# Pandemic Drugs at Pandemic Speed: Accelerating COVID-19 Drug Discovery with Hybrid Machine Learning- and Physics-based Simulations on High Performance Computers

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#### **Abstract**

The race to meet the challenges of the global pandemic has served as a reminder that the existing drug discovery process is expensive, inefficient and slow. There is a major bottleneck screening the vast number of potential small molecules to shortlist lead compounds for antiviral drug development. New opportunities to accelerate drug

discovery lie at the interface between machine learning methods, in this case developed for linear accelerators, and physics-based methods. The two *in silico* methods, each have their own advantages and limitations which, interestingly, complement each other. Here, we present an innovative method that combines both approaches to accelerate drug discovery. The scale of the resulting workflow is such that it is dependent on high performance computing. We have demonstrated the applicability of this workflow on four COVID-19 target proteins and our ability to perform the required large-scale calculations to identify lead compounds on a variety of supercomputers.

#### 1. Introduction

The COVID-19 pandemic has shaken the world, and the scale and rapidity of the crisis have also challenged existing methods of doing research, not least the current drug design process, which takes about 10 years and \$1-3 billion to develop a single marketable drug molecule [1,2]. The disease is caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a member of the coronavirus family, which was first identified in the mid-1960s at the Common Cold Unit in Wiltshire, England [3]. Discovering how to combat the pandemic rests on understanding recent outbreaks, such as severe acute respiratory syndrome coronavirus (SARS-CoV), which has the most closely-related genome, and middle east respiratory syndrome coronavirus (MERS-CoV), and taking advantage of the explosion of research in 2020 on various aspects of SARS-CoV-2 biology, from transmission to life cycle. Based on this research, notably experimentally-derived structures for the various viral target proteins, several drug repositioning and drug designing studies have been conducted using in silico computer-based modelling technologies [4–6]. However, the identification of conclusive drug molecules has been hampered by the huge chemical space that needs to be explored.

Because of the vast number of potential ligands (ranging from a few hundred million to billions), it is clearly not possible to synthesize them in wet labs, nor is it desirable given that most of them are not going to bind with SARS-CoV-2 proteins at all. This is where *in silico* methods can play an important role in screening the binding affinity of ligands with SARS-CoV-2 proteins to identify and rank potential drug candidates.

There is an increasingly large number of *in silico* methods available to screen candidate ligands. The two most popular categories are physics-based (PB) techniques including molecular dynamics (MD) based methods, and machine learning (ML) techniques. However, both have inevitable limitations and, even after months of research there is a disappointing lack of potential drug candidates for COVID-19 given that so many lives are at stake. There is an urgent need to accelerate the current drug design process and the work presented here is a step in the direction.

PB techniques involve *ab initio* as well as semi-empirical methods which are fully or partially derived from firm theoretical foundations [7–10]. For example, MD is a popular approach for conformational sampling which is derived from Newtonian equations of motion and the concepts of statistical thermodynamics. MD-based free energy calculation methods have been widely applied for predicting protein-ligand binding affinities and subject to extensive experimental validation [11,12,21,22,13–20]. There are many such free energy methods, some "approximate"; others more "accurate".

In the last decade or so, ensemble simulation based methods have been proposed which overcome the issue of variability in predictions from MD-based methods due to their extreme sensitivity to simulation initial conditions [13,19–23] which leads to chaotic behaviour, and non-Gaussian statistics [24,25]. In particular, two methods named Enhanced Sampling of Molecular Dynamics with Approximation of Continuum Solvent (ESMACS) [13,14,17,26] and Thermodynamic Integration with Enhanced Sampling (TIES) [19–22] have been shown to deliver accurate, precise and reproducible binding affinity predictions within a few hours. Their excellent scalability allows them to calculate binding affinities for a large number of protein-ligand complexes in parallel, utilizing the large size and multiple cores of current supercomputers.

Another important factor affecting the reliability of results is the extent of conformational sampling achieved by MD simulations. Thus, several enhanced methods have also been developed to better sample the phase space [27]. However, even such enhanced sampling is prone to variability in results due to extreme sensitivity to initial conditions. Once again, ensemble simulations are required to control uncertainties in predictions [20–22].

However, these *in silico* methods are computationally demanding and are unable to explore the extensive chemical space relevant for drug molecule generation. To focus the hunt, they require extensive consultation with chemists to suggest structural features or specific functional groups that may improve a ligand's interaction with the target protein, based on the chemical environment of the binding pocket. Drawing on human intelligence and insights takes time and slows the process of drug discovery by delaying the pipeline of candidate ligands to wet labs for testing. Even if this step is accelerated, another bottleneck in drug design looms because there is a limit to the number of compounds that can be studied experimentally.

To overcome the limitations of PB methods, ML methods can be employed. Prediction of binding affinities using a deep neural network has been an active area of research over the past few years. ML represents a set of techniques that rely on inferring complex relationships from big data and applications include diverse fields such as robotics, gaming, language processing and chemoinformatics. Some examples include classifying kinase conformations [28], predicting antimicrobial resistance [29], modelling quantitative structure-activity relationships [30], and predicting contact maps in protein folding [31], with AlphaFold making important progress in protein structure prediction [32].

In the field of drug discovery, ML, specifically deep learning (DL), allows us to generate novel drug-like molecules by sampling a significant subset of the chemical space of relevance. DL techniques are computationally much cheaper and enable quick turnaround of results which allows millions to billions of compounds to be handled [33]. Recent developments in DL allow generation of novel drug-like molecules *in silico* by sampling a large fraction of the chemical space of relevance (estimated to be about 10<sup>68</sup> compounds). However, the accuracy of ML/DL methods is very much dependent on the training data. Their predictive capability can be improved by providing them with reliable data and by curating them with theoretical understanding

[34], neither of which may always be available. This restricts their applicability in the drug discovery domain.

ML and PB methods have their own advantages and limitations. Fortunately, their strengths and weaknesses complement each other and so it makes sense to couple them in drug discovery. ML/DL techniques can be employed to augment human intelligence (HI) with artificial intelligence (AI) for exploring the large chemical space to predict "useful" ligand molecules. This substantially speeds up the process of ligand discovery. On the other hand, reliable PB free energy methods can rank the ligands on the basis of their binding affinities and ground the simulations on theoretical understanding. These binding affinities can then be fed back into the DL algorithm to augment its knowledge base and hone predictions. Such a combination can be an effective tool for drug design and can prove useful in prospective drug design projects. Robust predictive mechanistic models are of particular value for constraining ML when dealing with sparse data, exploring vast design spaces to seek correlations and, most importantly, testing if correlations are causal [35].

It is well accepted that drug targets can undergo significant conformational changes during their biological activity. Some of these changes may involve large-scale rearrangements, such as a domain motion over a hinge region, while some others may be more limited in size, such as the short-lived opening of a mostly hydrophobic cryptic site. The interesting point is that they can involve targetable structures that might otherwise remain hidden to experimental structural determination. Although the physics-based models, such as MD simulations, can explore conformational space to some extent, they can hardly achieve ergodicity, resulting in some of the potential new target structures remaining hidden. Here DL approaches are envisaged to explore whether a short stretch of a MD trajectory may exhibit the hallmarks of potentially biologically relevant structural transitions, even though such transitions are *not* observed in the trajectory itself.

Not only will exploitation of AI ensure that the best use is made of medicinal chemists for drug discovery, it also helps counter chemists' bias during exploration of the chemical space. Carefully trained DL algorithms may be expected to reach regions of the extensive chemical space that may remain untouched by humans.

In this work, we present a novel *in silico* method for drug design by coupling ML with PB methods. Rather than performing only blind ML/DL, we couple them with accurate PB methods to make them "smarter". Potential candidates are selected from the output of a DL algorithm and they are scored using PB methods to calculate binding free energies. This information is then fed back to the DL algorithm to refine its predictive capability. This loop proceeds iteratively involving a variety of PB scoring methods with increasing level of accuracies at each step ensuring that the DL algorithm gets progressively more "intelligent". We posit that our innovative integration of PB and ML-based methods can substantially reduce the throughput time for exploring a huge chemical space and improve the efficacy of exploration of chemical libraries for lead discovery.

Given the large-scale supercomputing infrastructure available to us, we are able to scale to the vast number of calculations required to provide input to the ML models. Equally important, our methods are designed to provide key uncertainty quantification, a feature

vital to our goal of using active learning to optimise campaigns of simulations to maximise the chance that predictive ML models will find promising drug candidates.

#### 2. Methods

No single algorithm or method can achieve the necessary accuracy with required efficiency to sample the huge chemical space inhabited by lead compounds for drug discovery. We innovated by combining multiple algorithms into a single unified pipeline (**Figure 1**), using an interactive and iterative methodology, allowing both upstream and downstream feedback to overcome the limitations of classical *in silico* drug design as described above.

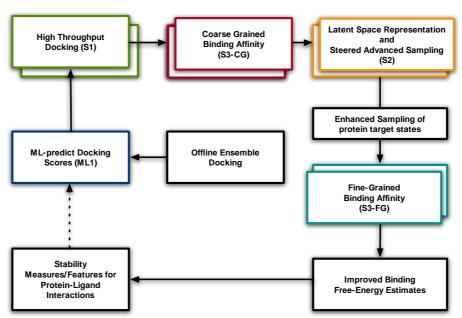


Figure 1. Integrated modelling pipeline for new COVID treatments where blind machine learning is made "smarter" with accurate physics based methods. It represents an entire virtual drug discovery pipeline, from hit to lead through to lead optimization. The constituent components are deep-learning based surrogate model for docking (ML1), Autodock-GPU (S1), coarse and fine-grained binding free energies (S3-CG and S3-FG) and S2 (DeepDriveMD). The arrows show the information transferred between the different methods. (Source: IMPECCABLE [36])

We first describe the different components of our workflow, notably their standalone strengths and weaknesses, then show how we couple them constructively in the workflow such that the sum is greater than the parts.

### a) High-throughput Docking

Protein-ligand docking involves ligand 3D structure (conformer) enumeration, exhaustive docking and scoring, and pose scoring. The input requires a protein structure with a designed binding region, or a crystallized ligand from which a region can be inferred, as well as a database of small molecules to dock, where the chemical structure is represented in the SMILES format.

Conversion of the 2D structures into 3D structures ready for structural docking is performed through proteinisation and conformer generation using Omega-Tautomers that also includes enumeration of enantiomers prior to conformer generation if stereochemistry is not specified [37]. Conformer generation is performed on the

ensemble of structures, typically generating 200-800 3D conformers for every enantiomer.

Each of the 3D structures so generated is docked against the protein binding pocket and scored. The best scoring pose is returned along with its ChemGauss4 score from exhaustive rigid docking [38]. The ranking obtained using such docking scores are useful in the initial hit identification stage of the drug discovery pipeline.

As a consequence, the outputs of docking runs include a 3D protein (receptor) structure with the docked ligand in its binding site. The docking score (evaluated by the scoring function specific to a docking protocol) provides a qualitative measure of the intrinsic complementarity between a given ligand and protein binding site. While docking protocols are generally good at estimating the binding poses (i.e., 3D conformation) of ligands within a binding site, the energetics of interaction can be challenging to determine and are a function of how a specific scoring function is implemented. This is why we employ MD-based binding affinity prediction methods for more accurate ranking of the available compounds on the top ranked compounds based on their docking scores.

Furthermore, there is a need to account for the intrinsic flexibility of the protein in response to the ligand (which may also induce conformational changes) that needs to be accounted for in the energetics of how ligands/proteins interact. For this purpose, extensive conformational sampling is often necessary. The enhanced/adaptive sampling techniques described below can help addressing some intrinsic limitations of these techniques.

### b) ML-based Conformation Transition Classifier

In order to investigate the conformational transitions during MD simulations, we used two 10  $\mu$ s trajectories, made available by D.E. Shaw Research [39], of the SARS-CoV-2 spike glycoprotein starting from two main different conformations (i.e., 6VYB and 6VXX, partially open and closed states, respectively). The dictionary of secondary structure of proteins (DSSP) [40] is used to classify each residue according to its secondary structure in all the frames of the trajectory. A total of 8334 frames are extracted from the 10  $\mu$ s simulations of the spike glycoprotein. The data used for the analysis consist of the atomic coordinates of the protein's  $C^{\alpha}$  atoms and secondary structures of the protein residues, according to DSSP. To analyse the conformations, we adapted the ML-based Anomaly Detection techniques previously designed and employed at the European Organization for Nuclear Research (CERN) for scientific and medical linear accelerators [41]. We predicted the probability of a local protein conformational change based on transitions occurring in individual trajectories.

The trajectory of each  $C^{\alpha}$  in class-space is followed in time until a change of class is observed at time  $t_a$ , with a running over the number of atoms in the simulation. From that time on, the transitions between different classes, if any, are tracked for 100 subsequent frames, forming a corresponding set of stochastic transitions matrices, whose elements  $T_{kl}$  represent the transition frequency from class k to class l, where  $k,l=\{0..7\}$  (cf. Table 1). Only a few transitions out of the possible 64 are effectively observed within the examined dataset. The most frequently observed are the transitions between identical or structurally adjacent classes.

**Table 1:** Classes of secondary structure that DSSP defines.

Letter	Number	Class of the secondary	
ID	ID	structure	
G	0	3 <sub>10</sub> helix (first helix)	
Н	1	α helix	
I	2	$\pi$ helix	
Е	3	β sheet	
В	4	β bridge	
T	5	helix turn	
S	6	bend	
C	7	coil (No SS found)	

The stochastic transition matrices are then turned into heat maps and fed into a Convolutional Neural Network (CNN). The neural network was a 2-layer CNN, trained using the Reptile meta-learning algorithm [42]. The input layer has a single channel of 8 by 8 pixels. It uses Keras implementation of the *relu* activation function, the Sparse Categorical Cross Entropy Loss Function and the Adam optimizer. The transition-based classification is used to predict the probability of belonging to a class, and of the class that the selected residue might land at a future time, typically after 1500 frames since the initial class change. We compared the prediction with the frequency of belonging to each class, as observed throughout the simulation that was not used for training, i.e. that starting from the 6VXX structure. The similarity between the different distributions was evaluated via the Jensen-Shannon divergence [43]. Our preliminary results, shown in Table 2, are encouraging, although subject to a number of caveats. First and foremost, the training and the validation data set (70:30) pertain to a single trajectory, which implies that some transitions are trained on a very small number of events. Hence, multi-trajectory data are needed to consolidate these preliminary results. Using more data would also allow to introduce additional classes, thus obtaining a more precise estimation of residues' behaviour. This is currently the subject of an on-going research.

**Table 2:** Jensen-Shannon divergence (a measure of the similarity between two probability distributions. bounded between 0 and 1) between predicted and observed secondary class transitions in the 6VXX trajectory of the spike protein system. Data are presented in decreasing order of similarity. The labels code for the initial and final class. When they are identical, it means that after some oscillation, the residue goes back to the initial class.

Transition	J-S divergence
"43"	4.91E-03
"34"	5.67E-03
"01"	7.70E-03
"33"	1.02E-02
"12"	1.21E-02
"00"	1.62E-02
"11"	1.93E-02
"21"	4.38E-02
"22"	6.14E-02
"44"	6.51E-02

"10"	1.54E-01
"04"	3.68E-01

### c) ML-driven Enhanced Sampling

DL methods have been widely applied to understand protein conformational dynamics, and a number of methods have been proposed to enhance sampling of conformational landscapes using adaptive sampling strategies that include DL methods in their workflows. One such approach, namely DeepDriveMD, uses variational autoencoders to cluster high dimensional data on conformations from multiple MD trajectories into a more manageable low dimensional manifold from which 'novel' conformations can be selected, based on certain reaction coordinates (RCs) or collective variables (CVs) and new simulations can be instantiated from such conformations [44]. This approach has been demonstrated for protein folding trajectories, offering at least 2x speedup compared to traditional conformational sampling methods, and in a recent application, DeepDriveMD was able to enhance sampling by nearly 25% with just 12% of compute time for studying conformational transitions of the SARS-CoV-2 Spike protein bound to the ACE2 receptor [45]. Thus, DeepDriveMD offers a way forward in sampling conformational events, providing a framework to extend its functionality to account for studying protein-ligand interactions.

Ligands bound to the protein target of interest induce specific conformational changes; some ligands may induce changes that are local to the binding site, whereas others may induce changes farther away from the binding site. We posit that even with reasonably short time-scale simulations, our variational autoencoder can cluster protein-ligand interaction landscapes based on such conformational differences and provide a quantitative way to extract ligand-specific protein conformational signatures that could help bound the uncertainty in binding affinity calculations. To this effect, we extracted the contact maps between the protein  $C^{\alpha}$ -atoms (defined at an 8 Å cut-off) and analysed them with our variational autoencoder. Optimal hyperparameters were determined as described previously [46] and the resulting latent space embedding was visualized using t-Stochastic neighbourhood embedding (t-SNE) approach. In our analysis, we observe clear separation between protein-ligand complexes as well as the fact that some ligands induce more conformational changes than others.

### d) MD-based Binding Affinity Prediction

Hit-to-Lead (H2L) is a step in the drug discovery process where promising lead compounds are identified from initial hits – small molecules which have the desired activity – generated during preceding stages. After evaluation of initial hits, optimization of promising compounds is carried out to achieve nanomolar affinities. The change in free energy between free and bound states of protein and ligand, also known as binding affinity, is a promising measure of the binding potency of a molecule and is used as a parameter for evaluating and optimising hits at the H2L stage.

A protocol known as ESMACS [13,17] was used to estimate binding affinities of protein-ligand complexes. It involves performing an ensemble of MD simulations followed by free energy estimation using a semi-empirical method called molecular mechanics Poisson-Boltzmann surface area (MMPBSA). The free energies for the

ensemble of conformations are analysed in a statistically robust manner, yielding precise free energy predictions for any given complex.

The use of ensembles is particularly important because the usual practice of performing MMPBSA calculations on conformations generated using a single MD simulation does not give reliable binding affinities [47]. Consequently, ESMACS predictions can be used to rank a large number of hits based on their binding affinities. ESMACS is able to handle large variations in ligand structures and hence is very suitable for H2L stage where hits have been picked out after covering a substantial region of chemical space.

The ensemble of conformations for the protein-ligand complex generated using MD simulations are also analysed using the variational autoencoder technique described above to get insights into favourable as well as unfavourable interactions of different functional groups in a molecule with the target protein. This knowledge is helpful in performing further optimization of the lead structures. The information and data generated with ESMACS is additionally used to train our ML model (described below) to improve its predictive capability.

Lead Optimization (LO) is the final step of pre-clinical drug discovery. It involves altering the structures of selected lead compounds in order to improve properties, such as selectivity, potency and pharmacokinetic parameters. Binding affinity is a useful parameter to make *in silico* predictions about the effects of any chemical alteration in a lead molecule. However, LO requires theoretically more accurate (without much/any approximations) methods to make predictions with high confidence. In addition, relative binding affinity of pairs of compounds which are structurally similar are of interest, rendering ESMACS unsuitable for LO.

Because of these issues, we employ thermodynamic integration with enhanced sampling (TIES) [19–21], which is based on an alchemical free energy method called thermodynamic integration (TI) [48]. Alchemical methods involve calculating free energy along a non-physical thermodynamic pathway to get relative free energy between the two end-points. Usually, the alchemical pathway corresponds to transformation of one chemical species into another defined with a coupling parameter  $(\lambda)$ , ranging between 0 and 1. TIES involves performing an ensemble simulation at each  $\lambda$  value to generate the ensemble of conformations to be used for calculating relative free energy. It also involves performing a robust error analysis to yield relative binding affinities with statistically meaningful error bars. The parameters such as the size of the ensemble and the length of simulations are determined keeping in mind the desired level of precision in the results [19].

#### e) ML-based Model to Predict Useful Ligands

In our drug discovery workflow, ML is used to gather and accumulate information from all the other PB components described above so as to quickly locate the most interesting region(s) in the chemical space in terms of the potential of a lead compound to bind strongly. We have created a ML surrogate model using a simple featurisation method, namely 2D image depictions, as it does not require complicated architectures such as graph convolution networks, while demonstrating good prediction. We obtain these image depictions from the nCov-Group Data Repository [49] that contains various descriptors for 4.2 billion molecules generated on HPC systems with Parsl [50]. By

using 2D images, we are able to initialise our models with pre-trained weights that are typically scale and rotation invariant under image classification. This model is used to generate ligand molecules that can be analysed using the PB methods described above. We train our ML model using data from both docking as well as MD based binding affinity predictions so as to enable it to actively relate structural/chemical features with corresponding binding potencies. This allows our ML model to progressively make more accurate predictions of ligand structures that can be classified as initial hits. The predicted structures are then fed into the PB pipeline to filter them, first using docking and then by ESMACS and TIES, to finally select those that bind most effectively. This is repeated with the ML model getting better after each iteration. Thus, we provide reliable training data to our ML models whereas potentially good initial structures are identified for our PB methods. In this way, our workflow couples ML and MD such that each compensates for the weaknesses in the other method. It is our expectation that, together, they are more effective.

#### 3. Workflow management

Our workflow (**Figure 1**) integrates different methods and dynamically selects active ligands for progressively computationally expensive methods. At each stage, only the most promising candidates advance to the next stage, yielding a pipeline in which each downstream stage is computationally more expensive, but also more accurate, than upstream stages. Execution of such a complicated workflow requires scalable tools with advanced resource management, task-placement and adaptive execution capabilities, in this case RADICAL-Cybertools (RCT) [51] middleware.

RCT executes tasks concurrently or sequentially, depending on their arbitrary priority relation. Tasks are grouped into stages and stages into pipelines, depending on the priority relation among tasks. Tasks without reciprocal priority relation can be grouped into the same stage, tasks that need to be executed before other tasks have to be grouped into different stages. Stages are then grouped into pipelines and, in turn, multiple pipelines can be executed either concurrently or sequentially. RCT uses RADICAL-Pilot (RP) [52] to execute tasks on HPC resources, allowing the execution of workflows with heterogeneous tasks.

### RCT middleware has been used in two ways:

Scalable concurrent multi-stage task-execution: A work around was required to use the middleware on one of Europe's largest supercomputers, SuperMUC-NG. As RADICAL-Cybertools depend on 3rd party software modules, the virtual environment required by RP couldn't be created on SuperMUC-NG because access is granted only to allowed IP addresses. Thus, we prepared RCT's virtual environment outside of the system and then moved it to SuperMUC-NG login node. In this way, RCT could be launched from a login node via the pre-set environment, without the need for outbound internet access. RCT uses MongoDB and RabbitMQ as communication services. These services need to be accessible from both login and compute nodes. On SuperMUC-NG, we automated the launching of both services on a dedicated compute node, which was provided by a special service queue with unlimited walltime, while the workers for RP were provided by the regular batch system.

Concurrent Multiple Workflow Execution: RCT's fine-level task-placement feature allows the concurrent use of both CPUs and GPUs on supercomputer nodes. That is achieved by employing RADICAL-Pilot's unique capability of concurrently executing heterogeneous tasks on CPU cores and GPUs as an integrated hybrid workflow. This allows the concurrent execution and interleaving of different workflows, making better use of compute resources. RP places tasks on specific compute nodes, cores and GPU [53]. When scheduling tasks that require different amounts of cores and/or GPUs, RP keeps tracks of the available slots on each compute node of its pilot. Depending on availability, RP schedules CPU tasks (e.g., MPI) within and across compute nodes and reserves a CPU core for each GPU task. This results in efficient placement of heterogeneous tasks on heterogeneous resources.

Leveraging aforementioned RP's heterogeneous task placement capabilities, we merge ESMACS and TIES into an integrated hybrid workflow with heterogeneous tasks that utilise CPU and GPU concurrently. Running these two calculations concurrently reduces the total execution time, substantially saving computational cost, thereby improving resource utilisation at scale.

#### 4. High performance computing resources

Our workflow is by design based on high throughput computational (HTC) calculations. Even though, it reduces the overall number of necessary computations tremendously, an acceptable time to solution is only achievable on HPC resources. To illustrate the impact of our workflow, we applied it to four target proteins of SARS-CoV-2 in this work, namely 3C like protease (3CLPro), papain-like protease (PLPro), ADP-ribose phosphatase (ADRP), and non-structural protein 15 (NSP15) (**Figure 2**). These proteins have diverse functions for the replication and transcription of the coronavirus, and are important targets for pharmaceutical drug design and discovery. For this, docking calculations were performed on thousands of ML-model-generated ligand conformations, leading to a ranking of candidates with corresponding ligand structures. Afterwards, we conducted several hundred ESMACS calculations on the top ranked ligands based on their docking and 19 TIES calculations on a selection of ligand pairs. Note that the ML-based generation of ligand structures accelerated the whole HTC process significantly.



Figure 2. Structures of the four target proteins studied, in each case shown bound to a compound. From left to right: 3CLPro, PLPro, ADRP and NSP15. The proteins are shown in cartoon representation, and compounds in stick representation.

All calculations were performed on a variety of supercomputers including Leibniz Rechenzentrum's SuperMUC-NG, Hartree Centre's ScafellPike, Oak Ridge National Laboratory's Summit and Texas Advanced Computing Center's Frontera. Table 2 summarizes performance and cost numbers for the calculations on Summit to understand the overall cost of the presented pipeline. Note that the ESMACS calculations were accelerated with OpenMM as MD engine on GPUs. TIES required longer wall-clock times as only CPUs were employed.

**Table 2:** Overview of computing cost for the different calculations in the computing pipeline

on Oak Ridge National Laboratory's Summit supercomputer.

Calculation	Physical time required in each MD simulation [ns]	# of independent MD simulations per ligandprotein complex	Computing time per calculation [node- hours]	Computing time per ligand- protein complex [node- hours]	Used theoretical node performance [TF]
Docking		Several thousands	0.0001		
ESMACS	12	25		10	420
TIES	6	65		700	29400

### 5. ESMACS and TIES applied to COVID-19 on high end resources

#### a) ESMACS findings

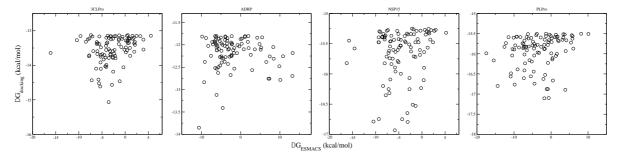
ESMACS is used at the hit identification and H2L stage of the drug discovery. The DL-based surrogate model was used to screen the small molecules in the Zinc database, a collection of commercially available chemical compounds. A high-throughput docking study was then performed to generate binding poses of the compounds to the 4 COVID-19 proteins (**Figure 2**). While docking programs are generally good at pose prediction, they are less effective in predicting binding free energy of the compounds to the target proteins. To better rank the binding potentials of the compounds, we performed ESMACS simulations for the top 100 compounds for each of the selected proteins. The compounds were chosen from 10,000 docked small molecules, based on their docking scores from the high throughput docking study.

Preparation and setup of the simulations were implemented using binding affinity calculator (BAC), including parametrization of the compounds, building simulation-ready topologies and structures of the complexes, and generating configurations files for the simulations. MD simulations were performed using two MD engines, NAMD and OpenMM, on three machines, Frontera, Summit and SuperMUC-NG. For each replica, energy minimisations were first performed, followed by 2 ns equilibration. Finally, 10 ns production simulations were run for each replica. MMPBSA calculations were then performed for all of the 1000 frames from the 10 ns production runs, while configurational entropies were calculated using NMODE on 48 or 56 frames for each replica, depending on the number of cores per node on the computers used for NMODE calculations.

For most of the molecular systems studied, about 4-19% of the compounds show promising binding affinities (cf. Table 3), with free energies more negative than -8.24 kcal/mol (corresponding to a  $K_D$  value on the nanomolar scale). Although the distributions of predicted free energies from independent simulations are non-normal [24,25], the ensemble-based ESMACS predictions are highly reproducible, independent of which MD code is used, or on which supercomputer the simulations are performed. As stated above, the docking scores are not a good indicator for binding affinities; the free energies from ESMACS calculations only show weak correlations with the docking scores (**Figure 3**). The inclusion of configurational entropy has a negligible impact on the ranking of the binding free energies. The ESMACS study shows that the most promising compounds can be selected more reliably using the ESMACS prediction than the docking scores.

**Table 3:** Number of the most promising compounds for each of the 4 proteins investigated. For each protein, the top 100 compounds, chosen from 10,000 docked small molecules, are evaluated by ESMACS approach. The number of compounds are listed, which have the most favourable binding free energies, in the ranges corresponding to  $K_D$  values of 10 nM (-10.98 kcal/mol), 100 nM (-9.61 kcal/mol), 1  $\mu$ M (-8.24 kcal/mol).

Energy (kcal/mol)	3CLPro	ADRP	NSP15	PLPro
$\Delta G < -10.98$	1	0	3	6
$-10.98 \le \Delta G < -9.61$	2	2	1	8
$-9.61 \le \Delta G < -8.24$	1	4	10	5
$\Delta G < -8.24 \text{ Total}$	4	6	14	19



*Figure 3.* Correlations between the ESMACS results and docking predictions. Weak or no correlations are obtained for the 4 protein targets – 3CLPro, ADRP, NSP15 and PLPro – with correlation coefficients of 0.25, -0.06, 0.16 and 0.20, respectively.

#### b) TIES findings

TIES is used at the LO stage of drug discovery to hone interactions between protein and ligand so to enhance the binding potency of selected lead compounds. To demonstrate this capability, we performed TIES on a set of 19 compound transformations (that is chemically mutating the "original" compound into a "new" compound) to study the effect of small structural changes on a compound's binding potency with ADRP. The calculated free energy differences show a non-normal nature, as we have recently reported [24,25]. The ensemble-based TIES approach ensures high precision predictions, with uncertainties less than 0.82 kcal/mol for all but one of the calculations (cf. Table 4). The relative binding affinities ( $\Delta\Delta G$ ) predicted by TIES for

these transformations fall between -0.55 to +4.62 kcal/mol (cf. Table 4). A positive value indicates a diminished relative binding potency for the "new" compound, whereas a negative value means that the transformation studied is favourable. 12 out of the 19 transformations studied have  $\Delta\Delta G > +1$  suggesting that they all correspond to unfavourable structural changes. The remaining seven transformations have statistically zero value for  $\Delta\Delta G$ , which implies that the corresponding structural modifications do not affect the binding. It is difficult to predict what structural changes will improve the binding. Thus, the knowledge of both "useful" as well as "rubbish" transformations is of much value at the LO stage so as to make informed structural changes. TIES provides us an excellent tool to do so with confidence. Such information then informs our ML predictive model about the desirable as well as undesirable chemical modifications to be introduced into the selected lead compounds. In this way, it improves the predictive accuracy of the ML models, progressively leading to quicker convergence towards the region of our interest in the huge chemical space.

**Table 4:** Results from TIES calculations on a set of ligand transformations studied for ADRP.  $\Delta\Delta G$  is the relative binding affinity for a transformation, that is the change in binding affinity on morphing one ligand into the other.  $\sigma$  corresponds to the uncertainty associated with the relative binding affinity predicted by TIES.

Transformation	$\Delta\Delta G$ (kcal/mol)	σ (kcal/mol)
a0-a2	1.48	0.60
a0-a4	1.82	0.66
a0-a5	1.14	0.60
a0-a6	3.22	0.44
a0-a7	1.32	0.43
a0-a9	0.25	0.57
a0-a10	1.52	0.70
a0-a41	3.41	0.53
a0-a44	1.18	0.49
a0-a45	-0.46	0.52
a0-a46	2.91	0.70
a0-a47	0.36	0.57
a0-a48	-0.55	0.57
a0-a49	1.84	0.46
a0-a50	0.52	0.64
a1-a42	-0.29	0.82
a1-a43	2.05	1.03
a3-a42	0.49	0.81
a42-a43	4.62	0.82

### 6. Conclusions

We describe an innovative, iterative and interactive heterogenous workflow that has the potential to accelerate the existing drug discovery process substantially by coupling machine learning with physics-based methods such that each compensates for the weaknesses of the other. This workflow requires high-throughput screening of a large number of small molecules based on their binding potencies evaluated using various types of methods. Molecules filtered at one stage are advanced to the next to be filtered

once again using a more accurate and computationally intensive method. A refined set of lead compounds emerges at the end of this multistage process for wet lab studies. With information relating structural features to energetics and binding potencies being fed into the ML model at each stage, it learns how to improve the prediction of the next set of compounds. This iterative process, along with the upstream and downstream flow of information, allows it to accelerate the sampling of relevant chemical space much faster than traditional methods. We have demonstrated the application of our workflow on four SARS-CoV-2 target proteins. The workflow requires HPC resources for efficient implementation and a dedicated workflow manager to handle the large number of heterogenous computational tasks on a multitude of supercomputers. We believe that this hybrid ML-PB approach offers the potential in the long term – with the rise of exascale, quantum and analogue processing – to deliver novel pandemic drugs at pandemic speed.

### **Data accessibility**

The models and simulation trajectories were generated at UCL. Models used for performing simulations and results obtained are available at the following public github repository: https://github.com/UCL-CCS/ML-PB-Covid-drug.

#### **Authors' contributions**

APB, SW and DA performed PB simulations, data curation and analysis. ARC, TB, AP, FX, XD, AF, HM, AR, WR, NS, SS, SV, YD and ADM performed ML related calculations and analyses. LT, MiT, AM, MaT and SJ provided workflow management infrastructure. DA, SJ, DK, AR and PVC acquired computational resources for the current study; GM and DW provided technical support. PVC organised and led the overall project. APB, SW, RH and PVC composed the paper with substantial input from all authors. All authors contributed to the editing and reviewing of the paper, and read and approved the manuscript.

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### **Competing interests**

The authors declare no competing financial interest.

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#### **References:**

- 1. Sullivan T. 2019 A Tough Road. *Rockpointe Publ*. See https://www.policymed.com/2014/12/a-tough-road-cost-to-develop-one-new-drug-is-26-billion-approval-rate-for-drugs-entering-clinical-de.html (accessed on 26 November 2020).
- 2. Wouters OJ, McKee M, Luyten J. 2020 Estimated Research and Development Investment Needed to Bring a New Medicine to Market, 2009-2018. *JAMA* 323, 844–853. (doi:10.1001/jama.2020.1166)
- 3. Tyrrell DAJ, Bynoe ML. 1965 Cultivation of a Novel Type of Common-cold Virus in Organ Cultures. *Br. Med. J.* **1**, 1467–1470. (doi:10.1136/bmj.1.5448.1467)
- 4. Das S, Sarmah S, Lyndem S, Singha Roy A. 2020 An investigation into the identification of potential inhibitors of SARS-CoV-2 main protease using molecular docking study. *J. Biomol. Struct. Dyn.*, 1–11. (doi:10.1080/07391102.2020.1763201)
- 5. Elmezayen AD, Al-Obaidi A, Şahin AT, Yelekçi K. 2020 Drug repurposing for coronavirus (COVID-19): in silico screening of known drugs against coronavirus 3CL hydrolase and protease enzymes. *J. Biomol. Struct. Dyn.*, 1–13. (doi:10.1080/07391102.2020.1758791)
- 6. Wang J. 2020 Fast Identification of Possible Drug Treatment of Coronavirus Disease-19 (COVID-19) through Computational Drug Repurposing Study. *J. Chem. Inf. Model.* **60**, 3277–3286. (doi:10.1021/acs.jcim.0c00179)
- 7. Knight J, Brooks C. 2009 Λ-Dynamics Free Energy Simulation Methods. *J. Comput. Chem.* **30**, 1692–1700. (doi:10.1002/jcc.21295.)
- 8. Zwanzig RW. 1954 High-Temperature Equation of State by a Perturbation Method. I. Nonpolar Gases. *J. Chem. Phys.* **22**, 1420–1426. (doi:10.1063/1.1740409)
- 9. Straatsma TP, Berendsen HJC. 1988 Free energy of ionic hydration: Analysis of a thermodynamic integration technique to evaluate free energy differences by molecular dynamics simulations. *J. Chem. Phys.* **89**, 5876–5886. (doi:10.1063/1.455539)
- 10. Bikkina S, Bhati AP, Padhi S, Priyakumar UD. 2017 Temperature dependence of the stability of ion pair interactions, and its implications on the thermostability of proteins from thermophiles. *J. Chem. Sci.* **129**, 405–414.
- 11. Beckstein O et al. 2018 Contributions to {High-Performance} Big Data Computing.
- 12. Genheden S, Ryde U. 2010 How to obtain statistically converged MM/GBSA results. *J. Comput. Chem.* **31**, 837–846. (doi:10.1002/jcc.21366)
- 13. Wan S, Bhati AP, Zasada SJ, Wall I, Green D, Bamborough P, Coveney P V. 2017 Rapid and Reliable Binding Affinity Prediction of Bromodomain Inhibitors: A

- Computational Study. *J. Chem. Theory Comput.* **13**, 784–795. (doi:10.1021/acs.jctc.6b00794)
- 14. Wan S, Bhati AP, Skerratt S, Omoto K, Shanmugasundaram V, Bagal SK, Coveney P V. 2017 Evaluation and Characterization of Trk Kinase Inhibitors for the Treatment of Pain: Reliable Binding Affinity Predictions from Theory and Computation. *J. Chem. Inf. Model.* **57**, 897–909. (doi:10.1021/acs.jcim.6b00780)
- 15. Genheden S, Ryde U. 2015 The MM/PBSA and MM/GBSA methods to estimate ligand-binding affinities. *Expert Opin. Drug Discov.* **10**, 449–461. (doi:10.1517/17460441.2015.1032936)
- 16. Wan S, Knapp B, Wright DW, Deane CM, Coveney P V. 2015 Rapid, Precise and Reproducible Prediction of Peptide-MHC Binding Affinities from Molecular Dynamics that Correlate Well with Experiment. *J. Chem. Theory Comput.*
- 17. Wright DW, Wan S, Meyer C, Van Vlijmen H, Tresadern G, Coveney P V. 2019 Application of ESMACS binding free energy protocols to diverse datasets: Bromodomain-containing protein 4. *Sci. Rep.* **9**, 1–15.
- 18. Chodera JD, Mobley DL, Shirts MR, Dixon RW, Branson K, Pande VS. 2011 Alchemical free energy methods for drug discovery: progress and challenges. *Curr. Opin. Struct. Biol.* 21, 150–160. (doi:https://doi.org/10.1016/j.sbi.2011.01.011)
- 19. Bhati AP, Wan S, Wright DW, Coveney P V. 2017 Rapid, Accurate, Precise, and Reliable Relative Free Energy Prediction Using Ensemble Based Thermodynamic Integration. *J. Chem. Theory Comput.* **13**, 210–222. (doi:10.1021/acs.jctc.6b00979)
- 20. Bhati AP, Wan S, Hu Y, Sherborne B, Coveney P V. 2018 Uncertainty Quantification in Alchemical Free Energy Methods. *J. Chem. Theory Comput.* **14**, 2867–2880. (doi:10.1021/acs.jctc.7b01143)
- 21. Bhati AP, Wan S, Coveney P V. 2019 Ensemble-Based Replica Exchange Alchemical Free Energy Methods: The Effect of Protein Mutations on Inhibitor Binding. *J. Chem. Theory Comput.* **15**, 1265–1277. (doi:10.1021/acs.jctc.8b01118)
- 22. Wan S, Tresadern G, Pérez-Benito L, van Vlijmen H, Coveney P V. 2020 Accuracy and Precision of Alchemical Relative Free Energy Predictions with and without Replica-Exchange. *Adv. Theory Simulations* **3**, 1900195. (doi:10.1002/adts.201900195)
- 23. Lawrenz M, Baron R, McCammon JA. 2009 Independent-Trajectories Thermodynamic-Integration Free-Energy Changes for Biomolecular Systems: Determinants of H5N1 Avian Influenza Virus Neuraminidase Inhibition by Peramivir. *J. Chem. Theory Comput.* **5**, 1106–1116. (doi:10.1021/ct800559d)
- 24. Bieniek MK, Bhati AP, Wan S, Coveney P V. 2021 TIES 20: Relative Binding Free Energy with a Flexible Superimposition Algorithm and Partial Ring Morphing. *J. Chem. Theory Comput.* (doi:10.1021/acs.jctc.0c01179)
- 25. Wan S, Bhati AP, Zasada SJ, Coveney P V. 2020 Rapid, accurate, precise and reproducible ligand-protein binding free energy prediction. *J. R. Soc. Interface Focus* **10**. (doi:http://dx.doi.org/10.1098/rsfs.2020.0007)
- 26. Wright DW, Husseini F, Wan S, Meyer C, van Vlijmen H, Tresadern G, Coveney P V. 2020 Application of the ESMACS Binding Free Energy Protocol to a Multi-Binding Site Lactate Dehydogenase A Ligand Dataset. *Adv. Theory Simulations* **3**, 1900194. (doi:10.1002/adts.201900194)
- 27. Yang YI, Shao Q, Zhang J, Yang L, Gao YQ. 2019 Enhanced sampling in molecular dynamics. *J. Chem. Phys.* **151**, 70902. (doi:10.1063/1.5109531)
- 28. McSkimming DI, Rasheed K, Kannan N. 2017 Classifying kinase conformations using a machine learning approach. *BMC Bioinf.* **18**.
- 29. Davis JJ et al. 2016 Antimicrobial resistance prediction in PATRIC and RAST. Sci.

- *Rep.* **6**.
- 30. Gomes J, Ramsundar B, Feinberg EN, Pande VS. 2017 Atomic Convolutional Networks for Predicting Protein-Ligand Binding Affinity. *arXiv Prepr. arXiv1703.10603*
- 31. Wang S, Sun S, Li Z, Zhang R, Xu J. 2017 Accurate De Novo Prediction of Protein Contact Map by Ultra-Deep Learning Model. *PLoS Comput. Biol.* **13**, e1005324.
- 32. Senior AW *et al.* 2020 Improved protein structure prediction using potentials from deep learning. *Nature* **577**, 706–710. (doi:10.1038/s41586-019-1923-7)
- 33. Konze K, Bos P, Dahlgren M, Leswing K, Tubert-Brohman I, Bortolato A, Robbason B, Abel R, Bhat S. 2019 Reaction-based Enumeration, Active Learning, and Free Energy Calculations to Rapidly Explore Synthetically Tractable Chemical Space and Optimize Potency of Cyclin Dependent Kinase 2 Inhibitors. *ChemRxiv* (doi:10.26434/chemrxiv.7841270.v3)
- 34. Coveney P V, Dougherty ER, Highfield RR. 2016 Big data need big theory too. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **374**, 20160153. (doi:10.1098/rsta.2016.0153)
- 35. Coveney P V., Highfield RR. 2020 When we can trust computers (and when we can't).
- 36. Saadi A Al *et al.* 2020 IMPECCABLE: Integrated Modeling PipelinE for COVID Cure by Assessing Better LEads.
- 37. 2019 OpenEye Toolkits 2019.Oct.2. Open Eye Sci.
- 38. Mcgann MR, Almond HR, Nicholls A, Grant JA, Brown FK. 2003 Gaussian docking functions. *Biopolym. Orig. Res. Biomol.* **68**, 76–90.
- 39. Shaw DE. 2020 D E Shaw. Mol. Dyn. Simulations Relat. to SARS-CoV-2.
- 40. Kabsch W, Sander C. 1983 Dictionary of protein secondary structure: pattern recognition of hydrogen-bonded and geometrical features. *Biopolymers* **22**, 2577–2637. (doi:10.1002/bip.360221211)
- 41. Donon Y, Kupriyanov A, Kirsh D, Meglio AD, Paringer R, Rytsarev I, Serafimovich P, Syomic S. 2020 Extended anomaly detection and breakdown prediction in LINAC 4's RF power source output. In 2020 International Conference on Information Technology and Nanotechnology (ITNT), pp. 1–7. (doi:10.1109/ITNT49337.2020.9253296)
- 42. Nichol A, Achiam J, Schulman J. 2018 On First-Order Meta-Learning Algorithms.
- 43. Fuglede B, Topsoe F. 2004 Jensen-Shannon divergence and Hilbert space embedding. In *International Symposium onInformation Theory*, 2004. *ISIT* 2004. *Proceedings.*, p. 31. (doi:10.1109/ISIT.2004.1365067)
- 44. Lee H, Turilli M, Jha S, Bhowmik D, Ma H, Ramanathan A. 2019 DeepDriveMD: Deep-Learning Driven Adaptive Molecular Simulations for Protein Folding. In 2019 IEEE/ACM Third Workshop on Deep Learning on Supercomputers (DLS), pp. 12–19.
- 45. Casalino L *et al.* 2020 AI-Driven Multiscale Simulations Illuminate Mechanisms of SARS-CoV-2 Spike Dynamics. *bioRxiv* , 2020.11.19.390187. (doi:10.1101/2020.11.19.390187)
- 46. Bhowmik D, Gao S, Young MT, Ramanathan A. 2018 Deep clustering of protein folding simulations. *BMC Bioinformatics* **19**, 484. (doi:10.1186/s12859-018-2507-5)
- 47. Wright DW, Hall BA, Kenway OA, Jha S, Coveney P V. 2014 Computing Clinically Relevant Binding Free Energies of HIV-1 Protease Inhibitors. *J. Chem. Theory Comput.* **10**, 1228–1241.
- 48. Straatsma TP, Berendsen HJC, Postma JPM. 1986 Free energy of hydrophobic hydration: A molecular dynamics study of noble gases in water. *J. Chem. Phys.* **85**, 6720–6727. (doi:10.1063/1.451846)
- 49. Babuji Y et al. 2020 Targeting SARS-CoV-2 with AI- and HPC-enabled Lead

- Generation: A First Data Release.
- 50. Babuji Y *et al.* 2019 Parsl: Pervasive parallel programming in {P}ython. In 28th International Symposium on High-Performance Parallel and Distributed Computing, pp. 25–36.
- 51. Balasubramanian V, Jha S, Merzky A, Turilli M. 2019 RADICAL-Cybertools: Middleware Building Blocks for Scalable Science.
- 52. Research in Advanced DIstributed Cyberinfrastructure and Applications Laboratory (RADICAL). 2019 RADICAL-Cybertools (RCT).
- 53. Lee H et al. 2020 Scalable HPC and AI Infrastructure for COVID-19 Therapeutics.