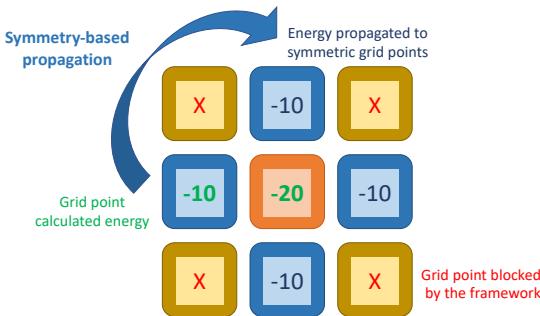
### 3.3 GRID ADSORPTION ENERGIES DESCRIPTORS (GRAED)

To finish the overview of novel methods of energy sampling, I will present a revisited version of the most standard grid sampling. A grid sampling is the most accurate approach since it is directly based on the averaging definitions of the equations ?? and 2.14. In this section, I will leverage the symmetry operations inherent to most material structures and the removal of framework occupied space to speed up this usually very slow method. This exhaustive approach enables the calculation of energy distributions that are much less biased than with any other methods. And from these energy distributions we began to build up some essential building blocks for the prediction of the ambient-pressure selectivity that will be carried out in the next section.

#### 3.3.1 Implementation of an efficient grid algorithm

To build more relevant energy descriptors, I will now go back to the definitions of the adsorption enthalpy and the Henry constant (equation 2.22 and 2.14) that call for a homogeneous sampling of the adsorption space. The easiest way of sampling consists in laying a grid in the 3D space. This method is, however, known to be the most time-consuming on in theory. Inspired by our work on surface sampling, I designed an approach based on a symmetry-respecting grid, generated using the algorithms of the Gemmi Project,<sup>231</sup> where the points overlapping with framework are discarded. In our grid adsorption energy descriptor (GrAED) calculation algorithm, these new features coupled with a grid sampling makes the calculation of adsorption energies much less time-consuming while being very accurate.

The corresponding algorithm has a core structure of a grid algorithm, where we need to evaluate the interaction energy at each point of the preset grid over the structure's unit cell. A naive approach would call for an expensive energy calculation at each grid point. To improve this approach, the algorithm is based on two main simplifications — a quick evaluation of the framework occupied grid points and the exploitation of symmetry. The grid points that overlap with the framework's atoms have highly positive energy mainly due to the interaction with the overlapping atom. High values of energy does not contribute much to any thermodynamic quantities displayed in the section 2.1.5. For this reason by using a rejection parameter similar



*Figure 3.22: Principle of the energy sampling on a symmetry-based grid. On the 9 grid points, 4 points are blocked because they are too close to the framework atoms, 2 points are really calculated using the LJ potential and 3 points are propagated using the inner symmetry of the framework.*

to the one developed for surface sampling introduced in the section 3.2.2, we can precalculate the interaction energy of the grid points within the sphere of radius  $\mu \times \sigma_{g-h}$ . If the value of this interaction energy is higher than a preset energy threshold  $E_{th}$ , then the associated grid point takes these values as the interaction energy and no further calculation will be performed for it. The symmetry of the grid is based on the symmetry of the structure determined using the Grid definition of the Gemmi Project. By using the symmetry operations on a grid point value, we can propagate it to the other symmetry-equivalent grid points as illustrated on Figure 3.22, which reduces the amount of time we need to calculate the interaction energy of a guest molecule at a given grid node with all the surrounding framework atoms within a given cutoff. Now that I presented the main building blocks of our optimized grid calculation, I will show how it integrates in the implementation of the algorithm.

1. We loop over the framework atoms and the grid points around a sphere of radius  $\mu \times \sigma_{g-h}$ , where  $\sigma_{g-h}$  is the distance at which the LJ potential energy between the guest atom  $g$  and the host atom is zero. The LJ potential energy between the guest molecule and the closest host atom is calculated and only the grid points with an energy lower than a predefined threshold  $E_{th}$  are considered “unvisited” and will be recalculated in the following loop, the others are considered blocked by the framework and will be considered already “visited”. This first loop over the framework atoms aims at filtering out the grid points that are blocked by the framework, and I will refer to this preliminary filtering step as “blocking” in Table 3.3.
2. A second loop over the “unvisited” grid points is performed – at each increment, if the point is “unvisited” we calculate the interaction energy between the guest and all the host atoms within the cutoff, then the symmetric images of this point are filled with the same energy value and are considered “visited” by the algorithm. This symmetry-aware grid exploration allows the algorithm to divide the time required by the average number symmetry images – this module will be referred to as “symmetry” in Table 3.3.

By combining both the “blocking” of the high energy grid points and the “symmetry” based calculation of the interaction energies, I built a “fast” version of the grid calculation algorithm that can compete with our previously developed rapid surface sampling method (RAESS). To control the trade-off between accuracy and computation time, we can vary the spacing between the grid points, whose computation time is theoretically inversely proportional to the cube

of the spacing. And, for some values of this spacing, this algorithm can even be faster than the surface sampling on the CoRE MOF database where the symmetry plays an important role (see Table 3.3). The full implementation of the GraED algorithm can be found at the following Github url: [github.com/coudertlab/GrAED.git](https://github.com/coudertlab/GrAED.git).

### 3.3.2 Performance on the adsorption equilibrium

Looking now at the performance of this new grid sampling algorithm compared to previously introduced sampling algorithms, it is very advantageous to use this new sampling on the CoRE MOF 2019 database because of its accuracy and its speed. The good time performance of the grid sampling on the structures of CoRE MOF 2019 database can be explained by their rather small porosity of the materials and their high order of symmetry. For instance, the average void fraction for a 1.2 Å probe radius is equal to 0.16 and the average number of symmetric images is equal to 5.8 (most MOFs present symmetry operations). On average, the “blocking” procedure means that only  $\sim 16\%$  of the grid points really need to be calculated. And the “symmetry” procedure implies that only  $\sim 17\%$  of points need to be considered, and the combination of both theoretical reduces the number of useful points to only 2.7% of the grid. This leads to a significant reduction in the CPU time of the calculation while keeping the accuracy level (low error on the Xe adsorption enthalpy  $0.014 \text{ kJ mol}^{-1}$ ) compared to the naive grid approach, as shown in Table 3.3. In the grid simulation, with the blocking procedure, the time required is reduced by  $\sim 70.6\%$  compared to the naive approach, and a similar reduction of  $\sim 76.6\%$  is observed for the symmetry-aware grid sampling. By combining both simplifications, the time required of the fast grid sampling is reduced by almost  $\sim 91.6\%$  for a grid spacing of 0.12 Å, which echoes with the fewer points needed to be sampled I mentioned above.

Energy sampling method	RMSE on xenon adsorption enthalpy ( $\text{kJ mol}^{-1}$ )	Average CPU time (s)
Grid – naive – 0.12 Å	0.014	35.4
Grid – blocking – 0.12 Å	0.014	10.4
Grid – symmetry – 0.12 Å	0.014	8.3
Grid – fast – 0.12 Å	0.014	2.96
Grid – fast – 0.2 Å	0.048	0.41
Grid – fast – 0.3 Å	0.21	0.13
Voronoi sampling	2.1	0.40
RAESS <sup>23</sup>	0.33	0.34
Widom <sup>202</sup> (12k cycles)	0.038	150

Table 3.3: Performance comparison of the new grid method to other standard techniques used to calculate the xenon adsorption enthalpies. The RMSE is calculated by comparing to the values given by a 100k-step Widom insertion considered as the ground truth. The associated calculations are performed on the structures with the LCD<sub>CCDC</sub> over 3.7 Å of CoRE MOF 2019 database with a single Intel Xeon Platinum 8168 core at 2.7 GHz. The GraED algorithm (with  $\mu = 0.8$   $E_{th} = 100 \text{ kJ mol}^{-1}$ ) is evaluated at different grid spacings (0.12, 0.20, 0.30).

As shown on Figure 3.24, the approach does not damage the accuracy of the adsorption enthalpy and of the Henry constant. There is an almost perfect accordance between the Widom insertion method and the grid-based approach for a very finely meshed grid (0.12 Å spacing). This was

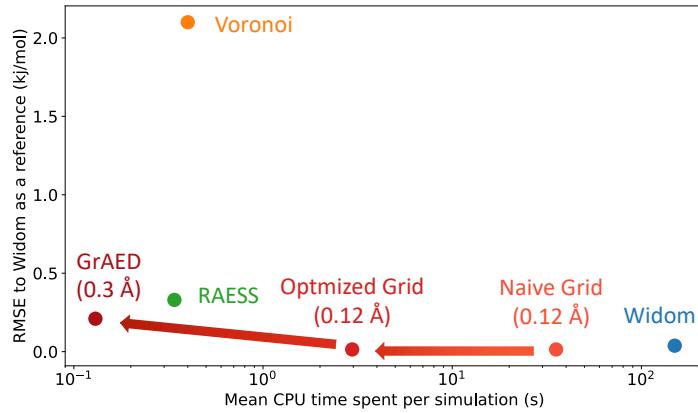


Figure 3.23: Comparison of the RMSE on Xe adsorption enthalpy and the average CPU time required to run a simulation on a structure of CoRE MOF 2019 ( $LCD_{CCDC} \geq 3.7 \text{ \AA}$ ) for different sampling techniques (Widom, Voronoi, RAESS and GrAED). The values are reported in Table 3.3.

expected since both methods are unbiased sampling of the adsorption energies. Almost no error can be detected if looking at the figure for both adsorption enthalpy and Henry constant. The RMSE on the adsorption enthalpy is only about  $0.01 \text{ kJ mol}^{-1}$ , while the RMSE on the  $\log_{10}$  of the Henry constants (in  $\text{mmol g}^{-1} \text{ Pa}^{-1}$ ) is also very low at 0.01. This method goes back to the initial definition of these quantities at infinite dilution, the perfect correspondence is therefore not very surprising.

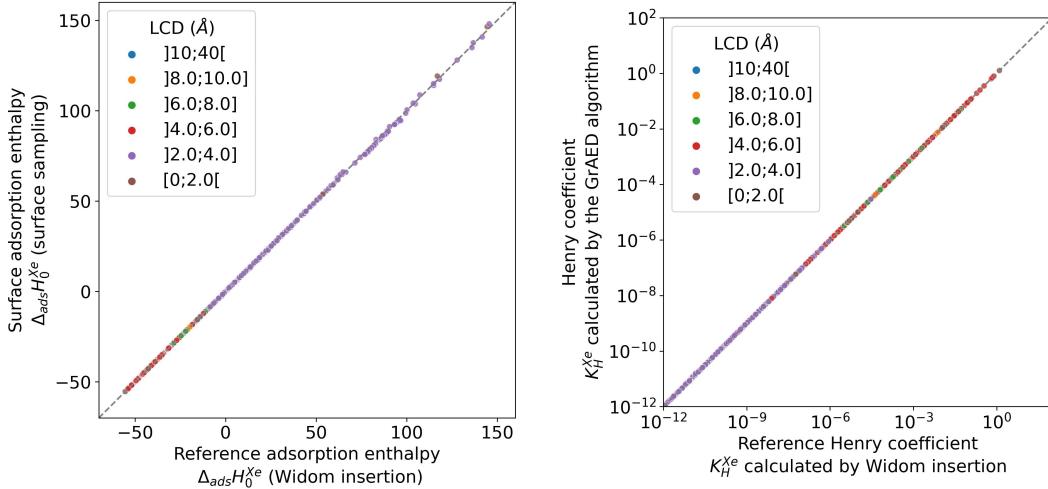
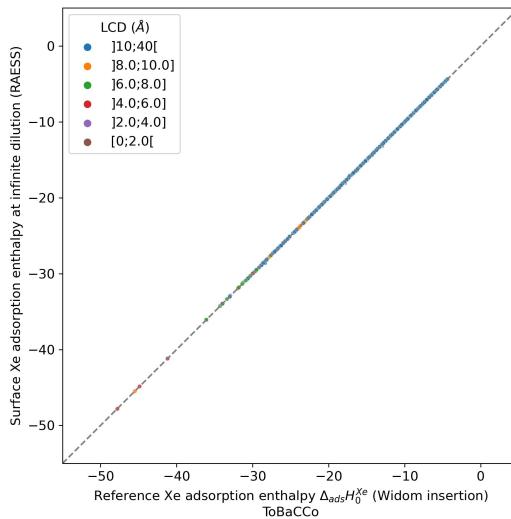


Figure 3.24: Comparison of the xenon adsorption enthalpies (left) and the Henry constants (right) calculated by the optimized grid energy sampling (for a  $0.12 \text{ \AA}$  spacing, a rejection parameter  $\mu = 0.8$  and an energy threshold  $E_{th}$  of  $100 \text{ kJ mol}^{-1}$ ) and by the Widom insertion of RASPA2 with 100,000 cycles on the CoRE MOF 2019 structures ( $LCD_{CCDC} \geq 3.7 \text{ \AA}$ ).

The little computation time required to achieve such an accuracy is, however, much more interesting. Looking at Table 3.3, the very accurate grid sampling reaches a similar accuracy than a 12k-cycle Widom insertion calculated using the RASPA2 software, while being 50 times faster. On the CoRE MOF 2019 database, by using a looser grid spacing of  $0.3 \text{ \AA}$ , the

GrAED algorithm can even be more interesting than the RAESS algorithm since it halves the computation time while being slightly more accurate. This very comparable performance compared to a dimensionally reduced sampling technique can be explained by two factors of the CoRE MOF database: first, the structures have smaller pores which means a greater surface to volume ratio, which increase the RAESS computation time; second, the highly symmetric structures of CoRE MOF reduces considerably the computation time required for GrAED, and the same cannot be said for other databases such as ToBaCCo or the amorphous database already studied in the section 3.2.4.

For instance, the computation time required is found to be 750 times higher for a grid sampling than a surface sampling on the amorphous database (see section 3.2.4), and the RMSE is only of  $0.83 \text{ kJ mol}^{-1}$ . For amorphous databases, the surface sampling would be much better than an exhaustive grid sampling because both symmetry and overlap consideration reduce much less the number of sampled points, and we see the effect of surface sampling dimension reduction much more than on the CoRE MOF database. For the ToBaCCo database,<sup>14</sup> the symmetry does not play any role anymore, and the pores are much larger, which means fewer points blocked by the framework. This impacts directly the performances of the grid sampling compared to the RAESS algorithm. The average time required on the thousand structures of ToBaCCo, considered in section 3.2.4, is now 735 s instead of less than 2 s for a surface sampling. By increasing the grid spacing to 0.3, we can expect to reduce the computational time required to 47 s (deduced using a rule of three). The accuracy, however, is much better than for a surface sampling (see Figure 3.25), reaching an extremely low RMSE of  $0.02 \text{ kJ mol}^{-1}$ . Depending on the number of structures and their nature (symmetry, porosity), we need to choose between the more efficient but less accurate RAESS and the GrAED software.



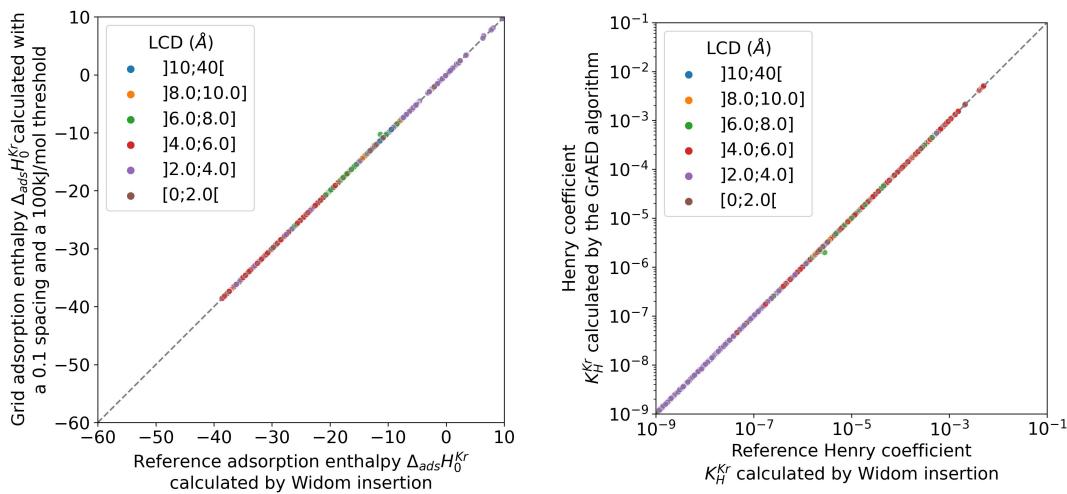
*Figure 3.25: Comparison of the xenon adsorption enthalpies (left) and the Henry constants (right) calculated by the optimized grid energy sampling (for a  $0.12 \text{ \AA}$  spacing, a rejection parameter  $\mu = 0.8$  and an energy threshold  $E_{th}$  of  $100 \text{ kJ mol}^{-1}$ ) and by the Widom insertion of RASPA2 with 100,000 cycles on 1000 randomly selected structure of the ToBaCCo.<sup>14</sup>*

From the energy values of this grid, we can now calculate many useful descriptors of the adsorption process. We have seen the performance on the Xe adsorption enthalpy and the Xe Henry constant. But as mentioned in the section 2.1.5, we can also derive the Xe adsorption

Gibbs free energy and the Xe adsorption entropy. Considering the krypton in addition to the xenon, we can naturally evaluate the Kr adsorption thermodynamic quantities but also the exchange thermodynamic quantities and especially the Xe/Kr selectivity (the key metric in evaluating the separation process we are interested in).

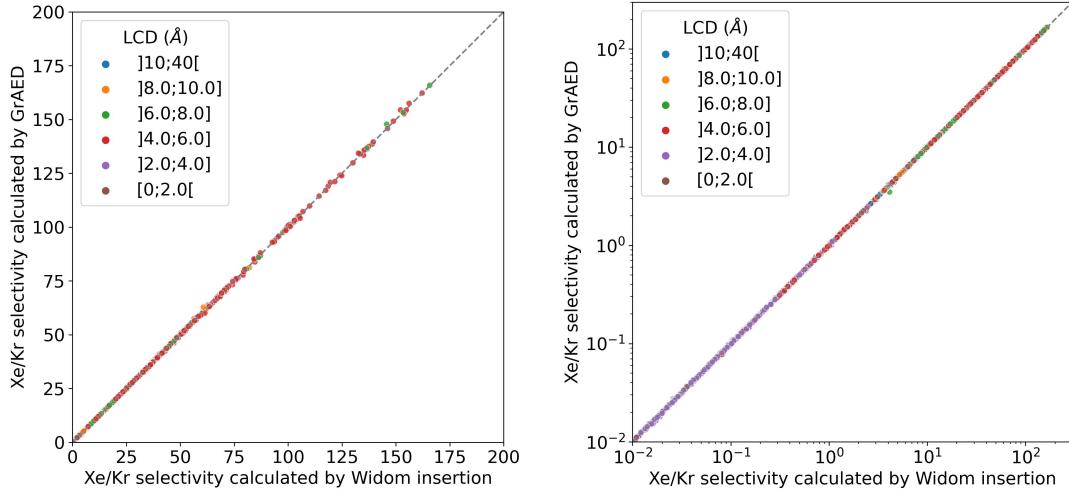
### 3.3.3 Performance on the exchange equilibrium

To characterize the competitive adsorption of the binary mixture of xenon and krypton we commonly use the Xe/Kr selectivity. Compared to a single component metric like the Henry constant, the relative uncertainty will mechanically increase since the selectivity is a quotient of the Henry constants of the competitive adsorbates. In this section, I want to measure this error and see if it is relevant to characterize the separation with this optimized grid sampling method.



*Figure 3.26: Comparison of the krypton adsorption enthalpies (left) and the Henry constants (right) calculated by the optimized grid energy sampling (for a 0.12 Å spacing, a rejection parameter  $\mu = 0.8$  and an energy threshold  $E_{\text{th}}$  of 100 kJ mol<sup>-1</sup>) and by the Widom insertion of RASPA2 with 100,000 cycles.*

First, we can look at the adsorption properties of krypton calculated using the same grid spacing of 0.12 Å. The accuracy is more or less equivalent with an RMSE and an MAE on the krypton adsorption enthalpy of about 0.02 kJ mol<sup>-1</sup> and 0.01 kJ mol<sup>-1</sup>. As shown on Figure 3.26, the correlation is very strong for both the adsorption enthalpy (linear scale) and the Henry constant (log scale). The base 10 logarithm of the Henry constant (in mmol g<sup>-1</sup> Pa<sup>-1</sup>) has typically an RMSE of 0.002, which is very similar to xenon. The relative error on the adsorption enthalpies of xenon and krypton does not go beyond 0.1% (values of the enthalpy have order of magnitude of dozens of kJ mol<sup>-1</sup>), and the error on the xenon/krypton exchange enthalpy would therefore be very close to it. There is no reason for a huge impact on the exchange enthalpy. For the selectivity, we need to consider the relative error on the adsorption free energy which is a logarithmic transform of the Henry constant. This relative error can be estimated to be around 0.2% (for a Henry constant of 10<sup>-4</sup> mmol g<sup>-1</sup> Pa<sup>-1</sup>), which also corresponds more or less to the relative error expected on the exchange Gibbs free energy or the log of the selectivity.



*Figure 3.27: Comparison of the Xe/Kr selectivity calculated by the optimized grid energy sampling (for a  $0.12 \text{ \AA}$  spacing, a rejection parameter  $\mu = 0.8$  and an energy threshold  $E_{th}$  of  $100 \text{ kJ mol}^{-1}$ ) and by the Widom insertion of RASPA2 with 100,000 cycles. On the left, the axes are in linear scale, whereas the log scale has been used on the right.*

On Figure 3.27, the selectivity is as expected very well represented by the new grid sampling, especially for the logarithmic transform. The RMSE and the MAE on the selectivity values are actually of around 0.097 and 0.035, which is very low compared to the values of selectivity of interest (over 10). For these selective structures, the relative error is actually below 0.1%. For base 10 logarithm of the selectivity or the exchange Gibbs free energy, the RMSE is around 0.014, which means that we have a very good knowledge on the order of magnitude of the selectivity; if the selectivity were written in powers of ten, the exponent would be known at a precision of  $\pm 0.014$ .

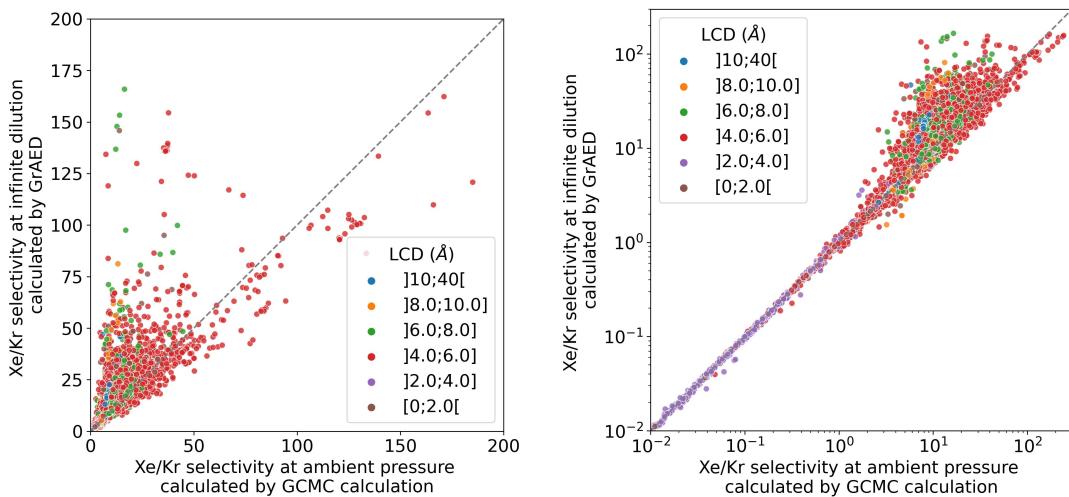
The computation time required to compute the selectivity value of a structure of the CoRE MOF 2019 database is in average 6.5 s, since the krypton takes about 3.5 s to compute. If an algorithm computes both selectivity values at the same time, we can at least save the time required for initializing the software, which can marginally improve this time. This computation time required is still much lower than the one required for two Widom insertions.

Now that I have shown the high accuracy and the efficiency of the GraED algorithm for low-pressure selectivity evaluation, I will try to find relations between descriptors obtained using the grid-based algorithm and the selectivity at ambient pressure.

### 3.3.4 Description of the ambient-pressure selectivity

At first sight, looking at the left plot of Figure 3.28, the selectivity at ambient pressure seems completely decorrelated to the selectivity at infinite dilution, which would mean that the sampling I have done is completely useless in determining the higher pressure selectivity values. However, the right plot suggests otherwise, the correlation between the logarithm of the selectivity does exist, the absence of correlation observed at linear scale is actually a phenomenon that only occurs on highly selective materials. This phenomenon is described in detail in the chapter 2 and corresponds to a selectivity drop experienced by some highly

(at infinite dilution) selective materials. To say it simply, the saturation of the most selective sites make the remaining sites way less selective for the xenon/krypton separation for these materials.



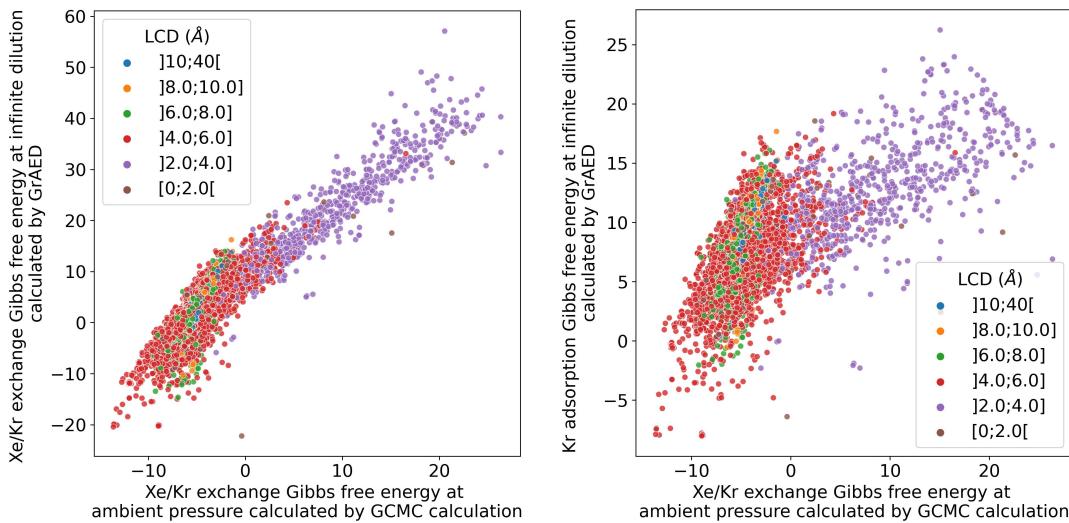
*Figure 3.28: Comparison of the low-pressure Xe/Kr selectivity calculated by the GraED algorithm (same parameters) and the ambient-pressure selectivity calculated by GCMC simulations of RASPA2 with 100,000 cycles. On the left, the axes are in linear scale, whereas the log scale has been used on the right.*

The goal is then to be able to design descriptors that could help distinguish this selectivity dropping materials with the materials keeping their high selectivity at higher pressure. I propose three concepts that could help better understand the origin of this drop of selectivity at higher pressure: (1) other adsorption thermodynamic quantities, (2) higher temperature averaging can also be a good proxy to understand higher pressure adsorption, and (3) statistical quantities derived from the energy distributions. All of these descriptors can be obtained through a grid sampling; however, one should note that the guest–guest interactions that occur at higher pressure cannot be captured by this method.

### THERMODYNAMIC QUANTITIES

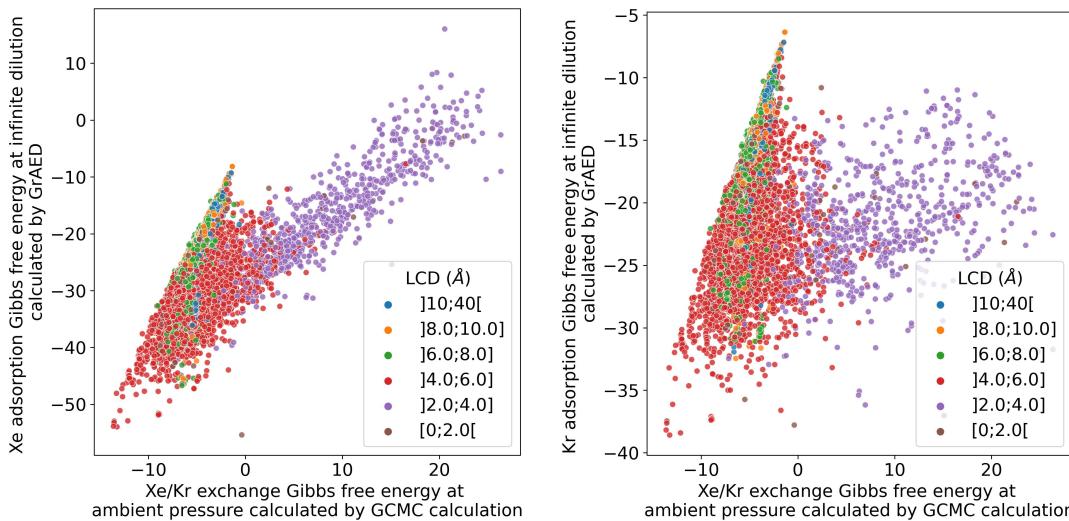
In the previous chapter, many thermodynamic quantities can be calculated at infinite dilution: adsorption and exchange Gibbs free energies, enthalpies and entropies. If we consider the xenon and krypton separation, we can generate 9 different descriptors. I will look at the relation between these quantities and the high-pressure selectivity values. In the introduction, I already tackled the relation between the exchange Gibbs free energy, since it is the logarithmic transform of the infinite dilution selectivity plotted on Figure 3.28. This quantity is the most important descriptor as it sets an initial reference value to understand the problem. The selectivity at high pressure can be seen as the selectivity at infinite dilution plus or minus a shift due to the specificity of the adsorption at higher pressure in a given material.

Without any surprise, Figure 3.29 confirms that a good adsorption of xenon is a good indication for the efficiency of the separation from krypton since we have a very strong correlation between the Xe/Kr exchange Gibbs free energy and the xenon adsorption Gibbs free energy. The correlation with the xenon adsorption Gibbs free energy is very weak and still positive,



*Figure 3.29: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the low-pressure adsorption free energies of xenon (left) and krypton (right) in  $\text{kJ mol}^{-1}$  calculated by the GraED algorithm (same parameters).*

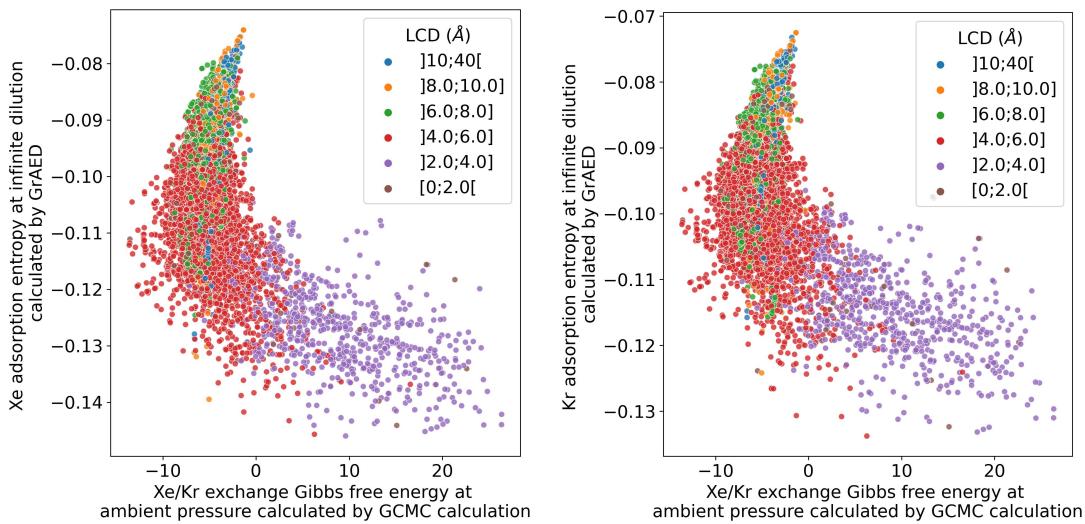
this means that a good material for the Xe/Kr separation would not be very bad for krypton adsorption but rather pretty average. Put differently, it is not possible to find a material very good for xenon adsorption and very bad for krypton, which explains an apparent theoretical limitation to the selectivity theoretically capped under 200 (in our level of theory for materials of CoRE MOF 2019, of course, see Figure 3.27 and 3.28). Experimentally, no material has exceeded a selectivity value of 100.



*Figure 3.30: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the low-pressure adsorption enthalpies of xenon (left) and krypton (right) in  $\text{kJ mol}^{-1}$  calculated by the GraED algorithm (same parameters).*

The same statement on the importance of the adsorption attractiveness of xenon holds true when looking at the adsorption enthalpies from Figure 3.30. The correlation is very strong for the most selective materials; however, for less selective materials, the xenon adsorption

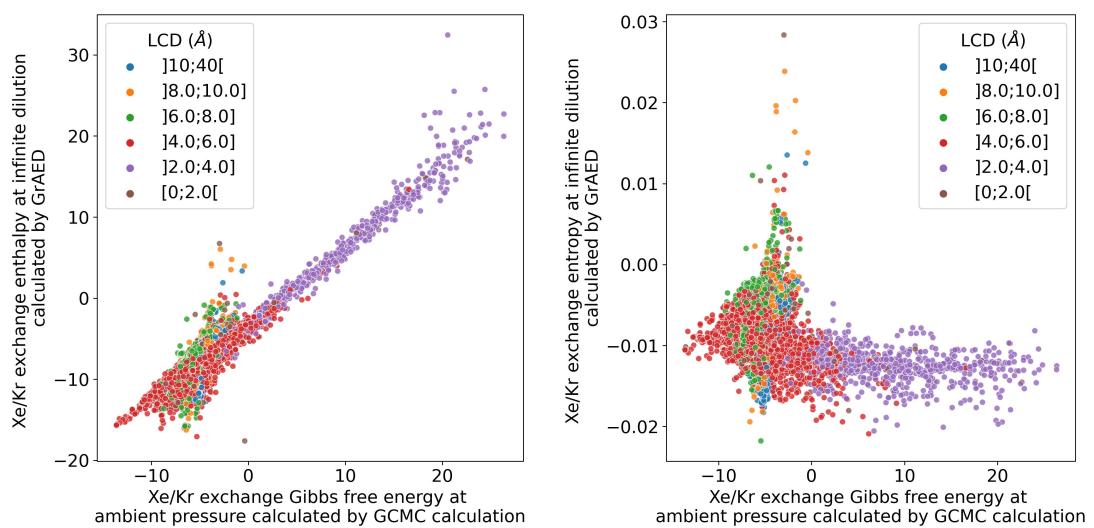
enthalpy is not enough in predicting the exchange Gibbs free energy at ambient pressure. The natural solution would, of course, be to include the krypton adsorption performance. The difference of both adsorption enthalpies gives the xenon/krypton exchange enthalpy which can be used as a separation evaluation metric. The comparison to the krypton adsorption enthalpy alone is not adequate either, the very loose correlation suggests that it is not the main explanatory factor in the separation process.



*Figure 3.31: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the low-pressure adsorption entropies of xenon (left) and krypton (right) in  $\text{kJ mol}^{-1} \text{K}^{-1}$  calculated by the GrAED algorithm (same parameters).*

The entropy values can explain why the adsorption free energy of xenon is well correlated to the Xe/Kr exchange free energy at ambient pressure and the adsorption enthalpy of xenon is weakly correlated. The difference between enthalpy and free energy being the entropic term ( $G = H - TS$ ), this entropic term has small influence on the correlation as shown on Figure 3.31. The values of the entropy are rather stable (between  $-0.15$  and  $-0.11 \text{ kJ mol}^{-1} \text{K}^{-1}$ ), but for some structures with an ambient-pressure exchange free energy between  $-10$  and  $0 \text{ kJ mol}^{-1}$ , there is a swing in entropy values going from  $-0.11$  and  $-0.07 \text{ kJ mol}^{-1} \text{K}^{-1}$  for structures with very similar values of enthalpy. This means difference between Gibbs free energy and enthalpy that could reach a span of  $12 \text{ kJ mol}^{-1}$ , which explains the points that go off the diagonal in the left plot of Figure 3.30.

Now, if I go back to the exchange thermodynamic quantities that are more relevant to our context, a good correlation is observed between the exchange enthalpy at low pressure calculated with GrAED and the exchange Gibbs free energy at ambient pressure calculated by GCMC on Figure 3.32. Some discrepancies can be detected around  $-10$  and  $0 \text{ kJ mol}^{-1}$  of the ambient-pressure exchange free energy, which can also be explained using the exchange entropy that is stable  $-0.01 \text{ kJ mol}^{-1} \text{K}^{-1}$  and experiences a peak for structures near the previously mentioned range of ambient-pressure exchange Gibbs free energy. The overall strong correlation can be explained using the previously identified enthalpic nature of the separation process of xenon from krypton (see chapter 2). And, the problematic range, where the correlation is weaker, also corresponds to the one associated with a selectivity drop on Figure 3.34. These



*Figure 3.32: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the low-pressure exchange enthalpy (left, in  $\text{kJ mol}^{-1}$ ) and entropy (right, in  $\text{kJ mol}^{-1} \text{K}^{-1}$ ) calculated by the GrAED algorithm (same parameters).*

exchange thermodynamic quantities can help distinguish the materials to better model the drop phenomenon, a more quantitative approach will be developed in the next chapter.

#### HIGH-TEMPERATURE QUANTITIES

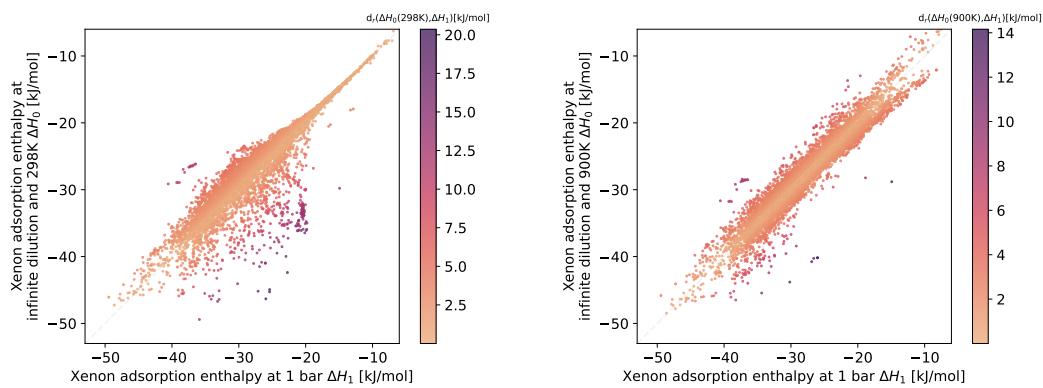
Although the previous quantities are valuable in modeling the adsorption at ambient pressure, they are still not enough, since they describe a state where the atoms are adsorbed on the most attractive sites only. The ambient-pressure state is actually characterized by an adsorption on a more diverse set of sites and with an increasingly important role of the guest–host interaction, which are also the main factors that contribute to the difference in selectivity between both pressure conditions and identified in the previous chapter.

In this section, I introduce a descriptor that better describes the energy distribution in the ambient-pressure case by increasing the weight of the more energetic adsorption sites. To achieve this the easiest way was to increase the temperature in the Boltzmann averaging for both the Gibbs free energy and the enthalpy defined in equations 2.9 and 2.22. Many temperatures were tested, and the one that yielded the higher correlation coefficient when comparing the adsorption enthalpies (infinite dilution and ambient pressure) was chosen.

A temperature of 900 K was found to be the optimal temperature to describe an ambient-pressure adsorption enthalpy of xenon across the structures of CoRE MOF 2019, and gives a minimal error (RMSE) of  $1.76 \text{ kJ mol}^{-1}$  instead of  $2.87 \text{ kJ mol}^{-1}$  for the 298 K case. This improvement impacts the exchange free energy metrics as well as the adsorption enthalpy associated with the separation of xenon from krypton. The exchange Gibbs free energy and the adsorption enthalpy of xenon at ambient pressure are better correlated to the equivalent values at lower pressure and higher temperature (900 K) than to the 298 K case. These observations support the use of higher temperature averaging to describe the ambient-pressure selectivity.

This new type of descriptor is very interesting since it performs better around the high selectivity region, where the standard Boltzmann average at 298 K loses its accuracy (see Figure 3.28). As shown on Figures 3.33 and 3.34, the averaging at higher temperature performs better on the most selective materials, while degrading the description of the less selective materials.

On Figure 3.33, the high-temperature averaging gives a better description of the xenon adsorption enthalpy, and the points are more centered around the  $y = x$  axis, but the correlation is not perfect. We also have a bigger uncertainty on the points that were initially very well predicted as badly performing materials. The high dispersion around the correlation is probably due to the guest–guest interactions that are not described in the high temperature averaging and plays a non-negligible role in the ambient pressure case.



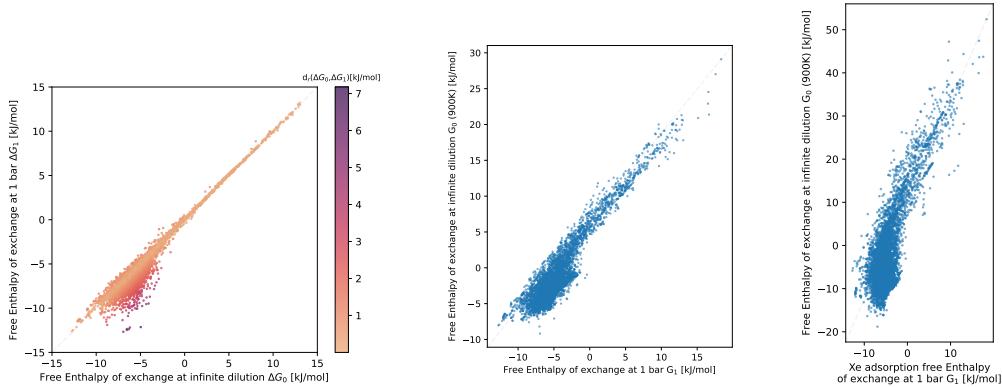
*Figure 3.33: Scatterplots of the low-pressure xenon adsorption enthalpy at 298 K (left) and at 900 K (right) calculated by the GraED algorithm against the ambient-pressure xenon adsorption enthalpy at 298 K. Using a higher temperature Boltzmann averaging, the correlation with the ambient-pressure case of interest is much higher, the R<sub>2</sub> coefficient improves from 0.80 to 0.92 for instance. The RMSE also decreased from 2.87 kJ mol<sup>-1</sup> to 1.76 kJ mol<sup>-1</sup>.*

On Figure 3.34, we can see that this improvement in the adsorption enthalpy of xenon is not directly translated into the performance on the exchange Gibbs free energy. The correlation is better overall between the exchange free energy at 298 K and infinite dilution and the one at ambient pressure (298 K). However, it is arguable that the exchange free energy at 900 K is, however, slightly better describing the materials that experience a selectivity drop as shown on Figure 3.28.

This high-temperature averaging can be used to better model the selectivity of the selective materials that loses selectivity between low and ambient pressure. These descriptors can quantitatively predict the selectivity at ambient pressure as I will show in the next chapter, but they can also give a qualitative description of the problematic structures. I expect that by exploiting the high-temperature averaging values I will be able to identify these problematic structures.

#### STATISTICAL CHARACTERIZATION OF THE ENERGY DISTRIBUTIONS

To better quantify the change of selectivity, it could be interesting to give statistics on the distribution of interaction energies for xenon and krypton calculated by our grid algorithm. A statistical analysis can let us glimpse the complexity of the pore adsorption process at higher pressure by showing the diversity of the energy values and how they are distributed



*Figure 3.34: Comparison plot between the low-pressure exchange free energy at 298 K (left) and 900 K (right) calculated by the GrAED algorithm and the ambient-pressure exchange free energy at 298 K calculated by Widom insertion.*

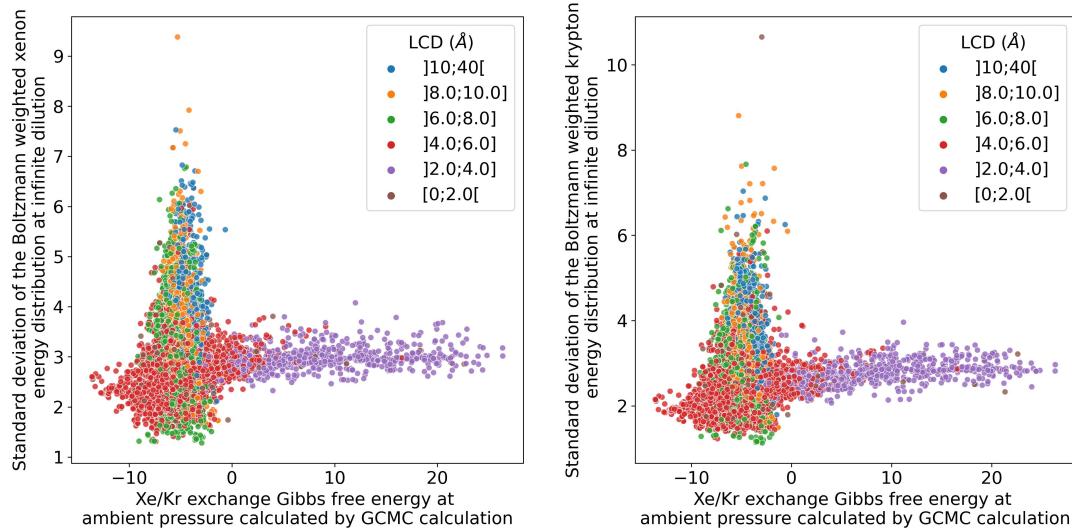
(the quantity of the higher energies in comparison to the lower ones, for example). The grid sampling I present here can use all the energy values from the sampled point to draw a histogram that can be used as an energy distribution and studied to retrieve interesting statistical information.

These statistics include the moments of different orders (up to 4) of the energy distribution, which informs on the adsorbate–adsorbent interaction energies in the nanopores at higher loading. The shape of the energy distribution can help assess quantitatively the change in selectivity. We can consider this as a way of compressing the whole energy distribution into a few statistical values, which is a standard method used in the field of data science to tackle distribution data. The energy distribution can be weighted uniformly or with the Boltzmann weights, both methods are explored here. The average of the Boltzmann weighted distribution is typically the definition of the adsorption enthalpy and it won't be tackled in this subsection.

### Boltzmann weighted distribution

The Boltzmann weighted distribution consists in assigning a weight  $\exp(-\beta E)$  according to the energy  $E$  of each point sampled by the GrAED algorithm. By doing so, we put a much higher weight on the most negative values of the energy (the most favorable adsorption sites) than the others. The unfavorable adsorption sites can be considered negligible since the exponential scaling crushed the importance of these points in the Boltzmann weighted distribution. This distribution has already been used to calculate the adsorption enthalpy (first-order moment or average) and also indirectly the Henry constant (sum of the weights used in the normalization of the distribution). And in this section, I will focus on other statistical quantities that could be derived from the distribution and are not commonly used in describing the thermodynamics of the system.

For instance, the standard deviation of the Boltzmann weighted energy distribution is one of the statistical quantities that could be interesting in evaluating the drop of selectivity. In the previous chapter, I identified the diversity of site attractiveness as one of the main factors that could explain the drop in selectivity. The standard deviation of the energies can therefore be



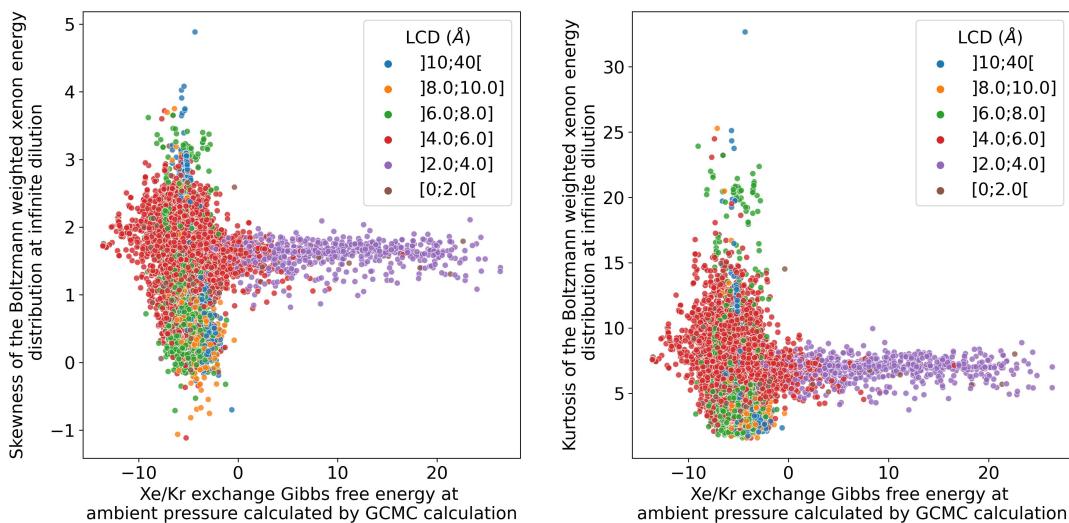
*Figure 3.35: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the standard deviations of the Boltzmann weighted energy distribution of xenon (left) and krypton (right) calculated by the GrAED algorithm at 298 K.*

useful characterization of the diversity of nature between the different adsorption sites. On Figure 3.35, this standard deviation is calculated for both xenon and krypton, and the higher variation of its values is concentrated in a range of values corresponding to the one I identified for the entropy change on one hand but more importantly to the range where the selectivity drop is observed on Figure 3.34 (between  $-10$  and  $0 \text{ kJ mol}^{-1}$ ). Qualitatively, it is understandable that the standard deviation informs us on the pore diversity which could help characterizing the origins of the selectivity drop; and a higher diversity usually implies a higher probability of experiencing a selectivity drop. The challenge is then to quantify this probability through a model, a simple theoretical model would never be accurate enough, this is the reason I will be looking into machine learning models in the next chapter.

I introduced two other statistical quantities that could be interesting in describing the distribution: the skewness that characterizes the asymmetry of the distribution and the kurtosis that quantifies the “tailedness” (the number of values in the tail of the distribution). The first one is a standardized third moment while the second is a standardized fourth moment of the distribution. For a random variable  $X$ , whose mean value is  $m$  and standard deviation  $\sigma$  an  $n$ -th order moment  $M_n(X)$  is defined as:

$$M_n(X) = \mathbb{E} \left[ \left( \frac{X - m}{\sigma} \right)^n \right] \quad (3.8)$$

These quantities bring in another information on the distribution. For instance, if the distribution is skewed toward the most negative pore energies it would favor the adsorption at higher pressure, while the opposite would explain a bigger drop in selectivity. The overall shape of the distribution needs to be defined by more than the standard deviation and the mean value in order to capture the origins of the drop in selectivity. Ideally, it would be better to have the whole information on the distribution, but visually speaking, it would be far too complex



*Figure 3.36: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the skewness (left) and the kurtosis (right) of the Boltzmann weighted energy distribution of xenon calculated by the GraED algorithm at 298 K.*

to compare the structures according to this multidimensional descriptor and the statistical quantities compress in a way the complex data on the energy distribution.

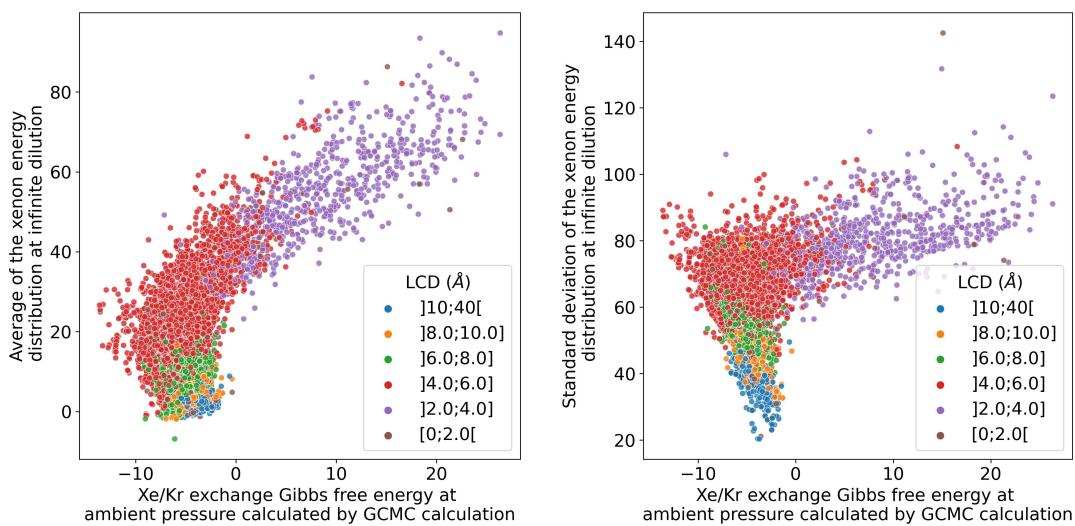
The Figure 3.36 further highlights the range of selectivity value I discussed across this section. The materials within this range can be sorted out using the different statistical quantities I introduced throughout this discussion. Depending on these skewness or kurtosis values it could be theoretically possible to identify a link with the selectivity drop previously identified, but without a model or a framework it is impossible to find the right relationship using our bare eyes.

### Uniformly weighted distribution

To finish this overview on the thermodynamic/energetic descriptors I can deduce from the new grid sampling developed, I will study a more uniformly weighted energy distribution, and since the much higher energy values corresponding to the overlap with a framework atom does not interest us, these values are removed naturally by our sampling. Since a threshold value of  $100 \text{ kJ mol}^{-1}$  has been used for the grid sampling here, the overlapping is defined very largely and for an energy below this value the energy point is taken into account. This distribution corresponds to the adsorbable sites (no overlap) that are weighted according to their sole occupancy of the void volume.

I studied the mean value and the standard deviation of this distribution. For the mean value, I can observe a weak correlation with the exchange Gibbs energy at ambient pressure, but the correlation stops for the materials with larger pores and therefore a more diverse set of energy values, the mean value is lower since the void fraction is larger and the weight on the more negative values increase, but it does not mean that very attractive sites are present since there is no Boltzmann weight – the exchange free energy is not continuing the trend and comes back to more positive values. We can note that the values are very high, this is because an energy

threshold value of  $100 \text{ kJ mol}^{-1}$  is used and a lot of points have values within zero and this threshold value, which shifts the mean toward these values. For this reason, I did not continue further than the standard deviation the statistical study of this distribution, and a better design of the distribution needs to be considered to focus more on the negative values — it could be through lowering the threshold or by using a less skewing Boltzmann average (averaging at higher temperature for instance).



*Figure 3.37: Comparison of the ambient-pressure Xe/Kr exchange Gibbs free energy calculated by GCMC simulations of RASPA2 with 100,000 cycles and the mean values (left) and the standard deviation (right) of the uniformly weighted energy distribution of xenon calculated by the GrAED algorithm at 298 K.*

The standard deviation of this distribution has a lower value for materials with larger pores, see Figure 3.37. This could be explained by a high number of points near the average value of the energy (around 0 and  $10 \text{ kJ mol}^{-1}$ ) according to the left plot of the figure. For the materials with a standard deviation between  $20$  and  $40 \text{ kJ mol}^{-1}$ , It seems clear that they have an exchange free energy that could not exceed  $-8 \text{ kJ mol}^{-1}$ , which mean they are not in the top selective materials. The standard deviation presented here can help us identify materials that could be promising at low pressure but are not really promising in reality.

To improve this approach, I explored the use of a higher temperature Boltzmann average for the weights of the distribution, not necessarily using a temperature of  $900 \text{ K}$ . We can also test out a uniformly weighted average on an energy distribution under different energy thresholds (zero or the mean kinetic energy of a gas  $1.5k_{\text{B}}T$ ). The general idea behind this is that we want to characterize a higher energy state close to the one at ambient pressure. And of course, higher orders of moments can also be tested to give a more complete picture of the distribution.

This GrAED algorithm can be a very efficient way of sampling energies when the structures are highly symmetrical and with a large occupied volume. The highly accurate description by a grid can allow the calculation of other description metrics that could be useful not only to

describe the adsorption at infinite dilution but also to explore correlations with higher pressure selectivity values. Finally, every computation details on the GraED sampling technique is available online at [github.com/coudertlab/GraED](https://github.com/coudertlab/GraED).

## 3.4 FROM DESCRIPTION TO PREDICTION

In this chapter, I brushed a large picture of fast sampling techniques to evaluate the adsorption performance at infinite dilution, set apart the standard Widom insertion that was presented in the previous chapter. Here, I proved that these quantities can very efficiently describe the thermodynamics behind the adsorption in nanoporous materials by comparing them to standard methods. The next question I want to explore is their value in the prediction of Xe/Kr selectivity in physical conditions that are closer to the industrial ones.

For instance, in the last section, I tried to single out each of the thermodynamic descriptor I can derive from a grid sampling to compare them to the ambient-pressure conditions, but this approach can only be descriptive and never predictive, and the limited number of dimensions in the visualization can only lead to a narrow picture of the correlations. Although I managed to understand some key features of the most selective materials (pores adapted to the kinetic diameter, pore shape that maximizes the interactions, etc.), I also identified key weaknesses of our correlation-based approach. The high-pressure selectivity is a very difficult quantity to understand using quantities based on solely a host–guest interaction energy grid. To overcome these difficulties, many modern approaches use statistical learning to learn this relationship from a large enough set of structures with some computed properties. In the next chapter, I will explore the possibilities opened up by these new descriptors for the prediction of selectivity values beyond the sole infinitely diluted case at a much lower computational cost.



# 4

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## STATISTICAL LEARNING OF ADSORPTION PROPERTIES

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### 4.1 MACHINE LEARNING MODELS

Machine learning (ML) models have been widely used in the field of nanoporous material study to characterize adsorption, transport, catalytic or mechanical properties, just to cite a few. It can in some cases replace very time-consuming simulations with simpler calculation of key descriptors that can help the model predict the desired properties. In other cases, it is used to describe the structure–property relationships learned by the ML model. However, machine learning is not a silver bullet, we cannot blindly apply it on any applications; it requires a thorough work on understanding the key variables that will improve the prediction. By using our work on thermodynamic descriptors and our knowledge on the effect of pressure on the selectivity developed in the previous chapters, I will build a machine learning model to characterize the separation of xenon from krypton at ambient pressure.

### 4.1.1 From algorithm to machine learning

To understand how a machine could learn, first, we need to understand how a computer accomplishes a task. The human operator plays a key role in the process — after designing the solution through theoretical considerations, he needs to write down a list of instructions, called an algorithm, that specifies all needed actions given the circumstances so that the computer achieves the desired outcome. In physical or chemical science, these algorithms usually articulate the different components of a theoretical model, which can be finding the solution of an equation without analytical solutions or an analytical expression or a probabilistic problem, etc. The previous chapters typically presented such algorithms for the simulation of adsorption processes; for instance, the GCMC simulations are based on the statistical physics of the phase equilibrium between a gas phase and an adsorption phase inside a nanoporous material, and a Monte Carlo model is used to reproduce the statistics associated to the grand canonical ensemble. The energy sampling algorithms, along with the Widom insertion, are also good examples of how the computer can help the theoretician model the systems under specific chemical and physical conditions.

A machine learning model is also based on an algorithm, but the goal is very different from the above-mentioned examples — it doesn't aim at giving all the details of the computation according to proven theoretical principles. As implied by the name, the ambition would be to learn underlying relations within the input data so that it performs the task itself. The machine learning (ML) algorithm is then the list of instructions that specifies how the machine is going to learn from the data. For example, clustering algorithms can distinguish different classes of elements within a disordered dataset so that new concepts emerge; this type of machine learning algorithm is called unsupervised learning because we do not predefine or pre-label the data and the machine helps us understand the underlying structure in the data; I will not go deeper in the details of this type of algorithm since it goes beyond the frame of this thesis. The class of algorithm I want to study is rather the supervised learning model, which learns from labeled data the relation between the label and the characteristics (called features or descriptors) from a given set of data points, and can predict the label from unlabeled data using the characteristics. For example, if we want to predict the weather of tomorrow, the model could use the past weather of similar dates to infer if it will rain tomorrow; the history of the weather forms the features of the ML model and the future weather is the target variable or the label of the data.

To articulate the differences between a standard algorithm and an ML algorithm, let me introduce a fascinating board game called Go. This game is traditionally played with 2 players on a  $19 \times 19$  board, where each player places black/white pieces to control the maximum of boxes. Based on these simple rules, different algorithms have been developed to make the computer play the game. The first Go program was written in the late '60s to mimic the pattern recognition of Go players when estimating the “score” through an influence function,<sup>232</sup> and from the '80s to the beginning of the 21<sup>st</sup> century the first Go programs capable of playing were releases. These programs were based on simple alpha-beta search algorithms that seeks at testing every possible move (while pruning the less promising ones); while they were working very well in other games like chess (IBM's Deep(er) Blue beat the world champion of chess in 1995), in Go these types of programs were only at the level of a novice player. The difference of performance lies in the combinatorics behind both games, the game of chess has a number

of legal positions lower than  $10^{47}$ <sup>233</sup> while for the game of Go there are approximately  $10^{171}$  legal positions.<sup>234,235</sup> The state space to explore is incomparably greater and a boost in the computing power that improved the performance for computer chess is not going to make a difference for Go. A drastic reduction of the space to be explored is needed for a computer program to work. The biggest improvement came, when in 2007, Coulom introduced a Monte Carlo tree search.<sup>236</sup> This algorithm uses heuristics to distinguish between bad a good move according to human perception of the game, a probability of selection is assigned to the moves according to their potential (policy), potential moves are randomly picked according to this probability; the average outcomes associated with a parent move gives the value of the move. The computer Go is now more efficient in the evaluation of the moves using a Monte Carlo sampling, and it can now play with average amateur players, but it is nowhere near surpassing them. Up until now, the algorithms are based on human knowledge that the programmer implements directly in the computer using machine instructions. Statistics and randomness are used to orient the machine toward the best moves and reduce their predictability, but the statistics that identifies the moves are based on human heuristics that are usually not generalizable. The big revolution brought about by machine learning in the field aims at better evaluating these statistics using the data from already played games. By using a dataset of 30 million moves, the Alpha Go is based on the same Monte Carlo tree search framework but it replaces the formulas behind the probability of searching a move by a machine learning model called the “policy network” and the one behind evaluating the confidence in winning of the position by a value “network”.<sup>237</sup> Alpha Go was the first computer program to beat a world champion in 2016. One year later, to further emancipate from human knowledge, an improved version, Alpha Go zero generates its own data by playing games against itself to train a similar machine learning structure than presented before. This new version beats 100 times out of 100 the former version,<sup>238</sup> which marks a new era of domination of computer go over the best player in the world, and the defeat of another top player just confirms the advent of this new era.

In this example, we can see how the machine learned the value of each moves by compiling the knowledge of huge datasets in a deep neural network. The main difference between conventional approaches to algorithmic and machine learning is very well illustrated in the previous example; the goal is not to tell the computer how to play using player knowledge implemented in formulas and explicit instructions, but it is to give an explicit framework with flexible parameters that the model needs to learn using a database. In other words, the parameters of a model are fitted to match the values of a database, while being capable of generalizing in situations outside of the database (this notion of generalizability will be further discussed in the following sections). In this section, the goal is not to give a complete overview of all existing models but rather to introduce the main concepts of ML through the example of the model I used for the problem of selectivity performance prediction.

### 4.1.2 Introduction to supervised learning

In this thesis, I will focus on the most common way to statistically learn from data, which is the supervised learning. As previously introduced, supervised learning corresponds to the extraction of a relationship between the labels of a set of data points and some of their known characteristics or features. This relationship can be called the model or the predictor and should ideally generalize to similar but unseen data. In this section, I will formalize the goal of the

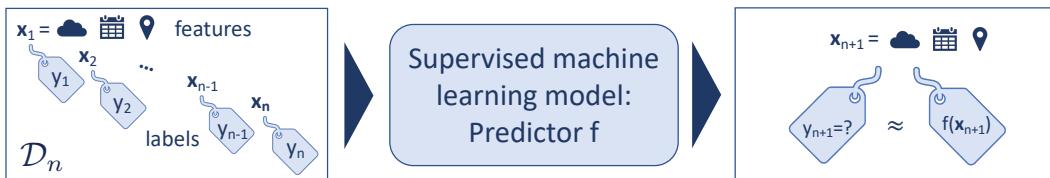
learning algorithm when given a set of labeled data in order to introduce more complex notions in machine learning like the bias–variance tradeoff and also more specific models that will be used in this chapter like the tree-based models. Different books have been used for the conception of this section, mainly the Elements of Statistical Learning<sup>239</sup> and an Introduction to machine learning (in French) from Azencott.<sup>240</sup>

### THEORETICAL CONSIDERATIONS

In supervised learning, the algorithm learns from a set of data noted  $\mathcal{D}_n = \{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)\}$  with  $n$  observed data points, where  $\mathbf{x}_i$  represents an input observable which is a vector of  $\mathbb{R}^p$  ( $p = 1$  for scalars) and  $y_i$  is the label of the data point  $i$  that belongs to a set  $\mathcal{Y}$  (numerical, categorical or vectorial). We can model the characteristics observed by a random variable  $X$  and the label by another random variable  $Y$ . The dataset only gives a fragmented view of the joint probability (see equation 4.1) and the goal will be to extrapolate the relation to unseen data.  $(X, Y)$  represents all possible combinations of data points seen and unseen.

$$\forall \mathbf{x} \in \mathbb{R}^p, y \in \mathcal{Y}, \mathbb{P}(X = \mathbf{x}, Y = y) = \mathbb{P}(X = \mathbf{x})\mathbb{P}(Y = y|X = \mathbf{x}) \quad (4.1)$$

The challenge of supervised learning lies in the fact that the data at our disposal does not give a complete picture of the probability law. And the goal is to give the most probable label  $y$  for a data point characterized by  $\mathbf{x}$ , which is determining the conditional expectation  $\mathbb{E}[Y|X = \mathbf{x}]$  of  $Y$  given the observable  $\mathbf{x}$ , which depends on the conditional probabilities  $\mathbb{P}(Y = y_i|X = \mathbf{x}_j)$  seen across all data points  $i, j \in \{1, \dots, n\}$ .



*Figure 4.1: Illustration of the core principle of supervised learning. A data point of  $\mathcal{D}_n$  corresponds to a set of features  $i$  labeled by  $y_i$ . The supervised machine learning model trains a predictor  $f$  on the dataset  $\mathcal{D}_n$  to predict unknown data  $y_{n+1}$  using the features  $x_{n+1}$  so that  $f(y_{n+1}) \approx y_{n+1}$  (approximate prediction).*

To achieve this, the learning algorithm uses a “predictor”  $f$  that can be defined as the function that associates values (features) from  $\mathcal{X} = \mathbb{R}^p$  to values of  $\mathcal{Y}$ . By changing the learning model (subsection 4.1.3) or by changing the feature space  $\mathcal{X}$  we can define different domains  $\mathcal{F} \subseteq \mathcal{Y}^{\mathcal{X}}$  where we search for the prediction function  $f$ . The domain  $\mathcal{F}$  can either be too restrictive and the optimum function found is too far from the theoretical one, or be too large and the optimization problem is nearly impossible to solve or the solution is way too close to the data, which raises question of fitting that will be discussed later.

This predictor can be interpreted as the function that gives the most probable outcome  $y$  for a given input  $\mathbf{x}$ . To evaluate the quality of the predictor, we can introduce a loss function  $\mathcal{L} : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R}^p$  that compares the predicted value  $f(\mathbf{x})$  to the true value  $y$  on the dataset at our disposal  $\mathcal{D}_n$ . This loss function needs to increase when  $f(\mathbf{x})$  moves away from  $y$ . To extend the definition of the loss to the entire possible space, we can introduce the theoretical risk  $\mathcal{R}$

of a predictor  $h$  using the random variables X and Y so that  $\mathcal{R}(h) = \mathbb{E}[\mathcal{L}(h(X), Y)]$ . However, since we do not know the exact mapping of the random variables, we will rather evaluate empirically the risk  $\mathcal{R}_n$  on the known dataset  $\mathcal{D}_n$ :

$$\mathcal{R}_n(h) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(h(\mathbf{x}_i), y_i) \quad (4.2)$$

The goal is therefore to find a function that minimizes the risk function across the known data, and this optimal predictor  $f^*$  can be defined as:

$$f_n^* = \arg \min_{f \in \mathcal{F}} \mathcal{R}_n(f) \quad (4.3)$$

Many loss functions can be used and depending on the definition, we emphasize more or less on the large errors. For instance, a quadratic cost function will penalize a lot the outlier so that a few medium errors are better than one great error, which is not the case for an absolute cost. Since I only used regression models for this thesis work, I will not go into the details of classification loss functions and will rather focus more on the regression loss functions. The quadratic loss or squared error loss  $\mathcal{L}_{SE}(f(\mathbf{x}), y) = 0.5(y - f(\mathbf{x}))^2$  of a predictor  $f$  on a data point  $(\mathbf{x}, y)$  is simply defined as the squared difference between the prediction and the true label. The multiplicative 0.5 coefficient is here to simplify in the derivatives. This loss is similar to the mean squared error (MSE) used to compare two quantities across a dataset, the risk function actually corresponds to half of the MSE on the predictions  $\mathcal{D}_n$ :

$$\mathcal{R}_{SE}(f) = 0.5 \frac{1}{n} \sum_{i=1}^n (y_i - f(\mathbf{x}_i))^2 \quad (4.4)$$

A second very common loss function is the absolute loss, which is associated with the mean absolute error (MAE) used in error evaluation. The loss can be expressed as  $\mathcal{L}_{AE}(f(\mathbf{x}), y) = |y - f(\mathbf{x})|$ , and the risk function associated is simply the MAE across the dataset predictions:

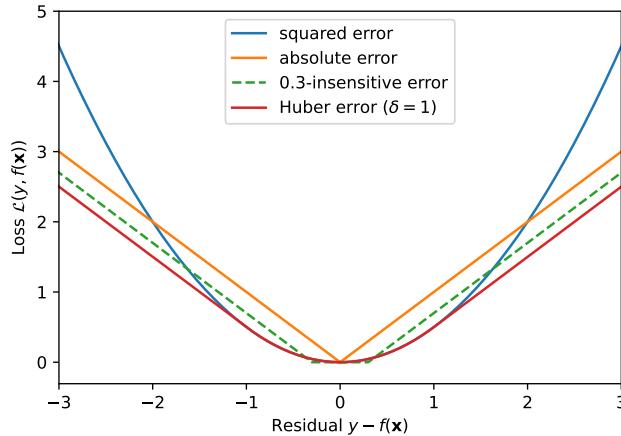
$$\mathcal{R}_{AE}(f) = \frac{1}{n} \sum_{i=1}^n |y_i - f(\mathbf{x}_i)| \quad (4.5)$$

It is also possible to make this loss function flatter near the minimal error by introducing a parameter  $\epsilon$ . The  $\epsilon$ -insensitive loss corresponds to a modified absolute loss  $\mathcal{L}_\epsilon(f(\mathbf{x}), y) = \max(0, |y - f(\mathbf{x})|)$ .

Finally, it is possible to combine the less outlier-sensitive absolute loss with the smoothness of the quadratic loss near the minimal error domain by using a Huber loss. For a given  $\delta$ , the Huber loss is defined as:

$$\mathcal{L}_\delta(f(\mathbf{x}), y) = \begin{cases} \frac{1}{2}(y - f(\mathbf{x}))^2 & \text{for } |y - f(\mathbf{x})| \leq \delta \\ \delta(|y - f(\mathbf{x})| - \frac{1}{2}\delta) & \text{otherwise.} \end{cases} \quad (4.6)$$

And a risk function  $\mathcal{R}_\delta$  can also be determined using this loss function. The Huber loss is considered as a robust loss function since it is less sensitive to the outliers (high values of error) and it has a very smooth gradient near the low values of error like the squared error. It can be



*Figure 4.2: Comparison of different loss functions (quadratic loss, absolute loss,  $\epsilon$ -insensitive and the Huber loss).*

seen as a combination of the advantages of both the absolute and squared errors as illustrated by the Figure 4.2.

Through these theoretical considerations, I hope the process of a machine learning from data was demystified by simply formulating this leaning process as an optimization of a cost function, which is a common tool in any scientific field. However, this optimization problem is challenging in the sense that the variable is a function that lies in a high dimension space and approximations are needed to reduce the space. This is why most of the engineering breakthrough happens in the conception of the architecture of the ML model that defines the form of the prediction function  $f$ . Another difficulty of machine learning is to deal with an ill-posed problem, which means that one of the three conditions of Hadamard is not verified. These conditions being the existence and unicity of a solution and its continuity with regard to the initial conditions. This issue is usually tackled using regularization techniques such as the one introduced by Tikhonov in the second half of the 20<sub>th</sub> century. Furthermore, the minimization of the empiric risk is not always consistent with the minimization of the more global risk (considering all possible observations), since minimizing  $\mathcal{R}_n$  does not always give the same solution as the minimization of  $\mathcal{R}$ . Therefore, the complexity of the risk optimization problem depends on the loss function chosen but also the domain  $\mathcal{F}$  defined by the model and different techniques can be used to construct a solution without anything that guarantees the optimality of it. One of the biggest challenges of ML is to overcome the problem of generalizability, which will be the topic of the next discussion.

## GENERALIZATION AND OVERFITTING

As previously discussed, the optimization problem is ill-defined and we have no guarantee for the model to work on other data points as  $n$  goes toward infinite. The generalizability of model consists in ensuring the predictability of unseen data so that the solution does not simply correspond to the minimal risk for the data  $\mathcal{D}_n$  but also for other  $m$  data points  $\{(\mathbf{x}_{n+1}, y_{n+1}), \dots, (\mathbf{x}_{n+m}, y_{n+m})\}$  all different from the previous set. One of the main phenomena that explain this discrepancy between the solution  $f_n^*$  and the ideal solution  $f^*$  (considering an infinite amount of data) is the noise in the dataset. The data is not perfectly measured, and the uncertainty attached to each  $\mathbf{x}_i$  and  $y_i$  values can create a residual noise that needs to be

ignored in the learning process. Moreover, sometimes, the  $p$  explanatory variables considered are not enough to model the target phenomenon. To train a generalizable model, we would need to learn enough to capture the inner relation between X and Y, but it should not fit the data too closely and capture the noise along the way, otherwise we say that the model overfits the data. If the model is very inaccurate even on the training data, we say that the model underfits, and generally it means that the model is too simplistic (not enough features or too low-level architecture).

This problem of overfitting can be summarized in the fundamental notion of bias–variance tradeoff in machine learning and more generally in statistics. The error can be broken down in two types: the bias error measures the error made on the available data  $\mathcal{D}_n$ , while the variance error measures the sensibility to small variations in the input values. A high bias error corresponds to an underfitting, we did not learn enough from the data; and a high variance error means an overfitting, we learned too much even superfluous relations. To formalize these errors, we can go back to the empiric risk function  $\mathcal{R}_n(f)$  that models the error of our predictor  $f \in \mathcal{F}$ ; to know if we reach the ideal optimum we would need to compare it to the minimal risk that a predictor with infinite knowledge would get  $\mathcal{R}^* = \min_{h \in \mathcal{Y}^\mathcal{X}} \mathcal{R}(h)$ . This excess error  $\mathcal{R}_n(f) - \mathcal{R}^*$  can then be broken down in two errors that could be interpreted as the bias and the variance errors:

$$\mathcal{R}_n(f) - \mathcal{R}^* = \left[ \mathcal{R}_n(f) - \min_{h \in \mathcal{F}} \mathcal{R}_n(h) \right] + \left[ \min_{h \in \mathcal{F}} \mathcal{R}_n(h) - \mathcal{R}^* \right] \quad (4.7)$$

The first term of the above-written sum corresponds to a bias error, because it measures how far the current predictor  $f$  is off of a minimum (there can be several in an ill-posed problem) risk predictor  $f_n^*$  determined using the  $n$  data points. The second term, on the other hand, is the residual error associated with the choice of the predictor domain  $\mathcal{F}$  and the fact that only a finite amount of data is accessible to the prediction model. With an infinite amount of data, the model  $f^*$  associated with the risk  $\mathcal{R}^*$  would not be influenced by the noise since several data points with similar features but with small noises would give a similar prediction. The difference of loss between this ideal function  $f^*$  and the current function we are testing  $f$  would correspond to an overfitting of the noise that could not be distinguished in the finite case, if we consider the domain  $\mathcal{F}$  defined by the model suitable. On the contrary, if there is a problem of model, this error also measures the approximation error due to the choice of a given set of features with a given model architecture.

In general, if the model is very complex in comparison to the amount of data we have, we would fit too closely to the data and have a very high change to overfit. The opposite is also true, a simplistic model would yield to a poor bias error and the model would be underfit. This principle is represented on Figure 4.3 and should guide us in the design of a new ML model. The complex art of fitting a model to a dataset consists in finding the right balance between the bias and the variance. Fortunately, some optimization tools can help us reduce the variance error by changing the loss function itself, and I will introduce them in the next part of our discussion.

### **REGULARIZATION TO FIGHT AGAINST OVERFITTING**

Regularization consists generally in adding implicit or explicit constraints on the optimization problem to find not only the most accurate solution (minimal loss) but also the simplest. This

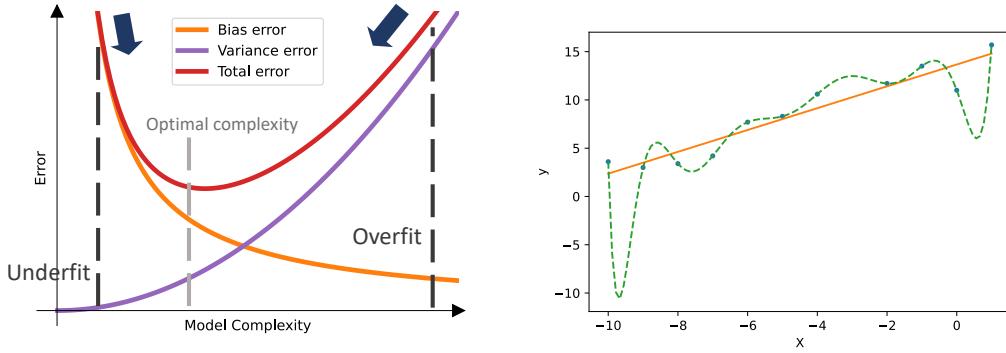


Figure 4.3: On the left, theoretical relation between the bias, variance and total errors and the model complexity. The overfit case is illustrated on the right plot when considering polynomial fits. The lower degree linear function is more generalizable than the biased high degree polynomial that fits perfectly the data.

criterion of simplicity is crucial in the generalization of the problem. We typically don't need a high degree polynomial when a linear function is a more suitable solution as shown on Figure 4.3.

The explicit regularization technique consists in penalizing the complexity of a model by adding to the global loss function an error term that scales with the complexity of the model. The error associated to a predictor  $f$  can be expressed with an additional regularization term  $\Omega_n(f)$ :

$$\mathcal{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(f(\mathbf{x}_i), y_i) + \Omega_n(f) \quad (4.8)$$

And, depending on the expression of the regularization term  $\Omega_n(f)$ , the regularization will have more or less influence on the optimization problem.

Since the regularization is a model-specific function (depends on  $f$ ), we need to define a model to study more specific expressions of regularization. Let's consider a multilinear model so that  $f(\mathbf{x}) = \boldsymbol{\beta} \mathbf{x}^T$ , where  $\boldsymbol{\beta} = (\beta^{(1)}, \dots, \beta^{(p)})$  is a vectorial representation of the weights of the  $p$  features contained in  $\mathbf{x}$  in the linear regression. In a standard multilinear regression, with a quadratic loss, the risk function to minimize can be expressed as:

$$\mathcal{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \left( \boldsymbol{\beta} \mathbf{x}_i^T - y_i \right)^2 \quad (4.9)$$

and  $y_i$  is now a scalar in a regression problem ( $\mathcal{Y} = \mathbb{R}$ ). One of the earliest regularization tools introduced by Tikhonov to deal with ill-posed optimization problem is the L2 regularization. Used in linear regression, this new type of model is called the ridge regression and consists simply in adding a L2-norm penalty on the model weights in the risk function as expressed in the following equation:

$$\mathcal{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(f(\mathbf{x}_i), y_i) + \lambda_2 \|\boldsymbol{\beta}\|_2^2 = \frac{1}{n} \sum_{i=1}^n \left( \boldsymbol{\beta} \mathbf{x}_i^T - y_i \right)^2 + \lambda_2 \sum_{k=1}^p |\beta^{(k)}|^2 \quad (4.10)$$

where  $\lambda_2$  is the parameter of the L2-regularization, it controls the importance of the regularization term in the optimization process. This parameter controls the complexity of the model

and needs to be tweaked to find the optimum between accuracy and generalizability as shown on Figure 4.3. If we now consider a polynomial function, the vector  $\mathbf{x}_i$  represents the vector of different exponentiations of a scalar  $x_i$  so that  $\mathbf{x}_i = (x_i^0, \dots, x_i^{n-1})$ , and the coefficients  $\beta$  are just the polynomial coefficients of the polynomial function  $f$ . This is a clear illustration of how the complexity of the model is penalized since regularization terms directly penalize the number of terms used and their influence on the fitting process. Note that this regularization can be adapted to other types of models, given that we manage to define a L2-norm of the prediction function  $f$ .

A second very common regularization term is based on the L1-norm of the prediction function. A L1-regularized least square linear regression is called a LASSO (Least Absolute Shrinkage and Selection Operator) regression, it allows for a sparser selection of the model weights by allowing zero weights in the model, which is not the case for a L2-regularization. The risk function associated with this regression model can be expressed as:

$$\mathcal{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(f(\mathbf{x}_i), y_i) + \lambda_1 \|\beta\|_1 = \frac{1}{n} \sum_{i=1}^n (\beta \mathbf{x}_i^\top - y_i)^2 + \lambda_1 \sum_{k=1}^p |\beta^{(k)}| \quad (4.11)$$

where  $\lambda_1$  is the L1-regularization parameter that controls its importance. The L1-norm can be defined differently depending on the model, but the core idea is that it is a function of the absolute values of the weights of the model.

Finally, if we combine both L1 and L2-regularization, the linear regression becomes an elastic net regression and the risk function becomes:

$$\mathcal{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(f(\mathbf{x}_i), y_i) + \lambda_{1,2} \left( \alpha \|\beta\|_1 + (1 - \alpha) \|\beta\|_2^2 \right) \quad (4.12)$$

where  $\alpha \in [0, 1]$  defines the relative weight of L1 and L2 regularization term and  $\lambda_{1,2}$  governs the importance of the combined regularization term. This regularization technique simply combines both L1 and L2 regularization, and the different regularization parameters can be tweaked to find the best bias–variance tradeoff for the final model. These parameters are also called hyperparameters in machine learning, because it changes the parameters at the higher model level.

Finally, implicit regularization corresponds to other forms of control of the complexity of the model. For instance, it could be the early stopping in a learning process so that we do not converge completely to the minimal error with the data. It could be discarding outliers that prevent the model from learning properly on the relevant data. It could also be in the architecture of the model, for instance the random forest is an ensemble approach that aims at reducing the overfit, and it will be presented in the next section. The learning rate in the gradient boosting is also a regularization parameter that smoothes the learning process and will be tackled in the dedicated section. The implicit regularization is related to the construction of the model itself and will therefore be explained in more details in the section on machine learning models.

### LEARNING STRATEGIES

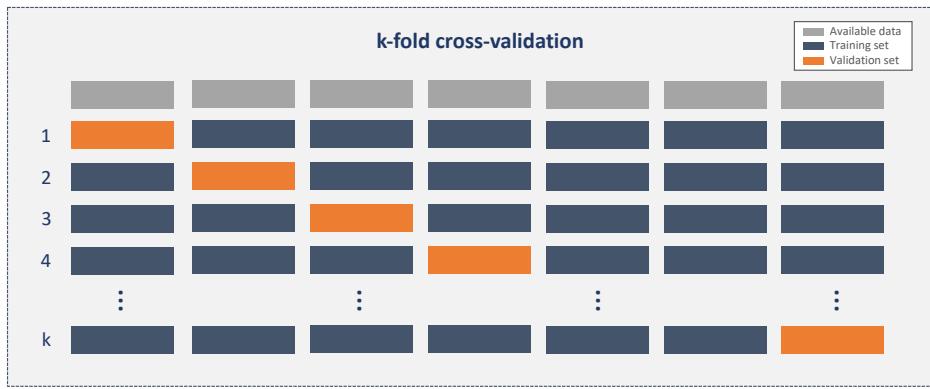
I previously introduced the theory behind the bias–variance tradeoff, which boils down to the generalization of model that has a partial glimpse of all the available data. Yet, in practice we

need to evaluate the generalization error  $\mathcal{R}_n(f) - \mathcal{R}^*$ . To achieve that, the common strategy is to randomly split the available data into two sets a training set  $\mathcal{D}^{\text{train}} = \{(\mathbf{x}_{i_1}, y_{i_1}), \dots, (\mathbf{x}_{i_N}, y_{i_N})\}$  and a test set  $\mathcal{D}^{\text{test}} = \{(\mathbf{x}_{j_1}, y_{j_1}), \dots, (\mathbf{x}_{j_{N-n}}, y_{j_{N-n}})\}$  so that  $\mathcal{D}_n = \mathcal{D}^{\text{train}} \cap \mathcal{D}^{\text{test}}$ . The training set is used to perform the optimization problem as defined in equations 4.2 and 4.3, and the test set is used to evaluate the generalization error since it is unseen data for the model. In practice, we choose a ratio of test data  $n - N/n$  (e.g. 20%) that defines the size of the test set from an initial dataset, and the randomness of the split ensures that the data from both sets are similar yet not exactly the same. However, in some cases, one should be aware that outliers can be present in the test set, which makes the performance on the test set worse than expected. Or in some cases, the dataset is too small and every data point is very different from each other, and the test set is very different from the training set, which makes it impossible for the model to predict on the test with the piecemeal information given by the training set. The percentage of the train/test split should therefore be chosen wisely and according to the dataset so that it remains representative of the training set.

The main property of the test set is that it is a completely unsee dataset, which means that the training of the model should be independent of this set except for the very final evaluation. But in some cases, we want to compare different models with each other or change a “hyperparameter” like the regularization parameter within the same model architecture. To evaluate these models, we cannot evaluate for every model the generalization error on the test set, because it would compromise the independence of the test set with the training process. Hence, we introduce validation sets within the initial training set. We could do a simple training/validation split similar to the train/test split. However it would weaken the model even more since there is less data available, and, furthermore, it does not use all the potential of the training set. A very common technique to test the performance of a model on a training set is the cross-validation. The idea is to use different training/validation splits to test the model in multiple configurations to have a better evaluation of the model performance by averaging the different performances.

The most used method is the k-fold cross-validation technique which consists in partitioning the training set  $\mathcal{D}^{\text{train}}$  in  $k$  equal size subsets  $\mathcal{S}_1, \dots, \mathcal{S}_k$ . The model is then trained on the union  $\bigcup_{l \neq m} \mathcal{S}_l$  of all subsets but one subset  $\mathcal{S}_m$  that will be used as a validation set for all  $m \in \{1, \dots, k\}$ . The principle of the k-fold approach is illustrated on Figure 4.4. The approximate generalization error of the model is then the average of every loss calculated on the validation subsets. This tool provides a way of comparing different models without using the test set, which is extremely useful especially in the parameterization of the ML model.

Other cross-validation techniques exist and are used in specific cases, for example the stratification cross-validation consists in ensuring the same repartition of the labels  $y_i$  in each subset, which is useful in classification problems. We can also make the validation process even more exhaustive by increasing the  $k$  in the k-fold validation. However it requires  $k$  training of the models, which increase the computation time required. When increase to the maximum  $k$  is equal to the size of the training set and the method is called leave-one-out cross-validation. Finally, for time series, the cross-validation technique usually requires to sort the data according to the time history so that the training set is always prior to the validation set, which creates a whole new approach to cross-validation. The core idea of cross-validation is to find multiple



*Figure 4.4: Illustration of a  $k$ -fold cross-validation. At each step, the machine learning model learns from the training set and is tested on the validation set. The average performance on all validation sets gives an approximation of the generalization error.*

training/validation splits to evaluate the model from more than one point of view, and different strategies exist depending on the training problem before us.

### 4.1.3 Machine learning models

In this chapter, I will go from the basic components of the model (decision tree) to the more complex ensemble model (e.g. random forest), in order to finish with the final stochastic gradient boosting model I used in this work. The discussion will be mainly focused on regression problems and not classification problems since the goal is to predict a continuous variable (the xenon/krypton selectivity).

#### REGRESSION TREE

Tree-based models are usually used in classification problems where depending on a set of “yes” or “no” questions the tree classifies the data points into the different predefined categories. The questions are in fact associated to threshold values of the  $p$  features or characteristics  $C_1, \dots, C_p$ ; for example, a node of the tree could ask the question, “Is  $C_1$  higher than 3?”, which splits the space into two categories the “yes” and the “no”. This is why we can see a decision tree model as a splitting of the space into rectangles (in 2D) or an equivalent of a rectangle in  $p$ -dimensional feature space. To adapt this type of model into a regression problem, we can regroup different label values  $y$  into categories that are represented by the average label value. To sum up, a decision tree for regression splits the feature space into a set of pseudo-rectangles (volumes separated by limited hyper-surfaces) defined by the nodes of the tree, and in each of these subspaces are given the average of the different points present in this subspace. To clarify the terminology, a splitting node correspond to a separation between regions, while a terminal node or leaf corresponds to the region itself.

The CART<sup>241</sup> algorithm developed by Breiman et al. is usually presented as the archetype of a decision tree model. The algorithm is pretty straightforward to understand, three steps are required: (i) Examine every split allowed on each feature  $C_i$ , (ii) select and use the best split according to a loss function (squared error or absolute error usually), and (iii) stop splitting a node when a stopping rule is satisfied (e.g. minimum samples split).<sup>242</sup> We could split indefinitely the decision tree so that each data point has its own region, but this would be a textbook case of overfitting, any new data point would never be correctly predicted with such a

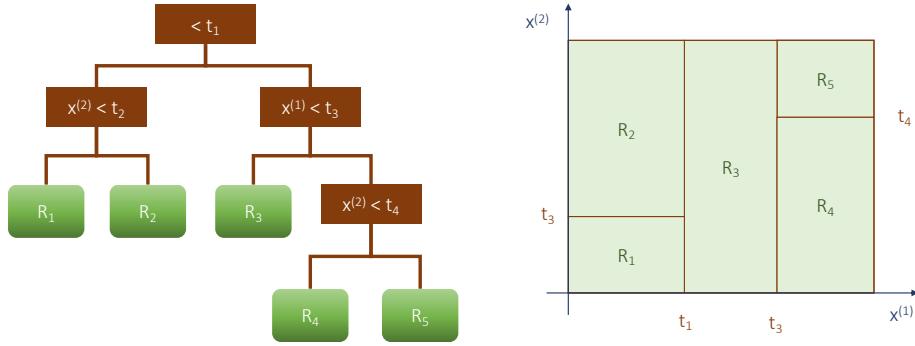


Figure 4.5: Illustration of the decision tree and the region splitting performed by a CART<sup>241</sup> algorithm. Adapted from an illustration of the book “Elements of Statistical Learning” [239].

model. To prevent this from happening, the decision tree has a regularization parameter called minimum samples split  $n_{\min}$  that only allows a further split; if the node contains less than a given number  $n_{\min}$ , then it is necessarily a terminal node. The decision trees are known to be very prone to overfitting, another useful regularization parameter can be used to prevent an ever-growing tree is the maximum depth of the tree, which can also stop the iterative process of tree growing. Finally, to further regularize the tree, a process called tree pruning simplifies the tree and outputs the final model. I won’t go into the details of tree pruning as it is not the main subject (see Ref. [239] for further details). The final tree  $f_{\text{tree}}$  can be expressed as a function of the different regions  $R_1, \dots, R_M$  carved by the splitting process:

$$f_{\text{tree}}(\mathbf{x}) = \sum_{m=1}^M c_m \mathbb{1}(\mathbf{x} \in R_m) \quad (4.13)$$

where  $c_m$  is the value of the leaf corresponding to  $R_m$ , and  $\mathbb{1}$  is an identity function that returns 1 if the argument is true and 0 otherwise. The coefficients  $c_m$  of this function are actually equal to the average of the labeling values of the dataset  $\mathcal{D}_n$  in the region  $R_m$ , i.e.  $c_m = \text{ave}_{i \in \mathcal{D}_n} (y_i | \mathbf{x}_i \in R_m)$ .

To put it simply, the tree function returns the average value of  $y$  (in the dataset) in the region where  $x$  (could be new data) is located.

The decision tree has the main advantage of being very easily interpretable as defined in the book of C. Molnar [243]. This interpretability boils down to the easily understandable binary decision at the root of the decision tree – we can easily see the explaining characteristics ( $R_m$ ) of a predicted value, we can easily imagine different predictions depending on the value of  $\mathbf{x}$ , and for small trees we can even run the model in our own head. However, this model has a reputation of being very inefficient in finding simple linear relations resulting in a step-like function. The model is not very smooth, slight changes in the input  $x$  can have a big impact on the predicted value (typically near the separation between two regions) and some change (noise) in the training data can totally change the structure of the tree. This instability of a single tree makes it very hard to generalize over unseen data.<sup>243</sup> To improve this single decision tree, Breiman introduced bagging predictors in 1996 to improve the accuracy of models that are unstable with regard to small changes in the learning set.<sup>244</sup> This new approach is at the origin of the random forest, and will be presented more in depth in the following subsection.

## RANDOM FOREST

The core idea behind random forest is that a collection of weak learners, called an ensemble model, is better than a single strong learner, this assumption relies on a proven theorem that states that the minimal error of a forest is lower than the error of a single tree (theorem 11.2. of Ref. [245]). The strength of a model depends on the amount of information we feed into the model and its complexity. To achieve a diverse forest of weaker decision trees, we need to introduce two concepts; the first one is the bootstrap aggregating (bagging) and second one is the random column subsampling. Both methods ensure a diversity in the generated trees by using random selections and also a relative weakness of the trees by reducing the amount of information it can access.

The bagging method consists in generating a set  $\{\phi_b\}_{b \in \{1, \dots, B\}}$  of  $B$  weaker learners from different bootstrap datasets  $\{\mathcal{D}_b^{\text{train}}\}_{b \in \{1, \dots, B\}}$ . Each bootstrap dataset  $\mathcal{D}_b^{\text{train}}$  is generated by randomly selecting  $t$  elements of  $\mathcal{D}^{\text{train}}$  using a sample with replacement — note that each bootstrap sample has the same number of elements than  $\mathcal{D}^{\text{train}}$  but data points can appear several times in it. The number of times a data point  $(\mathbf{x}_i, y_i)$  appears represents the weight of this data point in the bootstrap learning set. To simplify, we can say that each tree model  $\phi_b$  learns on the  $\mathcal{D}_b^{\text{train}}$  dataset that have randomly defined weights on the different data points, which means that every model will pay attention to different parts of the training data. We can also evaluate the generalization error of the model since some trees have never seen some data points, we can evaluate the generalization error on the unseen data for every tree (similar to cross-validation), this error is called the out-of-bag error.

The second technique consists in randomly choosing a subsample of the features on which to find the best split (second part of the CART tree growing algorithm). This technique is inspired from the one developed by Ho in 1998, where each tree of a forest is trained only on a randomly chosen feature subspace.<sup>246</sup> The only tweak in the procedure lies in the fact that the feature space changes at each iteration of the tree growing process instead of between each tree generation. This method also improves the generalizability of the method by weakening each tree so that they don't overfit, the accuracy is achieved by the aggregation of all the trees.

The random forest as formulated by Breiman combines these two randomness-based techniques to train a forest.<sup>245</sup> The algorithm starts by looping over the number of trees  $B$  in the forest, for each tree  $b$  a bootstrap sample  $\mathcal{D}_b^{\text{train}}$  is randomly drawn (with replacement) and this data is used to grow the tree (training procedure). In the training, a modified CART algorithm is applied to grow the tree by splitting recursively on each node: (i) instead of testing all features for the best splitting, only a random selection of  $m$  variables is considered among the  $p$  features, (ii) the best split point is selected among the  $m$  variables, and (iii) the node is split in two until the minimum leaf size  $n_{\min}$  is reached. The size of the column subsample defines the number of features to randomly consider at each split; this is another implicit regularization parameter associated with the random forest along with the previously identified regularization parameters of the decision tree such as the minimal leaf size  $n_{\min}$  or the maximal depth of a tree. Finally, we have a set of  $B$  trees  $\{\phi_b\}$  that can be used to make an ensemble model  $\Phi$  so that:

$$\Phi(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^B \phi_b(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^B \sum_{m=1}^{M_b} c_{m,b} \mathbb{1}(\mathbf{x} \in R_{m,b}) \quad (4.14)$$

Note that each tree has an equal amount of say in the prediction, and they are trained on different random samples of the initial training data. Random forest is known to be less prone to overfitting because it is the product of a sort of cross-validation process called bootstrapping. However, the algorithm does very little improve the accuracy (bias error) of the model it relies on the belief that each tree will naturally compensate their mutual weaknesses in the final ensemble model. In the next section, I will introduce another algorithm that focuses on guiding each tree based on the prior knowledge of previous trees to perform better — this new technique is called boosting.

### FROM BOOSTING TO GRADIENT BOOSTING

In the previous approach, the bootstrap dataset is a random selection of the samples in the training set  $\mathcal{D}^{\text{train}}$  and each tree has an equal vote in the final ensemble decision. In a boosting algorithm,<sup>247</sup> the paradigm changes, data samples are (i) selected according to how they were predicted by the previous trees in order to focus our attention on the poorly predicted sample points, and (ii) the tree  $\phi_b$  that is trained on this weighted dataset  $\mathcal{D}_b^{\text{train}} = \left\{ \left( w_i^{(b)}, \mathbf{x}_i, y_i \right) \right\}$  is also evaluated using a measure of confidence  $\alpha_b$  that depends on the error made (the higher the error, the lower the confidence), this measure of confidence is used to define the ensemble model:

$$\Phi_B = \frac{1}{\sum_{b=1}^B \alpha_b} \sum_{b=1}^B \alpha_b \phi_b \quad (4.15)$$

To train each individual tree  $\phi_b$  of this forest, we use the CART algorithm (described in the previous sections), but by minimizing a weighted risk function instead of the standard one:

$$\mathcal{R}(\phi_b) = \sum_{i=1}^N w_i^{(b)} \mathcal{L}(\phi_b(\mathbf{x}_i), y_i) \quad (4.16)$$

where  $w_i^{(b)}$  is the normalized weight corresponding to the error  $\mathcal{L}(\Phi_{b-1}(\mathbf{x}_i), y_i)$  made by the previous ensemble  $\Phi_{b-1}$  on each data point  $(\mathbf{x}_i, y_i)$ ; for  $b = 1$ , there is no previous model so the weights are just equidistributed across the samples, i.e.  $\forall i, w_i^{(1)} = 1/N$ . In practice, to simulate the weighting process, a random selection with probability  $w_i^{(b)}$  on each sample is performed to draw an equal-sized  $N$  training dataset  $\mathcal{D}_b^{\text{train}}$  for  $\phi_b$ .

I voluntarily did not go into the details of the confidence rate  $\alpha_b$ , because several implementations of it exist. But generally, it is a decreasing function of the total error of the tree on the weighted dataset. The AdaBoost algorithm typically uses the half the opposite of the logit transform function  $\alpha_b = 0.5 \log \left( (1 - \mathcal{R}(\phi_b)) / \mathcal{R}(\phi_b) \right)$  that goes to  $+\infty$  for very small errors and  $-\infty$  for very large ones.<sup>248,249</sup> Gentle AdaBoost would give an equal amount of say to each tree independently of their performance, which can in some cases allow better generalization performance than a regular AdaBoost. The very high values of  $\alpha_b$  could in some cases make the model overfit, because a very good performance on the weighted dataset could mean a good fit on noisy data points.<sup>250</sup> To prevent overfitting early stopping procedure with a cross-validation (k-fold usually) training procedure is performed to determine the ideal number of trees required to stay generalizable while having reduced the bias error — like always in machine learning it is a question of bias-variance tradeoff.

AdaBoost in its original implementation uses stamps which are trees composed of a unique splitting node and two leaves, but boosting algorithms can be applied to any tree depth. This tree depth hyperparameter is very important in tree-based models since it defines the complexity/strength of each learner tree. A smaller tree would usually overfit less (see link between complexity and variance on Figure 4.3), and the AdaBoost algorithm uses the smallest possible tree in order to compensate the very aggressive learning procedure used. The main takeaway from this study is that boosting focuses on the training trees that compensate the errors of previous trees, and it can play with tree-based hyperparameters (e.g. tree depth, number of trees) to control the variance error.

Actually boosting can be reformulated as a gradient descent problem as formulated by Mason et al.<sup>251</sup> We can prove that AdaBoost is simply a gradient boosting algorithm with an exponential loss (same loss and derivative) and with the steepest gradient descent logic.<sup>240,251</sup>

Each additional tree  $\phi_b$  in a gradient boosting can be interpreted as a contribution to a predictor  $\Phi_b$  to minimize an objective function  $\mathcal{R}(\Phi_b)$ . And the weight  $w_i^{(b)}$  which measures how badly each sample  $i$  are predicted, can be expressed as a derivative of a differentiable loss function  $\mathcal{L}$  since the minimum is reached for a zero derivative.

$$w_i^{(b)} = - \frac{\partial \mathcal{L}(y_i, \hat{y}_i)}{\partial \hat{y}_i} \Big|_{\hat{y}_i=\Phi_{b-1}(\mathbf{x}_i)} \quad (4.17)$$

where  $\hat{y}_i$  is a derivation variable describing the ensemble tree prediction, here evaluated at  $\Phi_{b-1}$ . Instead of predicting the  $y_i$  values, we can predict the weight, also called the pseudo-residual,  $w_i^{(b)}$  that measures how far the previous model  $\Phi_{b-1}$  is from the ideal  $\Phi$  (zero weights everywhere in an ideal world) and compensate it using a tree  $\phi_b$ . In other words, we use the CART framework to grow a tree  $\phi_b$  that predicts the gradients  $w_i^{(b)}$  from the features  $\mathbf{x}_i$ , which iteratively improves the model  $\Phi_b$  compared to  $\Phi_{b-1}$ :

$$\Phi_b = \Phi_{b-1} + \eta \phi_b \quad (4.18)$$

where  $\eta$  is the learning rate or shrinkage, introduced by Friedman in his stochastic gradient boosting, to slow down the learning process in order to limit overfitting.<sup>252</sup> In a steepest descent step, the values of this learning rate  $\eta$  actually minimizes the risk function  $\mathcal{R}(\Phi_{b-1} + \eta \phi_b)$  associated to the output model  $\Phi_b$ . If  $b = 1$ , the first estimator  $\Phi_1$  is simply a constant function that minimizes the risk over the training set  $\Phi_1(\mathbf{x}) = \arg \min_{c \in \mathbb{R}} \sum_{i=1}^N \mathcal{L}(y_i, c)$ . For a quadratic loss function, this constant corresponds simply to the average of the  $y_i$  values over the training set.

In the particular case of a quadratic loss  $\mathcal{L}_{SE} = \frac{1}{2}(y_i - f(\mathbf{x}_i))^2$  that is used in this chapter, the gradient boosting algorithm can be simply broken down into the three steps below:<sup>252</sup>

1. Initialization at  $b = 1$  with a constant:

$$\Phi_1(\mathbf{x}) = \frac{1}{N} \sum_{i=1}^N y_i$$

2. For  $b = 2$  to B:

- (a) Compute the pseudo-residuals that are actually real residuals in the case of a quadratic loss  $\forall i \in \{1, \dots, N\}, w_i^{(b)} = y_i - \Phi_{b-1}(\mathbf{x}_i)$

- (b) Train the weak tree  $\phi_b$  on the dataset  $\{(\mathbf{x}_i, w_i)\}_{i \in \{1, \dots, N\}}$ .
  - (c) Update the model using a fixed learning rate  $\eta \in [0, 1]$  instead of finding  $\eta = \arg \min_{c \in \mathbb{R}} \sum_{i=1}^N \mathcal{L}(y_i, \Phi_{b-1}(\mathbf{x}_i) + c\phi_b(\mathbf{x}_i))$  through a minimization problem (steepest gradient descent).  $\Phi_b = \Phi_{b-1} + \eta\phi_b$
3. Output the final ensemble model  $\Phi_B$

Up until now, I showed the different ways of using decision trees to perform a prediction on a training dataset  $\mathcal{D}^{\text{train}}$  by focusing on mainly two ensemble models: random forest and gradient boosted trees. The reason why I went through these models is to be able to present my prediction model that aggregates techniques from both ensemble models. This model, called eXtreme Gradient Boost or XGBoost, was introduced by Chen et al. and is an improvement compared to similar methodologies due to its scalability. I won't go into the details of the implementation improvement (for more details see Ref. [253]), but I will rather focus on the basic framework it uses to better understand the core components of the model.

### XGBOOST MODEL PARAMETERIZATION

The XGBoost model is basically a gradient boosting model as described in the previous section but with a few regularization parameters that could be fine-tuned to improve its generalizability. In a learning problem with  $N$  learning examples and  $p$  features/descriptors, we can express the predictor  $\Phi$  as the sum of weaker tree learners  $\phi_b$ :

$$\Phi(\mathbf{x}) = \sum_{b=1}^B \phi_b(\mathbf{x}) = \sum_{b=1}^B \sum_{m=1}^M c_m^{(b)} \mathbb{1}(\mathbf{x} \in R_m^{(b)}) \quad (4.19)$$

where  $M$  is the maximal number of leaves a tree can have, in our implementation – this number is fixed using the maximum depth  $\max_{\text{depth}}$  in the algorithm since  $M = 2^{\max_{\text{depth}}}$ , and  $B$  is the maximum number of estimators in the ensemble model. The number of estimators is usually determined using an early stopping in the k-fold cross-validation.

Then, we used a quadratic loss function regularized with L1 and L2-regularization terms on the  $M$  leaf weights  $c_m$  of a model  $\phi$  so that the loss function  $\mathcal{L}$  can simply be expressed as:

$$\mathcal{L}(y, \phi(\mathbf{x}_i)) = \frac{1}{2} (y - \phi(\mathbf{x}_i))^2 + \lambda_1 \sum_{m=1}^M |c_m| + \lambda_2 \sum_{m=1}^M |c_m|^2 \quad (4.20)$$

where  $\lambda_1$  and  $\lambda_2$  are the L1 and L2-regularization coefficients that control the importance of each regularization term.

The risk function  $\mathcal{R}$  of a tree  $\phi_b$  with  $M$  leaf weights  $c_m^{(b)}$  at the iteration  $b$  of the gradient boosting process can then be written:

$$\mathcal{R}(\phi_b) = \frac{1}{N} \sum_{i=1}^N \frac{1}{2} (w_i^{(b)} - \phi_b(\mathbf{x}_i))^2 + \lambda_1 \sum_{m=1}^M |c_m^{(b)}| + \lambda_2 \sum_{m=1}^M |c_m^{(b)}|^2 \quad (4.21)$$

where  $w_i^{(b)}$  is the pseudo-residuals of the previous model on the dataset. This expression of the risk is typically used in the tree-splitting process of the step 2.(b) of the gradient boosting algorithm (see previous subsection 4.1.3) to find the best tree to predict the pseudo-residuals.

As previously explained, the pseudo-residual is simply the difference between the observed value  $y_i$  and the previously predicted value  $\Phi_{b-1}(\mathbf{x}_i)$ , also known as the residual in regression problems, in the case of a quadratic loss:

$$w_i^{(b)} = - \frac{\partial \mathcal{L}(y_i, \hat{y}_i)}{\partial \hat{y}_i} \Big|_{\hat{y}_i=\Phi_{b-1}(\mathbf{x}_i)} = y_i - \Phi_{b-1}(\mathbf{x}_i) \quad (4.22)$$

The learning rate  $\eta$  used to update the ensemble model is also a key component of the final model that we will need to tweak in order to maximize the generalizability of the model. This parameter slows down and smoothens the convergence to the solution, which improves the bias-variance tradeoff. Small values below 0.1 are usually used.

Variable name in XGBoost	Variable in this work	Description of the hyperparameter
"n_estimators"	M	Number of trees in the final ensemble model
"max_depth"	$\simeq \log_2(T)$	Maximum number of levels allowed for each tree that can be expressed as a function of T the number of terminal nodes or leaves
"alpha"	$\lambda_1$	L1-regularization parameter
"lambda"	$\lambda_2$	L2-regularization parameter
"learning_rate"	$\eta$	The shrinkage or learning rate used to update the ensemble model with each basic tree.
"subsample"	$N_{\text{sample}}/N$	The ratio of data points randomly sampled (without replacement) for the training of each tree $\phi_b$
"colsample_bytree"	$p_{\text{tree}}/p$	The ratio of features randomly sampled per tree iteration (on $b = 1$ to B)
"colsample_bylevel"	$p_{\text{level}}/p$	The ratio of features randomly sampled per level iteration (on $k = 1$ to M, this would be on the leaves really but to simplify)

Table 4.1: Hyperparameters of XGBoost relevant to our work.

I also used three other parameters that are very close to the ones implemented in a random forest to add randomness in the gradient descent procedure. Augmented by these techniques, the model can now be called stochastic gradient boosting as described in the Ref. [252]. At each iteration, a subsample of the training data is drawn at random (without replacement) according to a parameter  $N_{\text{sample}}/N$ . This parameter has a similar effect as the bagging procedure of the random forest, it narrows the attention of each weak learner on a portion of the learning set, which reduces overfitting like in a cross-validation procedure. The different trees learn from different parts of the training set, which means that the ensemble model can never overfit on the whole dataset. This provides a handy solution to the infamous overfitting problem of standard gradient boosting. Another procedure concerns the random selection of the feature columns. This idea was developed in the Ref. [246] and randomly extracts a subsample of the features for training of one tree; a parameter needs to be chosen in order to determine the size of the portion of features  $p_{\text{tree}}/p$  used to train each tree. A similar idea is to make the column sampling at each level instead of each tree, and a proportion  $p_{\text{level}}/p$  can be defined

like this. Similarly, we can make a feature selection at the node level but this parameter was not used.

Finally, I compiled all the parameters used in the construction of the final model in Table 4.1. This table contains a tree-specific parameter "max\_depth", but also an ensemble specific one "n\_estimators", in addition to very general regularization parameters inspired by linear models "alpha" and "lambda", as well as more gradient boosting specific parameter "learning\_rate" and more randomness-based hyperparameters inspired by random forest such as "subsample", "colsample\_bytree" and "colsample\_bylevel". This model can be considered as a mixing pot of a variety of ideas coming from all corners of the data science field. Using this machine learning model, I will try to solve the selectivity drop problem that puzzled us in the previous chapter.

## 4.2 PREDICTION OF THE AMBIENT-PRESSURE SELECTIVITY

Before diving deep into the model of our work, I will quickly review the different literature contributions to xenon/krypton separation screenings. Simon et al. published one of the first articles on an ML-assisted screening approach for the separation of a Xe/Kr mixture extracted from the atmosphere.<sup>18</sup> Their model's performance was highly relying on the Voronoi energy, which is basically an average of the interaction energies of a xenon atom at each Voronoi node.<sup>188</sup> To rationalize this increase in performance, we can consider this Voronoi energy as a faster proxy for the adsorption enthalpy. By comparing it to the standard Widom insertion, I found that although it is faster, it is less accurate; and I developed a more effective alternative, the surface sampling (RAESS) using symmetry and non-accessible volumes blocking (see section 3.2). Recently, Shi et al. used an energy grid to generate energy histograms as a descriptor for their ML model, which gives an exhaustive description of the infinitely diluted adsorption energies,<sup>183</sup> but can be computationally expensive.

All the approaches described above have a good accuracy in the prediction of low-pressure adsorption (i.e., in the limit of zero loading) but are not suitable for prediction of adsorption in the high-pressure regime, when the material is near saturation uptake. While this later task is routinely performed by Grand Canonical Monte Carlo (GCMC) simulations, there is a lack of methods at lower computational cost for high-throughput screening. To better frame my challenge, I am essentially trying to predict the selectivity in the nanopores of a material at high pressure, where adsorbates are interacting with each other, while only having information on the interaction at infinite dilution. The comparison between the low and high-pressure cases gives key information on the origin of the differences of selectivity. For instance, I have previously shown that selectivity could drop between the low and ambient pressure cases in the Xe/Kr separation application (see chapters 2 and 3), and it was mainly attributed to the presence of different pore sizes and potential reorganizations due to adsorbate–adsorbate interactions.

I combined grid-based descriptors described in the previous chapter (section 3.3) to statistical characterizations of the pore size to propose a set of useful ML descriptors for fast and accurate ambient-pressure selectivity prediction using an optimized XGBoost model. And I highlight its performance on the case of xenon/krypton separation in the CoRE MOF 2019 database.<sup>72</sup>

## 4.2.1 Data Preparation

### TARGET VARIABLE

I want to predict the Xe/Kr ambient-pressure selectivity faster than standard techniques. To obtain reference values (ground truth), I used the RASPA2 software<sup>205</sup> to run GCMC calculations (introduced in section 2.1.3) of 20–80 Xe/Kr mixtures at 298 K and 1 atm on our cleaned database. The van der Waals interactions are described by a Lennard-Jones (LJ) potential with a cutoff distance of 12 Å. The LJ parameters of the framework atoms are given by the universal force field (UFF),<sup>189</sup> and the guest atoms (xenon and krypton) have their LJ parameters taken from a previous screening study.<sup>161</sup> The study only focuses on a given Xe/Kr composition usually obtained by cryogenic distillation of ambient air<sup>1</sup> as a first step toward predicting other mixtures at different physical conditions (e.g. Xe/Kr mixtures out of nuclear off-gases).

I decided to use a logarithmic transform of the selectivity instead of the raw value because I am more interested in the order of magnitude of the selectivity values than to predict the higher values of selectivity — an ML model that predicts selectivity values can lower down the errors by focusing the prediction more on the higher values than the lower ones. By focusing on the logarithmic transform of the selectivity, we can better separate the different orders of magnitude of the selectivity values. This approach distributes more evenly the efforts on all the different values of selectivity. Moreover, this logarithmic transformation is effectively a Gibbs free energy that was introduced in the section 2.1.5; it can therefore be easily compared with the energy descriptors I introduced in the previous chapter 3.

### DATABASE AND DATA GENERATION

To test our methodology on a set of realistic MOFs, I chose to screen the 12,020 all-solvent removed (ASR) structures of the CoRE MOF 2019 database.<sup>72</sup> After removing the disordered and the non-MOF structures as well as the ones with a large unit cell volume of 20 nm<sup>3</sup>, I obtained a set of 9,748 structures. Then, I analyze the string information given by the Zeo++ software<sup>254</sup> to reduce the number to 9,177 by removing the structures that are not tridimensional, where solvents are still detected (wrongly classified in “all solvent removed”), or where the metal is radioactive or fissile (e.g., Pu-MOF TAGCIP,<sup>255</sup> Np-MOF KASHUK,<sup>256</sup> U-MOF ABETAE<sup>257</sup> or Th-MOF ASAMUE<sup>258</sup>) — this can be a source of risks in a nuclear waste processing plant. Furthermore, I added a condition on the largest cavity diameter (LCD) to keep only the structures that can accept a xenon molecule: 8,529 structures have an LCD higher than 4 Å (approximately the size of a xenon molecule). This is equivalent to removing the structures with very unfavorable adsorption enthalpies, that are not promising for our adsorption-based separation (see section 3.2).

Then, the descriptors summarized below (and fully detailed in Supporting Information) were calculated on this restrained dataset. At this stage, 370 structures failed to be calculated in GCMC and 82 have no standard deviation for the pore distribution (skewness and kurtosis cannot be retrieved). A final dataset of 8,077 structures was therefore used to perform our ML-assisted method of screening the Xe/Kr adsorption selectivity. Based on this final set, 20% were randomly used for the test set and 80% were used to train our model. The goal is to learn from the training set a relationship between the descriptors and the target ambient-pressure selectivity in order to evaluate the performance on the test set. A CSV file of training and test sets can be found in the data availability section.

## 4.2.2 Feature engineering

### GEOMETRICAL AND CHEMICAL ML DESCRIPTORS

Looking at a number of different research papers on supervised ML for the prediction of adsorption properties,<sup>17,18,79,259,260</sup> I see that some descriptors are recurrent: (i) geometrical descriptors obtained by software like Zeo++<sup>254</sup> such as the surface area (SA), the void fraction (VF), the largest cavity diameter (LCD) and the pore limiting diameter (PLD); and (ii) physical and chemical descriptors such as the framework's density, the framework's molar mass, the percentage of carbon (C%), nitrogen (N%), oxygen (O%), hydrogen but also halogen, nonmetals, metalloids and metals, and the degree of unsaturation. Although these descriptors are very versatile and used in many ML models, they, however, fail to provide specific information for our ML task. As shown by Simon et al., energy descriptors are greatly influential in ML models for selectivity prediction.

The geometric analysis of the crystalline porous materials is typically based on the van der Waals (vdW) radii predefined by the Cambridge Crystallographic Data Centre (CCDC). This force field-independent choice can create a gap between the geometrical descriptors and the thermodynamic values obtained through molecular simulations. Inspired by a recent work on the comparison of PLDs and self-diffusion coefficients,<sup>51</sup> I defined a list of vdW radii to be read by the Zeo++ software (more details on [github.com/eren125/zeopp\\_radtable](https://github.com/eren125/zeopp_radtable)). In this study, all Zeo++ calculations use an atomic radius that corresponds to the distance where the LJ potential reaches  $3k_B T/2$ , for  $T = 298$  K.

The SA exposed to different probe sizes (1.2 Å, 1.8 Å and 2.0 Å) were tested. The probe occupiable volume was chosen to measure the void fraction (VF) for different adsorbent by using probe sizes of 1.8 Å (close to the radius of krypton) and 2.0 Å (close to that of xenon). This definition of the pore volume was found to be in better agreement with experimental nitrogen isotherms.<sup>191</sup>

Because our goal is to predict the difference between the low-pressure selectivity and the ambient-pressure one (for a given gas mixture composition), some of these descriptors have very little importance, and the key factor is the difference of accessible volume and the affinity of the remaining pore volume with xenon, compared to krypton. The intuition developed in chapter 2 sketched the role of a diverse distribution of pores with different xenon affinities. For all these reasons, from all the “standard” descriptors taken from the literature, I kept only the following 7 descriptors: C%, N%, O%, LCD ("D\_i\_vdw\_uff298"), PLD ("D\_f\_vdw\_uff298"), SA for a 1.2 Å probe ("ASA\_m2/cm3\_1.2") and VF for a 2.0 Å probe ("PO\_VF\_2.0"). I also built a new descriptor  $\Delta$ VF void fraction values, the difference of volumes occupiable by xenon (2.0 Å) and by krypton (1.8 Å). All these descriptors along with other pore size distribution based geometrical descriptors are presented in detail in Table S1 of the Supplementary Information (SI).

### PORE SIZE STATISTICS

To generate a histogram of pore sizes (or pore size distribution, PSD), Monte Carlo steps are used to measure the frequency of every accessible pore sizes binned by 0.1 Å.<sup>261</sup> This histogram can then be used to generate descriptors based on statistical parameters that describes the overall location, the dispersion, the shape and the modality of the distribution. In addition to the mean and standard deviation of the distribution, I introduced two additional moments: the

skewness ( $\gamma$ ) corresponds to the third standardized moment and measures the asymmetry of a distribution; and the kurtosis ( $k$ ), being the fourth standardized moment, measures the relative weight of the tails of the distribution. Knowing the importance of characterizing the number of different pore sizes suspected to be at the origin of the selectivity drop observed, I tried to find a simple descriptor to measure the number of modes in the distribution. The Sarle's bimodality coefficient,  $BC = (\gamma^2 + 1)/k$ , represents a simple quantification of how far the distribution is from the unimodality based only on skewness and kurtosis.<sup>262</sup>

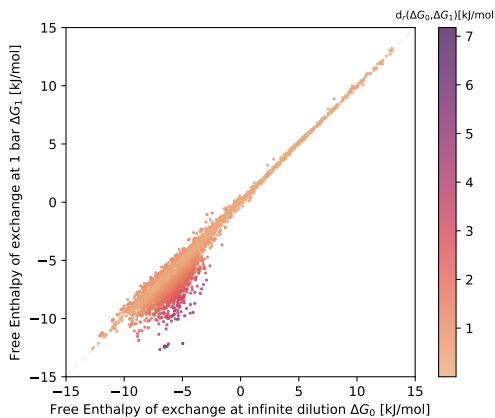
Finally, to further measure the diversity of pores, I introduced an effective number  $n_{\text{eff}} = N^2 / \sum n_i^2$  of pore sizes, where  $N$  is the total number of points in the histogram and  $n_i$  the number of points associated with the  $i^{\text{th}}$  bin. This number is very similar to a statistical number widely used in other scientific fields: in political science it is used to measure the effective number of political parties,<sup>263</sup> in ecology the inverse Simpson's index evaluates the species diversity in an ecosystem,<sup>264</sup> or in quantum physics the inverse participation number measures the degree of localization of a wave-function.<sup>265</sup> This effective number of pore sizes gives an idea of the diversity of pore sizes (considering a binning of  $0.1 \text{ \AA}$ ). A highly effective number would mean that multiple pore sizes are highly represented in the structure; this descriptor gives an idea of how scattered the pore sizes are. All these descriptors carry information on the form of the PSD needed to figure out the loading and selectivity situation in the framework near saturation uptake, which is crucial to predict the ambient-pressure selectivity.

### GRID-BASED AND GEOMETRICAL DESCRIPTORS

The low-pressure selectivity provides a first intuition of the selectivity at higher pressure, as demonstrated in our previous work showing a correlation between the selectivity at both pressures (section 2.3.1). If I adopt the Gibbs free energy formalism (Equation 2.26), which correspond to a logarithmic transform of the selectivity values, this correlation is confirmed and highlighted on Figure 4.6. We can also note that although a majority of structures have similar selectivity in both pressure conditions, a handful of structures experience a selectivity drop at higher pressure. The zero-loading selectivity calculated by grid sampling is always higher or similar to the ambient-pressure one, it gives therefore a solid ground on which to build an efficient prediction model. The second ingredient for a good prediction model is to build explanatory descriptors related to this selectivity drop phenomenon. One of the main causes to the selectivity drop being the presence of bigger pores that are less attractive xenon, therefore additional information on the pore size distributions or the energy landscape would be helpful for this task.

To incorporate information on the pore size diversity of the materials, I carried out statistical measurements on the PSD. By analyzing them, I detected explanatory factors at the origin of the observed selectivity drop. A high degree of multi-modality in the distribution would mean a diverse set of pores, which can lead to a selectivity drop if the pores are significantly different one from another. The more distant is the average pore size from the largest cavity diameter the higher the chance of observing a selectivity drop, because a big difference between the pore sizes bring about a lower selectivity. All these statistics are designed to give as much knowledge as possible on a hypothetical selectivity drop and on the quantitative estimation of its magnitude.

To better quantify the change of selectivity, it could be interesting to give statistics on the distribution of interaction energies for xenon and krypton calculated by our grid algorithm.



*Figure 4.6: Comparison between the Gibbs free energy of exchange at low pressure  $\Delta G_0$  and ambient pressure  $\Delta G_1$  labeled by the relative distance between them. This plot is equivalent to a logarithmic plot of the selectivity at these two pressure conditions.*

These statistics include moments of different orders (up to 4) of the energy distribution, which informs on the adsorbate–adsorbent interaction energies in the nanopores at higher loading. The shape of the energy distribution can help assess quantitatively the change in selectivity. We can consider this as a way of compressing the whole energy distribution into a few statistical values, which is a standard method used in the field of data science to tackle distribution data. The same approach has also been applied to the Boltzmann weighted distributions to generate temperature specific descriptors for the energy distributions. All these quantities have calculated and compared to the ambient-pressure selectivity in the previous chapter (section 3.3).

As explained in the previous chapter, Boltzmann averaging at higher temperature gave better result in describing the ambient-pressure selectivity description. This new type of descriptor is very interesting since it better performs around the high selectivity region, where the standard Boltzmann average at 298 K loses its accuracy (see Figure 3.33). I used this descriptor to build several descriptors presented in Table 4.3. As shown on Figure 4.12, the exchange Gibbs free energy at 900 K and the excess of free energy compared to the 298 K case are the second and third most influential descriptors of our ML model. They are complementary to the exchange Gibbs free energy at 298 K to predict the selectivity at higher pressures.

By combining the above-mentioned features with more standard geometrical descriptors, I trained an ML model for the ambient pressure selectivity that identifies the origins of the selectivity drop and gives promising prediction results.

Feature name	Description
"ASA_m2/cm3_1.2"	Volumetric surface area accessible to a nitrogen probe (1.2 Å) in m <sup>2</sup> cm <sup>-3</sup>
"delta_VF_18_20"	Difference of void fraction occupiable by a krypton (1.8 Å radius) and a xenon (2.0 Å radius) probe. Always positive due to the difference of probe radii.
"PO_VF_2.0"	Void fraction occupiable by a xenon probe of 2.0 Å radius
"D_i_vdw_uff298"	Largest cavity or largest included sphere diameter (LCD). Structures atom radii are defined using the UFF forcefield <sup>1</sup>
"D_f_vdw_uff298"	Pore Limiting Diameter (PLD) or largest free sphere diameter defined similarly to the LCD
"pore_dist_mean"	Mean value of the pore size distribution or the average pore size
"delta_pore"	Difference between the LCD and the average pore size: "delta_pore" = "D_i_vdw_uff298" - "pore_dist_mean"
"pore_dist_std"	Standard deviation of the pore size distribution
"pore_dist_skewness"	Skewness (third order standardized moment) of the pore size distribution
"pore_dist_kurtosis"	Kurtosis (fourth order standardized moment) of the pore size distribution
"pore_dist_neff"	Effective number of data associated to the pore size distribution: N <sub>eff</sub> = sum(weights) <sup>2</sup> / sum(weights <sup>2</sup> )
"pore_dist_modality"	Sarle's bimodality coefficient (BC) of the pore size distribution: BC = kurtosis - skewness <sup>2</sup>
"C%"	Percentage of carbon (C) in the MOF structure
"O%"	Percentage of oxygen (O) in the MOF structure
"N%"	Percentage of nitrogen (N) in the MOF structure

Table 4.2: Description of geometrical and chemical features used in the ML model.

<sup>1</sup>Using the approach of Ref. [51]

Feature name	Description
"G_0"	Low-pressure Xe/Kr exchange Gibbs free energy defined using the low-pressure selectivity: $\Delta_{\text{exc}}G^{\text{Xe/Kr}} = -RT \ln(s^{\text{Xe/Kr}})$
"G_Xe_900K"	High temperature Xe adsorption Gibbs free energy defined using the Henry's constant: $\Delta_{\text{ads}}G^{\text{Xe}}(T_h) = -RT_h \ln(RT_h \rho_f K_H^{\text{Xe}}(T_h))$
"G_Kr_900K"	High temperature Kr adsorption Gibbs free energy: $\Delta_{\text{ads}}G^{\text{Kr}}(T_h)$
"G_900K"	High temperature Xe/Kr exchange Gibbs free energy: $\Delta_{\text{exc}}G^{\text{Xe/Kr}}(T_h) = -RT_h \ln(K_H^{\text{Xe}}(T_h)/K_H^{\text{Kr}}(T_h))$
"delta_G0_298_900"	Difference of exchange free energies between the ambient temperature and high temperature: $\Delta_T H^{\text{Xe/Kr}} = \Delta_{\text{exc}}G^{\text{Xe/Kr}}(T_h) - \Delta_{\text{exc}}G^{\text{Xe/Kr}}(T_0)$
"delta_H0_Xe_298_900"	Difference of Xe adsorption enthalpy between the ambient temperature and high temperature: $\Delta_T H^{\text{Xe}} = \Delta_{\text{ads}}H^{\text{Xe}}(T_h) - \Delta_{\text{ads}}H^{\text{Xe}}(T_0)$
"delta_TS0_298_900"	Difference of exchange entropic term between the ambient temperature and high temperature: $\Delta_T (-T\Delta_{\text{exc}}S^{\text{Xe/Kr}}) = \Delta_T (\Delta_{\text{exc}}G^{\text{Xe/Kr}} - \Delta_{\text{exc}}H^{\text{Xe/Kr}})$
"enthalpy_std_xenon"	Standard deviation of the Boltzmann weighted Xe energy distribution
"enthalpy_std_krypton"	Standard deviation of the Boltzmann weighted Kr energy distribution
"enthalpy_skew"	Skewness of the Boltzmann weighted Xe energy distribution
"enthalpy_modality"	Bimodality coefficient of the Boltzmann weighted Xe energy distribution
"mean_grid_xenon"	mean value of the xenon interaction energy distribution
"mean_grid_krypton"	mean value of the krypton interaction energy distribution
"std_grid_xenon"	standard deviation of the xenon interaction energy distribution
"std_grid_krypton"	standard deviation of the krypton interaction energy distribution

Table 4.3: Description of the 15 energy-based features used in the ML model. Thermodynamic descriptors are always defined at low pressure since they are derived from an interaction energy grid. Temperatures are defined as follows:  $T_0=298\text{ K}$  and  $T_h=900\text{ K}$ . All these energy values are defined in  $\text{kJ mol}^{-1}$ .

### 4.2.3 Model training

#### THE MACHINE LEARNING MODEL

I chose to use eXtreme Gradient Boosting (XGBoost) as the machine learning framework for our predictive model because of its accuracy, efficiency and simplicity of use. Its performance has long been proven since 17 out 29 Kaggle Challenge winning solutions were based on this algorithm in 2015. The XGBoost system is highly scalable and parallelized, which gives very fast model training.<sup>253</sup> Compared to more standard tree-based algorithms such as random forest (commonly used in the field<sup>18</sup>), the boosting component of the algorithm means that it learns from previous mistakes and puts more efforts on the problematic data points, hence improving the accuracy of the final ML model.

In the next sections, I will introduce new descriptors for nanoporous materials, as well as new concepts of feature engineering based on energy and pore size histograms. The ML features presented have been selected by progressively filtering out the less influential ones on the accuracy of the final model, see the complete list in Table S1-3 of Supporting Information (SI). The influence or importance is defined later in a section dedicated to the interpretation of the model. The hyperparameters of the model were fine-tuned using random searches to design the best performing final model. Finally, the influence of the preselected descriptors on the final model is interpreted using a unified approach.

#### HYPERPARAMETER OPTIMIZATION

A hyperparameter search consists in finding the best model to optimize the generalization error as defined in equation 4.7. To achieve this, the most common strategy consists in doing cross-validations to evaluate different model configurations. This process is called the hyperparameter search or optimization. Here, I used the randomized search algorithm to find the best parameters within a predefined reasonable range of parameters. A set of optimal hyperparameters (please refer to Table 4.1 for the meaning of the parameters) for our final ML model was found using a random search of 30,000 iterations on the parameter space described by following python dictionary:

```
params = {
    'n_estimators': [1500],
    'max_depth': [5,6],
    'learning_rate': [0.02,0.04,0.06,0.08],
    'colsample_bytree': np.arange(0.6, 1.0, 0.05),
    'colsample_bylevel': np.arange(0.6, 1.0, 0.05),
    'alpha': np.arange(0, 4, 0.2),
    'subsample': np.arange(0.6, 0.95, 0.05),
}
```

At each iteration the training data was used to evaluate the hyperparameters of the model using a 5-fold cross-validation. The final set of optimal hyperparameters corresponding to the model with the lowest RMSE of 0.36 kJ mol<sup>-1</sup> is given below. This final set of parameter was the used to train the final model.

```
optimal_params = {
    'objective': 'reg:squarederror',
    'n_estimators': 1500,
```

```
'max_depth': 6,
'colsample_bytree': 0.85,
'colsample_bylevel': 0.65,
'subsample': 0.7,
'alpha': 0.4,
'lambda': 1,
'learning_rate': 0.04,
}
```

To confirm the relevance of the model, I performed another 5-fold cross-validation to obtain a convergence plot of the XGBoost model with this set of parameters shown in Figure 4.7. Given this configuration, the model is tested on the prior defined test-set and interpretation tools are used to better understand the structure-property relationships in play.

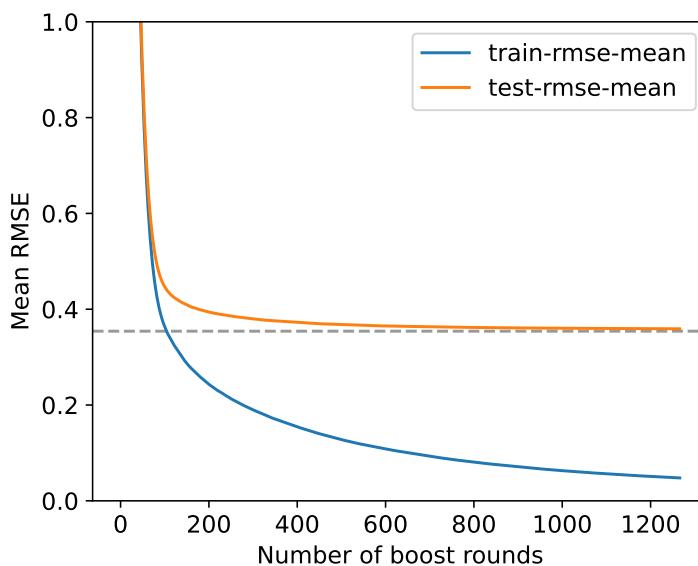
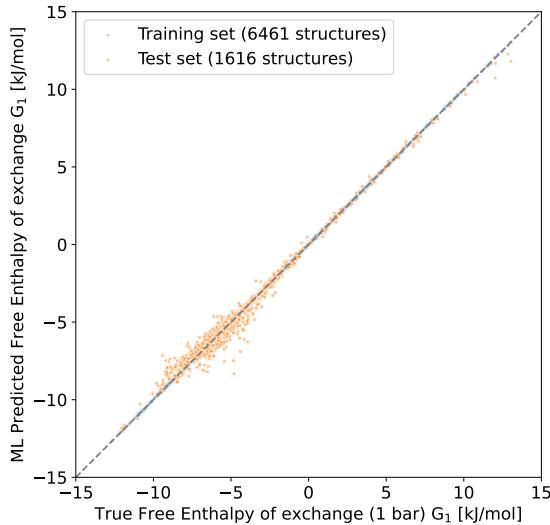


Figure 4.7: Convergence plot of the cross-validation training of our ML model. With the training set considered, the generalization error on the test set converges to  $0.36 \text{ kJ mol}^{-1}$ .

#### 4.2.4 ML model performance

In this section, I will present the performance of the ML model that learned the joint effects of all the newly introduced descriptors to detect and evaluate the observed drop between the easily accessible low-pressure selectivity and the more computationally demanding ambient-pressure selectivity. A GCMC simulation of a 20–80 xenon/krypton gas mixture takes in average 2 400 s per structure on the CoRE MOF 2019 database, while our grid-based adsorption calculation only takes about 5 s per structure (on a single Intel Xeon Platinum 8168 core at 2.7 GHz). To compute all features needed for our prediction, we would need less than a minute per structure, which is way faster than the 40 minutes required for a GCMC calculation. The ML-based approach has a very clear speed advantage over standard molecular simulations. But to be a good substitute, it needs to keep a good level of accuracy on an unseen set of structures.

I defined a set of 80% randomly chosen structures out of the final dataset to train and fine-tune the parameters of our model. A randomized search over a range of maximum depths, learning rates, sizes of feature samples used by tree and by level, sizes of data sample and alpha



*Figure 4.8: Scatterplot of the exchange free energy predicted by the model. There is a good agreement between the predicted and true values. On the test set, there is an RMSE of  $0.37 \text{ kJ mol}^{-1}$  and an MAE of  $0.21 \text{ kJ mol}^{-1}$ . This plot is equivalent to the scatterplot between the logarithm of the ambient-pressure selectivity (see Figure 4.10).*

regularization parameters has been performed and a set of hyperparameters have been chosen to minimize the average RMSE computed using a 5-fold cross-validation. The ranges used in the randomized search as well as the final hyperparameters set are given in the section 4.2.3. By using this parameterization, our XGBoost model has an RMSE of  $0.37 \text{ kJ mol}^{-1}$  and an MAE of  $0.21 \text{ kJ mol}^{-1}$  on the exchange Gibbs free energies of the test set of 1,616 structures. If we convert back these results to the selectivity values, the RMSE on the selectivity values would be 2.5 and 0.07 on the logarithm base 10 of the selectivity, which means that the order of magnitude of the selectivity is known with a very good accuracy. To prove that this good performance is not fortuitous, I used a 5-fold cross-validation procedure on the whole dataset and found an average RMSE of  $0.36 \text{ kJ mol}^{-1}$  with a standard deviation of  $0.01 \text{ kJ mol}^{-1}$ , which is consistent with the performance given by a standard train/test split.

To see if it would be possible to train a better model with more training data, we train different models with different fractions of the training set as shown on Figure 4.9. The RMSE unsurprisingly decreases as we increase the amount of data, but it seems to start stabilizing for a fraction of 95% of the training set. This means that the model has good the amount of training data to achieve what it seems to be the minimum error on this test set.

This method can later be used in a screening procedure that relies on cheap descriptors to skim off obviously undesirable structures to only keep the promising structures for the final ML model evaluation. For this is the reason, as previously explained in the methods, only the 3D MOF structures with an LCD above  $4 \text{ \AA}$  are kept because they have a positive xenon affinity, which is a necessary condition for a good Xe/Kr selectivity. Our model being very good at predicting the ambient pressure selectivity of structures with good xenon affinity, the proposed screening procedure, illustrated Figure 4.11, would include (i) a check of the nature of the structure to ensure it is a 3D MOF structure, (ii) then a filter on the LCD value (above  $4 \text{ \AA}$ ), (iii) a

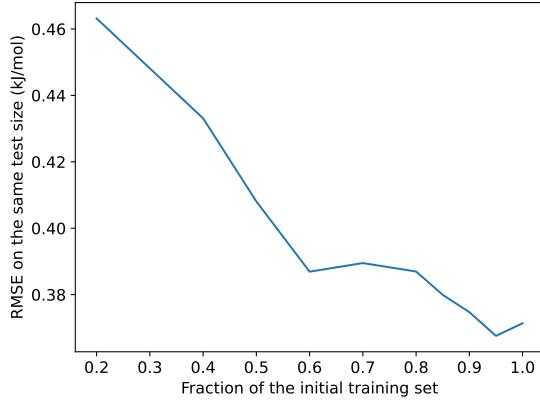


Figure 4.9: Root mean squared errors on the same test set (20% of all data) as a function of the fraction of the training set used to train smaller models. The error decreases as the amount of data increases.

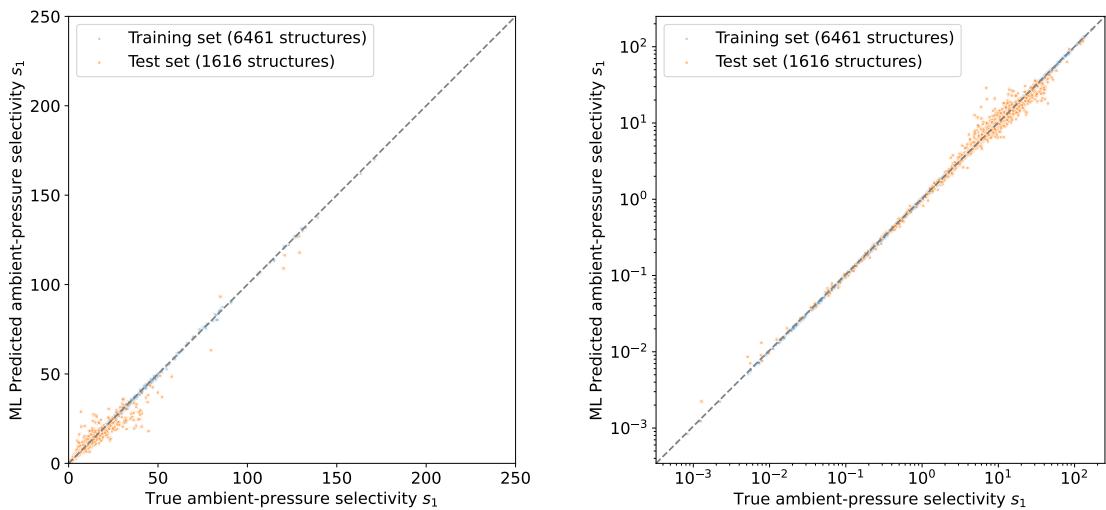
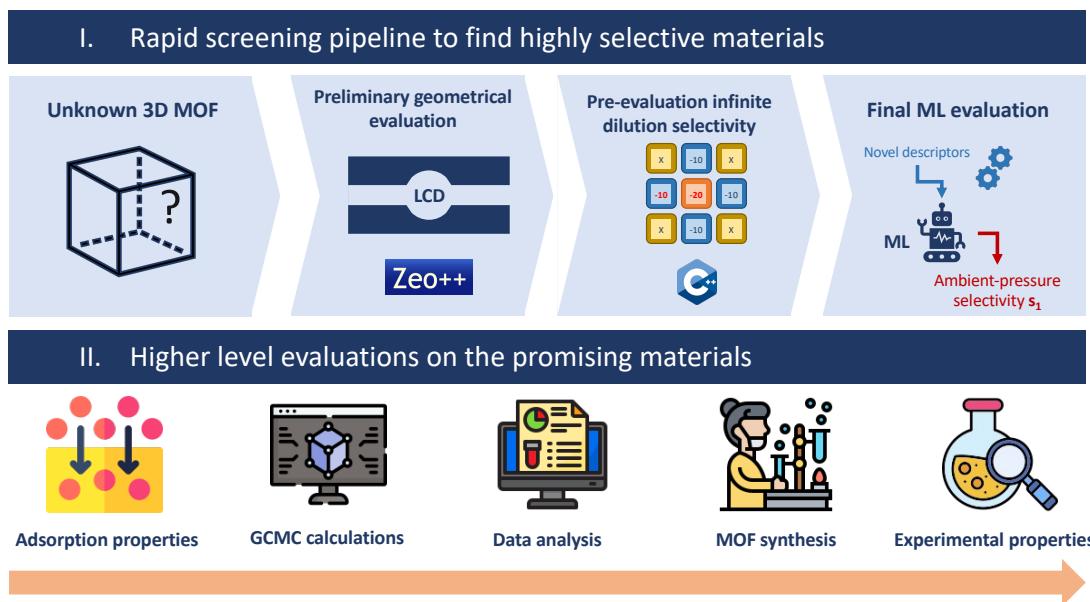


Figure 4.10: Scatterplots of the selectivity predicted by the model of ML compared to the selectivity calculated by GCMC in both log and linear scales. The blue points correspond to the training data while the test data is shown in orange. The focus is on the test data since it shows the generalization of the ML model to unseen data. The corresponding errors for the ambient-pressure selectivity are 2.5 and 1.1 for respectively the RMSE and MAE of the selectivity, and 0.065 and 0.038 for the RMSE and MAE of its base-10 logarithm.

pre-evaluation of the Xe/Kr selectivity at infinite dilution using the grid-based method, and (iv) finally the ML evaluation to keep only structures above a certain threshold of ambient-pressure selectivity (e.g. 30). We could possibly evaluate more thoroughly the top structures using GCMC simulations, *ab initio* calculations or adsorption experiments.



*Figure 4.11: An illustration of the screening procedure that could be used to find highly selective materials. The adsorption properties can be rapidly evaluated using structural and energetic conditions on the structure and by confirming it with the ML model. The structures chosen this way can then be tested with higher-level calculations and experiments.*

## 4.3 OPENING THE BLACK BOX

To better understand the intuition behind this selectivity drop, I used the SHAP<sup>243,266</sup> library of interpretation models to draw relationships between the descriptors and the predicted ambient-pressure selectivity. This code library is based on the calculation of Shapley values<sup>267</sup> that measure the contribution of each descriptor to the prediction to locally interpret our ML model. This interpretation model untangles the interdependence between the descriptors to extract an individual contribution. To go beyond the local interpretation, we can rapidly compute the Shapley values for the whole dataset using faster algorithms;<sup>266</sup> scatterplots of the contribution as a function of the descriptor values called SHAP dependence plots can then be drawn to make a more global interpretation of our ML model. Knowing a descriptor value, I then infer, with a certain level of uncertainty, how it changes the final predicted value, which highlights unknown structure–property relationships. Finally, I use the mean absolute Shapley values of each feature on the training set to measure the feature importance (see Figure 4.12).

### EXPLAINABLE AI

The final model is trained on the predefined training set using XGBoost with the fine-tuned hyperparameters. By testing it on the test set, I measured the accuracy of our approach, however, it is interesting to extract chemical insight into the hidden relationship between the predicted value and the descriptors, to better understand the thermodynamic origins of the performance. In this work, I used the Shapley values,<sup>267</sup> a game theory concept developed by Shapley in 1953, to measure the contribution of each descriptor in the predicted value. This tool is used locally to understand for a given structure how their characteristics had contributed to the prediction. To draw structure–property relationships, I would need to use a global interpretation method

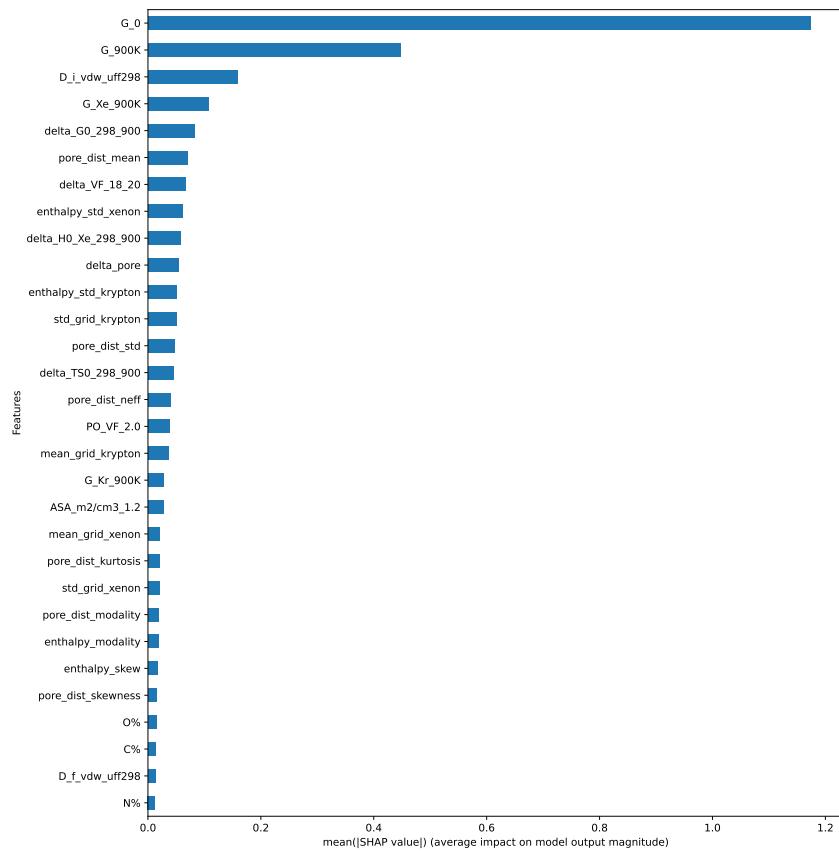


Figure 4.12: Barplot of the feature importance for all the descriptors of our final model. The descriptor labels used in this section are explained in more detail in Tables 4.2 and 4.3.

such as the SHapley Additive exPlanations (SHAP) method thoroughly detailed in the online book *Interpretable Machine Learning* of Christoph Molnar.<sup>243</sup> The SHAP tool developed by Lundberg and Lee<sup>266</sup> is based on a faster algorithm adapted to tree-based ML models like gradient boosting, TreeSHAP, and integrates useful global interpretation modules like SHAP feature importance and dependence plot.

### 4.3.1 Global interpretability

To rank the descriptors according to their average impact on the magnitude of the model output, I used the mean absolute Shapley values of each descriptor. The importance plot associated with these values are presented in Figure 4.12. Even if the low-selectivity exchange Gibbs free energy has a SHAP importance value way above the others, it only serves as a baseline where a correlation close to the one presented on Figure 4.6 can be reached; the other descriptors play a major role in moving the outliers of the figure closer to the diagonal line. Energy descriptors play a major role in the model’s prediction, and the geometry-based new descriptors, while playing a more secondary role, are key in evaluating the gaps between the low-pressure case with the ambient-pressure one that we are interested in. To dig deeper into the mechanisms that allow the model to predict the selectivity with a very good accuracy – the RMSE and MAE on the test set’s selectivity being respectively 2.5 and 1.1 – I am now going to look into the SHAP dependence plots of each interesting descriptor that plots the contribution to the predicted value as a function of the actual descriptor value.

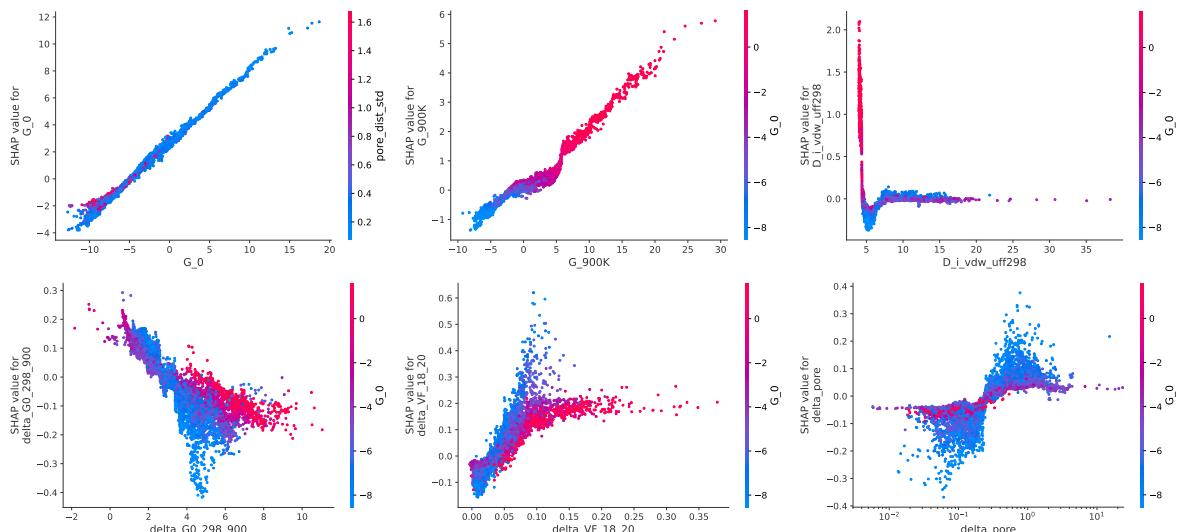
To make a global interpretation, I applied the partial dependence module provided by the SHAP library on our model. Although other methods to compute dependence plots exist (e.g. partial dependence plots),<sup>243</sup> we can keep a good level of consistency between our global and local interpretations by using the same underlying theory. The SHAP dependence plots of all the descriptors of the Figures S9 and S10, these plots have a rather distinct form, directions and shape, which is encouraging for the interpretability of our model. By looking at the profile of the dependence plots, I extracted valuable information on how the ML model predicts the ambient-pressure selectivity.

The most important descriptor is obviously the exchange free energy "G\_0" associated to the low-pressure selectivity, its contribution has a very strong positive linear correlation (see Figure 4.13), which gives a base value on top of which the other contributions will either reduce the free energy (more selective) or increase it (less selective). The model can be interpreted as the combination of a baseline combined with smaller tweaks that estimate the magnitude of the deviation from the ideal low dilution case. For instance, the next two descriptors "G\_900K" (900 K low-pressure exchange free energy) and "G\_Xe\_900K" (900 K low-pressure xenon adsorption free energy) continue to build up the baseline by providing information on the low-pressure selectivity, but they start giving a glimpse of deviations needed to differentiate between the structures experiencing a drop with the ones that keep their selectivity. As shown in the previous chapter (Figure 3.33 and 3.34), the thermodynamic quantities at high pressure is closer to the 900 K case than to the ambient temperature one, these two descriptors inform naturally on the selectivity at higher pressure. For "G\_900K" (see Figure 4.13), blue points (corresponding to a "G\_0" of around  $-8 \text{ kJ mol}^{-1}$ ) can have either negative or negligible contributions depending on the value; values below  $-4 \text{ kJ mol}^{-1}$  give a negative contribution with a linear relation, whereas values between  $-4$  and  $5 \text{ kJ mol}^{-1}$  give constantly almost zero contributions. This type of domain differentiation illustrates how the model can identify structures with a selectivity drop based on the values of a descriptor. I will introduce more telling examples of how the contribution to the selectivity values are determined using the values of the remaining descriptors.

The U-shape of some SHAP dependence plots can highlight optimal values for the associated descriptors. For instance, the optimal value of "D\_i\_vdw\_uff298" is around 5.1 (see Figure 4.13) and the optimal average of pore sizes is around 5.6. These optimal values match with the physical need of having pores of the size of a xenon to be more attractive to it, which was identified in several papers in the literature. These values are a bit higher than the ones mentioned in the literature due to the different definition of the atom radii.<sup>51</sup> Moreover, values of "delta\_G0\_298\_900" between 4 and  $6 \text{ kJ mol}^{-1}$  (see Figure 4.13) have a higher chance of giving a negative contribution, which means a lower ambient-pressure selectivity. These sweet spots constitute valuable hints to tell the truly selective materials from the others. Some SHAP dependence plots have a rather linear domain for the most selective structures (in blue) – the difference of pore volumes between Xe and Kr sized probes "delta\_VF\_18\_20" have a good linear contribution (see Figure 4.13), which means that a lower void fraction difference would imply a more selective structure. The same can be said for the standard deviations of the PSD "pore\_dist\_std" and of the Boltzmann weighted krypton interaction energies distribution "enthalpy\_std\_krypton". The optimal values for these descriptors are zero, the closest the value

gets to zero and the more negative the contribution will be, which means a more selective structure at ambient pressure.

Sometimes the optimal values are not around well-identified values but are contained within larger domains with threshold values separating them. For instance, the difference between the LCD and the average pore size "delta\_pore" has a threshold value around 0.3 Å below which the contribution for the most selective structures (blue) is negative (see Figure 4.13); even though no clear correlations can be found, we can at least find a threshold value (about 0.23) below which there is higher probability of having a high ambient-pressure selectivity. The same type of domain splits can be found for the average of krypton interaction energies distribution "mean\_grid\_krypton" (at around 15), the Boltzmann weighted xenon interaction energies distribution "enthalpy\_std\_xenon" (at around 2.5), the difference of exchange entropic term between the ambient temperature "delta\_TS0\_298\_900" (at around 3) and high temperature and the effective number associated to the PSD "pore\_dist\_neff" (at around 2.3). These domains separate structures that are selective at low pressure, which is key to telling apart the structures with a selectivity drop at ambient pressure from the ones without.



*Figure 4.13: Some relevant SHAP dependence plots that are given here. A SHAP dependence plot corresponds to the Shapley values as a function of the feature values for every structures. These SHAP plots show the contribution of the features to the prediction given by the ML model. Each Shapley value depends not only on the value of the feature itself but also on the other features, for this reason, the plots are labeled by a relevant second feature.*

### 4.3.2 Local interpretability

To put into practice our previous analysis, let's look at some archetypal structures and how the model predicted the selectivity based on the descriptor values. I chose two MOF structures from the test set, their CSD code being respectively VIWMIZ and BIMDIL. Both structures are selective at low pressure but the first one decreases in selectivity while the other maintains it at ambient pressure. It will be interesting to see what the model does to tell apart these two completely different behaviors.

VIWMIZ is part of the highly selective structures that experience a selectivity drop at ambient pressure. If I convert back the free energy values to selectivity values, its selectivity is 62.8 at

infinite dilution and 14.5 at ambient pressure. The ML model manages to give a close prediction of 12.0 for the ambient-pressure selectivity based on the given values of the descriptors. If we only look at "G\_0", it has one of the most negative values, which explains the rather high negative contribution of -1.81. However, the -0.57 contribution of "G\_900K" is rather low compared to other materials (see Figure 4.13), since a value of -4.05 is not the most negative considering all structures. On the other hand, the remaining descriptors have values in the domain of positive contributions, which lead to the drop of the selectivity. For example, the difference of pore sizes "delta\_pore" has a value of 1.38 Å (above the threshold of 0.23 Å), which contributes +0.25 to the predicted selectivity and is consistent with the value ranges of the associated dependence plot. By reporting the values to the dependence plots, the same analyses can be made on the other positive contributions of the Figure 4.14: "pore\_dist\_std" is above the threshold of 0.4, "enthalpy\_std\_krypton" is above 2.5 kJ mol<sup>-1</sup>, "pore\_dist\_neff" is above 2.3, "delta\_TS0\_298\_900" is below 3 kJ mol<sup>-1</sup> and "enthalpy\_modality" is around 0.75 where positive contributions are more commonly observed. However, the "delta\_G0\_298\_900" value is a bit too close to its optimal value, which explains its negative contribution in this particular prediction. The rest of the features have almost negligible contributions. By analyzing the contributions of each descriptor to the prediction given by our model, we can understand the underlying features of the VIWMIZ structure that explains the selectivity drop at higher pressure. The shape of the xenon and krypton energy distributions ("enthalpy\_std\_krypton" and "enthalpy\_modality") and of the PSD ("pore\_dist\_std" and "pore\_dist\_neff") as well as the void fraction difference "delta\_pore" are key descriptors at the origin of the lower selectivity at ambient pressure compared to the ideal infinite dilution case. Intuitively, one can easily understand that effective number of pores exceeding 2 can mean the presence of different pore sizes, which is consistent with the presence of pores that are less attractive to the xenon and leads necessarily to less selectivity. The previous statement is also very much consistent with a high standard deviation of the PSD or the Boltzmann weighted krypton interaction energy distribution. One can also conceive that a much larger difference between the average pore size and the LCD could mean a high disparity in pore sizes that leads to the presence of larger pores more and more loaded as the pressure rises. The entropic term is, however, way more complex to interpret and opens unexplored ways of tackling the problem of selectivity drop at higher pressure unraveled by our previous study (chapter 2).

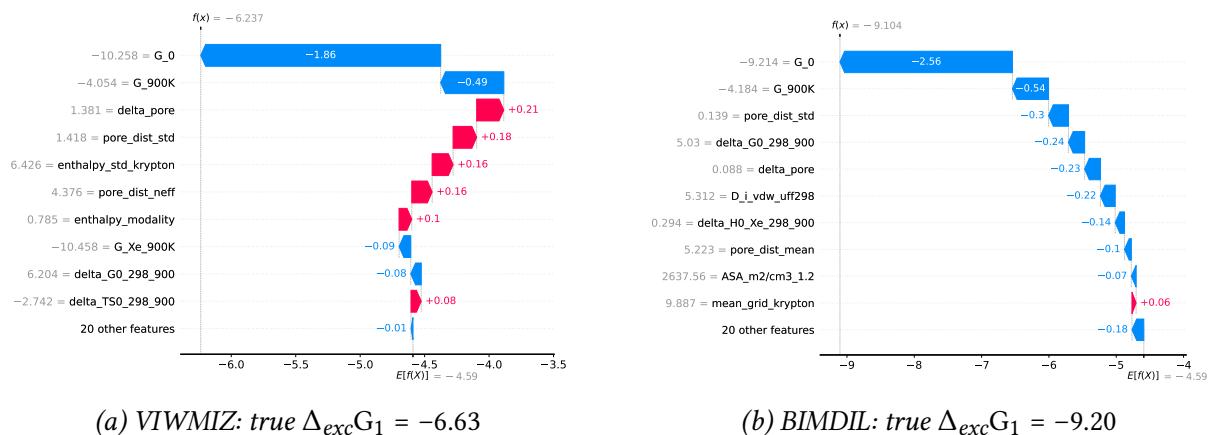


Figure 4.14: Main contributions of the descriptors on the selectivity prediction of two archetypal examples. The descriptor labels used are detailed in Table 4.2 and 4.3.

The second structure BIMDIL is also among the most selective with a selectivity at low pressure of 41.0, while maintaining it to 41.2 at ambient pressure. The model manages to predict this stability of the selectivity by giving a value of 40.0. Consequently, the first contribution of "G\_0" is among the most negative ones and set a baseline of -2.4 for the upcoming contributions. The contributions of "G\_900K" and "G\_900K" are not the highest possible but they continue to lower down the value of the predicted selectivity. It is the joint contributions of the other descriptors that will really discriminate between the two structures and decide why this one will keep its selectivity. Unlike the previously analyzed structure, this one has a "delta\_pore" value below 0.3 Å, which explains the negative Shapley value it has for our prediction. The contribution of "delta\_G0\_298\_900" that was only a little negative for the other one, is now playing a major role since it is right within the range of between 4 and 6 kJ mol<sup>-1</sup> (see Figure 4.14). We can also verify that "pore\_dist\_std" is now below the threshold instead of being above for the other structure. We can confirm that the other contributions are also following the rules implied by the SHAP dependence plots, no apparent anomalies are detected, and the joint efforts of all the descriptors tend to give a lower free energy value, which leads to the conservation of the selectivity value at higher pressure. The set of descriptor values is clearly very different from the previous structure, many values are in opposite contribution domains, which explains how the model manages to disentangle the highly selective structures to find out the ones that would keep their selectivity at higher pressure.

These two examples allow us to understand fairly more how the model tells apart the structures that will lose selectivity at higher pressure from the ones that will not. Most of the dependence plots can give very strong association between the descriptors and their effects; the outliers are rare enough that the inner logic of our model can be understood. As developed previously, the first three descriptors set a baseline on the observed selectivity drop with reasonably little information; then the other descriptors contribution is either positive, negligible or negative depending on the domain of values the descriptor is in. For instance, the average pore size and the largest cavity diameter need to be around very specific values to maximize the chance of keeping the selectivity at higher pressure, which was highlighted by previous works that emphasize on the importance of pore sizes close to the size of xenon for Xe/Kr separation. The difference of entropy between the ambient temperature and 900 K is surprising descriptor that separates selective structures depending on whether its value is within a given range. The difference of void fraction occupied by xenon and krypton is also very interesting since it impacts the selectivity differently depending on whether it is highly selective or not, and the contribution is more or less proportional to its value. Different ways of measuring the disparity of the PSD and interaction energy distribution are key in sorting highly selective structures (in blue on the dependence plot Figure 4.13) between the ones maintaining their performance and the ones decreasing in selectivity. Among others, we can find the difference between the average pore size and the LCD, as well as the standard deviation of the PSD or of the Boltzmann weighted energy distribution that would behave very differently according to the domain in which the value lies. The SHAP dependence plots are very valuable reading grid to understand the mechanisms behind our ML model and more broadly to what it understood from the origins of Xe/Kr separation.

**Data Availability:** [\[create a repo github with the different models and data\]](#)

## 4.4 BEYOND THERMODYNAMIC CONSIDERATIONS

In order to better understand separation processes inside nanoporous materials, I performed a machine learning prediction of Xe/Kr ambient-pressure selectivity that is faster than standard GCMC calculations. For MOF structures of the CoRE MOF 2019 database, a xenon/krypton selectivity evaluation would take less than a minute, while an equivalent GCMC calculation takes around 40 min. Unlike most of the selectivity predictions of the literature, I chose to predict a selectivity in the logarithmic scale, because it focuses more on the order magnitude than the exact value of the selectivity of highly selective materials. Moreover, the conversion to an exchange Gibbs free energy allows a more thermodynamic approach based on enthalpy, entropy and free energy values. The challenge was then to predict a free energy equivalent of the ambient-pressure selectivity by using the low-pressure selectivity along with key energy, geometrical and chemical descriptors. The final, fully optimized ML model performs very well with an RMSE of  $0.36 \text{ kJ mol}^{-1}$ , which corresponds to a 0.06 RMSE on the base-10 log of the selectivity.

One of our more specific goals was to uncover underlying reasons of a selectivity drop at high pressure observed on some highly selective materials at low pressure. Previous studies (chapter 2) found that a high diversity of pore sizes and channel sizes that favor adsorbate reorganizations could be at the origin of this phenomenon. By applying interpretability tools, I found quantitative factors that explain the conservation or the drop of the selectivity for highly selective materials. Depending on energy averaging at 900 K, on statistical characterizations of the energy or pore size distributions, and on the difference of volumes occupiable, a structure can either exhibit a selectivity similar to the infinite dilution case or that is much lower at higher pressure. All the quantitative rules are contained in a complex ensemble of decision trees constructed by our XGBoost model, and they can be extracted to build rule of thumbs in order to back our intuition on the Xe/Kr selectivity in MOF structures.

The final ML model can be used in a well-designed workflow to find the best performing materials. For instance, we could filter out the structures with pores that cannot fit a xenon in, then we could use a first calculation of the low-pressure selectivity to filter out the selectivity below a given threshold. Finally, we can use the model to remove the structures that would experience a selectivity drop. I tested our methodology on the Xe/Kr separation as proof of concept since it is one of the simplest adsorption systems (monoatomic species with no electrostatic interactions). A similar approach can be generalized to other separation applications by calculating the infinite dilution energies with a more standard method (e.g. Widom's insertion) and by adjusting the descriptor definitions to fit the adsorbates of interest.

This study ambitions to add new descriptor ideas to help the development of ever more efficient screening methodologies to find the best materials for target applications. However, like many other studies on the topic, this one also relies on a few strong assumptions — the simulations are performed in rigid frameworks with non-polarized classical force fields. As suggested in the literature, the most selective materials ever synthesized for Xe/Kr separation are all based on the effect of open-metal sites that uses the difference of polarizability between the two molecules to efficiently separate them.<sup>7,8</sup> Moreover, the structures can be made flexible using flexible force fields with adapted simulation methodologies<sup>268</sup> or by using multiple rigid simulations of snapshots from NPT simulations.<sup>162</sup> It would be possible to improve the simulations at the cost

of CPU times, if we coupled it with a reduction of simulation time like the one presented in this chapter. The quest of ever-faster evaluation tools will allow us to investigate more complex properties and uncover structures with ever more interesting characteristics. These potential improvements will be discussed more in depth in the chapter 6.

In the next chapter, I will focus on another shortcoming of the simple thermodynamic approach which is the consideration of kinetic limitations in the screening process. In our problem of adsorbent-material separation, the transport effect is not key in evaluating the separation performance of the material but is rather a constraint that could alter the performance of some seemingly top materials. Different methodologies will be explored in order to incorporate these computationally expensive and experimentally hard to get transport properties.





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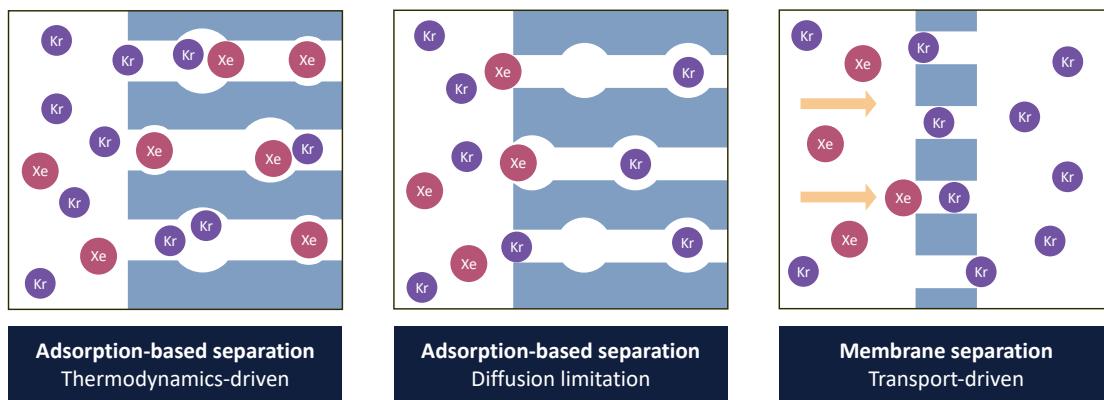
# XENON AND KRYPTON TRANSPORT PROPERTIES

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In separation processes, diffusion can either be the main performance metric or a neglected secondary parameter. There are actually two different use cases for separation using nanoporous materials: the adsorption-based separation that is mainly a thermodynamic process and the nanoporous separation membranes that relies on the kinetic properties. In a membrane-based process, the gas is sieved through a membrane material that blocks some molecules (e.g. Xe) and let other molecules (e.g.) diffuse freely. The performance of the separation is measured with the ratio of the diffusion coefficients instead of the thermodynamic selectivity  $I$  defined in chapter 2. The process of interest is, however, the adsorption-based separation performed industrially by pressure and/or temperature swing adsorption, and even if the thermodynamic selectivity is the main performance metric, the kinetic performances can improve the overall industrial process.<sup>20</sup> For instance, in breakthrough experiments (a lab equivalent of a pressure swing adsorption) used to characterize the comparative adsorption performances of a gas mixture, the shape of the curve can be explained by diffusion processes. The goal of this chapter is to explore this often neglected diffusion parameter in an adsorption-based Xe/Kr separation process.



*Figure 5.1: Illustration of the comparative role of the thermodynamic and transport properties for Xe/Kr separation in nanoporous materials. From the transport dominated process of membrane separation to the thermodynamically equilibrated separation processes in the nanopores, different more nuanced cases could emerge where the diffusion imposes kinetic limitations.*

## 5.1 MODELING THE DIFFUSION PROCESS

Since the pollen motion observations of the botanist Brown in 1826, scientists have observed and studied the seemingly erratic movement of particles in a static bulk medium. Later, Fick proposed a macroscopic model of this so-called Brownian motion by introduced the coefficient  $D$  of a diffusion equation 5.1 (1D) based on experimental measures of the concentration  $\phi$ .<sup>269</sup> According to this law (valid only for independent particles), at the macroscopic level, the particles tend to move from the most concentrated area of the bulk to the less concentrated one.

$$\frac{\partial \phi}{\partial t} = D_x \frac{\partial^2 \phi}{\partial x^2} \quad (5.1)$$

To better understand the Brownian motion of suspended particles on a liquid Einstein derived a microscopic model of the diffusion motion based on the molecular-kinetic theory of heat on the miraculous year of 1905.<sup>270</sup> To determine the so-called self-diffusion coefficient (in the following development I will use “diffusion coefficient” for short), he followed the motion of a particle assumed independent of other particles and time steps large enough to consider mutually independent two consecutive motions. By using the particle distribution of  $N$  independent diffusing particle, he redefined the diffusion coefficient as a function of the mean squared displacement (MSD) of a particle. In a tridimensional space, we have the following Einstein relation:

$$\langle r(t)^2 \rangle = 2dD_{\text{diff}}t = 6D_{\text{diff}}t \quad (5.2)$$

where  $d$  is the dimension of the space in which the particle diffuses ( $d = 3$  in a volume) and  $r(t)$  is the displacement of a particle from the time 0 to  $t$ . The brackets represent the average over all independent trajectories (different particles and different time origins). This equation can be generalized to the diffusion of an adsorbate in the adsorbed phase, which describes how easy it is for a particle to move inside a nanoporous material. A low diffusion coefficient means limited access to the pores of the structure as illustrated on Figure 5.1.

Using molecular simulations of the adsorbate displacements, I will try to model the diffusion coefficient of xenon and krypton inside a nanoporous material. Although other approaches like the Green-Kubo equation exist the relatively less complex Einstein law is preferred for self-diffusion calculations, as shown by the following comparative study [271]. In this section, I will focus on the different simulation techniques that can be used to evaluate the diffusion in high-throughput screenings. I will try to present different ways of accessing the MSD of a diffusing particles, by beginning from the most straight-forward molecular dynamics to faster methodologies more suitable in screenings such as machine learned surrogate models and kinetic Monte Carlo simulations.

### 5.1.1 Molecular dynamics

Molecular dynamics are used to simulate the motion of molecules in a given system. It is usually used to calculate thermodynamic averaging by using a hypothesis on the equivalence between the time averaging and ensemble averaging (ergodic hypothesis); in other system configurations, we can determine mechanical properties, thermodynamic properties or chemical properties. But here, I am more interested in the calculation of diffusion coefficients of monoatomic molecules, and the discussion will be driven toward averaging trajectories to obtain MSD values.

#### SIMULATION DETAILS

Molecular dynamics (MD) aims at describing the motion of particles subjected to the forces of the surrounding particles. It can therefore be seen as a complex integration of the Newton's law of motion. A particle  $i$  of position  $\mathbf{r}_i$  and mass  $m_i$  subjected to a force  $\mathbf{F}_i$  resulting of the cumulated interactions with its surrounding is accelerated according to this equation:

$$m_i \frac{d^2 \mathbf{r}_i}{dt^2} = \mathbf{F}_i \quad (5.3)$$

In a classical modeling, the forces are determined using the well-named forcefield that was previously introduced in the chapter 2. Back there, I only considered intermolecular interactions simply modeled by the Lennard-Jones (LJ) interaction potential between atom pairs, which is also what I will use in this section (of course, it is not the only way of defining a forcefield but just a simplification). Using the LJ potentials  $U_{ij}^{LJ}$  (defined in equation 2.4), we can derive a vectorial force  $\mathbf{f}_{ij}$  between two atoms  $i$  and  $j$ .

$$\mathbf{f}_{ij} = - \left. \frac{dU_{ij}^{LJ}}{dr} \right|_{r=r_{ij}} \frac{\mathbf{r}_{ij}}{r_{ij}} = 24\epsilon_{ij} \left( 2 \left( \frac{\sigma_{ij}}{r_{ij}} \right)^{12} - \left( \frac{\sigma_{ij}}{r_{ij}} \right)^6 \right) \frac{\mathbf{r}_{ij}}{r_{ij}^2} \quad (5.4)$$

where  $\epsilon_{ij}$  and  $\sigma_{ij}$  are the LJ parameters of the pair of atoms  $ij$ . And the resulting force is simply the sum of the forces  $\mathbf{F}_i = \sum_j \mathbf{f}_{ij}$  exerted by the surrounding atoms  $j$ . To reduce the computation time required, molecular simulations only consider the atoms within a given cutoff radius.

Now that we defined the force  $\mathbf{F}_i$ , we can put a molecule in motion by integrating the equation 5.3 from a time  $t$  to a time  $t + \delta t$ . There are different methods to integrate equation of motion such as the Euler or velocity-Verlet scheme presented in the book of Frenkel et al. [272]. Here, I will focus on the *leap frop* integration implemented in the RASPA2<sup>205</sup> software that

I used for our simulations. The position  $\mathbf{r}_i$  and the velocity  $\dot{\mathbf{r}}_i$  are between each time step  $\delta t$  using the following equations:

$$\begin{aligned}\dot{\mathbf{r}}_i(t + \frac{1}{2}\delta t) &= \dot{\mathbf{r}}_i(t - \frac{1}{2}\delta t) + \frac{1}{m_i} \mathbf{f}_i \\ \mathbf{r}_i(t + \delta t) &= \mathbf{r}_i(t) + \dot{\mathbf{r}}_i(t + \frac{1}{2}\delta t) \delta t\end{aligned}\quad (5.5)$$

From the initial conditions  $(\mathbf{r}_i(0), \dot{\mathbf{r}}_i(0.5\delta t))$ , we can translate the center of mass of the molecule  $i$  to any position  $\mathbf{r}_i(t_n = n * \delta t)$ . I will skip the rotation step required for polyatomic molecules since the study is restricted to the monoatomic noble gas. The different positions  $\{(t_n, \mathbf{r}_i(t_n))\}_{n=0, \dots, N_{\text{tot}}}$  constitute the total trajectory of the MD simulation (to simplify I do not mention the velocities). It is possible to use this total trajectory to derive an average of MSD that could be analyzed to calculate the diffusion coefficient.

### DIFFUSIVITY CALCULATION USING AN MD TRAJECTORY

I used the MSD sampling technique implemented in RASPA2<sup>205</sup> that was presented in an article [273] by a few authors of the adsorption simulation software. The approach is based on a modified approach of the order-n algorithm described in the book [274] of Frenkel and Smit. Therefore, I will focus on the so-called multiple-window algorithm used to calculate the diffusion coefficients of xenon and krypton in this chapter.

To understand it, I will start by explaining what a window algorithm would do and how it generalizes to the multiple-window algorithm. First, let us consider a single MD trajectory of duration  $t_{\text{tot}} = N_{\text{tot}}\delta t$ . This trajectory can be used to generate displacement of any size  $\tau$ . Naively, we can start by taking  $\|\mathbf{r}_i(\tau) - \mathbf{r}_i(0)\|^2$  as a square displacement of a sub-trajectory  $\mathcal{T}(0 \rightarrow \tau)$  of duration  $\tau$ . However, it is not enough to make a statistically meaningful average of the MSD as described in the Einstein equation 5.2. Using the hypothesis of independence between two movements of the same particle separated by a time  $\delta t$  used in Einstein's paper [270], a shift of the origin of time by  $\delta t$  would generate another trajectory. We can repeat this process  $i$  times while  $\tau + i\delta t \leq t_{\text{tot}}$ . This would be very accurate, but also very inefficient in the case where  $\tau \gg \delta t$  since two consecutive sub-trajectories  $\mathcal{T}(i\delta t \rightarrow \tau + i\delta t)$  and  $\mathcal{T}((i+1)\delta t \rightarrow \tau + (i+1)\delta t)$  would be very similar.

To efficiently sample the trajectory into sub-trajectories that are independent we can use a sampling time step of  $\delta\tau \lesssim \tau$  chosen to be in the same order of magnitude as  $\tau$ . To achieve this, the window approach would first define a value  $\delta\tau$  and generate  $N_\tau = \lfloor (t_{\text{tot}} - \tau)/\delta\tau \rfloor$  different sub-trajectories  $\{\mathcal{T}(0 \rightarrow \tau), \mathcal{T}(\delta\tau \rightarrow \tau + \delta\tau), \dots, \mathcal{T}(N_\tau\delta\tau \rightarrow \tau + N_\tau\delta\tau)\}$  of duration  $\tau = k\delta\tau$ , where  $k$  is an integer between 1 and  $K$  that defines the time window we want to sample. By doing so, we get the MSD  $\langle r(\tau)^2 \rangle$  for duration values  $\tau$  equal to  $\delta\tau, \dots, K\delta\tau$ . The relation  $\langle r(\tau)^2 \rangle$  can then be fitted to the equation 5.2 to obtain the diffusion coefficient if the relation is linear. The trajectory generation of the window approach is illustrated on Figure 5.2 for a decomposition into sub-trajectories of a duration  $\tau = 3\delta\tau$  shifted by  $\delta\tau$ .

The major drawback of this method is that we need to define a timescale  $\{\delta\tau, \dots, K\delta\tau\}$  beforehand. In order to be able to access the different timescales in a single simulation, we can perform a multiple-window algorithm developed by Dubbeldam et al. and used in the RASPA2 software to compute mean squared displacements (MSD) in a molecular dynamics simulation.

The different time windows are defined in a recursive way using the default parameters of RASPA2. The first time window is defined by  $K = 25$  displacements of duration  $\delta t, 2\delta t, \dots, (K -$

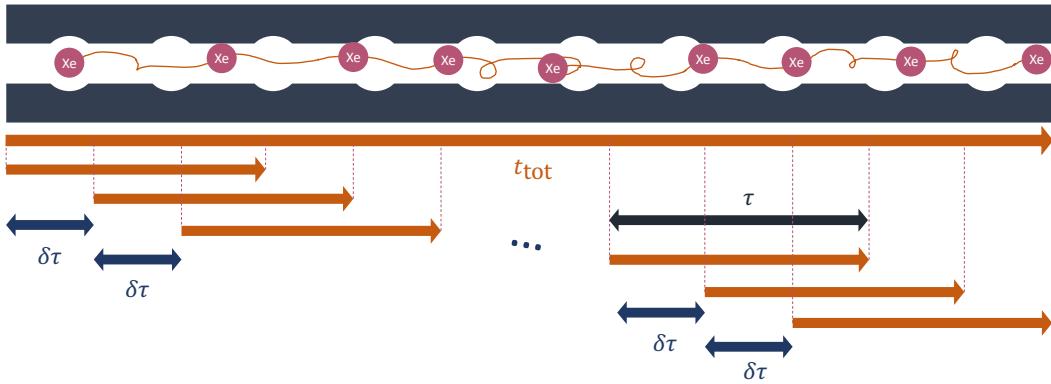


Figure 5.2: Illustration of the generation of trajectories of size  $\tau$  by shifting the origins of multiple durations  $\delta\tau$ .

$1)\delta t$  with a shift of  $\delta t$  (the default shift value  $\delta t$  of the first window can be changed with the parameter “SampleMSDEvery”). The second window is now based on a sampling time  $\delta\tau_1 = K\delta t$  and the sub-trajectories will have durations of  $(\tau_1^{(1)} = \delta\tau_1), \dots, (\tau_1^{(K-1)} = (K-1)\delta\tau_1)$ . We, then, repeat the process recursively, and the  $i_{\text{th}}$  window would have a sampling time of  $\delta\tau_i = K^i\delta t$  and sub-trajectories durations of  $(\tau_i^{(1)} = \delta\tau_i), \dots, (\tau_i^{(K-1)} = (K-1)\delta\tau_i)$ , for each of them a window algorithm similar to the one described above is applied. The algorithm stops when no window can be generated anymore, when  $\tau_n^{(k)} > t_{\text{tot}}$  with  $n$  being the index of the window and  $k$  the index in the single-window algorithm that defines the time we want to sample with regard to a sampling time  $\delta\tau_i$ . The timescale  $\delta\tau_i = K^i\delta t$  we sample follows a geometrical progression and very different timescales can be accessed using this method in order to find the timescale corresponding to the diffusion regime (linear relation between the MSD and the duration of the sub-trajectories used in the averaging). For example on Figure 5.5, we can see the different timescales and the exponent value  $b$  of a fit to a function of type  $x \mapsto ax^b$  for the different time windows – values of  $b$  near 1 can be associated to a diffusion regime. The determination of the diffusion coefficient is now reduced to a simple fitting problem that will be explained in more details in the presentation of the diffusion coefficient screening in section 5.2.

This methodology can then be used replicated to thousands of structures to characterize the diffusion properties of these materials. Several screenings have already been carried out in the literature as presented in the chapter 1 in the section dedicated to transport property screenings. I will now dive a little deeper in the prediction of these quantities using machine learning.

### ML MODELING

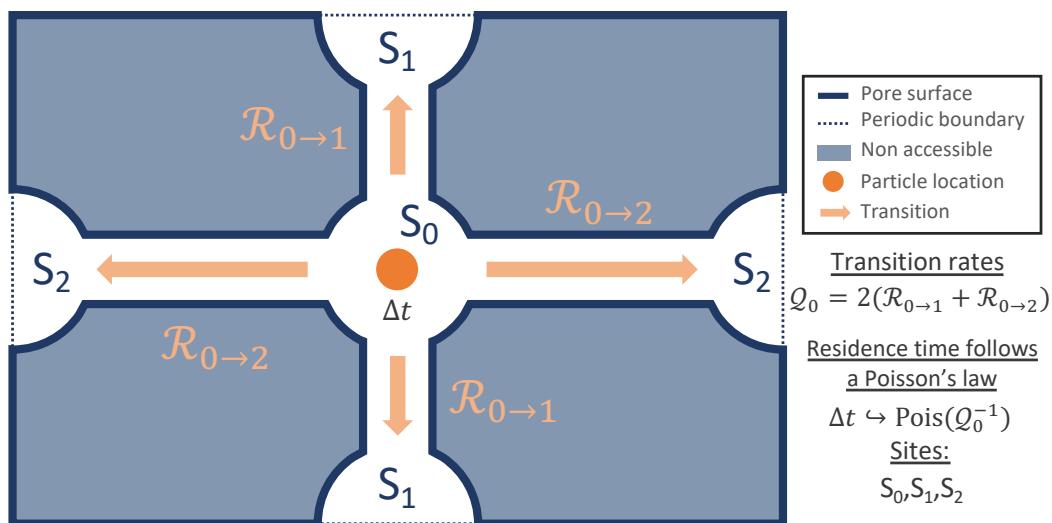
In a very recent study, Daglar et al. used an ML model to predict the diffusion coefficient of a 100 thousand hypothetical MOFs using the data for about 5000 CoRE MOF structures.<sup>275</sup> Along with very standard geometrical descriptors, they used chemical composition descriptors and the heat of adsorption as the input features of their machine learning model to predict the diffusion coefficients of H<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub> and He in the different MOF materials of CoRE MOF 2019 (training) and of hMOF (testing). The combination of kinetic data with thermodynamic data for the characterization of MOF materials is a very interesting approach. However, the

major drawback of most of the approaches in the literature is the lack of structure–property relationship to understand the microscopic origins of the diffusion coefficient values.

Similarly to what I have done on the thermodynamic screening (chapter 2–4), in our approach to transport property screening, I will also start by drawing structure–property relationships between the diffusion coefficient and the geometrical descriptors of the MOF structures. And in an attempt to have a deeper understanding of the diffusion process, I will try to evaluate the diffusion activation energy using energy grid-based methods described in the literature. All these techniques aim at better predicting the diffusion coefficients either in a direct calculation or in an ML surrogate model. To achieve that, I will start by introducing the kinetic Monte Carlo approach that is less accurate than the MD approach but is indeed much more efficient.

### 5.1.2 Lattice kinetic Monte Carlo

The lattice kinetic Monte Carlo method relies on a pre-defined lattice of stable points corresponding to adsorption sites. Each site connected to another if there is a diffusion path (narrow channel) that connects them. To calculate the probability of transition from one site to another, I need to define a transition state (TS) in the narrow channel which correspond to the highest energy point on the minimal energy diffusion path (the saddle point). The probability of transition would therefore be defined with regard to the energy barrier to overcome in order to cross the channel. Once the lattice defined, we only need to propagate an adsorbate from one site to another using the different transition probabilities, which gives a coarse-grained trajectory compared to the one obtained in an MD simulation, but is perfectly usable to compute the MSD and calculate a diffusion coefficient.



*Figure 5.3: Illustration of the core principle of lattice kinetic Monte Carlo in a periodic system. The particle moves inside the periodic system according to the transition probabilities to move from one site to another. The transition rates are determined using the activation energy needed to move to the transition state between the two stable adsorption sites as shown in equations 5.6 and 5.7.*

### TRANSITION STATE THEORY FOR DIFFUSION

The transition state theory is usually used in chemistry to explain the kinetics of a reaction. To achieve this it compares the energy of the reactants before reacting and the one of the transition state to calculate the rate of the reaction. This reaction rate along a reaction path is proportional to the ratio of the Boltzmann factor at the transition state and the integration of the Boltzmann factors along the reaction path.

This definition can be directly transposed to the case of a diffusion path instead of a reaction path, and we can define the diffusion rate  $\mathcal{R}_{0 \rightarrow 1}$  from site 0 to 1 as follows:

$$\mathcal{R}_{0 \rightarrow 1} = \kappa \sqrt{\frac{k_B T}{2\pi m}} \frac{e^{-\beta E(\mathbf{r}^{TS})/k_B T}}{\int_{\text{path}} e^{-\beta E(\mathbf{r})/k_B T} d\mathbf{r}} \quad (5.6)$$

where  $\kappa$  is the Bennet-Chandler dynamic correction factor,<sup>276</sup> and  $\kappa = \frac{1}{2}$  if it is equiprobable to reach both sites from the transition state. This approach calls for the determination of the optimal diffusion path before carrying out the determination for the diffusion rate. For instance, Wang et al. adopted this approach in their screening for noble gas separation, where they determined the minimal energy path before calculating diffusion rates.<sup>277</sup>

Another approach is to determine a surface of transition through which the adsorbate would pass to diffuse along the channel of the material. This approach calls for the determination of the surface of transition only, but it relies on another definition of the transition rate  $\mathcal{R}_{0 \rightarrow 1}$ :

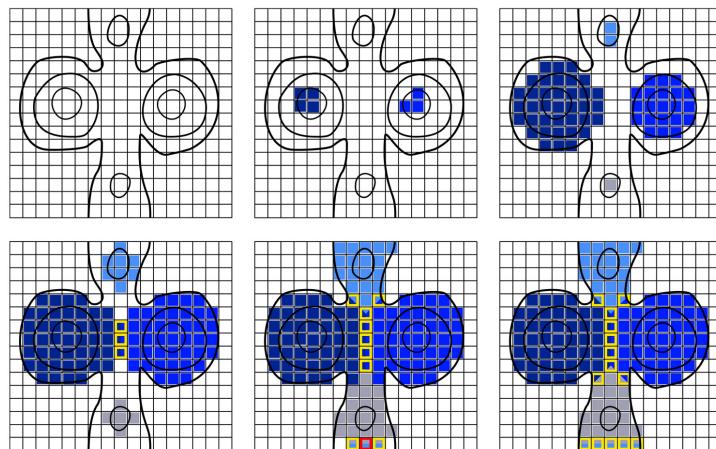
$$\mathcal{R}_{0 \rightarrow 1} = \kappa \sqrt{\frac{k_B T}{2\pi m}} \frac{\int_{S(TS)} e^{-\beta E(\mathbf{r})/k_B T} d\mathbf{r}}{\int_{V(S_0)} e^{-\beta E(\mathbf{r})/k_B T} d\mathbf{r}} \quad (5.7)$$

where the integration for the transition state is done on a bottleneck surface that a diffusing particle need to cross in order to go from the volume occupied by a site 0 to the one occupied by 1.

### TuTrast Algorithm for Kinetic MC

In this section, I will focus on the second approach that relies on the determination of a transition state as a surface. This approach has been developed by Mace et al.<sup>129</sup> and relies on detecting the merging points between basins representing the adsorption pores. The algorithm developed is called TuTrast, which stand for Tunnels and Transition States. It is a search algorithm that aims at finding the tunnels and the transition states that separate different adsorption “basins” within them. Once the adsorption sites, the transition states and the tunnels that connect them are found, we can calculate the hopping rates between the stable adsorption sites using the equation 5.7. Finally, a lattice kinetic Monte Carlo simulation can be used to move particles within simplified hopping diffusion system to determine the MSD and eventually the diffusion coefficient.

In practice, we need to calculate an energy grid that will be used to detect all the different components of lattice. The algorithm iterates over different energy values from  $E_{\min} + \delta E, \dots, E_{\min} + N\delta E$  so that the maximum energy is below an energy cutoff we fixed at the start  $E_{\min} + N\delta E < E_{\text{cutoff}}$ . At the initial step, the clusters of grid points with an energy below  $E_{\min} + \delta E$  are formed naturally depending on whether they are connected or not. Then, at an iteration level L, the previous clusters found at iteration L - 1 are grown layer by layer



*Figure 5.4: Illustration of the cluster growth and the identification of boundary points in the TuTraST algorithm.<sup>129</sup> The clusters are grown from left to right and top to bottom. A tunnel is detected when the points are connected all the way from one periodic boundary to another (red). The boundary points assigned to the TS surface are indicated in yellow. Reprinted with permission from the original paper [129] copyright © 2019 American Chemical Society.*

(one layer corresponds to the immediate neighbors on the grid), as shown on Figure 5.4. If the layer touches another cluster, then a boundary point is identified — it is only accepted if the energy difference between minimum energy of the two touching basins and the boundary point value is high enough, else the barrier is negligible, and the basins are merged. At the end, the boundary values will be clustered and assigned as the transition surface between different pairs of adsorption basins. If the points of basins and boundary surfaces are connected all through, then we can define a tunnel in which diffusion can occur. Finally, when we iterated enough steps, and tunnels with different basins separated by transition state surfaces are defined. We can now run a kinetic Monte Carlo to determine the diffusion coefficient within each tunnel. The diffusion coefficient in the material will correspond to a weighted average of the diffusion coefficient in each tunnel, the weight simply corresponds to the probability of presence in each tunnel, which corresponds to the sum of the Boltzmann factors (proportional to the Henry coefficient in a given tunnel).

This approach is very promising since it is much more efficient than the MD simulation based techniques. With an implementation in Matlab (not very computationally efficient), the code is already out-performing most of the MD simulations for diffusion coefficient calculation, with a minimal cost in accuracy as shown in their screening of diffusion coefficients in zeolites. By using the C++ programming language, I tried to rewrite the algorithm for a more efficient search of the transition states. At this point of the development, I stopped at the determination of the diffusion activation energy which is independent of the detection of the transition state. And, in section 5.3, I will give the algorithmic detail for the determination of the diffusion activation energy in nanoporous materials using our in-house algorithm as well as the projected development to achieve a faster lattice kinetic Monte Carlo simulation inspired by the TuTraST algorithm.

## 5.2 SELF-DIFFUSION SCREENING

To complete the thermodynamic screenings that I performed in the chapters 2–4, I also carried out a transport property screening. In this section, I will provide a description of the screening approach as well as the analysis of the diffusion coefficients compared with typical geometrical descriptors.

### 5.2.1 Diffusion in a selective material

Before going into the details of the screening study, I will present the approach adopted for the diffusion coefficient calculation using MSD values, on one example, SMOF-1.<sup>41</sup> This preliminary study will help us calibrate the time parameters (time step, maximum time) that will be used in the final screening study.

First, I ran a molecular dynamics simulation of 500 million steps (about 1–2 days of simulation) with a thousand initialization steps and 100 thousand equilibration steps to model a xenon diffusing in the KAXQIL<sup>278</sup> MOF at infinite dilution. To be at infinite dilution, I set the box size so that no interactions occur between the different adsorbates. And as shown on Figure 5.5, there are different timescales at which different transport phenomena occur.

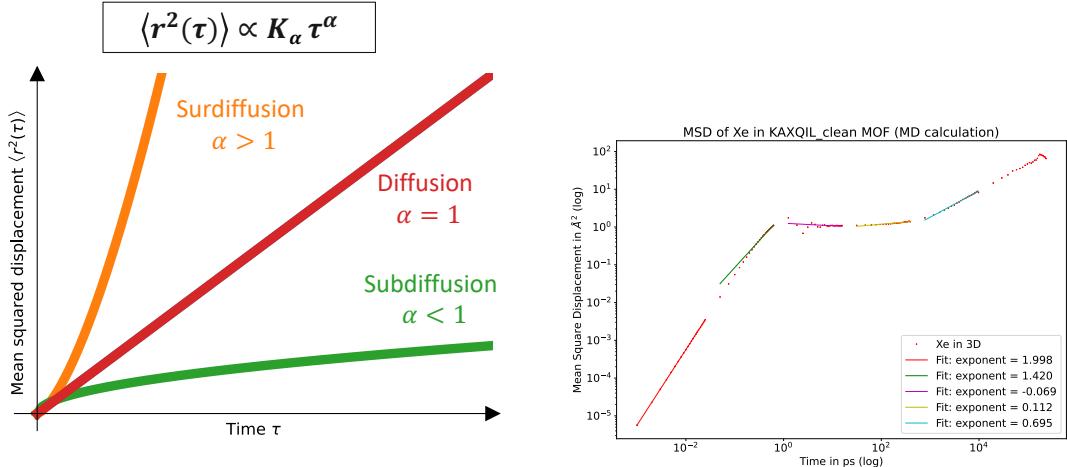
From 1 fs to 1 ps, there is a ballistic regime with a squared dependence of the mean squared displacement. For a particle of mass  $m$ , the MSD  $\langle r(\tau)^2 \rangle$  in this regime follows a simple ballistic relation (length equals velocity multiplied by time):

$$\langle r(\tau)^2 \rangle = v_m^2 \tau^2 = \frac{k_B T}{2\pi m} \tau^2 \quad (5.8)$$

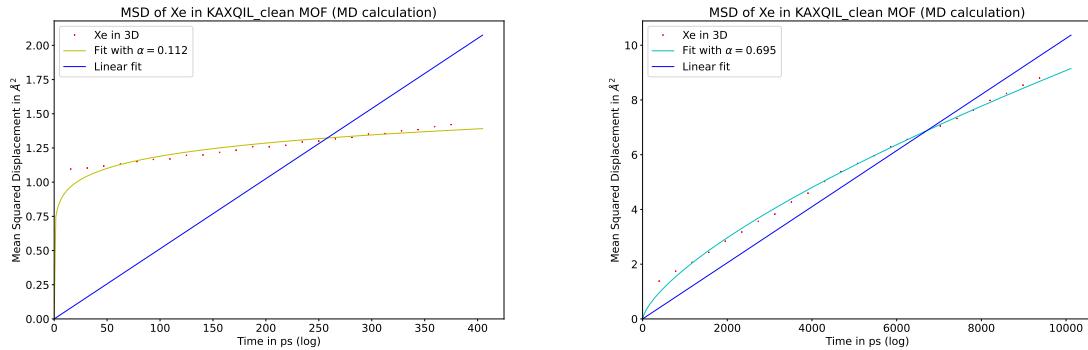
where  $v_m$  is the average velocity of a particle that follows the Maxwell-Boltzmann distribution at temperature  $T$ . If we calculate the squared mean velocity  $v_m^2$  using the standard Maxwell-Boltzmann relation, we get a value of  $3 \text{ m}^2 \text{ s}^{-2}$ , which is very close to the value of  $2.8 \text{ m}^2 \text{ s}^{-2}$  obtained by the fit shown right plot of Figure 5.5. This first regime simply corresponds to the movement of the particles subjected to the thermal agitation and is of little interest for diffusion.

Then, there is a transition from the ballistic regime to the pseudo-diffusional regime (the exponent does not reach 1 yet) that we observe in cyan on the plot. Between 1 ps and 100 ps, there is a so-called sub-diffusion regime, where the MSD has a power function of the time  $\langle r(\tau)^2 \rangle = K_\alpha \tau^\alpha$  with an exponent inferior to 1 as illustrated on the left plot of Figure 5.5. This regime corresponds to the confinement of the xenon particle inside an adsorption pore, there is only thermal vibration occurring and no diffusion hopping is observed at this timescale. And diffusion seems to start occurring at the 10 ns timescale. As shown on Figure 5.6, the MSD between 0.01 ns and 0.4 ns really represents a sub-diffusional regime due to the confinement imposed by the nanopores of KAXQIL, but at 0.4 ns–9 ns, the MSD start to have an exponent closer to 1 and a linear fit is possible although not perfect. Ideally, we would want to sample trajectories in the order of tens of nanoseconds, which is the next timescale. But with an MD time step of 1 fs, this would mean multiplying the computation time by at least 5 (1–2 weeks for one MD simulation), which begins to be prohibitive.

If we use the right plot of Figure 5.6 to fit a linear relation and deduct the diffusion coefficient, we can have an underestimated value of the diffusion coefficient of  $2.24 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$  – it is



*Figure 5.5: Left: Different regimes that could be observed in an MSD plot as a function of time. The ballistic regime can be considered super-diffusional, the normal diffusion is simply a linear relation as described in the Einstein equation 5.2, and the sub-diffusion regime often occurs in obstructed media like nanoporous materials. The different regimes can be found on the right plot of an actual MSD calculated using the multiple-window method. The fittings are done using a generic function  $K_\alpha \tau^\alpha$  and the exponents  $\alpha$  are given in the legend.*



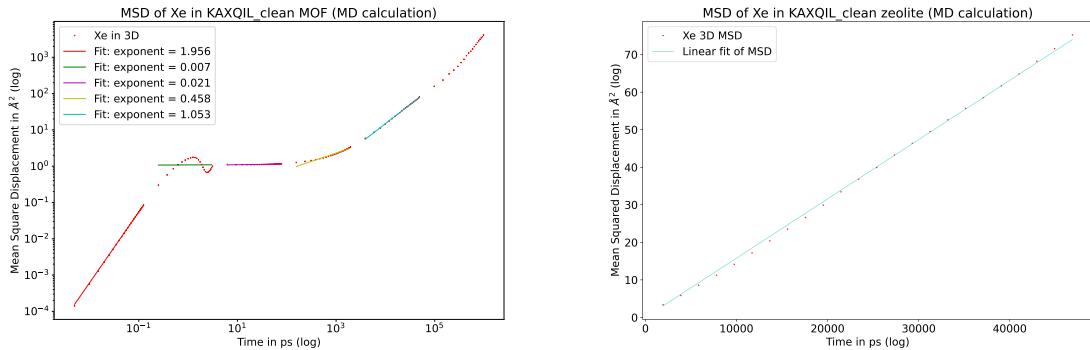
*Figure 5.6: Plots of the MSD at the last two timescales considered on Figure 5.5. On the left, the timescale between 0.01 ns and 0.4 ns is considered, the MSD is fitted by a power function with the same exponent as one determined earlier, and a linear fit is given to show the incompatibility with the diffusion equation. On the right, we have the same approach but for the timescale between 0.4 ns and 9 ns.*

an underestimation because the MSD is rather concave, which reduces the slope in the fitting process. This value is already a good estimation of the diffusion coefficient considering the rather high exponent  $\alpha$  value in the with regard to  $K_\alpha \tau^\alpha$ .

Since there is an element of randomness in the initial position of xenon (block pockets have been calculated for a 1.5 Å-radius probe), we need to measure the effect of running different MD simulations of the value of the diffusion coefficients. To measure this uncertainty across different MD simulations with different initial positions determined by with different random seed. In RASPA2, the random seed is simply equal to the UNIX time upon launching the MD simulation. This ensures that a different random seed is given to the 10 different MD

simulations we launched using the exact same parameters as mentioned previously. I found that the average diffusion coefficient value equals  $2.13 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$  and the standard deviation equals  $0.37 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$ , which represents about 17% of the average value. We could estimate the uncertainty to about 17% on the diffusion coefficient for a rather low coefficient around  $10^{-8} \text{ cm}^2 \text{ s}^{-1}$ , we could expect lower uncertainty for less obstructing materials.

Now that I have more confidence on the method, I will try to probe higher timescales than the one accessible with an MD time step of 1 fs, because the diffusion regime seems to be occurring rather at the 10 ns timescale. I ran a first calculation with 500 million steps to validate the diffusion coefficient value. The time window between 2 ns and 47 ns, and the MSD are calculated from about 200 sampled trajectories, which gives rather correct values. We can obtain a more accurate diffusion coefficient of  $2.6 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$ , which is very close to the one obtained in the previous approach. The value is slightly higher (which is expected) since the previous values was over-estimated. This approach is therefore consistent with the previous one.



*Figure 5.7: On the left, the MSD in log-log scale and a fit to the relation  $MSD(\tau) = K_\alpha \tau^\alpha$  using an MD simulation of a 5 fs-time step and 500 million steps. I find a better linear fit with this new configuration of the MD simulation than on Figure 5.5, because we explore more timescales using the same amount of computational resource. On the right, we can find the MSD on timescale of diffusion regime. The linear fit is better than on Figure 5.6.*

To further back-up the use of a higher time integration step, we need to understand the origin of the value of 1 fs. This value is usually justified by the Nyquist-Shannon sampling theorem that implies the integration step to be at most half of the period of the fastest vibration within the system. If we take a C–H vibration, the maximum time step value is 5 fs, and to be on the safe side, a time step of 1–2 fs is chosen in most of the diffusion studies in nanoporous materials.<sup>131</sup> But in our system of a xenon diffusing in a rigid environment, we actually don't have any vibrational limitations as described earlier. I think that the use of higher time steps in this situation can be an easy way to access higher timescales; however, further studies need to be performed to be sure of the validity of the quantities we derive from these MD simulations. The value of 5 fs is on the higher side of what we usually see in MD simulations, but it can be justified by the rigidity of the framework and the adsorbate we consider. Even higher time steps could be tested, but to be sure of the results I chose this reasonable middle ground of 5 fs for all our high-throughput screening of the transport properties.

## 5.2.2 High-throughput screening of diffusion coefficients

### SCREENING PROCEDURE

In order to include the transport properties in our analysis, I performed MD calculations of a xenon or krypton at infinite dilution (no guest–guest interactions) for the 6,525 non-disordered most selective materials. For each of them, 500 million steps of MD were planned in the RASPA2 script in the calculation machines and 2 to 3 restarts were done on the slowest simulations so that every MSD data were obtained after 2–3 days. After this process, only 432 structures have finished the planned 500 million steps, but it does not mean that the MSD is not exploitable for the determination of the diffusion coefficients.

To determine the diffusion coefficients I analyzed two timescales (2–47 ns and 50–950 ns) to fit the MSD with a linear function. I chose the linear fit with the highest determination coefficient (within 0 and 1) of both timescales to output a value of diffusion coefficient. After this step, I removed structures with a determination coefficient lower than 0.9 and used the 5,125 remaining structures to draw structure–diffusivity relationships — these structures for which I have a good degree of confidence on the diffusion coefficient values will be comparatively studied against different geometrical and thermodynamic quantities in this section

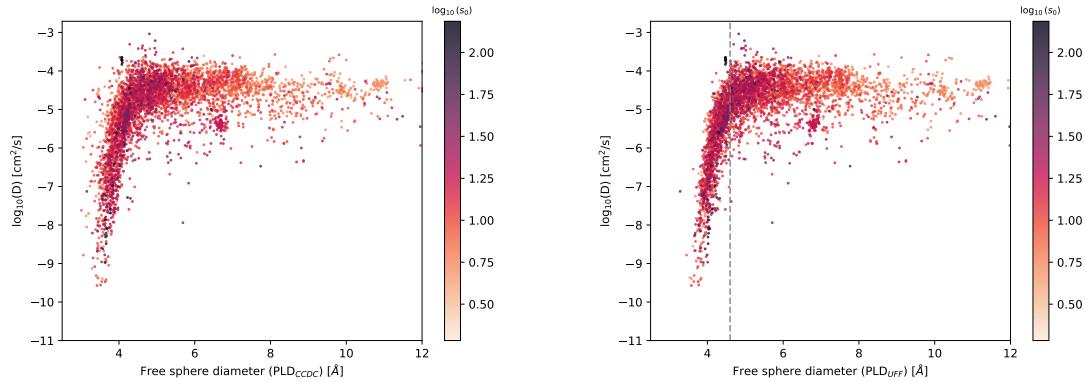
This approach only probes the linear relations between the MSD and time to determine the self-diffusion at infinite dilution. I did not analyze the nature of the transport property (e.g. single-file diffusion<sup>279</sup>) by comparing for example the exponent of a generalized formula  $MSD(\tau) = K_\alpha \tau^\alpha$  with structural descriptors. I did not study the more complex diffusion at higher loading values, which could be more accurately described by a collective diffusion coefficient instead of the self-diffusion coefficient. The goal of this study is to find materials that do not present a kinetic limitation as it is the case for KAXQIL<sup>278</sup> (xenon has a diffusion coefficient that is about ten thousand times lower in the material than outside).

### STRUCTURE–DIFFUSIVITY RELATIONSHIPS

In this section, I will present the different relations the diffusion coefficient may or may not have with the geometrical descriptors. I decided to use a forcefield-dependent definition of the radii so that it better correlates with the results of the MD simulation that uses the UFF forcefield. The different geometrical descriptors are then calculated using Zeo++ and these radii to calculate the PLD, the largest sphere diameter  $D_{if}$  along a free path, the surface area and the pore volume, as already explained in the chapter 2. To further justify the use of the UFF-based radii, the original paper [51] showed the better correlation of the PLD to the diffusion constant, and we can also see it from the Figure 5.8. The PLD calculated by the standard CCDC defined atom radii does not fit the diffusion coefficient as well as the UFF-defined PLD. As shown in a smaller scale in the article [127] (see Figure 1.6 in the chapter 1), there is a linear relation between the diffusion activation energy (logarithmic transform of the diffusion coefficient) and the PLD, and this linear relation is much more noisy for the PLD defined by the standard CCDC radii than for the UFF-based PLD.

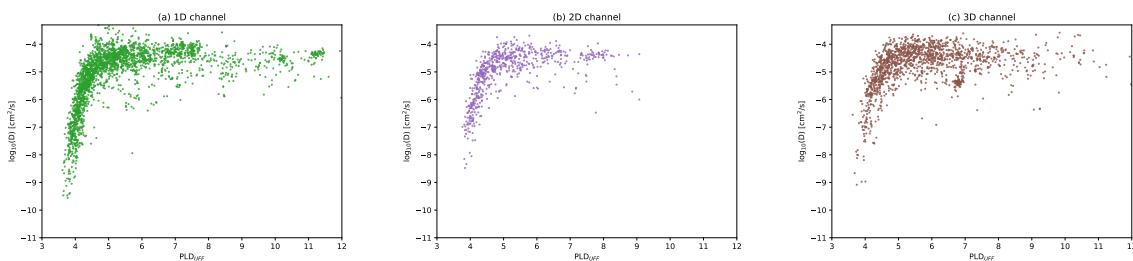
Beyond the practical considerations on the geometrical descriptor calculations, the PLD explains the outlines of the variation of diffusion performance inside a nanoporous material. First there is a linear relationship that was previously highlighted, and then there is a sort of noisy plateau. In the first zone, the xenon is constrained by channels narrower than its kinetic radius. The wider the channel the higher the diffusion coefficient is, and this positive correlation persists

until the channel is wider than about 4.6 Å. After this threshold, the diffusion coefficient is rather stable around  $3 \times 10^{-4} \text{ cm}^2 \text{ s}^{-1}$ , and the variations can only be explained by other phenomena such as the tortuosity inside nanopores or chemical nature of the surface of the nanopores. This value of diffusion coefficient can be interpreted as the diffusion coefficient of a “free” xenon that is less affected by the surrounding pore surface. The channels are large enough so that the xenon is only a little slowed down, for values of the PLD over 5 Å. These results are compatible with experimental data that measured the diffusion coefficient of xenon dissolved in water at different temperature conditions, and found a value of  $10^{-5} \text{ cm}^2 \text{ s}^{-1}$  at 303 K,<sup>280</sup> which is consistent with values centered around  $3 \times 10^{-4} \text{ cm}^2 \text{ s}^{-1}$  at the plateau.



*Figure 5.8: Xenon diffusion coefficient at infinite dilution as a function of the pore limiting diameter (PLD). The diameter of the largest free sphere is defined using two different radius systems: the standard CCDC-based PLD (on the left), and the one defined using the UFF forcefield (on the right)<sup>51</sup> – as defined in the chapter 2.*

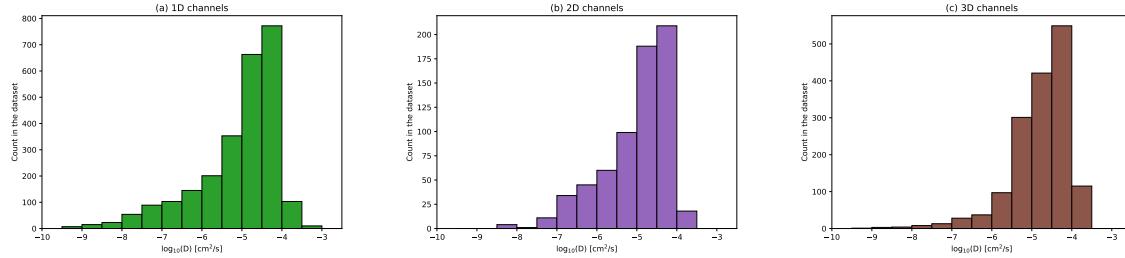
If I now analyze the channel dimensions (determined using Zeo++) that could partially inform us on the channel shape. As shown on Figure 5.9, the dispersion of the diffusion coefficients at the plateau is actually very hard to characterize using the channel dimension with bare eyes.



*Figure 5.9: Distributions of the base-10 logarithm of the diffusion coefficients of three different subsets of the screened structures. The first one (a) is composed of structures with a unidimensional channel, the second (b) bidimensional channels and the third one (c) tridimensional channels.*

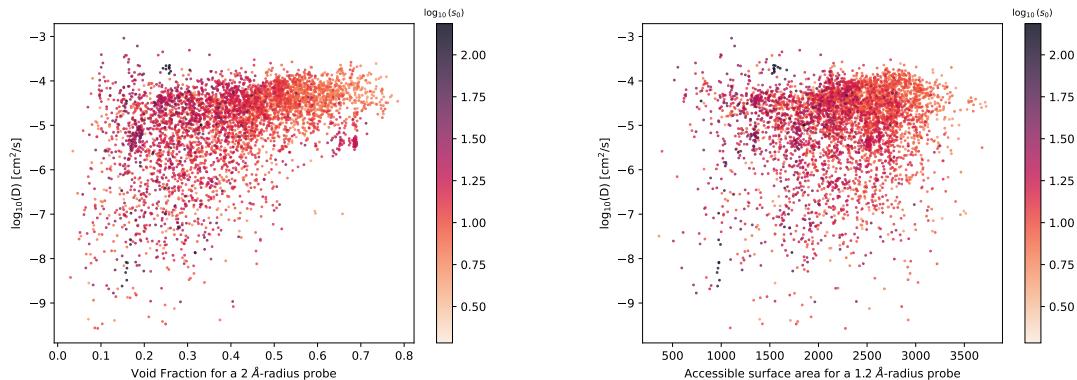
For this reason, I plotted on Figure 5.10 the distribution of diffusion coefficients that depends on the dimensionality of the channels within the framework. The distribution for structures containing 1D structures is much more heavy tail in terms of low diffusion coefficients. We can more easily find 1D structures with very low diffusion coefficients under  $3 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$ . The vast majority of structures with tridimensional channels has a rather higher diffusion

coefficient between  $3 \times 10^{-6} \text{ cm}^2 \text{ s}^{-1}$  and  $10^{-4} \text{ cm}^2 \text{ s}^{-1}$  with almost no structures with lower diffusion coefficients. This is not as blatant for bi- and unidimensional channels, we can more easily find structures between  $3 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$  and  $3 \times 10^{-6} \text{ cm}^2 \text{ s}^{-1}$ , even if theory are not that frequent. The dimensionality of the channels can therefore influence the values of diffusion coefficient, but the relation is not as clear as for PLD.



*Figure 5.10: Distributions of diffusion coefficient of three different subsets of the screened structures. The first one (a) is composed of structures with a unidimensional channel, the second (b) bidimensional channels and the third one (c) tridimensional channels.*

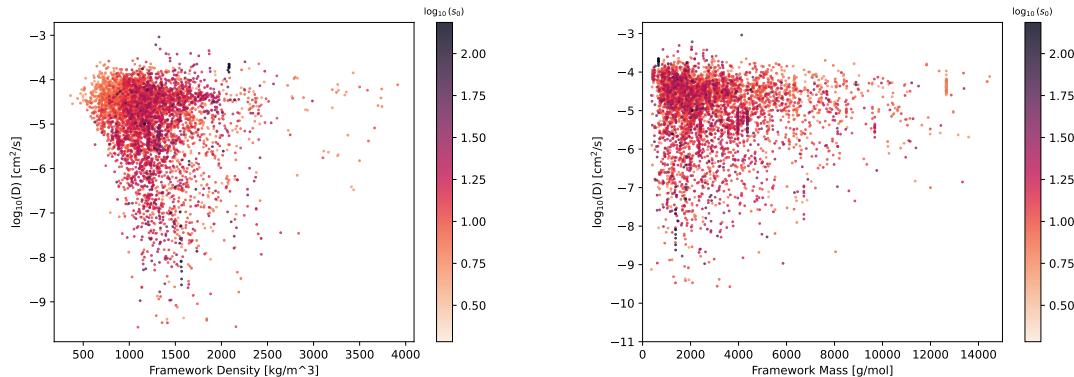
Other geometrical properties of the material that can influence the diffusion is the void fraction and surface area. The low diffusion coefficients usually happen in materials with small pore volumes below 0.6 as shown on Figure 5.11. However, it is difficult to draw a relationship between the void fraction and the diffusion coefficient. The only relation is that materials with void fraction higher than 0.6 have a diffusion coefficient over  $3 \times 10^{-6} \text{ cm}^2 \text{ s}^{-1}$ . This phenomenon is certainly due to the correlation between the PLD and the void fraction. Large PLD values are usually associated with large values of the void fraction. On the other hand, the accessible surface area for a probe of size 1.2 Å does not seem to influence the diffusion coefficient at all.



*Figure 5.11: Xenon diffusion coefficient at infinite dilution as a function of the accessible surface area (left) and the void fraction (right).*

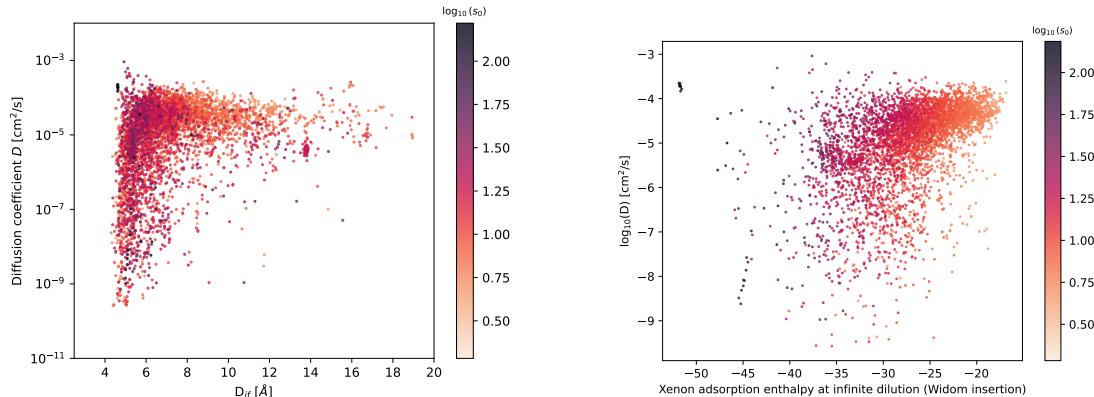
Framework density and molar mass are immediate characteristics of the structure since they do not require complicated simulations to obtain. The relation to the diffusion is, however, not that clear on Figure 5.12. We can probably say that low values of the density favors high values of the diffusion coefficient, this can be understood by the logical relation between low density and high porosity. Another relation to the diffusion coefficient concerns the higher probability

to find high diffusion coefficients as materials have a higher molar mass. This last assertion is harder to justify using simple geometrical reasoning.



*Figure 5.12: Xenon diffusion coefficient at infinite dilution as a function of the density (left) and the mass (right) of the frameworks.*

The largest sphere diameter  $D_{if}$  along a free diffusion path has a similar relation to the diffusion coefficient, but the correlations are much more noisy on the left plot of the Figure 5.13. This can be explained by the fact that  $D_{if}$  is always superior or equal to the pore limiting diameter  $D_f$  by definition. When both are equal it is equivalent to the Figure 5.8 with a linear relation and plateau, but if it is higher it creates the sort of noise that we see on the left plot of the Figure 5.13.



*Figure 5.13: Xenon diffusion coefficient at infinite dilution as a function of the largest sphere diameter  $D_{if}$  along a free diffusion path (left) and the xenon adsorption enthalpy (right).*

The last comparison is made with a thermodynamic quantity, the xenon adsorption enthalpy  $\Delta_{\text{ads}}^{\text{Xe}} H$ . There is no relation between diffusion coefficient and the xenon adsorption enthalpy, which is good thing because it means that any configurations are possible. A material can both have a high diffusion coefficient and a high xenon adsorption affinity (very negative values of enthalpy), which is the best configuration for adsorption at infinite dilution. However, it also means that we need to test the diffusivity when the material has a good affinity in order to optimize both properties. This approach will constitute the core discussion around the optimization of both the Xe/Kr selectivity and the diffusion coefficients of Xe and Kr.

### 5.2.3 A trade-off between the selectivity and the diffusion

In this section, I will analyze the screening of the diffusion and selectivity properties calculated for xenon and krypton to identify interesting materials that present both a good Xe/Kr selectivity and a good Xe/Kr diffusion coefficient ratio. To achieve this, I also performed a diffusion coefficient screening for krypton, and I end up with 4,816 structures that has good determination coefficient for both linear fits of xenon and krypton MSD. These structures are then tested to find materials with a good balance between thermodynamic and kinetic properties for the xenon/krypton separation.

#### SCREENING OF DIFFUSION SELECTIVITY VALUES: A TRADE-OFF BETWEEN ADSORPTION AND DIFFUSION

I will start by comparing the xenon/krypton selectivity at infinite dilution with the xenon and krypton diffusion coefficients. A highly selective materials can have a decent diffusion coefficient, the diffusion limitation observed on the KAXQIL structure is therefore not inevitable, which is good news. On the left plot of the Figure 5.14, we can clearly see that all configurations are possible: high selectivity (over 40) with high diffusion coefficient (over  $10^{-6} \text{ cm}^2 \text{ s}^{-1}$ ) and high selectivity with low diffusivity. The krypton coefficients seem to be rather stable between  $10^{-6} \text{ cm}^2 \text{ s}^{-1}$  and  $10^{-3} \text{ cm}^2 \text{ s}^{-1}$ . It means that it is not the main leverage to increase the diffusion selectivity since very low values of krypton diffusion coefficients do not appear for highly selective materials. To go beyond the thermodynamic selectivity, I will study a transport-related selectivity metric to find highly selective materials that do not show significant transport limitations.

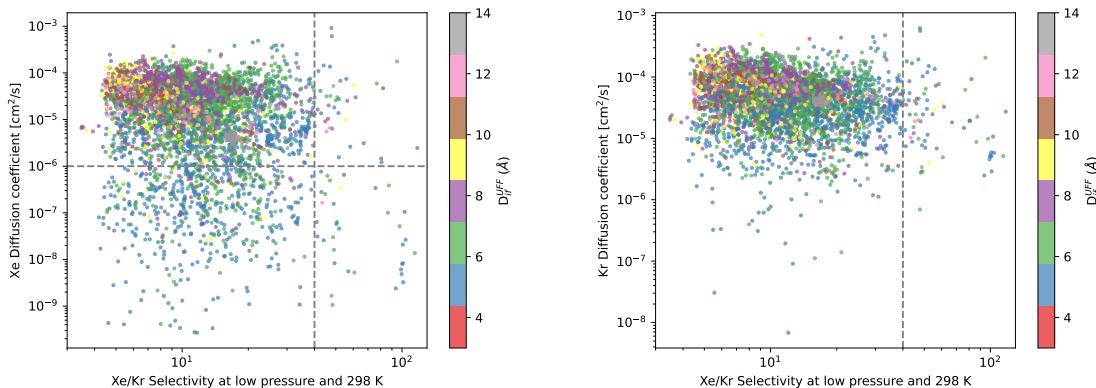


Figure 5.14

To take account of the transport properties in a separation process, we generally use the ratio of the diffusion coefficients or the diffusion selectivity as a performance metric. For xenon and krypton the diffusion selectivity can be defined as follows:<sup>281</sup>

$$s_{\text{diff}}^{\text{Xe/Kr}} = \frac{D^{\text{Xe}}}{D^{\text{Kr}}} \quad (5.9)$$

If we want to look at both the transport and thermodynamic effects, we can combine the thermodynamic adsorption selectivity defined in chapter 2 (equations 2.24 and 2.24) and the diffusion selectivity to define the membrane selectivity (used to characterize membranes). This membrane selectivity can also be called a perm-selectivity because it corresponds to the

ratio of the permeabilities of the components of the binary mixture we want to separate. The xenon/krypton permselectivity  $s_{\text{perm}}^{\text{Xe/Kr}}$  can therefore be defined as follows:

$$s_{\text{perm}}^{\text{Xe/Kr}} = s_{\text{diff}}^{\text{Xe/Kr}} \times s_{\text{ads}}^{\text{Xe/Kr}} \quad (5.10)$$

where  $s_{\text{ads}}^{\text{Xe/Kr}}$  corresponds to the adsorption selectivity used throughout the previous chapters (at infinite dilution or higher pressure).

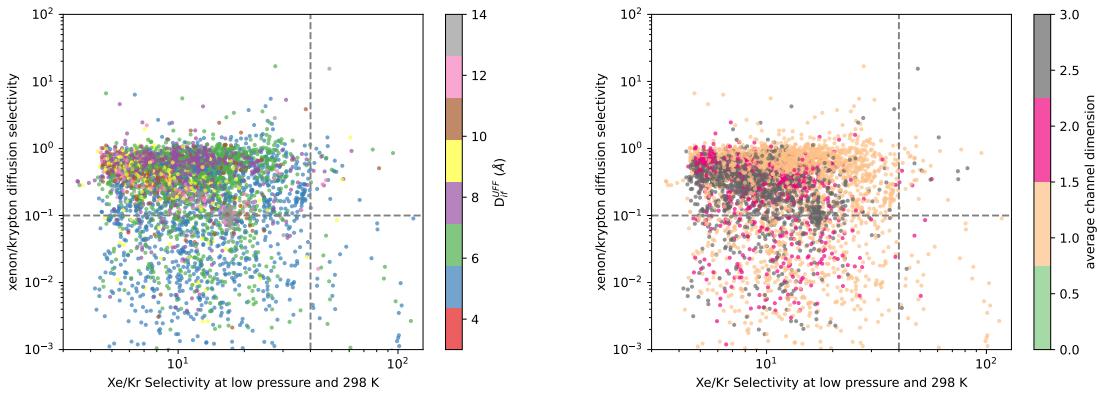


Figure 5.15

Using both  $s_{\text{diff}}^{\text{Xe/Kr}}$  and  $s_{\text{ads}}^{\text{Xe/Kr}}$  at different pressure conditions, I will try to find materials that exhibit a rather high selectivity with a high diffusion selectivity. The plots of the Figure 5.15 shows that 48 structures have a selectivity over 40 with a rather good diffusion selectivity over 0.1. These structures have rather high values of pore size represented by the largest included sphere along a free diffusion path  $D_{if}$  as shown on the left plot of the Figure 5.15. And these rather large pores are associated with structures with different dimensionalities. One remarkable structure among them has a very high diffusion selectivity (over 15, gray point on the upper right side of the left plot of Figure 5.15) coupled with a high adsorption selectivity at infinite dilution. This structure, with a CSD code ADOGEH[282], has a tridimensional channel framework with large pores and rather narrow connecting channels. The high adsorption selectivity at infinite dilution is however not conserved at ambient pressure as shown on Figure 5.16 (see Table 5.1).

If we look into the details of these structures, we can see that they combine large pores with smaller pores so that the diffusion is not obstructed, and the selectivity is high in more confined spaces. These type of materials with different sizes of pore could cause a selectivity drop at higher pressure, because the larger pores are less selective and are accessed when the gas pressure is increased. This phenomenon is observed when comparing the plots to the ones of Figure 5.16.

We can see that at higher pressure, some materials experience a shift toward lower selectivity values. And, only 2 structures have an ambient-pressure selectivity over 40: the MOFs with the following CSD code XUNSOQ<sup>283</sup> and GUMDEZ<sup>284</sup> (see Table 5.1). Most of these materials actually have a high value of cavity size, only structures with LCD near 6 Å are left in this area of the plot. We can also note that the dimension of the channel is equal to one too, which starts to brush a picture of the interesting materials. These materials are constituted of unidimensional channels with a small pore sizes so that the selectivity is conserved even at higher pressure

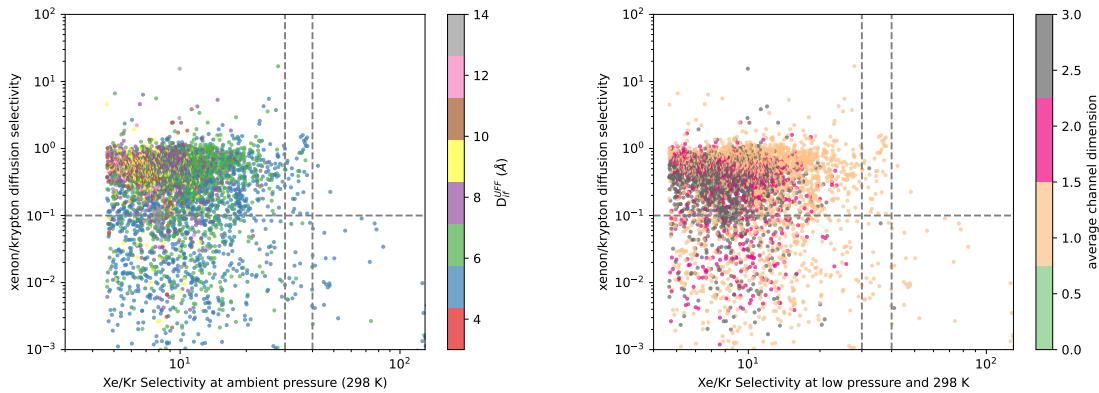


Figure 5.16

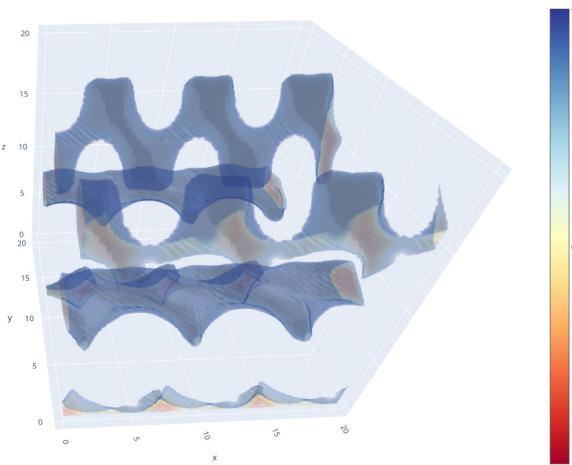
conditions. If we broaden the scope to the structures with a selectivity higher than 30 instead of 40, we now have 38 structures that also have similar features with rather low pore sizes and low channel dimensionality. Some of these structures have more or less kept their selectivity such as QOZDOY<sup>285</sup> and wasn't detected on the pre-screening on the low-pressure selectivity (Figure 5.15), but other structures, such as the MOF MISQIQ,<sup>286</sup> actually dropped significantly in selectivity values from infinite dilution to ambient pressure (see Table 5.1).

When considering the ambient-pressure selectivity, the large majority of highly selective materials actually have a rather low diffusion selectivity (lower than 0.1), as shown on Figure 5.16 (this was not the case for the low-pressure selectivity). This result suggest that a trade-off between adsorption selectivity and diffusion selectivity is actually needed. In my screening approach, I decided to lower the adsorption diffusivity to values around 40 to allow for higher diffusion selectivity values, because up until now standard screenings in the literature<sup>18,72</sup> and in my published work [22] only maximized the adsorption selectivity – this equivalent to working on the lower right side of the plots of Figure 5.16. To improve the former approach, I included a kinetic constraint in our screening. Another approach would be to optimize the perm-selectivity also known as the membrane selectivity (equation 5.10), but it would be the solution to another application, the membrane separation, which is broadly studied in the literature.<sup>157,277</sup> In the screening I presented here, we would like to find thermodynamically selective materials that are not limited by diffusion, and some interesting identified materials will be further studied in the following subsection.

#### IDENTIFICATION OF INTERESTING MATERIALS

By crossing the transport data with the thermodynamic one, we can optimize the Xe/Kr adsorption selectivity under some constraint on the diffusion selectivity so that it is in an acceptable range (over 0.1). The structures of the 65 structures with a low-pressure Xe/Kr selectivity higher than 40 or with an ambient-pressure Xe/Kr selectivity higher than 30 have been manually visualized and quickly analyzed, and different materials have been hand-picked for further analysis due to some special characteristics. I discarded some materials that have different type of channels that can artificially have a high diffusion coefficient. This phenomenon is due to the randomness of the initial condition, for example, when the xenon diffuses in a wider channel while the krypton diffuses in the narrower channel, the diffusion selectivity will inevitably be artificially higher. For example, the MOF with a CSD code OQESAF<sup>287</sup>

was concerned by this phenomenon as shown on Figure 5.17 it clearly has different diffusion coefficient values depending on the channel considered (a Henry coefficient weighted average need to be performed in this case). Other materials have a moderately high diffusion selectivity ( $\lesssim 1$ ), they are usually composed of a unidimensional channel that allows a rather free diffusion of a xenon (higher than 4.6 Å) with different cavity sizes. Different factors seem to influence the diffusion coefficients, the values of the channel size and the pore size could explain the values of the diffusion and adsorption selectivity, but more interestingly the shape of the channel composed of cavities connected by narrower walls is also very important. Depending on the tortuosity of the layout and the relative difference between the cavities and the connecting channels, diffusion properties can be very different.



*Figure 5.17: Snapshot of a 3D visualization of the xenon interaction energy inside the channels of the OQESAF<sup>287</sup> material. We can see two different unidimensional channels. In an MD simulation of a single xenon per box, we cannot test out all the initial positions.*

In this section, I will look into the details of the comparative transport and adsorption performances of some archetypal structures (Table 5.1) to better understand the key factors that could explain the difference in performance. This work can be used for the design of more quantitative characteristics that could explain the better transport performance, similarly to what I did for the thermodynamic screening that led to a series of key thermodynamic descriptors that led to the design of an ML model for adsorption selectivity prediction (chapters 3–4). To achieve this, I will use a visualization tool based on the grid calculation principle shown in the dedicated section 3.3, and the code is published in the same Github repository: [github.com/coudertlab/GrAED](https://github.com/coudertlab/GrAED).

The structure ADOGEH<sup>282</sup> was not found when crossing the transport data with ambient-pressure selectivity values by with the infinite dilution ones, which explains that the selectivity  $s_1$  is rather low (10) compared to the other materials (over 35). This structure was actually detected when looking at the selectivity  $s_0$  at infinite dilution, because of its extraordinary diffusion selectivity around (10). This would mean that as membrane material, its selectivity would be around 100, which is one of the highest. Even as an adsorption-based separation material, it has an outstanding low-pressure selectivity of 49 coupled with the high diffusion selectivity it can be considered for some applications at very low partial pressure of xenon and krypton.

Structure CSD ref. code	$s_0^{\text{Xe/Kr}}$	$s_1^{\text{Xe/Kr}}$	Pore size $D_{if}^{\text{UFF}} (\text{\AA})$	Channel size $\text{PLD}_{\text{uff}}^{\text{UFF}} (\text{\AA})$	$s_{\text{diff}}^{\text{Xe/Kr}}$	Diffusion Coeff. $D_{\text{diff}}^{\text{Xe}} (\text{cm}^2 \text{s}^{-1})$	Xe uptake (mmol g <sup>-1</sup> )
OQESAF [287]	28	28	5.8	5.0	17	$4 \times 10^{-5}$	3.2
ADOGEH [282]	49	10	12.9	5.3	15.5	$5 \times 10^{-5}$	1.7
KAXQIL [278]	104	133	5.2	4.1	0.005	$3 \times 10^{-8}$	1.4
XUNSOQ [283]	38	48	5.6	4.8	0.23	$7 \times 10^{-6}$	3.5
BAEDTA01 [288]	152	38	5.7	4.6	0.4	$4 \times 10^{-5}$	1.1
TONBII [289]	44	35	5.1	4.8	0.86	$1 \times 10^{-4}$	1.5
VOHQIS [290]	51	48	5.7	3.9	0.01	$6 \times 10^{-8}$	2.6
QOZDOY [285]	52	37	5.6	5.0	0.45	$7 \times 10^{-5}$	3.7
GUMDEZ [284]	56	42	5.5	5.1	0.55	$7 \times 10^{-5}$	3.0
MISQIQ [286]	140	37	4.6	4.5	1.4	$2 \times 10^{-4}$	2.3

Table 5.1: Transport and thermodynamic performances of top performing structures of CoRE MOF 2019 screened out by the approach developed in section 5.2.3. The thermodynamic properties are determined using xenon uptake at 1 bar and 298 K,  $s_0^{\text{Xe/Kr}}$  and  $s_1^{\text{Xe/Kr}}$  that correspond to the xenon/krypton adsorption selectivity values respectively at infinite dilution and ambient pressure condition. The pore size is defined as the largest cavity along a free diffusion path  $D_{if}^{\text{UFF}}$  and the channel size is defined using the pore limiting diameter  $\text{PLD}_{\text{uff}}^{\text{UFF}}$  using atom radii defined by the UFF. The transport properties are evaluated using the xenon/krypton diffusion selectivity  $s_{\text{diff}}^{\text{Xe/Kr}}$  and the xenon diffusion coefficient  $D_{\text{diff}}^{\text{Xe}}$  calculated by the MD-based screening presented above.

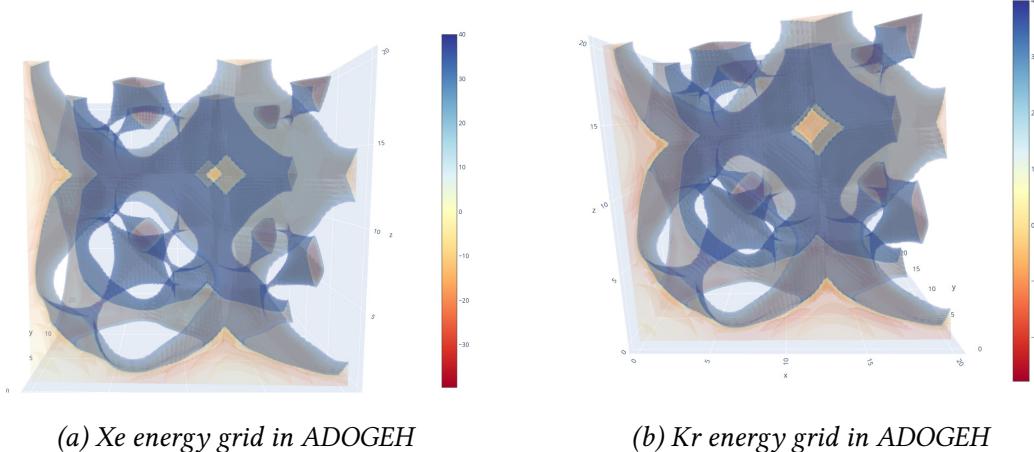


Figure 5.18: 3D volume plot of the xenon (a) and krypton (b) interaction energy values inside the material ADOGEH<sup>282</sup> calculated using an energy grid as described in section 3.3.

And even as an experimental material, the diffusion properties of xenon and krypton in this material are extremely interesting in themselves. On the Figure 5.15, only two materials have a diffusion selectivity over 10, but the other one actually has a falsely high value of diffusion selectivity due to the above-mentioned randomness of the initial position in the MD simulation and the presence of two types of channel (see Figure 5.17). ADOGEH is therefore the only material that shows such a high diffusion selectivity among all materials screened for their diffusion performance. In a unidimensional system, it is actually more natural to have a

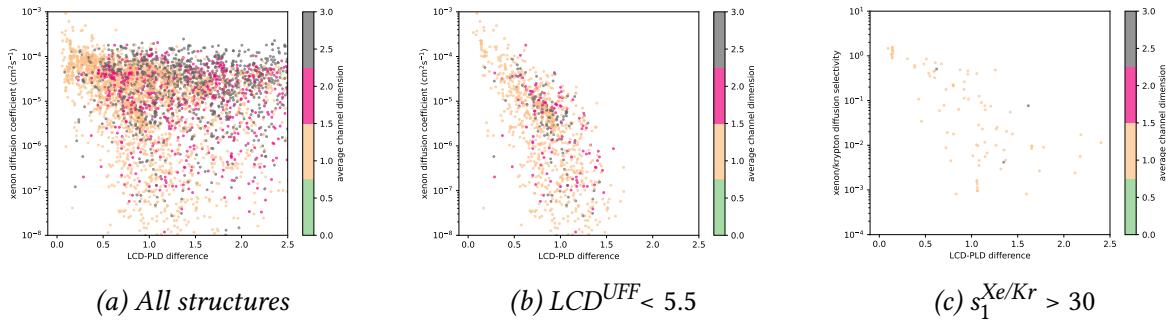
higher or equivalent diffusion coefficient for krypton than for xenon due to the obvious size difference.

It is possible to explain this exception by a special mechanism that happens in the tridimensional channel network of ADOGEH. As shown on Figure 5.18, for both xenon and krypton all dimensions are available for diffusion through the channels in the three cardinal directions. However, when we look at the sort of “pocket” (not a blocking pocket in the MD simulation) that connects the channels diagonally, the access to it is clearly not the same if we compare the two 3D energy grid plots. For xenon, on Figure 5.18a, the connection is way thinner than for krypton, on Figure 5.18b, for the same energy threshold. This can be interpreted as a higher energy barrier for xenon than for krypton to access this “pocket”. But, why would this explain the unusual difference in diffusion coefficients for xenon and krypton? This can be explained by the fact that the directions in which a krypton can diffuse is therefore much higher, which means that it has a higher probability of turning around than xenon. To say it more explicitly, a xenon can diffuse in the 3D space by taking only 3 main directions, but a krypton would lose time deviating from the cardinal directions — the same way as opening-up dimensions decreases the diffusion coefficient ( $\langle r(t)^2 \rangle = 2d\tau$ ). Moreover, when a krypton takes the small channel toward the “pocket”, it would have a non-negligible residence time inside, which further slows it down compared to a xenon. These “pockets” can be seen as traps for krypton, if it were a race between both adsorbate inside the nanoporous material.

Beyond the particular cases of OQESAF and ADOGEH, other nanoporous materials have lower diffusion selectivity values. For instance, all the other materials of Table 5.1 have a diffusion selectivity between 0.2 and 1.4. Depending on the shape and the size distribution of the porous channels, we would have higher or lower values of diffusion selectivity and xenon diffusion coefficient values. For instance, as shown on Figure 5.19b, there seems to be a weak correlation between a pore size characteristics ( $LCD^{\text{UFF}} - PLD^{\text{UFF}}$ ) and the diffusion performance for structures with a  $LCD^{\text{UFF}}$  value lower than 6 Å — for these structures, pore size have a higher chance to influence the transport properties. This correlation is logically due to the fact that if this difference between LCD and PLD is high, the diffusing xenon will have to cross a higher energy barrier to move inside the channels, therefore decreasing the diffusion coefficient. If we consider, all structures available, the correlation disappears because in the materials with a higher LCD value the movement of the diffusing xenon is not influenced as much by the pore walls. And actually for values of LCD higher than 7 Å, the diffusion coefficient is rather stabilized around  $10^{-5} \text{ cm}^2 \text{ s}^{-1}$  as shown on Figure 5.13.

For structures with a high ambient-pressure selectivity (Figure 5.19c), we can now see a negative linear relation between this LCD-PLD difference and the xenon/krypton diffusion selectivity. This is actually due to the fact that highly selective materials have pore size close to the size of a xenon as shown in details in the previous chapters. The effect on Xe diffusion coefficient can in fact be enlarged to the Xe/Kr diffusion selectivity as previously suggested by the noisy but stable values of Kr diffusion coefficients around  $3 \times 10^{-5} \text{ cm}^2 \text{ s}^{-1}$  (see Figure 5.14). The weakness of the correlation can be explained by the uncertainty inherent to the MD methodology for diffusion coefficient calculation (evaluated to around 20% for the material KAXQIL), but also by phenomena that I did not cover with the simple arithmetic difference of two pore characteristics. For instance the tortuosity of the channel, which is very tricky to evaluate in a tridimensional space can surely add some insight to the comprehension of the diffusion coefficient values.

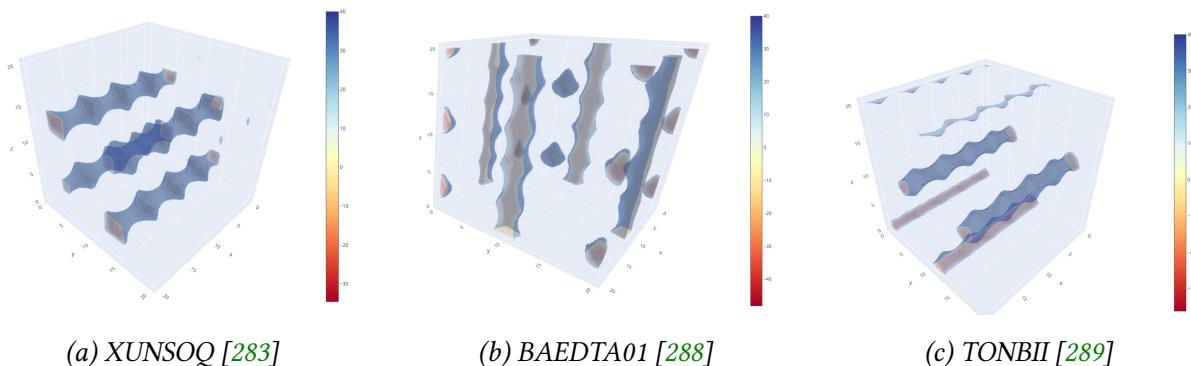
For instance, I will show different channel shape in the different examples below that can be qualitatively discussed but no effort to quantify these effects have been done in my current work.



*Figure 5.19: Scatterplots of the diffusion coefficient compared to the LCD-PLD difference labeled using the channel dimension for all structures (a) and for structures with an LCD above 5.5 Å (b). On the subfigure (c), the scatterplot of the xenon/krypton diffusion selectivity compared to the LCD-PLD difference for the most selective structures ( $s_1^{Xe/Kr} > 30$ ).*

The highly selective materials shown in the Figure 5.19c are actually shown in Table 5.1. The negative linear relation between the LCD-PLD difference and the Xe/Kr diffusion selectivity or the Xe diffusion coefficient can be reconfirmed by looking at the values of Table for materials with 1D channels (ADOGEH excepted). I am now going to split them into two categories in order to take a glimpse on the tortuosity difference between these materials.

We can first take a look at materials with nanopores composed of pseudo-spherical cavities connected by cylindrical channels following a straight line, as shown on Figure 5.20. These channels are actually forming straight lines, and if evaluated, their tortuosity would actually be very low. For TONBII, we actually have very small LCD-PLD difference, which explains the rather high diffusion selectivity near 1. There are almost no difference between xenon and krypton diffusing in the channels of this material. When the value of LCD increases, for a very similar value of PLD, the diffusion selectivity of such materials drops for BAEDTA01 and XUNSOQ as shown in Table 5.1. This drop can be explained by a now lower value of the xenon diffusion coefficient.



*Figure 5.20: 3D volume plot of the xenon interaction energy values inside materials with non-tortuous unidimensional channels calculated using an energy grid as previously described.*

Beyond consideration on the pure diffusion properties, the rather high adsorption selectivity coupled with very little diffusion limitations, make these materials fascinating for further study. The material BAEDETA01 has already been mentioned in the study on the selectivity drop due to pressure condition changes, the Figure 5.20b sheds a brighter light on the origins of this selectivity drop, we can clearly see the two different adsorption sites (one narrower than the other) — the narrower site is the one giving the very high low-pressure selectivity. The other two materials TONBII and XUNSOQ have a rather stable selectivity value between the low pressure and the ambient pressure cases. If we compare to the KAXQIL structure given by a previous high-throughput screening,<sup>18</sup> the diffusion coefficients are much higher and the problem of a potential diffusion limitation is solved, the selectivity values of these materials are however yet to be confirmed. The value of the PLD is of course the main factor that explains the lower diffusion coefficient of KAXQIL, but for similar values of PLD, the LCD-PLD difference can be a secondary variable that helps distinguish materials with similar PLD values but different diffusion coefficients.

If we now look at the other materials, as we can see of the Figure 5.21, the channels are much more tortuous than the previous type of channel. It seems to make a “zigzag” like shape. On this little amount of data, it is hard to quantify the effect of the tortuosity on the diffusion coefficient — to do so we would need to compare very similar materials (same chemical nature, same pore size) but has only a difference in tortuosity. However, in a theoretical point of view, the tortuosity usually has a negative effect on the diffusion coefficients. VOHQIS, for instance, has a high degree of tortuosity as shown on Figure 5.21a, and the diffusion properties are not very high, but it is hard to disentangle the effect of the pore size (very big difference between LCD and PLD) from the effect of the tortuosity. A more quantitative approach should be adopted to bring more insights on the diffusion process in nanoporous materials.

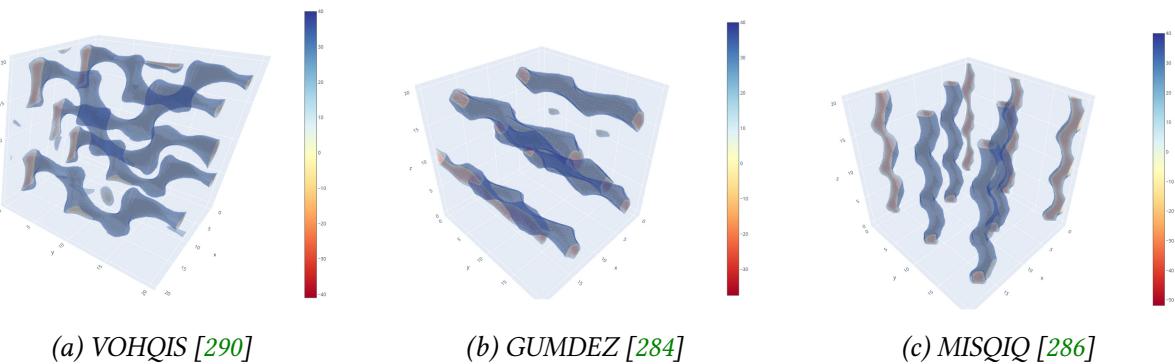


Figure 5.21: 3D volume plot of the xenon interaction energy values inside materials with tortuous unidimensional channels calculated using an energy grid as previously described.

If a similar analysis is made for these materials than for the previous materials with straight channels, there seem to be the same — it is not surprising since these materials are included in the correlation plot on Figure 5.19c. GUMDEZ is much less tortuous as shown on Figure 5.21b, but the difference in pore size is also lower, the diffusion coefficient is therefore higher, which explains the good diffusion selectivity. This material also has a much higher xenon uptake than more selective materials like KAXQIL, this is due to the notion uptake–selectivity trade-off I introduced on Figure 2.5 for instance. For this reason, this material along with QOZDOY was also previously identified in the literature by the xenon/krypton separation screening made by

Chung et al.<sup>72</sup> when introducing the CoRE MOF 2019 database. These materials were presented as having a high xenon/krypton selectivity and much higher xenon uptake, which is also a key metric for industrial separation process – it typically sets how much xenon can be retrieved per adsorption–desorption cycle. To improve the screening I could also add an optimization of the xenon uptake to optimization of the diffusion and selectivity properties. By chance, I found materials such as XUNSOQ, QOZDOY and GUMDEZ with good adsorption selectivity, diffusion selectivity and xenon uptake that could be much more versatile than very specialized materials such as KAXQIL.

To sum-up, I performed a screening of diffusion properties for xenon and krypton to inform the previous purely thermodynamic properties screening and I found materials with a good balance between both diffusion and adsorption selectivity values. Some of these materials also exhibit very high Xe uptake, which could improve the productivity of xenon in a separation process in addition to a high separative capacity and a fast penetration of the gas inside the material. This study further justifies the multivariate nature of the optimization problem when looking for a good material for xenon/krypton separation – it is not sufficient to only look at a single variable. This study brings a more exhaustive approach than already existing studies (on other systems) on the importance of kinetic effects in an adsorption process.<sup>291</sup> There are still some work to do on a finer comprehension between the diffusion properties and tortuosity and all the pore size effects. The next section will be dedicated to develop faster methodologies of the screening of transport properties so that I can scale the screening methodology to larger databases. To achieve faster transport property screening, I explored methods based on the transition state theory and machine learning prediction models.

### 5.3 FAST DIFFUSION CALCULATION ALGORITHM

To go beyond the very computationally demanding MD simulation, in this section, I will present alternative methods that I developed during my thesis to calculate the diffusion coefficient. For instance, methods based on the transition state theory can more efficiently generate MSD at larger timescales. If we apply a similar algorithm as in TuTraST, we can also overcome the initialization problem of MD simulation when different channels are available in an automated screening – of course it is always possible to manually put the particle in a given initial state, but it is hard to achieve in a screening process. At this stage of my work, I did not finish the implementation of the C++ algorithm that directly reproduces diffusion coefficients through a rejection-free lattice kinetic Monte Carlo algorithm. However, I used the initial implementation to calculate maximum energy barrier inside a material. This energy barrier was found to bring complementary information to the PLD values to predict the diffusion coefficient, and an ML model was trained to predict diffusion coefficients much faster than the current MD method.

#### 5.3.1 Code based on the TuTraST algorithm

I used the GraED algorithm presented on section 3.3 to calculate the xenon interaction energy with the material at each non-overlapping point of the symmetry-aware grid. With this energy grid, it is now possible to identify the different channels, adsorption pores and the transition surface that separate them.

I changed a bit the approach previously described in the section 5.1.2 and adopted by Mace et al. to identify the three main components of the lattice Monte Carlo approach. Instead of detecting the channels on the fly, I decided to detect the channels beforehand in order to restrict the cluster growth to a specific channel. This will help decreasing the computation time required during this clustering step since we can do the simulation only for one representing channel out of all the potentially equivalent channels — because of the high order of symmetry, there are usually equivalent channels within a single unit cell, as shown on Figures 5.20 and 5.21.

To identify the different channels, I used a breadth-first search algorithm to find all connected grid points with energy below a given energy threshold value  $E_{\text{cutoff}}$ . The connection is defined using the faces of the grid voxel, there are 6 such neighbors. Connections from the 8 edges can be added, and we end up with 14 nearest neighbors. If we add the vertices, we can go up to 26 nearest neighbors. To keep things simple, we only used the 6 obvious connections. The breadth-first search algorithm in a grid system is rather pretty simple:

We loop over all the points of our grid:

1. if the point is not already visited and the energy is below the threshold, then the point is saved in the cluster and to a queue, and a search can be initiated to find all the connected neighbors.
2. each (face-connected) neighbor of the point is tested, and is added to the cluster and to a queue if it is not already visited and the energy is below the threshold.
3. we repeat the process for every single elements of the queue until the queue becomes empty. At the end we end-up with all the grid points connected to the initial grid point. Then the main loop restarts, and the search restarts only if we find a point that has not yet been visited.

At the end of the breadth-first search we end up with clusters of connected points that are below a given energy threshold. Each of these clusters, can be tested to see if they are actually channels (connected all the way through a periodic boundary).

Now that we have well-defined channels and pockets of our nanoporous material, we can identify the symmetrically equivalent channels by using our symmetrical grid as already explained in the section 3.3. Then, we usually end up with a few unique channels (less than three in most cases) that can be used for the basin-cluster growth and the detection of TS surfaces that separate these basins.

Then, we will need to loop over the energy values (in the original paper a step of  $1 \text{ kJ mol}^{-1}$  is used), and grow the cluster layer by layer. At this point of the development, another point of improvement is added, I used the previous search algorithm to quickly count the number of clusters within a given channel. If this number changes, it means that some clusters merged. If the energy gap is high enough, we can start to detect the TS surfaces using a layer-by-layer growth within a small energy range ( $[E, E + \delta E]$ ) to generate a smoother surface.

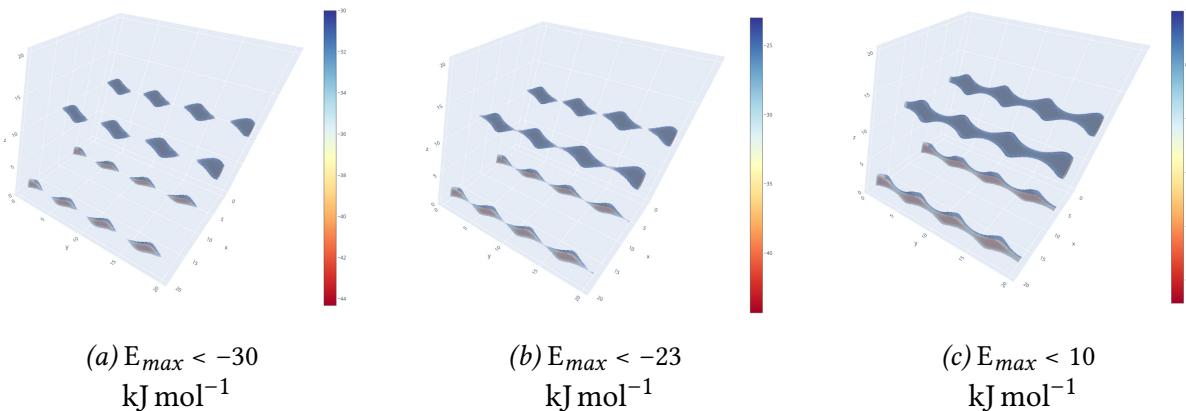
I am currently at the last step of the development of this detection algorithm, because the development was put in stand-by to focus on the analysis of the barrier energies calculated from a modified version of this first implementation, which will be detailed in the following discussions. The transition surface detection will be further discussed in the next chapter, and

I will try to implement a more optimized version of this detection that could avoid using a computationally expensive layer-by-layer growth.

### 5.3.2 Calculation of diffusion activation energy

Since we only want to determine the activation energy, we can skip the more computationally demanding TS detection and kinetic Monte Carlo steps. To achieve this we can simply use the breadth-first search algorithm to label the different connected components inside a given channel between  $E_{\min}$  and  $E_{\min} + i\delta E$  (at the  $i^{\text{th}}$  iteration). When the number of connected components changes between two energy values  $E$  and  $E + \delta E$ , there are new components appearing or old components that merged or both happening at the same time. By looking at the number of connected components, the code automatically detects the energy  $E_{\text{barrier}}$  at which the components connect back together and form a channel (possibility to go from one boundary to another). This energy corresponds to the energy required to be able to diffuse through a channel. Then, the activation energy  $E_a$  simply corresponds to the difference between this energy barrier  $E_{\text{barrier}}$  just calculated and the minimal energy  $E_{\min}$  within the channel.

In the case of KAXQIL, we can carry out a barrier detection using an energy step  $\delta E$  of  $0.3 \text{ kJ mol}^{-1}$ . There is only one symmetrically unique type of channel in KAXQIL with a minimal energy of  $-44.3 \text{ kJ mol}^{-1}$  – the different channels shown on Figure 5.22c are all symmetrically equivalent. The code only detects one merge that leads to an all connected component inside the channel. This merging occurs for an energy of  $-25.7 \text{ kJ mol}^{-1}$  (as shown on Figure 5.22b), which means that the activation energy is estimated to be  $18.6 \text{ kJ mol}^{-1}$  with an error of  $0.3 \text{ kJ mol}^{-1}$  (due to the energy step considered).



*Figure 5.22: 3D visualization of channels within KAXQIL using different energy thresholds  $E_{\max}$ . Depending on the maximum value of energy allowed, the channel is either composed of unconnected basins (a), or they are fully connected (b) and (c). This illustrates the principle of the energy barrier detection.*

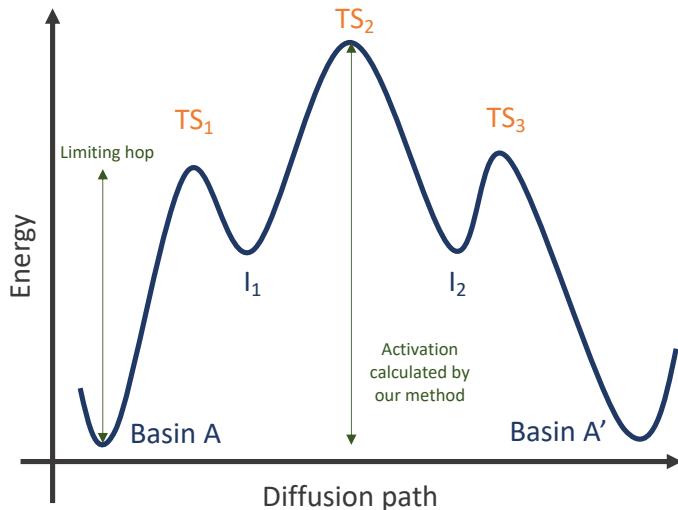
In this simple case of one unique merge of a unidimensional channel, the method works pretty well, and it is possible to associate this activation energy to a diffusion rate  $k_{\text{diff}}$  using the Arrhenius equation:

$$k_{\text{diff}} = A \exp \left( -\frac{E_a}{k_B T} \right) \quad (5.11)$$

where  $A$  is a prefactor that depend on the temperature and the system (adsorbate, adsorbent). This is a simplified version of the equations 5.6 and 5.7 used in transition state theory-based

methods. In the case of a unidimensional channel with only one transition possible, the diffusion coefficient is directly related to the diffusion rate. The problem can be reduced to a unidimensional random walk with a given transition probability, and the diffusion coefficient is then simply  $D = 0.5k_{\text{diff}}L^2$  where  $L$  is the distance between two basins (in one dimension). We end up in this special case with a direct relation between the diffusion coefficient and the activation energy  $\log(D) \propto E_a$ . If we consider more complex systems than KAXQIL, this methods may not work that well.

The case of multistep diffusion is much harder to describe, for example – a particle can cross a series of lower barrier instead of making the highest energy gap (calculated by our method) as illustrated on Figure 5.23. In this particular case, the relevant activation energy is in fact the maximum value between these two activation energies. And even if we take the maximum activation energy, in the case where they are similar in value, this approximation can be unjustified. Both transitions would influence the diffusion. This approximation is only true if one of the activation energy is much larger than the other ( $E_a^1 \gg E_a^2$ ).



*Figure 5.23: Multistep diffusion from a basin A to a basin A'. The diffusion process is modeled by transition states  $TS_1$ ,  $TS_2$  and  $TS_3$  and intermediate steps  $I_1$  and  $I_2$ . In this particular case, there is a difference between the real limiting activation energy and the activation energy calculated by our simplified method.*

To improve this approach, we could detect intermediate transition state energy values by looking at the change in the number of clusters for instance. But again it is hard to say which combinations of energy difference are relevant, and more detailed investigation of the location of these transition states are needed, which is the initial problem of TS surface detection that we put on stand-by. Aware of all these weaknesses, we can however use this quickly measurable activation energy as a proxy of the diffusion coefficient. This will be the object of the next discussion on the relation between this approximated activation energy value and the diffusion coefficients. This new diffusion descriptor can later be used in prediction models as a complementary descriptor to the PLD to give a more complete picture of the diffusion process.

### 5.3.3 Relation of the approximated activation energy to the diffusion coefficient

I calculated this xenon diffusion activation energy for all the 5,125 structures selected for the xenon diffusion coefficient screening presented in the section 5.2.2. I used an energy step  $\delta E$  of  $0.1 \text{ kJ mol}^{-1}$  for the loop over the energies to find the minimal energy barrier of each unique channels of the material. An activation energy can then be deduced and compared to the diffusion coefficients. To avoid any noise that could come from the MD simulation initialization problem, we removed all the materials with very different energy barrier values from one channel to the other (the standard deviation of the energy barrier values is higher than  $1 \text{ kJ mol}^{-1}$ ). These materials only represent 145 materials out of 5,125.

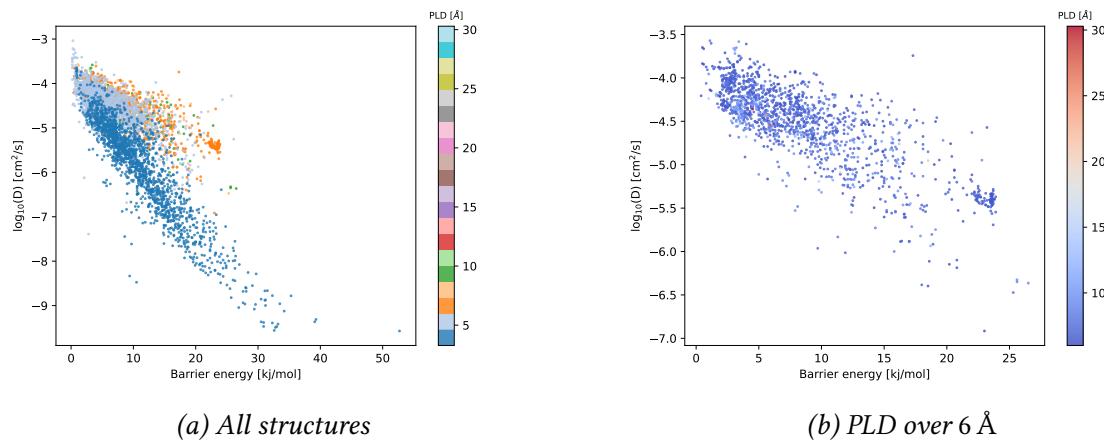
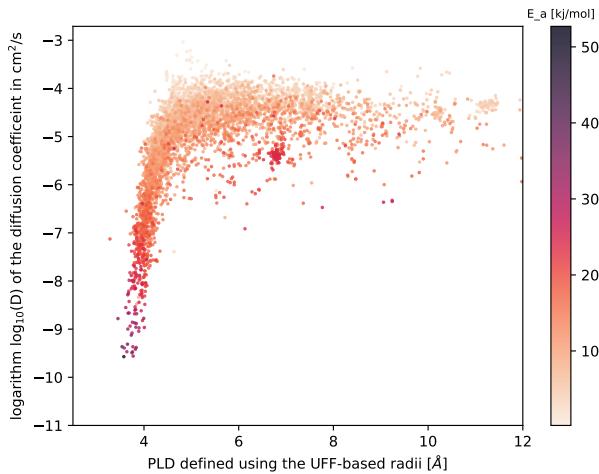


Figure 5.24: Scatterplots of the  $\log_{10}$  of the diffusion coefficient (in  $\text{cm}^2 \text{s}^{-1}$ ) compared to the diffusion activation energy  $E_a$  in  $\text{kJ mol}^{-1}$  (a) for all structures and (b) for the structures with a PLD above  $6 \text{ \AA}$ . For all structures, the Pearson correlation coefficient is equal to  $-0.77$ , whereas for the restriction to structures with a PLD below  $6 \text{ \AA}$  this correlation is stronger with a Pearson coefficient of  $-0.85$ . For structures with a PLD above  $6 \text{ \AA}$ , this coefficient decreases to  $-0.74$ .

As shown on Figure 5.24a, the activation energy is correlated to the diffusion coefficient for xenon. The correlation seems to be much stronger for the points with a PLD around  $4.5 \text{ \AA}$ , and for PLD values over  $6 \text{ \AA}$ , there still is a correlation but it seems weaker than for smaller values of PLD as shown by the Figure 5.24b

This correlation between the energy barrier and the diffusion coefficient is confirmed on Figure 5.25. The points are labeled according to the energy barrier value, and the highest energy barrier points are mostly concentrated on lower values of diffusion coefficient. We can, however, see some very high energy barrier points associated to points with quite low diffusion coefficient, there are two such points detectable with our bear eyes.

This barrier activation energy descriptor completes the description of the diffusion coefficient given by PLD values. As discussed in the dedicated section, the PLD values can not distinguish between the structures over  $6 \text{ \AA}$  in the “plateau”, and the difference of diffusion coefficient could only be considered as noise in the previous analysis. But it seems that on Figure 5.25, the higher values of barrier energies are found for lower diffusion coefficient in the plateau value, hence explaining the different values within the plateau by the value of the activation barrier. Although the correlation is not perfect, this barrier descriptor better informs on this uncharted



*Figure 5.25: Scatterplot of the  $\log_{10}$  of the diffusion coefficient in  $\text{cm}^2 \text{ s}^{-1}$  as a function of the PLD values and labeled by the barrier activation energy. The higher barriers seem to be corresponding to lower values of diffusion coefficient echoing to the correlation found on Figure 5.24.*

area of PLD values above 6 Å impossible to explain with simple geometrical considerations. This barrier activation energy value informs on the chemical nature of the diffusion barrier to be crossed.

In the final section of this chapter, I will therefore combine geometrical descriptors to this energy barrier to train a machine learning model following the same approach as in the previous chapter 4. The energy barrier and the PLD values are the most correlated descriptors and will play a prominent role in the final ML model. This model could then be used to evaluate the diffusion coefficient of xenon in other materials, which is much faster than using MD simulations.

### 5.3.4 ML prediction model

Diffusion coefficients are extremely time-consuming to calculate and with a lot of complications in the final fitting process. From the 6,525 initial structures, we lost more than a thousand structures, which corresponds to about 79% success rate due to either a lack of time to give a usable MSD or simply to MSD that describe non-diffusional regimes. By using a rather unconventionally higher time step, we managed to reduce the time required to probe the diffusion regime to only a couple of days per structure. Compared to the 12 second required for the energy barrier calculation with an energy step of  $0.1 \text{ kJ mol}^{-1}$ , and the few minutes required to run Zeo++, the MD method is extremely slow. If we use very optimistic hypothesis for the MD simulations, we are basically comparing 24 hours to maybe at most 10 minutes per structure, which corresponds to approximately 150-fold speed-up (in reality it is much higher). However, the relationships between the energy barrier, PLD and the diffusion coefficient are not clear – the Arrhenius law generalizes poorly considering the weak correlation shown by the Figure 5.24a. The ML model is here to draw this relation to achieve a good prediction, while spending less time in the future to predict the diffusion coefficient of future selective materials.

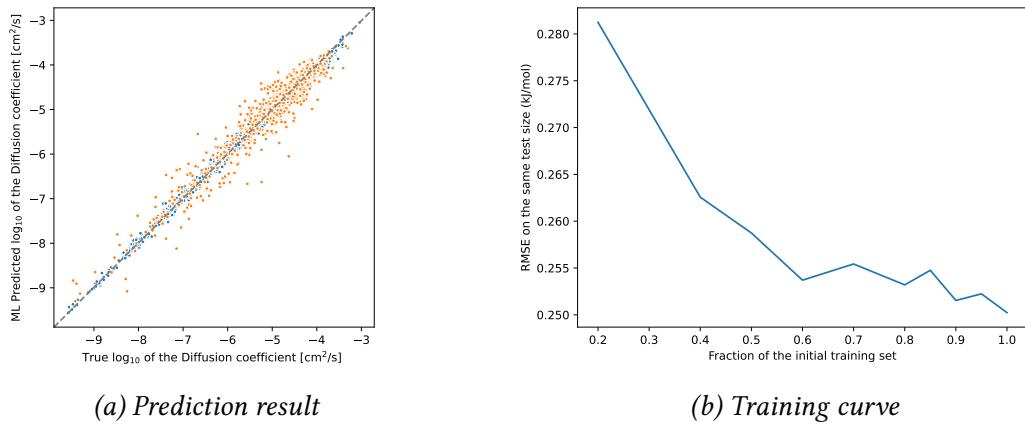
Feature name	Symbol	Description
"Framework Mass (g/mol)"	$M_f$	Molar mass of the framework material considered
"Framework Density (kg/m <sup>3</sup> )"	$\rho_f$	Mass density of the framework material considered
"ASA_m2/cm3_1.2"	SA	Surface area accessible to a 1.2 Å radius probe in m <sup>2</sup> cm <sup>-3</sup>
"PO_VF_2.0"	VF $\frac{V_{\text{pore}}}{V_{\text{tot}}}$	The void fraction or the ratio of the pore volume occupied by a 2 Å radius probe over the total material volume
"D_f_vdw_uff298"	PLD or $D_f$	Pore limiting diameter of largest free sphere diameter calculated using the UFF dependent definition
"D_if_vdw_uff298"	LCD or $D_{if}$	Largest included free sphere diameter in a free diffusion path calculated using the UFF dependent definition
"Adsorption_enthalpy"	$\Delta_{\text{ads}}H_0^{\text{Xe}}(\text{channel})$	Xenon adsorption enthalpy within a channel calculated using the barrier algorithm
"barrier_kjmol"	$E_a$	difference between energy barrier $E_{\text{barrier}}$ and the minimal energy $E_a$ within a channel
"delta_LCD_PLD"	LCD-PLD	difference between the LCD and PLD values
"1D_chan"	$\mathbb{1}_{1D}$	categorical feature: 1 if there is a unidimensional channel, 0 else
"2D_chan"	$\mathbb{1}_{2D}$	categorical feature: 1 if there is a bidimensional channel, 0 else
"3D_chan"	$\mathbb{1}_{3D}$	categorical feature: 1 if there is a tridimensional channel, 0 else

Table 5.2: Features used in the ML model for diffusion coefficient prediction.

To train the ML model, I used 80% of the 4,873 structures that survived all the different imposed filters. And I used 12 different descriptors described in Table 5.2 to train this model. The hyperparameters of the XGBoost model was determined using a similar approach as in the chapter 4, and the following were used:

```
optimal_params = {
    'objective': 'reg:squarederror',
    'n_estimators': 1500,
    'max_depth': 4,
    'colsample_bytree': 1,
    'colsample_bylevel': 0.75,
    'subsample': 0.75,
    'alpha': 0.6,
    'lambda': 1,
    'learning_rate': 0.04,
}
```

With this parameterization, this ML model predicts the  $\log_{10}$  of the diffusion coefficient ( $\text{cm}^2 \text{s}^{-1}$ ) with a root mean square error of 0.26 on the test set and a mean absolute error of 0.18. This means that the exponent  $\alpha$  is known with an error of about 0.2 if we express the diffusion coefficient as  $D = 10^\alpha$ . As a point of comparison the previous ML model for thermodynamic selectivity predicts the  $\log_{10}$  of the selectivity with an error of about 0.07. Here, we are not trying to predict the exact values of the diffusion coefficient as there is already a lot of noise in the values generated by MD simulation (about 20% relative error for KAXQIL), but we rather try to determine the order of magnitude of the diffusion coefficient value. This model achieves just that, as illustrated on Figure 5.26a, the predicted diffusion coefficient is very close to the true value in a log scale representation.



*Figure 5.26: (a) Comparison of the  $\log_{10}$  of the diffusion coefficient predicted by an ML model and the true values. (b) Root mean squared errors on the same test set (20% of all data) as a function of the fraction of the training set used to train smaller models. The error decreases as the amount of data increases and seems to stabilize near 0.25.*

To check if this model has enough training data, or that it needs more training data, I checked the training curve (Figure 5.26b). The error converges to 0.25 as we increase the amount of training data, which means that no further data is needed to train the model. However, we could imagine using fewer data to train a similar model (maybe 50% instead of 80% of the total data can be enough to train a similar model).

Finally, I used the SHAP algorithms already presented in the previous chapter to interpret the ML model. Unsurprisingly, the most important features are the PLD and the barrier activation energy as already shown in the previous section. The void fraction seems to play a non-negligible role also.

To unravel the relationship between these features and the target diffusion coefficient, I will now look into the partial dependence plots of these features given on Figure 5.28.

The PLD has a contribution that is very close to the one described in the section 5.2.2. We can see the linear contribution when the PLD values are below 6 Å, and then a constant contribution for PLD values above this threshold. The activation energy is negatively correlated to the log of the diffusion coefficient, which explains the linear contribution observed on the dependence plot.

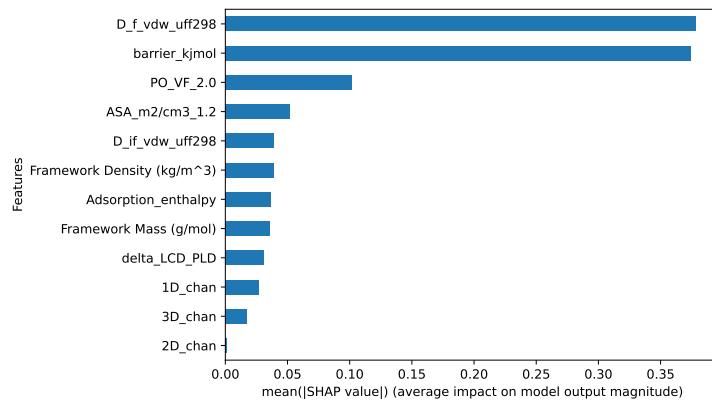
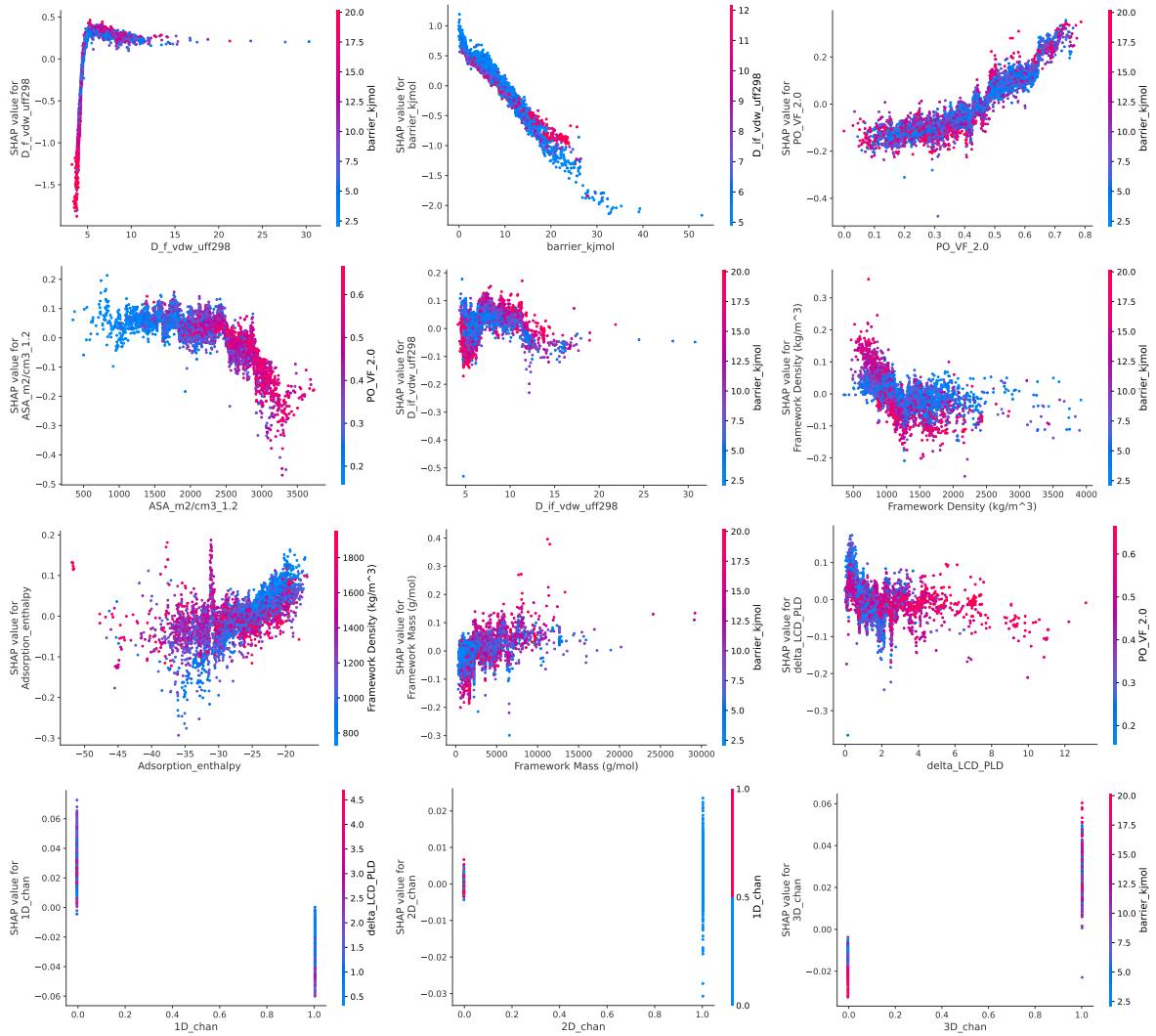


Figure 5.27: Feature importance determined using the average of the absolute Shapley values on every training data for each feature. An influential feature would have a very high average absolute SHAP value. The features are detailed in Table 5.2.

The model also uncovers less obvious contributions, looking at the Figure 5.11, we can not infer any relations between surface areas or void fractions and the diffusion coefficient. They have a more secondary role than corrects slightly the values obtained with contributions of the order of 0.2. For instance, the model finds a positive relation between the void fraction and the contribution to the diffusion coefficient value. This is physically true since lower void fraction logically means lower diffusion rate inside the material, if other parameters are considered equal. On the other hand, larger surface areas means more interaction with the pore walls, which slows down the diffusing particle. For the LCD, the LCD-PLD difference the xenon adsorption enthalpy, the framework's mass and density, we can not see clear behavior of the contributions. This is probably due to the fact that a lot of the contribution is already given by the previous features because of the correlation between all these features.

Finally, the channel dimension has a rather marginal contribution to the final predicted values, but it corresponds to a clear physical phenomenon. Depending on the dimensionality of the channel, the diffusion coefficients behave differently. As shown on Figure 5.28, a 1D channel would have a lower diffusion coefficient if all other features are similar. A 2D channel would have a higher contribution, which is also confirmed by the partial dependence plots. And a tridimensional plot would have an even higher diffusion coefficient. The model can distinguish the different types of materials using their channel dimension.

In this section, we have presented an ML-based approach to compute diffusion coefficient values using computationally cheaper energy descriptors combined with geometrical descriptors. This method is much more efficient than the conventional MD simulation since it requires only one costly training session using MD simulations at the beginning. To go even further in the speed-up process, we can generate the diffusion coefficients using alternative methods as shown by Mace et al. in their work.<sup>129</sup> This is a work in progress and I hope that the future implementation can recover the same diffusion values as the one derived by the MD simulations.



*Figure 5.28: A SHAP dependence plot corresponds to the Shapley values as a function of the feature values for every structure. These SHAP plots show the contribution of the features to the prediction given by the ML model. Each Shapley value depends not only on the value of the feature itself but also on the other features, for this reason, the plots are labeled by a relevant second feature. Every feature's partial dependence plot for the diffusion prediction model are presented here.*

## 5.4 BEYOND SELF-DIFFUSION SCREENINGS

In this chapter, I introduced different methods of evaluating the transport properties of an adsorbate inside a nanoporous material. The most accurate method requires much more computational time and personal attention to achieve the best accuracy. For instance, we need to choose carefully the parameters of the MD simulation so that we obtain a mean square displacement data relevant for diffusion coefficient calculation. I managed to perform a screening of diffusion coefficient values for xenon and krypton to find interesting materials that exhibit both good thermodynamic and kinetic separation performance. These values have also been used to serve as a baseline data to test out other methods such as the activation energy detection and an ML model. The final ML model seems to give very promising performance by achieving a root mean squared error of only 0.25 on the base-10 logarithm of the diffusion coefficient. This means that we can evaluate quite accurately the order of magnitude of the diffusion properties. This could help quickly identify possible diffusion limitations of a promising material, but also optimize this property for faster equilibration in an adsorption based separation. Beyond our study, the techniques developed and to be developed in my work can also apply to membrane separation processes.

Different follow-up studies can be initiated considering the results obtained. For instance, the effect of tortuosity on the diffusion coefficient values and finding relevant ways of defining it remain open questions. We can for example focus on unidimensional channels, where each change of direction can be analyzed to quantify how frequently it appears and the magnitude of the change of direction it makes.<sup>292</sup> Another challenge could be measuring different diffusion regimes such as the single-file diffusion that leads to an MSD that has a square root time relation.<sup>279</sup> The materials with MSD relations other than linear were in fact discarded in this study since I only took materials with high determination coefficients in the linear fit.

To go beyond standard studies, we can even use the diffusion coefficient to model the breakthrough experiments which is the closest a lab experiment can get from the industrial adsorption process. The recent development of the RUPTURA software,<sup>293</sup> enables much more perspectives in the field of modeling. We can for instance calculate the axial dispersion coefficient used in a breakthrough model using transport properties while also injecting the thermodynamic data we have on the adsorption process of xenon and krypton. This gives a real opportunity for experiment-theory comparison in order to start a virtuous feedback loop to improve modeling and help in discovering better materials.

The diffusion coefficient calculated by the above-mentioned methodologies are by definition only describing a self-diffusion in an infinitely diluted environment. To better describe the transport properties in industrial conditions, we need to study the diffusion coefficients in a higher loading environment to take account of host–host interactions. Furthermore, we can also directly run mixture simulations to retrieve the so-called Onsager diffusion coefficients that are based on the Maxwell-Stefan diffusion equation rather than the Fick’s equation.<sup>294</sup> The calculation of such quantities requires a lot of computational resources since we need to run MD simulations on mixtures at a rather high loading and for long enough in order to capture the diffusion regime. It is therefore unimaginable to apply it in a large-scale screening, but we could consider testing some interesting materials in order to study the mixture and loading effect on the transport properties.

In this chapter, I only presented one aspect that was not taken into account in standard high-throughput screenings for xenon/krypton separation, which is the transport properties. In the next chapter, I will focus on other effects that could help complete the picture in order to be closer to the experimental system. The flexibility of the nanoporous framework can for instance change the adsorption performances.<sup>162</sup> And, the difference in polarizability of xenon and krypton can be better leveraged in the screening procedure if we can properly model it using more high-level theories than the Lennard-Jones potential. Both the flexibility and the polarization are still at the project stage and some results will be presented, but it is mainly a compilation of possible research focuses and solutions that could improve our current understanding.



# 6

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## TOWARD THE NEXT GENERATION OF SCREENINGS

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### 6.1 LIMITS OF THE CURRENT SCREENING METHODOLOGIES

As presented in our review of the different screening methodologies in the chapter 1, it is very common to screen for one particular metric whether it is the selectivity or the permselectivity or the capacity depending on the targeted application. Attempts of screening that searches for the most selective materials but combined with a good capacity are more and more common.<sup>72,206,207</sup> If we take the problem of the selectivity screening, many improvements can be made in terms of calculation efficiency, or in terms of correctness of the molecular description. In the previous chapters, I mostly focused on the gain in efficiency by exploring many adsorption energy sampling techniques and by comparing their computational time and their accuracy. But I also started to incorporate other properties to the screening procedure by exploring the transport properties for instance. And improve even more the efficiency, I explored alternative calculation strategies besides the more standard ones.

To overcome the shortcomings of the current adsorption screening methodologies, we need to give a more accurate physical description of the nanoporous system. For example, the rigidity of the structures in most of the screening procedures could sometimes mislead toward materials that appear to have a very high selectivity, whereas the flexible nature of the material tend to lower the calculated selectivity. By taking into account flexibility, one could completely

change the rankings found by the screening and hence finding other maybe better materials through this new approach. The other property that could completely change the results obtained by current methodologies is the polarization. For adsorbates like xenon and krypton, the difference in polarizability is in fact at the origin of the separability of these gas using an adsorbent material. A better description of this particular property can in fact completely change the results of the screening. If we look at the best experimental materials, they are either decorated with polar groups like in the article [7] or they present open metal sites like in the article [8]. However, we do not find these criteria as being essential when looking at the results of the current screenings.

In this final chapter, I want to discuss three main research focuses: (i) the calculation of transport properties that could be further optimized, (ii) the adsorption calculations in flexible frameworks, and (iii) the better description of the polarization in the energy calculations.

## 6.2 FUTURE DEVELOPMENTS ON TRANSPORT PROPERTIES

Transport properties were thoroughly studied using MD simulations and an ML model mainly based on the PLD and a proxy of the diffusion activation energy. This approach gives very promising results since it speeds up considerably the evaluation of diffusion coefficient values. However, the generalizability to other types of system is not guaranteed when using an ML-based approach. To create a simulation that would be faster than MD simulations and more accurate than the MD-based approach, we will finish the development of the diffusion coefficient calculation code based on the transition state theory and on kinetic Monte Carlo simulations. As explained in the previous chapter, we are at the last step of the development. When developed, this new approach can give diffusion coefficient that could be fed into a breakthrough modelization tool in order to compare to experimental data. In this section, I will also talk about the perspectives opened up by the new RUPTURA software in terms of experiment-theory comparison.

### 6.2.1 Final development of the optimized version of TuTraST

The diffusion calculation code can already do several things: (i) the calculation of the energy grid using the GrAED algorithm, (ii) the identification of connected components or clusters using a breadth-first search algorithm, (iii) the detection of channels using a simple all-direction scanning algorithm on the identified clusters, (iv) the detection of the energy barrier by using (ii) and (iii) in a loop over the energy values. The energy barrier of a given channel is defined as the energy at which the channel is connected back into at least one channel connected through at least one direction.

To finish the implementation of the algorithm, the final step is to be able to detect the transition state surfaces that separate different clusters. This final mapping into basins connected by transition surfaces can then be used to run a simple kinetic Monte Carlo scheme and determine the diffusion coefficient. In the original paper of Mace et al.,<sup>129</sup> the authors make the clusters with energy values below  $E_{\min} + i\delta E$  grow layer by layer to clusters with energy values below  $E_{\min} + (i + 1)\delta E$ . When a point of a layer of one cluster touches another cluster, this point can be considered as a transition point if the energy gap is high enough, else the two clusters merge together to form a unique cluster. The reason to use a loop over the energy values is to control

the values of the transition points they can only between  $E_{\min} + (i)\delta E$  and  $E_{\min} + (i + 1)\delta E$ . If we think about it, the layer-by-layer growth does not find the highest energy point in a given direction as normally defined for transition states, instead they detect the points that are equidistant to the surface of two previous clusters. Both definitions are equivalent if  $\delta E$  is infinitely small.

To avoid using a computationally expensive layer-by-layer growth, it could be possible to assign a label using a breadth-first search to find. The boundary points between two connected components would be defined as the points that are “equidistant” to the clusters. The definition of equidistant depends on the definition of the distance. It can either be directly defined using the grid cells, which corresponds to the Manhattan distance. This distance could be sensitive to the deformation of the unit cell. To use the cartesian distance, we would need to save a coordinate grid and implement a bucket queue based on the cartesian distances instead of a standard queue (as presented in section 5.1.2).

In the end of the thesis, I will be studying the different approaches: layer-by-layer growth, breadth-first search with a standard queue or a bucket queue prioritized using the cartesian distance, and compare their time and accuracy performance.

### 6.2.2 Connection to the breakthrough experiments

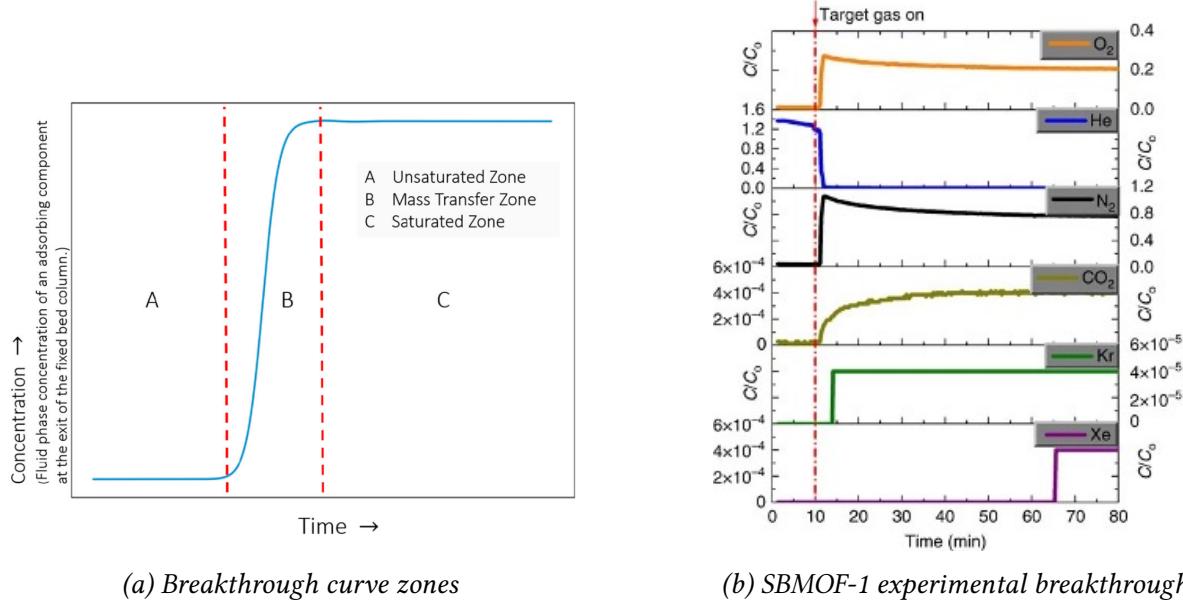
To test the relevance of the diffusion coefficient calculated by these methods, we need to be able to compare with experimental data. However, it is hard to directly access the diffusion coefficient inside a nanoporous material. The kinetic performance can only be glimpsed by analyzing the shape of the experimental breakthrough curves. If we can generate these breakthrough curves using diffusion coefficients as input, it could be possible to confirm or invalidate the results of our calculations.

A breakthrough curve can be broken down into three different zones: an unsaturated zone, a mass transfer zone and a saturated zone as shown on Figure 6.1a. Sharma et al. developed a tool to generate breakthrough curves based on adsorption quantities taken from a isotherm fit, and mass transfer properties such as the self-diffusion coefficient and material surface diffusion (Knudsen diffusion).<sup>293</sup> This tool can potentially be used to generate breakthrough curves and compare it to experimental curves. If the isotherm fitting properties come from experimental calculation, then the only variable can only be the mass transfer term. In this case, this tool can be used a qualitative way of validating a calculated self-diffusion coefficient value.

On the example of SBMOF-1, we can see that there is only a visible mass transfer zone for CO<sub>2</sub>. It suggests that there is a diffusion limitation for this adsorbate in the SBMOF-1 material. However, we do not see any diffusion limitation for xenon as previously suggested by the diffusion coefficient calculated by an MD simulation ( $3 \times 10^{-8}$  cm<sup>2</sup> s<sup>-1</sup>). In the next chapter, we will propose an explanation for this discrepancy between the experimental and simulated values.

## 6.3 SCREENING OF FLEXIBLE MATERIALS

The reason why people usually prefer rigid frameworks is the high complexity brought by the simulation of the dynamics of a flexible framework. We already saw the cost of simulating a



*Figure 6.1: (a) Different zones in a breakthrough curve reprinted from the open-access article [293]. (b) Experimental breakthrough curves in SBMOF-1 for a gas mixture with 400 ppm Xe and 40 ppm Kr balanced with dry air. Reprinted with permission from Ref. [41] copyright © 2016 Springer Nature.*

grand canonical ensemble using MC methods and developed strategies to avoid these types of calculations. The simulation of a flexible framework would require to relax the volume and simulate an osmotic ensemble ( $\mu, P, T$ ), which requires MC moves on the volume of the unit cell itself.<sup>268</sup> This type of MC simulation describes more accurately every aspect of the flexibility be it the intrinsic flexibility due to thermal agitation or the adsorbate-induced flexibility. However, in a screening procedure, this type of simulation can be prohibitively long, it should, however, be used as an accurate method to confirm the properties of a few top materials.

In order to incorporate flexibility effects in the screening procedure at a minimal computational cost, another approach is to use a set of rigid structures that reflects the structural diversity generated by the thermal agitation of the nanoporous material. A first study on the effect of this intrinsic flexibility on the Xe/Kr selectivity suggests that some materials could lose selectivity due to the less favorable pore size the structure vibrates.<sup>162</sup> For instance, the authors explained the discrepancies between the experimental and theoretical Xe/Kr selectivity of KAXQIL<sup>54</sup> by its intrinsic flexibility, which questions the performance ranking obtained by a rigid-framework screening. In this section, I will introduce in detail the study of Witman et al.<sup>162</sup> and I will especially focus on the case of KAXQIL presented by them. Then, I will present introduce another approach based on the structural diversity among similar deposited experimental structures. We can in fact count a dozen different structures with the same chemical nature as KAXQIL but with very different structural characteristics depending on the loaded adsorbate, which suggests an adsorbate-induced flexibility in addition to the intrinsic flexibility previously studied.

### 6.3.1 Snapshot method

#### METHODOLOGY

To model the dynamics of the framework, Witman et al. use the UFF forcefield to describe the non-electrostatic framework bond potentials except for the metal bonding. For the bond dynamics around the metal, a harmonic equilibrium is fixed around the values extracted from the experimental structure. For this reason, this forcefield definition is referred to as the UFF-fix-metal (UFF-FM). In addition of the Lennard-Jones description, the point charge Coulomb interactions are described using the standard Ewald summation technique based on the charges calculated by the density derived electrostatic and chemical (DDEC) method.<sup>295</sup> Using this forcefield, the authors carried out a systematic snapshot generation of the structures from the CoRE MOF 2014 database with pre-calculated DDEC charges. And these snapshots were used to determine flexible Xe and Kr Henry constant values as well as the infinite dilution Xe/Kr selectivity. The flexible selectivity was found to be lower for 95% of the materials with a rigid selectivity over 25 (as shown on Figure 6.2b), which suggests an overestimation of the top performing materials. Furthermore, the effect of flexibility is much more important for the smaller pore sizes, because of the intensity of the interactions at lower distance.

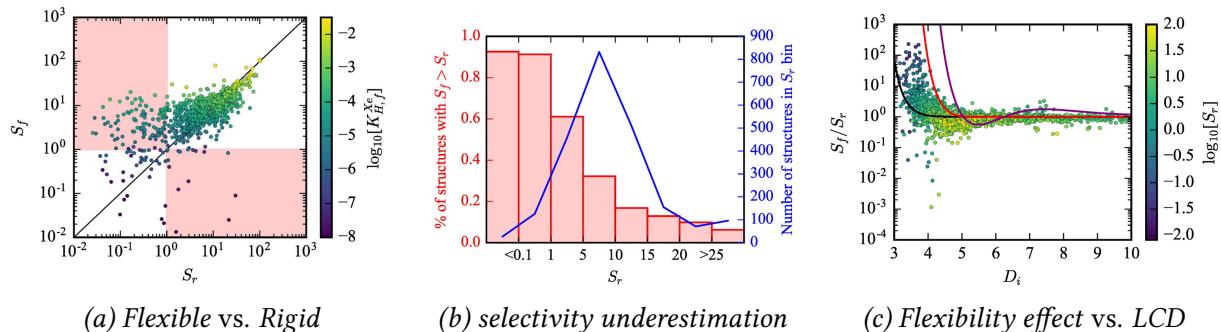


Figure 6.2: (a) A scatter plot of the flexible selectivity against the rigid selectivity labeled by the  $\log_{10}$  of the flexible Xe Henry constants. (b) Barplot of the fraction of the underestimated selectivity ( $s_f > s_r$ ) for different categories of materials going from the least selective ones to the most selective ones ( $s_r > 25$ ). (c) Effect of the flexibility measured using the ratio  $s_f/s_r$  as a function of the largest included sphere diameter. The line plots correspond to analytical modeling of the effect that will not be detailed here. Reprinted with permission from the original paper [162] copyright © 2017 American Chemical Society.

If we now focus on the issue of flexibility in KAXQIL, the authors used several methods to evaluate its effect on the Xe and Kr Henry constants and the Xe/Kr selectivity. For instance, they used another description of the metal-ligand bond using a cationic dummy model (UFF-CDM) and an *ab initio* MD simulation using the PBE DFT function,<sup>296</sup> with a Grimme's D3 van der Waals correction<sup>297</sup> (PBE+D3). Each of these three methods are used to generate about 30 snapshots that were eventually used to determine the flexible framework's adsorption properties for KAXQIL.

The authors found that the lower experimental selectivity value of 16 compared to the UFF-determined one could be partially explained by a flexibility effect. The selectivity evaluated on a rigid SBMOF-1 structure using the standard UFF forcefield is way higher than the one obtained when considering snapshots of a vibrating structure. The *ab initio* MD method that

Data source	Flexible structure	Xe Henry Constant mmol g <sup>-1</sup> Pa <sup>-1</sup>	Kr Henry Constant mmol g <sup>-1</sup> Pa <sup>-1</sup>	Xe/Kr selectivity
Experimental data <sup>41</sup>	maybe	$3.84 \times 10^{-4}$	$2.37 \times 10^{-5}$	16
Rigid structure SBMOF-1 <sup>41</sup>	no	$1.45 \times 10^{-2}$	$2.70 \times 10^{-4}$	54
PBE+D3 (2,2,1 unit cell)	yes	$6.80 \times 10^{-3}$	$1.77 \times 10^{-4}$	38
UFF-FM	yes	$6.24 \times 10^{-3}$	$1.67 \times 10^{-4}$	37
UFF-DCM	yes	$3.18 \times 10^{-3}$	$1.28 \times 10^{-4}$	25

Table 6.1: Results of the flexibility analysis carried out by Witman et al., flexibility reduces the values originally calculated in a rigid structure. Reproduced with permission from the original paper [162] copyright © 2017 American Chemical Society.

should be the closest to the actual dynamics does not recover the whole phenomenon because of the system size dependence. To see the crystallographic deformations, multiple unit cell replications are usually necessary. Moreover, the UFF forcefield does not give a perfect picture of the interaction energies at play in the system. But an overall trend is, however, drawn in this study since it is possible to attribute the discrepancies between experimental and theoretical data to the rigidity hypothesis.

This approach does not give a complete picture of the flexibility effect on the selectivity value, but can rapidly identify a weakness in the rigidity hypothesis and therefore warn on a possible over- or under-estimation of the selectivity, which can lead to identifying wrongfully a material as the best or missing the opportunity of finding a better material. The main advantage of this technique is the relative speed compared to an osmotic ensemble Monte Carlo simulation.<sup>268</sup> But the main drawback is the imperfect description of the intrinsic flexibility as the only phenomenon at play. For instance, in the following, I will show some adsorbate-induced effects that were neglected but can be retrieved by using the multiple works on the same SBMOF-1 material. In this approach, we avoid the issues around MD simulations and we only base our reasoning on observed structural changes.

### 6.3.2 Experimental database approach

According to original paper on SBMOF-1,<sup>41</sup> the theoretical selectivity calculated by UFF is around 70.6. However, the experimental selectivity is much lower, around 16. To solve this mystery, Witman et al. used a snapshot-based method to evaluate the effect of selectivity. The intrinsic flexibility lowers the selectivity, which goes in the right direction to explain the difference of selectivity, but it does not seem to capture the whole picture.

I think that the missing effect that could explain the discrepancies observed is the deformation induced by the loading of adsorbate inside the material. For instance, experimentally a structure is never empty when we resolve it by X-ray, and molecules are actually loaded inside. As shown on Table 6.2, the structure that was originally published for its good CO<sub>2</sub>/N<sub>2</sub> selectivity<sup>278,298</sup> was also tested for water adsorption, and two different structures emerged from this study: KAXQOR and KAXQIL. The first one is loaded by either air or CO<sub>2</sub>, and the structure does not seem to be stretched as much (low LCD values around 4.5 Å). The second one, on the other hand, is loaded by water that forms big clusters inside the pores and therefore stretches the pore size toward higher values (high LCD values around 5.0 Å). If we look at the structures resolved in the Nature Communications study,<sup>41</sup> depending on the adsorbate (hexane, water,

Experimental structure CCSD ref. code	Adsorbate in the structure	Selectivity $s_0^{\text{Xe/Kr}}$	$K_{\text{H}}^{\text{Xe}}$ (mmol g <sup>-1</sup> Pa <sup>-1</sup> )	LCD (Å)	PLD (Å)	Xe Diff. Coeff. cm <sup>2</sup> s <sup>-1</sup>
KAXQOR01 <sup>298</sup>	Not specified	101	$3 \times 10^{-2}$	4.99	3.66	$3 \times 10^{-09}$
KAXQOR <sup>278</sup>	Not specified	22	$4 \times 10^{-3}$	4.51	4.04	$7 \times 10^{-06}$
KAXQIL <sup>278</sup>	H <sub>2</sub> O	104	$3 \times 10^{-2}$	5.12	3.77	$3 \times 10^{-08}$
QUXRIM <sup>299</sup>	hexane	52	$1 \times 10^{-2}$	4.75	4.31	$3 \times 10^{-05}$
QUXRUY <sup>299</sup>	hexane	96	$3 \times 10^{-2}$	4.91	3.57	$9 \times 10^{-10}$
QUXRROS <sup>299</sup>	hexane	99	$3 \times 10^{-2}$	5.00	3.66	$5 \times 10^{-09}$
QUXREI <sup>299</sup>	hexane	101	$3 \times 10^{-2}$	5.02	3.67	$7 \times 10^{-09}$
QUXRRAE <sup>299</sup>	hexane	100	$3 \times 10^{-2}$	5.03	3.68	$7 \times 10^{-09}$
QUXQUX <sup>299</sup>	butane	103	$3 \times 10^{-2}$	5.17	3.83	$1 \times 10^{-07}$
QUWYEO <sup>299</sup>	butane	100	$3 \times 10^{-2}$	4.99	3.65	$5 \times 10^{-09}$
UQEFAZ <sup>41</sup>	krypton	23	$5 \times 10^{-3}$	4.53	4.08	$5 \times 10^{-06}$
UQEfed <sup>41</sup>	xenon	63	$3 \times 10^{-2}$	4.89	3.54	$1 \times 10^{-11}$

Table 6.2: Structural, adsorption and transport properties of structures in the CSD database that are similar to SBMOF-1.<sup>41</sup> The last structures actually correspond to the structures resolved in the paper presenting SBMOF-1 in *Nature Communications*. We can note the structural diversity that induces this diversity of properties. (The pore sizes are calculated using the CCDC radii definition.)

butane, krypton or xenon), the LCD and PLD values change in the first order according to the size of the adsorbate as illustrated on Figure 6.4. There are, of course, other effects, like the clustering we mentioned for water, but also less expected effects such as the orientation of the adsorbate inside the structure.

As shown on Figure 6.3, the orientation of the hexane molecule inside the material seems to favor either a configuration with a large LCD and a low PLD (QUXRUY), or a slightly lower LCD with a slightly higher PLD (QUXRIM). The material configurations are, however, a bit different from the ones observed with KXQOR or KAXQIL.

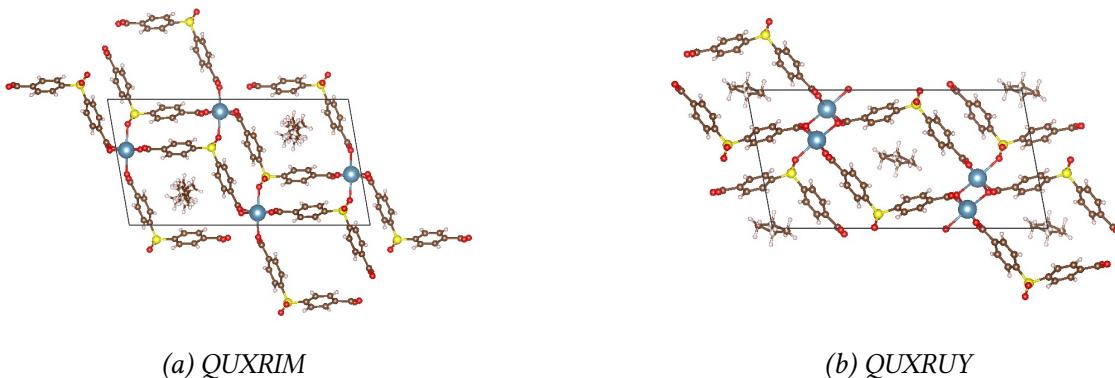


Figure 6.3: An illustration of the effect of the orientation of hexane inside a SBMOF-1-like material. In QUXRIM (a), the carbon atoms are oriented toward the S atoms, whereas in QUXRUY (b) they are oriented toward the Ca atoms. This difference in the orientation could explain the different structural properties of the materials reported on Table 6.2. Color code: brown for C, white for H, red for O, cyan for Ca, yellow for S. The structure visualizations are generated using the VESTA software.<sup>55</sup>

Now that I characterized the adsorbate effect on a few example configurations, we can better understand the thought process that leads to the identification of KAXQIL as a candidate for Xe/Kr separation. The KAXQIL structure is actually representing the material loaded by water with large pores which enables a good interaction with a large molecule like xenon. For this reason, it was identified as a top selective material. However, when it was experimentally tested for low-pressure adsorption using the Henry constant, it is most likely that the pores are not stretched, which implies lower Henry constants than expected. The structures UQEFAZ or KAXQOR seem to a better description of this low-pressure case since the experimental selectivity values are much more consistent with their theoretical selectivity values.

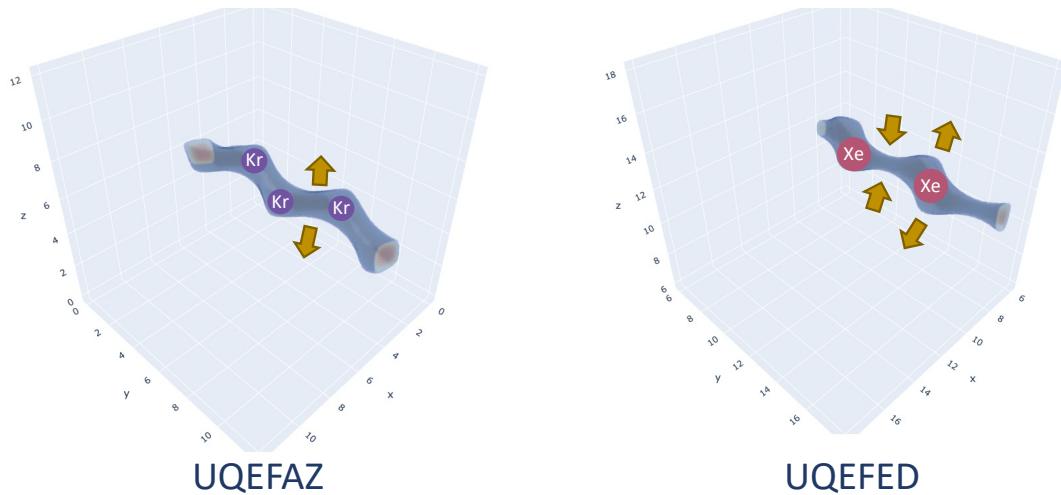
To confirm this hypothesis, we would need to measure a high-loading Xe/Kr binary mixture adsorption uptake. If xenon is highly represented in the adsorbent material, then the structure would be much more favorable to the xenon adsorption, hence increasing the selectivity value closer to the theoretically predicted one. This also highlights a composition effect, if the initial mixture has a low xenon content, the structure would most likely have narrower pores, which could decrease the selectivity. By changing the composition of the binary mixture, this effect could also be measured experimentally if the initial hypothesis on the adsorbate-induced flexibility is correct.

This method could be used on other materials by screening for materials with a similar chemical composition and topology, for example. However, due to the bias in research focus, it is not always possible to find structures in very different adsorption conditions. To work around these limitations, one could either experimentally generate these structures when a material seems interesting to see if the flexibility plays a role in the adsorption process. Alternatively, one could computationally generate these structures by running structure optimizations on loaded structures. Either way, this new approach to flexibility seems complementary to the ones mentioned previously because it seems to have a similar (or slightly higher due to the adsorbate) computational cost as the Witman approach, while avoiding the computationally prohibitive calculation (in a screening) presented by Bousquet et al.

### DIFFUSION IN A FLEXIBLE ENVIRONMENT

The transport can also be modulated by the adsorbate-induced flexibility of SBMOF-1. Depending on the structural configuration of the material, the diffusion coefficient is limiting only for some configurations of the material: it is equal to  $3 \times 10^{-8} \text{ cm}^2 \text{ s}^{-1}$  for KAXQIL and  $1 \times 10^{-11} \text{ cm}^2 \text{ s}^{-1}$  for UQEFD (Table 6.2). This lower diffusion coefficient can be simply explained by the change in PLD value induced by the stretching illustrated on Figure 6.4. For a material mostly loaded by krypton molecules, the diffusion coefficient of xenon is much higher ( $5 \times 10^{-6} \text{ cm}^2 \text{ s}^{-1}$ ), although it is not free diffusion, it can at least be considered as an unobstructed diffusion inside the material.

Now that we identified two completely different diffusion behaviors, we can extrapolate these results to hypothetical conditions. For instance, if there is a relation between the quantity of xenon inside the pores and the structural similarity toward UQEFD, then the material could kinetically limit the adsorption of xenon at a high loading of xenon. In other words, it could be kinetically harder to adsorb xenon at higher xenon loadings. But at lower xenon loading, it also means that there is no diffusion limitations as is suggested by the very steep mass transfer zone on the breakthrough curve of xenon on Figure 6.1b. If we connect this result on the influence of flexibility on the transport properties to the one obtained on the adsorption process itself, the



*Figure 6.4: Visualization of the pore size stretching effect using the GrAED algorithm. The xenon increases the LCD value while diminishing the PLD value.*

adsorption of xenon is also much more thermodynamically favorable at higher values of xenon loading. There seems to be a complex thermodynamics-kinetics trade-off as we articulated in the previous chapter since KAXQIL and UQEFED are structurally quite similar, but it occurs at higher partial pressure in xenon. At an industrial point of view, the inclusion of transport effects in the analysis highlights additional cost in adsorbing xenon at high loading values if this theoretical study is confirmed by experiments.

By using simple simulation methods (Widom insertion and MD) on rigid structures, I probed the effects of flexibility on both the adsorption and transport properties using experimentally resolved structures in different adsorption conditions. This study sheds light on the mystery around the experiment-theory discrepancies and opens up opportunities to understand similar problematic systems. In this study, I relied on the experimental data that was published on the SBFMOF structure, the same resources are not always available for other systems and maybe an effort of data generation using either experiments or simulations should be performed in these cases. If generalized, this approach can even be automatically applied on a series of structures, opening up the possibility of “flexibility-aware” screenings in the future. Aware of the importance of both flexibility and transport effects, other studies have tried to incorporate both in a small-scale screening process.<sup>291</sup> The authors used a flexible forcefield MD simulations to determine the diffusion coefficient and DFT calculations at the adsorption site to assess the adsorption performance. The main issue of this method is its computational cost, but it can be an alternative solution to the one introduced here, when no prior knowledge is available on the structure’s flexibility.

## 6.4 NOBLE GAS POLARIZABILITY

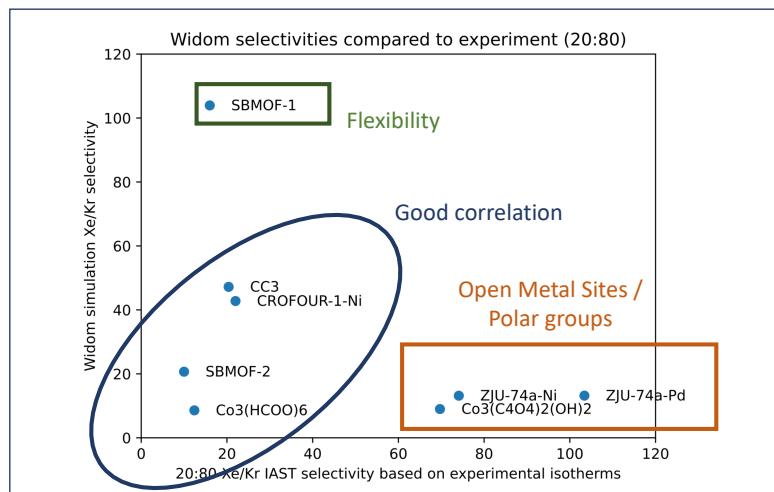
The last but not the least effect that could influence greatly the adsorption performances is, the level of theory behind the interaction energy modelization. In most screening studies, we use (me included) very low-level classical theories to describe the guest–host interactions, because of the low computational cost associated to it. To improve the description, some studies focus on a few specific structures and use higher levels of theory such as DFT calculations.

However, the prohibitive computational cost of these methods makes it hard to deploy it in high-throughput screenings.

But first, we should identify the limits of molecular modeling in the current screening methodologies before exploring higher cost methods. This work is actually motivated by the recent advances in experimental design of nanoporous materials for Xe/Kr separation. The most selective materials are based on highly polar groups or exposed open-metal sites.<sup>7,8</sup> The polarization is, therefore, central in these materials, but it is not well described by a simple Lennard-Jones potential especially when it is induced by high partial charge values (open-metal site or polar groups).

For this reason, it is necessary to develop a polarizable forcefield that includes the effect of the surrounding partial charges into the guest–host interactions. The difference of polarizability between xenon and krypton could let new materials emerge. The best material ranking obtained by this type of screening would be completely different from the standard one. In this section, I will introduce the problem of current methodologies through an experiment-theory comparison, and then I will introduce possible methodologies that could be used to take into account the polarization in the currently used Lennard-Jones potentials.

#### 6.4.1 Problem definition



*Figure 6.5: Comparison between the selectivity values obtained experimentally and computationally. The structures are split in three categories depending on the difference between experiments and theory. We can explain the case of SBMOF-1 by its flexibility. The discrepancies for the materials in the lower right correspond to the ones introduced by Li et al. and Pei et al.,<sup>7,8</sup> and the difference can be explained by the polarization that is not included in the level of theory considered. [higher resolution+change xaxis (IAST)]*

If we consider the selectivity of good materials for xenon/krypton separation that are often presented in the literature, the materials named  $\text{Co}_3(\text{HCOO})_6$ ,<sup>178</sup> CC3,<sup>6</sup> SBMOF-2,<sup>300</sup> CROFOUR-1-Ni,<sup>179</sup> SBMOF-1,<sup>41</sup>  $\text{Co}_3(\text{C}_4\text{O}_4)_2(\text{OH})_2$ <sup>7</sup> and ZJU-17a<sup>8</sup> often appear as top separation materials. When comparing their selectivity values obtained by a Widom insertion with the UFF forcefield to the experimental values as shown on Figure 6.5, there is generally a good correlation, however, in some cases like SBMOF-1, other effects could explain the difference

observed (see the previous section on flexibility). In other cases, it is the polarization effect that was not taken into account and could in fact explain the difference. To better understand this phenomenon, I will describe the two papers that found record-breaking Xe/Kr selectivity values based on polar hydroxyl groups and open metal sites.

The first paper of Li et al.<sup>7</sup> published in 2019 introduced a squarate-based MOF with a Xe/Kr selectivity of 69.7 for a 20:80 binary mixture estimated by the ideal adsorbed solution theory (IAST).<sup>301</sup> The authors explained this outstanding xenon affinity by two factors: a pore size close to the kinetic diameter of a xenon and the stabilization effect of the hydroxyl group. DFT calculations determined binding energies of the order of  $44.1 \text{ kJ mol}^{-1}$  for xenon and  $33.7 \text{ kJ mol}^{-1}$ , which suggests a separation process of enthalpic nature (usually the case for highly selective materials). Because of the high electronegativity of the oxygen atom, the hydroxyl group pointing to the pore center (as illustrated on Figure 6.6a) interacts strongly with the xenon through a permanent dipole–induced dipole interaction (introduced in the section 2.1.2). This high xenon affinity is illustrated by the experimental isotherms of the Figure 6.6b. On the other hand, the pore wall creates unidimensional channels that present adsorption pores with a  $4.1 \text{ \AA} \times 4.3 \text{ \AA}$  size, which is very close to the xenon kinetic diameter of about  $4.0 \text{ \AA}$ .

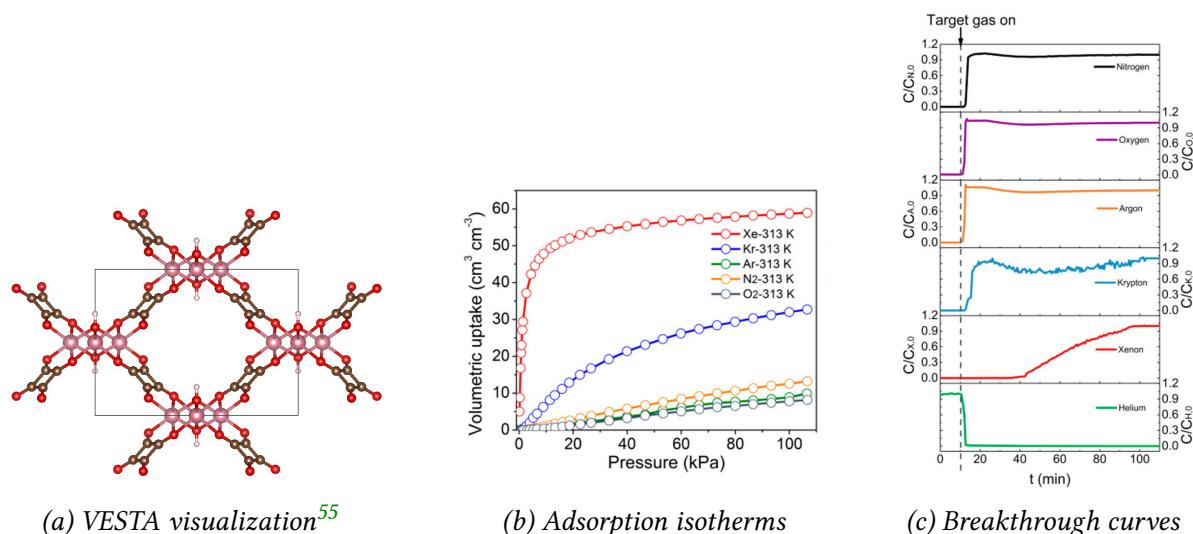
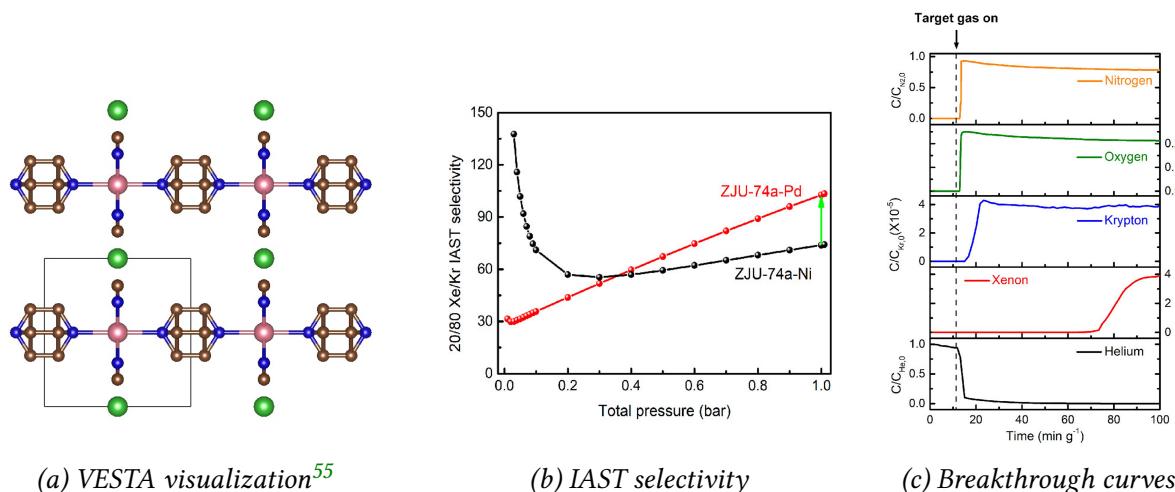


Figure 6.6: (a) Representation of the squarate-MOF  $\text{Ce}_3(\text{C}_4\text{O}_4)_2(\text{OH})_2$  structure with the color code: brown for C, white for H, red for O, pink for Co. We can see the hydroxyl group to which the authors attribute the high Xe/Kr selectivity. (b) Mono-component adsorption isotherm measured experimentally for Xe, Kr, Ar, N<sub>2</sub> and O<sub>2</sub>. (c) Experimental breakthrough curves for a gas mixture with 400 ppm Xe and 40 ppm Kr balanced with dry air. Reprinted with permission from Ref. [7] copyright © 2019 American Chemical Society.

Finally, if we look at the breakthrough experiment data (on Figure 6.6c), we observe a rather slow release of xenon in the mass transfer zone, which suggests a rather low xenon diffusion coefficient in this material. It seems that the diffusion limitation occurs even at very low xenon partial pressure (400 ppm) in this material. This was not the case for SBMOF-1, as the xenon breakthrough curve was much steeper (rapid mass transfer) as shown on Figure 6.1b. To have a closer look at the transport effect in this squarate-MOF, we should carry out similar simulations as for SBMOF-1 with a polarizable forcefield.

In the second work,<sup>8</sup> Pei et al. introduced two Hofmann-type MOFs with record-breaking Xe/Kr selectivity values. The first Co/Ni-based MOF, called ZJU-74a-Ni, has an estimated IAST selectivity of 74.1 for a Xe/Kr binary mixture of composition 20:80 at 1 bar and 298 K, while the second Co/Pd-biased MOF, ZJU-74a-Pd, displays a selectivity of 103.4 in the same ambient-pressure conditions. As shown on Figure 6.7b, the IAST selectivity of ZJU-74a-Pd is not always that high and can decrease to 30 at very low-pressure conditions. The authors attribute the record-breaking selectivity values of these materials by a size close to the kinetic diameter of Xe and above all the increased interaction with the open metal site either be it the nickel or the palladium atoms. The Horvath–Kawazoe method gave a pore size of 4.0 Å and 3.8 Å for respectively the Ni and Pd-based MOFs. And the xenon binding energy was evaluated to be around 38 kJ mol<sup>-1</sup> for ZJU-74a-Ni using a UFF-based method. We can note that this value is much lower than the one obtained for the squarate-based MOF. Since the experimental performance is much higher, this is probably due to the level of theory they employed probably to save time. This material needs to be tested with either a DFT method in order to find the real binding energy.



*Figure 6.7: (a) Representation of the ZJU-74a-Ni structure with the color code: brown for C, white for H, red for O, pink for Co, green for Ni. We can see the open metal sites or coordinatively unsaturated nickel metals that could interact with an adsorbate in the center of the pore. (b) Selectivity values at different pressure conditions for a 20:80 Xe/Kr binary mixture calculated by the IAST theory. (c) Experimental breakthrough curves of a gas mixture with 400 ppm Xe and 40 ppm Kr balanced with dry air in ZJU-74a-Pd. Reprinted with permission from Ref. [8] copyright © 2022 American Chemical Society.*

Finally, the breakthrough experiment suggests a rather slow mass transfer in the material. However, if compared to the squarate-based material in similar conditions, the mass transfer seems to be much faster, since the mass transfer zone is shorter. ZJU-74a-Pd is, therefore, probably a better material than  $\text{Co}_3(\text{C}_4\text{O}_4)_2(\text{OH})_2$  because its better adsorption and transport properties for a Xe/Kr separation. When compared to SBMOF-1 with a rather low xenon partial pressure, there seems to be a slight diffusion limitation phenomenon. The retention of xenon is, on the other hand, longer in ZJU-74a-Pd (around 70 s) than in SBMOF-1 (around 65 s). We probably need more information on the ambient-pressure selectivity of SBMOF-1, to complete the comparison. This material is also interesting for its robustness in different pH, humidity

and radiation conditions, which makes it a material of choice in nuclear installations to capture the xenon produced by the nuclear reactions.

These two studies show clearly the failure of current screening methodologies to find materials whose performance is due to polarization effects. In the next and final discussion, we will introduce some methods of incorporating polarization into Lennard-Jones potentials that could be used in a screening procedure.

#### 6.4.2 Studying the polarization

The physical reason behind considering the polarization effect for xenon/krypton separation is to exploit the difference of polarizability between Xe ( $4.0 \text{ \AA}^3$ ) and Kr ( $2.5 \text{ \AA}^3$ )<sup>302</sup> at its full potential. And in a broader perspective, the order of magnitude of the induction energy is actually higher than other standard van der Waals energies as explained in the section 2.1.2. For instance, the ion-induced dipole interaction is said to be of the order of  $40\text{-}600 \text{ kJ mol}^{-1}$ . In the case of ZJU-74a-Ni, the  $\text{Ni}^{2+}\text{--Xe--Ni}^{2+}$  interaction at the origin of selectivity is precisely this type of interaction, which mostly explains the experimental values of selectivity. The incorporation of polarization in the screening procedure could completely change the type of structures obtained and the type of the interactions at play.

With this in mind, Becker et al. carried out an interesting study on a series of MOF materials with a high density of open-metal sites, the M-MOF-74 with M = Co, Cr, Cu, Fe, Mg, Mn, Ni, Ti, V, and Zn.<sup>199</sup> The authors found that by adding a potential induced by the surrounding partial charges to a modified LJ potential, they could reproduce the  $\text{CO}_2$  and  $\text{CH}_4$  experimental isotherm data for this series of MOFs. They also showed that the standard UFF forcefield does no describe the adsorption behavior of  $\text{CO}_2$  on the open-metal sites, hence missing out on a strong adsorption site at infinite dilution.

This new method is based on the procedure developed by Lachet et al..<sup>198</sup> This procedure is based on the induced dipole method where the induction energy  $U_{\text{ind}}$  is expressed as follows:

$$U_{\text{ind}} = -\frac{1}{2} \sum_{i=1}^N \boldsymbol{\mu}_i \cdot \mathbf{E}_i^0 \quad (6.1)$$

where  $\boldsymbol{\mu}_i$  is the induced dipole, and  $\mathbf{E}_i^0$  is the electric field created by the surrounding atoms' partial charges on the particle  $i$ . Since the induced dipole also interacts with the surrounding induced dipoles  $j \neq i$ , the induced dipole is usually calculated using a back-propagation algorithm as described in the Ref. [198]. However, back-propagation was found to only account for less than 5% of the total induction energy. For this reason the equation can be simplified to the simple interaction between the induced dipole and the surrounding electric field without taking into account the induced-dipole-induced-dipole interactions. Moreover, by skipping the back-propagation step, we can save valuable computation time in a screening. The induction energy can then be simply expressed as follows:

$$U_{\text{ind}} = -\frac{1}{2} \sum_{i=1}^N \alpha_i |\mathbf{E}_i^0|^2 \quad (6.2)$$

Since a part of the induction energy is already contained in the Lennard-Jones potential, the authors rescaled the LJ parameters to remove the induction part from the LJ energy. This part seems to be system-dependent and could in fact be questionable since we can use it to fit to experimental data without solid theoretical reasons to back it. To do it properly, one should design a forcefield around this concept in order to tweak the LJ-parameters according to a given experimental data as it is usually done in any forcefield development.

If we manage to customize this method to the xenon/krypton separation case, it could be possible to carry out screenings that find materials comparable to ZJU-74a-Pd. To further optimize the process, we can reduce the number of materials by restricting the screening process to a certain pore size and that contains open metal sites within a database, and then evaluate this restricted list using higher-level methods.





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# GENERAL CONCLUSIONS

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This thesis explored different approaches to find the best nanoporous materials for adsorption-based industrial xenon/krypton separation (e.g., pressure-swing adsorption). As highlighted in our literature review,<sup>21</sup> a high-throughput screening focus on one specific property of the nanoporous material in order to find the best material for a targeted application. There are three main challenges for screenings: (i) the accuracy of the methods used to characterize the key properties at play, (ii) the experimental/computation time required to determine those properties, and (iii) other properties that are often neglected can be added to the evaluation of the performance. For instance, to evaluate the separation performance, one usually uses the adsorption selectivity.

The second chapter focused on different methodologies to evaluate this selectivity in different physical conditions, and how a screening can draw a realistic picture of a selective material.<sup>22</sup> The influence of the composition, the pressure and the some structural descriptors were studied thoroughly. To achieve maximal selectivity, the pore size needs to be tailored to the size of a xenon. The Xe/Kr separation can be approximately described by the xenon affinity with the material, and this affinity is enthalpic in nature. The effect of a higher partial pressure of xenon results in the saturation of the most favorable pores for xenon adsorption, which is at the origin of the observed selectivity decrease in some materials.

Because of the prominent role of the enthalpic term, the third chapter introduced faster sampling techniques to evaluate the selectivity in the infinite-dilution case. Along with the most used Widom insertion, this work described various biased sampling techniques such as the Voronoi sampling or the surface sampling (RAESS). The RAESS algorithm<sup>23</sup> were proven to be faster than a Widom insertion and much more accurate than the previously introduced Voronoi energy<sup>18</sup> on the CoRE MOF 2019 database. Finally, an unbiased sampling based on a symmetric grid (GrAED) was introduced to provide valuable energy descriptors to design finely tuned energetic descriptors. The GrAED algorithm provides interesting descriptors that can be further used in an ML modeling, for instance. These techniques can be used in a multiscale screening to faster single out interesting materials for more time-consuming calculations or experiments.

To get a GCMC level of accuracy combined with a speed comparable with faster low-dilution calculations, an ML model based on structural, chemical and energetic descriptors was proposed in the fourth chapter.<sup>24</sup> This model was proven to be very accurate and could be used to provide GCMC grade evaluations with minimal computation resources. The interpretation of this ML model opened up new ways of tackling the structure-property relationship through other methods than the standard correlation analyses.

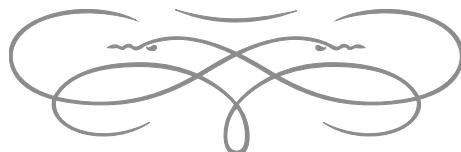
Up until now, thermodynamic properties calculated under rather simple assumptions have been thoroughly studied using multiple correlation analysis and the development of multiple performance evaluation tools. To consider different key properties, the transport properties were studied in the fifth chapter. Different methodologies were explored: (i) the most physically accurate but also the slowest method is based on molecular dynamics of at least a few tens of nanoseconds; (ii) the transition state based methodologies that approximate the diffusion process by hopping from one site to another; (iii) Finally, the ML-based method that uses some descriptors based on activation energies (transition state theory) to predict the diffusion coefficient. Using these calculated transport properties, the screening uncovered selective materials without kinetic limitations (that also happens to have high xenon capacity), which confirms the multivariate nature of the screening process since these types of materials would be much more productive with more output at each pressure-swing cycle and also faster cycles (in a PSA process).

The final chapter opens perspectives on studies of other physical properties of the material, neglected throughout this thesis, such as the flexibility of the material or the interactions induced by charged atoms or polar groups. The polarization effect should be directly integrated in a screening to identify materials with much higher experimental selectivity as suggested by the characteristics of the recent top-performing materials for Xe/Kr separation.<sup>7,8</sup> And the flexibility of the material could explain some theory–experiment discrepancies that would otherwise go unsolved, which proves the more accurate description of flexibility-aware molecular simulations.

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This work opens perspectives for faster screening strategies of separation properties in different physical and chemical conditions. Moreover, the different tools developed in this thesis can be used to easily integrate transport properties in future screening for gas separation in nanoporous materials. By integrating these tools with the recently emerging idea of Digital Reticular Chemistry,<sup>9</sup> new perspectives on material design could be envisioned.

The different methodologies developed also enable the integration of understudied properties that have a key role in the industrial process of xenon/krypton separation. By combining the faster methods that introduced throughout this thesis, it is now possible to incorporate usually neglected physical phenomena in the screening procedure. The faster sampling of the adsorption energies can serve as building ground to model a flexible material through a snapshot approach, for example.<sup>162</sup> The evaluation of the induced energy<sup>198</sup> can also be integrated in the evaluation tools used throughout this thesis.







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# LIST OF PUBLICATIONS

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## PEER-REVIEWED PAPERS

1. Emmanuel Ren and François-Xavier Coudert. “Thermodynamic exploration of xenon/krypton separation based on a high-throughput screening”. In: *Faraday Discussions* 231 (2021), pp. 201–223. [DOI: 10.1039/D1FD00024A](https://doi.org/10.1039/D1FD00024A).
2. Emmanuel Ren, Philippe Guilbaud, and François-Xavier Coudert. “High-throughput computational screening of nanoporous materials in targeted applications”. In: *Digital Discovery* 1.4 (2022), pp. 355–374. [DOI: 10.1039/D2DD00018K](https://doi.org/10.1039/D2DD00018K).
3. Emmanuel Ren and François-Xavier Coudert. “Rapid adsorption enthalpy surface sampling (RAESS) to characterize nanoporous materials”. In: *Chemical Science* 14.7 (2023), pp. 1797–1807. [DOI: 10.1039/D2SC05810C](https://doi.org/10.1039/D2SC05810C).

## PREPRINT

4. Emmanuel Ren and François-Xavier Coudert. “Gas Separation Selectivity Prediction Based on Finely Designed Descriptors”. In: (June 2023). [DOI: 10.26434/chemrxiv-2023-q841f](https://doi.org/10.26434/chemrxiv-2023-q841f).



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## INTRODUCTION

Les procédés industriels de séparation des gaz sont largement utilisés pour fournir des réactifs purifiés et des gaz inertes aux industries chimiques, sanitaires, agricoles et alimentaires pour les industries de la chimie, de la santé, de l'agriculture et de l'alimentation. Ils peuvent également être utilisés pour atténuer l'impact négatif de certaines activités industrielles sur l'environnement : dans les usines de production de béton ou d'acier, les émissions très problématiques de CO<sub>2</sub> pourraient être piégées ; mais aussi dans les usines de retraitement des combustibles nucléaires, des composés radioactifs volatils peuvent être séparés des autres gaz. Différentes petites molécules comme le diazote, le dioxygène, le dioxyde de carbone, le dihydrogène, le méthane, le protoxyde d'azote ou les gaz rares sont ainsi séparées, purifiées puis stockées. La séparation xénon/krypton étudiée dans cette thèse est communément utilisée pour extraire ces gaz de l'atmosphère, mais l'industrie du nucléaire constitue une source bien plus abondante de xénon et de krypton.

Les procédés industriels de séparation Xe/Kr sont encore bien souvent basés sur la distillation cryogénique de l'air ambiant, ce qui requiert beaucoup d'énergie, une infrastructure complexe et un contrôle minutieux des risques. On peut par exemple évoquer les récents accidents d'exploitation d'usine de séparation de gaz (1997) qui ont été causés notamment par la réaction d'hydrocarbures de l'environnement avec l'oxygène liquéfié de l'usine. Pour éviter les problèmes de sécurité et de coûts importants, de nombreux chercheurs s'attellent à développer des méthodes de séparation industrielle basées sur l'adsorption dans des matériaux nanoporeux. Ces matériaux nanoporeux sont constitués de pores à l'échelle nanoscopique qui offrent une large surface aux molécules pour y interagir puis s'adsorber. Des procédés industriels basés sur cette technologie existent déjà, ils utilisent notamment le *pressure swing adsorption* (PSA) qui consiste à remplir les pores d'un mélange de gaz à haute pression, puis de récupérer un gaz ainsi purifié. En effet, les pores du matériau permettent l'adsorption préférentielle d'une molécule par rapport aux autres ce qui permet d'augmenter la teneur en une certaine molécule du mélange sortant. En

répétant ce procédé, on peut ainsi séparer les différentes molécules d'un gaz. Dans le cadre de ma thèse, le xénon étant chimiquement proche du krypton, la purification par ce procédé reste un défi majeur. Certains prototypes industriels ont déjà été imaginés, mais la recherche d'un matériau pour effectuer au mieux cette tâche reste aujourd'hui une question ouverte.

Pour développer un procédé viable, il faut donc choisir avec soin les matériaux que l'on utilise dans ces dispositifs industriels. La recherche se focalise aujourd'hui sur la conception de matériaux toujours plus sélectifs en se basant sur des intuitions chimiques construites au fil des études. Afin d'éviter les expériences coûteuses pour tester tous les matériaux, les criblages computationnels sont de plus en plus utilisés. Ces criblages ou *screenings* en anglais permettent de passer en revue de grandes quantités de structures afin d'en évaluer leur potentielle performance. Tout l'enjeu est donc de former une bonne synergie entre la conception minutieuse de matériaux et la recherche et évaluation rapide des matériaux via des méthodes informatiques. Du côté du traitement informatique des matériaux, les deux défis majeurs sont la génération de données fiables et diverses afin de couvrir le spectre des possibles et le développement de nouveaux outils pour l'évaluation rapidement et avec précision les performances de ces matériaux.

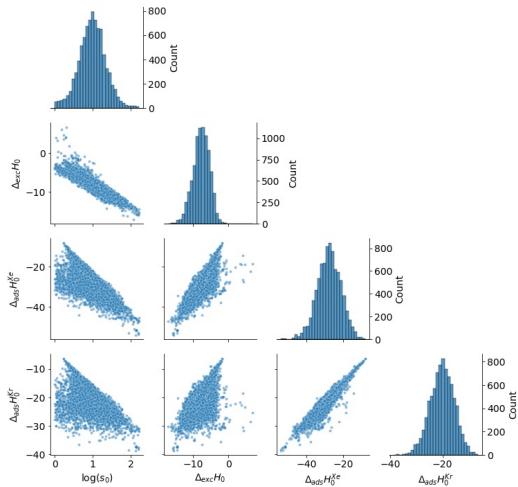
La quantité de matériaux est potentiellement infinie, rien que pour les *metal-organic frameworks* (MOFs) en anglais, plus de 90 000 structures ont été synthétisées et 500 000 ont été construits de manière digitale. Pour pouvoir évaluer tous ces matériaux, différentes stratégies ont été élaborées. Certains utilisent des criblages à plusieurs niveaux qui permettent de réduire au fur et à mesure les matériaux à évaluer avec des méthodes plus coûteuses, d'autres se basent sur des algorithmes d'apprentissage statistiques. Cependant, peu d'études se focalisent sur les outils de calcul, en eux-mêmes, qui sont souvent davantage adaptés à des calculs sur des structures uniques plutôt que pour être déployés sur des centaines de milliers de structures. Cette thèse s'emploie donc à développer des outils pour accélérer les procédés de criblages actuels tout en travaillant sur la précision des évaluations de performance. Outre la sélectivité, d'autres variables revêtent une importance significative : la capacité d'adsorption du matériau, la cinétique et la thermodynamique derrière la régénération du matériau (c'est-à-dire en vider les pores). Pour cette raison, ma thèse étudie également les propriétés de transport du xénon et du krypton dans ces matériaux nanoporeux.

## ÉTUDE THERMODYNAMIQUE DE LA SÉPARATION XE/KR

En premier lieu, mes travaux ont porté sur l'analyse poussée des corrélations qu'il pouvait exister entre les différentes grandeurs thermodynamiques décrivant la séparation xénon/krypton. Pour cela, mes travaux se basent sur la base de données CoRE MOF 2019 pour comparer les différentes grandeurs thermodynamiques grâce à des analyses de corrélation. Différentes conditions de pression et de composition ont été étudiées et des explications physiques à l'échelle microscopique sont proposées pour comprendre l'origine des différences observées.

Pour commencer, j'ai étudié les corrélations entre l'enthalpie et la sélectivité. Sur la figure R1, l'enthalpie d'adsorption du xénon est assez bien corrélée au logarithme de la sélectivité à basse pression suggérant ainsi que l'affinité du xénon avec le matériau peut expliquer la sélectivité. Cette corrélation diminue cependant pour les matériaux moins sélectifs. Les matériaux les plus sélectifs ont en effet des pores dont la taille est très favorable à l'adsorption du xénon

comme le suggèrent d'autres études. Pour des gaz nobles, seules les interactions de Van der Waals jouent un rôle important, ainsi la taille des pores permettent d'expliquer en grande partie l'affinité comparée entre deux molécules de tailles différentes le xénon et le krypton. Ainsi, dans des matériaux avec de petits pores, les phénomènes sont dominés par les interactions entre les pores et l'adsorbat, c'est-à-dire par l'enthalpie. Alors que dans de larges pores, les effets entropiques jouent un rôle plus important.

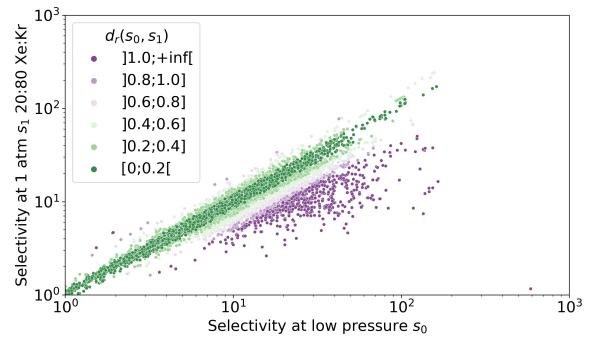


**FIGURE R1 :** Pour 8 401 MOFs avec une sélectivité Xe/Kr favorable ( $s_0 > 1$ ), pair-plots entre les différentes grandeurs  $\log(s_0)$ ,  $\Delta_{\text{exc}}H_0$ ,  $\Delta_{\text{ads}}H_0^{\text{Xe}}$  et  $\Delta_{\text{ads}}H_0^{\text{Kr}}$  (les enthalpies sont en  $\text{kJ mol}^{-1}$ ) en dehors de la diagonale et la distribution de chaque grandeur sur la diagonale.

D'autre part, nous observons sur la figure R1 que l'enthalpie d'échange est très bien corrélée à la sélectivité. Cela peut s'interpréter à l'aide de l'équation suivante  $\Delta_{\text{exc}}H = T\Delta_{\text{exc}}S - RT \ln s$  dans le cas où  $T\Delta_{\text{exc}}S$  serait quasi constante. En effet, l'entropie joue le rôle de bruit d'un point de vue statistique ce qui est confirmé par d'autres figures au chapitre 2 de cette thèse, où l'on observe clairement l'absence totale de corrélation avec la sélectivité. Cette première figure nous renseigne ainsi sur le rôle prédominant de l'enthalpie d'échange pour expliquer la sélectivité observée.

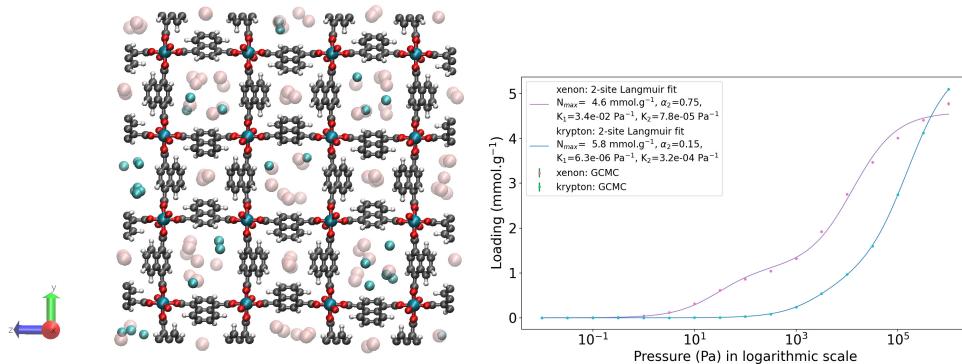
La figure R2 quant à elle met en évidence la chute de la sélectivité de certains matériaux lorsque l'on passe de la basse pression à la pression ambiante. Cette différence de sélectivité est étudiée à l'aide de l'enthalpie et l'entropie d'échange. Et nous remarquons à nouveau que ce changement de sélectivité est en grande partie expliqué par une augmentation de l'enthalpie d'échange pour ces structures. L'entropie joue encore un rôle relativement mineur sur ce phénomène. L'étude des données thermodynamiques sur un ensemble de 9 668 structures nous suggère que l'enthalpie d'échange définie précédemment permet d'expliquer en grande partie les tendances des sélectivités thermodynamiques à haute et basse pression. La séparation xénon/krypton est donc dominée par des effets enthalpiques.

Pour mettre en évidence les phénomènes physiques à l'origine de la chute de sélectivité pour certains matériaux, nous allons présenter dans ce résumé une structure problématique en particulier pour illustrer les caractéristiques de la structure. Dans ce matériau, il n'y a pas



**FIGURE R2 :** Sélectivité à 1 atm de pression en fonction de la sélectivité à basse pression pour une composition 20:80 Xe/Kr. Les points sont étiquetés selon la différence relative entre les deux sélectivités. Les points violets ont une grande différence relative entre les sélectivités.

qu'un seul type de site d'adsorption ni un seul canal unidirectionnel. Le matériau WOJJOV (figure R3) est un exemple de structure contenant deux types de pores comme on peut le voir sur la représentation graphique et ce qui est confirmé par la validité d'un modèle à 2 sites pour décrire les isothermes corps pur. Le premier type de type est plus petit et a une taille parfaite pour adsorber le xénon. C'est pourquoi, à basse pression la sélectivité calculée est très élevée  $s_0 = 146$ . Lorsqu'on augmente la pression, les sites plus larges commencent à être occupés. Or ces sites plus larges sont moins sélectifs du fait de leur taille. C'est pourquoi la sélectivité diminue grandement et passe à  $s_1 = 14$  à pression ambiante. D'autres structures ayant un système plus complexe de canaux baissent également en sélectivité avec la pression.



*FIGURE R3 : WOJJOV : Représentation d'un MOF  $[\text{Al}(\text{OH})(1,4-\text{NDC})] \cdot 2(\text{H}_2\text{O})$  où NDC signifie naphthalene-dicarboxylate. Code couleur : Cu en cyan foncé, C en gris, O en rouge, H en blanc ; Xe en rose et Kr en cyan clair. Sur la droite, les isothermes corps pur du xénon et krypton à 298 K ainsi qu'un modèle d'isotherme à deux sites.*

Pour conclure, la présence de différents types de site et les réorganisations dues aux interactions du mélange Xe/Kr dans la phase d'adsorption permettent d'expliquer à l'échelle moléculaire la différence de sélectivité à basse et haute pression pour un certain nombre d'exemples. De plus, la séparation Xe/Kr est dominée par les effets enthalpiques, donc une bonne description de l'énergie d'adsorption est primordiale pour décrire la sélectivité d'un matériau.

## DÉVELOPPEMENT D'OUTILS DE CRIBLAGE

Dans cette partie on va s'intéresser à différentes méthodes de calcul de l'enthalpie d'adsorption qui joue un rôle central dans la performance d'un matériau. Cette enthalpie à basse pression peut être théoriquement calculée grâce à un échantillonnage des énergies d'interaction pour tous les points accessibles de l'espace, mais cette méthode est coûteuse en temps de calcul. C'est pourquoi les méthodes d'échantillonnage aléatoire des points de l'espace se basant sur les algorithmes Monte Carlo sont plus souvent utilisées (insertion de Widom). Cependant, cet échantillonnage aléatoire ne tient donc pas en compte des informations que l'on a sur les matériaux nanoporeux. En effet, les adsorbats ne se situent pas à des endroits imprévisibles, ils sont souvent aux centres des pores (si la taille est adaptée) ou sur la surface des pores. On a donc exploité ces informations afin de diminuer le temps de calcul nécessaire à la détermination de l'enthalpie d'adsorption.

La première méthode approchée d'échantillonnage consiste à calculer les énergies sur les nœuds de Voronoï. Les nœuds de Voronoï sont des points équidistants à au moins quatre atomes de la

structure. Si on considère uniquement les points de Voronoï accessibles, ces points seront situés au centre des pores. La deuxième méthode quant à elle échantillonne les surfaces des pores. Pour cela l'algorithme RAESS parcourt les points à la surface des atomes de la structure et y calcule l'énergie d'interaction avec le matériau. Et enfin, la dernière méthode développée durant cette thèse se base sur une grille symétrique optimisée pour faire baisser le temps de calcul par rapport à l'approche usuelle par grille. L'algorithme associé GrAED (*Grid Adsorption Energy Descriptors*) est ainsi très intéressant pour des bases de données ayant des petits pores et des structures avec un haut degré de symétrie. La figure R4 compile les différentes performances de précision et de temps pour toutes les méthodes de calcul de l'enthalpie d'adsorption étudiée durant ma thèse.

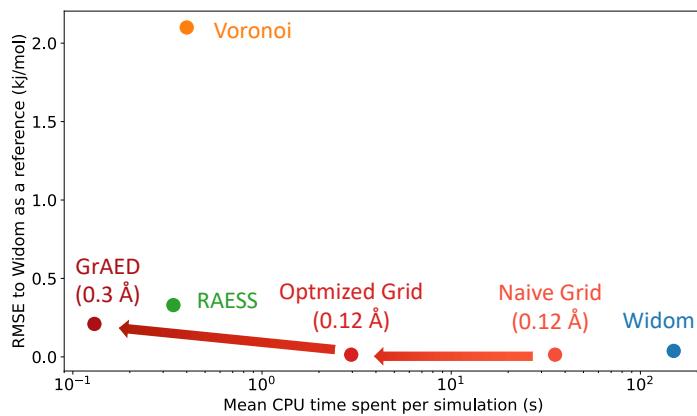


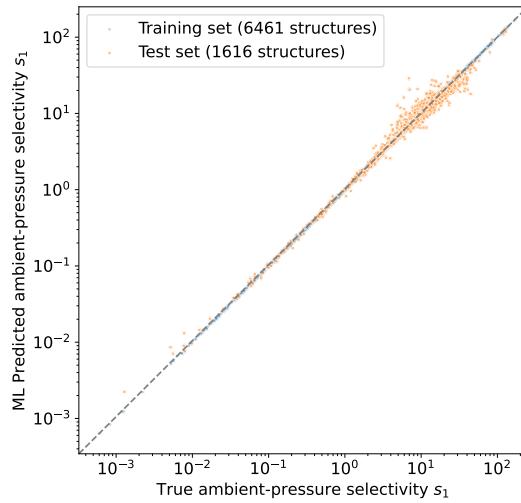
FIGURE R4 : Comparaison de la racine de l'erreur quadratique moyenne sur l'enthalpie d'adsorption du xénon et le temps de simulation par structure pour différentes méthodes d'échantillonnage sur la base de données CoRE MOF 2019 (pour une taille de pore supérieure à 3.7 Å).

Finalement, j'ai également développé un modèle de machine learning basé sur les descripteurs de GrAED et des descripteurs structurels plus couramment utilisés. Ce modèle donne de très bons résultats de prédiction tout en étant bien plus rapide que les simulations GCMC plus couramment utilisées. La figure R5 montre l'excellent accord entre les valeurs réelles et celles prédites par le modèle. Quantitativement, l'erreur sur le logarithme base 10 de la sélectivité vaut environ 0,07 (RMSE).

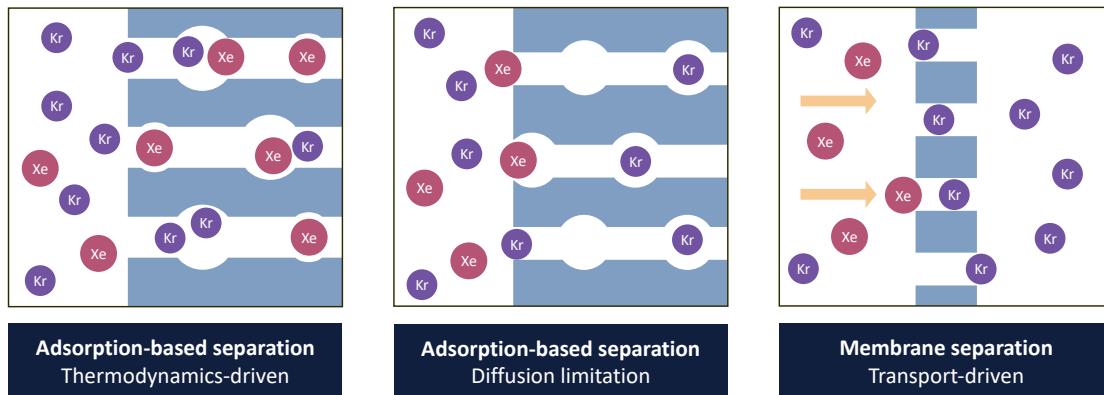
Ce modèle peut ensuite être utilisé pour accélérer l'évaluation de la sélectivité Xe/Kr à pression ambiante pour trouver plus rapidement les meilleurs matériaux pour la séparation. Cette partie conclut l'étude des effets thermodynamiques de la séparation xénon/krypton.

## PROPRIÉTÉS DE TRANSPORT

Enfin, mes derniers travaux portent sur la modélisation des effets de transport du xénon et du krypton dans les structures poreuses de CoRE MOF 2019. Les effets de transport peuvent influencer les performances d'un matériau utilisé comme un adsorbant, comme illustré sur la figure R6. L'accès aux pores pour adsorption peut être plus ou moins rapide selon la vitesse de diffusion dans le matériau. Pour des membranes de séparation, l'effet de transport devient même la mesure principale de performance. Les effets de transport ont été estimés en utilisant des simulations de dynamique moléculaire.



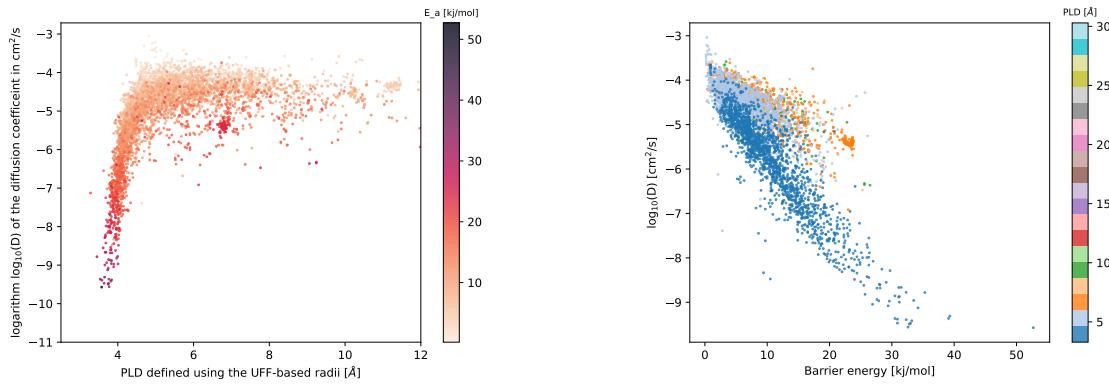
*FIGURE R5 : Graphe de comparaison de la sélectivité Xe/Kr (à pression et température ambiantes pour une composition 20:80) prédite par le modèle et celle calculée par GCMC en échelle logarithmique. Les points colorés en bleu correspondent au jeu de données d'entraînement, tandis que ceux en orange correspondent au jeu de test. La superposition des points est faite de tel sorte que l'on voit davantage les résultats sur le jeu de test pour évaluer la généralisabilité du modèle.*



*FIGURE R6 : Illustration of the comparative role of the thermodynamic and transport properties for Xe/Kr separation in nanoporous materials. From the transport dominated process of membrane separation to the thermodynamically equilibrated separation processes in the nanopores, different more nuanced cases could emerge where the diffusion imposes kinetic limitations.*

Dans cette étude, de nombreuses corrélations ont été analysées et deux descripteurs semblent expliquer les valeurs du coefficient de diffusion. En effet, le diamètre de la plus petite sphère pouvant diffuser librement dans les canaux du matériau (PLD), une caractéristique structurale facilement calculable, semble corrélé au logarithme du coefficient de diffusion. On peut distinguer deux régimes sur la figure R7a : une relation plutôt linéaire suivie d'un plateau.

Une mesure de la barrière énergétique de diffusion est également proposée en utilisant une grille calculée par l'algorithme GraED. Cette barrière d'énergie semble inversement proportionnelle au logarithme du coefficient de diffusion comme on peut le voir sur la figure R7b. Cette



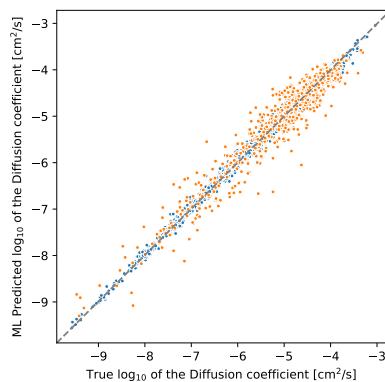
(a) Taille caractéristique des canaux

(b) Barrière énergétique de diffusion

*FIGURE R7 : (a) Graphe comparant le logarithme base 10 du coefficient de diffusion du xénon à la taille des canaux mesurée par le diamètre minimal du canal (PLD, en anglais), et les points sont étiquetés par les énergies de barrière. (b) Graphe comparant le logarithme base 10 du coefficient de diffusion du xénon à la barrière énergétique de diffusion, les points sont étiquetés par le diamètre PLD.*

corrélation n'est pas très forte avec un coefficient de Pearson de l'ordre de  $-0.77$  si on considère toutes les structures.

En suivant une approche similaire à celle utilisée pour prédire la sélectivité, le logarithme du coefficient de coefficient du xénon a été prédit en utilisant le diamètre PLD, la barrière énergétique et d'autres descripteurs thermodynamiques et structurels. Ce modèle de machine learning permet ainsi de remplacer la méthode coûteuse de dynamique moléculaire par l'utilisation de simulations moins coûteuses (barrière d'énergie et descripteurs structurels).



*FIGURE R8 : (a) Comparaison du  $\log_{10}$  du coefficient de diffusion du xénon prédict par le modèle ML et les valeurs simulées par dynamique moléculaire. La racine de l'erreur quadratique moyenne sur le logarithme base 10 vaut 0.25.*

Comme on peut le voir sur la figure R8, le modèle semble bien prédire l'ordre de grandeur du coefficient de diffusion du xénon avec une erreur de l'ordre de 0.25 sur le  $\log_{10}$  de ce coefficient. Cela signifie que l'on a une bonne connaissance de l'exposant du coefficient de diffusion exprimé comme une puissance de 10.

D'autres méthodes basées sur la théorie des états de transition ont également été explorées pour calculer le coefficient de diffusion. Ces travaux ont notamment mené à la conception de l'algorithme utilisé pour calculer des barrières d'énergie.

Enfin, en comparant les rapports des coefficients de diffusion du xénon et du krypton aux valeurs de la sélectivité Xe/Kr, il est possible d'identifier de nouveaux matériaux qui ne présentent pas de blocage cinétique tout en ayant une sélectivité très importante.

## CONCLUSION

Cette thèse étudie ainsi les grandeurs thermodynamiques et cinétiques de la séparation xénon/krypton dans les matériaux nanoporeux. On a pu caractériser de manière plus fine les caractéristiques des matériaux les plus sélectifs. En ajoutant des contraintes sur la diffusibilité, différents types de matériaux ont été identifiés.

La prise en compte de phénomènes physiques non inclus dans les études de cette thèse ouvre des perspectives pour de nombreux travaux sur ce sujet. En effet, de nouveaux travaux expérimentaux montrent l'importance de la prise en compte de la polarisation. Le matériau le plus sélectif à ce jour pour la séparation xénon/krypton se base sur l'interaction induite par des métaux non coordinés.<sup>8</sup> Enfin, la flexibilité du matériau est également importante à prendre en compte. Dans certains cas, la flexibilité permet même de mieux comprendre l'incohérence entre les résultats expérimentaux et théoriques. De nombreuses pistes peuvent être explorées pour intégrer ces effets dans un criblage dans le futur.<sup>162,198</sup>





## RÉSUMÉ

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Mes travaux portent sur la description microscopique de matériaux nanoporeux à différent niveaux de modélisation moléculaire, incluant des approches de criblage à haut débit et d'apprentissage statistique sur des bases de données de matériaux.

## MOTS CLÉS

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simulation moléculaire, matériaux nanoporeux, criblage haut-débit, adsorption, apprentissage statistique

## ABSTRACT

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My work concerns the high-throughput screening of nanoporous materials (mostly but not only metal-organic frameworks) at different levels of molecular modeling, focusing on Xe/Kr separation as an application.

## KEYWORDS

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molecular simulation, nanoporous materials, high-throughput screening, adsorption, machine learning