

APPLIED COMPUTER-AIDED DRUG DESIGN: MODELS AND METHODS

Editor:
Igor José dos Santos Nascimento

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Applied Computer-Aided Drug Design: Models and Methods

Edited by

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CONTENTS

PREFACE	i
REFERENCES	ii
LIST OF CONTRIBUTORS	iii
CHAPTER 1 LIGAND AND STRUCTURE-BASED DRUG DESIGN (LBDD AND SBDD):	
PROMISING APPROACHES TO DISCOVER NEW DRUGS	1
<i>Igor José dos Santos Nascimento and Ricardo Olimpio de Moura</i>	
INTRODUCTION	2
DRUG DESIGN AND DISCOVERY: PAST AND TODAY METHODS AND OTHER	
APPROACHES	3
Natural Compounds (NC)	3
Synthetic Drugs: Classical Approaches	4
Bioisosterism	4
Molecular Simplification	5
Molecular Hybridization	5
Combinatorial Chemistry	6
High Throughput Screening (HTS)	8
Target-Based Drug Discovery (TBDD)	8
Phenotypic-Based Drug Discovery (PBDD)	9
Multitarget Drug Design (MDD)	10
Computer-Aided Drug Design (CADD)	10
SBDD AND LBDD METHODS IN DRUG DESIGN	11
Structure-Based Drug Design (SBDD)	11
Homology Modeling	12
Molecular Docking and Molecular Dynamics Simulations	13
Fragment-Based Drug Design (FBDD) or <i>de novo</i> Drug Design	15
Density Function Theory (DFT)	17
Ligand-Based Drug Design (LBDD)	18
Quantitative Structure-Activity Relationship (QSAR)	18
Pharmacophore Modeling	19
Machine and Deep Learning and Artificial Methods	20
CHALLENGES AND OPPORTUNITIES IN LBDD AND SBDD APPROACHES TO	
DESIGN AND DISCOVER NEW DRUGS	21
CONCLUSION	22
ACKNOWLEDGMENTS	23
REFERENCES	23
CHAPTER 2 QUANTITATIVE STRUCTURE-ACTIVITY RELATIONSHIP (QSAR) IN	
STUDYING THE BIOLOGICALLY ACTIVE MOLECULES	33
<i>Serap ÇETINKAYA, Burak TÜZÜN and Emin SARIPINAR</i>	
INTRODUCTION	33
QSAR's Use	35
QSAR Model Development	36
2D-QSAR Analysis	37
<i>Fragment-Based 2D-QSAR Methods</i>	38
3D-QSAR	39
4D-QSAR	40
5D- and 6D-QSARs	40
Molecular Modelling and QSAR	40
Importance of the Validation of QSAR Models	41

<i>Means of Proof for QSAR Models</i>	41
<i>Internal Validation</i>	42
<i>External Validation</i>	44
Easily Reproducible QSAR Protocol	46
CONCLUSION	50
REFERENCES	50
CHAPTER 3 PHARMACOPHORE MAPPING: AN IMPORTANT TOOL IN MODERN DRUG DESIGN AND DISCOVERY	
<i>Dharmraj V. Pathak, Abha Vyas, Sneha R. Sagar, Hardik G. Bhatt and Paresh K. Patel</i>	
INTRODUCTION	58
Definitions of Pharmacophore	58
Pharmacophore: History	59
Pharmacophoric Features	61
LIGAND BASED PHARMACOPHORE	64
Ligand-Based Pharmacophore Modeling	66
<i>Selection of the Right Set of Compounds and their Initial Structure</i>	66
<i>Conformational Search</i>	66
<i>Feature Representation and Extraction</i>	67
<i>Pattern Identification/Molecular Alignment</i>	68
<i>Scoring the Common Pharmacophore</i>	68
Pharmacophore Tools and their Algorithms	69
Pharmacophore Validation	76
<i>Cost Analysis</i>	77
<i>Fisher's Randomization Test</i>	77
<i>Test Set Prediction</i>	77
<i>Leave-one-out Method</i>	78
3D-QSAR	78
Pharmacophore Based 3D QSAR	79
STRUCTURE BASED PHARMACOPHORE	80
Structure Based Pharmacophore Model Generation	81
<i>Active Site Identification</i>	81
<i>Complementary Image Construction</i>	81
<i>Query Generation, Searching and Hit Analysis</i>	81
<i>Validation</i>	86
<i>Virtual Screening</i>	91
<i>Prefiltering</i>	91
APPLICATION OF PHARMACOPHORE MAPPING	94
A Successful Example of Pharmacophore-based Drug Design: An Example of How Anthranilamide Derivatives Were Successfully Shown to be Promising Factor Xa Inhibitors [163]	98
Applications of Artificial Intelligence in Pharmacophore Mapping	101
Limitations of Pharmacophore Modeling	102
CONCLUSION	103
ACKNOWLEDGEMENTS	103
REFERENCES	103
CHAPTER 4 UP-TO-DATE DEVELOPMENTS IN HOMOLOGY MODELING	
<i>Muhammed Tilahun Muhammed and Esin Aki-Yalcin</i>	
INTRODUCTION	117
BRIEF HISTORY OF HOMOLOGY MODELING	118

HOMOLOGY MODELING PROCEDURE	118
Identification and Selection of templates	118
Sequence Alignments and Alignment Correction	119
Model Building	120
Loop Modeling	120
Side-Chain Modeling	121
Model Optimization	121
Model Evaluation and Validation	121
OVERVIEW OF HOMOLOGY MODELING TOOLS	121
MODELLER	122
I-TASSER	122
SWISS-MODEL	123
Prime	123
Phyre2	123
HHPRED	124
RosettaCM	124
Alpha Fold	124
CASE STUDY	125
APPLICATIONS OF HOMOLOGY MODELING IN DRUG DISCOVERY	127
CONCLUSION	128
REFERENCES	129
CHAPTER 5 ANTICANCER ACTIVITY OF MEDICINAL PLANTS EXTRACT AND MOLECULAR DOCKING STUDIES	136
<i>Serap ÇETINKAYA and Burak TÜZÜN</i>	
INTRODUCTION	136
Computer Aided Drug Design (CADD)	137
<i>Ligand-based Approach</i>	138
<i>Structure (Receptor)-based Approach</i>	139
Covalent Interactions in Biological Systems	139
Molecular Docking: Non-Covalent and Covalent Docking	140
Docking Methods in Software	140
<i>Fixed Docking</i>	141
<i>Flexible-Fixed Docking</i>	141
<i>Flexible Docking</i>	141
Types of Docking Calculations Algorithms	141
<i>Stepwise Structure Algorithm</i>	141
<i>Monte Carlo Sampling Algorithm</i>	141
<i>Genetic Algorithm</i>	141
<i>Lamarckian Genetic Algorithm</i>	142
<i>Biplane Space Sampling</i>	142
<i>Shape Matching Algorithm</i>	142
Molecular Docking Software	142
<i>Artemisia sieversiana</i>	145
<i>Rosmarinus officinalis</i>	147
<i>Allium sativum</i>	148
<i>Zingiber officinale</i>	149
CONCLUSION	151
REFERENCES	151
CHAPTER 6 FBDD & DE NOVO DRUG DESIGN	159
<i>Anwesha Das, Arijit Nandi, Vijeta Kumari and Mallika Alvala</i>	

INTRODUCTION	160
TYPES OF DRUG DESIGN	161
Structure or Receptor-based Drug Design (SBDD)	161
Ligand-based Drug Design (LBDD)	162
Sampling Methods in De novo Drug Design (DNDD)	163
EVOLUTIONARY ALGORITHMS IN DNDD	163
ARTIFICIAL INTELLIGENCE (AI) IN DNDD	164
DEEP REINFORCEMENT LEARNING (DRL) IN DNDD	164
Recurrent Neural Networks (RNN)	165
Convolutional Neural Network (CNN)	168
Generative Adversarial Network (GAN)	168
Autoencoder (AE)	168
<i>Variational Autoencoder (VAE)</i>	168
<i>Sequence-to-Sequence Autoencoder (seq2seq AE)</i>	169
<i>Adversarial Autoencoder (AAE)</i>	169
PARTICLE SWARM OPTIMIZATION (PSO) FOR DNDD	170
PARAMETERS OF EVALUATION	170
Diversity and Novelty	171
Desired Properties	172
Synthetic Feasibility	172
BRIDGING TOXICOGENOMICS AND MOLECULAR DESIGN	173
DNDD FOR COVID-19	174
BUILDING COMMUNITY AND REGULATORY ACCEPTANCE OF DL-METHOD FOR DNDD	175
FBDD	175
Fragment Libraries	175
Fragment Expansion Strategy	176
Fragment Optimization Strategy	176
<i>Fragment Growing</i>	179
<i>Fragment Linking</i>	179
<i>Fragment Merging</i>	180
In silico Strategies for Fragment-to-ligand Optimization	180
<i>Hotspot Analysis and Pocket Druggability Prediction</i>	180
<i>SAR Catalogue</i>	181
<i>Molecular Docking</i>	182
<i>Machine Learning and Deep Learning</i>	182
DNDD	183
<i>Novel Molecules Generating Software for The Binding Pocket of Protein's Binding Site</i>	183
<i>Pharmacokinetic Property Prediction of The Novel Compounds</i>	186
<i>Prediction of Synthesizability with The Novel Compounds</i>	186
<i>Synthesizability-aware Methods</i>	186
Case Studies	186
PROTAC AND MOLECULAR GLUE	186
CONCLUSION	188
REFERENCES	188
CHAPTER 7 MOLECULAR SIMULATION IN DRUG DESIGN: AN OVERVIEW OF MOLECULAR DYNAMICS METHODS	202
<i>Fernando D. Prieto-Martínez, Yelzyn Galván-Ciprés and Blanca Colín-Lozano</i>	
INTRODUCTION	202

Historical Background	205
THEORETICAL INTERLUDE	206
The Basics: Generating Equations of Motion	206
Breaking Molecular Interactions Down to Physical Contributions: Enter Molecular Force Field	210
A Primer on Thermodynamics and Statistical Mechanics	211
THE OVERARCHING PROBLEM: SAMPLING	214
CURRENT LIMITATIONS OF MOLECULAR DYNAMICS	218
MOLECULAR DYNAMICS PRACTICE AT A GLANCE	219
Prior to Simulation	219
First Steps	220
Commonly Used Force Fields	221
Available Software	222
<i>Desmond</i>	224
<i>GROMACS</i>	224
<i>NAMD</i>	225
<i>OpenMM</i>	225
<i>YASARA</i>	226
Building the System	226
Running a MD Simulation	228
Simulation Analysis	232
RALTEGRAVIR: A CASE STUDY	233
A Look into the HIV-1 Integrase	234
The Drug Discovery Process	236
The Development of Raltegravir	238
WORKING EXAMPLE: MOLECULAR DYNAMICS TUTORIAL USING DESMOND ..	241
Generalities	241
Making an Atomistic Simulation of Crambin	241
<i>Setting Up the System</i>	242
<i>Building the Simulation Box</i>	243
<i>Reparametrization Using the AMBER99SB-ILDN Force Field</i>	243
<i>Initializing the Simulation Protocol: Minimization</i>	244
<i>Equilibration and Dynamics</i>	244
<i>Trajectory Analysis</i>	245
<i>Analysis with MDTraj</i>	246
CONCLUSION	248
ACKNOWLEDGEMENTS	249
REFERENCES	249
CHAPTER 8 QUANTUM CHEMISTRY IN DRUG DESIGN: DENSITY FUNCTION THEORY (DFT) AND OTHER QUANTUM MECHANICS (QM)-RELATED APPROACHES	258
<i>Samuel Baraque de Freitas Rodrigues, Rodrigo Santos Aquino de Araújo, Thayane Regine Dantas de Mendonça, Francisco Jaime Bezerra Mendonça-Júnior, Peng Zhan and Edeildo Ferreira da Silva-Júnior</i>	
INTRODUCTION TO THE HISTORY OF QUANTUM CHEMISTRY (QC)	259
HOHENBERG-KOHN-SHAM THEOREM – DENSITY FUNCTIONAL THEORY (DFT)	261
Hohenberg-Kohn Existence Theorem	263
Hohenberg-Kohn Variational Theorem	264
Kohn-Sham Self-Consistent Field Methodology	264
CHEMICAL REACTIVITY INDEXES BY DENSITY FUNCTIONAL THEORY (DFT) ..	265
Chemical Potential and Electronegativity	265

Fukui Functions	266
DENSITY FUNCTIONAL THEORY (DFT)-RELATED APPROACHES	267
Hybrid Method: Quantum Mechanics / Molecular Mechanics (QM/MM)	267
DFT CALCULATIONS IN DRUG DESIGN & DEVELOPMENT	268
Drug-Target Interactions	268
<i>GABAA Receptor Inhibition</i>	272
Understand Enzymatic Mechanisms of Catalysis	273
<i>Cytidine Deaminase</i>	274
<i>RNA-dependent RNA Polymerase (RdRp) in Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)</i>	275
<i>Oxidized Polyvinyl Alcohol Hydrolase (OPH) from Pseudomonas O-3 Strain</i>	276
<i>Polyethylene Terephthalate Hydrolase (PETase) from Ideonella Sakaiensis</i>	277
Exploring Catalytic Reactions of Cysteine Protease (Papain-like Proteins)	279
<i>Papain Protease</i>	279
<i>Falcipain-2 from Plasmodium Falciparum</i>	280
<i>Cruzain Protease from Trypanosoma cruzi, and Rhodesain from T. brucei</i>	282
<i>Main Protease (Mpro or 3CLpro) from Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)</i>	286
METALLOPROTEASES	289
Iron(III)-Catalyzed Aerobic Degradation by Biphenyl 2,3-dioxygenase (BphA)	291
Mushroom Copper-Containing Tyrosinase	292
[NiFe] Hydrogenase from Desulfovibrio Gigas	293
QUANTUM CHEMICAL (QC) METHODS AND THEIR USES FOR DESIGNING DRUGS – VIEWPOINT AND COMPUTER REQUIRE- MENTS	295
CONCLUSION	296
LIST OF ABBREVIATIONS	297
ACKNOWLEDGMENTS	299
REFERENCES	299
CHAPTER 9 FREE ENERGY ESTIMATION FOR DRUG DISCOVERY: BACKGROUND AND PERSPECTIVES	310
<i>Fernando D. Prieto-Martínez and Yelzyn Galván-Ciprés</i>	
INTRODUCTION	310
THEORETICAL BACKGROUND	313
End-point Methods	315
FREE ENERGY PERTURBATION THEORY	321
METADYNAMICS	324
Software and Workflows	325
Current Developments	326
Best Practices	327
BOCEPREVIR AS A CASE STUDY: A RELEVANT ANTIVIRAL FOR THE TREATMENT OF HEP C	330
CONCLUSION	332
ACKNOWLEDGEMENTS	334
REFERENCES	334
SUBJECT INDEX	568

PREFACE

The drug discovery and development process is time-consuming and demands a high financial cost. In this way, it is estimated to take approximately 10 to 17 years, costing around 4 billion dollars. This stimulates the advancement of new methodologies that can accelerate the discovery process and increase the probability of a promising molecule. In addition, constant developments in informatics and computations have led to the routine use of high-performance computing in medicinal chemistry. Thus, Computer-Aided Drug Design (CADD) methods emerge, capable of providing critical information for the design of new molecules, essential in any new drug discovery program [1, 2].

In this context, the book “*Applied Computer-Aided Drug Design: Models and Methods*” appears, presenting the computational methods used by researchers and pharmaceutical companies. Each chapter explains a technique with high precision so that readers can apply it in their research.

This first edition is organized into nine chapters, namely:

Chapter 1 “**Ligand- and Structure-Based Drug Design (SBDD and LBDD)**”: Promising Approaches to Discover New Drugs. Here, the reader will have an approach from a historical perspective on strategies used in designing new drugs until the development of LBDD and SBDD strategies, exemplifying important discoveries of commercial drugs.

Chapter 2 “**Quantitative Structure-activity relationship (QSAR) in studying the biologically active molecules**”. This chapter will bring the principles and methods of this technique based on LBDD. It will present a historical perspective from the first QSAR models to the most current ones like 6D-QSAR. Furthermore, it provides a great read on protocol validation procedures, which are crucial to successful QSAR studies.

Chapter 3 “**Pharmacophore Mapping: An Important Tool in Modern Drug Design and Discovery**”. This chapter approaches a method that can be applied to SBDD and LBDD protocols. The reader will have a historical perspective of the evolution of the method, a presentation of the leading software used, and, in the end, a great background on carrying out a well-validated virtual screening protocol based on pharmacophore. Further, the text addresses successful studies and how their protocols were carried out.

Chapter 4 “**Up-To-Date Developments In Homology Modeling**”. Similar to the previous chapters, the readers will have a theoretical basis on the technique, quite explored when there is information about the target without an experimental structure. Homology modeling is a powerful tool for constructing and applying molecular targets in drug design studies. With this, readers can perform this protocol safely and efficiently.

Chapter 5 “**Anticancer Activity of Medicinal Plants Extract and Molecular Docking Studies**”. In fact, this is the most used tool by drug developers worldwide. Through this technique, new drugs can be safely planned, or even virtual screenings can be carried out to find new drugs. Thus, the authors will bring the technique's theoretical framework, the method's evolution, computational software, and studies in which the application of molecular docking was vital to finding promising molecules.

Chapter 6 “**FBDD & de novo Drug Design**”. In this chapter, the main tools used in Fragment-Based Drug Design (FBDD) and *de novo* Drug Design (DNDD) will be presented,

mainly through in silico approaches. It is essential to highlight that these methods control molecules from scratch, generating critical *hits* that later become optimizable *leads*. In addition, all the theoretical frameworks and important discoveries are applied through these strategies.

Chapter 7 “**Molecular simulation in drug design; an overview of molecular dynamics methods**”. Despite being a promising technique, molecular docking has several problems, such as disregarding the flexibility of the active site during simulation. Thus, this chapter will address the molecular dynamics technique, which tries to solve some problems from molecular docking. In fact, with the popularization of computers in drug design, this is the fastest-growing technique, and its application is essential in drug discovery programs. Thus, with great clarity, the authors present the theoretical framework and how to apply it in a design campaign for new drugs.

Chapter 8 “**Quantum Chemistry in Drug Design: density function theory (DFT) and other quantum mechanics (QM)-related approaches**”. The application of quantum chemistry (QM) protocols in predicting biological activity or enzymatic mechanism are highlighted in the current drug discovery process. Increasingly, researchers are adopting these tools in their drug development projects. Thus, in this chapter Rodrigues et al. They explored the entire theoretical foundation of QM, focusing on applying Density Functional Theory, providing new insights to medicinal chemists to use in their projects.

Chapter 9 “**Free energy estimations for drug discovery: Background and perspectives**”. This chapter is one of the most current and essential in this book. Here are shown energy predictions and applications of perturbation theory in drug design. This approach has gained increasing prominence in medicinal chemistry, mainly for solving some limitations related to classic MD simulations. In this way, an excellent theoretical framework and its application in drug design are shown with updated examples.

I hope that with this book, readers will have new insights and be able to safely apply the protocols shown here, providing new trends that help discover new drugs to improve the quality of life of the world's population.

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CHAPTER 1

Ligand and Structure-Based Drug Design (LBDD and SBDD): Promising Approaches to Discover New Drugs

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Abstract: The drug discovery and development process are challenging and have undergone many changes over the last few years. Academic researchers and pharmaceutical companies invest thousands of dollars a year to search for drugs capable of improving and increasing people's life quality. This is an expensive, time-consuming, and multifaceted process requiring the integration of several fields of knowledge. For many years, the search for new drugs was focused on Target-Based Drug Design methods, identifying natural compounds or through empirical synthesis. However, with the improvement of molecular modeling techniques and the growth of computer science, Computer-Aided Drug Design (CADD) emerges as a promising alternative. Since the 1970s, its main approaches, Structure-Based Drug Design (SBDD) and Ligand-Based Drug Design (LBDD), have been responsible for discovering and designing several revolutionary drugs and promising *lead* and *hit* compounds. Based on this information, it is clear that these methods are essential in drug design campaigns. Finally, this chapter will explore approaches used in drug design, from the past to the present, from classical methods such as bioisosterism, molecular simplification, and hybridization, to computational methods such as docking, molecular dynamics (MD) simulations, and virtual screenings, and how these methods have been vital to the identification and design of promising drugs or compounds. Finally, we hope that this chapter guides researchers worldwide in rational drug design methods in which readers will learn about approaches and choose the one that best fits their research.

Keywords: CADD, Computational methods, Drug design, Drug discovery, Drug Development, Docking, FBDD, LBDD, QSAR, Rational Design, SBDD.

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INTRODUCTION

The process of designing and developing new drugs is challenging and has evolved constantly in recent years, from empirical approaches related to natural products to the current phase with the use of computers and artificial intelligence [1 - 3]. One of the most significant advances in this area has been high-throughput screening (HTS), in which thousands of compounds can be screened in a few hours. In addition, the growth of genomics, proteomics, metabolomics, and molecular modeling promoted substantial advances in the knowledge of critical biochemical pathways for the P&D of drugs [4 - 6]. Associated with this, the synthetic approach exploring combinatorial chemistry could masterfully explore the available chemical space, supporting the discovery of new molecules [5]. However, the high financial cost and time-related to these approaches have driven researchers to adopt *in silico* methods [7, 8]. In this way, Computer-Aided Drug Design (CADD) emerged and perfected itself, indispensable in any new drug design discovery program [7, 9].

Traditionally, the discovery of a new drug can take between 10 and 15 years, with an investment of approximately US\$800 million to US\$1.8 billion [10, 11]. In this context, developing new drug design tools has become a constant quest to overcome old paradigms and speed up the discovery process at a lower financial investment [10, 12]. Over time, the scientific community accepted the new paradigm in the rational design of new drugs through CADD [13, 14]. The main reason is constant failures in the clinical evolution of prototypes identified and designed through classical techniques [13]. Thus, this paradigm shift facilitated the identification of new drugs, designing drugs with optimal physicochemical properties, and evaluating their potential *in silico* before they were synthesized [13]. With this, virtual screenings (VS) are increasingly explored, finding drug candidates in libraries of thousands of compounds. In addition, this method can be used in scaffolds identification as a starting point in molecular modeling studies, further confirming the *in silico* methods and rational design in the new era of P&D of drugs [15].

CADD can usually be divided into Structure-Based Drug Design (SBDD), and Ligand-Based Drug Design (LBDD) approaches. The researcher's choice between these approaches is related to the availability of key information about the clinical condition or known compounds against the same [16, 17]. For an SBDD protocol, the main requirement is the knowledge and availability of the target related to the explored clinical condition, in which the ligands are designed to interact with the target in question [18, 19]. On the other hand, in LBDD, there is no information about the target, but there are ligands of known activity against the clinical

condition in question, and new molecules can be designed based on the production of pharmacophoric models or Quantitative Structure-Activity Relationship studies (QSAR) [20]. Traditionally, SBDD is preferred by the scientific community mainly due to the easy access to software and the wide availability of experimental structures of biological targets [21 - 23].

Currently, CADD methods using SBDD or LBDD approaches are vital in discovering new molecules and identifying critical information in drug design. Thus, this chapter will present a historical perspective on the evolution of drug design methods to CADD approaches. We hope that this chapter will guide drug developers in deciding on the type of strategy in their studies, increasingly promoting scientific advances in rational drug design.

DRUG DESIGN AND DISCOVERY: PAST AND TODAY METHODS AND OTHER APPROACHES

Strategies used in drug design and discovery have improved over the years [24]. In a historical context, each strategy was responsible for numerous discoveries. However, the improvement of methods made the process faster and more effective in the search for innovative molecules until the arrival of computational methods [25]. The following topics will address the evolution of the methods and their historical importance.

Natural Compounds (NC)

Before any study of rational drug design, Natural Compounds (NC) were the primary sources of drugs explored. During the last five decades, NCs were the target of isolation or total syntheses, as they presented high biological potential and challenging structural complexity. The discovery of numerous NCs against threatening diseases like cancer and infectious diseases has increased the interest in discovering new revolutionary NCs [26]. Indeed, most drugs introduced into the pharmaceutical market since 1994 are NCs or modified synthetic analogs, highlighting their potential for many years [27].

Traditionally, drug discovery by NCs starts with testing the extract of interest in vitro or in vivo assays. After demonstrating the pharmacological effect, the responsible compounds are then isolated [27, 28]. These compounds can be modified from then on to improve their pharmacological effect [27]. In a more current approach, drug repurposing using known NCs is used to find new potentials for available structures [29, 30]. Examples of natural compounds include Artemisinin (1), Atropine (2), Metformin (3), and Quinine (4) (Fig. 1). It is essential to highlight that these molecules were useful as molecular scaffolds that led to important clinical discoveries, which highlights the role of NCs in the

CHAPTER 2

Quantitative Structure-activity Relationship (QSAR) in Studying the Biologically Active Molecules

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Abstract: Recently, many new methods have been used in the research and development of a new drug. In this article, QSAR, which is one of the usable areas of artificial intelligence during molecule research, and the analysis and formulation studies related to the suitability of this area are discussed. It is explained how a model to be created is prepared and calculation formulas for how to verify this model are shown. Examples of the most recent 4D-QSAR calculations are given.

Keywords: Molecular Modelling, Pharmacophore, QSAR, Quantitative Structure-activity Relationship, Validation.

INTRODUCTION

Quantitative structure-activity relationship (QSAR) analysis uses the molecular structure of a compound or ligand to predict its biological activity. It presupposes that similar biological activities are retained in similar molecular structures [1]. It also uses known biological activity data to predict unknown activities. This approach has been adapted to diverse but related scientific disciplines [2-5], including the design of new chemical entities (NCEs) [5, 6] with high biological potentials.

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QSAR is a systematic multi-step process (Fig. 1), made up of dataset preparation, selection, and generation of molecular descriptors; derivation of mathematical or statistical models; model training and validation using a training dataset; and model testing on a test dataset [7 - 10].

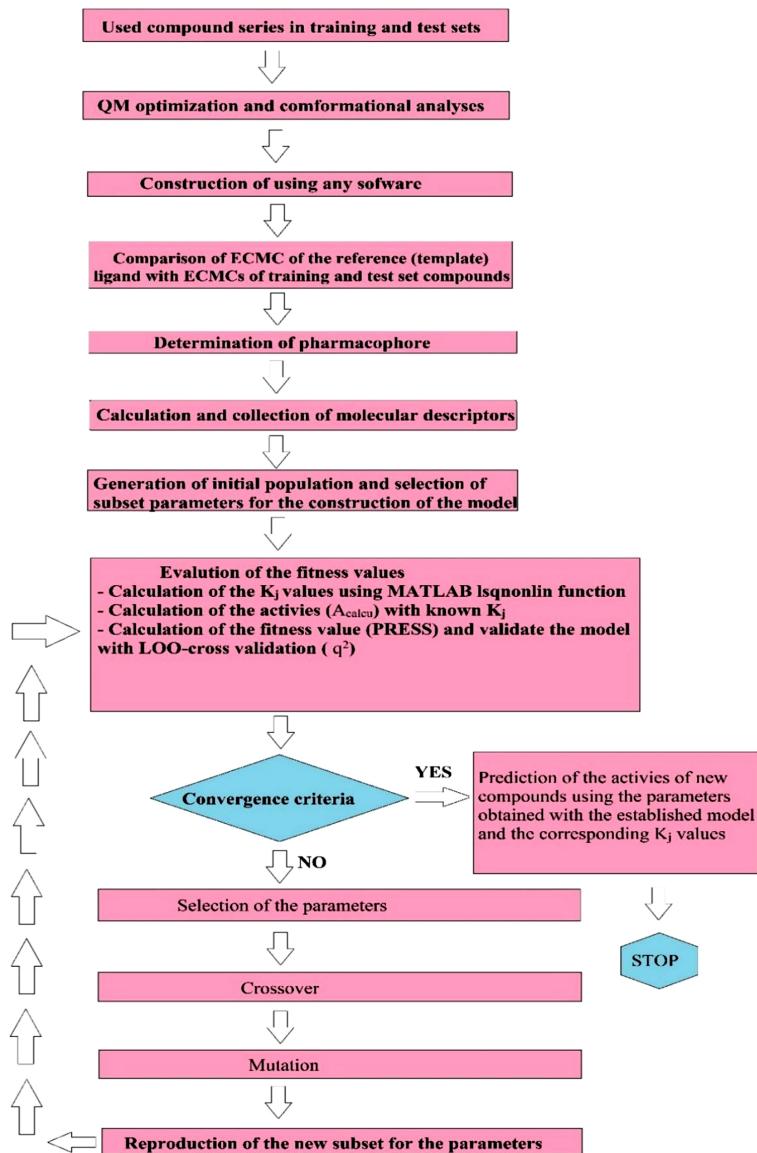


Fig. (1). Outlines of a QSAR model development.

In order to create a consistent QSAR model, it is central to utilize high-quality data that have been derived from bioassays, and to use an adequate number of compounds. Biological data are preferred to have been produced in a single laboratory [5, 11].

Selection and generation of molecular identifiers form the second step. Here the selection of appropriate descriptors, describing structural variations, is important. Various methods, such as machine learning techniques (*e.g.*, forward selection) and evolutionary algorithms (*e.g.*, genetic algorithm [11]), are utilized for descriptor/variable/feature selection.

A suitable mathematical or statistical model must be chosen to define the correlation between relevant descriptors and biological activities. The model can be linear partial least squares (PLS) [12], multiple linear regression (MLR) [13] or nonlinear. The selected model is then trained on a randomly chosen dataset, and the rest is used as test compounds. Model training often involves validation procedures, for example, exclusion cross validation (LOOCV) [14]. The training process is reiterated in order to reach an acceptable performance. The final step involves the testing process [11].

The concept of QSAR was first envisioned by Free, Wilson, Hansch and Fujita in 1964 [15, 16]. Subsequently, a new 3D-QSAR method, named comparative molecular field analysis (CoMFA) [17], has been worked out to overwhelm general 3D-QSAR problems. It has provided the basis for the development of multidimensional (nD) QSARs.

QSAR's Use

QSAR should not be seen as an academic tool that allows for the subsequent rationalization of data. It aims to derive molecular structure relationships between biology and chemistry for a valid reason. Models can be developed from these relationships and are thought to be predictive with common sense, luck, and expertise. A QSAR model can have many practical commitments [18, 19]:

- Rational estimation of biological activity and physicochemical properties.
- Understand and rationalize the action mechanisms of a wide variety of chemicals.
- Cost-effective product development.
- Minimization of the production time.
- Elimination of the ethical concerns.
- Spurring of “green” chemistry.

CHAPTER 3

Pharmacophore Mapping: An Important Tool in Modern Drug Design and Discovery

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Abstract: Computer-Aided Drug Design (CADD) has become an integral part of drug discovery and development efforts in the pharmaceutical and biotechnology industry. Since the 1980s, structure-based design technology has evolved, and today, these techniques are being widely employed and credited for the discovery and design of most of the recent drug products in the market. Pharmacophore-based drug design provides fundamental approach strategies for both structure-based and ligand-based pharmacophore approaches. The different programs and methodologies enable the implementation of more accurate and sophisticated pharmacophore model generation and application in drug discovery. Commonly used programmes are GALAHAD, GASP, PHASE, HYPOGEN, ligand scout etc. In modern computational chemistry, pharmacophores are used to define the essential features of one or more molecules with the same biological activity. A database of diverse chemical compounds can then be searched for more molecules which share the same features located at a similar distance apart from each other. Pharmacophore requires knowledge of either active ligands and/or the active site of the target receptor. There are a number of ways to build a pharmacophore. It can be done by common feature analysis to find the chemical features shared by a set of active compounds that seem commonly important for receptor interaction. Alternately, diverse chemical structures for certain numbers of training set molecules, along with the corresponding IC₅₀ or Ki values, can be used to correlate the three-dimensional arrangement of their chemical features with the biological activities of training set molecules. There are many advantages in pharmacophore based virtual screening as well as pharmacophore based QSAR, which exemplify the detailed application workflow. Pharmacophore based drug design process includes pharmacophore modelling and validation, pharmacophore based virtual screening, virtual hits profiling, and lead identification. The current chapter on pharmacophores also describes case studies and applications of pharmacophore mapping in finding new drug molecules of specific targets.

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Keywords: Features, Ligand Based, Pharmacophore Query, Pharmacophore, Structure Based, Virtual Screening.

INTRODUCTION

Currently engaged in creating a new medicine, drug design and development is a costly and time-consuming process [1]. From foundational research to commercial products, a new medicine requires 10 to 14 years of research and billions of dollars *via* several preclinical and clinical phases [2]. With the amazing advancement of computational resources, computer aided drug design (CADD) and discovery technologies are highly valued all over the world. Designing small lead and drug-like molecules with expected multitarget actions increasingly employs both ligand and structure-based methods. CADD has advanced significantly in recent years, boosting the comprehension of multiple and complicated biological processes, allowing for the fast development of novel pharmacologically active drugs [3]. One such CADD tool employed in drug design and discovery is pharmacophore mapping or pharmacophore modeling. In the late 19th century, *Paul Ehrlich* was the first who propose that certain groups inside a molecule (phoros) are responsible for a molecule's biological activity (pharmacon), giving rise to the idea of "pharmacophores" [4, 5]. The pharmacophore theory postulates that a collection of shared properties that engage a group of contrasting locations on a biological target can explain how a class of chemicals recognizes that target on a molecular level [6]. In the contemporary drug discovery process, the pharmacophore approach serves as a helpful bridge between medicinal chemistry and computational chemistry, both in virtual screening (VS) and library design for effective hit finding and in the optimization of lead compounds to final therapeutic candidates.

Definitions of Pharmacophore

As per the IUPAC definition, "A pharmacophore is the ensemble of steric and electronic features that is necessary to ensure the optimal supramolecular interactions with a specific biological target structure and to trigger (or to block) its biological response."

Apart from the official IUPAC definition, other similar definitions have also been given in the literature. "A pharmacophore does not represent a real molecule or a real association of functional groups, but a purely abstract concept that accounts for the common molecular interaction capacities of a group of compounds with their target structure."

“A pharmacophore is defined by pharmacophoric descriptors, including H-bonding, hydrophobic, and electrostatic interaction sites, defined by atoms, ring centers, and virtual points.

“A pharmacophore can be considered the largest common denominator shared by a set of active molecules”. This definition discards a misuse often found in the medicinal chemistry literature, which consists of naming as pharmacophores simple chemical functionalities such as guanidine, sulphonamides, or dihydroimidazoles (formerly imidazolines), or typical structural skeletons such as flavones, phenothiazines, prostaglandins, or steroids [5, 7].

To describe unique functional groups or chemical classes with biological activity, scientists frequently use the terms “pharmacophore” or “pharmacophoric group. In this context, the word “pharmacophore” is used in conjunction with the concept of “privileged structures,” which refers to the alternative idea of structure and function. The chemical scaffolds and retroactive examination of medicinal molecules' chemical structures allowed for the identification of a few structural motifs that are frequently linked to bioactive compounds. Evans *et al.* referred to these patterns as “privileged structures” to describe substructures that bestow activity against a number of different targets [8]. Dihydropyridines, arylethylamines, *N*-arylpiperazines, diphenylmethane derivatives, biphenyls, pyridazines, sulphonamides and benzodiazepines are a few well-known instances of the advantaged structures [7 - 10].

Pharmacophore: History

The pharmacophore was first envisioned by Paul Ehrlich, the pioneer of chemotherapy, and that idea has remained unchanged for the past 100 years [11]. Langley, who coined the phrase “receptive substance,” first proposed the notion that bioactive compounds interact with receptors in 1878 [12]. Paul Ehrlich, meanwhile, coined the word “receptor” a few years down the line [13], as well as introduced the term “pharmacophore”. In conjunction with Emil Fischer's lock-and-key concept, it tends to be evident but not the properties of a molecule, the “key”, are equally significant aimed at biological action [14]. Biological activity can be dramatically altered by small changes in some parts of a molecule, while minor changes in others can do the same. Modern drug discovery and development is based on Langley, Ehrlich, and Fischer's concepts. As soon as they were confirmed according to the earliest protein-ligand complex crystal structures half a decade later, they established a new paradigm [15]. Before the development of computers and modelling software, simple pharmacophores were documented in the literature and recognised as tools for the discovery of novel compounds. Modest 2D models remained first proposed in the 1940s based on the

CHAPTER 4

Up-to-Date Developments in Homology Modeling

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Abstract: Homology modeling is used to predict protein 3D structure from its amino acid sequence. It is the most accurate computational approach to estimate 3D structures. It has straightforward steps that save time and labor. There are several homology modeling tools under use. There is no sole tool that is superior in every aspect. Hence, the user should select the most appropriate one carefully. It is also a common practice to use two or more tools at a time and choose the best model among the resulting models.

Homology modeling has various applications in the drug design and development process. Such applications need high-quality 3D structures. It is widely used in combination with other computational methods including molecular docking and molecular dynamics simulation. Like the other computational methods, it has been influenced by the involvement of artificial intelligence. In this regard, homology modeling tools, like AlphaFold, have been introduced. This type of method is expected to contribute to filling the gap between protein sequence release and 3D structure determination.

This chapter sheds light on the history, relatively popular tools and steps of homology modeling. A detailed explanation of MODELLER is also given as a case study protocol. Furthermore, homology modeling's application in drug discovery is explained by exemplifying its role in the fight against the novel Coronavirus. Considering the new advances in the area, better tools and thus high-quality models are expected. These, in turn, pave the way for more applications of it.

Keywords: Computer Aided Drug Design, 3D Structure, Drug Discovery, Homology Modeling, Modeller, Molecular Modeling.

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INTRODUCTION

Proteins' 3D (3-dimensional) structures play a crucial role in defining their functions [1]. Hence, investigations about protein structures have an important contribution to understanding the mechanism of diseases [2]. Thus, knowledge about protein 3D structure has a vital role in rational drug design and discovery [3]. As a result, a number of Nobel Prizes have been awarded to researchers in this area. Scientists have been awarded the prize for elucidating the structures of myoglobin, lysozyme, integral membrane protein, HIV (human immunodeficiency virus) protease, ion channels, RNA (ribonucleic acid) polymerase, and GPCR (G protein-coupled receptor). In addition to this, the prize was awarded to researchers who pioneered in using X-ray crystallography, NMR (nuclear magnetic resonance), and Cryo-electron microscopy (Cryo-EM) for protein structure determination [4].

The quality of protein 3D structures solved has been improved as the available techniques improved [5]. Together with this, the experimental methods are not applicable to solving the structure of each protein. In this regard, NMR is used to solve the 3D structure of relatively small molecules, which are dissolvable [6]. Similarly, X-ray crystallography is used to solve protein 3D structures in a crystal state [7]. Cryo-EM is preferred to large macromolecule complexes with low resolution [8]. In addition to this, the experimental methods take a long time, labor and resource [9]. As a result, the experimental protein 3D structure determination could not keep pace with the protein sequence release. Consequently, the gap between the protein sequences available and the experimentally solved protein structures has been widening. Hence, computational protein 3D structure prediction methods can play a substantial role in filling this gap [10].

Homology (comparative) modeling is protein 3D structure prediction from its amino acid sequence. Homology modeling is used when the query sequence and templates selected share a common ancestor. In comparative modeling, there is just sequence similarity without shared ancestral history [11]. Homology modeling yields 3D structures with better reliability than the other computational structure prediction approaches [12, 13]. In addition to this, it has straightforward steps that take relatively less time. Hence, homology modeling is used to generate high quality structures that have the potential to convert the applications of the other computational methods in case they require 3D structures [14].

In this chapter, the brief history and the general procedures of homology modeling are presented. Homology modeling tools that are widely used these days are also given. Together with this, a case study protocol with MODELLER is included.

Furthermore, applications of homology modeling in the drug discovery process is summarized with a special focus on the latest ones. So, this chapter is expected to provide updated information on homology modeling.

BRIEF HISTORY OF HOMOLOGY MODELING

The idea of protein structure prediction has a long history since 1894 when Emin Fischer suggested that a protein's 3D structure determines its function [11]. Thereafter, Christian Anfinsen suggested that among the possible conformations, the native conformation has the lowest energy. In the 1970s, he proposed that the structure of a protein is determined by its amino acid sequence in a particular physiological condition [15]. This is the basis for the concept of homology modeling. The α -lactalbumin 3D structure, which was built based on the structure of lysozyme in 1969, is considered the first homology model [16]. After this time, various homology modeling programs and servers were developed. In this regard, MODELLER was revealed in 1993 [17]. In the same year, the concept of a server for automated homology modeling was introduced through SWISS-MODEL [18]. The milestones in the history of homology modeling are summarized in Fig. (1).

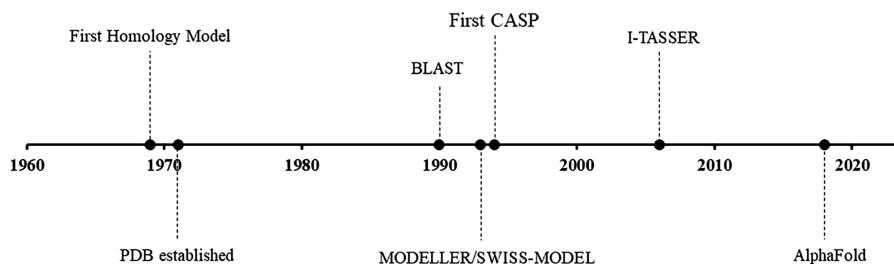


Fig. (1). Milestones in the history of homology modeling.

HOMOLOGY MODELING PROCEDURE

Homology modeling has straightforward major steps (Fig. 2). General information about each step is presented in this section.

Identification and Selection of templates

In the first step of the process, the target (query) sequence is used to identify template structures in the worldwide PDB (<https://www.wwpdb.org/>) or other structural databases [19]. First, the protein basic local alignment search tool (BLASTp) search is performed by using the target sequence as a query and PDB as a database in NCBI (national center for biotechnology information) (<https://blast.ncbi.nlm.nih.gov/Blast.cgi>) [20, 21]. BLASTp search gives the 3D structures inside the PDB with high identity and coverage of the query. In case

CHAPTER 5

Anticancer Activity of Medicinal Plants Extract and Molecular Docking Studies

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Abstract: Molecular docking involves the interaction of a molecule with another place, usually in the protein structure, and simulating the placement of the molecule in the protein structure with certain score algorithms, taking into account many quantities, such as the electro-negativity of atoms, their positions to each other, and the conformation of the molecule to be inserted into the protein structure. Finally, the activity of the molecule with the highest percentage by mass against various cancer proteins was investigated according to the GC-MS results made on some medicinal and aromatic plants in order to set an example of molecular docking calculations.

Keywords: Activity, Aromatic plants, Cancer proteins, Molecular docking, Medicinal.

INTRODUCTION

Molecular docking involves the interaction of a molecule with another place, usually in the protein structure, and consists of simulating the placement of the molecule in the protein structure with certain score algorithms, taking into account many quantities such as the electro-negativity of the atoms, the positions of the atoms to each other, and the conformation of the molecule to be inserted into the protein structure [1, 2].

The docking process plays an important role in explaining the receptor-ligand, enzyme-ligand relationship. Finding suitable antagonist and agonist compounds has an important place in enzyme inhibition studies [3].

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Molecular docking studies are the theoretical method that plays an important role in determining whether millions of synthesized compounds are effective drug substances [4]. It is impossible to study each of the millions of chemical substances individually *in vitro*, and molecular docking studies have a very important role in selecting the most effective substances.

By converting the effect of a chemical substance on a protein structure into a numerical value, it saves money by preventing *in vitro* and *in vivo* studies of molecules that are impossible to be effective [5, 6]. It also lays the groundwork for the modification of the molecule with the correct estimation of the binding modes of the relevant molecule, and creates a strategic infrastructure by guiding the synthesis of molecules that are likely to be more effective.

The docking process plays an important role in explaining the receptor-ligand, enzyme-ligand relationship [7, 8]. It enables the comparison of the activities of molecules against proteins in studies to inhibit the enzyme in finding suitable antagonist compounds.

In addition to all these important and useful features of molecular docking studies, it also needs to be supported by molecular dynamics. Because the molecule clamped into the protein structure may have achieved good coupling and high scores in the first place, but both the enzyme and the relevant molecule in the solvent are in interaction [9]. This dynamic and synergetic state means that the chelating molecule cannot stay in the docked place for a long time, and its effect will be limited as it is related to the residence time in the attached area. Due to this situation, molecular docking calculations in computational chemistry are supported by molecular dynamics and the problem is solved.

Computer Aided Drug Design (CADD)

In silico methods are increasingly used for the development of new drugs. Computer-aided drug design (CADD) [10, 11] is a discipline that uses computational methods to simulate drug-receptor, drug-enzyme interactions. Calculations made by examining the 3-D properties of chemical molecules accelerate the optimization process of precursor compounds [12]. Thus, the success rate in drug research and development (R&D) studies increases, R&D costs decrease and R&D period shortens [13].

Computer-aided drug design programs require knowledge of ligands and receptors; bioinformatics develops depending on tools, applications and databases. If a target (receptor) exists, its 3D structure (by x-ray or NMR) together with its ligand must be known; If there is no experimental data, the 3D structure

of the target molecule is tried to be created by homology modeling based on the sequence data.

There are two basic approaches to drug design: ligand-based and receptor-based molecular design methods.

Ligand-based Approach

The second and more branched approach to drug discovery is the ligand-based route. The general assumption of ligand-based methods [14, 15] is that the active site of a target protein may have similar atoms, functional groups, or moieties to have 11 similar functional properties. Nitrogen atoms in a Histidine residue at a particular position in the protein sequence must make a Hydrogen bond interaction with a polar Hydrogen atom on the ligand for the protein to lose its biological function (also called “inhibition”) [16]. Of course, the change in the properties of a protein cannot be brought about by a single interaction on a single atom. However, if this approach is embodied for an entire molecule that has several interactions with more than one amino acid in the binding gap, the desired switch of function can be established. One of the first uses of ligand-based methods is seen as structure-activity relationship (SAR) studies, a method that has been used for decades [17].

However, the problem with the activity of small molecules in the body is that it cannot be predicted with sufficient accuracy. The reasons behind this disadvantage are [18]:

- i) A full quantum-mechanical description of a ligand (*i.e.*, accurate calculation of the partial charges on each of its atoms) cannot be made,
- ii) Actual activity depends on numerous factors such as: the character of the target, its environment, and the interactions established between a target and the ligand.

Perhaps the most promising avenues in a ligand-based approach are 3D pharmacophore modeling or 3D quantitative structure-activity relationship (QSAR) methods. Pharmacophore modeling encompasses the discovery of the spatial arrangement of pharmacophore groups in a molecule because that molecule is considered biologically active or relevant. The term “pharmacophore” was first defined by Schueler in the 1960s [19, 20] as functionalities in a molecule that determine its biological activity [21].

These chemical groups responsible for the activity of a drug molecule can be searched for and compared with desired activities through chemical libraries

CHAPTER 6

FBDD & *De Novo* Drug Design

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Abstract: Fragment-based drug or lead discovery (FBDD or FBLD) refers to as one of the most significant approaches in the domain of current research in the pharmaceutical industry as well as academia. It offers a number of advantages compared to the conventional drug discovery approach, which include – 1) It needs the lesser size of chemical databases for the development of fragments, 2) A wide spectrum of biophysical methodologies can be utilized for the selection of the best fit fragments against a particular receptor, and 3) It is far more simpler, feasible, and scalable in terms of the application when compared to the classical high-throughput screening methods, making it more popular day by day. For a fragment to become a drug candidate, they are analyzed and evaluated on the basis of numerous strategies and criteria, which are thoroughly explained in this chapter. One important term in the field of FBDD is *de novo* drug design (DNDD), which means the design and development of new ligand molecules or drug candidates from scratch using a wide range of *in silico* approaches and algorithmic tools, among which AI-based platforms are gaining large attraction. A principle segment of AI includes DRL that finds numerous applicabilities in the DNDD sector, such as the discovery of novel inhibitors of BACE1 enzyme, identification and optimization of new antagonists of DDR1 kinase enzyme, and development and design of ligand molecules specific to target adenosine A2A, etc. In this book chapter, several aspects of both FBDD and DNDD are briefly discussed.

Keywords: Artificial Intelligence, Autoencoder, Deep Learning, *De Novo* Drug Design, Drug Development, Drug Discovery, Evaluation Criteria, Expansion, Fragment-based Fragment to Lead, Hotspot analysis, *In silico*, Lead Optimization, Machine Learning, Molecular Docking, Optimization, Pharmacokinetic Properties, Property Prediction, Synthetic Accessibility.

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INTRODUCTION

Since the last two decades, FBDD or FBLD has become one of the most triumphant methodologies in the area of early-stage drug development in the pharmaceutical industry as well as academia [1]. FBDD constitutes the screening of numerous molecules with lower molecular weights against clinically significant biological targets as these smaller fragments may fit into one or multiple binding sites of the protein and can act as potential beginning points in case of lead development. For fragment development, the physicochemical, pharmacokinetic, and toxic properties must be considered. One of the most popular methods, structure-based fragment screening, firstly employs a combination of multiple techniques, such as biophysical methods (thermophoresis, surface plasmon resonance [SPR], and differential scanning fluorimetry [DSF] etc.), later the employment of experimentations like X-ray crystallography or NMR, optimizes and structurally characterizes the fragments. Followed by that, further analytical stages like fragment growth also require the structural characterization of the screened hit fragments. The entire workflow of FBLD includes a massive high-throughput screening of all fragments that ultimately leads to the lead compound, and this approach is known as fragment-to-ligand optimization (F2L approach).

FBDD is referred to as one of the most attractive, effective, and popular approaches for chemical space exploration for perfectly fitting into the binding site of a biological target. While in the case of classical high-throughput screening (HTS), the screening of large libraries of complex molecules takes place against a target [2], in the case of FBDD, smaller libraries of lesser complex molecules that make fragments of larger drug-like molecules are usually screened against the target binding site for evaluating their binding efficiencies [3]. In spite of having lower potency than the larger drug-like compounds obtained *via* HTS, the fragments are considered potential starting points for designing larger drug-like molecules with higher affinity towards the target using the prior knowledge of the targets. This downside-up approach yields lead compounds with higher affinity and specificity, where a greater range of chemical space can be explored. Another advantage of FBDD includes that it requires lower expenses and lesser time for drug development through FBDD approach [4]. For example, Vemurafenib (ZelborafTM) is the first FBDD-derived drug that took only 6 years in all phases of the drug discovery pipeline before it went to FDA approval [5]. NMR can also be used in FBDD; for example, Bruker's Ligand Observed NMR is one of the most popular techniques for FBDD [6]. In the case of the computationally derived FBDD-approach, numerous tools can be employed for rationally designing a molecule. For example, AutoGrow4 is a genetic algorithm-based open source platform that can predict and design ligands computationally [7, 8]. Moreover, LigBuilder employs computational approaches to design ligands that can bind to

multiple targets, multiple binding sites of a single target, or multiple conformations of a single target, thus forming a multi-target directed ligand (MTDL) [9]. This way, FBDD offers numerous attractive opportunities in the domain of drug discovery.

On the other hand, *De novo* drug design (DNDD) refers to the design of novel molecules that perfectly fit into a protein's binding site using several computational algorithms and approaches [10]. The meaning of the word "*De Novo*" is "starting from scratch or from the beginning", which implies that in DNDD, novel chemicals can be designed without any prior information of the starting point [11]. Among the several advantages of DNDD, such as larger chemical space exploration, new intellectual property containing compound design, time- and cost-effective development of novel chemical entities, and the strength of newer improved therapies as well as therapeutics, *etc.*, it shows one major disadvantage or challenge of synthesizability [12]. In this book chapter, several aspects of both FBDD and DNDD are briefly discussed.

TYPES OF DRUG DESIGN

DNDD can be defined as a drug designing methodology where new chemical entities (NCE) can be found from scratch from either the information related to the enzyme/receptor/biological target or its already known ligands having a strong inhibitory activity or good binding affinity towards the enzyme [13 - 25]. Needless to say, the main workflow behind the DNDD approach is - 1) A proper description and demonstration of the target's active binding site, 2) Pharmacophore modeling of the binding ligands, 3) Construction or generation of ligands by sampling, and 4) Evaluation of the constructed ligands. Principally, there are two types of DNDD approaches, namely, structure or receptor-based drug design (SBDD) and ligand-based drug design (LBDD).

Structure or Receptor-based Drug Design (SBDD)

SBDD is based on the three-dimensional structure (3D) of the biological target, where its structure is elucidated mainly by three methods, viz, electron microscopy, Nuclear magnetic resonance (NMR), and X-ray crystallography [26, 27]. Principally, SBDD starts with the determination of the receptor's active site. It is one of the most significant steps in SBDD as the reduction in the higher number of generated conformers and structures improves the specificity and selectivity towards the ligand. This specificity and tightness of the ligand binding at the receptor's active site are governed by the shape of the ligand molecule and its physical and chemical properties (non-covalent interactions, such as

CHAPTER 7

Molecular Simulation in Drug Design: An Overview of Molecular Dynamics Methods

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Abstract: Molecular interaction is the basis for protein and cellular function. Careful inhibition or modulation of these is the main goal of therapeutic compounds. In the pharmaceutical field, this process is referred to as pharmacodynamics. Over the years, there have been several hypotheses attempting to describe this complex phenomenon. From a purely biophysical point of view, molecular interactions may be attributed to pairwise contributions such as charge angles, torsions, and overall energy. Thus, the computation of binding affinity is possible, at least in principle. Over the last half of the past century, molecular simulation was developed using a combination of physics, mathematics, and thermodynamics. Currently, these methods are known as structure-based drug design (SBDD) and it has become a staple of computer-aided drug design (CADD). In this chapter, we present an overview of the theory, current advances, and limitations of molecular dynamics simulations. We put a special focus on their application to virtual screening and drug development.

Keywords: Drug Design, Enhanced Sampling, Molecular Interaction, Molecular Simulation.

INTRODUCTION

Traditional methods for drug development often involve a multidisciplinary approach; the process usually begins by selecting what is known as a drug target and the consequent study of its biochemistry. Then comes the molecular design followed by organic synthesis, and subsequently, pre-clinical *in vitro*, *ex vivo*, and *in vivo* studies are carried out, when possible, depending on the task at hand. After

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gathering enough information, the research team can now decide which compounds can be considered as leads and a pharmacophore is then identifiable. Later, the ADMET (absorption, distribution, metabolism, elimination and toxicity) properties are optimized for clinical trials to finally market the best compound as a drug [1]. It should be noted, however, that this route represents a challenging, long, and expensive process that, on average, takes up to 15 years. Since 2019, the average cost of developing a drug can go from \$161 to \$4,540 million dollars, being anticancer drugs the most expensive to develop with a cost that goes between \$944 and \$4,540 million dollars [2].

Interestingly, around 90% of clinical drug development fails due to poor ADMET properties: absorption, solubility, permeability, efficacy, metabolism, excretion and high toxicity [3].

As a result of the above, there are several more novel strategies for discovering new drug candidates, such as: optimization of existing drugs, drug repurposing, systematic biological assays, use of available biological information, rational drug design and computer-aided drug design (CADD) also called *in silico* drug discovery methods.

The term *in silico* comes from Latin ‘in silicon’ and it refers to performed by using computers or *via* computer simulation. A mathematician Pedro Miramontes from the Universidad Nacional Autónoma de México (UNAM), who was the son of Luis Ernesto Miramontes Cárdenas, responsible for the synthesis of the active pharmaceutical ingredient (API) norethisterone of the first anticontraceptive pill, presented in his talk “DNA and RNA Physicochemical Constraints, Cellular Automata and Molecular Evolution” the term “*in silico*” to explain biological experiments performed *via* computer simulation [4].

CADD provides a complement to explain and predict biological activities and it comprises various methods, such as QSAR, virtual high-throughput screening, pharmacophore modeling, fragment-based screening, molecular docking and molecular dynamics simulations (MDS). It is worth mentioning that in recent years, these techniques have been put in the spotlight since they considerably reduce time and costs in all stages of drug development from the initial lead design to final stage clinical trials. Particularly in 2021, *in silico* drug discovery methods have gained popularity, as they have made it possible to optimize research work even remotely, which is a very useful tool in complex scenarios such as the COVID-19 pandemic.

Molecular recognition processes arise from pairwise interactions. Physical descriptions of these are possible using potential energy functions. In the literature, these functions are referred to as force fields, serving as angular stones

in molecular mechanics and other related methods. In CADD, these approaches are grouped under structure-based (SBDD) approaches where computational resources are used to make numerical simulations of molecular phenomena. As of today, molecular docking has become the most prominent method for SBDD efforts, mostly due to its ease of implementation, flexibility, and overall prompt results.

Nevertheless, even with such positive attributes, there is no denying that molecular docking is prone to erratic or even aberrant results. Moreover, the technique has been trivialized in recent years. This has led to what we may call ‘literature flooding’, as evidenced in the trend for keyword docking (Fig. 1) in recent years. Of course, the causes for this are multifactorial; still, a conserved tendency seems to be an overreliance on docking scores.

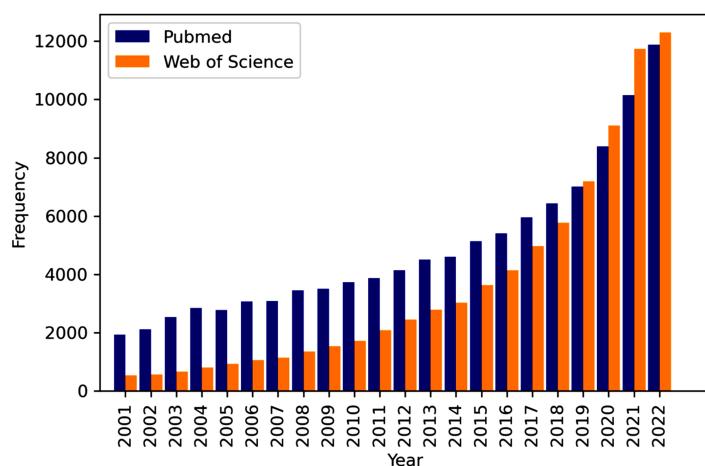


Fig. (1). Trends for “molecular docking” as a search query from two major academic search engines.

The truth of the matter is that the development of these tools has proven to be a complex task. Even with recent implementations of artificial intelligence, the development of universal scoring functions remains daunting. This raises the need for more exhaustive methods, such as MM-PBSA/GBSA and free energy perturbations (see Chapter 9).

For decades, one of the main problems was the computing power needed to solve the equations of motion for the N -atoms composing the system. In the beginning, a rather small system, *i.e.*, a couple of thousand atoms, could take months to simulate the movement for a couple of hundred picoseconds. Recently, thanks to technological advances, it has been possible to build powerful workstations that are on par with the last generation high computing clusters (HPC). In sharp contrast, on today’s hardware, even a rather “discrete” workstation can increase up

CHAPTER 8

Quantum Chemistry in Drug Design: Density Function Theory (DFT) and Other Quantum Mechanics (QM)-related Approaches

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Abstract: Drug design and development are expensive and time-consuming processes, which in many cases result in failures during the clinical investigation steps. In order to increase the chances to obtain potential drug candidates, several *in silico* approaches have emerged in the last years, most of them based on molecular or quantum mechanics theories. These computational strategies have been developed to treat a large dataset of chemical information associated with drug candidates. In this context, quantum chemistry is highlighted since it is based on the Schrödinger equation with mathematic solutions, especially the Born-Oppenheimer approximation. Among the Hartree-Fock-based methods, the Density Functional Theory (DFT) of Hohenberg-Kohn represents an interesting and powerful tool to obtain accurate results for electronic properties of molecules or even solids, which in many cases are corroborated by experimental data. Additionally, DFT-related methods exhibit a moderate time-consuming cost when compared to other *ab initio* methods. In this chapter, we provide a deep overview focused on the formalism behind DFT, including historical aspects of its development and improvements. Moreover, different examples of the application of DFT in studies involving GABA inhibitors, or catalytic mechanisms of enzymes, such as RNA-dependent RNA polymerase (RdRp) of SARS-CoV-2, and different proteases

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associated impacting diseases, such as malaria, Chagas disease, human African trypanosomiasis, and others. Moreover, the role of metal ions in catalytic enzymatic mechanisms is also covered, discussing iron-, copper-, and nickel-catalyzed processes. Finally, this chapter comprises several aspects associated with the elucidation of catalytic mechanisms of inhibition, which could be used to develop new potential pharmacological agents.

Keywords: Catalytic Mechanism, Copper, Hydrolase, Nickel, Protease, Quantum Mechanics.

INTRODUCTION TO THE HISTORY OF QUANTUM CHEMISTRY (QC)

Currently, there is a constant rise in the need for growing efficiency in a drug design and discovery campaign or even during the lead optimization since the central idea is reducing the time costs, yielding more effective drugs in the pipeline. Thus, this increased necessity requests accurate software for processing a large amount of information in a limited time, overstimulating software upgrades, and the development of novel protocols using well-known programs. In this context, different methods have been developed to treat a large dataset of chemical information, aiming to fill the lack that emerged during the development of a new drug. Well, before discussing how some computer-aided methods can help to elucidate essential information for designing drugs, we need a better understanding of what formalism these methods are based on, as well as their possible applicability. In the next pages, this chapter will lead the reader on a journey from the emergence of the most important computer methods and their current utilization focused on drug design and development, starting from the *Schrödinger equation*.

The main point of *quantum chemistry* (QC) is the obtainment of solutions for the Schrödinger equation to accurately determine the chemical properties of atoms and even more complex molecular systems. Then, we typically are searching solutions for stationary states that could involve different approximation methods. Thus, QC methods depend not only on computer advances but also on the development of new theories or methodologies. Currently, there are several methods involving QC for solving chemical problems associated with molecules, among them, the *ab initio* Hartree-Fock (HF) has been used to provide great approximated solutions for *many-electron problems*. Its theory treats the electrons individually, moving in an average field for all other electrons and nuclei, which allows the generation of a set of electron-coupled equations. Years later, *semi-empirical methods* emerged to reduce computational time-consuming. Otherwise, chemical problems that previously were treated with HF approximation are currently frequently treated by using the *Density Functional Theory* (DFT) calculations, resulting in values even closer to the experimental data. It has been

used to study the electronic properties of molecules and solids. Furthermore, the development of more precise exchange correlation functionals and efficient algorithms of numerical integration has contributed to the development of the DFT method.

In 1927, Max Born and J. Robert Oppenheimer formulated the *Born-Oppenheimer approximation*, which assumes that the nuclei are much heavier than electrons and, as a consequence, they move more slowly, making this theory considered the heart of QC [1]. Considering this approximation, its main problem still remains in solving the non-relativistic time-independent Schrödinger equation:

$$\hat{H} |\Phi\rangle = \varepsilon |\Phi\rangle$$

in which,

$$\hat{H} = -\sum_{i=1}^N \frac{\hbar^2}{2m} \nabla_i^2 - \sum_{i=1}^N \sum_{A=1}^M \frac{Z_A e^2}{4\pi\epsilon_0 r_{iA}} + \sum_{i=1}^N \sum_{j>i}^N \frac{e^2}{4\pi\epsilon_0 r_{ij}}$$

Where m represents the electron mass, Z_A means the atomic number of the nucleus A , r_{ij} is the distance between i and j electrons, whereas r_{iA} means the distance between electron i and nucleus A . Finally, N and M represent the number of electrons and nuclei in the system, respectively. The above equation expresses the electronic term for the molecular *Hamiltonian operator* \hat{H} . Since the electrons in a molecule are considered moving faster than nuclei, the second term of this equation (kinetic energy of the nuclei) can be neglected. Moreover, the repulsion between the nuclei (the last term) is taken to be constant. Thusly, the remaining terms are called the *electronic Hamiltonian* [2]:

$$\hat{H}_{elec} = -\sum_{i=1}^N \frac{1}{2} \nabla_i^2 - \sum_{i=1}^N \sum_{A=1}^M \frac{Z_A}{r_{iA}} + \sum_{i=1}^N \sum_{j>i}^N \frac{1}{r_{ij}}$$

Then, HF approximation has an essential role in the development of modern QC concepts [2]. Douglas Hartree's methods were guided by some earlier semi-empirical methods of the early 1920s set in the old quantum theory of Bohr [3]. In general, HF approximation substitutes the many-electron problem with a one-electron problem, considering the electron-electron repulsion term as an average way [2]. In this context, the *Self-Consistent-Field* (SCF) method is used as a procedure for solving the HF equation. In essence, this approach creates an initial guess for the spin orbitals, from which it can calculate the average field seen by each electron, solving the eigenvalue equation for a new set of spin orbitals.

CHAPTER 9

Free Energy Estimation for Drug Discovery: Background and Perspectives

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Abstract: Drug development is a remarkably complex subject, with potency and specificity being the desired traits in the early stages of research. Yet, these need careful thought and rational design, which has led to the inclusion of multidisciplinary efforts and non-chemistry methods in the ever-changing landscape of medicinal chemistry. Computational approximation of protein-ligand interactions is the main goal of the so-called structure-based methods. Over the years, there has been a notable improvement in the predictive power of approaches like molecular force fields. Mainstream applications of these include molecular docking, a well-known method for high-throughput virtual screening. Still, even with notable success cases, the search for accurate and efficient methods for free energy estimation remains a major goal in the field. Recently, with the advent of technology, more exhaustive simulations are possible in a reasonable time. Herein, we discuss free energy predictions and applications of perturbation theory, with emphasis on their role in molecular design and drug discovery. Our aim is to provide a concise but comprehensive view of current trends, best practices, and overall perspectives in this maturing field of computational chemistry.

Keywords: Alchemy, Computer-aided Drug Design, Free Energy Methods and Simulation.

INTRODUCTION

As of today, drug development is a multidisciplinary field where the areas of competence go beyond pharmacology or organic synthesis. Within such a context, the first question we must answer is; what exactly do we mean by the drug? The International Union for Pure and Applied Chemistry (IUPAC) has the following definition:

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“Any substance which, when absorbed into a living organism, may modify one or more of its functions” [1].

Starting from it, we may add that for our intent and purposes, a drug shall be any “small” molecule (*i.e.*, with a molecular weight < 650 Da) with an intended target, rationally designed or optimized and with the clear goal of having a therapeutic use.

Since the dawn of civilization, along with agriculture, mankind has indirectly learned of the medicinal potential of some plant species. In a historical context, it has been a long and slow transition from mystical to therapeutic. A paragon example is perhaps salicylic acid; a natural product which led to the development of one of the most well-known drugs: aspirin. It is very remarkable that this rather “simple” structure is, in fact, a prodrug from a metabolite present in the willow tree bark, which came to be associated with a Nobel Prize in physiology while also being one of the most commercially successful drugs of all time [2].

At first, drug design relied on mimicking endogenous ligands of known targets. This may seem rather straightforward, but quite the opposite is true. Returning to the aspirin example, its active ingredient, salicylic acid, had its mode of action identified and described until the latter half of the XX century. Thus, since the development and maturing of pharmacology, approaches towards drug design have become more systematic and less form of art and chance. A prime example to consider is the development of angiotensin converting enzyme (ACE) inhibitors. It was between the decades of 1960 and 1970 that John Vane’s group actively researched the cause of hypertension. Studying the effect of the venom from a Brazilian viper (*Bothrops jararaca*) *in vitro*, Vane recognized the importance of ACE as a major regulator of blood pressure [3]. This led to the involvement of Squibb, specifically David Cushman and Miguel Ondetti, who characterized several peptides as antihypertensive agents and hypothesized that ACE was a zinc metallopeptidase [4]. From here, the main challenge to overcome was oral bioavailability, so the group turned to recently described carboxypeptidase A inhibitors, hypothesizing structural similarities towards ACE (Fig. 1). This rationale led to the eventual synthesis of captopril [5]. Nonetheless, such a decision proved to be fortuitous, as the crystal structures of ACE (published almost 30 years later) showed that its catalytic domain is actually unrelated to that of carboxypeptidase A [6].

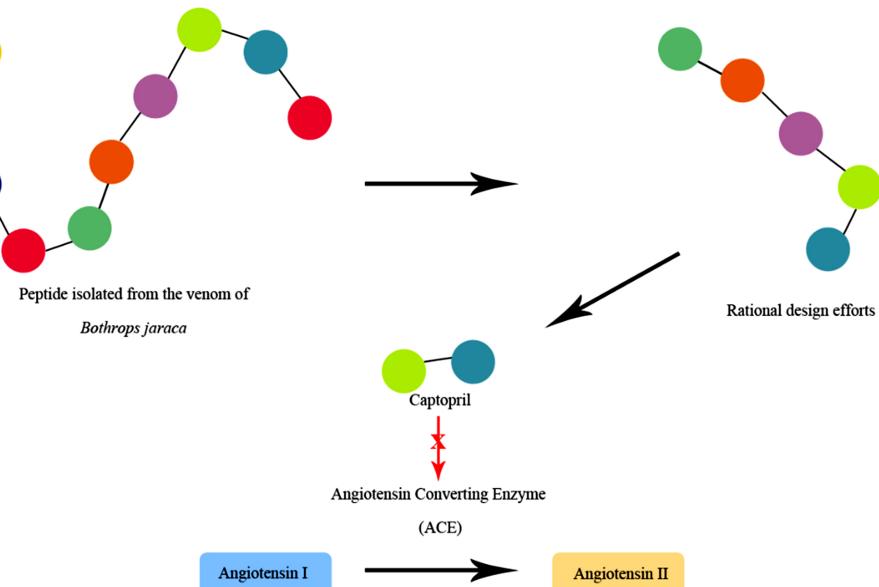


Fig. (1). Schematic view of the optimization process leading to the development of captopril.

From here, it becomes clear that drug development endeavours involve a great deal of complexity. For instance, during the 1980s, combinatorial chemistry was seen as a promising venue to tackle molecular diversity. The proposal of synthesizing hundreds of compounds in a systematic and rather efficient way was very appealing, leading to the development of high-throughput screening methods. A framework where thousands of compounds could be quickly evaluated using a combination of biochemical assays and robotic machinery [7]. While HTS has had notable success cases, the overall rate of developed drugs from it is rather discrete. Additionally, HTS campaigns gave rise to a phenomenon known as frequent hitters or pan-assay interference compounds (PAINS). Said designation is given to compounds showing “promiscuity” to a broad range of proteins or more generally to false positives due to interference with assay elements [8]. Indeed, this situation revealed that drug development cannot be solved by brute force, as it demands both critical and creative thinking [9].

Thus, the industry turned to state-of-the-art methodologies. Parallel to the development of HTS, there was a significant shift towards other computational modelling techniques. Early examples of this include the pharmacophore elucidation studies during the late 1960s and 1970s [10]. Nonetheless, pharmacophore models proved insufficient tools, as no information on the target is obtained. The pressing need for methods capable of predicting the binding

SUBJECT INDEX

A

- Acid(s) 63, 67, 117, 147, 239, 290
 - caffeic 147
 - caffeoquinic 147
 - carnosic 147
 - glucuronic 239
 - nucleic 290
 - ribonucleic 117
 - sulphonamides 63
- Activation, immune system 173
- Active pharmaceutical ingredient (API) 203, 235
- Adaptatively biased molecular dynamics (ABMD) 280
- Algorithms 22, 144, 321
 - artificial intelligence 22
 - machine learning 321
 - virtual Scanning 144
- Alzheimer's disease 8, 188
- American trypanosomiasis 282
- Aminolysis 280
- Angiogenesis 145
- Angiotensin converting enzyme (ACE) 127, 311
- Anticancer agents 188
- Anticholinergic agents 188
- Antimicrobial therapy 14
- Antiviral agents 330
- Apoptosis 145, 279
- Artificial neural networks (ANN) 21, 164, 168
- Atomic absorption spectroscopy 8
- ATP binding site 235
- Automatic extraction 168

B

- Binding 37, 326
 - ligand-protein 37
 - thermodynamics 326
- Bioluminescence 8
- Biomacromolecules, degradable 205

- Bond dissociation energy (BDE) 273
- Born equation 320
- Breast cancer protein 150
- Bridge toxicogenomics 174
- Brownian 230, 244
 - dynamics 244
 - motion 230
- Bruton's tyrosine kinase 17

C

- Cancer 150
 - colorectal 150
 - liver 150
- Carcinoma, hepatocellular 330
- Catalytic 259, 279, 289, 290
 - amino acids 289
 - reactions of cysteine protease 279
- Catalyzed aerobic degradation 291
- Chemical databases 82, 87, 159, 166, 177
 - commercial 177
- Chemical properties 161, 169, 170, 259
- Chemoenzymatic peptide synthesis 279, 280
- Chronic myelogenous leukemia 234
- Colon cancer protein 148
- Comparative molecular field alignment (CoMFA) 35, 39, 40, 79
- Computational 117, 310
 - approximation of protein-ligand interactions 310
 - protein 117
- Conditions, isobaric isothermal 229
- Convolutional neural network (CNN) 167, 168, 169
- Coronavirus disease 275
- Covalent ligand 272, 287
 - protein 287
 - target 272
- COVID-19 pandemic 13, 174, 176, 203, 205, 332
- Cryo-electron microscopy 117

Cysteine proteases 279, 280, 281, 282, 284, 285, 287

Cystic fibrosis 187

Cytidine deaminase 274

D

Deep reinforcement learning (DRL) 159, 164, 166, 187

Degradation 187, 235, 273, 277, 281

pathways 235

process 277

proteasomal 187

Dehydrogenase 147, 277

aldehyde 147

Dengue virus 187

Detection technologies 8

Dihydrofolate reductase 219

Diseases 3, 8, 13, 21, 103, 117, 279, 280, 282, 291, 330

coronary artery 21

infectious 3, 282, 330

neurodegenerative 291

DNA Gyrase 101

Douglas Hartree's methods 260

E

Ebola virus 128

Effects 145, 174, 240, 275

entropic 275

inhibitory 240

phenotypic 174

therapeutic 145

Electron density 18, 68, 218, 262, 265, 290

simulations 290

Electron microscopy 161

Electronic density 17, 261, 262, 263, 265, 266, 268, 269, 271, 289

lesser 271

molecular 268, 269

Electronic mobility 289

Electrophilic attack 267

Electrophilicity 271

Energy 17, 18, 47, 213, 229, 261, 262, 263, 264, 265, 267, 268, 271, 277, 279, 281, 282, 284

conformational 271

derivatives 267

thermal 229

Environments, thermal 231

Enzyme(s) 179, 279, 289, 293

inhibition 293

inhibitor 289

monooxygenase 179

protease 279

F

Factor, transcription 150

FDA approval 93, 160

Fluorescence resonance energy transfer (FRET) 8

Food and drug administration (FDA) 17, 18, 19, 20, 237, 282

Force-field calculations 183

Framework, contemporary computing 101

FRET-based assay 8

Frontier molecular orbitals (FMO) 269, 288

G

GABAA receptor inhibition 272

Gastrointestinal 140, 145, 150, 234

cancers 150

disorders 140, 145

stromal tumors 234

Gene(s) 8, 147, 174

detoxifying enzyme 147

expression 174

Global distance test (GDT) 121

Glucose-stimulated insulin secretion (GSIS) 10

GOLD and glide software 143

H

Haemostasis 98

Hamiltonian 209, 210, 213, 260, 262, 263, 264

electronic 260

mechanics 213

system 262

Hamilton's equations 210

Hansch equation 19

Hepatitis 330

HF-based technique 296

High 11, 204, 219, 296

-performance computing (HPC) 11, 204, 219, 296
High-throughput screening (HTS) 2, 8, 101, 160, 177, 179, 312, 330
methods 312
Highest-occupied molecular orbital (HOMO) 38, 39, 267
HIV 12, 234, 239
protease inhibitors 12, 234
replication 239
Hohenberg-Kohn-Sham theorem 261
HQ SAR method 38
Human immunodeficiency virus (HIV) 11, 117, 205, 239, 240
Hydrogen 281, 314
bonding energy 314
transfer 281
Hydrogenase 293, 294
Hydrolase 259, 277
Hydrolysis 273, 280, 282, 283
peptide 283

I

Inhibitors 17, 95, 96, 98, 99, 101, 139, 140, 187, 235, 236, 237, 239, 271, 272, 287, 311, 333
integrase 235
protease 239
reversible 287
thrombin 333
traditional 187
Integrase 236, 237, 240
Integration 1, 22, 84, 90, 207, 208, 215, 224, 237, 260
numerical 90, 260
Interaction energies 68, 139, 270, 288, 293
grid-based 68
Interaction(s) 137, 139, 140, 143, 162, 222, 236, 269, 277, 289, 315, 331
drug-enzyme 137
electronic 139
electrostatic 140, 162, 269, 277, 289, 315, 331
energy calculation 143
metal-chelating 269
substrate-DNA-integrase 236
substrate-enzyme 222

L

Linear regression equation 38, 274
Liouville theorem 213
Lipophilic efficiency 178
Lipophilicity 235
Liver cancer protein 146

M

Machine learning techniques 35, 79
Macromolecular-based pharmacophores 80
Marshall's method 60
Mathematical 38, 209, 227
regression equation 38
transformation 209, 227
MATLAB application 47
Maxwell relations 213
MBAR equations 323
Mechanisms 235, 259, 273, 279
dehydration 235
enzymatic 259, 273, 279
Medicinal plant 147
Medicine, traditional 150
Mediterranean diet 147
Metabolic processes 78, 281
Metalloholoenzyme 290
Metalloproteases 289, 297
Methods, spectrophotometric 272
Molecular 13, 202, 203, 205, 207, 208, 233, 234, 235, 236, 237, 247, 248, 314, 315
dynamics simulations (MDS) 13, 202, 203, 205, 207, 208, 233, 234, 235, 236, 237, 247, 248, 314, 315
recognition processes 203
Molecular docking 19, 22, 141, 142, 143
software 22, 141, 142, 143
technique 19
Multiple 35, 37, 79, 209, 318
harmonic oscillators 318
linear regression (MLR) 35, 37, 79
particle system 209
Multitarget drug design (MDD) 10
Mushroom copper-containing tyrosinase 292
Mycobacterium leprae 187

N

Natural products 2, 4, 311, 314
Newton's laws of motion 206

Nuclear magnetic resonance (NMR) 15, 41, 117, 137, 160, 161
Nucleophilic attack 267, 278, 281, 282, 283, 284, 285, 287, 297
Nucleoside reverse transcriptase inhibitors 239

O

Orbital energy 36
Oxidant agent 277
Oxidative degradation pathways 147

P

Pandemic virus 275
Papain cysteine protease 282
Parasite infections 205
Perturbation theory 261, 310, 313
PET degradation 277
Pharmacokinetic 4, 5, 10, 11, 20, 159, 160, 171, 173, 182, 184, 185, 239, 295, 332 profiles 5, 239, 332 properties 10, 11, 20, 159, 184, 185
Pharmacological activity 5, 17, 19
Pharmacophore 61, 75 software 75 techniques 61
Physicochemical properties 4, 20, 35, 38, 166, 185
Polymerase 117, 239
Polyprotein processing 330
Problems, thromboembolic 98
Process, dioxygenation 291
Proteases 117, 127, 258, 259, 279, 280, 281, 285, 286, 287, 297
Protein(s) 12, 13, 14, 81, 83, 117, 118, 119, 124, 125, 128, 138, 144, 178, 186, 205, 220, 221, 225, 233, 235, 237, 240, 242, 246, 247, 279, 289, 318, 328 catalytic 289 data bank (PDB) 81, 118, 119, 124, 125, 205, 220, 237, 242, 246, 247 degradation 186, 279 disordered 235 dynamics 205, 221 finger 318 mutant 240 preparation 225, 328
Proteolysis-targeting chimeras 186

Prothrombin time (PT) 98

Q

Quantum theory 260

R

Random forest (RF) 184, 186
Reaction 239, 261, 274, 277, 279, 280, 284, 290, 291
adiabatic 261
biomolecular 274
deacylation 279
diacylation 284
enzyme-catalyzed 291
hydrolysis 277, 280
metabolic reduction 239
oxidation-reduction 290
Recursive neural networks (RNN) 102, 165, 166, 167, 169, 170
Regression analysis 78
Relationship 35, 43, 77, 80, 136, 137, 206, 211, 269
enzyme-ligand 136, 137
Repulsion 260, 269 electronic 269
Reversibility assays 286
Rho-kinase inhibitory 95
Rieske-type enzyme 291
RNA 13, 127, 234, 258, 275, 330 -based virus 330 -dependent RNA Polymerase 13, 127, 258, 275 viral 234
Robotic machinery 312
Root mean square (RMS) 41, 64, 68, 80, 125, 147, 232, 245 deviation 232 fluctuation 232
ROS metabolism 147

S

SAR, quantitative 162

SARS-CoV-2 13, 174, 175, 236, 240, 258, 275, 286, 288, 331
coronavirus 174
pathological agent 13
RNA-dependent RNA polymerase 275
SBDD techniques 313
Schrödinger equation 18, 258, 259, 260, 263, 265
electronic 18
time-independent 260
Severe acute respiratory syndrome 286
Signalling pathways 147
SMILES codes 88
Software, flexible docking 143
Solid-phase peptide synthesis (SPPS) 280
Stereospecific pathway 281
Steric constraints 182
Structure-activity relationships (SAR) 5, 37, 39, 40, 138, 162, 171, 182, 188
Support vector machine (SVM) 184, 186
Surface constraint atom solvent (SCAAS) 284, 287

T

Techniques 9, 10, 11, 14, 16, 46, 60, 65, 66, 68, 76, 77, 93, 101, 102, 139, 170, 182, 203, 204, 312
clustering 93
computational modelling 312
crucial 46
evolutionary algorithm 170
ligand-based 139
silico screening 60
Technologies, luminescence 8
Thermal fluctuations 230
Thermodynamic(s) 36, 47, 48, 202, 211, 216, 245, 261, 280, 315, 316, 317, 323
cycle 315, 316
Thermophoresis 160
Toxicogenomics 173
Toxicological profile 4
Transformations, chemical 102
Transition mutations 275
Transmembrane proteins 123
Transplantable tumours 149
Trypanosoma cruzi 282, 283, 284

V

VEGF inhibitors 235
Viral DNA 234, 240
Virtual screening process 88
Virus(s) 11, 117, 174, 239, 286, 330
human immunodeficiency 11, 117
replication process 330
multidrug-resistant 239

W

Waals 140, 269, 314, 318
forces 314
interactions 140, 269, 318



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