

Computer Assisted Geometry Optimization for *in silico* Modeling

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Abstract

This paper aimed to present a methodology for the geometry optimization of molecules in order to analyze structure-activity/property relationships. The main objective was to reduce the probability of carrying out misleading analyses while preparing the molecules for modeling. An algorithm that used HyperChem 8.0 software was developed and implemented in a series of PHP programs. A sample of 319 drug-like compounds was used to test the implemented algorithm. The program executed the geometry optimization protocols efficiently and quickly on both small and large sample sizes. The results obtained in the investigated sample of 319 compounds showed that our programs performed well on the investigated compound collection thus increasing the reliability of compound preparation for quantitative structure-activity relationships analysis.

Keywords: Computer Assisted/Automated System; Geometry Optimization; *in silico* Modeling; Accuracy.

Introduction

The molecular structures are optimized at the beginning of any structure-activity/property relationship modeling approach (mathematical representation of the activity/property of molecules in relation with their physical and chemical properties [1]). Energy minimization and geometry optimization are both applied on molecular structures before computing the molecular descriptors.

A series of methods are applied to optimize the geometry of molecules: empirical force field methods (molecular mechanics, a less expensive method in terms of computational speed, able to provide excellent structural parameters), semi-empirical methods (that can solve the Schrödinger equation, with certain approximations, in order to describe the electron properties of atoms and molecules), and *ad initio* methods (e.g. Hartree-Fock, Post-Hartree Fock, Density Functional Theory).

The characteristics of some molecular mechanics force fields (known to neglect electrons) and their applicability domains are as follows:

- MM+: developed as an extension of MM2 [2] for organic molecules [3].
- AMBER (Assisted Model Building with Energy Refinement): a family of force fields for molecular dynamics (biomolecules) [4-6].
- BIO+: a method similar with the CHARMM (Chemistry at HARvard Molecular Mechanics)

functional form developed for proteins [7].

- OPLS (Optimized Potential for Liquid Simulations): a molecular mechanics method similar to AMBER for chemical calculations developed for proteins and nucleic acids (it reproduces liquid properties such as heat of vaporization and density) [8,9].

The semi-empirical methods (calculations are faster compared to ab initio methods) are known to neglect core electrons. The characteristics of some semi-empirical methods are as follows:

- CNDO, INDO, NDDO: rarely used today but their methodology constitutes the basis of newer methods [10].
- MINDO, MNDO [11], AM1 [12], PM3 [13,14]: use parameters to fit the experimental heats of formation, dipole moments, ionization potentials and geometries. The Austin Model 1 eliminates the problem of MINDO (tendency to overestimate repulsions between atoms). The PM3 method is the third parametrization of MNDO and it uses parameters derived by “chemical intuition”.
- ZINDO [15] and SINDO [16-18]: calculate excited states and predict electronic spectra.
- Semi-empirical extended Hückel [19]: used for single point calculations to produce quantitative and semi-quantitative descriptors.

Ab initio methods fully count the electrons and use only theoretical principles to solve the Schrödinger equation associated with the molecular Hamiltonian [20].

Energy minimization and geometry optimization are essential tasks in molecular modeling and drug design. The failure to minimize energy and/or optimize geometry is directly translated into incorrect molecular descriptors and thus into unreliable QSAR/QSPR (quantitative Structure-Activity Relationship / quantitative Structure-Property Relationship) models. The probability of geometry optimization to fail is directly related to the number of compounds in the dataset. This probability increases as the number of compounds in the data set increase. The aim of the research was to develop a methodology able to carry out optimal geometry optimization of biologic active compounds and to implement as well as assess the proposed methodology.

Material and Method

The PHP (Hypertext Preprocessor) language was used in order to develop the automated geometry optimization application. The application was developed to use the functions implemented in HyperChem (Version 8.0) under Windows operating system.

Dataset for Design

Data previously used to validate a QSAR model were used to design and validate procedures for the proposed algorithm [21]. The sample comprised 319 drug-like molecules belonging to classes of compounds with different structures, which are known as active (BBB+, BBB = blood-brain barrier) or not active (BBB-) compounds in the central nervous system (CNS).

The PubChem (<http://pubchem.ncbi.nlm.nih.gov/>) database was used to download the *.sdf files of the BBB compounds. The name of the drug-like molecule, the PubChem compound identifier (CID) and active/not active status in the CNS are presented in **Supplementary material**.

Algorithm

The main objective of the research was to create an automated application able to perform geometry optimization of biological active compounds that are subject of QSAR/QSPR analyses. The 3-step protocol put forward for implementation contains is:

- Turn the 2-dimensional sketch of the molecule into a 3-dimensional structure: [Build – Add H & Model Build].
- Define a model of molecular mechanics (AMBER were defined) and optimize the molecular structure by applying the AM1 method, Polak-Ribiere algorithm.
- Minimize the energy of the molecule.

The protocol is applied to each molecule in the dataset as a first procedure in QSAR/QSPR analyses.

Figure 1 presents the algorithm proposed for the automated optimization of molecular geometry.

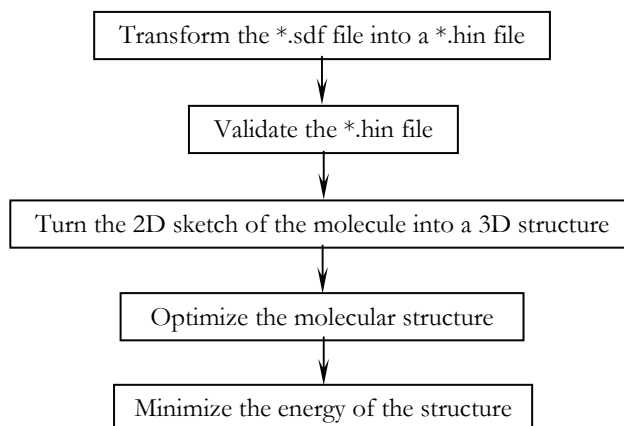


Figure 1. Protocol for automated optimization of molecular geometry

The following parameters were used:

1. Apply the molecular mechanics method: AMBER
2. Optimize the molecular geometry: ▪ Scf-convergence = 1e-8; ▪ Max-iterations = 100; ▪ Optim – max – cycles = 1000; ▪ Optim – coverage = 0.01; ▪ Optim algorithm = PolakRibiere [22]; ▪ Query-value optim-converged.
3. Compute partial charges: ▪ Semi-empirical-method = AM1, ▪ Do-single-point.
4. Save the results in Job_Results.txt file: ▪ Value of optim-converged = True/False, ▪ Value current-file-name = name of the file, ▪ Value total-energy = value (kcal/mol), ▪ Value dipole-moment = (Debyes) - Sum(Point-Chg., sp Hybrid, pd Hybrid), ▪ Value scf-atom-energy = Isolated Atomic Energy (kcal/mol), ▪ Value scf-binding-energy = Binding Energy (kcal/mol), ▪ Value scf-core-energy = Core-Core Interaction (kcal/mol), ▪ Value scf-electronic-energy = Electronic Energy (kcal/mol), ▪ Value heat-of-formation = Heat of Formation (kcal/mol)

Validation.

The analysis of the developed programs in terms of speed and accuracy was first performed on a small sample and later on the 319 data set of BBB compounds. The program was assessed with Intel® Core™2 Quad CPU, 2.66 GHz, 2 GB RAM using the HyperChem 8.0 for Windows.

A series of parameters were counted and analyzed in order to assess the implemented algorithm: (1) overall time needed for optimization; (2) optimization performance (in terms of accuracy expressed as the ratio between the number of optimized molecules and the total number of molecules in the sample); (3) the numbers of runs needed to optimize all compounds in the sample.

The program was first run for all the molecules in the sample (319 compounds). For non-optimized compounds, the program was run again but this time it only had to perform geometry optimization.

Results

Program Description

A series of steps are applied for obtaining the information of a 3D structure: define a model of molecular mechanics, optimize the molecular geometry until convergence with a specified algorithm, define the semi-empirical method for energy calculation and obtain a series of energetic parameters that characterize the optimum geometry as well as the electrical partial charges (see

Figure 2). The proposed method applied the AMBER mechanical model [4], the Polak-Ribiere optimization algorithm [22] and the AM1 semi-empirical method [12] for energy calculations. The results of optimization and energy minimization were saved in a *.hin file which defined the chemical structure of each model built (a structure with many rows, one row for each atom of molecule (number, name, partial charge, spatial coordination, number and type of bounds)).

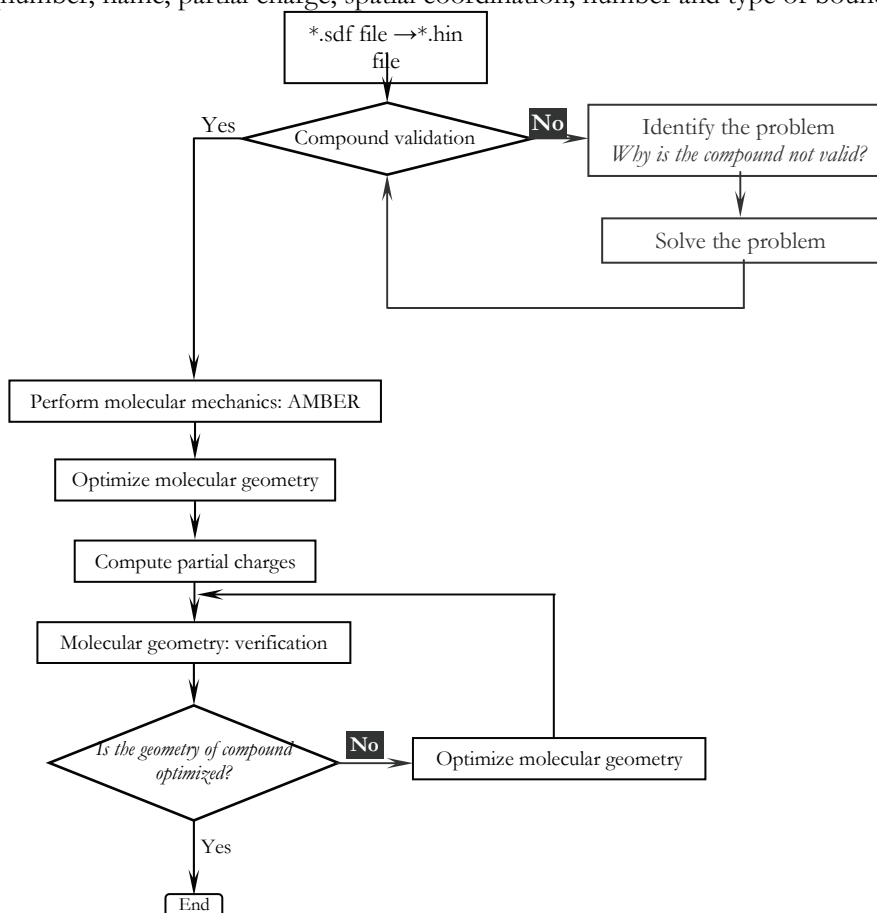


Figure 2. Process flow for optimizing the geometry of the compounds

Two changes could be observed on the *.hin file after applying the proposed algorithm for optimization geometry: the atoms and the position of the atoms in the structure (Figure 3).

The *.hin structural files before and after applying the developed and implemented algorithm are presented in Figure 4.

A PrintScreen from the results opened with Microsoft Excel is presented in Figure 5.

The time needed to optimize the geometry depends on computer hardware. The implemented algorithm runs properly with HyperChem 8.0. The program sources are available upon request (a PHP program that generates HyperChem script files and runs the HyperChem application once).

Analysis of Program Runs

The analysis of the program was performed while implementing a sample of three molecules drawn randomly from the sample. The program was applied in order to optimize the sample of 319 compounds after release of its final form.

The first compound in the sample was optimized in 2.20 minutes. The average time needed to optimize the geometry was of almost 8 minutes. The overall time needed for the entire sample was of 42.72 hours. The shortest time was needed for molecules with a small number of atoms and a less complex structure.

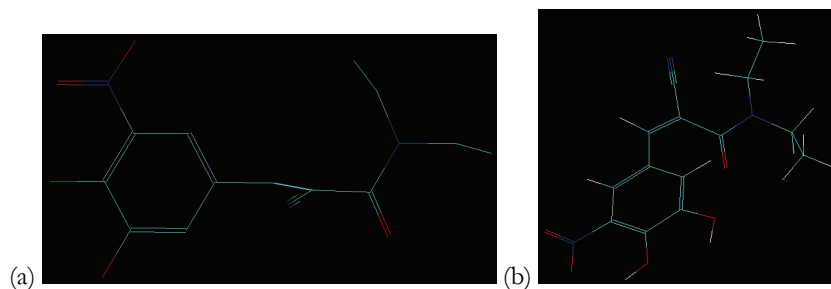


Figure 3. Structural refinement of molecule before (a) and after (b) applying the algorithm

```

forcefield amber94
sys 0 0 1
view 40 0.21229 40 15 1 0 0 0 1 0 0 0 1 -5.6344 -3.0066 -40
seed -1111
smol 1
atom 1 - O ** - -0.56 0.9362 -3.0997 0.2653 2 11 s 13 s
atom 2 - O ** - -0.68 1.9329 -0.0026 0.6466 1 10 s
atom 3 - O ** - -0.68 0.0690 -1.4104 2.0674 1 12 s
atom 4 - O ** - -0.68 2.4710 -3.3340 -3.0317 1 14 s
atom 5 - N ** - 0.05 -0.9268 -2.0371 1.2756 3 11 s 15 s 16 s
atom 6 - N ** - -0.57 -3.0699 -2.6098 1.0540 2 16 d 17 s
atom 7 - N ** - -0.57 -1.0277 -0.8580 3.3969 2 15 d 19 s
atom 8 - N ** - -0.62 -3.2996 -0.8292 4.2877 2 18 s 19 d
atom 9 - N ** - -0.9 -5.1379 -1.8581 3.1524 1 18 s
atom 10 - C ** - 0.28 0.9306 -0.7087 0.0818 3 2 s 11 s 12 s
atom 11 - C ** - 0.54 0.4981 -1.9183 0.9600 3 1 s 5 s 10 s
atom 12 - C ** - 0.28 1.2289 -1.3146 -1.2508 3 3 s 10 s 13 s
atom 13 - C ** - 0.28 1.7482 -2.6902 -0.8476 3 1 s 12 s 14 s
atom 14 - C ** - 0.28 1.6947 -3.7592 -1.9233 2 4 s 13 s
atom 15 - C ** - 0.11 -1.5653 -1.5465 2.3788 3 5 s 7 d 17 s
atom 16 - C ** - 0.04 -1.8721 -2.6667 0.5100 2 5 s 6 d
atom 17 - C ** - 0.23 -2.8927 -1.9125 2.2225 3 6 s 15 s 18 d
atom 18 - C ** - 0.41 -3.7738 -1.5280 3.2283 3 8 s 9 s 17 d
atom 19 - C ** - 0.47 -1.9756 -0.5418 4.3059 2 7 s 8 d
endmol 1
    
```

Figure 4. Content of a *.hin file before and after applying the algorithm

optim-converged	current-file-name	total-energy	dipole-moment	scf-atom-energy	scf-binding-energy	scf-core-energy	scf-electronic-energy	heating formation
TRUE	131_191.hin	-87051.97	2.616018	-83774.8	-3277.171	458296.2	-545348.2	-87.70886
FALSE	132_51263.hin	-122879.8	3.952207	-116793.7	6086.073	997701.8	-1120582	26.55836
TRUE	133_2099.hin	-82236.04	4.345716	-78056.3	-4280.736	510573.9	-692908.9	73.78911
TRUE	134_16231.hin	-69651.65	6.323501	-67366.21	-2285.342	286214	-355655.5	36.36267
FALSE	135_60795.hin	-122814.2	2.867873	-118925.7	8088.428	819410.2	-930154.3	35.10727
TRUE	136_2344.hin	-82012.22	0.6501277	-77036.29	-4975.953	577559.3	-695671.5	97.98526
FALSE	137_2369.hin	-89295.8	2.939988	-84308.25	-4987.556	544658.1	-633954	-108.9007
TRUE	138_2405.hin	-97344.4	2.237763	-92123.44	-5220.958	571194.4	-668438.8	-178.54
TRUE	139_2435.hin	-67611.72	2.101606	-64738.91	-2872.805	320807.5	-388419.2	119.7452
FALSE	140_31101.hin	-176120.1	4.527873	-167579.8	8540.328	1680861	-1856981	98.23335
TRUE	141_2487.hin	-90706.32	1.755899	-85377.08	-5329.239	691597.9	-782304.3	2.527497
TRUE	142_2707.hin	-47513.1	2.239162	-46689.62	-623.4765	102907.9	-150421	-119.3025
TRUE	143_2712.hin	-81903.99	4.777861	-78133.48	-3770.507	472394.3	-554298.2	120.7101

Figure 5. Structural refinement of molecule before (a) and after (b) applying the algorithm

A number of 199 compounds out of 319 were optimized after the first run of the program. Thus, a 62% (95%CI [57% – 68%]) accuracy was obtained after the first run.

The statistical characteristics in terms of number of atoms in optimized and non-optimized compounds after the first run are presented in Table 1.

Table 1. Statistical characteristics for optimized and non-optimized compounds after the first run: number of atoms

Parameter	Optimized (n = 199)		Non-optimized (n = 119)	
	Total no. of atoms	No. of atoms other than H	Total no. of atoms	No. of atoms other than H
Mean [95%CI]	38 [37 – 40]	21 [20 – 21]	50 [47 – 52]	26 [25 – 27]
StdDev	12.53	6.01	11.93	5.71
Median	39	21	49	25
Mode	32	21	48	25
Min	10	7	17	14
Max	72	36	87	44

Mean = arithmetic mean, 95%CI = 95% confidence interval; StdDev = standard deviation

The mean of the total number of atoms in optimized compounds proved to be statistically significant smaller compared to the number of atoms in not-optimized compounds when first run was analyzed ($t = -7.76$, $p = 1.19 \cdot 10^{-13}$, significance level of 5%). The mean of the number of atoms other than H in optimized compounds proved to be statistically significant smaller compared to not-optimized compounds in first run ($t = -8.17$, $p = 7.58 \cdot 10^{-15}$, significance level of 5%).

The second run aimed to optimize the not-optimized geometry after the first run. A number of 6.34 hours was needed with an average of 0.05 hours per compound. All compound proved to be optimized after the second run (resulting an accuracy of 100%).

Discussion

The proposed algorithm was implemented for the HyperChem 8.0 software. The implemented PHP programs led to the efficient optimization of geometry on the investigated sample of compounds. The users can select the parameter of energy minimization and geometry optimization as well as different protocols. The programs were initially tested on a small sample size. The program is currently being developed to include other QSAR/QSPR calculations.

Computer based geometry optimization was successfully developed, implemented and assessed. These files represent the input data in molecular modeling and are used to calculate the molecular descriptors for each compound.

Structure-activity/property approaches use molecular structures by neglecting the contribution of hydrogen atoms as structural information related to the active activity/property. The following are explanations for not using hydrogen atoms:

- Biological activities are determined in vivo in an aqueous medium where partial dissociation processes take place. Thus, a form without hydrogen atoms is presented in this experiment.
- Hydrogen atoms have a single bound. Since hydrogen atoms have one bound, they do not contribute to molecular complexity (they do not create chains and braches being only terminal elements) and they do not provide information able to characterize compound structure, unlike the information supplied by all the other atoms.
- Since hydrogen atoms are not taken into consideration, the amount of calculations required reduces significantly if hydrogen atoms are deleted (e.g. the amount of calculations for the C_nH_{2n+2} alkane is reduced by 1/3 if the calculations are proportional to molecule size).

The following strategies could be used in order to verify that the program works properly:

- Display the optimized molecules (Figure 3):
 - The file before optimization did not contain hydrogen atoms while molecules after optimization contain all atoms including hydrogen atoms. &
 - The position of the atoms in the structure is quite different after applying the proposed algorithm.

The analysis of the files showed in Figure 4 revealed the following:

- AMBER was applied to the molecules stored in PubChem.
- The structure of the compound was correct if only one molecule was present. Our program is not able to optimize the geometry of any structures that have more than 1 molecule.
- The number of atoms before applying the methodology was smaller compared to the number of atoms after using the program. This difference was due to the absence of hydrogen atoms from the structures downloaded from PubChem (see Figure 3).

Some of the numbers that characterize each atom were not changed by applying the proposed methodology (the last five numbers of each atom) while all the other values changed as the result of energy minimization and geometry optimization. The program was developed to include in the report file a series of parameters that characterize the optimized compound (see Figure 5).

Two main advantages were identified while running the program:

- The time needed to prepare the molecule for structure-activity/property analyses was reduced. All the processes implemented in the algorithm were performed automatically; there was no coffee break during the process and the program will never get tired regardless of the number of compounds processed. Time was reduced by almost 1/2 when the automated program was used.
- The possibility of any mistakes / false analyses was minimized. Energy minimization and/or

geometry optimization are always accurate since the processes are performed by the program.

The program stops in two situations: the analysis is complete (all molecules in the set were analyzed) or a power cut occurs in the laboratory. The power shortage can be prevented by using UPS devices.

Some structures could not be optimized by applying the parameter used for optimization. The program ran for our sample requires a maximum of 1000 cycles and an optimal coverage of 0.01. The program stops while processing a compound if the maximum number of cycles required is reached or if optimal coverage is obtained. This problem could be solved by changing the parameters of the optimization algorithm. This solution may be used if the structures are similar in terms of number of compounds and/or complexity. Another solution is to apply the program again on the structures that were not optimized. This strategy was more suitable for our sample given the heterogeneity of compounds.

A series of *in silico* molecular modeling methods use automated processes to prepare compounds but none could be identified for geometry optimization using the HyperChem software. Pencheva et al. [23] proposed an automated molecular mechanics optimization tool for *in silico* screening. The development and implementation of automated methods applied to *in silico* screening represent a research problem to which a series of researchers have already found several solutions: conformation generator and rigid docking [24]; web server ligand-based screening [25]; 3D ligand similarity search [26], etc.

In 2009, Lagorce et al. proposed a DG-AMMOS source program, which allows the generation of 3D conformation of small molecules using distance geometry and their energy minimization via automated molecular mechanics optimization [27]. Helgee et al. developed and implemented a method that optimizes a compound based on the interpretation of quantitative structure-activity relationship models [28]. Miteva et al. proposed a web tool for generating the conformation ensembles of small molecules starting from 1D, 2D or 3D descriptions of the compounds [29]. We were not able to identify any program similar with our proposed algorithm. We are currently working on implementing other facilities to our program in terms of QSAR descriptors.

Conclusions

An efficient geometry optimization algorithm was developed and implemented to be used with HyperChem 8.0 software in order to prepare molecules for QSAR/QSPR analyses. Fully automatic PHP programs can perform geometry optimization according to the defined characteristics specified by the user. The program executes efficiently and quickly the implemented geometry optimization protocols on both small and large sample sizes. The results obtained in the investigated sample of 319 compounds showed that our program performed well on the investigated compound collection thus increasing the reliability of the compounds included in the QSAR analysis.

Conflict of Interest

The author declares that he has no conflict of interest.

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References

1. Hansch C, Fujita T. ρ - σ - π Analysis. A Method for the Correlation of Biological Activity and Chemical Structure. *Am Chem Soc* 1964;86(8):1616-1630.
2. Allinger NL. Conformational analysis. 130. MM2. A hydrocarbon force field utilizing V1 and V2 torsional terms. *J Am Chem Soc* 1977;99:8127-8134.
3. Hocquet A, Langgard M. An Evaluation of the MM+ Force Field. *J Mol Model* 1998;4:94-112.

4. Weiner SJ, Kollman PA, Case DA, Singh UC, Chio C, Alagona G, et al. A new force field for molecular mechanical simulation of nucleic acids and proteins. *J Am Chem Soc* 1984;106:765-784.
5. Weiner SJ, Kollman PA, Nguyer DT, Case DA. An all atom force field for simulations of proteins and nucleic acids. *J Comput Chem* 1986;7:230-252.
6. Cornell WD, Cieplak P, Bayly CI, Gould IR, Merz KM Jr, Ferguson DM, Spellmeyer DC, Fox T, Caldwell JW, Kollman PA. A Second Generation Force Field for the Simulation of Proteins, Nucleic Acids, and Organic Molecules. *J Am Chem Soc* 1995;117:5179-5197.
7. Brooks BR, Brucoleri RE, Olafson BD, States DJ, Swaminathan S, Karplus M. Charmm: a program for macromolecular energy, minimization, and dynamics calculations. *J Comp Chem* 1983;4(2):187-217.
8. Jorgensen WL, Tirado-Rives J. The OPLS Force Field for Proteins. Energy Minimizations for Crystals of Cyclic Peptides and Crambin. *J Am Chem Soc* 1988;110:1657-1666.
9. Pranata J., Wierschke S.G., Jorgensen W.L. OPLS potential functions for nucleotide bases. Relative association constants of hydrogen-bonded base pairs in chloroform. *J Am Chem Soc* 1991;113:2810-2819.
10. Cramer CJ. *Essential of Computational Chemistry*. Wiley, Chichester, 2002, pp. 126-131.
11. Dewar MJS, Thiel W. Ground states of molecules. 38. The MNDO method. Approximations and parameters. *J Am Chem Soc* 1977;99(15):4899-4907.
12. Dewar MJS, Zoebisch EG, Healy EF, Stewart JJP. AM1: A New General Purpose Quantum Mechanical Molecular Model. *J Am Chem Soc* 1985;107:3902-3909.
13. Stewart JJP. Optimization of parameters for semiempirical methods I. Method. *Comput Chem* 1989;10:209-220.
14. Stewart JJP. Optimization of parameters for semiempirical methods. II. Applications. *J Comput Chem* 1989;10:221-264.
15. Zerner M. *Reviews in Computational Chemistry, Volume 2*, Eds. Lipkowitz KB, Boyd DB, VCH, New York, 313, (1991).
16. Nanda DN, Jug K. SINDO1. A semiempirical SCF MO method for molecular binding energy and geometry I. Approximations and parametrization. *Theor Chim Acta* 1980;57(2):95-106.
17. Jug K, Nanda DN. SINDO1 II. Application to ground states of molecules containing carbon, nitrogen and oxygen atoms. *Theor Chim Acta* 1980;57(2):107-130.
18. Jug K, Nanda DN. SINDO1 III. Application to ground states of molecules containing fluorine, boron, beryllium and lithium atoms. *Theor Chim Acta* 1980;57(2):131-144.
19. Hoffmann R. An Extended Hückel Theory. I. Hydrocarbons. *J Chem Phys* 1963;39:1397-1412.
20. Joachim Sauer. Molecular models in ab initio studies of solids and surfaces: from ionic crystals and semiconductors to catalysts. *Chem Rev* 1989;89(1):199-255.
21. Kortagere S, Chekmarev D, Welsh WJ, Ekins S. New Predictive Models for Blood-Brain Barrier Permeability of Drug-like Molecules. *Pharm Res* 2008;25(8):1836-1845.
22. Polak B, Ribiere G. Note sur la convergence des méthodes de directions conjuguées. *Rev Fr Inform Rech Oper* 1969;16:35-43.
23. Pencheva T, Lagorce D, Pajeva I, Villoutreix BO, Miteva MA. AMMOS: Automated Molecular Mechanics Optimization tool for in silico Screening. *BMC Bioinformatics* 2008;9:438.
24. Sauton N, Lagorce D, Villoutreix BO, Miteva MA. MS-DOCK: accurate multiple conformation generator and rigid docking protocol for multi-step virtual ligand screening. *BMC Bioinformatics* 2008;9:184.
25. Sperandio O, Petitjean M, Tuffery P. wwLigCSRre: a 3D ligand-based server for hit identification and optimization. *Nucleic Acids Res* 2009;37(Web Server issue):W504-9.
26. Quintus F, Sperandio O, Grynberg J, Petitjean M, Tuffery P. Ligand scaffold hopping combining 3D maximal substructure search and molecular similarity. *BMC Bioinformatics* 2009;10:245.
27. Lagorce D, Pencheva T, Villoutreix BO, Miteva MA. DG-AMMOS: a new tool to generate 3d conformation of small molecules using distance geometry and automated molecular mechanics optimization for in silico screening. *BMC Chem Biol* 2009;9:6.
28. Helgee EA, Carlsson L, Boyer S. A method for automated molecular optimization applied to Ames mutagenicity data. *J Chem Inf Model* 2009;49(11):2559-63.
29. Miteva MA, Guyon F, Tufféry P. Frog2: Efficient 3D conformation ensemble generator for small compounds. *Nucleic Acids Res* 2010;38(Web Server issue):W622-7.

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Table 1. The name of the drug-like molecule, the PubChem compound identifier (CID) and active/not active status in the CNS (central nervous system)

Name	CID	CNSA	Name	CID	CNSA	Name	CID	CNSA
Adenosine	191	1	Amprenavir	2177	0	Isradipine	3784	0
Alfentanil	51263	1	Amrinone	3698	0	Ketotifen	3827	0
Alosetron	2099	1	Anastrozole	2187	0	Lamivudine	3877	0
Amiloride	16231	1	Anthralin	2202	0	Lansoprazole	3883	0
Aripiprazole	60795	1	Argatroban	92722	0	Latanoprost	5311221	0
Benzotropine	2344	1	Azathioprine	2265	0	Leflunomide	3899	0
Betaxolol	2369	1	Aztreonam	5362041	0	Letrozole	3902	0
Bisoprolol	2405	1	Baclofen	2284	0	Levamisole	26879	0
Brimonidine	2435	1	Balsalazide	5362070	0	Lindane	727	0
Bromocriptine	31101	1	Beclometasone	20469	0	Linezolid	3929	0
Butorphanol	2487	1	Benazepril	2311	0	Lisinopril	5362119	0
Chloralhydrate	2707	1	Bepidril	2351	0	Lodoxamide	44564	0
Chlordiazepoxide	2712	1	Brinzolamide	68844	0	Loracarbef	3956	0
Chlorpheniramine	2725	1	Budesonide	63006	0	Losartan	3961	0
Chlorzoxazone	2733	1	Bumetanide	2471	0	Lovastatin	53232	0
Citalopram	2771	1	Bupivacaine	2474	0	Mechlorethamine	4033	0
Clemastine	2781	1	Calcitriol	6398761	0	Medroxyprogesterone	10631	0
Clonazepam	2802	1	Candesartan	2541	0	Melphalan	4053	0
Clorzepate	2809	1	Capsaicine	2548	0	Mercaptopurine	667490	0
Clozapine	2818	1	Captopril	2550	0	Meropenem	64778	0
Cyclobenzaprine	2895	1	Cefaclor	2609	0	Mesalamine	4075	0
Cyproheptadine	2913	1	Cefadroxil	2610	0	Metaproterenol	4086	0
Dezocine	40841	1	Cefazolin	33255	0	Metformin	4091	0
Dipivefrin	3105	1	Cefdinir	6399011	0	Methimazole	1349907	0
Dolasetron	3148	1	Cefditoren	6437877	0	Methylergonovine	8226	0
Doxazosin	3157	1	Cefepime	2622	0	Metoclopramide	4168	0
Doxepin	667477	1	Cefixime	54362	0	Metolazone	4170	0
Dronabinol	2978	1	Cefmetazole	2626	0	Metyrosine	3125	0
Droperidol	3168	1	Cefonicid	43592	0	Mexiletine	4178	0
Emedastine	3219	1	Cefoperazone	135784	0	Miglitol	441314	0
Entacapone	5281081	1	Cefotaxime	2632	0	Milrinone	4197	0
Esmolol	59768	1	Cefoxitin	37194	0	Minoxidil	4201	0
Estazolam	3261	1	Cefpodoxime	6335986	0	Moexipril	91270	0
Fexofenadine	3348	1	Ceftazidime	157706	0	Moricizine	34633	0

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Table 1. (continued)

Name	CID	CNSA	Name	CID	CNSA	Name	CID	CNSA
Fluoxetine	3386	1	Ceftibuten	5282242	0	Moxifloxacin	4259	0
Flurazepam	3393	1	Ceftizoxime	2655	0	MycophenolicAcid	446541	0
Fluvoxamine	5324346	1	Ceftriaxone	5479530	0	Nabumetone	4409	0
Formoterol	3410	1	Cefuroxime	2659	0	Naloxone	4425	0
Fosphenytoin	56339	1	Celecoxib	2662	0	Naphazoline	4436	0
Galantamine	3449	1	Cephalexin	27447	0	Naproxen	1302	0
Granisetron	3510	1	Chlorpropamide	2727	0	Nateglinide	4443	0
Hydrocodone	411697	1	Chlorthalidone	2732	0	Nedocromil	50294	0
Hydromorphone	3648	1	Cholecalciferol	6221	0	Nicardipine	4474	0
Isotretinoin	5538	1	Cholestyramine	3086319	0	Nifedipine	4485	0
Labetalol	3869	1	Ciclopirox	2749	0	Nimodipine	4497	0
Levobunolol	39468	1	Cidofovir	60613	0	Nisoldipine	4499	0
Levocabastine	54385	1	Cladribine	1546	0	Nitazoxanide	41684	0
Maprotiline	4011	1	Clindamycin	29029	0	Nitrofurantoin	4509	0
Meperidide	3034126	1	Clopidogrel	2806	0	Nitroglycerin	4510	0
Metaxalone	15459	1	Clotrimazole	2812	0	Nizatidine	4513	0
Methadone	4095	1	Colchicine	2833	0	Norgestrel	13109	0
Methocarbamol	4107	1	Cromolyn	2882	0	Ofloxacin	4583	0
Methoxamine	6082	1	Cyclopentolate	2905	0	Olopatadine	60865	0
Methyl dopa	4138	1	Cyclophosphamide	2907	0	Olsalazine	6816262	0
Molindone	23897	1	Cytarabine	596	0	Oseltamivir	65028	0
Nalbuphine	4419	1	Dantrolene	2952	0	Oxaprozin	4614	0
Naratriptan	4440	1	Dapsone	2955	0	Oxybutynin	4634	0
Nefazodone	4449	1	Delavirdinemesylate	5625	0	Pantoprazole	4679	0
Nortriptyline	4543	1	Dexamethasone	5743	0	Pemirolast	57697	0
Ondansetron	4595	1	Dexpanthenol	4678	0	Penbutolol	37464	0
Orphenadrine	4601	1	Diazoxide	3019	0	Penciclovir	4725	0
Oxcarbazepine	34312	1	Dibucaine	3025	0	Pentamidine	4735	0
Oxycodone	4635	1	Dicloxacillin	3041	0	Pentoxifylline	4740	0
Oxymorphone	4639	1	Digoxin	15478	0	Perindopril	107807	0
Paroxetine	4691	1	Diltiazem	3076	0	Pindolol	4828	0
Phenelzine	3675	1	Dinoprostone	9691	0	Pioglitazone	4829	0
Phenylephrine	6041	1	Disopyramide	3114	0	Pramoxine	4886	0
Pirbuterol	4845	1	Dofetilide	71329	0	Procainamide	4913	0
Pramipexole	4885	1	Dorzolamide	3154	0	Procarbazine	4915	0
Prazosin	4893	1	Econazole	33745	0	Propafenone	4932	0
Procyclidine	4919	1	Edrophoniumchloride	3202	0	Propylthiouracil	657298	0
Propoxyphene	10100	1	Ephedrine	5032	0	Pyridoxine	1054	0
Pseudoephedrine	7028	1	Eplerenone	443872	0	Quinapril	54892	0
Quazepam	4999	1	Epoprostenol	5280427	0	Quinidine	1065	0
Quetiapine	5002	1	Eprosartan	60879	0	Ramipril	5038	0
Rizatriptan	5078	1	Estramustine	18140	0	Rivastigmine	77991	0
Scopolamine	5184	1	Etidronicacid	3305	0	Rofecoxib	5090	0
Secobarbital	5193	1	Etodolac	3308	0	Rosiglitazone	77999	0
Sertraline	5203	1	Famciclovir	3324	0	Sildenafil	5212	0
Sibutramine	5210	1	Famotidine	3325	0	Simvastatin	54454	0
Sufentanil	41693	1	Fenoldopam	3341	0	Streptozocin	5299	0
Sumatriptan	5358	1	Fenopropfen	3342	0	Sulfacetamide	5320	0
Thiethylperazine	5440	1	Flavoxate	3354	0	Sulfasalazine	5353980	0
Thiothixene	5454	1	Flecainide	3356	0	Sulfipyrazone	5342	0
Tiagabine	5466	1	Floxuridine	3363	0	Sulindac	5352	0
Timolol	5478	1	Flunisolide	82153	0	Tamsulosin	129211	0
Tolazoline	5504	1	Fluoxymesterone	6446	0	Tazarotene	5381	0
Tramadol	5523	1	Flurbiprofen	3394	0	Terazosin	5401	0
Trazodone	5533	1	Flutamide	3397	0	Terbutaline	5403	0
Trimethobenzamide	5577	1	Fluvastatin	446155	0	Theophylline	2153	0
Venlafaxine	5656	1	Fosfomycin	3417	0	Thiamine	1130	0
Zaleplon	5719	1	Furosemide	3440	0	Ticlopidine	5472	0

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Table 1. (continued)

Name	CID	CNSA	Name	CID	CNSA	Name	CID	CNSA
Ziprasidone	60854	1	Ganciclovir	3454	0	Tocainide	38945	0
Zolpidem	5732	1	Gatifloxacin	5379	0	Tolazamide	5503	0
Zolmitriptan	5731	1	Gemcitabine	60750	0	Tolbutamide	5505	0
Acarbose	41774	0	Gemfibrozil	3463	0	Tolmetin	5509	0
Acetazolamide	1986	0	Glimepiride	3476	0	Torasemide	41781	0
Acetylcysteine	581	0	Glipizide	3478	0	Trandolapril	5484727	0
Acyclovir	2022	0	Glyburide	3488	0	Triamcinolone	31307	0
Adefovir	60172	0	Hydralazine	3637	0	Triamterene	5546	0
Allopurinol	2094	0	Ibutilide	60753	0	Valacyclovir	5647	0
Alprostadil	214	0	Idarubicin	42890	0	Voriconazole	5231054	0
Altretamine	2123	0	Ifosfamide	3690	0	Warfarin	6691	0
Aminoglutethimide	2145	0	Imiquimod	57469	0	Zileuton	60490	0
Amlodipine	2162	0	Indapamide	3702	0	ZoledronicAcid	68740	0
Amoxicillin	2171	0	Isoetharine	3762	0			
Ampicillin	2174	0	Isosorbidedinitrate	170113	0			

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