Computational Materials Design: From Molecular Mechanics to Artificial Intelligence

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Brief professional history

- MS from Mendeleev University of Chemical Technology of Russia
- •PhD from Lomonosov Moscow State University
- 10 years researcher in Soviet Union Academy of Science
- 4 years research in Germany: University of Erlangen-Nurnberg and Max-Planck Institute in Muelheim-an-der-Ruhr
- 2 years research at the University of Florida
- 6 years R & D at Motorola, Phoenix, Arizona
- 9 years at Arizona State University
- Short research visits at Dalhousie University, Canada, Tyndall Institute, Ireland, and University of Tokyo, Japan
- 15 years of consulting experience



Research areas

Modeling reaction centers of photosynthetic bacteria PhD work at Moscow State University

Computational studies of structures and properties of the compounds 1st and 2nd rows Russian Academy of sciences and Nurnberg University, Germany

Computational studies of biologically active oligopyrroles – models of phytochrome Max-Planck Institute, Germany

Computational design of advanced propellants and explosives University of Florida, USA, Dalhousie University, Canada

Computational design of electronic materials and devices Motorola, USA, University of Tokyo, Japan, Tyndall Institute, Ireland





University of the 21st Century – Knowledge Factory







Ancient Medieval Modern Education => Research => Innovations



Computational Materials Science: General

What computational materials scientists do? Theory development => Software design => Applications

How materials scientists work? Top down approach: Start from macro scale properties Bottom up approach: Start from atomic scale structures

Interaction between theory and experiment:

Design of novel materials with desired properties, guidance for reaction paths and technology, atomic scale knowledge of materials and properties as a guidance for experiments.

Knowledge base for computational materials sciences General: Quantum mechanics, molecular mechanics and dynamics, applied mathematics, statistical methods, computer science

Where computational materials scientists work? Academia: chemistry, physics, biology, engineering Industry: pharma, chemicals, construction, electronics



Computational Materials Science: Software

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Software for Atomic Scale Education and Research

This page lists links to the web sites which have information about software and software developers (academic centers, national labs, industrial companies and individuals). If such information is available we indicate whether software is non-commercial (but you may need to sign a license agreement), commercial or semi-commercial (e.g. free for academia and commercial for companies). Some software packages include several applications, e.g. visualization and classical and quantum mechanical computational engines. Such programs can be listed in several sections below, which are grouped as:

Visualization & Design
Classical Mechanics & Molecular Dynamics
Quantum Mechanics
Non-Profit Research Centers
Companies
Forums
Databases & Supplementary Software
Design and Visualization
Aglie Molecule (Biomolecular simulations: Non-commercial)
ADEGUI (GUI to ADE, BAND, DETE, MOPAC2008, ResxEE, COSMO-RS; commercial))
ArouaLab (Non-commercial)
Aten (Non-commercial)
Avocsetro (Non-commercial)
Bodil (Non-commercial)

BRAGI (Proteins visualization; Non-commercial)

Earce Eleid Explorer O/isualizer for Tinker: non-commercial

Chimera (Semi-commercial)

Computational Materials Science: Lectures



The unexpected behavior of nanoworld

https://asu-teacherscollege.wistia.com/medias/s91tu3bqxu



Feeding biology with electrons

https://www.youtube.com/watch?v=qEvmKGBFpRs



Nanotechnology pathways to next generation photovoltaics

https://www.youtube.com/watch?v=g9q2WBRe4jQ



Computational Materials Science: Online

Computational materials science, M.Sc. (Sweden, Malmo University)

https://www.mastersportal.com/studies/39616/computational-materials-science.html

Quantum world, course offered by Harvard

https://opencourser.com/course/ia8xfq/edx-the-quantum-world

Quantum mechanics of molecular structures offered by University of Tokyo

https://opencourser.com/course/xdbaim/edx-quantum-mechanics-of-molecular-structures

Atomistic computer modeling of materials offered by MIT

https://ocw.mit.edu/courses/materials-science-and-engineering/3-320-atomistic-computer-modeling-of-materials-sma-5107-spring-2005/

Computational materials science and engineering by Nanohub.org https://nanohub.org/resources/22124#series



Molecular mechanics and dynamics $E_{total} = E_{bond} + E_{angle} + E_{torsion} + E_{electro} + E_{vdw}$

Advantage: simplicity, computational efficiency, possibility to compute larges systems

<u>Deficiency:</u> description of phenomena where quantum mechanical effects are essential and can not be emulated by classical force-field potentials

<u>Applications:</u> large systems such as polymers, proteins, DNA, amorphous materials, education, initial structures for subsequent quantum mechanical calculations

Structure optimization: Simulated annealing, Monte-Carlo, evolutionary algorithms



Computational design of biomolecules: Samples

Progress in computational protein design Shaun M.Lippow , Bruce Tidor Current Opinion in Biotechnology, V 18 (2007) 305-311

Computational Design of Ligand Binding Proteins with High Affinity and Selectivity Christine E. Tinberg, et al. Nature 501 (2013) 212–216.

Design of a Novel Globular Protein Fold with Atomic-Level Accuracy Brian Kuhlman, et al Science, B 302 (2003) 1364-1368

Paradigms for computational nucleic acid design Robert M. Dirks Milo Lin Erik Winfree Niles A. Pierce Nucleic Acids Research, Volume 32, 2004 1392–1403



Hartree-Fock and DFT methods

$$\begin{aligned} &\text{Hartree-Fock method:} \qquad &\hat{F}(1)\phi_i(1) = \epsilon_i \phi_i(1) \qquad \phi_i = \sum_r c_{ri} \chi_r \\ &\hat{F}[\{\phi_j\}](1) = \hat{H}^{\text{core}}(1) + \sum_{j=1}^{N/2} [2\hat{J}_j(1) - \hat{K}_j(1)] \qquad &\hat{H}^{\text{core}}(1) = -\frac{1}{2} \nabla_1^2 - \sum_{\alpha} \frac{Z_{\alpha}}{r_{1\alpha}} \end{aligned}$$

<u>Approximations:</u> 1. Born-Oppenheimer; 2. Non-relativistic. 3. Finite basis set; 4. Wave function – single Slater determinant; 5. Mean-field approximation

DFT:
$$\begin{bmatrix} -\frac{\hbar^2}{2m} \nabla^2 + V_{\rm s}(\vec{r}) \end{bmatrix} \varphi_i(\vec{r}) = \varepsilon_i \varphi_i(\vec{r}) \qquad n(\vec{r}) \stackrel{\text{def}}{=} n_{\rm s}(\vec{r}) = \sum_i^N |\varphi_i(\vec{r})|^2.$$
$$V_{\rm s}(\vec{r}) = V(\vec{r}) + \int \frac{e^2 n_{\rm s}\left(\vec{r}'\right)}{\left|\vec{r} - \vec{r}'\right|} \, \mathrm{d}^3 r' + V_{\rm XC}\left[n_{\rm s}(\vec{r})\right]$$

Advantage: Quantum mechanical nature of molecules considered explicitly

Disadvantage: Accuracy comes with a higher computational costs and complexity



Quantum chemistry tools set

NDDO <= HF => Mueller-Plesset => Coupled-Cluster => CAS SCF

Pseudo-potentials <= LDA <= DFT => GGA => B3LYP => TD-DFT; FT-DFT

Quantum mechanics => QM + Molecular Mechanics + Continuum

Reactions in liquids

Chemical deposition

Catalysis









Qualitative Analysis of Electron Distribution



<= Polyene cyclization

Photocatalysis =>





<= Electrophilic substitution

Nucleophilic substitution =>







Theory vs Experiment: SN2 Reaction



Energy

DFT Theory: Many flavors of potentials



$$V_{
m s}(ec{r}) = V(ec{r}) + \int rac{e^2 n_{
m s}\left(ec{r}'
ight)}{\left|ec{r}-ec{r}'
ight|}\,{
m d}^3r' + V_{
m XC}[n_{
m s}(ec{r})]$$

 $E_{\mathrm{xc}}^{\mathrm{B3LYP}} = E_{\mathrm{x}}^{\mathrm{LDA}} + a_0 (E_{\mathrm{x}}^{\mathrm{HF}} - E_{\mathrm{x}}^{\mathrm{LDA}}) + a_{\mathrm{x}} (E_{\mathrm{x}}^{\mathrm{GGA}} - E_{\mathrm{x}}^{\mathrm{LDA}}) + E_{\mathrm{c}}^{\mathrm{LDA}} + a_{\mathrm{c}} (E_{\mathrm{c}}^{\mathrm{GGA}} - E_{\mathrm{c}}^{\mathrm{LDA}}),$

Thomas-Fermi (1927) => Honenberg-Kohn (1964) => TDDFT (1984) => LDA+GGA (1990s)

DFT Development: TDDFT

Runge-Gross theorem (1984): Analogue of Kohn-Sham theorem for TD

$$egin{aligned} &\left(-rac{1}{2}
abla^2+v_s(\mathbf{r},t)
ight)\phi_i(\mathbf{r},t)=irac{\partial}{\partial t}\phi_i(\mathbf{r},t) & \phi_i(\mathbf{r},0)=\phi_i(\mathbf{r}),\ v_s(\mathbf{r},t)=v_{ ext{ext}}(\mathbf{r},t)+v_J(\mathbf{r},t)+v_{ ext{xc}}(\mathbf{r},t), &
ho_s(\mathbf{r},t)=\sum_{i=1}^{N_{ ext{b}}}f_i(t)|\phi_i(\mathbf{r},t)|^2, \end{aligned}$$

Linear response TDFT

 $egin{aligned} H'(t) &= H + \delta V^{ext}(t) & H'_{KS}[
ho](t) = H_{KS}[
ho] + \delta V_{H}[
ho](t) + \delta V_{xc}[
ho](t) + \delta V^{ext}(t) \ \delta
ho(\mathbf{r}t) &= \chi_{KS}(\mathbf{r}t,\mathbf{r}'t') \delta V^{eff}[
ho](\mathbf{r}'t') \end{aligned}$

Dyson equation

$$\chi(\mathbf{r}_1 t_1, \mathbf{r}_2 t_2) = \chi_{KS}(\mathbf{r}_1 t_1, \mathbf{r}_2 t_2) + \chi_{KS}(\mathbf{r}_1 t_1, \mathbf{r}_2' t_2') \left(\frac{1}{|\mathbf{r}_2' - \mathbf{r}_1'|} + f_{xe}(\mathbf{r}_2' t_2', \mathbf{r}_1' t_1')\right) \chi(\mathbf{r}_1' t_1', \mathbf{r}_2 t_2)$$

Excitation energies are the poles of the linear response function

DFT Development: FT-KS-DFT



Molecular dynamics

Born-Oppenheimer energy surface:

 $m_{I} \ddot{\mathbf{R}}_{I} = -\vec{\nabla}_{I} V(\mathbf{R}_{1}, \mathbf{R}_{2}, \dots, \mathbf{R}_{N})$ $V(\{\mathbf{R}\}) = \Omega(\{\mathbf{R}\}) + E_{ion-ion}(\{\mathbf{R}\})$

Current best practice uses Free Energy Density Functional Theory with one-electron Kohn-Sham orbitals

$$\Omega[n] = F[n] + \int d\mathbf{r} (v_{ext}(\mathbf{r}) - \mu) n(\mathbf{r}) - \text{Grand potential}$$

$$F[n] = F_s[n] + F_{a}[n] + F_{ax}[n] - \text{Free-energy functional}$$

$$F_H[n] - \text{Hartree energy}$$

$$n(\mathbf{r}; \{\mathbf{R}\})$$

 $F_{xc}[n]$ -- Exchange-Correlation (XC) free-energy





 $\left\{ -\frac{1}{2} \nabla^2 + v_{\rm H} \left(\mathbf{r}; \{\mathbf{R}\} \right) + v_{\rm xc} \left(\mathbf{r}; \{\mathbf{R}\} \right) + v_{\rm ext} \left(\mathbf{r}; \{\mathbf{R}\} \right) \right\} \varphi_j \left(\mathbf{r}; \{\mathbf{R}\} \right) = \varepsilon_j \varphi_j \left(\mathbf{r}; \{\mathbf{R}\} \right)$ $n \left(\mathbf{r}; \{\mathbf{R}\} \right) = \sum_j f(\varepsilon_j; \beta) \left| \varphi_j \left(\mathbf{r}; \{\mathbf{R}\} \right) \right|^2 \quad ; \quad v_{\rm xc} \left[n \right] = \frac{\delta F_{\rm xc}}{\delta n} \quad ; \quad \beta = 1/k_{\rm B} T$

Material properties

- Thermal conductivity;
- Absorption coefficients
- Electrical conductivity;
- Reflectivity
- © V. Karasev



R.P. Drake, Physics Today, June 2010, 28-33

DFT Applications to solid state materials Two most popular solid-state DFT codes VASP VASP SIESTA Siesta Siesta Localized orbitals

Interplay of quantum chemistry and solid state theory applications

Deposition

Defect formation

Device design







Defect generation at Si/SiO₂ interface



Bersuker, G.; Korkin, A.; et al., Microelectronic Engineering, 2003, 118-129.



Modeling of LaAlO₃/Si Interface



Knizhnik, A.A.; Iskandarova И.; Bagaturyants, A.; Potapkin, Б.B.; Fonseca, L.R.C.; Korkin A. Phys. Rev.B. 2005, 72, 235329.

Modeling of Si/SiO₂/Si Interfaces



Korkin, A.A.; Greer, J.; Bersuker, G.; Karasiev, V.; Bartlett, R.J. Phys. Rev. B. 2006, 73, 165312.

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ZrSiO₄ Polymorphs

Why do we care about ZrSiO₄ polymorphism?

Electronics: Potential high-k material. Various nanocrystalline forms or different bonding patterns may exist in deposited thin films

- Nuclear safety: Zircon is used to preserve nucleotides imbedded in its lattice. Defects and radioactive damage may modify the structure
- Geochemistry: Computational design help to discover new minerals and study the earth history and resources.

What is known about ZrSiO₄ polymorphism?

Zircon: Stable form



Tetragonal I4₁/a Z=4 ABO



Reidite: High pressure

Korkin, A.A.; Kamisaka, H.; Yamashita, K.; Safonov, A.; Bagatur'yants, Appl. Phys. Lett. 2006, 88, 181913.



High density crystal structures

Alumotantite (AlTaO₄)

Zr/Si:

6/6:



Orthorombic E=0.78 eV; d=4.95

Raspite (PbWO₄)



Monoclinic E=0.79; d=5.03

Stibiocolumbite (SbNbO₄)

8/4:



Orthorombic E=0.72; d=5.18

Anhydrite (CaSO₄)



Monoclinic E=0.74; d=4.66

Anatoli Korkin

Wolframite (MnWO₄)



Monoclinic E=1.06; d=5.28

Monazite (EuPO₄)



Monoclinic E=1.04; d=4.91



Low density crystal structures

Anhydrite (CaSO₄)



6/4:

Orthorombic E=0.49 eV; d=3.23

β-Crystobalite (SiO₂)

Chalcocyanite (CuSO₄)

Orthorombic E=0.96; d=4.06

Rodolicoite (FePO₄)





Orthorombic E=1.25; d=4.52 Crystobalite (SiO₂)

4/4:



Cubic E=0.94; d=2.40



Hexagonal E=1.25; d=3.13



tetragonal E=1.32; d=2.75



Size & Time Scale Limits of Different Models



Monte Carlo Simulation

General idea => Considering a statistically representative part of the system instead of the whole system to study any given property

Metropolis algorithm

Energy minimization and calculation of average properties => accepting structures with lower energy than starting point (P = 1) and higher energy ($P = \exp \left[-(E2-E1)/kT\right]$

Kinetic Monte Carlo





Computational materials and devices at electronic industry





An Integrated kMC-MD approach: ZrO₂ ALD Modleing

DFT cluster & periodic study: reacting molecules and barriers

Chemical kinetics calculations: elementary chemical reactions

Molecular dynamic simulation: conformations & surface relaxation

Kinetic Monte Carlo simulation: interface formation & film growth



A snapshot of an interface formation



ZrCl₄ Adsorption on OH Terminated Si(100) Surface



Kinetics of Gas-Surface Reactions







Lattice kMC Model of Zirconia Film Growth



Second ALD step

- > $Zr(OH)(s) + ZrCl4(g) \Rightarrow$ ZrOZrCl3(s) + HCl(g)
- > $2Zr(OH)(s) + ZrCl4(g) \Rightarrow$ (ZrO)2ZrCl2(s) + 2HCl(g)
- > $3Zr(OH)(s) + ZrCl4(g) \Rightarrow$ (ZrO)3ZrCl(s) + 3HCl(g)
- > $ZrOZrCl3(s) + Zr(OH)(s) \Rightarrow$ (ZrO)2ZrCl2(s) + HCl(g)



ZrCl₄ + H₂O ALD: Low density of the first layers



Deminsky, M.; Knizhnik, A.; Belov, I.; Umanskii, S.; Rykova, E.; Bagatur'yants, A.; Potapkin, B.; Stoker, M.; Korkin, A. Surface Science, 2004, 549, 67-86.



Si/ZrO₂/Si Gate Stack Model

Total potential (eV)





Plug Flow Reactor Model





KHIMERA: Kinetics from Molecules to Reactor

I. Quantum chemistry







Transition state



Product



II. Chemical Kinetics

III. Reactor Modeling







Cheminformatics: Application of Data Science in Chemistry and Materials Science

Term introduced by F.K. Brown in 1998

Basic paradigm

Quantum chemistry => wave/particle dualism Molecular mechanics => atomic structure of matter Cheminformatics => chemical space

Basic model

Quantum chemistry => electron and nuclei Molecular mechanics = > atoms and bonds Chemoinformatics => molecular graph and decsriptor vectors

Basic theory

Quantum chemistry => Schroedinger equation Molecular mechanics => classical and statistics mechanics Cheminformatics => graph theory and statistics based learing

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Cheminformatics: from Data to Knowledge

Chemical Space Paradigm

graphs-based

descriptors -based

SPACE = objects + metric

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Chemical Space Representation and Vizualization

Desired property = *f* (structure + properties descriptors)

H. A. Gaspar, I. I. Baskin, G. Marcou, D. Horvath, A. Varnek Mol. Informatics, 2015

Pre-informatics: Periodic Table and Prediction of new elements

Mendeléev left space for new elements, and predicted four yet-to-be-discovered elements: Ga (1875), Sc (1879) Ge (1886) and Hf (1923) © A. Varnek

Selected Books in Cheminformatics

Computer-Aided Drug Design (CADD): Purpose

- Accelerate the delivery of a drug candidate
- Identify hit compounds
- Support hit-to-lead progression
- Contribute to lead optimization
- Support other discovery activities

Computer-Aided Drug Design (CADD): Toolkit

Virtual screening of commercially available or feasible compounds for potential hits

Structure-based design using 3D Models: Protein + potential drug

Molecular dynamics simulations of a protein's biological function and how it can be modulated by a drug molecule

In silico prediction of adsorption, distribution, metabolism and excretion

<u>Chemoinformatics</u>: Library design, data mining, Machine Learning

© D. Kireev

Virtual Screening "funnel"

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Pharmacophore and protein docking modeling

M. Stepniewska-Dziubinska, P. Zielenkiewicz, p. Siedlecki, Molecules 2017, 22(7), 1128

TAM-targeted cancer therapeutics

© D. Kireev

MER project evolution

Evolutionary algorithm

Genetic Algorithm applications in Materials Science

Design of self-assembling materials

Fig. 4. Construction of a molecule from the building block library.

M. Keser and S.I. Stupp, Comput. Methods Appl. Mech. Engrg. 186 (2000) 373-385

Optimizing nanoparticle catalysts

N.S. Froemming, G. Henkelman, J. chem. Phys., 131, 234103, 2009 Binary alloys design

FIG. 2 (color). Enthalpies of formation for the fcc-like L1₂ structure of binary alloys. Horizontally are the elements of 75% abundance in the binary alloy, vertically are the elements of 25% abundance.

G.H. Johannesson et al, PhysRevLett. 88. 255506

Review of applications in nanomaterials

W. Paszkowicz, Comp. methods in Mat. Sci. 2013, 13, 127-134

Artificial Neural Network

Training set => Back propagation algorithm => Finding weights

Nano-Au-Cu catalysts

Surface reactions

<u>N. Artrith</u>, A. <u>M. Kolpak</u>, *Nano Lett.*, 2014, *14* (5), pp 2670–2676

Drug design

S. Agatonovic-Kustrin, R. Beresford, J.Pharm. Biomed. Analysis 22 (2000) 717–727

DFT Study of Dye-sensitized solar cells

MaPbl₃ Structure

Ru(II)-polypyridyl complex

F. De Angelis, Acc. Chem. Res., 2014, 47, 3349

Ru(II)-complex on TiO₂

Computational screening of organic photovoltaics

2,3 millions of compounds from 26 blocks

Harvard Clean Energy Project

Leading candidates

DFT + Cheminformatics

IBM World Community Grid

Hachmann et al, Energy Environ. Sci., 2014, 7, 698

DFT + AI Screening of electrolytes for Li-batteries

Computational high-throughput screening of electrocatalytic materials for hydrogen evolution

Thank you for your attention

