

Metalloprotein Simulations: a Neural Network based Approach

Bettina Lier

Supervisor: Chris Oostenbrink

Collaborator: Philipp Marquetand

Institute of Molecular Modeling and Simulation
University of Natural Resources and Life Sciences, Vienna

Institute of Theoretical Chemistry, University of Vienna

Outline

Metalloproteins are important biomolecules that incorporate metal-ion cofactors. They are essential for various biological functions, among others, involved in infections and diseases.

Metal-sites are notoriously difficult to describe via classical MD simulations as they involve coordinate bonds. Transition metals with their open shell of d-electrons further require the quantum level of theory. However, quantum mechanics (QM) is not feasible for huge systems, while molecular mechanics (MM) is not very accurate.

We have developed a hybrid QM/MM¹ approach that employs Neural Networks² (NN) for increased efficiency and additionally introduces a Buffer Region to reduce artifacts and smooth the transition between QM and MM: BuRNN³.

We aim to apply this NN/MM simulation method to metalloproteins in order to investigate their complex nature.

In short

- accurate metalloprotein simulations require QM
- BuRNN is a novel alternative to QM/MM simulations
- BuRNN is an efficient NN/MM simulation approach

Next steps

- release of the BuRNN code in the GROMOS Software
- training and simulation of porphyrin systems



Contact me

Bettina Lier @BettinaLier

E-mail: bettina.lier@boku.ac.at

ORCID: 0000-0002-8032-0084



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QM/MM¹ simulations are powerful:

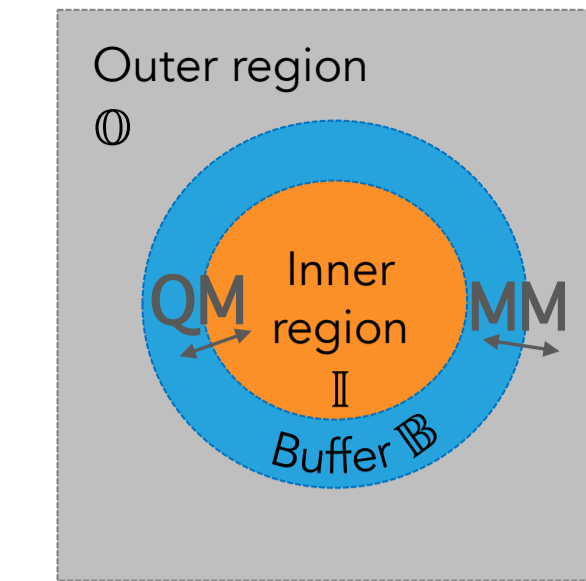
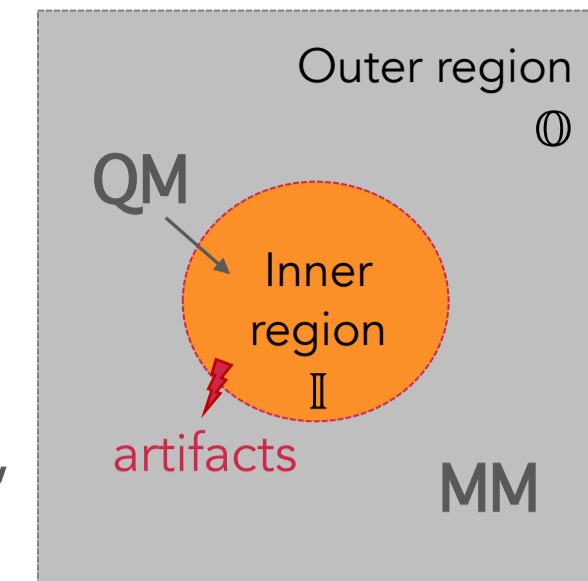
- accurate for small part - QM level of theory (inner region II)
- efficient for rest - classical MM force fields (outer region I)

QM/MM simulations are limited:

- high computational costs
- artifacts at the interface

QM/MM

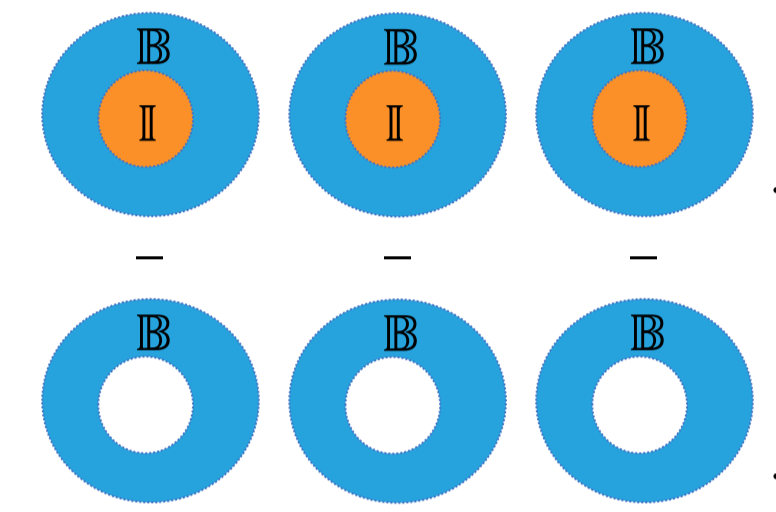
"conventional method"



The BuRNN Approach

- BuRNN reduces costs by machine learning
- BuRNN reduces artifacts by embedding scheme

The BuRNN Workflow

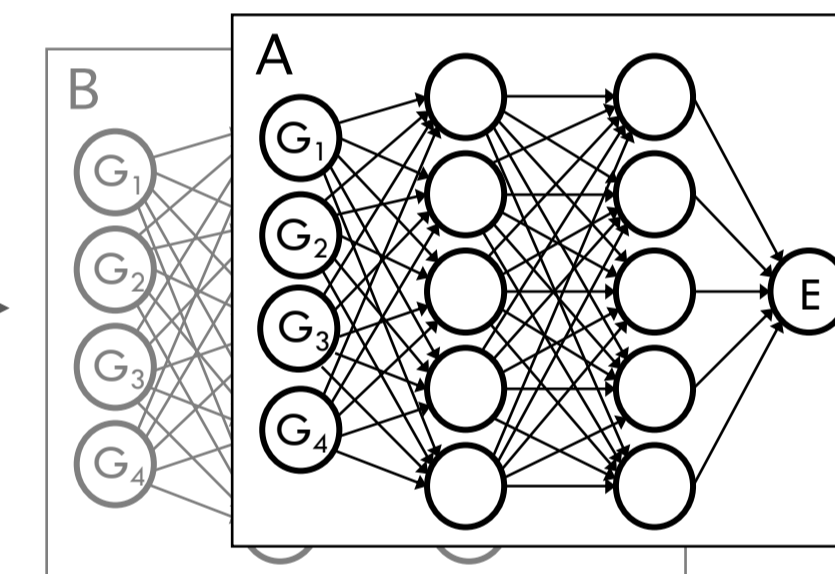


Training Set Generation

$$V_{tot} = V_{I+B}^{QM} - V_B^{QM} + V_B^{MM} + V_{O(I+B+O)}^{MM} \cong V_{I+\Delta B}^{NN} + V_{B+O}^{MM}$$

coordinates / energies / forces / charges

NN Training



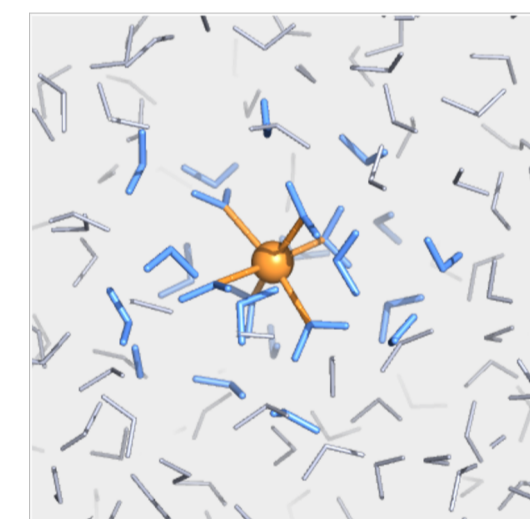
NN/MM Simulation

energies / forces / charges

$$V_{I+\Delta B}^{NN(A)} \approx V_{I+\Delta B}^{NN(B)}$$

$$V_{I+\Delta B}^{NN(A)} \neq V_{I+\Delta B}^{NN(B)}$$

Expansion ?

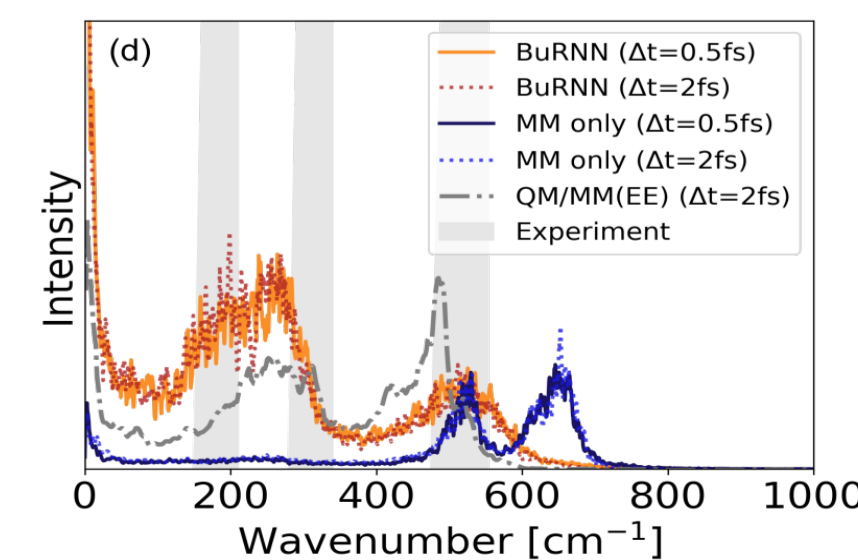
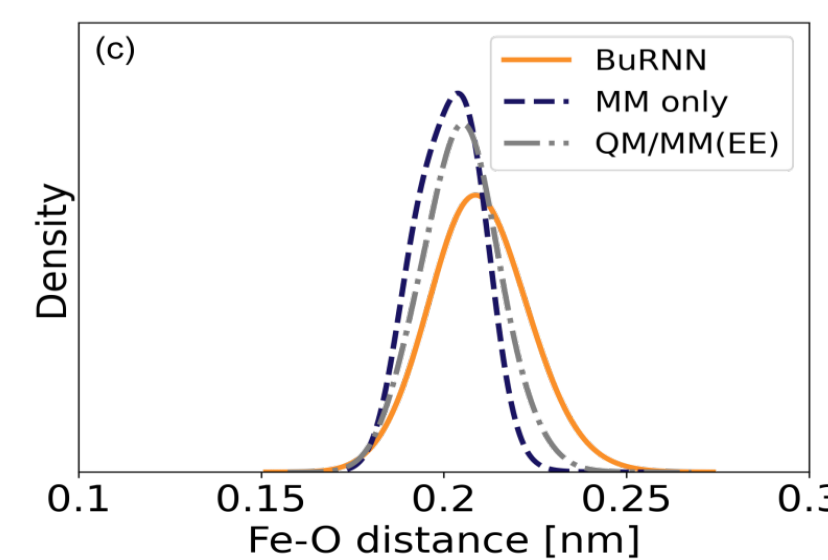
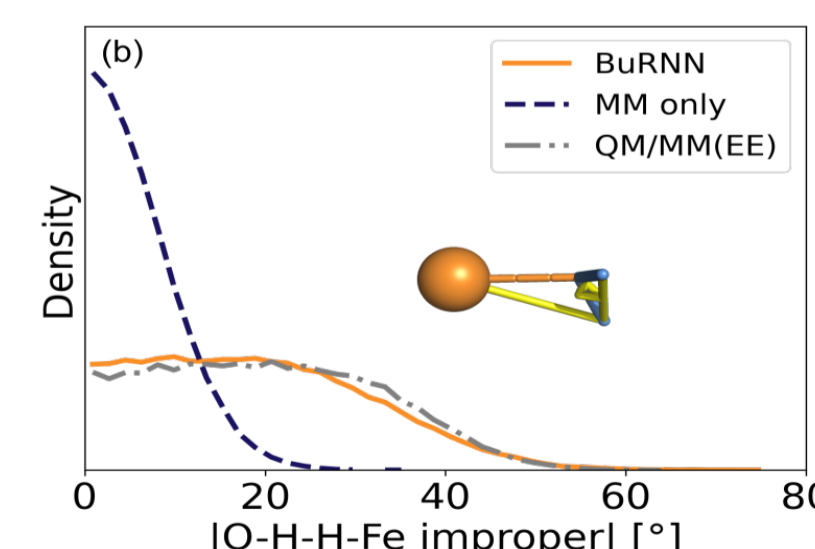
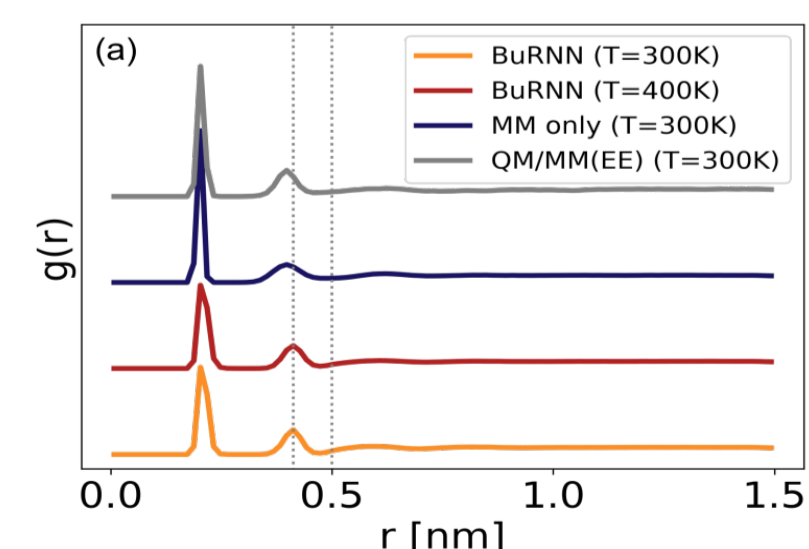


metal-ligand complex

Proof of Concept

[Fe(H₂O)₆]³⁺ complex in water:

- small system with metal-ligand interactions
- stable simulations, expected geometries
- agreement with QM/MM and experiments



Training Set Generation

- sampling of configurations (coordinates) by MD simulations
- extending configurations by QM energy minimization and adaptive sampling
- 2 QM calculations for each configuration: I+B and B
- training database for energy (force) differences and charges



More details: read the BuRNN paper!

References

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4. Schütt, Sauceda, Kindermans, Tkatchenko & Müller.

BuRNN³ introduces Buffer Region:

- buffer B described at both levels
- $V_B^{MM} - V_B^{QM}$ smooths transitions
- 2 QM calculations required
- artifacts at the interface cancel
- full electronic polarization of B by I

BuRNN employs Neural Networks:

- difference of 2 QM calculations trained by deep NN³
- interaction energies simplify training
- second NN for charge training

Neural Network Training

- training atomistic NN on interaction energies (forces) with SchNet⁴
- training atomistic NN on partial charges without final pooling layer

Hybrid NN/MM Simulations

- BuRNN implemented in GROMOS⁵ with direct interface to SchNetPack⁶
- buffer region by cut-off
- MM terms V_{B+O}^{MM} with force field
- QM interaction energies by a call of the NN $V_{I+\Delta B}^{NN}$
- partial charges to polarize B by I in the interaction with I
- validation by 2 individual NNs (A and B)
- comparing the NN $V_{I+\Delta B}^{NN(A)} \approx V_{I+\Delta B}^{NN(B)}$?
- expanding training set when predictions diverge $V_{I+\Delta B}^{NN(A)} \neq V_{I+\Delta B}^{NN(B)}$ and retrain

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6. Schütt, Kessel, Gastegger, Nicolli, Tkatchenko & Müller. *J. Chem. Theory Comput.* 15, 448–455 (2019)