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$\mathscr{J}_{0}$ my dear pacento

$\mathscr{J o}_{0}$ my husband

$\mathscr{J}_{0}$ my siblings
$\mathcal{J}_{0}$ all those whe ave dear to me

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## General Introduction

Molecular modeling is a broad term encompassing different molecular graphing and computational chemistry techniques to display, simulate, analyze, calculate and store the properties of molecules; to determine the geometry of a molecule and to evaluate the associated physicochemical properties.

The comparison of the biological activity of certain molecules and their structures has made it possible in many cases to establish correlations between the structural parameters and the properties of a molecule.

The majority of heterocycles play a very important therapeutic role. Due to their biological interest, the chemistry of heterocycles is growing.

The majority of the heterocycles more to the complexes of therapeutic interest currently used clinically were obtained by chemical modification from natural molecules or by a total synthesis.

The research and synthesis of new chemical and biochemical compounds are today often associated with a molecular modeling study. Thanks to the computer development of recent years and the rise of intensive parallel computing in particular, molecular modeling has become a real game.

Molecular modeling can be defined as an application of computing to create, manipulate, calculate and predict molecular structures and associated properties.

There are many theoretical chemistry methods aimed at determining the physical or chemical properties of isolated molecules, be they thermodynamic properties such as binding enthalpies, relative energies of different conformers, or simulations of infrared, Raman or electronic.

Two main classes of simulation methods can be distinguished: on the one hand quantum chemistry methods that allow the precise determination of the electronic properties of molecules, on the other hand molecular mechanics methods that are based on empirical parameters that allow in particular to determine the structural parameters and secondly these methods make it possible to calculate the physicochemical parameters used in the QSAR study.

Quantitative Structure Activity Relationship (QSAR), as their names suggest, sets up a mathematical relationship using data analysis methods, linking microscopic molecular properties called descriptors, to an effect experimental (biological activity, toxicity, affinity for a receptor), for a series of similar chemical compounds. The starting point for such methods is the definition of empirical or theoretical molecular

## General Introduction

descriptors. The latter take into account information on the structure and the physicochemical characteristics of the molecules.

The choice of experimental reference databases is decisive in a QSAR study. It must consist of reliable experimental data obtained by following a unique experimental protocol. Indeed, the robustness of the model strongly depends on the base on which it is based.

Finally, the link between the descriptors and the database is determined through analysis tools such as multilinear regressions (MLRs), partial least squares (PLS) regressions, neural networks, and component analysis.

The main objective of this study is to predict molecules of pharmaceutical interest, ie to sort molecules before going to the experimental stage, or to interpret or predict the biological activation of molecules already synthesized. So, look for the preferred conformations by quantum and semi-empirical calculations of heterocyclic compounds of pharmaceutical interest (eg: carbazole and chalcone....) whose majority of derivatives are bioactive.

The effect of the substituents on their basic skeletons and the main structural motifs will be examined, and qualitative and quantitative studies of the structure-activity relationships, using the QSAR model, will be carried out in order to arrive at models for some series of these heterocycles of pharmaceutical interest.

## Chapter I

Drug discovery: finding a lead

## I. Context: drug research

Drug discovery is a multidisciplinary cycle that takes quite a while (10-20 years) and costs a ton of cash. In the writing, there is an assortment of assessments for his complete expense, which goes from $\$ 300$ million to more than $\$ 1.75$ billion dollars [1]. DiMasi's investigation [2, 3], which is quite possibly frequently referred to, puts the expense at around 802 million dollars, while a later report puts it at under $\$ 12$ million [4]. Nonetheless, most of the studies concur on the huge measure of assets needed to finish a task, just as the continuous expansion in general interaction costs, which were assessed to be 138 million dollars during the 1970s and 300 million dollars during the 1980s [5]. To exacerbate the situation, the achievement pace of drug industry projects stays low [6], and the quantity of new drugs acquainted with the market has stayed stable, if not declining, since the year 2000 [5].

Subsequently, drug scientists are continually endeavoring to improve every one of the means prompting the commercialization of a medication. Drug organizations, for instance, are among the most universally contributed, with 10 to $20 \%$ of their income put resources into innovative work (R\&D)[7].

The whole drug research interaction can be separated into four significant stages, as demonstrated in Figure 1. We'll portray them momentarily in the parts that follow, with an attention on the stages for which the techniques introduced in this theory were created.


Figure .1.The (simplified) process of drug discovery is divided into four major steps.

## I.1. Research and Development (R\&D)

One of the most goals of the R\&D part is to deliver one or additional active and innovative drug candidates with quantity amount of toxicity potential, giving them the most effective probability of passing the next stages.

## I.1.1. Target identification and validation

The initial step is to recognize at least one biological entities whose movement can be regulated to give an advantageous impact with regard to a particular illness. Because all following research will be predicated on the notion that these targets are effectively related to the disease and that the medication's action would have a favorable effect on humans, this phase is crucial. It's a lot more delicate because the target's relevance to the targeted disease must be evaluated against the potential negative consequences of modifying the target's activity. The search for new targets has intensified since the human genome was sequenced and bioinformatics methods for comparing sequences and protein structures were developed. Many authors have also questioned the classic "one disease, one target, one drug" approach, claiming that biological network regulation can compensate for a molecule's influence on its target [8, 9], even if the molecule has a high chance of interacting with other proteins. Polypharmacology [10] and chemogenomic are two new sciences that have arisen in recent decades.

## I.1.1.1. Choosing a disease

## I.1.1.1.1. General about cancer

Cancer is one of the most important health problems of the current era and also a leading cause of death among populations. Cancer can simply be defined as unregulated cell division leading to a tumor formation in any part of the body. In its natural course, tumor mass continues to grow invading the surrounding tissues and finally tumor cells get access to the lymphatic and vascular systems spreading to distant organs which results in metastasis. In order to be successful in the treatment of cancer, early diagnosis, before the tumor spreads to the surrounding tissues or distant organs, is mandatory. It is now known that most cancer types result from accumulation
of multiple errors in DNA that may affect primarily the regulatory pathways in the cell. Although the currently used treatment modalities are mainly directed to the macroscopic destruction of the tumor mass, the presence of systemic dissemination could not be denied and systemic treatments are widely used in order to control the microscopic disease. Despite these advances in treatment, the development of new strategies towards the correction of molecular impairments in the cell is indispensable.

## I.1.1.1.1.1. Definition of cancer

Cancer is defined by the uncontrollable growth and spread of aberrant cells, as well as apoptosis resistance. External agents or hereditary genetic factors are responsible for its occurrence. When a cell's repair system allows the accumulation of microscopic changes to escape, the cell becomes malignant.


Figure .2. Understanding cancer start.
This cell divides fast and uncontrolled, resulting in an organ tumor. Through blood vessels and lymphatics, malignant cells can escape and spread to other tissues, causing metastases [11].

Sometimes cells don't grow, divide and die in the usual way. This may cause blood or lymph fluid in the body to become abnormal, or form a lump called a tumour. A tumour can be benign or malignant.

Benign tumour: Cells are confined to one area and are not able to spread to other parts of the body. This is not cancer.

Malignant tumour: This is made up of cancerous cells which have the ability to spread by travelling through the bloodstream or lymphatic system (lymph fluid).

Carcinogenesis is separated into three stages: initiation, promotion, and tumor progression [12].


Figure .3.How cancer spreads?

## I.1.1.1.2 Types of cancer

Doctors divide cancer into types based on where it begins. Four main types of cancer are:

- Carcinomas: A carcinoma begins in the skin or the tissue that covers the surface of internal organs and glands. Carcinomas usually form solid tumors. They are the most common type of cancer. Examples of carcinomas include prostate cancer, breast cancer, lung cancer, and colorectal cancer.
- Sarcomas: A sarcoma begins in the tissues that support and connect the body. A sarcoma can develop in fat, muscles, nerves, tendons, joints, blood vessels, lymph vessels, cartilage, or bone.
- Leukemias: Leukemia is a cancer of the blood. Leukemia begins when healthy blood cells change and grow uncontrollably. The 4 main types of leukemia are acute lymphocytic leukemia, chronic lymphocytic leukemia, acute myeloid leukemia, and chronic myeloid leukemia.
- Lymphomas: Lymphoma is a cancer that begins in the lymphatic system. The lymphatic system is a network of vessels and glands that help fight infection. There are 2 main types of lymphomas: Hodgkin lymphoma and non-Hodgkin lymphoma.


## I.1.1.1.3Distribution of cancer

Cancer ranks as a leading cause of death and an important barrier to increasing life expectancy in every country of the world. According to estimates from the World Health Organization (WHO) in 2019, cancer is the first or second leading cause of death before the age of 70 years in 112 of 183 countries and ranks third or fourth in a further 23 countries (Fig. 4). Cancer's rising prominence as a leading cause of death partly reflects marked declines in mortality rates of stroke and coronary heart disease, relative to cancer, in many countries.

Overall, the burden of cancer incidence and mortality is rapidly growing worldwide; this reflects both aging and growth of the population as well as changes in the prevalence and distribution of the main risk factors for cancer, several of which are associated with socioeconomic development. [13]


Figure.4.National Ranking of Cancer as a Cause of Death at Ages <70 Years in 2019. The numbers of countries represented in each ranking group are included in the legend.

## I.1.1.1.4 Anticancer drugs

Anticancer agents are drugs that are used in chemo-therapies to treat cancer. It is used alone or in combination. They want to stop cells from proliferating uncontrollably because they have genetic and functional defects that set them apart from healthy cells. This chemotherapy isn't meant to kill the tumor locally; rather, it's meant to prevent tumor escape through the production of distant metastases [14].

## I.1.1.1.4.1 The various types of anticancer drugs and their mechanisms of action

These compounds have been divided into three groups based on their pharmacological mechanisms:

- Cytotoxic anticancer drugs: The compounds employed in cytotoxic chemotherapy vary in their modes of action and chemical family membership. Alkylating agents, topoisomerase I and II inhibitors, microtubule poisons (intercalating agents), antimetabolites, and splitting agents are the six primary families.
- Targeted therapies: these are medications that operate on tumor cells at a specific level of their function or development. Extracellular medications (such as avastin, erbitux, etc.) are aimed against a membrane receptor located on the tumor cell, whereas intracellular medications (such as: multikinases, glivec ...) disrupt the proliferative signal transmission cell through enzymatic inhibition.
- Other anticancer drugs: these are anticancer drugs with different modes of action of two classes mentioned above.

Table 1: Overview of anticancer drugs.

| DRUGS | DRUGS DESCRIPTION |
| :--- | :--- |
| AVASTIN® | is a monoclonal anti-vascular endothelial growth factor antibody <br> used in combination with antineoplastic agents for the treatment <br> of many types of cancer. |
| ERBITUX® | is an endothelial growth factor receptor binding fragment used to <br> treat colorectal cancer as well as squamous cell carcinoma of the <br> head and neck. |
| GLIVEC® | is a tyrosine kinase inhibitor used to treat a number of leukemias, <br> myelodysplastic/myeloproliferative disease, systemic <br> mastocytosis,hypereosinophilic syndrome, dermatofibrosarcoma <br> protuberans, andgastrointestinal stromal tumors. |
| CABOMETYX® | is a tyrosine kinase inhibitor used to treat advanced renal cell <br> carcinoma, hepatocellular carcinoma, and medullary thyroid <br> cancer. (multikinases inhibitors). |
| PLATINOL® | is a platinum based chemotherapy agent used to treat various <br> sarcomas, carcinomas, lymphomas, and germ cell tumors. <br> (Alkylating agents). |
| ETOPOSIDE® | is a podophyllotoxin derivative used to treat testicular and small <br> cell lung tumors. (topoisomerase I and II inhibitors) |
| AMSIDINE®is a cytotoxic agent used to induce remission in acute adult |  |

leukemia that is not adequately responsive to other agents.(intercalating agents)

## I.1.1.1.4.2 Toxicity of anticancer drugs

The many drugs used in chemotherapy procedures are not only harmful to tumor cells, but they can also be toxic to healthy cells, particularly those that proliferate quickly. Cardiotoxicity, neurotoxicity, nephrotoxicity, hepatotoxicity, alopecia, dehydration, exhaustion, infertility, undernutrition, skin issues, allergies, and many more are examples of toxic effects [15].

## I.1.1.1.5 Signs and symptoms

No matter your age or health, it's good to know the possible signs of cancer.

Common signs and symptoms of cancer in both men and women include:

- Pain. Bone cancer often hurts from the beginning. Some brain tumors cause headaches that last for days and don't get better with treatment. Pain can also be a late sign of cancer.
- Weight loss without trying. Almost half of people who have cancer lose weight. It's often one of the signs that they notice first.
- Fatigue. If you're tired all the time and rest doesn't help.
- Fever. If it's high or lasts more than 3 days. Some blood cancers, like lymphoma, cause a fever for days or even weeks.
- Changes in your skin.
- Sores that don't heal. Spots that bleed and won't go away are also signs of skin cancer.
- Cough or hoarseness that doesn't go away. A cough is one sign of lung cancer, and hoarseness may mean cancer of your voice box (larynx) or thyroid gland.
- Unusual bleeding. Cancer can make blood show up where it shouldn't be.

Blood in your poop is a symptom of colon or rectal cancer. And tumors along your urinary tract can cause blood in your urine.

- Anemia. This is when your body doesn't have enough red blood cells, which are made in your bone marrow. Cancers like leukemia, lymphoma, and multiple myeloma can damage your marrow. Tumors that spread there from other places might crowd out regular red blood cells.


## I.1.1.1.6 Treatment

The treatment of a cancer patient requires a multidisciplinary approach. It employs a variety of techniques, the most well-known of which are surgery, radiation, and chemotherapy. Its goal is to get rid of the cancerous tumor and prevent it from spreading to other parts of the body [16].

## I.1.1.1.6.1 Surgery

This method entails interfering directly at the tumor's level, i.e., removing the tumor, either partially or completely. When the tumor is localized, it is usually the first and most successful treatment.

## I.1.1.1.6.2 Radiotherapy

It is a cancer treatment strategy based on the biological effect of ionizing radiation, particularly high-energy X-rays. It tries to modify cancer cells' reproduction capability by exposing them to high doses of radiation while maintaining as much healthy tissue and surrounding organs as feasible. It can be given alone or in conjunction with chemotherapy.

## I.1.1.1.6.3 Medical treatment

Chemotherapy for cancer is designed to kill cells that are actively dividing. It is a treatment that involves ingesting a medication that slows the growth of tumor cells in an attempt to extend the patient's life expectancy and minimize pain from metastases.

## I.1.1.1.6.4 Radiation therapy

This treatment kills cancer cells with high dosages of radiation. In some instances, radiation may be given at the same time as chemotherapy.

## I.1.1.1.6.5 Hormone therapy

Sometimes hormones can block other cancer-causing hormones. For example, men with prostate cancer might be given hormones to keep testosterone (which contributes to prostate cancer) at bay.

## I.1.1.1.6.6 Biological response modifier therapy

This treatment stimulates your immune system and helps it perform more effectively. It does this by changing your body's natural processes.

## I.1.1.1.6.7 Immunotherapy

Sometimes called biological therapy, immunotherapy treats disease by using the power of your body's immune system. It can target cancer cells while leaving healthy cells intact.

## I.1.1.1.6.8 Bone marrow transplant

Also called stem cell transplantation, this treatment replaces damaged stem cells with healthy ones. Prior to transplantation, you'll undergo chemotherapy to prepare your body for the process.

## I.1.1.2 Choosing a drug target

## I.1.1.2.1 Historical Overview

Heterocycles are common structural units in marketed drugs and in medicinal chemistry targets in the drug discovery process. Over $80 \%$ of top small molecule drugs by US retail sales in 2010 contain at least one heterocyclic fragment in their structures. The one reason behind such high prevalence of oxygen, sulfur, and especially nitrogen- containing rings in drug molecules is obvious. The research process that leads to identification of an effective therapeutic treatment is largely based on mimicking nature by "fooling" it in a very subtle way. Because heterocycles are the core elements of a wide range of natural products such as nucleic acids, amino acids, carbohydrates, vitamins, and alkaloids, medicinal chemistry efforts often evolve around simulating such structural motifs. However, heterocycles play a much bigger
role in the modern repertoire of medicinal chemists. Some of the drug properties that can be modulated by a strategic inclusion of heterocyclic moiety into the molecule include:

1) Potency and selectivity through bioisosteric replacements, 2) Lipophilicity, 3) Polarity, and4) Aqueous solubility [17].

## - Heterocyclic Compounds

The IUPAC Gold Book describes heterocyclic compounds as:
$\checkmark$ Cyclic compounds having as ring members atoms of at least two different elements, e.g. Carbazole, Carbazole Derivatives containing Chalcone Analogues (CDCAs) [18].
$\checkmark$ Rings are considered as "heterocycles" only if they contain at least one atom selected from halogen, N, O, S, Se or Te as a ring member. Heterocyclic rings may be present as distinct entities or condensed, either with carbocycles or among themselves.

## I.1.1.2.2 Drug targets

The next step is to find an appropriate pharmacological target once a therapeutic area has been identified (e.g., receptor, enzyme, or nucleic acid). It's evident that knowing which biomacromolecules are involved in a given disease state is crucial. This enables the medicinal research team to determine if agonists or antagonists for a certain receptor or inhibitors for a certain enzyme should be developed. Many chemotherapeutic agents have been shown to be promising cancer weapons. Anticancer drugs as etoposide (Fig .5), doxorubixin, and amonafide, for example, strongly inhibit topoisomerase II (Topo II) [19]. Topo II is one of the most promising anticancer therapeutic targets because it can interfere with the enzyme-DNA complex, causing persistent DNA damage and cell death [20]. Over the past 40 years, topoisomerase inhibitors have been widely employed in the clinical treatment of cancer. At least one drug that targets these enzymes is used in around half of all chemotherapy regimens [21].

## $>$ Etoposide (VP-16)

Etoposide is an antitumor agent currently in clinical use for the treatment of small cell lung cancer, testicular cancer and lymphomas. Since the introduction of etoposide in 1971, its mechanism of action and potent antineoplastic activity has served as the impetus for intensive research activities in chemistry and biology. This drug acts by stabilizing a normally transient DNA-topoisomerase II complex, thus increasing the concentration of double-stranded DNA breaks. This phenomenon triggers mutagenic and cell death pathways. The function of topoisomerase II is understood in some detail, as is the mechanism of inhibition of etoposide at a molecular level. Etoposide has shortcomings of limited neoplastic activity against several solid tumors such as non-small cell lung cancer, cross-resistance to MDR tumor cell lines and low bioavailability. The design and synthesis of etoposide analogs is an activity of fundamental interest to the field of cancer chemotherapy.[22]



Figure .5. 2D \& 3D structure for Etoposide (VP-16).

## I.1.1.2.3 Discovering drug targets

If a drug or poison has a biological impact, that substance must have a molecular target in the body. Previously, finding drug targets necessitated first finding the drug.

Most Topo II inhibitors, like other anticancer drugs, have serious side effects, including cardiotoxicity, specific luckemia, and multidrug resistance [23-25]. As a result, finding new Topo II inhibitors in the form of CDCAs (carbazole derivatives including chalcone analogs) with high efficacy and low toxicity is a hot topic of research [26-31]. Many bioactive natural products and synthetic compounds with a wide range of biological activities, including antimalarial, antibacterial, and anticancer activity, contain the carbazole scaffold [32-34].

Furthermore, studies have revealed that carbazole derivatives may inhibit Topo II, which could explain their antitumor effects [35, 36]. Modifications/substitutions of the carbazole ring have become a hot focus in the development of novel Topo II-targeting anticancer agents in recent years. For example (Figure 6), Compound 1 operates as a possible non-intercalative Topo II catalytic inhibitor (Figure 6) [37]. Compound 2 showed substantial cytotoxicity against the HL-60 cell line as a Topo II catalytic inhibitor [38].


Compound 1




Compound 4



Compound 1


Figure.6. Design of CDCAs as novel Topo II-targeting anticancer agents.

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Compound 3 showed modest cytotoxicity against cancer cell lines when used as a Topo II poison. These findings sparked a lot of interest in looking into carbazole derivatives as a new type of potential anticancer drug that targets Topo II. Chalcone's pharmacological activities, including anticancer, antioxidant, anti-inflammatory, and anti-infective activity, piqued researchers' interest in the twenty-first century. Compounds 4, 5, and 6 (Figure 6), which are naturally occurring and synthesized chalcone analogs, are now being studied as cytotoxic agents. In several cancer cell lines; these chemicals have been shown to suppress cancer cell proliferation and cause apoptosis. Tubulin polymerization inhibition, apoptosis induction, and Topo II inhibition have all been identified as modes of action for chalcone analogs. The mechanism of action of the most bioactive substances was investigated further. CDCAs appear to be non-intercalative Topo II catalytic inhibitors, certain CDCAs showed significant cytotoxic activity with low micromolar IC50.[18]

## I.1.1.3 Finding a lead compound

## I.1.1.3.1 Generation of Hits and Leads

Once the target has been identified, the vast majority of drug development projects move on to the screening stage. Its goal is to identify a first group of active molecules, more commonly referred to as hits. During a screening test, a molecule must have a certain level of activity (usually in the micromolar range) in order to be identified as such. Because the precise value of the required level of activity is not absolute, a hit will be defined as a molecule that demonstrated moderate or strong activity during an experimental test. There are a variety of experimental methods available for identifying hits. Today, high-throughput screening (HTS) [39-41] is most likely the most widely used method in the pharmaceutical industry. There are two main types of experimental screening. [5, 42-44].

## I.1.1.3.2 Screening on the targets

Molecules are tested on relatively small biochemical systems, usually for their affinity or ability to inhibit a certain protein. This is the most common sort of screening because it allows you to test many molecules in a short amount of time and
because it closely resembles the traditional pharmacological research paradigm: a target / a drug.

## I.1.1.3.3 Phenotypical screening

Molecules are tested on whole cells or animal models of a specific disease. They are slower and more expensive, but they allow researchers to study molecule activity in a cell-like environment and so achieve more goals. Several decades ago, this sort of screening was widely used. It has gradually been phased out in favor of target screening in order to save costs and shorten test times while increasing the number of molecules tested. Moreover, a number of authors have recently highlighted its benefits [42, 45, 46].

Once identified, the hits must be confirmed using more detailed testing, primarily to ensure that the observed activity is not due to artefacts related to the experimental method or the presence of impurities. A lead is a compound that has demonstrated a moderate or significant activity and is considered a good place to start looking for a potential drug candidate. After the effectiveness of the activity has been confirmed, more advanced tests will be conducted. These studies will aim to determine not only the activity of molecules (selectivity, low-concentration inhibition) but also their physico-chemical properties (solubility, lipophilic, metabolic stability, etc.) in order to select the most promising molecules. The selection of leads is a crucial step because the rest of the project will be focused on the few molecules that are obtained. Once a lead has been identified, and if it is successful, one or more molecules will be submitted to the optimization stage, representing as many paths as feasible for the discovery of a potential drug candidate.

## I.1.1.4 Lead Optimization

During this stage, medicinal chemists will begin an iterative process in which chemical alterations will be made to a few molecules obtained during screening in order to improve the activity and properties of future drug candidates. The goal of this step is to obtain some molecules with a high level of activity (the level of activity depends on the project and the goal, with the goal being to maximize the ratio of
activity to concentration) and appropriate Physicochemical, biological, and toxicological properties.

This is by far the most difficult step, as it necessitates optimizing both activity and other properties that will turn the molecule into a drug that is both effective and low (or non-toxic). In general, multi-objective optimization is discussed, and numerous studies have been conducted in this area, including in cheminformatics [47-49].

## I.1.1.4.1 Rationalize the selection

The elimination of false selection allows for a reduction in the number of unnecessary tests and hence significant cost savings. There are also methods for selecting more precisely the components to test in order to reduce the chances of success in relation to the project's goals.

## I.1.1.4.1.1"Drug-like" compounds

Ideally, only molecules with a high potential to become a drug should be tested: no toxicity, high therapeutic efficacy, good absorption for oral prescription drugs, and so on. In the absence of a universal definition or a perfect predictive method, numerous studies have attempted to distinguish between a biologically active molecule and a "drug-like" molecule that approaches the ideal drug [50-54].

Lipinski's [55]definition of the term "drug-like" is the most well-known. The molecules with the best probability of being absorbed by voice oral satisfy at least three of the following characteristics, based on compounds administered by voice oral that passed phase 2 of clinical tests successfully:

- Molecular weight < 500 Da ,
- $\log \mathrm{P}<5$,
- Number of hydrogen bond acceptors < 10,
- Number of hydrogen bond donors < 5 .

With a similar specific goal, Veber et al [56]:

- Polar surface area $\leq 140 \AA^{2}$ and $\leq 10$ rotatable bonds


## I.1.1.4.1.2 'lead-like" compounds

Despite being frequently associated with Lipinski's rules, the term "drug-like" is quite vague and has thus been repurposed to describe more specific classes of molecules. Numerous studies have been conducted, for example, in order to distinguish between the leads of pharmaceuticals and other molecules. Once again, the definition of a lead remains mostly speculative, and other studies have attempted to establish analogous rules to Lipinski's. The concept stems from the observation that molecules entering clinical trials are frequently more complicated and larger than the leads from which they were derived [57-60]. As a result, more restrictive filters for obtaining simpler compounds have been developed, the most famous of which is that of Hann and Oprea[59]:

Molecular weight < 460 Da;

$$
-4<\log \mathrm{P}<4,2
$$

$\log \mathrm{Sw}>=-5 ;$
rotatable bonds $<10$;

Number of hydrogen bond donors < 5 ;

Number of hydrogen bond acceptors <9;
Number of cycles <4;
Other criteria have recently been introduced as well. Hopkins et al.'s of "Ligand Efficiency" [61]suggest that the ratio between liaison energy and the number of heavy atoms is an effective measure for lead selection. It allows, for example, to distinguish between an active and complicated molecule and a molecule with a similar activity but a lower complexity, allowing for the selection of leads with a higher potential for further modification. Further groups have proposed other indices of this sort, this time taking into account the area of the polar topological surface or lipophilicity.

## I.1.2 Pre-clinical trials

After obtaining optimized "leads", the pre-clinical trials consist of numerous studies aimed at qualifying the drug candidate from a pharmacological, pharmacokinetic and toxicological point of view. The use of rational animal experiments will allow consideration of the administration of the candidate drug in humans during subsequent clinical trials. The aim of pharmacological studies is to validate the mechanism of action of the candidate drug and to measure its activity in experimental models of the pathology, in vitro and in vivo in animals. Pharmacokinetic studies can describe the fate of a compound, its distribution, absorption and metabolism, and then its elimination from the body. Toxicological studies are used to determine the toxic doses of the drug candidate in the organism studied (mainly mice or rats, more rarely cats, dogs, pigs, or primates) .[62, 63]

These data will help determine the doses to be administered to humans during clinical trials and constitute a first approach in the study of potential adverse effects of the candidate drug, allowing these effects to be monitored proactively. An ancillary part of the pre-clinical development also consists of the assessment of the environmental risk associated with the marketing of the candidate drug. All the information collected during the pre-clinical trials will be compiled in a marketing authorization application for the candidate drug. This will be closely studied by the competent health authorities (in France, this is the National Medicines Safety Agency (ANSM) and the People Protection Committee (CPP)), before authorizing, or no, the entry of the drug candidate into the clinical trial phase. $[62,63]$

## I.1.3 Clinical tests

Clinical trials represent the most critical step in the drug design process, whether or not validating several years of pre-clinical and extremely expensive research. They are divided into four phases. The first three make it possible to establish the efficacy and safety of the drug candidate in order to obtain Marketing Authorization, while the fourth consists of the monitoring of side effects throughout the period of marketing and use of the drug (pharmacovigilance phase ). [64]The
supervision of clinical trials by health authorities is very strict. In France, the informed consent of volunteers is required and a national register kept by the ANSM lists all the subjects, the amount of their compensation (capped at 4,500 euros per year to avoid possible abuses), the date and duration of their protocols. During each phase, if adverse reactions are detected, the clinical study may be terminated and the drug candidate may be permanently discontinued.

Phase I is preliminary to the study of the efficacy of a drug candidate. It takes place on a small number of healthy volunteers ( 20 to 80 ) and its sole objective is to assess the tolerance or absence of any side effects associated with the administration of the candidate drug. However, these trials can be offered to patients with treatment failure, for whom the studied treatment represents the only chance of survival. Approximately $54 \%$ of the compounds tested in phase I will advance to the next phase.[65] Phase II aims to determine the optimal dosage, the efficacy of the drug candidate at this dosage and its short-term tolerance. It is generally carried out on a homogeneous group of 100 to 200 patients. Only $18 \%$ of the clinical trials started go on to phase III.[65]These trials, on a larger scale, are carried out on several thousand patients representative of the patient population for which the treatment is intended. These are controlled trials in which the drug in development is compared either with an effective treatment already on the market or with a placebo.

Phase III trials are most often carried out double-blind and with random draw:
the treatments or placebo are randomly assigned to patients and to the doctors in charge of monitoring, without them being informed of what assignment they have been subject to. This method avoids biases related to the patient management process, commonly known as the "placebo effect". The complete clinical trial process results in a Marketing Authorization being obtained for $11 \%$ of the drug candidates.[6, 65]

When Marketing Authorization is granted, the marketing and application of the treatment can begin. Phase IV of clinical trials, also called pharmacovigilance, then consists of monitoring the potential side effects of the treatment on all the patients who benefit from it (large and heterogeneous population). In this context, physicians have
the obligation to report the adverse effects described by their patients, which makes it possible to quickly identify the emergence of new effects which would not have been detected during clinical trials and guarantees greater safety. of use to patients.

## I.2. Limitations and failures

Pharmaceutical research therefore faces major challenges, mainly scientific, but also financial and political. The success rate of the clinical trial phases is about $11 \%$, all types of pathologies combined.[6,65] This varies according to the types of pathologies, from around $5 \%$ for those involving the central nervous system to around $20 \%$ for cardiovascular disease (Figure 7). [6]


Figure. 7. Success rate of phase I clinical trials in obtaining marketing authorization for the ten largest pharmaceutical companies between 1991 and 2000. The success rate varies according to the pathologies targeted.

These low success rates can be explained in several ways: pharmaceutical research is currently focused on pathologies of great complexity (cancer, AIDS, etc.), competition between different pharmaceutical companies is increasing in parallel with standards of care and health authorities are becoming more demanding. In 1991, poor pharmacokinetic characteristics of drug candidates were the leading cause of clinical trial failure (40\%). In 2000, pharmacokinetic problems represented only $10 \%$ of

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clinical trial failures. Today, the main causes of failure during clinical trial phases are the lack of efficacy of compounds (30\%) and their toxicity (30\%). [6] The failures linked to the lack of efficacy of compounds are more frequent when the animal models used are not very predictive, in particular for pathologies of the central nervous system and cancers, inducing high failure rates in phases II and III (Figure 7) .[6]

## I.3. Medicinal Chemists Today

Medicinal chemists today are facing a serious challenge because of the increased cost and enormous amount of time taken to discover a new drug , and also because of fierce competition amongst different drug companies.

Pharma Industry development became one of the important targets for different Governments in the last three decades, especially with the tremendous achievements of the multinational companies in this area of industry.

Challenges of this industry in third world have been increased; the discovery of a new active marketed molecule costs millions of USD, which increase the problem we are facing. Many worldwide companies have been merged to increase their ability in new drug discovery area. Most of them on the other hand adopted new technologies to discover and develop new drug entities, among these are computational and modeling techniques, which help in decreasing the time and cost of discovery researches, that's why importance of Computer Aided Drug Design and Molecular Modeling is increasing nowadays[6].

## I. 4 Conclusion

It was discovered that chemical libraries were at the heart of the process of developing drug candidates. With the passage of time and ever-increasing storage capacities, the size of chemical libraries and the number of molecules available have grown significantly. The management and analysis of such a large amount of data necessitate the use of computer systems capable of implementing various data analysis and composition selection strategies. In the following section, we will introduce the field of discussing methods for responding to the issues raised in the previous section, putting the work of this thesis into context.

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## Chapter II

## Part I: Computer in medicinal chemistry

All theoretical research is underpinned by two essential motivations: understanding and forecasting, that is, understanding what has already been done and forecasting what may be achievable. The forecast answers questions like: "What would happen if ...?", Or "Can we do ...?" or "What would be the value of...?". The traditional answer would be to experiment. But at a time when the price of computer calculations is continually falling, while chemicals, devices, skilled labor, etc. continues to grow, it is increasingly interesting to exploit theoretical models of all kinds to help design new chemical species [1].

The ambition of a theoretical chemist is to be able to predict, confirm or reinterpret the experiment using molecular modeling. Indeed, the perseverance of researchers, and above all the power of their computer resources, play in favor of theoretical chemistry, and its field of application.

The research and synthesis of new chemical and biochemical compounds is often associated today with a study by molecular modeling. Molecular modeling is a commonly used methodology. For a little over thirty years, it has gradually established itself as a tool of choice for the discovery and oriented design of new active molecules. Previously, only systematic biological tests were performed on a large number of molecules and, often, only luck made it possible to highlight an interesting lead [2].

Molecular modeling is a tool for researchers concerned with the structure and reactivity of molecules. Knowing the structure of molecular edifices makes it possible to understand what is achieved in a physical, chemical or biological transformation. It can also make it possible to predict such transformations. Both understanding and forecasting are greatly facilitated when one can visualize the structures. A molecule is correctly described by its geometry and its thermodynamic properties. The visualization must account for all of these characteristics. The essential question is to represent a molecule on the screen as close as possible to "reality" [3].

## II. 1 Theoretical Background for Quantum Mechanical Calculations

The goal of this chapter is to go over some uses of quantum mechanical calculations in medicinal chemistry and drug design. These introductions, on the other hand, will be kept to a bare minimum, focusing on the key differences between methodologies and their known strengths and shortcomings in respect to medicinal chemistry applications, with only one mathematical equation, probably to the relief of the majority of readers.

The Schrödinger equation is the foundation of quantum mechanics, and it has a simple eigenvalue problem form:

$$
H \psi=E \psi
$$

Even with today's computing power, this famous equation cannot be solved directly for anything greater than hydrogen. As a result, a number of assumptions were devised to allow for the quantum mechanical treatment of molecules of more immediate concern to most chemists.

For example, the Born-Oppenheimer approximation treats atom nuclei as fixed, and the Hartree-Fock (HF) approximation replaces the genuine electron- electron potential description with an effective potential, thus eliminating electron correlation. Another is the use of basis sets instead of actual electron integrals, which are designed to approximate the structure of orbitals. For ab initio computations, the quality of these basis sets is critical, and the larger they are and the more individual Gaussian functions they contain, the better. The utility and correctness of calculations based on these approximations are typically confirmed by comparison with experiment, especially for molecular geometries and properties such as dipole moments, and the findings are often surprisingly exact despite the use of these simplifications.

Some approximations, on the other hand, are more dubious, and the magnitude of inaccuracy imposed is frequently unknown. Despite the use of a variety of approximations, quantum mechanical calculations are often quite accurate and useful in answering questions and defining molecule structures, characteristics, and interactions that are crucial in medicinal chemistry. It should also be noted that some

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of these questions, such as those relating to chemical reactivity, molecular properties such as nucleophilicity, electrophilicity, charge distribution, spin-orbit coupling, dipole, and higher multipole moments relating to polarizability, infrared, Raman, and NMR chemical shifts, circular dichroism, and magnetic susceptibility [4], must be answered in the affirmative, the computational and medicinal chemist's only choice for obtaining reliable predictions is quantum mechanical computations.

In contrast to molecular mechanics, quantum mechanical calculations are obtained directly from the physical rules that affect molecular structure through an approximate solution of the Schrödinger equation. Ab initio, DFT, and semiempirical approaches are the three types of methodologies available. While ab initio and density functional approaches do not need parametrization to solve the Schrödinger equation, semiempirical methods use parameters to avoid having to compute some of the timeconsuming integrals that ab initio and DFT computations require. Furthermore, semiempirical approaches only consider the valence electrons, and despite having significantly fewer parameters than molecular mechanics methods, are also less comprehensible. All three approaches (ab initio, DFT, and semiempirical) produce a wave function that may be used to calculate all electrical properties [5].

## II.1.1 Molecularmechanics

## II.1.1.1 Introduction

Molecular modellers usually have a different goal in mind: they want a force field that can be transmitted from molecule to molecule so that they may anticipate (for example, the shape of a new molecule) using data from other molecules. They use the bond notion and appeal to classical chemists' ideas that a molecule is made up of a collection of bonded atoms; a large molecule contains the same qualities as small molecules, and in various combinations [6].

Because of non-bonded van der Waals and Coulombic interactions, molecules are described in terms of "bonded atoms," which have been distorted from some idealized shape. The success of molecular mechanics models is determined by the geometrical parameters' great transferability from one molecule to the next, as well as the parameters' predictable dependency on atomic hybridization.

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Carbon-carbon single bond lengths, for example, are typically in the tiny range of 1.45 to 1.55 , and grow in length as the "p character" of the carbon hybrids increases. As a result, if the molecule has already been represented in terms of a certain valence structure, it is possible to make a pretty accurate "guess" about molecular geometry in terms of bond lengths, bond angles, and torsion angles. This group includes the vast majority of organic compounds.

The "energy" of a molecule in molecular mechanics is described as a sum of contributions from distortions in "ideal" bond distances (stretch contributions), bond angles (bond contributions), and torsion angles (torsion contributions), as well as contributions from "non-bonded" (van der Waals and Coulombic) interactions.

$$
\begin{aligned}
& E=\sum_{\text {bonds }} \frac{k_{i}}{2}\left(l_{i}-l_{i, 0}\right)^{2}+\sum_{\text {angles }} \frac{k_{i}}{2}\left(\theta_{i}-\theta_{i, 0}\right)^{2}+\sum_{\text {torsions }} \frac{V_{n}}{2}(1+\cos (n \omega-\gamma)) \\
&+\sum_{i=1}^{N} \sum_{j>i}^{N}\left(4 \varepsilon_{i j}\left[\left(\frac{\sigma_{i j}}{r_{i j}}\right)^{12}-\left(\frac{\sigma_{i j}}{r_{i j}}\right)^{6}\right]+\frac{q_{i} q_{j}}{4 \pi \varepsilon_{0} r_{i j}}\right)
\end{aligned}
$$



Figure .8. An illustration of the various terms that contribute to a typical force field.

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## II.1.1.1.1 Elongation energy

Bonds between atoms in a molecular structure often tend to elongate or contract (Figure 9).


Figure.9.Elongation between two atoms.
This deformation is governed as a first approximation by the "Hooke" law of spring elongation. We can thus associate it with an energy of elongation of the form:

$$
E(L)=1 / 2\left[K_{1}(L-L o)^{2}\right]
$$

Where $\mathbf{K}_{1}$ : is the constant of elongation or constant of Hooke

Lo: the length of the reference link.
$\mathbf{L}$ : the length of the link in the model.

All of these elongation terms are summed over all of the bonds in the molecule.

A cubic term (L-Lo) ${ }^{3}$ is generally added for large deformations. The computation of this energy thus imposes to know at least the two indissociable parameters ( $\mathrm{K}_{1}$ and Lo ) which represent a subset of the force field. Indeed, it emerges from the serial development of the mathematical expression of the Morse curve reflecting the existing interaction between two atoms according to their respective distance [7].

## II.1.1.1.2. Bending energy

The fluctuation of atoms around their equilibrium position generates $a$ deformation of the valence angles (figure 10) [7].


Figure.10.Deformation of valence angles.

This phenomenon is governed by a bending energy which can be expressed in the same forms as above, namely, to put it simply:

$$
\mathrm{E}(\theta)=1 / 2\left[\mathrm{~K}_{\mathrm{f}}(\theta-\theta \mathbf{0})^{2}\right]
$$

$\mathbf{K}_{\mathbf{f}}$ : bending constant
$\theta 0$ : reference valence angle
$\theta$ : valence angle in the molecule

The pair $(\mathbf{K f}, \boldsymbol{\theta} \mathbf{0})$ represents here again a subset of the force field.

## II.1.1.1.3. Torsional energy

It concerns the dihedral angle formed by atoms 1-2-3-4. It notably takes into account the 3D structure of the molecule (figure 11) [7].

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Figure.11.Dihedral angle formed by atoms 1-2-3-4.

The evaluation of this energy E (f) is done by a function developed in Fourier series.

$$
E(f)=1 / 2[V 1(1+\cos f)+V 2(1-\cos 2 f)+V 3(1+\cos 3 f)]
$$

The dihedral angle (f) defines the twist around link 2-3.
$\mathbf{V 1 , V 2 , V 3}$ are the constants of the potential of torsional energy.

## II.1.1.1.4. Van der Waals energy

This energy concerns atoms not linked to each other and not linked to a common atom [8]. It consists of two parts, one repellent and the other attractive, and can be expressed by the following equation[7]:

$$
\mathbf{E}(\mathrm{vdw})=\mathrm{e}^{*}\left[-\mathrm{C} 1\left(\mathrm{r}^{*} / \mathrm{r}\right) 6+\mathrm{C} 2 \exp \left(-\mathrm{C} 3\left(\mathrm{r} / \mathrm{r}^{*}\right)\right]\right.
$$

e*: :energy parameter which characterizes the depth of the potential well at the distance $r^{*}$, also called "hardness".
$\mathbf{r}$ *: sum of the VdW radii of the interacting atoms.
r: interatomic distance.

C1, C2, C3: constants of the force field.

We can therefore represent this energy as a function of the interatomic distance " r " as follows:


Figure.12.Van der Waals energy curve.

## II.1.1.1.5. Electrostatic energy

The electrostatic interactions can, in certain cases, take on a considerable importance, in particular in the case of molecules comprising two or more heteroatoms, Meyer et al [9], have proposed to introduce an electrostatic term even for hydrocarbons. It can be expressed from the atomic charges or the dipole moments of each bond [7].

In the first case:

$$
E(e)=S \text { q1q2 } / \mathbf{D . d 1 2}
$$

D: local dielectric constant of the medium
$\mathbf{q}_{1} \mathbf{q}_{2}:$ atomic partial charges of atoms 1,2
$\mathbf{d}_{12}$ : interatomic distance.
In the second:

$$
E(e)=\mathrm{m} 1 \mathrm{~m} 2(\cos X-3 \cos a 1 \cdot \cos b 2) / D \cdot r 12^{-3}
$$

r: distance between the midpoints of the two links
$\mathbf{m}_{1}, \mathbf{m}_{\mathbf{2}}$ : respectively represent the dipole moments of the two bonds.
$\mathbf{X}$ : the angle between the two moment vectors.
$\mathbf{a}_{1}, \mathbf{b} 2$ : angles formed respectively between $\mu 1$ and r and $\mu 2$ and r


Figure.13.Electrostatic interactions between two atoms.

## II.1.1.2 Force Fields

Models of molecular mechanics differ in terms of the number and nature of terms they include, as well as the details of their parameterization. The combination of functional form and parameterization is known as a force field.

We have been vague so far about which variables are the 'correct' ones to take. Chemists visualize molecules in terms of bond lengths, bond angles and dihedral angles, yet this information is also contained in the set of Cartesian coordinates for the constituent atoms. Both are therefore 'correct'; it is largely a matter of personal choice and professional training.

Spectroscopists have developed systematic simplifications to the force fields in order to make as many as possible of the small terms vanish. If the force field contains only 'chemical' terms such as bond lengths, bond angles and dihedral angles, then it is referred to as avalence force field (VFF). There are other types of force fields in the literature, intermediate between the VFF and the general force field[10].

With these principles in mind, many different force fields were build in professional molecular modelling programs such as :Dreiding, MM1, MM2, Amber, OPLS...etc.

## II.1.1.3 Limitations of Molecular Mechanics

The primary advantage of molecular mechanics models, is their simplicity. Except for very small systems, computation cost is completely dominated by evaluation of non-bonded van der Waals and Coulombic terms, the number of which is given by the square of the number of atoms.

However, the magnitude of these terms falls off rapidly with increasing interatomic distance and, in practice, computation cost scales linearly with molecular size for sufficiently large molecules.

Molecular mechanics calculations may easily be performed on molecules comprising several thousand atoms. Additionally, molecular mechanics calculations are sufficiently rapid to permit extensive conformational searching on molecules containing upwards of 100-200 atoms.

The fact that molecular mechanics models are parameterized may also be seen as providing an advantage over quantum chemical models. It is possible, at least in principle, to construct molecular mechanics models which will accurately reproduce known experimental data, and hopefully will anticipate (unknown) data on closelyrelated systems.

There are important limitations of molecular mechanics models. First, they are limited to the description of equilibrium geometries and equilibrium conformations. Because the mechanics "strain energy" is specific to a given molecule (as a measure of how far this molecule deviates from its "ideal arrangement"). Two important exceptions are: calculations involving isomers with exactly the same bonding, e.g., comparison of cis and trans-2-butene, and conformational energy comparisons, where different conformers necessarily have exactly the same bonding.

In addition, molecular mechanics calculations reveal nothing about bonding or, more generally, about electron distributions in molecules. As will become evident later,

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information about electron distributions is key to modeling chemical reactivity and selectivity. There are however, important situations where purely steric effects are responsible for trends in reactivity and selectivity, and here molecular mechanics would be expected to be of somevalue.

Finally, it needs to be noted that molecular mechanics is essentially an interpolation scheme, the success of which depends not only on good parameters, but also on systematics among related molecules. Molecular mechanics models would not be expected to be highly successful in describing the structures and conformations of "new") unfamiliar (molecules outside the range of parameterization [11].

## II.1.2 Quantum Mechanics

## II.1.2 . 1 Introduction

There are two approaches to quantum mechanics. One is to follow the historical development of the theory from the first indications that the whole fabric of classical mechanics and electrodynamics should be held in doubt to the resolution of the problem in the work of Planck, Einstein, Heisenberg, Schrödinger, and Dirac. The other is to stand back at a point late in the development of the theory and to see its underlying theoretical structure[12].Quantum mechanics can be thought of roughly as the study of physics on very small length scales, although here are also certain macroscopic systems it directly applies to. In quantum mechanics, particles have wave like properties, and a particular wave equation, the Schrodinger equation, governs how these waves behave.

What are we looking for in quantum mechanics? we search to solve the equation of Schrödinger of an electron using Born-Oppenheimer approximations. We can use the Born- Oppenheimer approximation to construct an electronic Hamiltonian, which neglects the kinetic energy term of the nuclei since the weight of a typical nucleus is thousands of times greater than that of an electron.

$$
\begin{equation*}
A=-\frac{h}{2 m_{e}} \nabla_{i}^{2}+\sum_{l} \sum_{J<1} \frac{z_{l} z_{J} e^{2}}{r_{I J}}-\sum_{I} \sum_{j} \frac{z_{l} e^{2}}{r_{i l}}+\sum_{J} \sum_{i>j} \frac{e^{2}}{r_{i j}} \tag{8}
\end{equation*}
$$

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This Hamiltonian is used in the Schrödinger equation describing the motion of the electrons in the field of the fixed nuclei:

$$
\begin{equation*}
\hat{H}_{e l e} \Psi_{e l e}=E_{e f f} \Psi_{e l e} \tag{9}
\end{equation*}
$$

Solving this equation for the electronic wave function will produce the effective nuclear potential function $E_{\text {eff }}$ that depends on the nuclear coordinates and describes the potential energy surface of the system.

For bond electronic problem, should satisfy two requirements: antisymmetricity and normalization. should change sign when two electrons of the molecule interchange and the integral of overall space should be equal to the number of electrons of the molecule [13].

## II.1.2.2 HF and DFT Methods

Many aspects of molecular structure and dynamics canbe modeled usingclassicalmethods in the form of molecular mechanics and dynamics. The classical force field is based on empirical results, averaged over a large number of molecules. Because of this extensive averaging, the results can be good for standard systems, but there are many important questions in chemistry that cannot at all be addressed by means of this empirical approach. If one wants to know more than just structure or other properties that are derived only from the potential energy surface, in particular properties that depend directly on the electron density distribution, one has to resort to a more fundamental and general approach: quantum chemistry. The same holds for all non-standard cases for which molecular mechanics is simply not applicable[14].In these methods, we use a set of basic functions from which we define all the molecular orbitals of the chemical system studied by LCAO approximation (linear combination of atomic orbitals).

The choice of basic orbital is essential for quantum chemistry calculations. There are two types of basic functions mainly used in electronic structure calculations: The Orbital Type Slater (STO) and those of Gaussian type (GTO).

The question here is, what basis to choose? Is it the biggest possible?

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The answer is: all depend of your studied system.

With the increase in computing power, the minimum size of a calculation base is currently around 6-31G (d).

- Double zeta at least.
- With polarization at least on the heavy atoms.
- Diffuse functions in the case of an anion or a system performing hydrogen bonds or a system having free doublets.
- A good basis: 6-31G** (or6-31++G**).
- A very good basis: 6-311 ++ G (2df,2p).


## II.1.2.3. Semi-empirical methods

In ab-initio methods almost all of the computation time is consumed by the calculations of the integrals, and in order to reduce this computation time, it is necessary to simplify the Roothann equations.

A semi-empirical method is a method in which part of the calculations necessary for Hartree-Fock calculations are replaced by parameters fitted to experimental values (the Hamiltonian is always parameterized by comparison with references). In general, all these methods are very precise for given families of products similar to those used for parameterization. Depending on the nature of the approximations used [15], there are several variants:

- CNDO / 2: (Complete Neglect of Differential Overlep) 1st semi-empirical method, it was proposed by Pople, Segal and Santry in 1965. Method presenting certain defects among others: it does not take into account Hund's rule.
- INDO: (Intermediate Neglect of Differential Overlap) Proposed by Pople, Beveridge and Dobosh in 1967. It distinguishes between singlet states and triplet states of a system by keeping the exchange integrals.
- NDDO: method (Neglect of Diatomic Differential Overlap): proposed by Pople in 1965. All bicenter bi-electronic integrals are retained.
- MINDO / 3: Proposed by Bingham, Dewar and Lo in 1975. Parameterization carried out with reference to experimental results and not to initial results, moreover the optimization algorithm used is very efficient (DavidonFletcherPowel). However, it overestimates the heat of formation of unsaturated systems and underestimates that of molecules containing neighboring atoms with free pairs.
- MNDO: (Modified Neglect of Diatomic Overlap) Proposed by Dewar and Thiel in 1977. Methods based on the NDDO (Neglect of Diatomic Differential Overlap) approximation which consists in neglecting the differential overlap between atomic orbitals on different atoms. This method does not deal with transition metals and presents difficulties for conjugate systems.
- AM 1: (Austrin Model 1) Proposed by Dewar in 1985. He tried to correct the flaws of MNDO.
- PM 3: (Parametric Method 3) Proposed by Stewart in 1989. Presents many points in common with AM1, moreover there is still a debate concerning the relative merits of parametrization of each of them.
- SAM 1: (Semi-ab initio Model 1) The most recent method proposed by Dewar in 1993. It includes electronic correlation.


## II.1.2.4 Limitations of Quantum Mechanics

However, these methods draw back calculations could be sometimes very long, the size of the system studied is limited and there must be very good calculation equipment.

One of the major challenges for computer-aided drug design is that it is not governed by the clear-cut rules of design in engineering, and hence, these methods do not produce a finished product by a fully prescribed procedure. The limitations of the rational computer aided drug design approach arise because of the complexity of the biological processes involved in drug actions and metabolism at the molecular level and the level of approximation that must be used in describing molecular properties.[5]However, there is clear evidence in the literature that molecular modeling and computer-aided drug design methods and also data analysis and chemoinformatics
approaches have become very important tools for drug discovery and that they have been successfully applied to medicinal chemistry,[16]particularly hit and lead generation as well as at the lead development stages.[17-19] Accepting that molecular modeling and chemoinformatics are useful techniques does however not sufficiently explain why one needs quantum mechanical methods. This has been done by Clark in a recent review, where he indicates that calculational techniques used to describe molecules should be able to describe the intermolecular interactions adequately. [20]He points out that this can only be achieved if the molecular electrostatics and the molecular polarizability are described well. The former is responsible for strong interactions and the latter is directly related to dispersion and other weak interactions. Therefore, following this argument, molecular interactions of any type can only be described adequately and accurately by using quantum mechanical calculations. We will divide the application of quantum mechanical calculations to answer medicinal chemistry related questions in a drug design environment into a total of four sections on:
(1)the accurate calculation of molecular structure,
(2) the calculation of quantum mechanical descriptors for prediction of molecular propertiesand QSAR, [21, 22]
(3) applications to chemical reactivity and the investigation of enzyme mechanisms, and
(4) the calculation of interactions and binding energies of small molecules with proteins.

This selection of topics is meant to reflect the main areas of interest to medicinal chemists working in the field of drug discovery. It is noted that although there are a great number of publications on the use of quantum mechanical calculations to medicinal chemistry, however, a large number of them are retrospective studies concerned with the validation of new technology rather than the prospective application to problem solving and design of new chemical entity (NCEs).

## II. 2 Choice of method

The method of calculation chosen depends on what calculation needs to be done, as well as the size of the molecule. As far as size of molecule is concerned, ab initio calculations are limited to molecules containing tens of atoms, semi-empirical calculations on molecules containing hundreds of atoms, and molecular mechanics on molecules containing thousands of atoms.

Molecular mechanics is useful for the following operations or calculations: [23]

- Energy minimization ;
- Identifying stable conformations;
- Energy calculations for specific conformations;
- Generating different conformations;
- Studying molecular motion.

Quantum mechanical methods are suitable for calculating the following:

- Molecular orbital energies and coefficients;
- Heat of formation for specific conformations;
- Partial atomic charges calculated from molecular orbital coefficients;
- Electrostatic potentials;
- Dipole moments;
- Transition state geometries and energies;
- Bond dissociation energies.


## II. 3 Minima search method

## II.3.1 Introduction

Minimization sometimes results in hydrogens and doublets arranged around the atom in impossible structural positions. This is often due to improper initial movement of these light atoms when a strongly distorted structure is introduced.

This can also happen if you start with a planar structure. This is why the program performs a "second pass" of minimization after having repositioned the light atoms.

Another difficulty of minimization concerns the problem of the local minimum. The constrained optimization routines indeed have the unfortunate tendency to find a minimum energy closest to the input structure [24].

In general, bond distances and angles are properly minimized, so the local minimum problem can boil down to optimizing dihedral angles (it takes a lot more energy to deform a bond or valence angle by compared to a dihedral angle). The following approaches aim to extract the molecule from its potential well.

Almost all minimization methods have at least one point in common: we start at a given place in the hypersurface and work our way down to the nearest minimum, without knowing whether this minimum is local or absolute. We must therefore present to the computer several starting conformations, in the form of internal coordinates, taking inspiration from molecular models [7].

## II.3.2 Minimization algorithms

For a molecule comprising N atoms, the function to be minimized therefore comprises 3 N variables. Such a function generally comprises a global minimum and local minimisa.

From the initial geometry, we look for the set of Cartesian coordinates which reduces to a minimum the sum of all the energy contributions.

In principle, it suffices to take the first derivative of the steric energy with respect to each of the degrees of freedom of the molecule and to find the place on the energetic hypersurface where, for each coordinate ri, $(\mathrm{dE} / \mathrm{dri})=0$.

The procedures to achieve this goal are of two types: Some use only the slope of the surface (first derivative), others, both this slope and the curvature of the surface (the first and second derivatives).

## II.3.2.1 The 'steepest descent' method

The first minimization program that can perform geometry optimization is due to Wiberg[25] and uses the steepest descent method. After having calculated the energy

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corresponding to an initial geometry, we move each atom individually according to its three Cartesian coordinates and we recalculate the energy after each displacement. This amounts to calculating the first derivative only. Then we move all the atoms over a distance that depends on (dE / dri), and so on. This algorithm will therefore follow the direction imposed by the dominant interatomic forces.

This is why it proves to be very effective in removing bad contacts or the main stereochemical problems which exist in the coarse coordinates of a crystalline or modeled structure, while disturbing the latter very little.

However, this random method is generally long towards the end of each minimization cycle and convergence becomes very slow beyond the first cycles (oscillating phenomena, energy rise).

In fact, the method consists in finding the direction of the greatest slope during which the objective function F ( x ) decreases the most rapidly. The direction followed will be that indicated by the opposite of the energy gradient, i.e. the direction of the greatest slope of the energy function, which is the direction in which the energy decreases the fastest, at least locally.

## II.3.2.2. The conjugate gradient method

This method, based on the same principle as the previous one (direction opposite to the energy gradient), also takes into account the previous steps, in order to more precisely determine the direction and the pitch. For a quadratic energy surface, function of 3 N variables, this method converges in 3 N not [26].

It retains good efficiency, but is more costly in computation time (a factor of 2 compared to "steepest descent"). The step is adjusted at each cycle to obtain the best reduction in energy. The interest of this algorithm is to avoid an oscillatory behavior around the minimum and to accelerate the convergence. However, it turns out to be less efficient or even unusable (no convergence) for structures which present a lot of bad contacts, such as structures averaged over the trajectory of a molecular dynamic.

## II.3.2.3. The Newton-Raphson method.

An additional improvement of convergence can still be obtained by having recourse to a quadratic approximation $Q$ of the function $F$, obtained by development in series of Taylor [27].

The method consists in seeking at each step the minimum of the development at order 2 of the function F. This method known as "Newton-Raphson", uses the second derivatives. Now we use this optimization technique instead. It evaluates the second derivatives of molecular energy with respect to the geometric parameters and therefore converges more quickly.

In summary, the complete optimization according to the Newton Raphson method requires calculating the complete matrix of second derivatives (matrix of force constants). This matrix contains 3N X 3N elements for a molecule of N atoms. The 3N dimensions correspond to the three degrees of motion for each atom.

The optimization of the geometry however requires only $3 \mathrm{~N}-6$ degrees of freedom since the three translations and the three rotations are not accompanied by changes of energy. The force constants are then manipulated in the form of a matrix of second derivatives.

## II.3.2.4. The simulated annealing method.

The methods that we have just described have the particularity of making the function F decrease at each step; these methods cannot thus escape the local minimum close to the starting structure and consequently have a radius of convergence always restricted. The "anneal" simulated annealing method, developed by Kirkpatrick [28], allows the F function to increase momentarily in order to cross energy barriers and fall back to a deeper minimum.

The crossing of these barriers makes it possible to go beyond the local minima in the vicinity of the initial structure to explore more extensively the accessible
conformational space, in order to discover deeper minima and more distant from the initial structure than the minima. local.

In conclusion, a minimizer is a mathematical black box which remains an important tool in the search for a minimum of energy. In general, several minimizers are used. We go to a second or a third if it does not converge quickly enough. Everything also depends on the number of variables or the number of variations in the connection angle introduced.

## II. 4 Molecular Modeling

## II.4.1 Elements of Computational Chemistry

## II.4.1.1 Drawing chemical structures

Various software packages, such as ChemDraw, Hyperchem, MarvinSketch, ChemWindow, and IsisDraw, are available which can be used to construct diagrams quickly and to a professional standard.

For example, the diagrams in this thesis have all been prepared using the Hyperchem package. Some drawing packages are linked to other items of software which allow quick calculations of various molecular properties. For example, the following properties for 'adrenaline' were obtained using Hyperchem and, gaussian: the structure's correct IUPAC chemical name, molecular formula, molecular weight, exact mass, and theoretical elemental analysis. It was also possible to get calculated predictions of the compound's ${ }^{1} \mathrm{H}$ and ${ }^{13} \mathrm{C}$ nuclear magnetic resonance (NMR) chemical shifts, Energies of the HOMO and LUMO, melting point, freezing point, log $P$ value, molar refractivity, and heat of formation ect...( Fig.14)


Calculated properties
$\mathrm{C}_{9} \mathrm{H}_{13} \mathrm{NO}_{3}$
Exact Mass: 183.09
Mol. Wt.: 183.20
C, 59.00; H, 7.15; N, 7.65; O, 26.20
Predicted properties
$\log P=-0.61-0.63$
Molar refractivity $48.66-49.08$ [cm.cm.cm/mol] b.pt. 618.55 K; Freezing point 539.03 K Heat of formation $-451.22 \mathrm{~kJ} / \mathrm{mol}$

Predicted ${ }^{13} \mathrm{C} \mathrm{nmr}$



Predicted ${ }^{1} \mathrm{H} n m r$

Figure .14.Drawing chemical structures.

A vast number of organic molecules are known. In order to distinguish one from another, chemists give them names. There are two kinds of names: trivial and systematic. Trivial names are often brand names (such as adrenaline). Trivial names don't give any real clue as to the structure of a molecule, unless you are the recipient of divine inspiration. TheIUPAC systematic name for adrenaline is 1-(3,4 dihydroxyphenyl)-2-methylaminoethanol. Any professional scientist with training in chemistry would be able to translate the systematic name into (Figure 14).

There are various conventions that we can follow when drawing chemical structures, but the conventions are well understood amongst professionals. First of all, we haven't shown the hydrogen atoms attached to the benzene ring (or indeed the carbon atoms within), and we have taken for granted that we understand that the normal valence of carbon is four. Everyone understands that hydrogens are present, and so we needn't clutter up an already complicated drawing.

In the Figure 14 the benzene ring as alternate single and double bonds, yet we understand that the $\mathrm{C}-\mathrm{C}$ bonds in benzene are all the same. This may not be the case in the molecule shown; some of the bonds may well have more double bond character than others and so have different lengths, but once again it is a well-understood convention. Sometimes a benzene ring is given its own symbol Ph or $\Phi$. Then again, we drawn the NHMe and the OH groups as 'composites' rather than showing the
individual $\mathrm{O}-\mathrm{H}$ and $\mathrm{N}-\mathrm{H}$ bonds, and so on. We followed to some extent the convention that all atoms are carbon atoms unless otherwise stated.

Much of this is personal preference, but the important point is that no one with a professional qualification in chemistry would mistake this drawing for another molecule. Equally, given the systematic name, no one could possibly write down an incorrect molecule.

The aim of this chapter is to show how chemistry is a well-structured science, with a vast literature. There are a number of important databases that contain information about syntheses, crystal structures, physical properties and so on. Many databases use a molecular structure drawing as the key to their information, rather than the systematic name. Structure drawing is therefore a key chemical skill.

## II.4.1.2 Three-dimensional structures

Molecular modelling software allows the chemist to construct a threedimensional (3D) molecular structure on the computer. There are several software packages available, such as Chem3D, Alchemy, Sybyl, Hyperchem, Discovery Studio Pro, Spartan, and CAChe. The 3D model can be made by constructing the molecule atom by atom, and bond by bond. It is also possible to automatically convert a twodimensional (2D) drawing into a 3D structure, and most molecular modelling packages have this facility. For example, the 2D structure of adrenaline in Fig. 15 was drawn in ChemDraw, then copied and pasted into Chem3D, resulting in the automatic construction of the 3D model shown. The 3D structures of a large number of small molecules can also be accessed from the Cambridge Structural Database (CSD) and downloaded. This database contains over 200,000 molecules which have been crystallized and their structure determined by X-ray crystallography.


Figure .15.Conversion of a 2D drawing to a 3D model.

## II.4.1.3 Molecular Structure Databases

Molecular geometries can be determined for gas-phase molecules by microwave spectroscopy and by electron diffraction. In the solid state, the field of structure determination is dominated by X-ray and neutron diffraction and many crystal structures are known. Also, nuclear magnetic resonance (NMR) also has a role to play, especially for proteins.

Over the years, a vast number of molecular structures have been determined and there are several well-known structural databases. One is the Cambridge Structural Database $(\mathrm{CSD})($ http://ccdc.cam.ac.uk= ), which is supported by the Cambridge Crystallographic Data Centre (CCDC). The CCDC was established in 1965 to undertake the compilation of acomputerized data base containing comprehensive data for organic and metal-organic compounds studied by X-ray and neutron diffraction. At the time of writing, there are some 272000 structures in the database[29].


Figure.16.The Cambridge Crystallographic Data Centre (CCDC).

For each entry in the CSD, three types of information are stored. First, the bibliographic information: who reported the crystal structure, where they reported it and so on. Next comes the connectivity data; this is a list showing which atom is bonded to which in the molecule. Finally, the molecular geometry and the crystal structure. The molecular geometry consists of cartesian coordinates. The database can be easily reached through the Internet, but individual records can only be accessed on a fee-paying basis.

The Protein Data Bank (PDB) is the single worldwide repository for the processing and distribution of three-dimensional biological macromolecular structural data. It is operated by the Research Collaboratory for Structural Bioinformatics[30].

At the time of writing, there were 19749 structures in the data bank, relating to proteins, nucleic acids, protein-nucleic acid complexes and viruses. The databank is available free of charge to anyone who can navigate to their site
http://www.rcsb.org/.Information can be retrieved from the main website. A fourcharacter alphanumeric identifier, such as 1 PCN , represents each structure. The PDB database can be searched using a number of techniques, all of which are described in detail at the homepage.


Figure.17.TheProteinDataBank(PDB).

## II.4.1.4 Energy minimization

Whichever software program is used to create a 3D structure, a process called energy minimization should be carried out once the structure is built. This is because the construction process may have resulted in unfavorable bond lengths, bond angles, or torsion angles. Unfavorable non-bonded interactions may also be present (i.e. atoms from different parts of the molecule occupying the same region of space).[14]The energy minimization process is usually carried out by a molecular mechanics program which calculates the energy of the starting molecule, then varies the bond lengths, bond angles, and torsion angles to create a new structure. The energy of the new structure is calculated to see whether it is energetically more stable or not. If the

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starting structure is inherently unstable, a slight alteration in bond angle or bond length will have a large effect on the overall energy of the molecule resulting in a large energy difference ( $\Delta \mathrm{E}$; Fig. 18 ).

The program will recognize this and carry out more changes, recognizing those which lead to stabilization and those which do not. Eventually, a structure will be found where structural variations result in only slight changes in energy-an energy minimum. The program will interpret this as the most stable structure and will stop at that stage.


Figure.18. Diagram ofenergy minimization.

## II.3.1.5 Molecular dimensions

Once a structure has been energy minimized, it can be rotated in various axes to study its shape from different angles. It is also possible to display the structure in different formats (i.e. cylindrical bonds, wire frame, ball and stick, space-filling; Fig. 19).


Figure .19. Different methods of visualizing molecules.

Once a 3D model of a structure has been constructed, it is a straightforward procedure to measure all of its bond lengths, bond angles, and torsion (or dihedral) angles. These values can be read from tables or by highlighting the relevant atoms and bonds on the structure itself. The various bond lengths, bond angles, and torsion angles measured for adrenaline are illustrated in Fig. 20. It is also a straightforward process to measure the separation between any two atoms in a molecule.



Bond angles


Dihedral angles

Figure .20. Molecular dimensions for adrenaline (3D Hyperchem).

## II.4.2 Molecular properties

Various properties of the 3D structure can be calculated once it has been built and minimized. For example, the steric energy is automatically measured as part of the minimization process and takes into account the various strain energies within the molecule, such as bond stretching or bond compression, deformed bond angles, deformed torsion angles, non-bonded interactions arising from atoms which are too

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close to each other in space, and unfavorable dipole-dipole interactions. The steric energy is useful when comparing different conformations of the same structure, but the steric energies of different molecules should not be compared.

## II.4.2.1 Geometric Parameters

## II.4.2.1.1 Bond length

Is the distance between atomic centers involved in a chemical bond. The notion of bond length is defined differently in various experimental methods of determination of molecular geometry; this leads to small (usually $0.01-0.02 \AA$ ) differences in bond lengths obtained by different techniques. For example, in gas-phase electrondiffraction experiments, the bond length is the interatomic distance averaged over all occupied vibrational states at a given temperature. In an X-ray crystal structural method, the bond length is associated with the distance between the centroids of electron densities around the nuclei. In gas-phase microwave spectroscopy, the bond length is an effective inter atomic distance derived from measurements on a number of isotopic molecules, etc[31].

## II.4.2.1.2 Valence angle

The shape of a molecule is determined by its Valence angles, the angles made by the lines joining the nuclei of the atoms in the molecule. The bond angles of a molecule, together with the bond lengths, define the shape and size of the molecule. In Figure 21, we can see that there are six bond angles $\mathrm{Cl}^{-} \mathrm{C} \mathrm{ClinCCl}_{4}$, all of which have the same value.That bond angle, $109.5^{\circ}$, is characteristic of a tetrahedron. In addition, all four $\mathrm{C}-\mathrm{Cl}$ bonds are of the same length $(1.78 \AA)$. Thus, the shape and size of $\mathrm{CCl}_{4}$ are completely described by stating that the molecule is tetrahedral with $\mathrm{C}-\mathrm{Cl}$ bonds of length $1.78 \AA[31]$.


Figure .21. Tetrahedral shape of $\mathrm{CCl}_{4}$.

## II.4.2.1.3 Dihedral Angle (Torsion angle)

In a chain of atoms A-B-C-D, the dihedral angle between the plane containing the atoms A,B,C and that containing B,C,D. In a Newman projection (Fig.22) the torsion angle is the angle (having an absolute value between $0^{\circ}$ and $180^{\circ}$ ) between bonds to two specified (fiducial) groups, one from the atom nearer (proximal) to the observer and the other from the further (distal) atom. The torsion angle between groups A and D is then considered to be positive if the bond $\mathrm{A}-\mathrm{B}$ is rotated in a clockwise direction through less than $180^{\circ}$ in order that it may eclipse the bond C-D: a negative torsion angle requires rotation in the opposite sense[31].


Figure .22. Newman projection.

Other properties for the structure can be calculated, such as Atomic charges, the predicted electrostatic potential, Fukui function, and infrared vibrational frequencies. Some of these are described in the following sections:

## II.4.3 Electronic Parameters

## II.4.3.1 Atomic charges

A main problem in comparing different point-charge models is the missing of clearcriterion for the quality of the charges. This is probably the reason why so many charge models have been suggested such as:

- CHelpG: Produce charges fit to the electrostatic potential at points selected according to the CHelpG scheme.
- NBO: Requests a full Natural Bond Orbital analysis.
- Mulliken: retains only the density terms involving pairs of basic functions on different centers. HLY: Hu, Lu, and Yang charge fitting method.

Furthermore, different applications put different demands on the charges. For example, in molecular dynamics, molecules move, so the charges must be able to describe the electrostatics properly in all accessible points in the phase space, and they should also be in variant to changes in the internal coordinates of the molecule [32-34].

## II.4.3.2 Molecular electrostatic potentials

The molecular electrostatic potential (MESP) surface which is a plot of electrostatic potential mapped onto the iso-electron density surface [35], the importance of the MESP lies in the fact that it simultaneously displays the molecular size and shape as well as positive, negative and neutral electrostatic potential regions in terms of the electrostatic surface, which explain the investigation of the molecular structure with its physiochemical property relationships also be useful in identifying how compounds with different structures might line up to interact with corresponding electron rich and electron-poor areas in a binding site [36, 37].

An example of how electrostatic potentials have been used in drug design can be seen in the design of the cromakalim analogue (II; Fig.23), where the cyano aromatic ring

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was replaced by a pyridine ring. This was part of a study looking into analogues of cromakalim which would have similar antihypertensive properties, but which might have different pharmacokinetics. In order to retain activity, it was important that any replacement heteroaromatic ring was as similar in character to the original aromatic ring as possible. Consequently, the MEPs of various bicyclic systems were calculated and compared with the parent bicyclic system (III; Fig. 24).


Figure .23. Ring variation on cromakalim.

In order to simplify the analysis, the study was carried out in 2D within the plane of the bicyclic systems, and maps were created showing areas of negative potential (Fig.25). The contours represent the various levels of the MEP and can be taken to indicate possible hydrogen bonding regions around each molecule. The analysis demonstrated that the bicyclic system (IV) had similar electrostatic properties to (III), resulting in the choice of structure (II) as an analogue.


III


IV

Figure .24. Bicyclic models in cromakalim study.


Figure .25. Molecular electrostatic potentials (MEPs) of bicyclic models (III) and (IV).

## II.4.3.3 Molecular orbitals

The most important orbitals in a molecule are the frontier molecular orbitals, called highest occupied molecular orbital (HOMO) which explains the ionization energy and lowest unoccupied molecular orbital (LUMO) which explains the electron affinity in a molecule.

These orbitals determine the way the molecule interacts with other species including the interactions between a ligand and its receptor [38]. Whereas, electrophilic and nucleophilic attack will most likely occur at atoms where the coefficients of the corresponding atomic orbitals in HOMO and LUMO, respectively, are large [39]. For example, ethene can be shown to have 12 molecular orbitals. The highest occupied molecular orbital (HOMO) and lowest unoccupied molecular orbital (LUMO) are shown in Fig. 26.


Figure .26.HOMO and LUMO molecular orbitals for ethene.

## II.4.3.4 Fukui functions

The Fukui functions are some of these indexes. They represent a local reactivity of the studied compounds. They are given by [40]:

$$
\overrightarrow{f(r)}=\left(\frac{\partial \rho(r)}{\partial N}\right) v(r)
$$

where $\rho(r)$ is the electronic density, $N$ is the number of electrons and $v(r)$ is a constant external potential. The reactivity of an atom k in a molecule can be described, by a condensed Fukui function fk . As $\rho(\mathrm{r})$ is a discontinuous function of N , Yang and Parr [41, 42]have proposed approximated atomic indices fk by applying the finite difference approximation to the condensed electronic population on any atom. Three indices were defined to describe nucleophilic, electrophilic, and radical attack. These can be written respectively as:

$$
\begin{aligned}
& \mathrm{f}_{+}(\mathrm{A})=\left[\mathrm{q}_{\mathrm{N}+1}(\mathrm{~A})-\mathrm{q}_{\mathrm{N}}(\mathrm{~A})\right] \\
& \mathrm{f}_{-}(\mathrm{A})=\left[\mathrm{q}_{\mathrm{N}}(\mathrm{~A})-\mathrm{q}_{\mathrm{N}-1}(\mathrm{~A})\right] \\
& \mathrm{f}_{0}(\mathrm{~A})=\left[\mathrm{q}_{\mathrm{N}+1}(\mathrm{~A})-\mathrm{q}_{\mathrm{N}-1}(\mathrm{~A})\right] / 2
\end{aligned}
$$

$\mathrm{qk}(\mathrm{N})$ : electronic population of k atom in neutral molecule. $\mathrm{qk}(\mathrm{N}+1)$ : electronic population of k atom in anionic molecule. $\mathrm{qk}(\mathrm{N}-1)$ : electronic population of k atom in cationic molecule.

In this approximation, the indices depend widely on the used population analysis approach. The electronic population around an atom k can be evaluated using Mulliken[43], Hirshfield[44], or natural orbital [45]approximations. These indices are some of the widely used local density functional descriptors to model chemical reactivity and site selectivity [41, 46]. The atom with the highest Fukui indices is the most reactive compared to the other atoms in the molecule.

## II.5. Studies of vibrational properties

## II.5.1. Introduction

Molecular modeling is essential for the interpretation and understanding of experimental observations. In the molecular domain, all properties are related to the nature and shape of the molecule. Being able to optimize the geometry of a molecule by a theoretical model (quantum chemistry methods) is to approach its molecular conformation observed experimentally [47, 48].

The object of this part of our work, which was oriented towards the search for a molecular conformation of the calculated indole similar to that given by the experiment, is to make a contribution to the understanding of the structural, vibrational properties and electronics to exhibit the most stable molecular conformation and also the arrangement and atomic environment of carbazole.

## II.5.2. Theoretical aspects of infrared vibration spectroscopy

The movements of atoms in a molecule can be classified into three categories:
translations, rotations and vibrations. Nowadays, studies by vibrational spectroscopy are, more and more, supplemented by calculations of quantum chemistry [49, 50].

In this case, the contribution of molecular modeling is very important to understand reaction mechanisms or have access to chemical properties. Indeed, the methods of quantum chemistry make it possible to model a very large number of quantities characteristic of atomic or molecular systems or to simulate a wide variety

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of reaction processes. Also, the combination of these two techniques is proving to be very powerful in explaining mechanistic details at the molecular level [51].

The main purpose of vibrational spectroscopy is the determination of the vibrational frequencies of a molecule. These frequencies depend on the mass of the atoms involved in the normal mode of vibration as well as the strength of the interatomic bonds. Therefore, precise information about the structure of a molecule can be deduced from a vibrational spectrum [52,53].

Molecular vibrations take place at different frequencies ( v vib) which depend on the nature of the bonds as well as their environment. These frequencies correspond to the infrared range of electromagnetic radiation [54].

## II.5.3. Principle of infrared spectroscopy

## II.5.3.1. Electromagnetic radiation

Electromagnetic radiation consists of a beam of particles: photons, the movement of which is described by means of equations of wave mechanics.

The latter has shown that light participates in both wave and particle properties. When it collides with matter, it can be thought of as discrete packets of energy (quanta) called photons [55]. The interactions between matter and a radiation to which it is subjected are numerous. The most interesting and the most studied involve absorption phenomena (molecules can absorb the energy quanta of certain radiations). In this case, their fundamental energy states are altered by transition, or transition, to excited states of higher energy. Each state of matter is quantified and excitation takes place by absorption of a discrete amount of energy $\Delta \mathrm{E}$ [56]. To be absorbed, the radiation must be at the same frequency corresponding to this quantity of energy either: the recording of the energy absorbed or transmitted according to the frequency or the wavelength, constitutes the absorption spectrum of the compound in the spectral region of interest [55,57]. The frequency $v$ of an electromagnetic wave is related to its wavelength by the relation $[56,57]$ :

$$
v=C / \lambda
$$

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where $\mathbf{C}$ represents the speed of light propagation in vacuum and $\lambda$ the wavelength.

The energy $\mathbf{E}$ of the radiation or photon is directly proportional to the frequency of the electromagnetic wave or the field wave.

It is written:

$$
E=h v
$$

Normally, a spectrum should appear as a succession of fine lines. In fact, there is for a molecule a succession of energetic states close to each other.

Hence the obtaining of more or less broad peaks or absorption bands even with equipment with high resolving power. The purpose of studying infrared spectra is most often to characterize compounds or to verify their compliance with a reference sample. Absorption in the infrared spectral region corresponds to transitions in the energies of molecular vibrations.


Figure .27.The various spectral domains of electromagnetic radiation.

Quantum mechanics shows us that only vibrational transitions in which there is variation in the dipole moment of the molecule, can cause an absorption peak in IR to appear. Many lines are due to the different modes of vibration of the bonds.

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## II.5.3.2. Infrared

Understood between the visible and the microwaves, the infrared is subdivided into three parts: the near infrared located between 13,000 and $4,000 \mathrm{~cm}^{-1}$, the medium infrared located between 4,000 and $200 \mathrm{~cm}^{-1}$, and the far infrared located between 200 and $10 \mathrm{~cm}^{-1}[56]$. Infrared spectroscopy is based on the study of the reactions between matter and electromagnetic radiation. The latter can be defined by its frequency $v$ expressed in hertz $(\mathrm{Hz})$ or by its wave number, V is usually expressed in $\mathrm{cm}^{-1}$ or in kayser. It represents the number of waves contained in the interval of 1 cm [57]. In our investigation, we limited ourselves to the mid-infrared range (in the region of 4000 to $600 \mathrm{~cm}^{-1}$ ), this corresponds to energies ranging from 4 to $40 \mathrm{~kJ} \cdot \mathrm{~mol}^{-1}$.

An infrared spectrum is complex. This complexity can be increased by the appearance of additional bands due to the harmonics of the fundamental absorption frequencies $v f$ of lower intensity. They can be observed at $2_{\mathrm{vf}}, 3_{\mathrm{vf}}$, or at frequency combination bands, which correspond to the sum of two fundamental frequencies.

Fundamental bands may not appear in the following cases: the vibration does not cause a variation in the dipole moment of the molecule, which often occurs in the case of compounds with a very symmetrical structure; vibrations occur at very close frequencies or at the same frequency; absorption is too low for the band to be visible.

## II.5.3.3. Infrared absorption

Any molecule excited by electromagnetic radiation absorbs an amount of energy and goes into an excited state. According to the mechanics, the absorption process is quantified and only particular frequencies can be absorbed by the molecule.

Vibrational excitation can be considered simply by considering two atoms $\mathrm{A}_{1}$ and $\mathrm{A}_{2}$ united by a bond as being two masses connected by a spring (figure 28) which stretches and relaxes at a certain frequency $v$.


Figure.28.Movement of atoms during the phenomenon of vibration
In this representation, the frequency of vibrations between the two atoms depends both on the bond strength between them and on their atomic masses. It can be shown that it is governed by the following Hooke's law which describes the motions of a spring.

$$
\bar{v}=k \sqrt{f \frac{(m 1+m 2)}{m 1 \cdot m 2}}
$$

$V^{-}$: vibrational frequency in wavenumbers $\left(\mathrm{cm}^{-1}\right)$
K: constant
$\mathbf{f}$ :force constant, indicating the stiffness of the spring (of the connection)
$\mathbf{m 1}$ and $\mathbf{m 2}$ : values of the masses attached to the spring (masses of the united atoms)

This equation could lead us to think that each individual bond in a molecule gives rise to a specific absorption band in the infrared spectrum. Which is not the case.

The energies of radiation absorption correspond to movements of elongation, or deformation of most of the covalent bonds of molecules. In the process of absorption, the frequencies of infrared radiation coincide with those of the natural vibrational frequencies of molecules [58]. Not all bonds are capable of absorbing infrared energy even if their frequency coincides perfectly with that of movement of the bond. Only groups whose dipole moment varies during vibration are bonds which admit a dipole movement are able to absorb infrared radiation [57].

A bond must have an electric dipole which must oscillate at the same frequency as that of the excitation radiation, so that energy can be transferred.

In the case of infrared spectroscopy the molecule absorbs infrared light if and only if the dipole moment of the molecule changes during vibration [58].

The advantage with infrared is that it avoids unwanted photochemical or luminescence reactions. Electromagnetic radiation in the infrared (located in the region of 10,000 to $20 \mathrm{~cm}^{-1}$ ), causing a change in the vibrational level nevertheless leaves the molecule at its fundamental electronic level [58, 59]. To understand the phenomenon of atomic vibration, it must be visualized as the interaction of two particles linked together by a spring [58]. When this spring is pulled and released, the two particles enter into a stretching motion. The amplitude of their movement is not only a function of the mass of the particles but also of the force of the spring (see figure 28). During the vibration phenomenon, other movements can be described: stretching, folding, twisting, swaying, shearing. In biological membranes, these movements become all the more complex as the chemical structures of the membrane constituents are more elaborate.

## II.5.4. Theoretical aspects

## II.5.4.1. Internal vibration modes

In a polyatomic molecule comprising N atoms, the atoms can perform oscillating movements around their position of equilibrium. The rather weak oscillations of the molecule cause small displacements of the atoms formed. In this case the harmonic oscillation model is adapted to describe the movements of the atoms of the molecule. In a molecule made up of N atoms, each atom is assigned three coordinates to define its position. There by; an atom has three independent degrees of freedom of movement in the three directions of space. This results in 3 N degrees of freedom to describe the motion of an entire molecule (Table 2). Of these 3 N degrees of freedom, three are the coordinates that define the position of the center of mass of the molecule (translational degrees of freedom), and three other coordinates necessary to specify the molecular orientation around the center of gravity. These represent the degrees of freedom of

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rotation. Note that a linear molecule has only two degrees, since rotation around the molecular axis does not cause the nuclei to shift. In conclusion, a molecule with N atoms has $3 \mathrm{~N}-6$ (3N 5 for a linear molecule) degrees of freedom, responsible for all changes in the shape of the molecule without moving or rotating the center of gravity of the molecule $[60,61]$.

Table.2. Molecular degrees of freedom

|  | Degrés de liberté | Translation | Rotation | Vibration |
| :---: | :---: | :---: | :---: | :---: |
| Atome | 3 | - | - | - |
| Molécule linéaire <br> (N atomes) | 3 N | 3 | 2 | $3 \mathrm{~N}-5$ |
| Molécule non linéaire <br> (N atomes) | 3 N | 3 | 3 | $3 \mathrm{~N}-6$ |

## II.5.4.2. Classification of vibration modes

Vibrations can be classified into two categories: in-plane and out-of-plane [62, 63].

- In the plane: we distinguish the elongation $(v)$ and the angular deformation ( $\delta$ ) which can be either symmetrical ( $\delta \mathrm{s}$ and vs ), or antisymmetric ( $\delta$ as and vas). Symmetric and antisymmetric angular deformations correspond to shearing or rotational movements of three atoms forming the angle $\theta$ (Figure 29).
- Out of plane: these are angular deformations outside a molecular plane that can induce collective movement of the molecule corresponding to torsion $(\tau)$ or sway $(\gamma)$ movements.
Modes d'élongation

Figure.29. Movements associated with normal modes of vibration of a molecule containing 3 atoms.

## II.5.4.3. Factors that influence vibration frequencies

Analysis of an IR spectrum most often carried out in solution or in the solid state shows that a number of factors influence the vibration frequencies as well as their intensities.

The intensity of the bands depends on the nature and polarity of the bond. The vibration frequency, for its part, depends on the atoms constituting the bond, the multiplicity of the bond and its environment. Generally speaking, bonds between light atoms vibrate at a higher frequency than bonds between heavier atoms. The higher the constant K (bond strength constant), the higher the vibration frequency.

The link environment can have an electronic or mechanical impact on the vibration of this frequency. We will cite a few examples:
$\checkmark$ Electrical effects: The effects of electronegativity and conjugation can cause significant shifts in vibration frequencies.
$\checkmark$ Hydrogen bond: For some functions such as $-\mathrm{OH},-\mathrm{NH},-\mathrm{SH}$, there is the possibility of hydrogen bond formation when they perceive in their molecular neighborhood the presence of an electronegative atom. This results in an elongation of the $\mathrm{X}-\mathrm{H}$ bond and therefore a weakening of its force constant.
$\checkmark$ Steric Effects: The frequency of a vibration depends on the steric constraints associated with this vibrator. The vibration $v(\mathrm{C}=\mathrm{O})$ occurs at a frequency so much higher as the valence angle COC is small.

Mechanical coupling: When in a molecule vibration of the same nature are found in the vicinity of one another, having an atom in common for example, they do not vibrate independently of one another. As a result, the frequencies are affected compared to those generally observed. This phenomenon is due to the existence of a mechanical coupling.

## II.5.5. Application

Infrared spectrometry [64]thus provides detailed information on:

- The chemical structure of macromolecules and the composition of the polymer: identification of the basic unit, branches, analysis of chain ends, determination of the nature and concentration of additives, structural defects, impurities.
- Intra- or intermolecular interactions, chain conformation, polymer crystallinity, orientation of macromolecules.
- Infrared spectrometry is also an effective tool for studying the structural modifications of polymers resulting from chemical treatments, degradations or aging of various origins.


## II. 6 Conclusion

Chemoinformatics and molecular modeling methods are among the recent techniques now routinely applied in the research phases and in particular for the management and analysis of chemical libraries. They certainly arouse as much hope as they do criticism, but nevertheless constitute a very active line of research over the past two decades. In this chapter, we have presented most of the methods used in chemoinformatics for the analysis of chemical libraries. All of these concepts were used during this thesis in order, on the one hand, to make our own contribution through the creation of new methods allowing to characterize the chemical libraries and on the other hand, to develop a software allowing to implement some of these methods.

## Part II:

Computer-Assisted Drug Design

What is computer-assisted drug design (CADD), and why is it important? There is no clear definition, although a consensus view has emerged. Simply, CADD is the coalescence of information on chemical structures, their properties, and their interactions with biological macromolecules. Further, these data are transformed into knowledge intended to aid in making better decisions for drug discovery and development.

These are representative of some questions facing the current drug-design community and significant applications of CADD.

Of the compounds included in our dataset, how many could be predicted to lack drug likeproperties based on similarity in properties to known orally active drugs?

How many would be predicted to be inactive based on the known structure-activity dataavailable on topoisomerase II inhibitors?
Given the structure-activity relationships (SARs) available on the inhibitors, what could one determine regarding the active site of topoisomerase II?
What novel classes of compounds could be suggested based on the SAR of inhibitors, or based on the new crystal structure of the complex?

Do the most potent compounds share a set of properties that can be identified and used to optimize a novel lead structure?

Can a predictive equation relating properties and affinity for the isolated enzyme be established?

## II. 1 Predictive Quantitative Structure-Activity Relationship Modeling

At the beginning of its over 40 years of existence as an independent area of research,quantitative structure-activity relationship (QSAR) modeling was viewed strictly as analytical physical chemical approach applicable only to small congeneric series of molecules. The technique was first introduced by Hanschet al.[65]on the basis of implications from linear free energy relationships in general and the Hammett equation in particular. [66]
It is based upon the assumption that differences in physicochemical properties account for the differences in biological activities of compounds. According to this approach,
the changes in physicochemical properties that affect the biological activities of a set of congeners are of three major types: electronic, steric, and hydrophobic.[67]

The quantitative relationships between biological activity (or chemical property) and the structural parameters could be conventionally obtained using multiple linear regression (MLR) analysis. The fundamentals and applications of this method in chemistry and biology have been summarized by Hansch and Leo.[67]This traditional QSAR approach has generated many useful and, in some cases, predictive QSAR equations and led to several documented drug discoveries.[68-70]

Many years of active research in QSAR have dramatically changed the breadth and the depth of this field in all its components including the diversity of target properties, descriptor types, data modeling approaches, and applications. The most important changes in QSAR deal with a substantial increase in the size of data sets available for the analysis and an increasing use of QSAR models as virtual screening tools to discover biologically active molecules in chemical databases and virtual chemical libraries.

## II.2. Principle of QSPR / QSAR methods

The principle of the QSPR / QSAR methods is to establish a mathematical relationship linking in a quantitative manner molecular properties, called descriptors, with a macroscopic observable (biological activity, toxicity, physicochemical property, etc.), for a series of similar chemical compounds. using data analysis methods. The general form of such a model is as follows:
Property / Activity = f(D1, D2,...Dn ,,...)

D1, D2, Dn are descriptors of molecular structures.

The aim of such a method is to analyze structural data in order to detect the determining factors for the property / activity being measured. To do this, different types of statistical tools can be used:

- Simple and multiple linear regressions [71],
- Partial least squares regressions (PLS) [72],

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- Decision trees [73],
- Neural networks [74-76],
- Genetic algorithms[77],
- Machine Vectors [76],

Once this relationship is established and validated, it can then be employed for the prediction of the property / activity of new molecules, for which experimental values are not available. Such models can also be used to better understand mechanisms and modes of action.

## II. 3 Key Quantitative Structure-Activity Relationship Concepts

An inexperienced user or sometimes even an avid practitioner of QSAR could be easily confused by the diversity of methodologies and naming conventions used in QSAR studies. 2D or three-dimensional (3D) QSAR, variable selection or artificial neural network (ANN) methods, Comparative molecular field analysis (CoMFA), or binary QSAR present examples of various terms that may appear to describe totally independent approaches, which cannot be generalized or even compared to each other. In fact, any QSAR method can be generally defined as an application of mathematical and statistical methods to the problem of finding empirical relationships (QSAR models) of the form $P i=k(D 1, D 2, \ldots D n)$, where $P i$ are biological activities (or other properties of interest) of molecules, $D 1, D 2, \ldots D n$ are calculated (or, sometimes, experimentally measured) structural properties (molecular descriptors) of compounds, and $k$ is some empirically established mathematical transformation that should be applied to descriptors to calculate the property values for all molecules.

The relationship between values of descriptors D and target properties P can be linear (e.g., MLR as in the Hansch QSAR approach), where target property can be predicted directly from the descriptor values, or nonlinear (such as ANNs or classification QSAR methods) where descriptor values are used in characterizing chemical similarity between molecules, which in turn is used to predict compound activity.

The differences in various QSAR methodologies can be understood in terms of the types of target property values, descriptors, and optimization algorithms used to relate descriptors to the target properties and generate statistically significant models.

A- Target properties(regarded as dependent variables in statistical data modeling sense) can generally be of three types:
(1) continuous, i.e., real values covering certain range, e.g., IC50, MIC values, or binding constants.
(2) categorical related, classes of target properties covering certain range of values, e.g., active and inactive compounds, frequently encoded numerically for the purpose of the subsequent analysis as 1 (for active) or 0 (for inactive), or adjacent classes of metabolic stability such as unstable, moderately stable, and stable.
(3) categorical unrelated, classes of target properties that do not relate to each other in any continuum, e.g., compounds that belong to different pharmacological classes, or compounds that are classified as drugs versus non drugs.

B- Chemical descriptors(or independent variables in terms of statistical data modeling) can be typically classified into two types:
(1) continuous (i.e., range of real values, e.g., as simple as molecular weight or many molecular connectivity indices); or
(2) categorical related (i.e., classes corresponding to adjacent ranges of real values, e.g., counts of functional groups or binary descriptors indicating presence or absence of a chemical functional group or an atom in a molecule).

Descriptors can be generated from various representations of molecules, e.g., 2D chemical graphs or 3D molecular geometries, giving rise to the terms of 2D or 3D QSAR, respectively.

C- Correlation methods(which can be used either with or without variable selection) can be classified into two major categories:
(1) linear (e.g., linear regression (LR), or principal component regression (PCR), or partial least squares (PLS)) or
(2) nonlinear (e.g., k nearest neighbor (kNN), recursive partitioning (RP), ANNs, or support vector machines (SVMs). [78]


Figure .30.Molecular descriptors and fingerprints are examples of strategies that allow researchers to extract important information about compounds that can be used in additional computer-aided drug design techniques, such as virtual screening, quantitative-structure-activity relationship (QSAR).

In some cases, the types of biological data, the choice of descriptors, and the class of optimization methods are closely related and mutually inclusive. For instance, MLR can only be applied when a relatively small number of molecular descriptors are used (at least five to six times less than the total number of compounds) and the target property is characterized by a continuous range of values. The use of multiple descriptors makes it impossible to use MLR due to a high chance of spurious correlation [79] and requires the use of PLS or nonlinear optimization techniques.

## II.3.1 Molecular Descriptors

Theoretical descriptors derived from physical and physico-chemical theories show some natural overlap with experimental measurements. Several quantum chemical descriptors, surface areas, and volume descriptors are examples of such descriptors also having an experimental counterpart.

With respect to experimental measurements, the greatest recognized advantages of the theoretical descriptors are usually (but not always) in terms of cost, time, and availability.

Each molecular descriptor takes into account a small part of the whole chemical information contained in to the real molecule and,asaconsequence, the number of descriptors
iscontinuouslyincreasingwiththeincreasingrequestofdeeperinvestigationsonchemicalan d biological systems. Different descriptors have independent methods or perspectives to view
molecule,takingintoaccountthevariousfeaturesofchemicalstructure.Moleculardescriptor s have now become some of the most important variables used in molecular modeling, and, consequently, managed by statistics, chemometrics, and chemoinformatics[80].

There are many different descriptors and many different kinds of classification based on the effect (steric, hydrophobic, electronic, etc.) or based on its dimension that called Descriptors Block, whereas we find four types of molecular descriptors 0D, 1D, 2D and 3D [80].

- Molecular descriptors 0D, 1D: contains numbers of atoms, functional groups, molecules properties, and charges (eg.MolecularWeight, MolecularRefractivity,etc.).
- Moleculardescriptors2D:containssimpledescriptorsandotherderivativesofalgorit hms applied to a topological representation (eg. Number of Cl atoms, presence of hydroxyl group,etc.).
- Molecular descriptors 3D: contains descriptors derived from a geometric representation also called geometric descriptors (eg. Molecular volume, Surface area,etc.).


## II.3.3 Quantitative Structure-Activity Relationship Modeling Approaches

## II.3.3.1 General Classification

Many different approaches to QSAR have been developed since Hansch's seminal work. As briefly discussed above, the major differences between these methods can be analyzed from two viewpoints:
(1) the types of structural parameters that are used to characterize molecular identities starting from different representation of molecules, from simple chemical formulas to 3D conformations, and
(2) the mathematical procedure that is employed to obtain the quantitative relationship between these structural parameters and biological activity.

Based on the origin of molecular descriptors used in calculations, QSAR methods can be divided into three groups.
One group is based on a relatively small number (usually many times smaller than the number of compounds in a data set) of physicochemical properties and parameters describing hydrophobic, steric, electrostatic, etc. effects. Usually, these descriptors are used as independent variables in multiple regression approaches. In the literature, these methods are typically referred to as Hansch analysis.

A more recent group of methods is based on quantitative characteristics of molecular graphs (molecular topological descriptors). Since molecular graphs or structural formulas are 'two dimensional,' these methods are described as 2D QSAR. Most of the 2D QSAR methods are based on graph theoretical indices. Although these structural indices represent different aspects of molecular structures, and, what is important for QSAR, different structures provide numerically different values of indices, their physicochemical meaning is frequently unclear.

The third group of methods is based on descriptors derived from spatial (3D) representation of molecular structures. Correspondingly, these methods are referred to as 3D QSAR; they have become increasingly popular with the development of fast and accurate computational methods for generating 3D conformations and alignments of chemical structures. Perhaps the most popular example of 3D QSAR is CoMFA, developed by Cramer et al.,[81]which has combined the power of molecular graphics and PLS technique and has found wide applications in medicinal chemistry and toxicity analysis.[82]

## II.3.3.2. General Methodology of a QSPR / QSAR study

The general methodology of a QSAR / QSPR study is as follows:
a- Build up a database from reliable experimental measurements of the property or activity of each compound.
b- Select the descriptors in relation to the property or activity studied.
c- Divide this database, randomly, into a training set which generally contains $2 / 3$ of the database and a test series (test set) consisting of the remaining $1 / 3$.
d- Establish mathematical models using the learning series.
e- Characterize the models developed by their internal validation indices and check their robustness by a randomization test (Randomization) of the dependent variable Y (response).
f-Validate the models developed using the test series and calculate their statistical parameters for external validation.

## II.3.3.3 Transforming the Bioactivities

The main advantage of transforming data is to guarantee linearity, to achieve normality, or to stabilize the variance. Several simple nonlinear regression relationships can be made linear through the appropriate transformations. The simplest and most common method of transforming [83]bioactivity data is to take the log or negative $\log$ of the bioactivities to reduce the range of the data.

The method of creating Training and Test Sets that are representative of the population is to choose molecules that represent all the molecules of interest based on molecular structure and bioactivity. The number of molecules in the Test Set is determined ( $20 \%$ of the total molecules in this study) and then all the molecules are placed in a table and ordered based on bioactivities. With the table prepared, the extraction of the molecules for the Test Set can begin through an iterative process starting at the top of the table.

## II.3.3.4 Determination of the Best Set of Descriptors Approaches

Both 2D and 3D QSAR studies have focused on the development of optimal QSAR models through variable selection. This implies that only a subset of available descriptors of chemical structures, which are the most meaningful and statistically significant in terms of correlation with biological activity, is selected. The Stepwise Method Search selects a model by adding or removing individual descriptors, a step at a time, based on their statistical significance. The end result of this process is a single regression model, which makes it nice and simple. The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value ( $<0.05$ ) indicates that you can reject the null hypothesis. In other words, a descriptor that has a low p-value is likely to be a meaningful addition to
your model because changes in the descriptor's value are related to changes in the response variable (bioactivity). Conversely, a larger (insignificant) p-value suggests that changes in the descriptor are not associated with changes in the response.

## II.4. Building Predictive Quantitative Structure-Activity Relationship Models: <br> The Approaches to Model Validation

## II.4.1. Data analysis methods

To develop a QSPR / QSAR model we need a data analysis method, this method allows to quantify the relationship between the property / Activity and the Structure (descriptors).

There are several methods to build a model and analyze its statistical data, some are linear such as multiple linear regression (MLR), partial least squares (PLS) regression, others are nonlinear such as trees of decisions, neural networks... these methods are available in software such as, Excel, Origin Microcal, Minitab, Statistica, SPSS, JMP, $R, \ldots$

The method used in our studies is the Multiple Linear Regression (MLR) and Neural Networks (ANN) method.

## II.4.1.1. Neural networks

The formal neural networks initiated in 1943 by Mc Culloch and Pitts are analogous to biological nervous systems.[84]

Formal neurons (Figure 31) perform a linear combination of the inputs received(descriptors), then apply to this value an activation function $f$, generally nonlinear (sigmoidal, tangent, hyperbolic). The obtained value Y (biological activity) is the output of the neuron.[85]

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Figure.31.Representation of a formal neuron.
$\mathbf{X k}$ (where $\mathrm{k}=1,2, \cdots, \mathrm{n}$ ) are the input neurons (descriptors) and $\mathbf{W} \mathbf{k}$
(where $\mathrm{k}=0,1,2, \cdots, \mathrm{n}$ ) are the weights. W0 is the weight associated with an entry set at 1 , called bias. The neuron equation looks like this:

$$
y=f\left(W_{0}+\sum_{k=1}^{n} W_{k} X_{k}\right)
$$

Neurons alone perform fairly simple functions, and it is their combinations, called neural networks, that make it possible to construct particularly interesting functions (Figure 31).


Figure.32.Architecture of neural networks.

The architecture of neural networks consists of three layers:

- An input layer: made up of input neurons, their number is equal to the number of input variables (descriptors) plus one (bias). Each neuron is connected to the hidden neurons.
- A hidden layer: made up of a variable number of neurons. For each hidden neuron, the network performs a weighted sum operation with the different weights of each input neuron.
- An output layer: where the number of output neurons is equal to the number of properties (activities) to be modeled.

Each connection between the neurons of the different layers is associated with a weight. The number of weights then depends on the number of neurons in the hidden layer, so it is possible to vary the complexity of the network by increasing or decreasing the number of hidden neurons. To do this, data presentation cycles are established via a learning algorithm. The one used in our approach is a backpropagation algorithm.[86]

The principle of the back-propagation algorithm is to minimize the difference between the calculated output (calculated activity) and the experimental values of the activity.

Defined in two stages, the algorithm propagates in a first stage the inputs (descriptors) forward until obtaining an output (biological activity) calculated by the network. In a second step, the calculated output is compared with the experimental value. The error obtained by this comparison is then propagated back to the input layer by modifying the weights of the neurons. This process is repeated until a negligible error is obtained.[87]

## II.4.1.2 Multiple linear regression

Multiple linear regression is the simplest statistical modeling method and the most applied in studies of the structure-activity relationship [88]. The method was popularized by Hanch by relating biological activity to experimental lipophilic, electronic and steric properties for series of compounds.[89]

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The RLM method is based on the assumption that there is a linear relationship between a dependent variable Y (in our case the biological activity) and a series of n independent variables Xi (here, the molecular descriptors)[90]. The objective is to arrive at a mathematical equation of the form:

$$
y=a_{0}+a_{1} x_{1}+a_{2} x_{2}+\cdots+a_{n} x_{n}
$$

Where $a_{i}(i=0,1, \ldots, n)$ are the coefficients of the regression.

Determining the equation from a data set of $p$ samples is like solving a system of $p$ equations.

$$
\begin{aligned}
& y_{1}=a_{0}+a_{1} x_{1,1}+a_{2} x_{2,1}+\cdots+a_{n} x_{n, 1}+b_{1} \\
& y_{2}=a_{0}+a_{1} x_{1,2}+a_{2} x_{2,2}+\cdots+a_{n} x_{n, 2}+b_{2} \\
& \\
& y_{p}=a_{0}+a_{1} x_{1, p}+a_{2} x_{2, p}+\cdots+a_{n} x_{n, p}+b_{p}
\end{aligned}
$$

Or:

The residuals bi $(i=1,2, \ldots, p)$ represent the model error, yi $(i=1,2, \ldots, p)$ represent the dependent variables (activities), $x i(i=1,2, \ldots, p)$ represent the independent variables (descriptors), ai $(i=1,2, \ldots, p)$ represent the coefficients of the regression.

This set of equations can be written in the following matrix form:

$$
\left(\begin{array}{c}
y_{1} \\
y_{2} \\
\vdots \\
\vdots \\
y_{p}
\end{array}\right)=\left(\begin{array}{cccccc}
1 & x_{1,1} & x_{2,1} & \cdots & \cdots & x_{n, 1} \\
1 & x_{1,2} & x_{2,2} & \cdots & \cdots & x_{n, 2} \\
\vdots & \vdots & & & & \\
\vdots & \vdots & & & & \\
1 & x_{1, p} & x_{2, p} & \cdots & \cdots & x_{n, p}
\end{array}\right)\left(\begin{array}{c}
a_{0} \\
a_{1} \\
\vdots \\
\vdots \\
a_{p}
\end{array}\right)+\left(\begin{array}{c}
b_{1} \\
b_{2} \\
\vdots \\
\vdots \\
b_{p}
\end{array}\right)
$$

Or in a condensed way:

$$
\mathbf{Y}=\mathbf{X A}+\mathbf{B}
$$

Where $\mathbf{Y}, \mathbf{X}, \mathbf{A}$, and B represent the property vector, the attribute matrix (descriptors), the coefficient matrix, and the regression error matrix, respectively.

The RLM method then consists in choosing the coefficients ai so as to minimize the sum of the squares of the differences between the calculated values of the property and the experimental ones, the equation of the model therefore becomes:

$$
\hat{y}_{i}=\hat{a}_{0}+\hat{a}_{1} x_{1, i}+\hat{a}_{2} x_{2, i}+\cdots+\hat{a}_{n} x_{n, i}
$$

Or in matrix form:

$$
X . A=Y
$$

The coefficients can be obtained from the following matrix equation:

$$
A=\left(X^{T} \cdot X\right)^{-1} X^{T} \cdot Y
$$

## II.4.1.2.1. Randomization test

The randomization test is used by the modeler to assert that the good correlations, between descriptors and activity, presented by the QSAR model are not due to luck. To do this, the observations are randomly disorganized, for example ten times, by randomly changing the activity column, but the descriptor columns remain unchanged[91]. We therefore obtain ten models with specific statistical characteristics. If the randomization of the observations leads to weak forecast models, this means that
the predictive capacities of the constructed QSAR model are not due to the correlations of luck.[92]

## II.4.2. Interpretation and validation of a QSPR / QSAR model

Once developed, the model must be interpreted by analyzing all the statistical parameters of this model, its quality must also be studied, this quality is checked by what is called validation. Its robustness, ie the influence of the compounds of the training series on the model, is estimated by internal validation methods. In order to estimate its predictive power, additional experimental data is needed to determine the ability of the model to predict these values, this is called external validation. Finally, it is important to know which type of molecules used with which model.

## II.4.2.1. The Importance of Validation

The process of QSAR model development is divided into three key steps: (1) data preparation, (2) data analysis, and (3) model validation. The implementation and relative merit of these steps is generally determined by the researcher's interests and experience, and the availability of software. The resulting models are then frequently employed, at least in theory, to design new molecules based on chemical features or trends found to be statistically significant with respect to underlying biological activity.

The first stage includes the selection of a data set for QSAR studies and the calculation of molecular descriptors. The second stage deals with the selection of a statistical data analysis technique, either linear or nonlinear such as MLR, PLS or ANN. A variety of different algorithms and computer software are available for this purpose. In all approaches, descriptors are considered as independent variables, and biological activities as dependent variables.

Typically, the final part of QSAR model development is model validation, [93, 94]in which estimates of the predictive power of the model are calculated. This predictive power is one of the most important characteristics of QSAR models. Ideally, it should be defined as the ability of the model to predict accurately the target property (e.g., biological activity) of compounds that were not used in model
development.
Here, we are going to discuss about the validation parameters for the QSAR models which are developed by multiple linear regression (MLR). Four tools of assessing validity of QSAR models [95]are (i) cross-validation, (ii) bootstrapping, (iii) randomization of the response data, and (iv) external validation. Where we are using the data that created the model (an internal method) and using a separate data set (an external method).

The methods of least squares fit ( $\mathrm{R}^{2}$ ), cross validation $\left(\mathrm{Q}^{2}\right)$ [96, 97], adjusted $\mathrm{R}^{2}$ ( $\mathrm{R}^{2}$ adj), chisquared test ( $\chi^{2}$ ), rootmean-squared error (RMSE), bootstrapping and scrambling (YRandomization) [98, 99] are internal methods of validating a model. The best method of validating a model is an external method, such as evaluating the QSAR model on a test set of compounds.

## II.4.2.1.1. Internal Validation

## II.4.2.1.1.1. Least Squares Fit

The most common internal method of validating the model is least squares fitting. This method of validation is similar to linear regression and is the $R^{2}$ (squared correlation coefficient) for the comparison between the predicted and experimental activities. An improved method of determining $R^{2}$ is the robust straight line fit, where data points are away from the central data points (essentially data points a specified standard deviation away from the model) are given less weight when calculating the $R^{2}$. An alternative to this method is the removal of outliers (compounds from the training set) from the dataset in an attempt to optimize the QSAR model and is only valid if strict statistical rules are followed. The difference between the $R^{2}$ and $R^{2} a d j$ value is less than 0.3 indicates that the number of descriptors involved in the QSAR model is acceptable. The number of descriptors is not acceptable if the difference is more than 0.3.

$$
\begin{aligned}
& R^{2}=1-\frac{\text { PRESS }}{\sum_{i=1}^{n}\left(y_{i}-y_{m}\right)^{2}} \\
& \text { PRESS }=\sum_{i=1}^{n}\left(\hat{y}_{i}-y_{i}\right)^{2}
\end{aligned}
$$

Where, $y$ and $\hat{y}$ are the experimental and predicted bioactivity for an individual compound in the training set, $y_{m}$ is the mean of the experimental bioactivities, and $n$ is the number of molecules in the set of data being examined. PRESS is the predictive residual sum of the squares.

## II.4.2.1.1.2 Fit of the Model

Fit of the QSAR models can be determined by the methods of chi-squared $\left(\chi^{2}\right)$ and root-mean squared error ( $R M S E$ ). These methods are used to decide if the model possesses the predictive quality reflected in the $R^{2}$. The use of $R M S E$ shows the error between the mean of the experimental values and predicted activities. The chi squared value exhibits the difference between the experimental and predicted bioactivities:

$$
\begin{gathered}
\chi^{2}=\sum_{i=1}^{n}\left(\frac{\left(y_{i}-\hat{y}_{i}\right)^{2}}{\hat{y}_{i}}\right) \\
R M S E=\sqrt{\sum_{i=1}^{n} \frac{\left(\hat{y}_{i}-y_{m}\right)^{2}}{n-1}}
\end{gathered}
$$

Large chi-square or $R M S E$ values ( $\geq 0.5$ and 1.0 , respectively) reflect the model's poor ability to accurately predict the bioactivities even the model is having large $R^{2}$ value ( $\geq 0.7$ ).

For good predictive model the chi and $R M S E$ values should be low ( $<0.5$ and $<0.3$, respectively). These methods of error checking can also be used to aid in creating models and are especially useful in creating and validating models for nonlinear data sets, such as those created with Artificial Neural Network (ANN) [100]. However, excellent values of $R^{2}, \chi^{2}$ and $R M S E$ are not sufficient indicators of model validity. Thus, alternative parameters must be provided to indicate the predictive ability of models. In principle, two reasonable approaches of validation can be envisaged one based on prediction and the other based on the fit of the predictor variables to rearranged response variables.

## II.4.2.1.2 External validation

Several authors have suggested that the only way to estimate the true predictive power of a QSAR model is to compare the predicted and observed activities of an (sufficiently large)external test set of compounds that were not used in the model development [94, 101-104]. The problem in external validation is how can we select the training and test set? Roy et al. clearly discussed that how we can solve this problem in one of their article. [105]

To estimate the predictive power of a QSAR model, Golbraikh and Tropsha recommended use of the following statistical characteristics of the test set [93]: (i) correlation coefficient R between the predicted and observed activities; (ii) coefficients of determination ( $R 2$ ) (predicted vs. observed activities $\mathrm{r}_{0}{ }^{2}$, and observed vs. predicted activities $\mathrm{r}_{0}{ }^{\prime}$ ); (iii) slopes k and $\mathrm{k}^{\prime}$ of the regression lines through the origin. They consider a QSAR model is predictive, if the following conditions are satisfied [93]:

$$
\begin{gathered}
R_{\text {test }}^{2}>0.6 ; \\
r^{2}-\frac{r_{0}^{2}}{r^{2}}<0.1 \quad ; \quad r^{2}-\frac{r_{0}^{\prime 2}}{r^{2}}<0.1 \quad \text { and } \\
0.85 \leq k \leq 1.15 \quad \text { or } \quad 0.85 \leq k^{\prime} \leq 1.15
\end{gathered}
$$

The predictive ability of the selected model was also confirmed by external $R^{2}$ test. A value of $R^{2}$ test is greater than 0.6 may be taken as an indicator of good external predictability.

$$
R_{\text {test }}^{2}=1-\frac{\sum_{i=1}^{t e s t}\left(y_{\text {exp }}-y_{p r e d}\right)^{2}}{\sum_{i=1}^{t e s t}\left(y_{\exp }-\bar{y}_{t r}\right)^{2}}
$$

Where $\overline{y t r}$ is the average value for the dependent variable for the training set. Kubinyi et al[94], Novellino et al.[102], Norinder[103], and Golbraikh and

Tropsha[93]demonstrated that all of the above-mentioned criteria are necessary to adequately assess the predictive ability of a QSAR model. Norinder suggest [103]that the external test set must contain at least five compounds, representing the whole range of both descriptor and activities of compounds included into the training set.

## II.5. Application of QSAR

There are a large number of applications of QSAR models in industry, in university research, in economics, in weather forecasting, ...etc.

We report below some possible applications of QSAR models:

- Rational identification of new leads with: optimization of pharmacological, biocidal or pesticide activity.
- Rational design of many products such as surfactants, perfumes, dyes and fine chemicals.
- The identification of dangerous compounds in the early stages of development.
- Prediction of toxicity and side effects of new compounds.
- The selection of compounds with optimal pharmacokinetic properties, be it stability or availability in biological systems.



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Figure.33. Schematic overview of the QSAR process.

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## Chapter III

## Results and Discussion

Many researches have been carried out for the development of anticancer drugs; nevertheless, no drug could achieve a parasitological cure and some of them presented serious toxic side effects.

While, RESEARCHES NEVER END WITH NOTHING, some compounds were found to be important candidates as inhibitors against topoisomerase II and cytotoxic activity.

Therefore, following our interest in this field, we applied several computational methods on the most effective Topo II candidates in order to, study structures and properties of these ligands, evaluate their biological response and better understand topoisomerase II inhibition mode.

To simplify our ideas, we divide this chapter to three big titles as fellow:

## - Molecular Geometry, Electronic Properties, MPO Methods and Structure

 Activity/Property Relationship Studies of carbazole derivatives containing chalcone Analogues (CDCAs).At first, we aim to study the Structure, spectroscopy and electronic properties of carbazole subunit using DFT methods, Afterward, we extend a dataset of Carbazole Derivatives containing Chalcone Analogues, in order to identify compounds with higher potency, we study physicochemical properties, descriptors and drug-likeness scoring.

- Quantitative Structure-Activity Relationships of Topo II inhibition activity of carbazole derivatives containing chalcone analogues (CDCAs).

Next, in this part we develop QSAR models of CDCAs analogues with respect to their topoisomerase II inhibition activities.

## Result and discussion

## III . 1 Introduction

Carbazole is a tricyclic compound (figure 34) belonging to the general class of nitrogen heterocycles. It possesses photoluminescent properties and good thermal stabilities [1,2]due its extended $\pi$-conjugation and aromatic character. [1]Carbazole derivatives exhibit interesting biological activities, with high potential for use as antibacterial, antifungal, antiviral, antimalarial, anticancer and anti-Alzheimer agents. [3,4]Additionally, carbazole-based compounds have potential applications for the symptomatic and disease-modifying treatment of Parkinson's disease. [5] Some derivatives of carbazole, such as N -substituted carbazole-imidazole hybrids, N substituted carbazole imidazolium salts [6], N-thioalkylcarbazoles [7]and carbazole aminoalcohols, [8]have shown anti-proliferative activity against several tumor cell lines by a variety of mechanisms based on the inhibition of topoisomerase I and II (Topo I and Topo II, respectively). Further, according to recent studies, [9,10] it has been found that the carbazole scaffold functionalized with small substitution groups leads to stabilization of the intramolecular G-quadruplex, thus inhibiting the telomerase activity.


Figure .34.Chemical structure of carbazole with atom numbering.

A new set of Carbazole Derivatives containing Chalcone Analogues (CDCAs) was reported by Li et al in 2018. [11]All these compounds (from 1 to 24, see Table 3) possess a carbazole moiety connected to a chalcone group, with the only exception of

## Result and discussion

compound 8 , in which the phenyl group of chalcone is replaced by a thiophene unit. Although etoposide (VP-16), here numbered as compound 25, is chemically different from the other compounds in Table 3, it was chosen as a reference drug. Indeed, its use as an efficient antineoplastic agent is well established since more than five decades.
$[12,13] \mathrm{Li}$ et al. showed that the carbazole subunit in these compounds acts as a scaffold for Topo II inhibition, and that the chalcone moiety of CDCAs plays a key role in anticancer activity. This CDCAs series exhibits also a strong Topo II inhibitory and moderate cytotoxic activity against different tested cancer cell lines such as Hela, HL-60, A549, and PC-3. The different inhibitory activity shown by these molecules in laboratory studies is related to the differences in their molecular structures.

Table 3: Chemical structure and experimental activity ( $\mathrm{pIC}_{50}[11]$ ) of the CDCAs under study. pIC 50 is $\log _{10}(1 / \mathrm{IC} 50)$. * denotes the compounds selected for external validation (test set).
(
(13

Computational chemistry and modelling are useful tools in modern pharmacological and medicinal chemistry for both drug discovery and drug development. Indeed, their interplay with biological sciences have resulted in a better understanding of the mechanisms of action of drugs and body functions at the cellular and molecular levels. Consequently, most research projects in the pharmaceutical industry start by identifying a suitable target in the body and designing drugs able to interact with it. Knowledge of the structure and function of the target, as well as the mechanisms by which it interacts with drug molecules, is crucial to this approach. [14]In this respect, Density Functional Theory (DFT) [15-17] is a very elegant approach to describe the chemical processes and provides a powerful theoretical framework for the study of both reactivity and selectivity [17]of medium-sized molecular systems. In addition, the

## Result and discussion

Quantitative Structure-Activity Relationships (QSAR) approach attempts to establish a mathematical relation between the physicochemical and structural properties of a potential drug and its biological activity, [18]expressed in terms of $\mathrm{pIC}_{50}$. Thus, it allows designing drug molecules with improved pharmacokinetic properties, reducing the number of compounds to be tested and limiting development failures. [14]

In this paper, we carried out several benchmark computations on the structure and spectroscopy of the carbazole subunit using the DFT technique. After comparison to experiments, it turns out that the B3LYP/6-311 $\mathrm{G}(\mathrm{d}, \mathrm{p})$ level is accurate enough to derive accurate physicochemical properties and parameters for the 25 CDCA derivatives identified in the recent work by Li et al. [11]In order to predict the pharmacological activity of these compounds, we incorporated these parameters into quantitative models based on two statistical methods: Multiple Linear Regression (MLR) and Artificial Neural Network (ANN). As implemented, the present combined QSAR-DFT approach [19-23] for the calculation of descriptors allows us to build simpler (less parameterized) models, thus reducing the risk of over-parameterization, for an easier and more direct interpretation of the drug activity at the phenomenological level. In order to develop an accurate model capable of explaining the role of CDCAs derivatives in chemotherapy, we have performed drug-like calculations, evaluations of physicochemical properties and QSAR study of carbazole derivatives containing chalcone analogues targeting Topo II inhibition (Figure 35) and presenting strong cytotoxic activity. In addition, our model will facilitate the design of new CDCAs for this purpose.


Figure .35. The Synthetic or natural carbazole derivatives induces cancer cells death triggering the intrinsic apoptotic pathway by inhibition of Topoisomerase II.

## III . 2 Structure, spectroscopy and electronic properties of carbazole and its derivatives

The choice of the approach for electronic structure computations on a given molecular system is crucial to accurateely describe its reactivity, selectivity and most stable molecular conformation. Indeed, the latter is closely connected to the identification of interactions between the drug and active site of the enzyme. Due to the relatively large size of drug molecules, post Hartree-Fock ab initio computations on these systems are out of reach. Instead, various studies showed that DFT calculations on large molecules yield good results on different systems (organic, inorganic, and organometallic ...) [23-26] at a reasonable computational cost. Indeed, DFT takes into account the dynamic correlation of electrons [27], which is mandatory for the accurate description of the structure and the spectroscopic properties of these compounds. Hence, in this study we opted for DFT-based approaches. For instance, computations were performed using gradient-corrected DFT with the Becke 3 exchange [28] and Lee-Yang-Parr correlation functions (B3LYP), in conjunction with three different basis sets $6-31 \mathrm{G}+(\mathrm{d}, \mathrm{p}), 6-311 \mathrm{G}$ and $6-311 \mathrm{G}(\mathrm{d}, \mathrm{p})$, as implemented in GAUSSIAN 09 program package. [29]

## III . 2.1 Carbazole structure and properties

Prior to deriving the properties of the CDCAs of interest, we performed geometry optimizations of the carbazole subunit in its electronic ground state. We carried out these computations at the B3LYP/6-31G+(d,p), B3LYP/6-311G and B3LYP/6-311G(d,p) levels of theory in order to select an appropriate atomic basis set for the molecular systems studied herein. The results are listed in Table 2.

## Result and discussion

Table 4: Equilibrium Geometrical Parameters (Bond lengths in $\AA$ and angles in degrees) of carbazole in its electronicground state. The numbering of the atoms is given in Figure 34.

|  | DFT/B3LYP |  |  | Exp. ${ }^{\text {a }}$ |
| :---: | :---: | :---: | :---: | :---: |
| Parameters | 6-31G+(d.p) | 6-311G | 6-311G(d,p) |  |
| C1-C2 | 1.398 | 1.397 | 1.395 | 1.393 |
| C1-C6 | 1.421 | 1.424 | 1.419 | 1.401 |
| C1-N13 | 1.388 | 1.396 | 1.385 | 1.387 |
| C2-C3 | 1.395 | 1.395 | 1.390 | 1.373 |
| C2-H14 | 1.087 | 1.082 | 1.085 | 1.00 |
| C3-C4 | 1.408 | 1.408 | 1.404 | 1.379 |
| C3-H15 | 1.086 | 1.082 | 1.084 | 0.96 |
| C4-C5 | 1.394 | 1.395 | 1.390 | 1.379 |
| C4-H16 | 1.086 | 1.082 | 1.084 | 1.02 |
| C5-C6 | 1.402 | 1.400 | 1.398 | 1.388 |
| C5-H17 | 1.087 | 1.082 | 1.085 | 1.01 |
| C6-C7 | 1.450 | 1.454 | 1.449 | 1.415 |
| C7-C8 | 1.402 | 1.400 | 1.398 | 1.388 |
| C7-C12 | 1.421 | 1.424 | 1.419 | 1.401 |
| C8-C9 | 1.394 | 1.395 | 1.390 | 1.379 |
| C8-H18 | 1.087 | 1.082 | 1.085 | 1.01 |
| C9-C10 | 1.408 | 1.408 | 1.404 | 1.379 |
| C9-H19 | 1.086 | 1.082 | 1.084 | 1.02 |
| C10-C11 | 1.395 | 1.395 | 1.390 | 1.373 |
| C10-H20 | 1.086 | 1.082 | 1.084 | 0.96 |
| C11-C12 | 1.398 | 1.397 | 1.395 | 1.393 |
| C11-H21 | 1.087 | 1.082 | 1.085 | 1.00 |
| C12-N13 | 1.388 | 1.396 | 1.385 | 1.387 |
| N13-H22 | 1.007 | 1.003 | 1.057 | 0.98 |
| C2-C1-C6 | 121.9 | 121.8 | 121.8 | 122.3 |
| C2-C1-N13 | 129.6 | 129.8 | 129.7 | 128.7 |
| C6-C1-N13 | 108.4 | 108.3 | 108.4 | 109 |
| C1-C2-C3 | 117.6 | 117.7 | 117.7 | 116.7 |
| C1-C2-H14 | 121.4 | 121.3 | 121.3 | 121 |
| C3-C2-H14 | 120.9 | 120.8 | 120.9 | 122 |
| C2-C3-C4 | 121.3 | 121.2 | 121.3 | 122 |

## Result and discussion

| C2-C3-H15 | 119.2 | 119.3 | 119.2 | 119 |
| :---: | :---: | :---: | :---: | :---: |
| C4-C3-H15 | 119.4 | 119.4 | 119.4 | 119 |
| C3-C4-C5 | 120.7 | 120.7 | 120.7 | 121 |
| C3-C4-H16 | 119.5 | 119.4 | 119.4 | 118 |
| C5-C4-H16 | 119.8 | 119.8 | 119.8 | 121 |
| C4-C5-C6 | 119.2 | 119.2 | 119.2 | 118.4 |
| C4-C5-H17 | 120.3 | 120.3 | 120.3 | 124 |
| C6-C5-H17 | 120.5 | 120.5 | 120.4 | 118 |
| C1-C6-C5 | 119.2 | 119.2 | 119.2 | 119.7 |
| C1-C6-C7 | 106.7 | 106.9 | 106.7 | 106.6 |
| C5-C6-C7 | 134.0 | 133.9 | 134.1 | 133.7 |
| C6-C7-C8 | 134.0 | 133.9 | 134.1 | 133.7 |
| C6-C7-C12 | 106.7 | 106.9 | 106.7 | 106.6 |
| C8-C7-C12 | 119.2 | 119.2 | 119.2 | 119.7 |
| C7-C8-C9 | 119.2 | 119.2 | 119.2 | 118.4 |
| C7-C8-H18 | 120.4 | 120.5 | 120.4 | 118 |
| C9-C8-H18 | 120.3 | 120.3 | 120.3 | 124 |
| C8-C9-C10 | 120.7 | 120.7 | 120.7 | 121 |
| C8-C9-H19 | 119.8 | 119.8 | 119.8 | 121 |
| C10-C9-H19 | 119.5 | 119.4 | 119.4 | 118 |
| C9-C10-C11 | 121.3 | 121.2 | 121.3 | 122 |
| C9-C10-H20 | 119.4 | 119.4 | 119.4 | 119 |
| C11-C10-H20 | 119.2 | 119.3 | 119.2 | 119 |
| C10-C11-C12 | 117.6 | 117.7 | 117.7 | 116.7 |
| C10-C11-H21 | 120.9 | 120.8 | 120.9 | 122 |
| C12-C11-H21 | 121.4 | 121.3 | 121.3 | 121 |
| C7-C12-C11 | 121.9 | 121.8 | 121.8 | 122.3 |
| C7-C12-N13 | 108.5 | 108.3 | 108.4 | 109 |
| C11-C12-N13 | 129.6 | 129.8 | 129.7 | 128.7 |
| C1-N13-C12 | 109.6 | 109.5 | 109.6 | 108.7 |
| C1-N13-H22 | 125.2 | 125.2 | 125.8 | 125.65 |
| C12-N13-H22 | 125.2 | 125.2 | 125.8 | 125.65 |

a. Ref. [30].
where a comparison is made between these theoretical data and the experimental results by Gerkin and Reppart. [30] As expected, the larger basis set (i.e.

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6-311G(d,p)) performs better than the smaller ones. Indeed, a good agreement between the experimental data and those deduced using the $6-311 \mathrm{G}(\mathrm{d}, \mathrm{p})$ basis set is found. For instance, deviations between the computed and measured distances are mostly in the range $0.002-0.2 \AA$. For the angles, the differences between the two sets are mostly less than $1^{\circ}$, except for a few ones that are $3.7^{\circ}$ off. Such deviations may be related to the gas phase structure (here) and the crystal structure of carbazole determined in Gerkin and Reppart's experiments. Overall, this basis set is reliable enough for the study of the molecular and electronic structure of this molecule and of its derivatives. For further confirmation, we computed the anharmonic frequencies of carbazole. Table 3 gives the computed values for the 60 normal modes of vibration of carbazole, together with the comparison to the measured fundamentals by Bree and Zwarich. [31]Again, a good agreement is found between the two sets of data, where the differences between both sets are less than $30 \mathrm{~cm}^{-1}$, except for $\mathrm{U}_{1}$ ( NH stretching), for which we computed $3501 \mathrm{~cm}^{-1}$, while Bree and Zwarich measured $3421 \mathrm{~cm}^{-1}$. In sum, we conclude that B3LYP, in conjunction with the $6-311 \mathrm{G}(\mathrm{d}, \mathrm{p})$ basis set, is accurate enough for investigating the carbazole derivatives. In the following, this level of theory will be used for the treatment of the structural and physicochemical properties of the CDCAs of interest.

Table 5:Comparison of the experimental and calculated anharmonic frequencies ( $\mathrm{v}, \mathrm{in}_{\mathrm{cm}}{ }^{-1}$ ) ) of carbazole. Computed at the B3LYP/6-311G(d,p) level of theory and we give also the computing of IR intensity (I in (km/mol). Abbreviations used:v,stretching; vs, sym. stretching; vas, asym. stretching; b, in-plane-bending; g, out-of-plane bending; Ben: Benzene; Pyr: pyrrole.

| Sym | Calculated |  |  | $\operatorname{Exp}^{\text {a) }}$ |
| :--- | :--- | :--- | :--- | :--- |
|  | $v$ | I | Assignment |  |
| $\mathrm{a}_{1}$ | 3501 | 41.0 |  | v NH (Ben) |
|  | 3056 | 43.2 | 3084 | vs CH (Ben) |
|  | 3051 | 2.3 | 3077 | vs CH (Ben) |
|  | 3048 | 1.2 | 3055 | vs CH (Ben) |
|  | 3046 | 55.6 | 3039 | vas CH (Ben) |
|  | 1628 | 2.9 | 1625 | $\beta$ CCC (Ben) + v CC (Pyr) |


|  | 1580 | 0.8 | 1576 | v C=C (Ben-Pyr) |
| :---: | :---: | :---: | :---: | :---: |
|  | 1486 | 0.0 | 1481 | $v$ CC (Pyr) |
|  | 1449 | 27.1 | 1449 | v C=C (Ben-Pyr) |
|  | 1340 | 8.2 | 1334 | $\beta \mathrm{CNC}(\mathrm{Pyr})+\mathrm{v}$ C=C (Ben-Pyr) |
|  | 1312 | 0.1 | 1288 | $v \mathrm{CC}(\mathrm{Pyr})+\mathrm{v}^{\mathrm{C}=\mathrm{C}}$ (Ben) |
|  | 1235 | 78.8 | 1205 | $v \mathrm{C}=\mathrm{C}(\mathrm{Ben}-\mathrm{Pyr})+\mathrm{v} \mathrm{CN}(\mathrm{Pyr})$ |
|  | 1162 | 4.6 | 1136 | $v^{\mathrm{C}=\mathrm{C}}$ (Ben-Pyr) |
|  | 1113 | 2.3 | 1107 | $v \mathrm{CC}(\mathrm{Pyr})+\beta \mathrm{CCC}(\mathrm{Ben})$ |
|  | 1021 | 0.3 | 1012 | $v \mathrm{C}=\mathrm{C}$ (Ben) |
|  | 932 | 3.6 | 910 | $\gamma \mathrm{CH}$ (Ben) |
|  | 851 | 0.0 | 856 | $\gamma$ CH (Ben) $+\gamma$ CCC (Ben-Pyr) |
|  | 755 | 47.3 | 747 | $\gamma \mathrm{CH}(\mathrm{Ben})+\gamma \mathrm{CNH}(\mathrm{Pyr})$ |
|  | 642 | 0.5 | 658 | $\beta$ CNC $+\beta$ CCC (Ben-Pyr) |
|  | 426 | 10.4 | 425 | $\gamma \mathrm{CH}(\mathrm{Ben})+\gamma \mathrm{NH}(\mathrm{Pyr})$ |
|  | 216 | 0.3 | 220 | $\beta$ CCC (Ben-Pyr) |
| $\mathrm{a}_{2}$ | 969 | 0.0 |  | $\gamma \mathrm{CH}$ (Ben) |
|  | 968 | 0.0 |  | $\gamma \mathrm{CH}$ (Ben) |
|  | 846 | 2.7 |  | $\beta$ CCN $+\beta$ CCC (Ben-Pyr) |
|  | 780 | 0.0 |  | $\gamma \mathrm{CH}(\mathrm{Ben})+\gamma \mathrm{CCC}(\mathrm{Pyr})$ |
|  | 580 | 0.0 |  | $\gamma \mathrm{CH}$ (Ben) |
|  | 429 | 1.0 |  | $\beta$ CCC + CCN (Ben-Pyr) |
|  | 290 | 0.0 |  | $\gamma$ ring Ben |
|  | 298 | 3.9 | 299 | $\gamma \mathrm{CH}(\mathrm{Ben})+\gamma \mathrm{NH}(\mathrm{Pyr})$ |
|  | 107 | 3.0 | 104 | $\gamma \mathrm{CH}$ (Ben) |
| $\mathrm{b}_{2}$ | 3059 | 0.3 | 3094 | vas CH (Ben) |
|  | 3048 | 10.6 | 3050 | vs CH (Ben) |
|  | 3027 | 5.5 | 3030 | $v \mathrm{CH}$ (Ben) |
|  | 3013 | 1.6 | 2940 | $v$ CH (Ben) |
|  | 1582 | 1.5 | 1594 | v C=C (Ben-Pyr) |
|  | 1495 | 15.0 | 1490 | $v^{\text {C }}=\mathrm{C}(\mathrm{Ben})+\mathrm{v}^{\text {CN }}$ (Pyr) |
|  | 1465 | 30.0 | 1452 | v C=C (Ben-Pyr) |
|  | 1395 | 21.2 | 1380 | $v \mathrm{C}=\mathrm{C}(\mathrm{Ben})+\mathrm{v}^{\text {CN }}$ (Pyr) |
|  | 1324 | 29.4 | 1320 | v C=C (Ben-Pyr) |
|  | 1281 | 1.7 | 1233 | $\checkmark \mathrm{CN}$ (Pyr) |
|  | 1216 | 6.4 | 1204 | $v \mathrm{C}=\mathrm{C}($ Ben $)+\mathrm{v} \mathrm{CN}(\mathrm{Pyr})$ |
|  | 1207 | 6.0 | 1158 | v C=C (Ben-Pyr) |
|  | 1126 | 5.6 | 1118 | $v^{\mathrm{C}=\mathrm{C}}$ (Ben) |
|  | 1031 | 0.3 | 1022 | v $\mathrm{C}=\mathrm{C}$ (Ben) |
|  | 1002 | 6.4 | 995 | $\beta \mathrm{CCC}(\mathrm{Ben})+\beta \mathrm{CH}$ (Ben) |
|  | 844 | 1.3 | 835 | $\gamma \mathrm{CH}$ (Ben) |
|  | 741 | 0.0 | 737 | $\gamma \mathrm{CH}$ (Ben) |
|  | 627 | 5.9 | 616 | $\beta$ CCC (Ben-Pyr) |
|  | 559 | 0.1 | 548 | $\beta$ CCC (Ben) |
|  | 510 | 3.5 | 505 | $\beta$ ringPyr |
| $\mathrm{b}_{1}$ | 1605 | 23.7 |  | $\beta \mathrm{CCC}(\mathrm{Pyr})+v \mathrm{C}=\mathrm{C}$ (Ben) |
|  | 1169 | 0.5 | 1152 | $v \mathrm{C}=\mathrm{C}$ (Ben) |
|  | 937 | 0.1 | 926 | $\gamma \mathrm{CH}$ (Ben) |
|  | 882 | 0.2 | 880 | $\beta$ CNC $+\beta$ CCC (Ben-Pyr) |
|  | 749 | 0.1 | 741 | $\beta$ CCC (Ben) |
|  | 731 | 87.5 | 722 | $\gamma \mathrm{CH}$ (Ben) |
|  | 569 | 6.6 | 566 | $\gamma \mathrm{CH}(\mathrm{Ben})+\gamma \mathrm{NH}(\mathrm{Pyr})$ |
|  | 444 | 0.0 | 445 | $\gamma \mathrm{CH}(\mathrm{Ben})+\gamma$ CCC (Ben-Pyr) |
|  | 342 | 70.7 | 310 | $\gamma \mathrm{NH}(\mathrm{pyr})$ |
|  | 149 | 0.0 | 139 | $\gamma \mathrm{CH}$ (Ben) |

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a) The detection of these observed frequencies of the bands has been made in the gas state.[2]

Since carbazole is the scaffold for Topo II inhibition, we studied its reactivity. A powerful practical model for describing chemical reactivity is the frontier molecular orbital theory, which is useful to explain drug-receptor interactions. [32]These are related to the overlap between the highest occupied molecular orbital (HOMO) and the lowest unoccupied molecular orbital (LUMO) of the two molecular entities, which provides information on their electron-donating and electron-withdrawing character, [33]respectively. These molecular orbitals (MOs) are displayed in Table 6. This figure shows that the HOMO and LUMO correspond to $\pi$ bonding and anti-bonding MOs, respectively, spreading over the whole carbazole molecule.

Table 6: Outermost molecular orbitals of carbazole and of its derivatives of interest in the present study. $\Delta \mathrm{E}$ (in eV ) corresponds to the energy HOMO - LUMO gap.

| Compound | HOMO | LUMO | AE |
| :---: | :---: | :---: | :---: |
| Carbazole |  |  |  |
| Chalcone |  | 4.73 |  |
| 1 |  |  | 4 |


| 2 |  |  | 3.53 |
| :---: | :---: | :---: | :---: |
| 3 |  |  | 3.63 |
| 4 |  |  | 3.31 |
| 5 |  |  | 3.84 |
| 6 |  |  | 3.45 |

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| 7 |  |  | 3.50 |
| :---: | :---: | :---: | :---: |
| 8 |  |  | 3.70 |
| 9 |  |  | 3.65 |
| 10 |  |  | 3.65 |
| 11 |  |  | 3.76 |
| 12 |  |  | 3.41 |

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| 13 |  |  | 3.94 |
| :---: | :---: | :---: | :---: |
| 14 |  |  | 3.86 |
| 15 |  |  | 3.48 |
| 16 |  |  | 3.43 |
| 17 |  |  | 3.71 |
| 18 |  |  | 3.67 |

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| 19 |
| :---: | :---: | :---: | :---: | :---: |
| 20 |
| 21 |



In addition, we analyzed the Fukui function of carbazole. This function describes how the electron density responds to the change in the total number of electrons and allows us to recognize the favored sites for electrophilic and nucleophilic attacks. $[17,34,35]$ The reactivity of an atom A in a molecule can be described by the following condensed Fukui functions [17]:

$$
\begin{aligned}
& \mathrm{f}_{+}(\mathrm{A})=\left[\mathrm{q}_{\mathrm{N}+1}(\mathrm{~A})-\mathrm{q}_{\mathrm{N}}(\mathrm{~A})\right] \\
& \mathrm{f}_{-}(\mathrm{A})=\left[\mathrm{q}_{\mathrm{N}}(\mathrm{~A})-\mathrm{q}_{\mathrm{N}-1}(\mathrm{~A})\right] \\
& \mathrm{f}_{0}(\mathrm{~A})=\left[\mathrm{q}_{\mathrm{N}+1}(\mathrm{~A})-\mathrm{q}_{\mathrm{N}-1}(\mathrm{~A})\right] / 2
\end{aligned}
$$

where $\mathrm{q}_{\mathrm{N}}(\mathrm{A}), \mathrm{q}_{\mathrm{N}+1}(\mathrm{~A})$ and $\mathrm{q}_{\mathrm{N}-1}(\mathrm{~A})$ are the electronic populations of atom A in a neutral molecule and in the corresponding anionic and cationic species, respectively. Atoms with large values of $f_{+}(A)$, $f_{-}(A)$ and $f_{0}(A)$ in a given molecule will be more easily attacked by nucleophiles, electrophiles and radicals, respectively.

We also computed the dual function, $\Delta \mathrm{f}(\mathrm{r})$, [37] which is calculated as the difference between the nucleophilic and electrophilic condensed Fukui functions:

$$
\Delta \mathrm{f}(\mathrm{~A})=\left[\mathrm{f}^{+}(\mathrm{A})-\mathrm{f}^{-}(\mathrm{A})\right]
$$

Thus, $\Delta \mathrm{f}$ is positive for atoms that are more easily attacked by nucleophiles and negative for those that are more easily attacked by electrophiles. [37]Results are given in Table 7.

Table 7: Values of the Fukui functions of carbazole. See text for the definition of the different terms.

| Atoms | $\mathrm{q}(\mathrm{N})$ | $\mathrm{q}(\mathrm{N}+1)$ | $\mathrm{q}(\mathrm{N}-1)$ | $\mathrm{f}_{+}$ | $\mathrm{f}_{-}$ | $\mathrm{f}_{0}$ | $\Delta \mathrm{f}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| C 1 | 0.2050 | 0.1950 | 0.1990 | -0.0100 | 0.0060 | -0.0020 | -0.0160 |

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| C2 | $-0.0660$ | 0.0060 | -0.1350 | 0.0720 | 0.0690 | 0.0705 | 0.0030 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| C3 | -0.0960 | -0.0750 | -0.1590 | 0.0210 | 0.0630 | 0.0420 | -0.0420 |
| C4 | -0.1110 | -0.0580 | -0.1120 | 0.0530 | 0.0010 | 0.0270 | 0.0520 |
| C5 | -0.0390 | 0.0070 | -0.1290 | 0.0460 | 0.0900 | 0.0680 | -0.0440 |
| C6 | -0.0920 | -0.0710 | -0.0940 | 0.0210 | 0.0020 | 0.0115 | 0.0190 |
| C7 | -0.0920 | -0.0710 | -0.0940 | 0.0210 | 0.0020 | 0.0115 | 0.0190 |
| C8 | -0.0390 | 0.0071 | -0.1290 | 0.0461 | 0.0900 | 0.0681 | -0.0439 |
| C9 | -0.1110 | -0.0580 | -0.1120 | 0.0530 | 0.0010 | 0.0270 | 0.0520 |
| C10 | -0.0960 | -0.0750 | -0.1590 | 0.0210 | 0.0630 | 0.0420 | -0.0420 |
| C11 | -0.0660 | 0.0060 | -0.1350 | 0.0720 | 0.0690 | 0.0705 | 0.0030 |
| C12 | 0.2050 | 0.1950 | 0.1990 | -0.0100 | 0.0060 | -0.0020 | -0.0160 |
| N13 | -0.5250 | -0.4350 | -0.5310 | 0.0900 | 0.0060 | 0.0480 | 0.0840 |
| H14 | 0.0850 | 0.1430 | 0.0230 | 0.0580 | 0.0620 | 0.0600 | -0.0040 |
| H15 | 0.0910 | 0.1470 | 0.0240 | 0.0560 | 0.0670 | 0.0615 | -0.0110 |
| H16 | 0.0890 | 0.1520 | 0.0270 | 0.0630 | 0.0620 | 0.0625 | 0.0010 |
| H17 | 0.0820 | 0.1330 | 0.0270 | 0.0510 | 0.0550 | 0.0530 | -0.0040 |
| H18 | 0.0820 | 0.1330 | 0.0270 | 0.0510 | 0.0550 | 0.0530 | -0.0040 |
| H19 | 0.0890 | 0.1520 | 0.0270 | 0.0630 | 0.0620 | 0.0625 | 0.0010 |
| H20 | 0.0910 | 0.1470 | 0.0240 | 0.0560 | 0.0670 | 0.0615 | -0.0110 |
| H21 | 0.0850 | 0.1430 | 0.0230 | 0.0580 | 0.0620 | 0.0600 | -0.0040 |
| H22 | 0.2250 | 0.2770 | 0.1860 | 0.0520 | 0.0390 | 0.0455 | 0.0130 |

Apart from the hydrogens atoms, (Table 7,Figure 36) shows that negative $\Delta \mathrm{f}$ values are determined for the $\mathrm{C}_{1}, \mathrm{C}_{3}, \mathrm{C}_{5}, \mathrm{C}_{8}, \mathrm{C}_{10}$ and $\mathrm{C}_{12}$ atoms. This reveals that the ortho positions of the aromatic cycles in carbazole are highly reactive with respect to electrophilic attacks. In contrast, the other carbon atoms, except $\mathrm{C}_{2}$ and $\mathrm{C}_{11}$, of carbazole and especially the nitrogen

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atom present positive $\Delta \mathrm{f}$ values. Therefore, these atomic centers are mostly subject to nucleophilic attacks. We expect that the $\mathrm{C}_{2}$ and $\mathrm{C}_{11}$ atoms, i.e. those associated with the largest $f_{0}$ values (Table 7), will be the most probable sites for radical attacks.


Figure.36.Dual descriptor ( $\Delta \mathrm{f}$ ) Vs Atoms.

## III . 3 Carbazole derivatives structures

At first, we preoptimized the CDCAs to get minimal energy structures using the Molecular Mechanics Force Field (MM+) followed by the semi-empirical AM1 method, with a convergence threshold of $0.01 \mathrm{kcal} / \AA$ in the gradient norm, as implemented in the HyperChem (version 8.08) package. [38]This allowed us to identify the most stable forms that were further optimized using the DFT B3LYP/6$311++G(d, p)$ method. The resulting structures, in Cartesian coordinates, are displayed in Table S1 (in Appendix). Close examination of this table reveals that the carbazole subunit exhibits slight changes compared to the isolated carbazole, whereas the chalcone part of the CDCAs either resembles the isolated chalcone or presents strong changes. This justifies a posteriorithe choice of chalcone for the above-mentioned benchmark computations.

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According to the structure of the chalcone moiety, we can easily classify the CDCAs into two conformational types: i) Type 1 compounds, showing slight changes in the chalcone subunit, and ii) Type 2 compounds, with a non-planar arrangement of the enone/chalcone moiety.


Figure .37. Face and profile views of Compounds 1 and 3.

The central part of Type 1 compounds, the one formed by the chalcone and carbazole moieties, is almost planar. Type 1 molecules have similar shapes as Compound 1, displayed in the upper part of Figure 37, and correspond to Compounds $1,2,4,5,6,7,12,15,16,19$ and 23 . These molecules are stabilized by extended electron conjugation over the aromatic rings of carbazole and chalcone through the connecting enone. Type 2 molecules have similar shapes as Compound 3, displayed in the lower part of Figure 37, and correspond to Compounds 3, 8, 9, 10, 11, 13, 14, 17, $1820,21,22$ and 24 . The stabilization here is due to $\pi$-stacking interactions between the phenyl of chalcone and the aromatic rings of carbazole. Indeed, the mesomerism and the $\pi$-stacking interactions are in competition to lead to Type 1 or Type 2 compounds. Nevertheless, we cannot observe any clear relation between the structure of these CDCAs and their measured biological activity (Table 3). For instance, Compounds 15 and 7 have $\mathrm{pIC}_{50}$ values of $\sim 3.5$ and 6.7 despite both of them being of Type 1. Table 3 shows also that Compound 20 has a $\mathrm{pIC}_{50}$ of 6.174 close to that of Compound 7, despite being of Type 2. Consequently, different shapes are obtained for these CDCAs even if all of them possess similar biological and cytotoxic effects. Therefore, the interaction of these CDCAs with Topo II should be more complex than the commonly admitted key-lock mechanism, which is based on shape complementarity between the substrate and enzymatic active site. We conclude that an induced-fit mechanism is more plausible, where conformational fluctuations in the enzyme-substrate complex should influence the dynamics of the inhibition process, thus affecting the biological activity of the studied compounds.

## III. 4 CDCAs derivatives physicochemical properties, descriptors and druglikeness scoring

The molecular orbital theory is extremely useful for physicists and chemists. In particular, the HOMO and LUMO of a chemical species are important for discussing the molecular reactivity and can help to interpret the intermolecular protein-ligand interactions. The DFT B3LYP/6-311G(d,p) method as implemented in Gaussian 09

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was employed to derive the outermost molecular orbitals (HOMO, LUMO and related energies) of carbazole derivatives. These orbitals are displayed in Table 6. These compounds have a HOMO/LUMO mostly localized on the carbazole and chalcone moiety, respectively. Interestingly the HOMO-LUMO gap for all CDCAs is almost the same (of $\sim 3.5 \mathrm{eV}$ ).

In order to obtain validated QSAR models, several molecular descriptors, encoding various information about size, hydrophilicity, electronic and topological properties, were calculated using the Molecular Operating Environment (MOE) [39]software and the QSAR Properties (version 8.0.6) module integrated in the HyperChem package. The deduced properties correspond to molar weight (MW), surface area grid (SAG), volume (V), molecular refractivity (MR), polarizability (Pol), octanol-water partition coefficient $\left(\log _{10} \mathrm{P}\right)$, hydration energy (HE), hydrogen bond donors (HBDs, counting the sum of all NH and OH groups), hydrogen bond acceptors (HBA, counting all N and O atoms), number of rotatable bonds ( $\mathrm{N}_{\mathrm{brot}}$ ) and topological polar surface area (TPSA). We also deduced the number of atoms ( $\mathrm{N}_{\text {atom }}$ ) and the number of heavy atoms $\left(\mathrm{N}_{\mathrm{H}}\right)$. These data are listed in Tables 8 and 9. These tables show that large values of MR and Pol correspond to large values of V and MW, in agreement with the Lorentz-Lorenz equation. [40] For example, Compound 24, the one with the p-chlorophenyl and nitrophenyl groups, has rather large values of Pol ( $68.74 \AA^{3}$ ) and MR $\left(149.41 \AA^{3}\right)$, which are associated with large values of V (1409.29 $\AA^{3}$ ) and MW (466.92 amu). Whereas, Compound 1 has the smallest values of MR ( $115.47 \AA^{3}$ ) and Pol ( $55.05 \AA^{3}$ ). HE is an important parameter connected to the stabilization of molecules bearing polar groups and a great predictive index for molecule accessibility in biologic media. [41,42]Compound 14 has the smallest |HE| value ( $1.1 \mathrm{kcal} / \mathrm{mol}$ ), while the largest $|\mathrm{HE}|$ values are observed for Compounds 24 and 25 (VP-16) ( 9.05 and $22.75 \mathrm{kcal} / \mathrm{mol}$, respectively), which bear hydrophilic groups (e.g. $\mathrm{NO}_{2}, \mathrm{CO}, \mathrm{CN}$, and OH ).

Table 8:Physicochemical properties of CDCAs derivatives. For each compound, we give the energies of the HOMO ( $\mathrm{E}_{\text {номо }}$ in a.u.) and of the LUMO ( $\mathrm{E}_{\text {LUMо }}$ in a.u.), the polarizability (Pol in $\AA^{3}$ ), the volume ( V in $\AA^{3}$ ), the surface area grid (SAG in $\AA^{3}$ ) and the hydration energy (HE in $\mathrm{kcal} / \mathrm{mol}$ ). * denotes the selected compounds for external validation (test set).

| Compound | Еномо | Elumo | Pol | V | SAG | HE |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1* | -0.2052 | -0.07763 | 55.05 | 953.84 | 559.04 | -2.86 |
| 2 | -019969 | -0.06997 | 68.66 | 1177.74 | 678.02 | -3.56 |
| 3 | -0.20881 | -0.0735 | 56.56 | 955.41 | 543.72 | -2.47 |
| 4* | -0.21087 | -0.08925 | 57.82 | 1033.16 | 601.92 | -2.29 |
| 5 | -0.20883 | -0.06771 | 58.42 | 1020.74 | 604.76 | -7.10 |
| 6 | -0.20716 | -0.08021 | 54.94 | 962.56 | 566.94 | -2.57 |
| 7 | -0.20385 | -0.07526 | 58.14 | 1007.58 | 584.98 | -4.46 |
| 8 | -0.20599 | -0.06983 | 53.10 | 906.05 | 535.90 | -3.12 |
| 9 | -0.21001 | -0.07562 | 57.43 | 983.06 | 557.22 | -2.76 |
| 10 | -0.21069 | -0.07664 | 56.56 | 976.37 | 573.38 | -2.70 |
| 11 | -0.21046 | -0.07214 | 56.56 | 992.69 | 584.95 | -2.89 |
| 12* | -0.20561 | -0.08033 | 54.94 | 960.25 | 562.34 | -2.68 |
| 13 | -0.20507 | -0.06008 | 62.84 | 1065.32 | 596.47 | -5.22 |
| 14 | -0.20475 | -0.06289 | 61.24 | 1092.35 | 596.88 | -1.10 |
| 15 | -0.20476 | -0.07672 | 58.84 | 1039.58 | 609.74 | -3.87 |
| 16 | -0.20417 | -0.07786 | 58.03 | 1014.3 | 588.16 | -1.55 |
| 17 | -0.21414 | -0.07771 | 66.59 | 1089.36 | 597.18 | -3.76 |
| 18 | -0.21053 | -0.07575 | 69.79 | 1133.75 | 618.72 | -2.92 |
| 19 | -0.21022 | -0.08467 | 66.70 | 1144.15 | 665.11 | -4.04 |
| 20 | -0.21105 | -0.07607 | 66.59 | 1123.72 | 634.55 | -3.92 |
| 21 | -0.21356 | -0.0757 | 66.48 | 1127.34 | 637.58 | -3.72 |
| 22 | -0.21514 | -0.07723 | 66.59 | 1132.60 | 644.85 | -4.02 |
| 23 | -0.21404 | -0.08698 | 68.21 | 1189.24 | 693.69 | -3.74 |
| 24* | -0.22107 | -0.10003 | 68.74 | 1183.65 | 676.29 | -9.05 |
| 25 (VP-16) | -0.21034 | -0.02485 | 82.80 | 1409.29 | 785.78 | -22.75 |

Ideally, from a pharmacological point of view, a drug should be orally bioavailable. The oral route is particularly praised especially for those drugs that have to be selfadministered by the patients on a continuous basis. [43]The quickest strategy for assessing the drug-likeness of a given compound is to apply "rules" as a standard guideline. Orally ingested drugs should, in general, obey Lipinski's rule of five,

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[44]which is summarized as: MW < 500; HBD < 5; $\log _{10} \mathrm{P}<5$; and HBAs < 10 . Additionally, Veber and Ghose's rules complement the Lipinski's one. For instance, Veber et al. [45]
showed that compounds with $\mathrm{N}_{\text {brot }}<10$ and TPSA $<140 \AA^{2}$ present a good oral bioavailability in rats. Also, Ghose et al. [46] suggested a qualifying range that could be used in the development of drug-like chemical libraries, recommending the following constraints: $160 \leq \mathrm{MW} \leq 480 ;-0.4 \leq \log _{10} \mathrm{P} \leq 5.6 ; 40 \leq \mathrm{MR} \leq 130$ and $20 \leq$ $\mathrm{N}_{\text {atom }} \leq 70$. In the following, we will discuss the oral bioavailability of the CDCAs of interest in light of the parameters presented in Tables 8 and 9:

- MW is closely connected to the molecular size. As the size of a compound gets larger, a bigger cavity must be shaped in water to accommodate it, thus decreasing the corresponding solubility. Growing MW reduces the compound fixation at the surface of the intestinal epithelium, hence reducing its absorption. In addition, a large molecular size obstructs passive diffusion through the firmly pressed aliphatic side chains of the cellular bilayer membrane. [47]Table 9 shows that all the considered compounds, except Compound 25, verify both Ghose and Lipinski’s rules, because their MW are in the $325-470$ range. Most likely, all these compounds will easily pass through cell membranes.
- The relative hydrophilic/hydrophobic properties of a drug are crucial in influencing its solubility, ADME (Absorption, Distribution, Metabolism, and Excretion) properties, as well as pharmacological activity. Absorption in the gastrointestinal tract is most effective when the drug has the right balance of solubility in water and fat, which is the case for moderate values of $\log _{10} \mathrm{P}$ (i.e. $0<\log _{10} \mathrm{P}<3$ ). If the drug is polar with low $\log _{10} \mathrm{P}$ (hydrophilic), it will fail to penetrate across the intestinal epithelial cell layer. Whereas if the molecule is nonpolar, with high $\log _{10} \mathrm{P}$ (hydrophobic), it will dissolve in fat globules, leading to poor contact with the intestinal walls and resulting in malabsorption. [14] As can be seen in Table 9, all compounds present a $\log _{10} \mathrm{P}$ in this range, except Compounds 24 and 25, which have out-of-range values of -2.22 and -4.27 , respectively.
- TPSA of a molecule corresponds to the surface sum over every single polar atom (e.g., oxygen, nitrogen), where we include also attached hydrogens. Generally, a molecule with TPSA > $140 \AA^{2}$ will have low oral absorption. For the central nervous system, the upper limit of TPSA for the drug to cross the blood-brain barrier is even reduced to $80 \AA^{2}$. [48]Table 9 shows that the TPSA values are in the range $22-40$ for Compounds 1-23 and that Compound 24 is still within the acceptable range ( $<140 \AA^{2}$ ), whereas Compound 25 is out-of-range. The percentage of absorption (\%ABS, Table 9) is related to TPSA via $\% \mathrm{ABS}=109 \pm 0.345 \times$ TPSA. [49]Except Compound 25, \%ABS values are close to $100 \%$. Again, these compounds should have good cellular plasmatic membrane permeability.
- $\mathrm{N}_{\text {brot }}$ counts any single bond bound to a nonterminal heavy atom and not being part of a ring. [50,51] Table 9 shows that $\mathrm{N}_{\text {brot }}$ is smaller than 8 for all compounds. This is a signature of relatively good molecular flexibility, which helps the drug to traverse the membrane and better interact with the enzyme.
- Ligand efficiency ( $\mathrm{LE}=1.4 \times \mathrm{pIC}_{50} / \mathrm{N}_{\mathrm{H}}$ ) measures the potency per heavy atom of a given compound, where, for drugs of comparable activity, the smaller ones have greater LE than the larger ones. As can be seen in Table 9, Compounds 7, 3 and 11 have a rather small number of $\mathrm{N}_{\mathrm{H}}$, and thus possess relatively high LE values (of $0.358,0.299,0.277,0.273$ ), whereas Compounds 15, 23, 25 have higher values of $\mathrm{N}_{\mathrm{H}}$ leading to small values of LE ( $0.179,0.209,0.224$ ). Hence, the latter ones may exhibit bad physicochemical and ADME properties.
- Lipophilic ligand efficiency $\left(\mathrm{LLE}=\mathrm{pIC}_{50}-\log _{10} \mathrm{P}\right)$ gives insight into the interaction of a molecule with its own receptor, where low lipophilicity should be maintained [52] for good interaction. Concerning the studied series, Table 9 shows that all compounds have positive LLE values, which is considered as a favorable quality to create highly efficient interactions with the biological targets.


## Result and discussion

In sum, the Lipinski, Veber and Ghose's rules are verified by most of our compounds, except number 25 . Therefore, these compounds are ideal for oral bioavailability. They have also large chance of achieving high intestinal permeability and solubility.

| Compound | $\log _{10} \mathrm{P}$ | MW | HBA | HBD | TPSA | Natom | MR | $\mathrm{N}_{\text {brot }}$ | Lipinski Score | Ghose Score | Veber Score | $\mathrm{N}_{\mathrm{H}}$ | LE | LLE | ABS \% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1* | 2.01 | 325 | 1 | 0 | 22.00 | 44 | 115.47 | 4 | 4 | 4 | 2 | 25 | 0.273 | 2.864 | 101.41 |
| 2 | 0.72 | 411 | 3 | 0 | 34.47 | 57 | 138.17 | 5 | 4 | 3 | 2 | 31 | 0.208 | 3.880 | 97.11 |
| 3 | 1.78 | 360 | 2 | 0 | 22.00 | 44 | 120.19 | 4 | 4 | 4 | 2 | 26 | 0.299 | 3.765 | 101.41 |
| 4* | 2.58 | 393 | 4 | 0 | 22.00 | 47 | 120.69 | 5 | 4 | 4 | 2 | 29 | 0.251 | 2.629 | 101.41 |
| 5 | 0.21 | 369 | 3 | 0 | 40.46 | 47 | 121.06 | 4 | 4 | 4 | 2 | 28 | 0.229 | 4.364 | 95.04 |
| 6 | 1.41 | 343 | 2 | 0 | 22.00 | 44 | 115.60 | 4 | 4 | 4 | 2 | 26 | 0.263 | 3.478 | 101.41 |
| 7 | 2.16 | 339 | 1 | 0 | 22.00 | 47 | 119.75 | 4 | 4 | 4 | 2 | 26 | 0.358 | 4.498 | 101.41 |
| 8 | 0.62 | 331 | 1 | 0 | 22.00 | 41 | 112.77 | 4 | 4 | 4 | 2 | 26 | 0.258 | 4.167 | 101.41 |
| 9 | 2.06 | 404 | 2 | 0 | 22.00 | 44 | 123.01 | 4 | 4 | 4 | 2 | 26 | 0.249 | 2.563 | 101.41 |
| 10 | 2.52 | 360 | 2 | 0 | 22.00 | 44 | 120.19 | 4 | 4 | 4 | 2 | 26 | 0.271 | 2.518 | 101.41 |
| 11 | 1.78 | 360 | 2 | 0 | 22.00 | 44 | 120.19 | 4 | 4 | 4 | 2 | 26 | 0.277 | 3.364 | 101.41 |
| 12* | 0.02 | 343 | 2 | 0 | 22.00 | 44 | 115.60 | 4 | 4 | 4 | 2 | 26 | 0.280 | 5.175 | 101.41 |
| 13 | 2.31 | 385 | 3 | 0 | 40.46 | 52 | 128.22 | 6 | 4 | 4 | 2 | 29 | 0.254 | 2.955 | 95.04 |
| 14 | 2.31 | 353 | 1 | 0 | 22.00 | 50 | 124.04 | 4 | 4 | 4 | 2 | 27 | 0.235 | 2.215 | 101.41 |
| 15 | 0.41 | 373 | 3 | 0 | 31.23 | 48 | 121.97 | 5 | 4 | 4 | 2 | 28 | 0.179 | 3.163 | 98.23 |
| 16 | 1.56 | 357 | 2 | 0 | 22.00 | 47 | 119.88 | 4 | 4 | 4 | 2 | 27 | 0.281 | 3.853 | 101.41 |
| 17 | 1.85 | 440 | 3 | 0 | 22.00 | 51 | 144.32 | 5 | 4 | 4 | 2 | 32 | 0.263 | 4.163 | 101.41 |
| 18 | 2.61 | 436 | 2 | 0 | 22.00 | 54 | 148.47 | 5 | 4 | 3 | 2 | 32 | 0.248 | 3.056 | 101.41 |
| 19 | 2.46 | 422 | 2 | 0 | 22.00 | 51 | 144.19 | 5 | 4 | 3 | 2 | 31 | 0.244 | 2.951 | 101.41 |
| 20 | 1.85 | 440 | 3 | 0 | 22.00 | 51 | 144.32 | 5 | 4 | 3 | 2 | 32 | 0.270 | 4.324 | 101.41 |
| 21 | 1.25 | 458 | 4 | 0 | 22.00 | 51 | 144.45 | 5 | 4 | 3 | 2 | 33 | 0.233 | 4.235 | 101.41 |
| 22 | 1.85 | 440 | 3 | 0 | 22.00 | 51 | 144.32 | 5 | 4 | 3 | 2 | 32 | 0.234 | 3.493 | 101.41 |
| 23 | 2.23 | 456 | 3 | 0 | 22.00 | 51 | 148.91 | 5 | 4 | 3 | 2 | 32 | 0.209 | 2.558 | 101.41 |
| 24* | -2.22 | 467 | 4 | 0 | 67.82 | 53 | 149.41 | 6 | 4 | 2 | 2 | 34 | 0.243 | 8.123 | 85.60 |
| 25 (VP-16) | -4.27 | 589 | 12 | 3 | 160.83 | 74 | 145.81 | 5 | 2 | 0 | 1 | 42 | 0.224 | 10.991 | 53.51 |

Table 9: Drug-likeness parameters and lipophilicity indices for the CDCAs under study. See text for the definition of these parameters and their description.

## III. 5 QSAR modelling studies

QSAR studies have proved their applicability in modern drug discovery protocols. The goal of QSAR models is to establish quantitative relations connecting the physicochemical properties of classes of drugs to their biological activity. Typically, this involves the synthesis of a series of differently substituted analogue compounds, and the study of how their biological activities depend on the physicochemical properties of the substituents. [14]Several linear and nonlinear statistical model-building methods have been applied to QSAR, [53]where the needed physicochemical descriptors are treated as independent variables. We used both multiple linear regressions (MLR) and artificial neural network (ANN), as implemented in the software JMP 8.0.2 and XLSTAT, $[54,55]$ to correlate these parameters with the biological activities of CDCAs. For internal, external validation and Y-randomization [56,57] of the QSAR model, we used different statistical parameters such as:
(i) The leave-one-out cross-validation coefficient $\left(\mathrm{R}^{2} \mathrm{c}_{(\mathrm{LOO})}\right)$, used to predict the internal validation of a model. The threshold for acceptability is $\mathrm{R}^{2} \mathrm{CV}(\mathrm{LOO})>0.5$. [58]
(ii) The significance level (P-value). It should be $<0.05$.
(iii) The square correlation coefficient for external validation ( $\mathrm{R}^{2}{ }_{\text {ext }}$ ). It is taken as a good indicator when its value is greater than 0.6. [58-60]
(iv) The PRESS/SSY ratio, where PRESS is the predicted residual sum of squares and SSY is the sum of squares deviation. It should be smaller than 0.4. [61]
(v) The $\mathrm{r}_{\mathrm{m}}{ }^{2}$ metric introduced by Roy et al. [62]It should be ensured that $\overline{\mathrm{r}}_{\mathrm{m}}{ }^{2}$ > 0.5 and $\Delta \mathrm{r}_{\mathrm{m}}{ }^{2}<0.2$ to prevent bias in model predictability. This applies to both the training (internal validation) and the test (external validation) sets.

## III.5.1.1 Internal validation

The internal validation of a QSAR model is carried out using a cross-validation method, using the molecules from the training set. In this paper, we used the cross-
validation leave-one-out (LOO) approach, where a large value of the cross-validated squared correlation coefficient $\mathrm{R}^{2}{ }_{\mathrm{cv}}$ is considered as a proof of high predictive capacity of the model. [58]

An acceptable $\mathrm{Q}^{2}{ }_{\mathrm{cv}}$ does not guarantee that the predicted activity values are close to the observed ones, but simply attests that a good overall correlation exist between them. So, to avoid this error and better highlight the predictability of the model, we considered also the $r_{m}{ }^{2}$ metrics, including average $r_{m}{ }^{2}(\mathrm{LOO})$ (the average value of $\mathrm{r}_{\mathrm{m}}{ }^{2}$ and $\mathrm{r}_{\mathrm{m}}^{\prime 2}$ ) and $\Delta \mathrm{r}^{2}{ }_{\mathrm{m}(\mathrm{LOO})}$ (the absolute difference between $\mathrm{r}_{\mathrm{m}}{ }^{2}$ and $\mathrm{r}^{\prime}{ }_{\mathrm{m}}{ }^{2}$ )(Table 10), introduced by Roy and colleagues. [62] For a good prediction of the QSAR model $\Delta \mathrm{r}^{2}{ }_{\mathrm{m}(\mathrm{LOO})}$ should be less than 0.2 , provided that the average value of $r_{m}{ }^{2}$ is greater than 0.5 .

## III.5.1.2 External validation

External validation guarantees the predictability of the developed QSAR model and its applicability to potential new drugs. The correlation between observed and predicted data is measured by the $\mathrm{R}^{2}$ ext metric (Table 10). According to Golbraikh and Tropsha[58-60], the following criteria for the external validation, based on the validation set, were adopted:
(i) $\quad \mathrm{R}^{2}{ }_{\text {ext }}>0.6$
(ii) $\quad\left(\mathrm{r}^{2}-\mathrm{r}_{0}^{2} / \mathrm{r}^{2}\right)<0.1$ and $0.85 \leq \mathrm{k} \leq 1.15$ or $\left(\mathrm{r}^{2}-\mathrm{r}^{\prime} 0^{2} / \mathrm{r}^{2}\right)<0.1$ and $0.85 \leq \mathrm{k}^{\prime} \leq 1.15$
(iii) $\left|\mathrm{r}_{\mathrm{m}}{ }^{2}-\mathrm{r}_{\mathrm{m}}^{\prime 2}\right|<0.3$

## III.5.1.3 Y-randomization

Y-randomization [56] is a widely accepted validation technique used to check the robustness of the models. In this validation approach, the values of the target variable are randomly redistributed over the entire learning set and a new model is derived. The whole operation is repeated several times. For robustness, the squared mean correlation coefficient $\left(\mathrm{R}^{2}{ }_{\mathrm{r}}\right)$ of randomized models should be less than the squared correlation coefficient $\left(\mathrm{R}^{2}\right)$ of non-randomized ones. Based on the results of the

## Result and discussion

randomization tests, the $\mathrm{R}_{\mathrm{p}}^{2}\left(=\mathrm{R}^{2} \sqrt{\left(\mathrm{R}^{2}+\mathrm{R}_{r}^{2}\right.}\right)$ ) [53] value should be greater than 0.5 to ensure that the good predictive capacity of the so-developed models is not reached by mere chance.

## III. 6 Multiple linear regression (MLR)

Despite being the oldest, MLR still remains one of the most popular approaches to build QSAR models. This is due to its simple practical use, ease of interpretation and transparency. Indeed, the key algorithm is available and accurate predictions can be provided. [63]The values of the calculated descriptors are those listed in Tables 8 and 9. Data were randomly divided into two groups: a training set (internal validation) and a testing set (external validation). The significant correlation analysis between Topo II inhibition activity and descriptors is represented by the following equation:

$$
\begin{aligned}
\mathrm{pIC}_{50}= & 6,759-0,135 \times \mathrm{TPSA}+0,314 \times \mathrm{N}_{\text {atom }}-0,015 \times \mathrm{V}-0,485 \times \mathrm{HE}+ \\
& 0,314 \times \log _{10} \mathrm{P} \ldots \ldots . \quad(\text { Eq. } 1)
\end{aligned}
$$

Table 10: Numerical parameters used to confirm the QSAR model validity. See text for more details.

| Model | Training set |  |  |  |  | Test set |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{R}^{2}{ }_{\text {inter }}$ | $\mathrm{R}^{2}{ }_{\mathrm{cv}}$ | $\overline{\mathrm{r}}_{\mathrm{m}}{ }^{2}{ }^{2}$ (LOO) | $\Delta \mathrm{r}_{\mathrm{m}}{ }^{2}{ }^{(\text {LOO })}$ | RMSE | PRESS/SST | $\mathrm{R}^{2}{ }_{\text {ext }}$ | $\overline{\mathrm{r}}_{\mathrm{m}}{ }^{2}$ (test) | $\Delta \mathrm{r}_{\mathrm{m}}{ }^{2}$ (test) | RMSE | PRESS/SST |
| MLR | 0.768 | 0.686 | 0.601 | 0.162 | 1.224 | 0.341 | 0.800 | 0.596 | 0.197 | 0.545 | 0.092 |
| ANN | 0.999 | 0.991 | 0.988 | 0.000 | 0.005 | 0.000 | 0.650 | 0.598 | 0.108 | 0.372 | 0.135 |

The statistical parameters of this model are listed in Table 10. The high values of the correlation coefficient $\left(\mathrm{R}^{2}\right)$ for the training set ( $\mathrm{R}^{2}{ }_{\text {inter }}=0.768$ ) and test set $\left(\mathrm{R}^{2}{ }_{\text {ext }}=0.800\right)$ indicate the significant correlation between different independent variables with Topo II inhibition activity. In addition, Table 10 shows that RMSE and PRESS/SSY ratio are low for both internal validation ( $=0.341<0.4$ ) and external validation ( $=0.092<0.4$ ). This confirms the reliability of our model.


Figure.38. Generic leverage plot of observed [11] (Observed $\mathrm{pIC}_{50}$ ) versus predicted (Predicted $\mathrm{pIC}_{50}$ ) activity according to the MLR model. The oblique line is the diagonal.

The model was checked by applying the Y-randomisation test. Several Y vector random shuffles were performed and small average values of 0.1445 for $\mathrm{R}^{2}$ and -0.327 for $\mathrm{Q}^{2}$ (Table 11) were obtained after 1000 random tests, thus proving that the good results of our original model are not due to chance correlation or structural dependence of the training set.

Table 11:Random MLR model parameters.

| Average R | 0.3646 |
| :--- | ---: |
| Average R ${ }^{2}$ | 0.1445 |
| Average Q ${ }^{2}$ | -0.327 |
| ${ }^{{ }^{c} \mathrm{R}_{\mathrm{p}}{ }^{2}}$ | 0.768 |

For further testing the reliability and stability of our model (Eq.1), we used the "Leave-One-Out" (LOO) technique. Again, the high value of cross-validation correlation coefficient $\left(\mathrm{R}^{2} \mathrm{CV}=0.686>0.5\right)$ for this model allows us to qualify it as valid. [58]Other criteria such as parameters metric ( $\overline{\mathrm{r}}_{\mathrm{m}}{ }^{2}$ and $\Delta \mathrm{r}_{\mathrm{m}}{ }^{2}$, Table 10) confirm that this QSAR model is acceptable. The plot of the predicted values of biological activity $\mathrm{pIC}_{50}$ vs. the experimental values is shown in Figure 38, which certifies once more the validity of the predicted model.

Let us now analyze the coefficients in Eq.1. The positive values of $\log _{10} \mathrm{P}$ and $\mathrm{N}_{\text {atom }}$ indicate a promoter effect on Topo II inhibition activity. Indeed, any increase in the octanol-water partition coefficient and number of atoms of the molecules causes an increase in the biological activity. This is related to the stabilization of the polar groups in the CDCAs and represents a good criterion for molecule accessibility in the biologic medium. Also, since the octanol-water partition coefficient provides an indication of the lipophilic character of the drug and its aptitude to cross the cell membrane, it represents a key parameter to measure the drug inhibitory activity.

No contribution from the HOMO-LUMO gap appears in Eq.1. Thus, the model is independent of this parameter. This may be related to the almost constant value of this gap computed for all the CDCAs of interest, as noted earlier. Eq. 1 does not include any dependence on HBD since this parameter is zero for all compounds, except Compound 25 (Table 9). Similarly, MR and HBA parameters seem to have no influence on the biological activity, since they do not appear in our model.

## III. 7 Artificial Neural Networks (ANN)

ANN [64,65]is a popular nonlinear model, which is used to predict the biological activity (i.e. $\mathrm{IC}_{50}$ ) of the datasets of therapeutic molecules. It presents several benefits like better prediction, adaptation and generalization capacity beyond the studied sample, and better stability of the coefficients. It is employed in complex drug design, drug engineering and medicinal chemistry domains. [66]


Figure .39.The architecture (6-4-1) of the adopted ANN model.

In this work, the neural network is a system of fully interconnected neurons arranged in three layers. The input layer is made of six neurons, where each of them receive one of the six descriptors selected from the correlation matrix of the model. The intermediate (hidden) layer is composed of four neurons that form the deep internal pattern that discovers the most significant correlations between predicted and experimental data. One neuron constitutes the output layer, which returns the value of $\mathrm{IC}_{50}$ (Figure 39). [67]


Figure .40.Correlation plot of observed (Observed $\mathrm{pIC}_{50}$ ) [11] versus predicted activity (Predicted $\mathrm{pIC}_{50}$ ) calculated using ANN.

As can be seen in Figure 40, a good agreement between experimental data and predicted $\mathrm{pIC}_{50}$ issued from the ANN model is observed. Indeed, the statistical parameters for this model, as given in Table 10, reveal a correlation coefficient close to $1\left(\mathrm{R}^{2}{ }_{\text {inter }}=0.999\right)$, associated with lower values of RMSE and PRESS/SSY for both external and internal validations. Note that these parameters are better than those found for the MLR model, indicating that the ANN one is more reliable. Furthermore, the robustness of the model was further confirmed by the significant $R^{2}{ }_{\text {ext }}$ value of the test data set $\left(\mathrm{R}^{2}{ }_{\text {ext }}=0.650\right)$. To further evaluate our model, we applied the Leave-OneOut cross-validation method. The resulting $\overline{\mathrm{r}}_{\mathrm{m}}{ }^{2}$ (LOO), $\left.\Delta \mathrm{r}_{\mathrm{m}}{ }^{2}{ }^{(L O O}\right), \overline{\mathrm{r}}_{\mathrm{m}}{ }^{2}$ (test), $\Delta \mathrm{r}_{\mathrm{m}}{ }^{2}$ (test) statistical criteria (Table 10) support the validity of our model, since they fall within the ranges specified by Roy et al. [62]

## General Conclusion

## General conclusion

Using first principle methodologies, we studied the molecular structure and the vibrational/electronic spectroscopic properties of the set of CDCAs recently synthetized by Li et al. as potential Topo II inhibitors. We also characterized the carbazole subunit of these CDCAs. Afterwards, we derived a set of physicochemical parameters for these compounds, which are incorporated later into MPO, MLR and ANN methods for screening the lipophilicity indices, structure-activity relationship and to construct a QSAR model. The results indicate that these compounds have a $98 \%$ chance of being orally active. As can be seen in Table 10, the ANN network has substantially better predictive capabilities compared to MLR, leading to $\mathrm{pIC}_{50}$ values closer to the experimental determinations. Nevertheless, both models remain satisfactory and exhibit a high predictive power, thus validating their use to explore and propose new molecules as active inhibitors of Topo II.

Table .10. Measured [11] and predicted $\mathrm{pIC}_{50}$ using MLR and ANN methods. * denotes the compounds selected for external validation (test set).

| Compound | MLR predicted $\mathrm{pIC}_{50}$ | ANN predicted $\mathrm{pIC}_{50}$ | Observed pIC $5_{0}$ |
| :---: | :---: | :---: | :---: |
| $1^{*}$ | 5.496 | 4.873 | 4.874 |
| 2 | 4.600 | 4.599 | 4.600 |
| 3 | 5.574 | 5.536 | 5.545 |
| $4^{*}$ | 5.166 | 5.209 | 5.209 |
| 5 | 4.456 | 4.573 | 4.574 |
| 6 | 5.039 | 4.886 | 4.888 |
| 7 | 6.466 | 6.656 | 6.658 |
| 8 | 4.953 | 4.804 | 4.787 |
| 9 | 5.031 | 4.623 | 4.623 |
| 10 | 5.245 | 5.039 | 5.038 |
| 11 | 4.864 | 5.138 | 5.144 |
| $12^{*}$ | 4.690 | 5.195 | 5.195 |
| 13 | 5.111 | 5.265 | 5.265 |
| 14 | 4.568 | 4.527 | 4.525 |
| 15 | 4.228 | 3.574 | 3.573 |
| 16 | 4.766 | 5.413 | 5.413 |
| 17 | 6.073 | 6.013 | 6.013 |

## General conclusion

| 18 | 6.188 | 5.768 | 5.666 |
| :---: | :--- | :--- | :--- |
| 19 | 5.588 | 5.411 | 5.411 |
| 20 | 5.642 | 5.466 | 6.174 |
| 21 | 5.303 | 5.284 | 5.485 |
| 22 | 5.558 | 5.342 | 5.343 |
| 23 | 4.703 | 5.098 | 4.788 |
| $24^{*}$ | 0.427 | 5.898 | 5.903 |

The investigation of CDCAs at the microscopic level allows a screening of the physicochemical properties related to their activity in biological media. In contrast to the statement by Li et al., we did not notice any obvious relation between the incorporation of a halogen on the chemical composition of these CDCAs and their biological activity. Our work shows, however, that among the physicochemical parameters considered here, only $\log _{10} \mathrm{P}$ and $\mathrm{N}_{\text {atom }}$ play a role. These two parameters are connected with the flexibility of these compounds, which seems increasing the Topo II inhibitory activity and more generally improves the anticancer potency of these compounds. For instance, the coefficient in front of $\log _{10} \mathrm{P}$ in our model (Eq.1) is positive and relatively large. This means that the flexibility of the CDCAs, by facilitating cell membrane crossing, will enhance the Topo II inhibition. This may be related to the mechanism of action of Topo II itself, which consists in a balanced flexibility-rigidity associated with structural changes of the quaternary structure [68] of this enzyme during the CDCA-Topo II-DNA interaction. These findings were already suggested by Guedes et al. [69] This work discloses the phenomenological relations existing between potential biological activities and molecular descriptors of a relatively large panel of compounds to be used as Topo II inhibitors, and pave the way for specific investigations of their complex mechanisms of action at a molecular dynamics level.

## APPENDIX

## Appendix

Table S1: Chemical structure of the investigated CDCAs (Table 1) as configured at the theory level of B3LYP/6-311G(d,p). In Angstrom, we give the Cartesian coordinates (X,Y,Z). The number of the atom in the structure and its atomic number, respectively, correspond to CN (Center Number) and AN (Atomic Number).


## Appendix



| 3 |  | 1 | 6 | -0.000002374 | 0.000007476 | 0.000004949 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2 | 6 | 0.000002054 | -0.000002553 | -0.000004138 |
|  |  | 3 | 6 | 0.000001781 | 0.000003233 | 0.000001714 |
|  |  | 4 | 8 | 0.000001748 | -0.000002198 | -0.000001319 |
|  |  | 5 | 6 | -0.000001364 | 0.000001494 | 0.000000223 |
|  |  | 6 | 6 | -0.000001931 | -0.000000292 | -0.000000019 |
|  |  | 7 | 6 | 0.000000625 | 0.000003596 | -0.000000494 |
|  |  | 8 | 6 | 0.000001917 | -0.000004596 | -0.000005448 |
|  |  | 9 | 6 | 0.000000256 | 0.000000398 | 0.000004834 |
|  |  | 10 | 6 | -0.000001224 | 0.000000733 | -0.000003669 |
|  |  | 11 | 7 | -0.000005575 | -0.000002626 | -0.000007410 |
|  |  | 12 | 6 | 0.000008422 | 0.000011938 | 0.000000365 |
|  |  | 13 | 6 | -0.000005594 | -0.000008105 | -0.0000005551 |
|  |  | 14 | 6 | 0.000006020 | 0.000013871 | 0.000010474 |
|  |  | 15 | 6 | 0.000004224 | -0.000008850 | -0.000012944 |
|  |  | 16 | 6 | -0.000007568 | 0.000002809 | 0.000006967 |
|  |  | 17 | 6 | -0.000001471 | -0.000001042 | 0.000005360 |
|  |  | 18 | 6 | 0.000000487 | 0.000001726 | 0.000000965 |
|  |  | 19 | 6 | 0.000001729 | 0.000000780 | -0.000001226 |
|  |  | 20 | 6 | 0.000001918 | -0.000009630 | 0.000003597 |
|  |  | 21 | 6 | -0.000000113 | 0.000001721 | 0.000000444 |
|  |  | 22 | 6 | -0.000000471 | -0.000002961 | 0.000002398 |
|  |  | 23 | 6 | -0.000000716 | -0.000001259 | -0.000000655 |
|  |  | 24 | 6 | 0.000000269 | -0.000004837 | 0.000003692 |
|  |  | 25 | 6 | -0.000001674 | 0.000005013 | 0.000000404 |
|  |  | 26 | 17 | -0.000001129 | -0.000002381 | 0.000001497 |
|  |  | 27 | 1 | 0.000000696 | 0.000000668 | 0.000002053 |
|  |  | 28 | 1 | 0.000001785 | 0.000000085 | 0.000001143 |
|  |  | 29 | 1 | -0.000001276 | 0.000000258 | -0.000001698 |
|  |  | 30 | 1 | -0.000000889 | 0.000000322 | -0.000000922 |
|  |  | 31 | 1 | -0.000000302 | -0.000000242 | 0.000000055 |
|  |  | 32 | 1 | -0.000001018 | 0.000000843 | -0.000001107 |
|  |  | 33 | 1 | -0.000001468 | -0.000004245 | -0.000001668 |
|  |  | 34 | 1 | 0.000002528 | 0.000000933 | 0.000000111 |
|  |  | 35 | 1 | 0.000001925 | -0.000001633 | 0.000000505 |
|  |  | 36 | 1 | 0.000000203 | -0.000000605 | -0.000000926 |
|  |  | 37 | 1 | -0.000001016 | 0.000000861 | -0.000001798 |
|  |  | 38 | 1 | 0.000000253 | 0.000001703 | -0.000001758 |
|  |  | 39 | 1 | 0.000000037 | 0.000001681 | -0.000001378 |
|  |  | 40 | 1 | 0.000000496 | 0.000001548 | -0.000001383 |
|  |  | 41 | 1 | -0.000000406 | -0.000001817 | 0.000001532 |
|  |  | 42 | 1 | -0.000001454 | -0.000001223 | 0.000001198 |
|  |  | 43 | 1 | -0.000000665 | -0.000000942 | 0.000000464 |
|  |  | 44 | 1 | 0.000000324 | -0.000001653 | 0.000000568 |

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|  |  | 43 44 | 1 | $\begin{aligned} & \hline 0.000001390 \\ & 0.000000537 \end{aligned}$ | $\begin{aligned} & \hline-0.000001632 \\ & -0.000001581 \end{aligned}$ | $\begin{aligned} & \hline 0.000000704 \\ & 0.000002563 \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 10 |  | 1 | 6 | -0.000013947 | -0.000008364 | 0.000024202 |
|  |  | 2 | 6 | -0.000002657 | -0.000016791 | -0.000010074 |
|  |  | 3 | 6 | 0.000005463 | 0.000011580 | -0.000000548 |
|  |  | 4 | 8 | 0.000008547 | 0.000001360 | -0.000010796 |
|  |  | 5 | 6 | 0.000000312 | 0.000001391 | 0.000002380 |
|  |  | 6 | 6 | 0.000001011 | 0.000000983 | 0.000000675 |
|  |  | 7 | 6 | 0.000000549 | 0.000000295 | 0.000001152 |
|  |  | 8 | 6 | -0.000009502 | -0.000001562 | 0.000001210 |
|  |  | 9 | 6 | -0.000001728 | 0.000006856 | -0.000006834 |
|  |  | 10 | 6 | 0.000000787 | -0.000001214 | 0.000004555 |
|  |  | 11 | 7 | 0.000007110 | -0.000007136 | 0.000018747 |
|  |  | 12 | 6 | -0.000003074 | -0.000002686 | -0.000007821 |
|  |  | 13 | 6 | -0.000001202 | 0.000000956 | 0.000004789 |
|  |  | 14 | 6 | 0.000001559 | -0.000004744 | -0.000001981 |
|  |  | 15 | 6 | -0.000002210 | -0.000000815 | 0.000002755 |
|  |  | 16 | 6 | -0.000003984 | -0.000004762 | -0.000004497 |
|  |  | 17 | 6 | 0.000011295 | 0.000008160 | 0.000000988 |
|  |  | 18 | 6 | -0.000004862 | 0.000003269 | -0.000004812 |
|  |  | 19 | 6 | -0.000003277 | -0.000000467 | 0.000001415 |
|  |  | 20 | 6 | 0.000003873 | 0.000015963 | -0.000022679 |
|  |  | 21 | 6 | -0.000001179 | -0.000002536 | -0.000001030 |
|  |  | 22 | 6 | 0.000003545 | -0.000004562 | -0.000001827 |
|  |  | 23 | 6 | -0.000000808 | 0.000002739 | -0.000000452 |
|  |  | 24 | 6 | 0.000001462 | 0.000002690 | -0.000003253 |
|  |  | 25 | 6 | -0.000001479 | -0.000003420 | 0.000007828 |
|  |  | 26 | 17 | -0.000002148 | 0.000001844 | -0.000000519 |
|  |  | 27 | 1 | 0.000004287 | -0.000000324 | -0.000000347 |
|  |  | 28 | 1 | 0.000000027 | -0.000001567 | -0.000001589 |
|  |  | 29 | 1 | -0.000000262 | 0.000002044 | 0.000002498 |
|  |  | 30 | 1 | 0.000000720 | 0.000001617 | 0.000001935 |
|  |  | 31 | 1 | 0.000000890 | 0.000001494 | 0.000000181 |
|  |  | 32 | 1 | -0.000000314 | 0.000001018 | 0.000001914 |
|  |  | 33 | 1 | -0.000000198 | -0.0000000804 | -0.000000392 |
|  |  | 34 | 1 | 0.000001232 | -0.000001220 | -0.000000504 |
|  |  | 35 | 1 | 0.000001874 | 0.000000653 | 0.000000617 |
|  |  | 36 | 1 | -0.000000777 | 0.000000647 | 0.000000415 |
|  |  | 37 | 1 | 0.000000177 | -0.000000377 | 0.000003050 |
|  |  | 38 | 1 | -0.000001847 | -0.0000000823 | 0.000002025 |
|  |  | 39 | 1 | -0.000001521 | -0.0000000099 | 0.000001956 |
|  |  | 40 | 1 | -0.000001039 | -0.0000001125 | 0.000001001 |
|  |  | 41 | 1 | -0.000000298 | -0.000000795 | -0.000001963 |
|  |  | 42 | 1 | 0.000000788 | -0.000000293 | -0.000001022 |
|  |  | 43 | 1 | 0.000001460 | 0.000000244 | -0.000000266 |
|  |  | 44 | 1 | 0.000001344 | 0.000000685 | -0.000003085 |
| 11 |  | 1 | 6 | -0.000002954 | 0.000016443 | -0.000012367 |
|  |  | 2 | 6 | -0.000012066 | 0.000003650 | 0.000003206 |
|  |  | 3 | 6 | 0.000005797 | -0.000001726 | -0.000002509 |
|  |  | 4 | 8 | 0.000002263 | -0.000004701 | 0.000001724 |
|  |  | 5 | 6 | 0.000000564 | 0.000000324 | -0.000000401 |
|  |  | 6 | 6 | -0.000000805 | -0.000000784 | 0.000000829 |
|  |  | 7 | 6 | 0.000001161 | -0.000001369 | 0.000000412 |
|  |  | 8 | 6 | -0.000006983 | 0.000000333 | 0.000001223 |
|  |  | 9 | 6 | 0.000000479 | 0.000006460 | 0.000002178 |
|  |  | 10 | 6 | 0.000000869 | -0.000000368 | -0.000001694 |
|  |  | 11 | 7 | 0.000002216 | -0.000011663 | -0.000012554 |
|  |  | 12 | 6 | -0.000002319 | 0.000005243 | 0.000004459 |
|  |  | 13 | 6 | -0.000000061 | -0.0000000061 | -0.000001563 |
|  |  | 14 | 6 | 0.000000647 | 0.000004526 | -0.000000725 |
|  |  | 15 | 6 | -0.000005754 | -0.000002979 | 0.000005192 |
|  |  | 16 | 6 | 0.000001303 | -0.000003627 | -0.000002154 |
|  |  | 17 | 6 | 0.000005379 | -0.000002074 | 0.000003654 |
|  |  | 18 | 6 | 0.000000017 | 0.000004542 | 0.000005120 |
|  |  | 19 | 6 | -0.000000292 | 0.000000103 | 0.000000162 |
|  |  | 20 | 6 | 0.000011094 | -0.000018236 | 0.000004400 |
|  |  | 21 | 6 | -0.000007823 | 0.000010071 | -0.000000258 |

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| 4 |  |  | 1 | 6 | 0.000001667 | -0.0000015735 | 0.000012842 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2 | 6 | -0.000007798 | -0.000002308 | -0.000001298 |
|  |  | 3 | 6 | 0.000011391 | 0.000014491 | 0.000000457 |
|  |  | 4 | 8 | 0.000002293 | 0.000003062 | -0.0000006049 |
|  |  | 5 | 6 | -0.000000899 | -0.000000059 | -0.000000207 |
|  |  | 6 | 6 | -0.000000454 | 0.000002121 | 0.000000805 |
|  |  | 7 | 6 | 0.000001467 | 0.000001562 | -0.000001736 |
|  |  | 8 | 6 | -0.000008593 | -0.000003864 | 0.000005984 |
|  |  | 9 | 6 | 0.000000466 | 0.000001895 | -0.000004312 |
|  |  | 10 | 6 | -0.000000726 | -0.000001267 | 0.000002682 |
|  |  | 11 | 7 | 0.000009840 | -0.000003859 | 0.000013148 |
|  |  | 12 | 6 | -0.000010675 | 0.000001492 | -0.000006164 |
|  |  | 13 | 6 | 0.000006301 | -0.000000347 | 0.000002472 |
|  |  | 14 | 6 | 0.000001204 | -0.000003627 | -0.000003115 |
|  |  | 15 | 6 | -0.000009749 | -0.000008825 | 0.000001964 |
|  |  | 16 | 6 | 0.000001508 | -0.000000759 | -0.000002404 |
|  |  | 17 | 6 | 0.000008649 | 0.000006294 | -0.000004788 |
|  |  | 18 | 6 | -0.000004041 | -0.000001189 | -0.000004674 |
|  |  | 19 | 6 | 0.000000069 | 0.000000153 | 0.000000130 |
|  |  | 20 | 6 | -0.000001978 | 0.000017268 | -0.000013129 |
|  |  | 21 | 6 | 0.000002091 | -0.000006538 | -0.000000570 |
|  |  | 22 | 6 | 0.000000459 | 0.000000468 | -0.000000674 |
|  |  | 23 | 6 | 0.000001090 | -0.000002482 | 0.000001741 |
|  |  | 24 | 6 | -0.000002651 | 0.000006949 | -0.000002453 |
|  |  | 25 | 6 | -0.000001473 | -0.000005510 | 0.000007267 |
|  |  | 26 | 6 | 0.000001017 | -0.000000809 | -0.000001111 |
|  |  | 27 | 6 | -0.000001080 | 0.000002311 | -0.000000061 |
|  |  | 28 | 1 | 0.000002372 | -0.000001205 | -0.000002703 |
|  |  | 29 | 1 | -0.000000073 | -0.000002247 | -0.000000261 |
|  |  | 30 | 1 | 0.000000688 | 0.000000820 | 0.000000917 |
|  |  | 31 | 1 | 0.000000487 | 0.000000531 | -0.000000152 |
|  |  | 32 | 1 | 0.000000323 | 0.000000486 | -0.000000749 |
|  |  | 33 | 1 | -0.000000601 | 0.000000898 | 0.000000639 |
|  |  | 34 | 1 | -0.000001107 | -0.000000242 | -0.000000078 |
|  |  | 35 | 1 | -0.000000205 | -0.000000636 | 0.000000583 |
|  |  | 36 | 1 | 0.000001030 | 0.000000269 | -0.000000672 |
|  |  | 37 | 1 | -0.000001190 | 0.000000547 | 0.000001403 |
|  |  | 38 | 1 | -0.000000386 | -0.000000072 | 0.000000487 |
|  |  | 39 | 1 | -0.000000316 | 0.000000420 | 0.000001827 |
|  |  | 40 | 1 | 0.000000016 | -0.000000810 | 0.000001320 |
|  |  | 41 | 1 | -0.000000274 | -0.000000998 | 0.000000379 |
|  |  | 42 | 1 | -0.000000891 | 0.000000616 | 0.000000349 |
|  |  | 43 | 1 | 0.000000866 | -0.000000060 | 0.000000307 |
|  |  | 44 | 1 | 0.000000186 | 0.000000904 | -0.000002400 |
|  |  | 45 | 1 | -0.000000391 | -0.000000514 | 0.000000517 |
|  |  | 46 | 1 | -0.000000946 | -0.000000589 | 0.000000081 |
|  |  | 47 | 1 | 0.000000305 | -0.000000097 | 0.000000578 |
|  |  | 48 | 1 | 0.000000518 | 0.000000641 | 0.000000295 |
|  |  | 49 | 1 | 0.000000327 | 0.000000465 | 0.000000577 |
|  |  | 50 | 1 | -0.000000135 | -0.000000015 | 0.000000006 |
| 15 |  |  |  | 1 | 6 | 0.000008162 | -0.000017837 | -0.000002323 |
|  |  | 2 |  | 6 | -0.000008618 | 0.000001749 | 0.000001814 |
|  |  | 3 |  | 6 | 0.000003462 | 0.000005606 | 0.000004070 |
|  |  | 4 |  | 8 | -0.000004583 | 0.000009666 | 0.000001028 |
|  |  | 5 |  | 6 | 0.000006219 | 0.000005729 | 0.000002135 |
|  |  | 6 |  | 6 | 0.000002048 | -0.000000293 | 0.000000557 |
|  |  | 7 |  | 6 | -0.000002021 | -0.000000045 | 0.000003135 |
|  |  | 8 |  | 6 | 0.000002605 | -0.000006838 | 0.000001376 |
|  |  | 9 |  | 6 | 0.000002066 | 0.000004350 | -0.000000104 |
|  |  | 10 |  | 6 | -0.000005643 | -0.000002849 | -0.0000000297 |
|  |  | 11 |  | 8 | 0.000001601 | 0.000002401 | -0.000003174 |
|  |  | 12 |  | 6 | 0.000002192 | -0.000000875 | 0.000001785 |
|  |  | 13 |  | 9 | 0.000002910 | -0.000002507 | 0.000002695 |
|  |  | 14 |  | 6 | -0.000001375 | 0.000000353 | -0.000004087 |
|  |  | 15 |  | 6 | -0.000001188 | -0.000000569 | -0.000004317 |
|  |  | 16 |  | 6 | -0.000001740 | 0.000000432 | -0.000002903 |
|  |  | 17 |  | 6 | -0.000001571 | 0.000000894 | -0.000003899 |

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| 18 |  | 1 | 6 | -0.000002392 | 0.000013555 | 0.000007636 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2 | 6 | 0.000007207 | -0.000011040 | -0.000003831 |
|  |  | 3 | 6 | 0.000005100 | 0.000006459 | -0.000000324 |
|  |  | 4 | 8 | -0.000000023 | -0.000003003 | -0.000000846 |
|  |  | 5 | 6 | 0.000001101 | 0.000002482 | -0.000000903 |
|  |  | 6 | 6 | 0.000000857 | 0.000002000 | -0.000001404 |
|  |  | 7 | 6 | 0.000004466 | 0.000001370 | -0.000005038 |
|  |  | 8 | 6 | -0.000008605 | -0.000000599 | 0.000003877 |
|  |  | 9 | 6 | -0.000000266 | 0.000006024 | 0.000002010 |
|  |  | 10 | 6 | 0.000001474 | 0.000001839 | -0.000002278 |
|  |  | 11 | 7 | 0.000002565 | 0.000002603 | -0.0000000058 |
|  |  | 12 | 6 | -0.000002266 | 0.000000728 | -0.000004393 |
|  |  | 13 | 6 | 0.000001447 | 0.000000822 | 0.000001005 |
|  |  | 14 | 6 | 0.000000937 | 0.000001856 | -0.0000000863 |
|  |  | 15 | 6 | -0.000002582 | -0.000005279 | -0.000002614 |
|  |  | 16 | 6 | -0.000000011 | 0.000000760 | 0.000000741 |
|  |  | 17 | 6 | 0.000008415 | 0.000001377 | -0.000004346 |
|  |  | 18 | 6 | -0.000000286 | -0.000000332 | 0.000001338 |
|  |  | 19 | 6 | -0.000001681 | 0.000001335 | 0.000002701 |
|  |  | 20 | 6 | -0.000000472 | -0.000000986 | -0.000000367 |
|  |  | 21 | 6 | -0.000000248 | 0.000001780 | 0.000002938 |
|  |  | 22 | 6 | -0.000004579 | -0.000003042 | 0.000003553 |
|  |  | 23 | 6 | -0.000000741 | 0.000000895 | -0.0000000185 |
|  |  | 24 | 6 | -0.000001781 | 0.000002119 | 0.000003266 |
|  |  | 25 | 6 | -0.000002067 | -0.000000979 | 0.000002812 |
|  |  | 26 | 6 | 0.000001003 | -0.000006924 | -0.000009285 |
|  |  | 27 | 6 | 0.000000238 | -0.000001164 | 0.000000563 |
|  |  | 28 | 6 | -0.000000567 | -0.000003584 | -0.000001264 |
|  |  | 29 | 6 | 0.000000948 | -0.000001392 | 0.000004590 |
|  |  | 30 | 6 | -0.000000057 | -0.000001550 | -0.000000406 |
|  |  | 31 | 6 | 0.000000031 | -0.000003433 | -0.000000621 |
|  |  | 32 | 17 | -0.000000468 | -0.000005289 | -0.000001661 |
|  |  | 33 | 1 | 0.000002172 | -0.000000333 | -0.000002414 |
|  |  | 34 | 1 | 0.000002080 | 0.000000056 | -0.000003464 |
|  |  | 35 | 1 | 0.000000599 | 0.000002408 | -0.000000620 |
|  |  | 36 | 1 | 0.000001919 | 0.000002006 | -0.000002436 |
|  |  | 37 | 1 | 0.000001621 | 0.000001516 | -0.000001220 |
|  |  | 38 | 1 | -0.000001084 | 0.000002406 | 0.000001041 |
|  |  | 39 | 1 | -0.000000799 | 0.000001238 | 0.000000172 |
|  |  | 40 | 1 | -0.000000162 | 0.000000199 | -0.000000899 |
|  |  | 41 | 1 | 0.000002204 | 0.000000856 | -0.000002218 |
|  |  | 42 | 1 | -0.000001567 | 0.000000837 | 0.000001512 |
|  |  | 43 | 1 | -0.000000652 | 0.000002493 | 0.000000200 |
|  |  | 44 | 1 | -0.000000758 | -0.000000713 | 0.000000657 |
|  |  | 45 | 1 | -0.000001618 | -0.000001535 | 0.000001284 |
|  |  | 46 | 1 | -0.000002876 | 0.000000725 | 0.000003264 |
|  |  | 47 | 1 | -0.000002248 | 0.000002004 | 0.000001714 |
|  |  | 48 | 1 | -0.000002918 | -0.000001006 | 0.000003222 |
|  |  | 49 | 1 | -0.000002158 | -0.000001695 | 0.000002364 |
|  |  | 50 | 1 | -0.000002516 | -0.000001960 | 0.000002741 |
|  |  | 51 | 1 | -0.000000081 | -0.000001626 | 0.000000329 |
|  |  | 52 | 1 | -0.000000495 | -0.000002941 | 0.000000510 |
|  |  | 53 | 1 | 0.000001165 | -0.000003279 | -0.000000879 |
|  |  | 54 | 1 | 0.000001479 | -0.000001063 | -0.000001206 |

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| 24 |  | 1 | 6 | -0.000001169 | 0.000002971 | 0.000001256 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2 | 6 | 0.000000558 | -0.000004440 | -0.000008397 |
|  |  | 3 | 6 | -0.000002299 | 0.000000481 | 0.000003322 |
|  |  | 4 | 8 | 0.000001275 | 0.000000700 | 0.000000477 |
|  |  | 5 | 6 | -0.000001527 | 0.000000783 | -0.000000479 |
|  |  | 6 | 6 | -0.000000376 | -0.000000834 | -0.000000506 |
|  |  | 7 | 6 | -0.000000376 | 0.000000338 | -0.000001924 |
|  |  | 8 | 6 | -0.000004703 | -0.000002660 | 0.000001113 |
|  |  | 9 | 6 | -0.000000840 | 0.000002756 | 0.000004446 |
|  |  | 10 | 6 | 0.000000616 | -0.000001492 | -0.000002517 |
|  |  | 11 | 7 | -0.000000406 | 0.000003398 | -0.000012724 |
|  |  | 12 | 6 | 0.000000975 | -0.000003151 | 0.000003892 |
|  |  | 13 | 6 | -0.000000978 | 0.000002216 | 0.000000398 |
|  |  | 14 | 6 | 0.000000927 | -0.000005225 | 0.000000358 |
|  |  | 15 | 6 | 0.000002523 | 0.000006454 | -0.000001820 |
|  |  | 16 | 6 | -0.000003515 | -0.000003802 | -0.000004454 |
|  |  | 17 | 6 | 0.000005935 | 0.000004693 | 0.000000337 |
|  |  | 18 | 6 | 0.000001670 | -0.000002552 | 0.000006920 |
|  |  | 19 | 6 | -0.000000244 | -0.000002865 | -0.000001343 |
|  |  | 20 | 6 | 0.000000565 | -0.000001022 | 0.000000137 |
|  |  | 21 | 6 | 0.000001896 | -0.000002214 | 0.000002095 |
|  |  | 22 | 6 | -0.000000483 | -0.000000155 | 0.000000800 |
|  |  | 23 | 6 | 0.000000464 | -0.000000287 | -0.000000414 |
|  |  | 24 | 6 | -0.000000478 | -0.000000517 | 0.000001884 |
|  |  | 25 | 7 | 0.000006080 | 0.000002554 | 0.000006280 |
|  |  | 26 | 6 | -0.000001235 | 0.000004290 | -0.000005017 |
|  |  | 27 | 6 | 0.000000361 | -0.000001772 | 0.000002183 |
|  |  | 28 | 6 | -0.000002208 | 0.000001766 | 0.000000872 |
|  |  | 29 | 6 | 0.000002022 | -0.000001648 | 0.000000684 |
|  |  | 30 | 6 | -0.000001728 | 0.000005765 | -0.000003113 |
|  |  | 31 | 6 | -0.000000135 | 0.000000073 | 0.000006958 |
|  |  | 32 | 17 | -0.000000944 | 0.000002438 | 0.000000502 |
|  |  | 33 | 1 | -0.000000135 | 0.000000721 | 0.000001196 |
|  |  | 34 | 1 | -0.000001174 | -0.000000346 | 0.000002053 |
|  |  | 35 | 1 | -0.000000160 | -0.000000075 | -0.000000567 |
|  |  | 36 | 1 | -0.000000639 | -0.000000153 | -0.000001849 |
|  |  | 37 | 1 | -0.000000375 | -0.000000269 | -0.000001062 |
|  |  | 38 | 1 | 0.000000664 | -0.000000370 | -0.000000122 |
|  |  | 39 | 1 | 0.000001233 | -0.000000182 | 0.000000387 |
|  |  | 40 | 1 | -0.000001129 | -0.000000465 | -0.000000004 |
|  |  | 41 | 1 | 0.000000103 | 0.000000367 | -0.000000547 |
|  |  | 42 | 1 | -0.000000444 | 0.000001147 | -0.000000737 |
|  |  | 43 | 1 | 0.000000159 | 0.000000695 | 0.000001967 |
|  |  | 44 | 1 | 0.000001343 | 0.000000133 | 0.000001515 |
|  |  | 45 | 1 | 0.000000957 | -0.000000256 | 0.000000932 |
|  |  | 46 | 1 | 0.000000578 | -0.000002518 | -0.000000270 |
|  |  | 47 | 1 | 0.000000844 | -0.000000932 | -0.000000266 |
|  |  | 48 | 1 | -0.000000685 | 0.000001367 | 0.000000259 |
|  |  | 49 | 1 | 0.000000021 | 0.000001608 | 0.000001118 |
|  |  | 50 | 1 | -0.000000664 | 0.000000928 | 0.000000322 |
|  |  | 51 | 1 | -0.000001268 | 0.000000336 | -0.000001383 |
|  |  | 52 | 8 | -0.000001061 | -0.000005883 | -0.000002149 |
|  |  | 53 | 8 | -0.000000389 | -0.000002891 | -0.000002999 |

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ecently, a series of carbazole derivatives containing chalcone analogues (CDCAs) were synthetized
as potent anticancer agents and apoptosis inducers. These compounds target the inhibition of topoisomerase II and present cytotoxic activities. After comparison to experiment, we validated the use of B3LYP, a density functional theory-based approach, to describe the structure and molecular properties of the carbazole subunit and CDCAs compounds of interest. Then, we derived relationships between the chemical descriptors and activity of these carbazole derivatives using multi-parameter optimization and quantitative structure activity relationships (QSAR) approaches. For the QSAR studies, we used multiple linear regression and artificial neural network statistical modelling. Our predicted activities are in good agreement with the experimental ones. We found that the most important parameter influencing the activity of the considered compounds is the octanol-water partition coefficient, highlighting the importance of flexibility as a key molecular parameter to favor cell membrane crossing and enhance the action of these CDCAs against topoisomerase II. Our results provide useful guidelines for designing new oral active CDCAs medicaments for cytotoxic inhibition.
Keywords: Carbazole derivatives; Topo II inhibition; Molecular structure; QSAR model.

Récemment, une série de dérivés du carbazole contenant des analogues de la chalcone (CDCA) ont été synthétisés en tant qu'agents anticancéreux puissants et inducteurs de l'apoptose. Ces composés ciblent l'inhibition de la topoisomérase II et présentent des activités cytotoxiques. Après comparaison à l'expérience, nous avons validé l'utilisation de B3LYP, une approche basée sur la théorie fonctionnelle de la densité, pour décrire la structure et les propriétés moléculaires de la sous-unité carbazole et des composés CDCA d'intérêt. Ensuite, nous avons dérivé des relations entre les descripteurs chimiques et l'activité de ces dérivés de carbazole en utilisant des approches d'optimisation multi-paramètres et de relations quantitatives structureactivité (QSAR). Pour les études QSAR, nous avons utilisé une régression linéaire multiple et une modélisation statistique des réseaux de neurones artificiels. Nos activités prédites sont en bon accord avec celles expérimentales. Nous avons constaté que le paramètre le plus important influençant l'activité des composés considérés est le coefficient de partage octanol-eau, soulignant l'importance de la flexibilité en tant que paramètre moléculaire clé pour favoriser le franchissement de la membrane cellulaire et renforcer l'action de ces CDCA contre la topoisomérase II. Nos résultats fournissent des lignes directrices utiles pour la conception de nouveaux médicaments CDCA actifs oraux pour l'inhibition cytotoxique.

Mots clés : Dérivés du carbazole ; Inhibition de Topo II; Structure moleculaire; Modèle QSAR.

