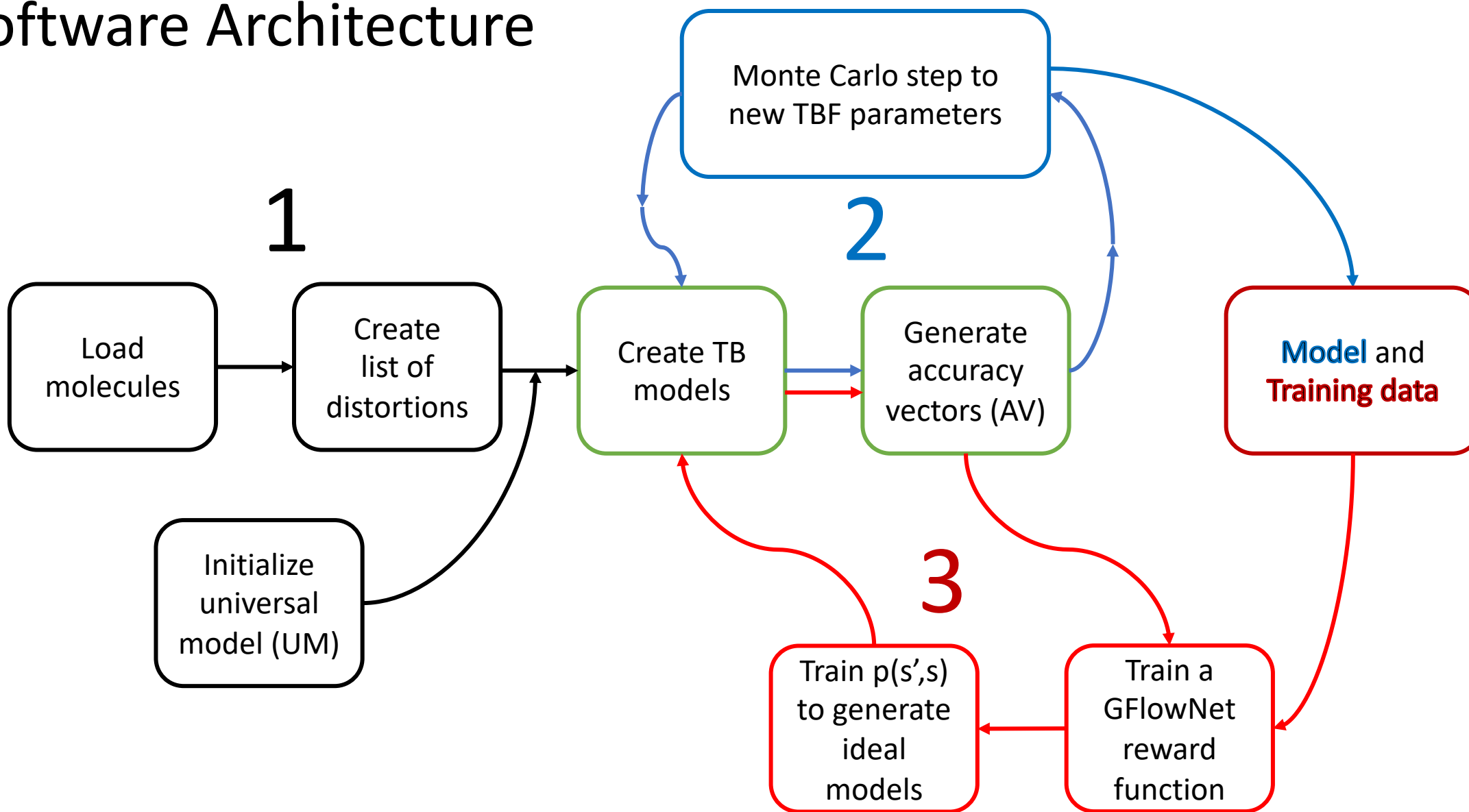
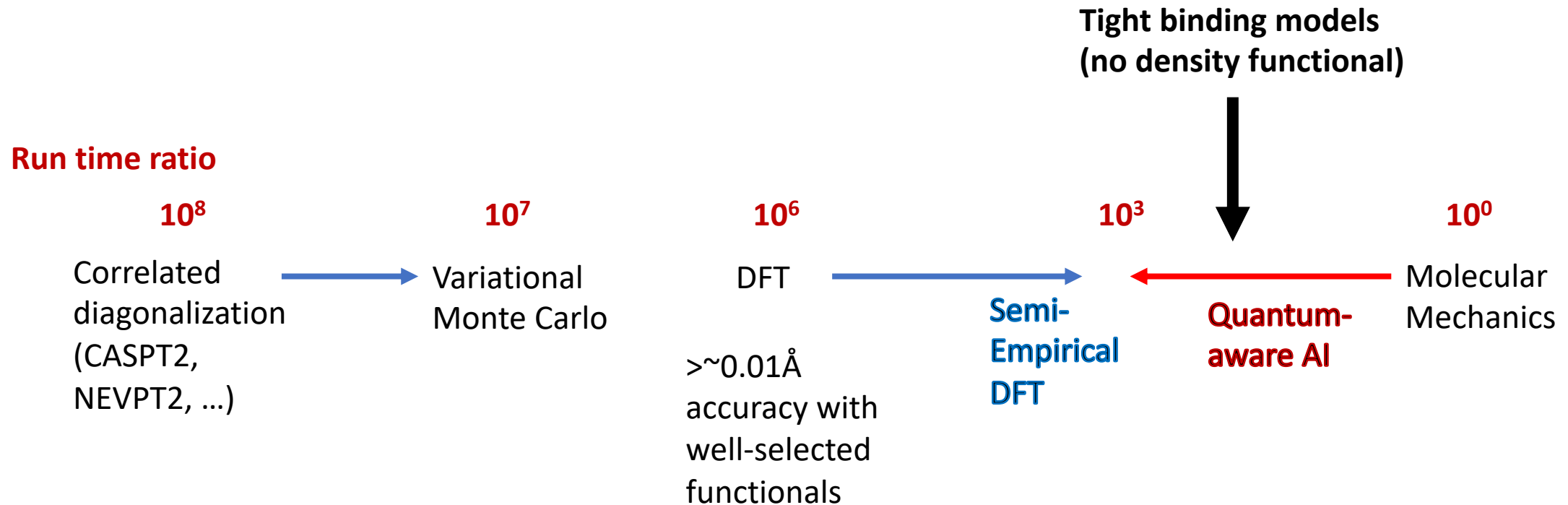


# Software Architecture



Related NN approaches are used for model optimization in high energy physics due to similar 'curse of dimensionality' challenges.

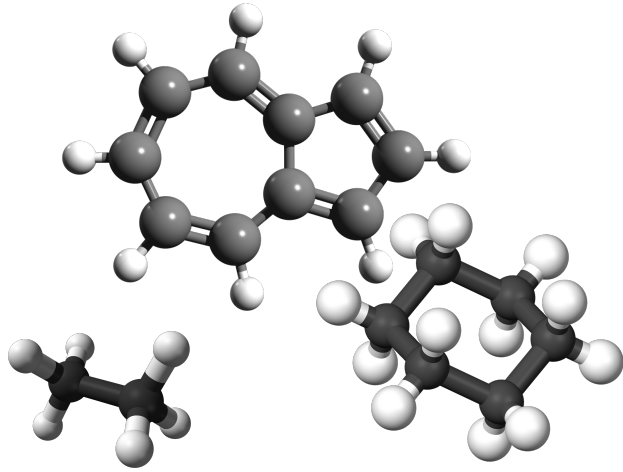
# Context and Motivation



*Density functional tight binding: values of semi-empirical methods in an ab initio era, Q. Cui and M. Elstner, Phys. Chem. Chem. Phys., 2014, 16, 14368–14377*

*Using Neural Network Force Fields to Ascertain the Quality of Ab Initio Simulations of Liquid Water, A Torres, LS Pedroza, M Fernandez-Serra, AR Rocha - The Journal of Physical Chemistry B 125 (38), 10772-10778*

# Tight binding field



A universal model mapping from **bond lengths** to **tight binding parameters**

Demo case: s, p basis; C, H atoms; curves defined by 5 parameters → 87 dimensions

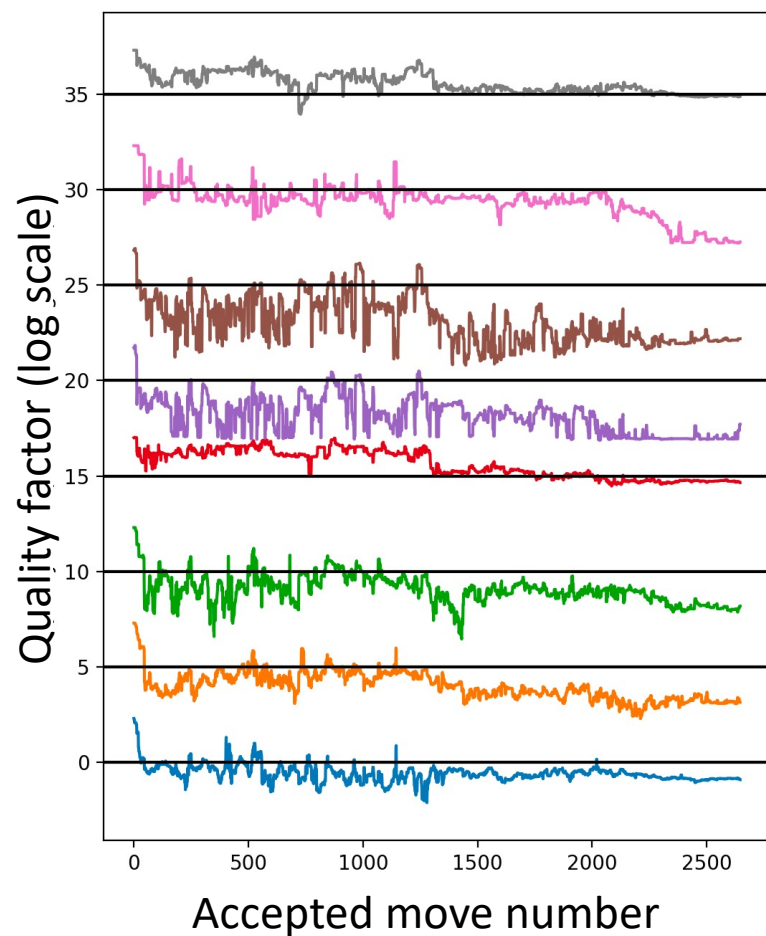
Fields respect Slater-Koster symmetry and are:

1. Coulomb: atom-atom
2. Coulomb: atom-orbital
3. Coulomb: orbital-orbital
4. Coulomb: atom-2 orbital (allowing hybridized sp orbitals)
5. Hopping (all Slater-Koster-allowed orbital combinations)

Non-field parameters:

Orbital energy

# 3-step Monte Carlo convergence for 8 molecules



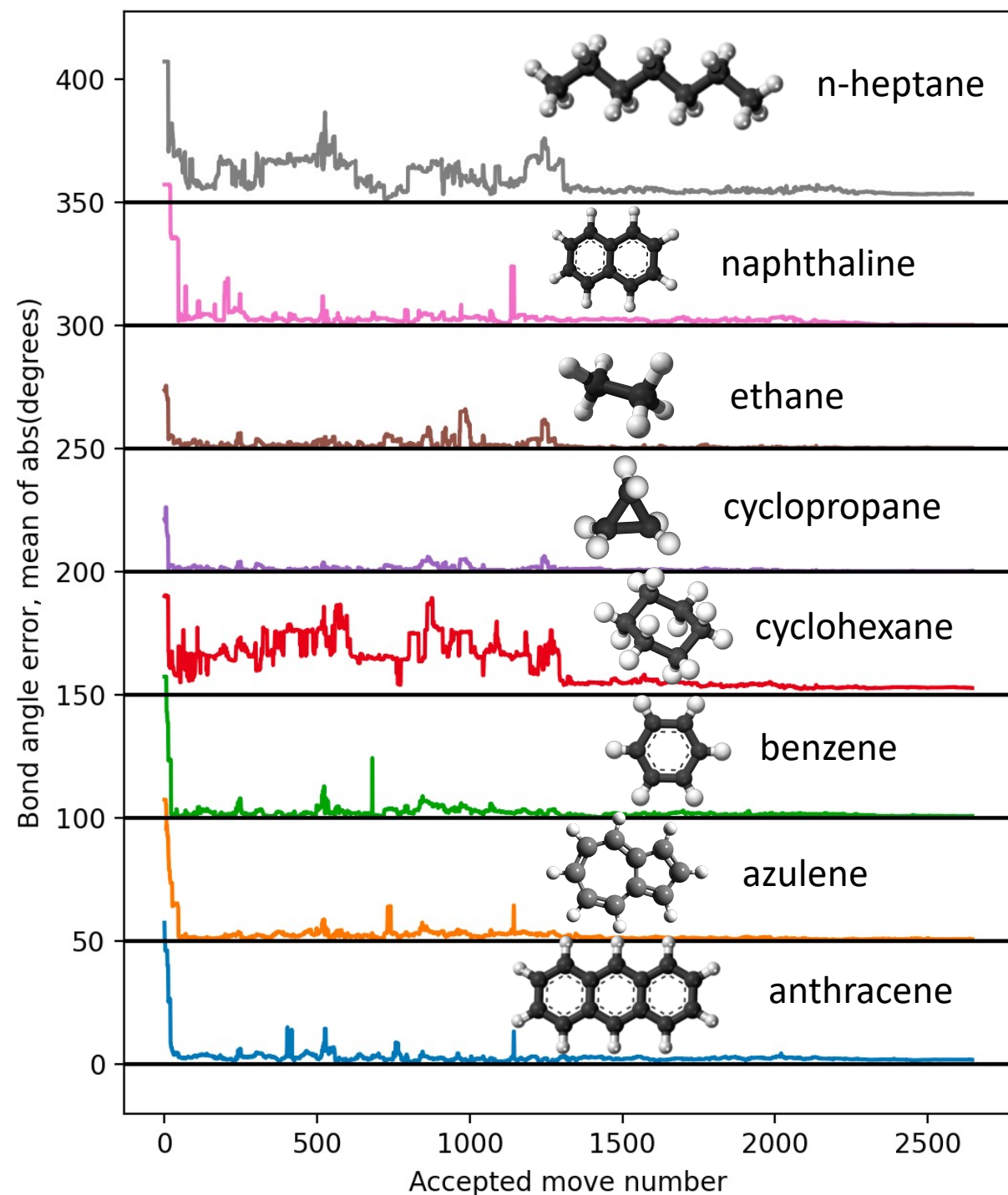
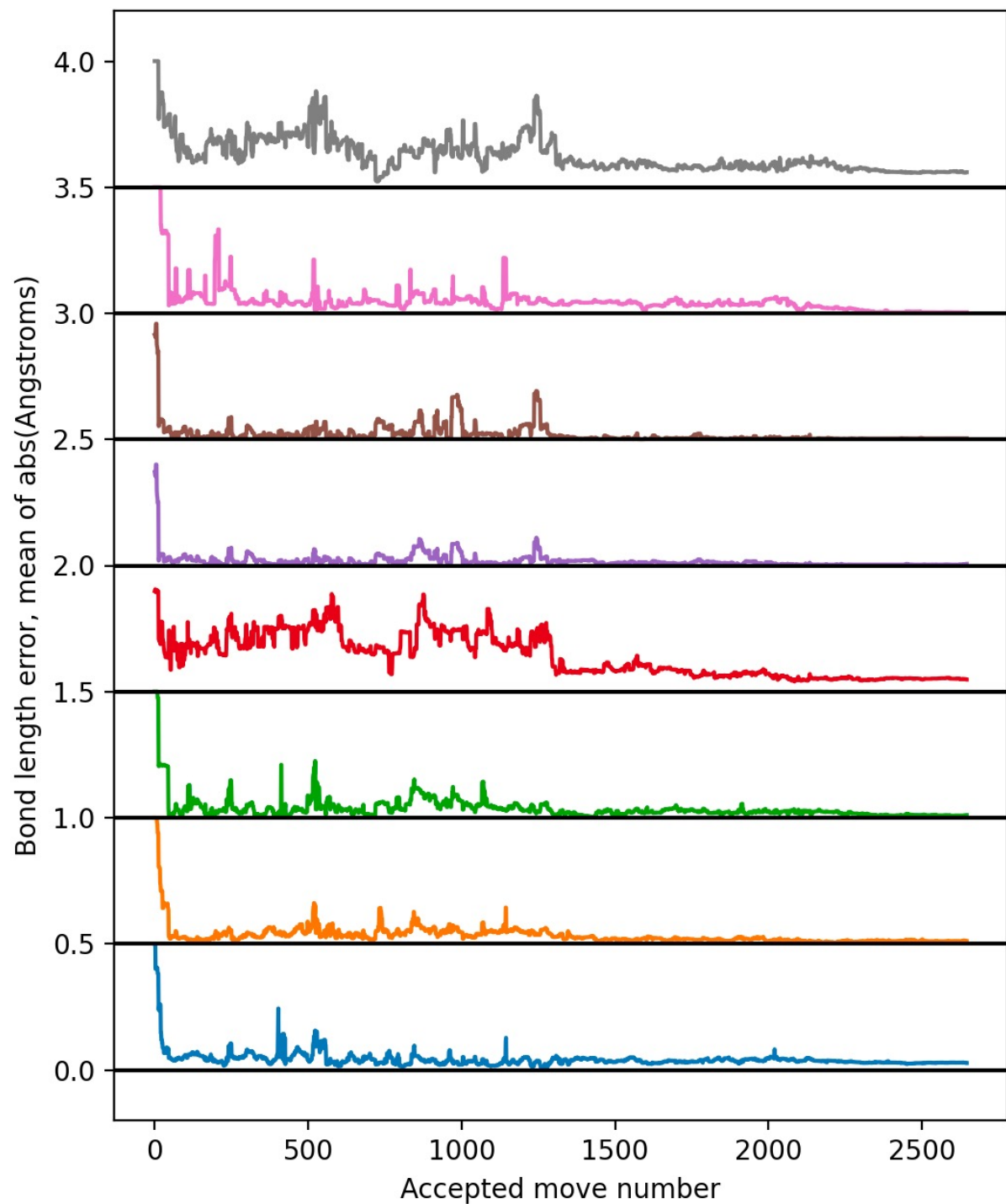
```
Current temperature is: 2  
Current temperature is: 0.2  
Current temperature is: 0.020000000000000004
```

```
Monte Carlo runtime is 260.2200481891632 s, or 0.0578266773753696s per attempted step.
```

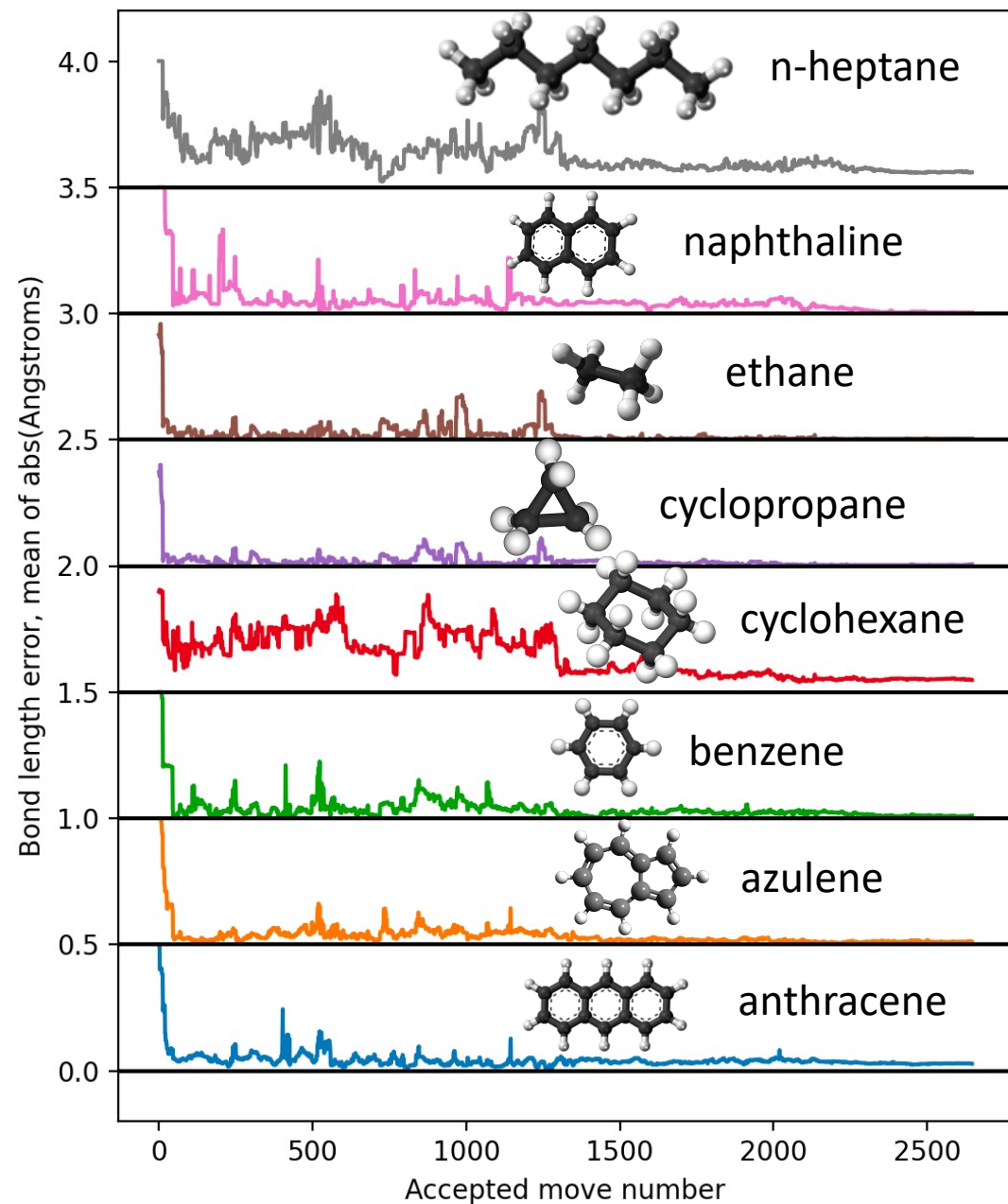
*Each step involves  
diagonalizing for 40  
configurations*

Lines represent  
~0.1 Å/bond

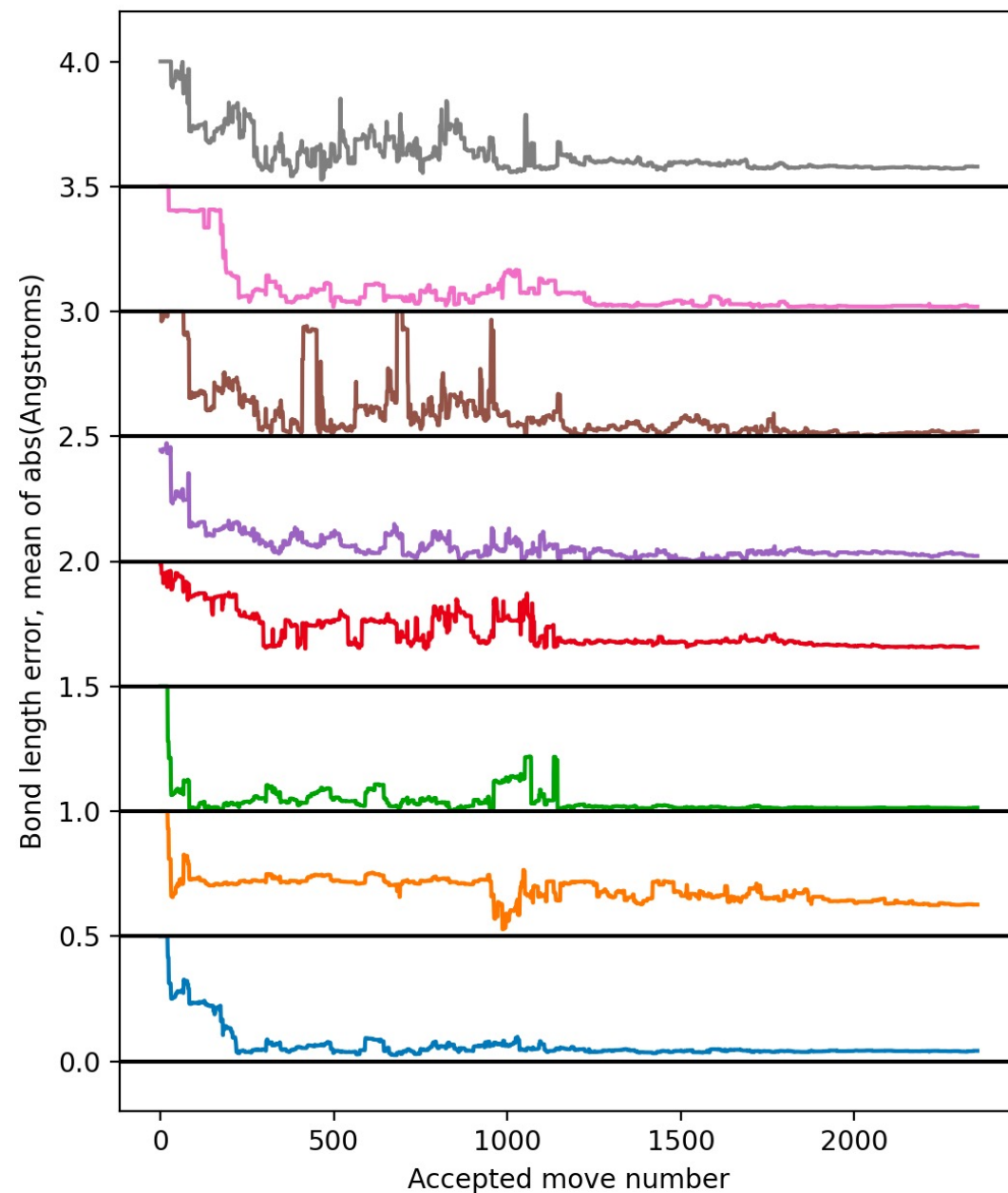
*Molecular structures selected from the Cambridge Structural Database  
(CSD) hosted by the Cambridge Crystallographic Data Centre (CCDC)*



Full Model



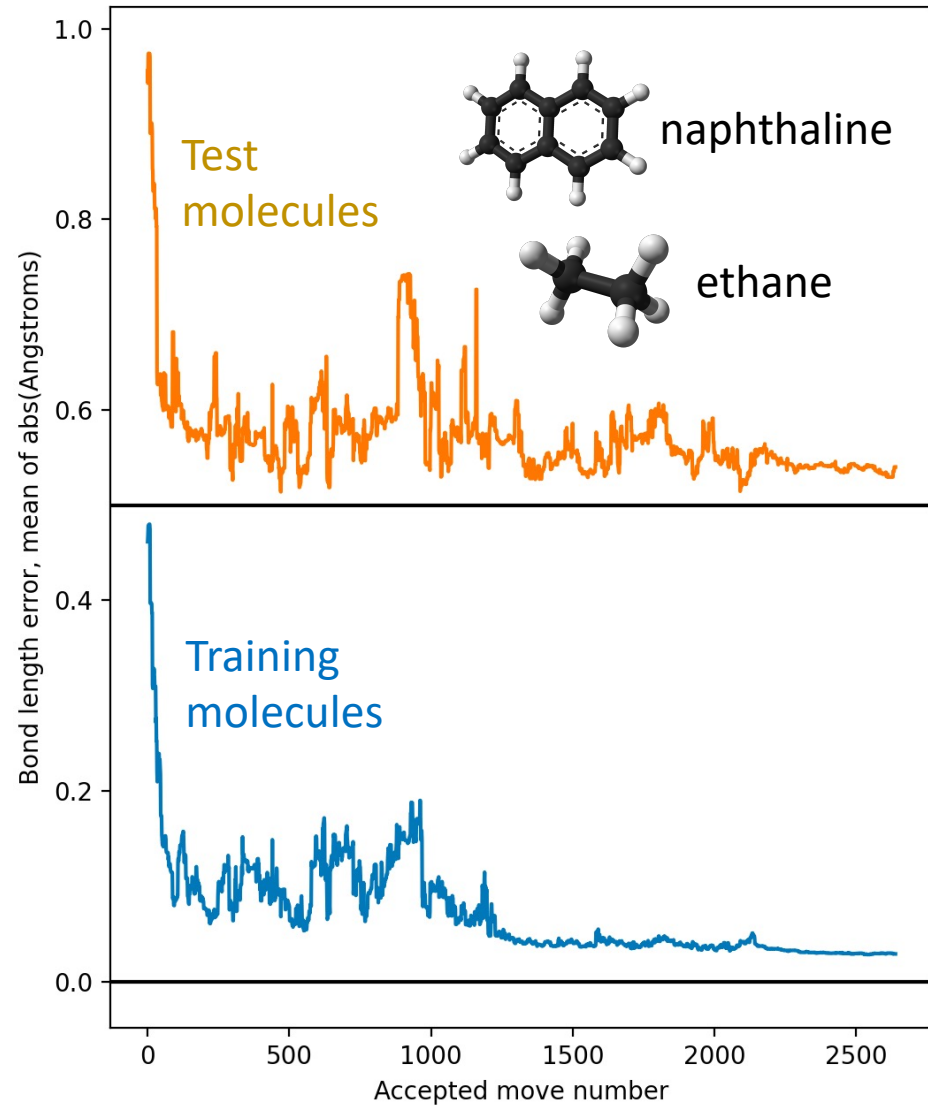
No Hopping (2-body bond type-resolved interactions)



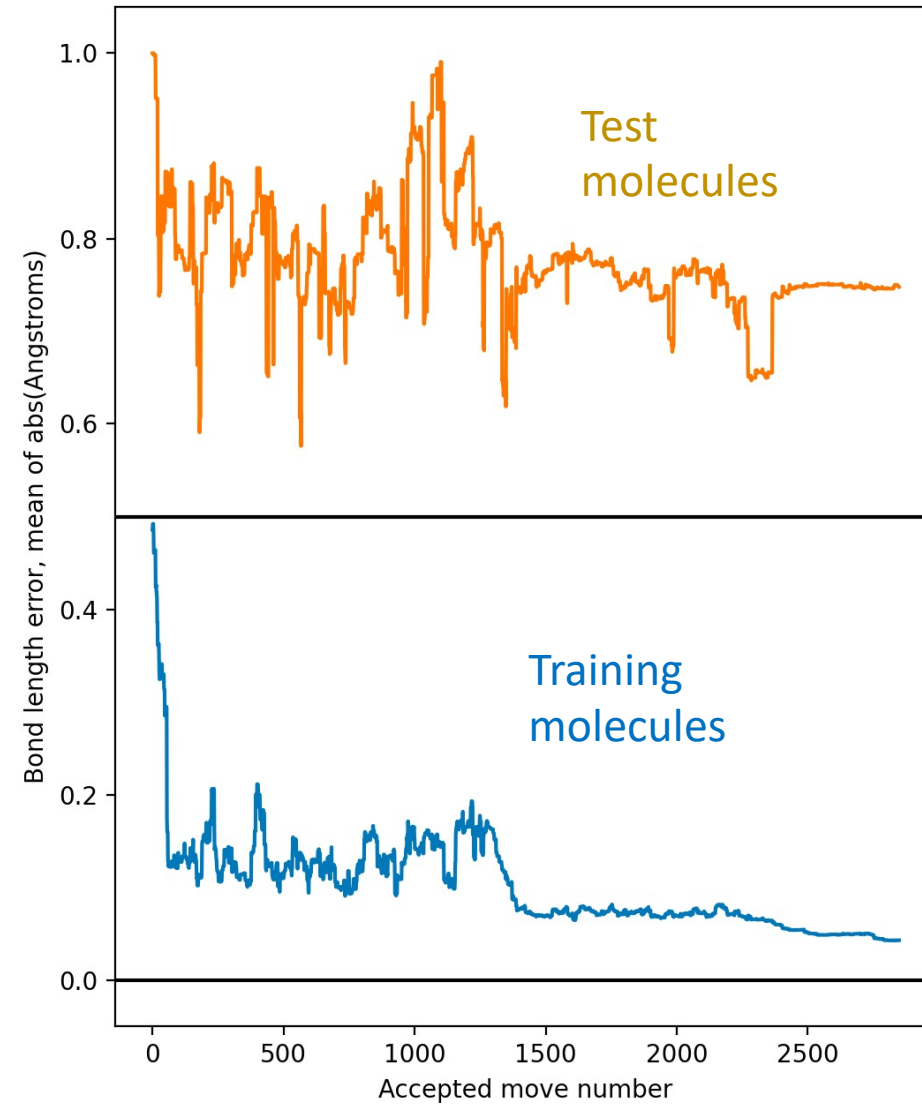


# Evaluating test data

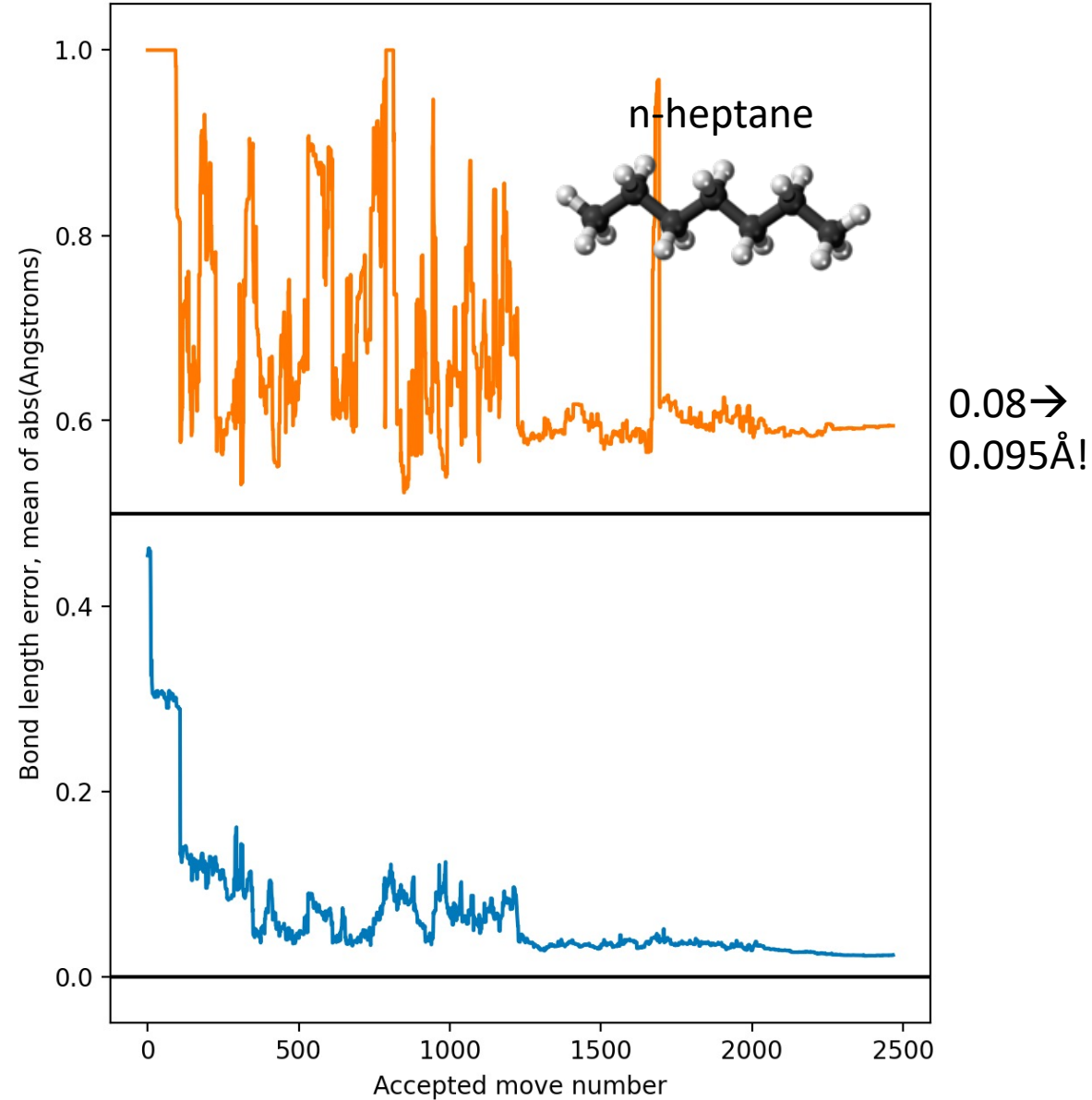
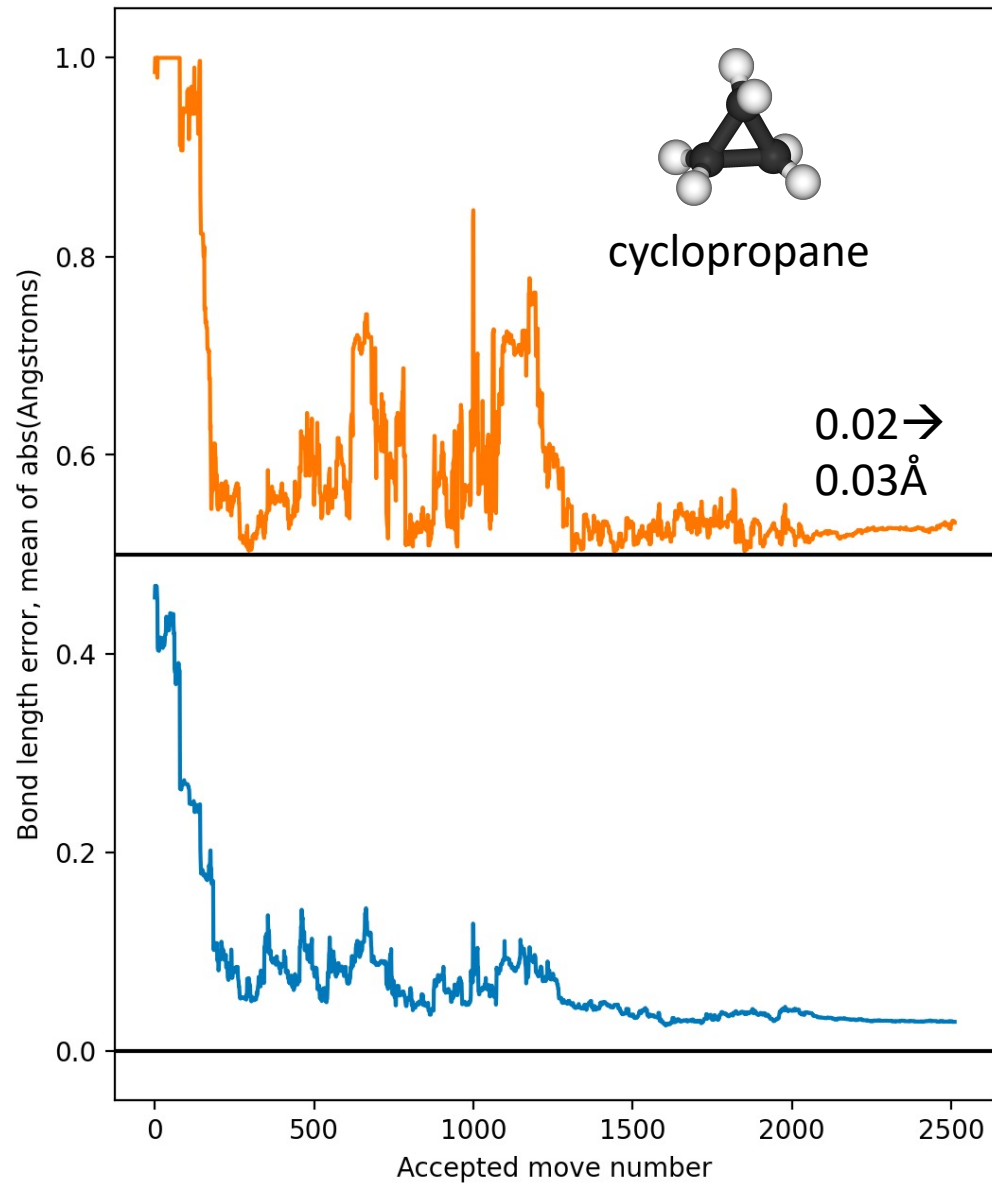
Full Model



No Hopping



# Overfitting the training data





## Advantages

1. Can handle delocalized wavefunctions (rings, chains).
2. Speed of **~5 ms/config** for a 20 atom molecule. (time $\sim n^3$ )
3. Error can be comparable to DFT (~1% of bond length) following Monte Carlo optimization, and possibly superior.
4. If successful scenarios are identified, it can plug into existing use cases for better-than-MM optimization.

## Development frontiers/**Limits**

1. The quantum model is partly missing charge density dependence. Density terms can be added at a cost of  $\sim 1.2$ -10 times the computational time.
2. Fields should depend on whether there is another atom in the way (3-body terms). This is currently mitigated by making the hopping field short range. Limited 3-body terms can be added with negligible computational overhead.
3. Converged TBF parameter sets from different runs can look quite different, but give similar performance. A random forest approach may increase accuracy at the cost of time.
4. As for AI-based approaches, model dimensionality includes terms that grow as the factorial of the number of elements. Adding  $O$  and  $N$  multiplies dimensionality by 4.6. Going beyond  $\sim 6$  elements will likely require sequential training for cycles with different groups of elements, even after the AI optimization loop is implemented.
5. Cluster physics is missing. Accuracy may hit a DFT-like limit.

## Immediate next steps

1. Full implementation of the neural network loop.
2. Close characterization of model performance, including more manipulations (twists, full structure relaxation).
3. Characterization for nitrogen- and oxygen-bearing molecules.