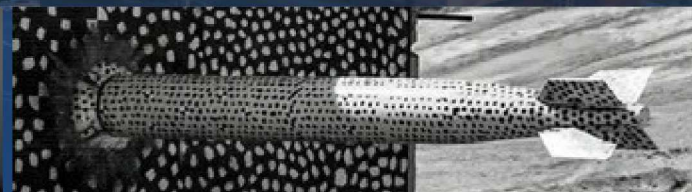
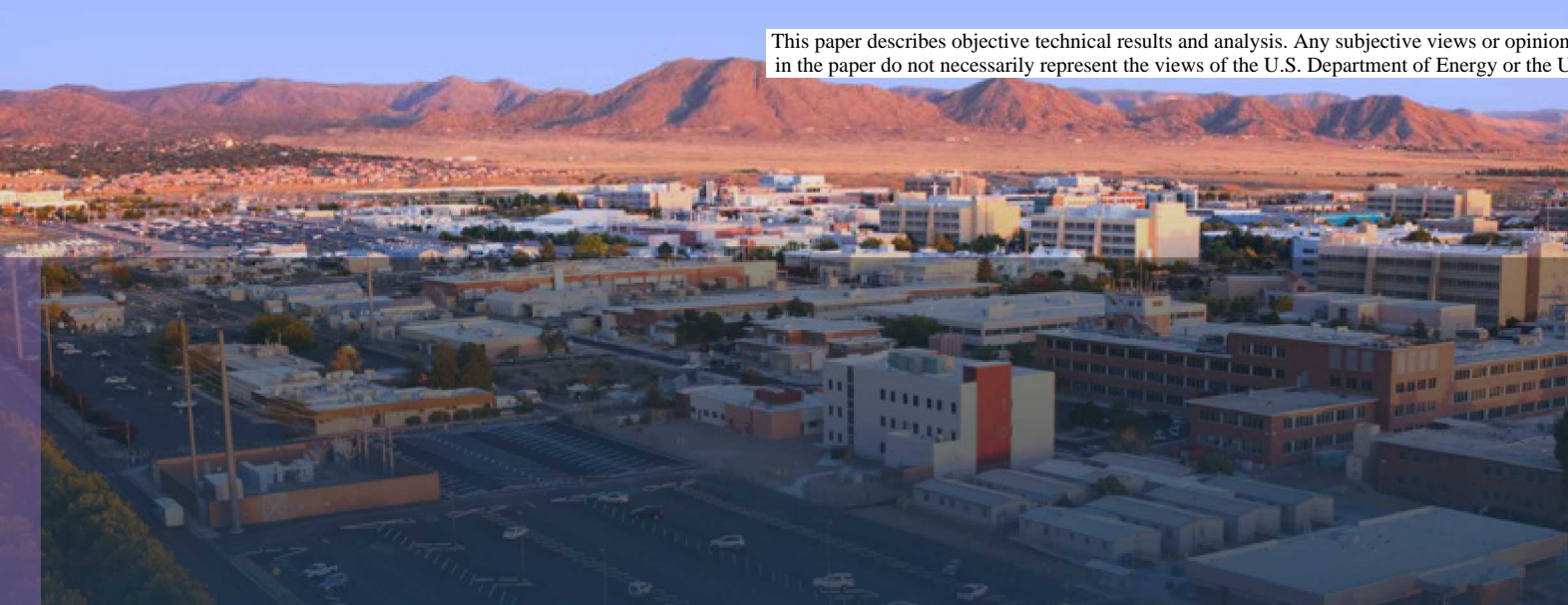


This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.



Sandia
National
Laboratories

SAND2020-4050C



Improving the accuracy of spin-lattice simulations with machine-learning interatomic potentials

PRESENTED BY

J. Tranchida, A.Cangi, M.A. Wood, A.P. Thompson, M. Desjarlais

Contact: jtranch@sandia.gov



Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

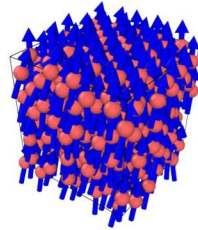
Coupled Spin Dynamics and Molecular Dynamics (SD-MD) methodology

SD-MD methodology:

- ▶ Adding classical magnetic spins to MD:

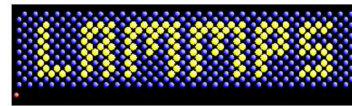
▶ For every magnetic atom in the system, one has:

$$\begin{cases} \frac{\partial \mathbf{r}_i}{\partial t} = \mathbf{v}_i \\ \frac{\partial \mathbf{v}_i}{\partial t} = \mathbf{F}_i(\mathbf{r}_{ij}, \mathbf{s}_{i,j}) \\ \frac{\partial \mathbf{s}_i}{\partial t} = \boldsymbol{\omega}_i \times \mathbf{s}_i \end{cases}$$



$$H_{sl} = \underbrace{\sum_{i=1}^N \frac{|\mathbf{p}_i|^2}{2m_i} + \sum_{i,j=1}^N V(r_{ij})}_{\text{MD Hamiltonian}} - \underbrace{\sum_{i,j,i \neq j}^N J(r_{ij}) \mathbf{s}_i \cdot \mathbf{s}_j - \mu_B \mu_0 \sum_{i=0}^N g_i \mathbf{s}_i \cdot \mathbf{H}_{ext}}_{\text{Spin-lattice coupling}}$$

SPIN package in LAMMPS



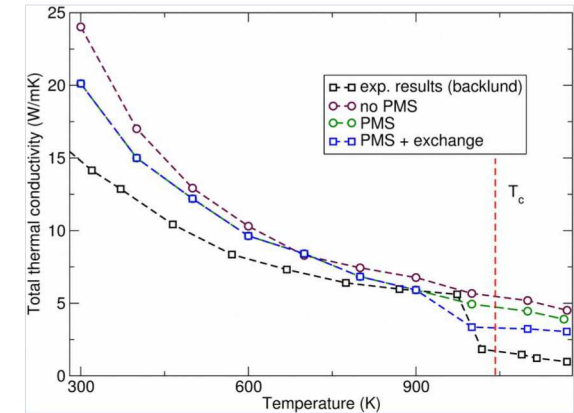
- ▶ Scalable symplectic algorithms (massively parallel spin-lattice dynamics).
- ▶ Nine types of magnetic interactions (exchange, Zeeman, DMI, ...).
- ▶ Resolution of long-range magnetic interactions (Ewald and P3M).
- ▶ Three spin minimizers and magnetic GNEB method.

Tranchida, Julien, et al. "Massively parallel symplectic algorithm for coupled magnetic spin dynamics and molecular dynamics." *Journal of Computational Physics* 372 (2018): 406-425.

Examples of application:

Thermal transport in magnetic materials

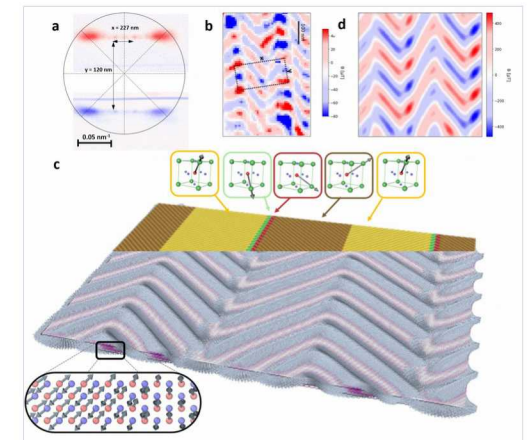
- ▶ Abnormal behavior: drop of the lattice thermal conductivity at T_c .
- ▶ Green-Kubo equilibrium atomic and spin dynamics approach.



Zhou, Yanguang, et al. "Atomistic Simulation of Phonon and Magnon Thermal Transport across the Ferro-Paramagnetic Transition." *arXiv preprint arXiv:1901.00966* (2019).

Magnetic textures in multiferroic materials

- ▶ Large scale simulation of spin textures in Bismuth ferrite.
- ▶ Simulation of magnetic configurations at ferroelectric domain walls.



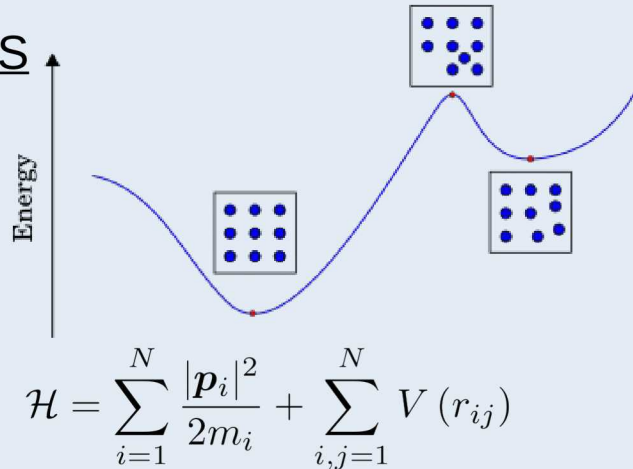
Chauleau, J-Y., et al. "Electric and antiferromagnetic chiral textures at multiferroic domain walls." *Nature materials* (2019): 1-5.

Spin and Lattice potential energy surfaces (PES), and common approach in S-L dynamics



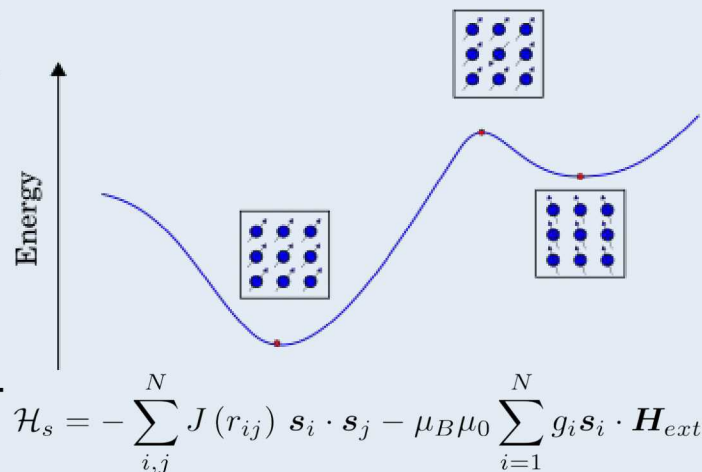
Molecular dynamics PES

- ▶ In metals, usually an EAM-like potential.
- ▶ Parametrization can be on ab-initio data, or on experiments (elastic constants, binding-energies, ...).



Spin dynamics PES

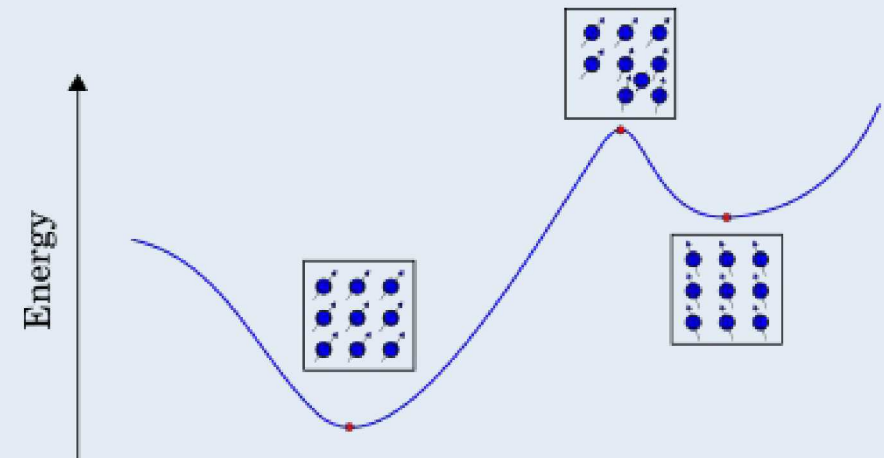
- ▶ Exchange interaction, Zeeman, anisotropy, ...
- ▶ Parametrized from 1st principles calculations (spin-spirals, ...), or exp. observables (T_c, ...).



Coupled spin-lattice PES

- ▶ Usual approach: overlaying the magnetic and mechanical PES.

$$\mathcal{H}_{sl} = \underbrace{\sum_{i=1}^N \frac{|\mathbf{p}_i|^2}{2m_i} + \sum_{i,j=1}^N V(r_{ij})}_{\text{MD Hamiltonian}} - \underbrace{\sum_{i,j,i \neq j}^N J(r_{ij}) \mathbf{s}_i \cdot \mathbf{s}_j - \mu_B \mu_0 \sum_{i=0}^N g_i \mathbf{s}_i \cdot \mathbf{H}_{ext}}_{\text{Spin-lattice coupling}}$$



- ▶ Proved sufficient to reproduce qualitative results (magnon-phonon scattering, thermal conductivity, ...).

✗ Limitations: not internally consistent, cannot reproduce quantitative DFT results.

A framework for generating magneto-elastic PES for iron, using machine-learning interatomic potentials



Generating DB

Fitting a Spin Hamiltonian

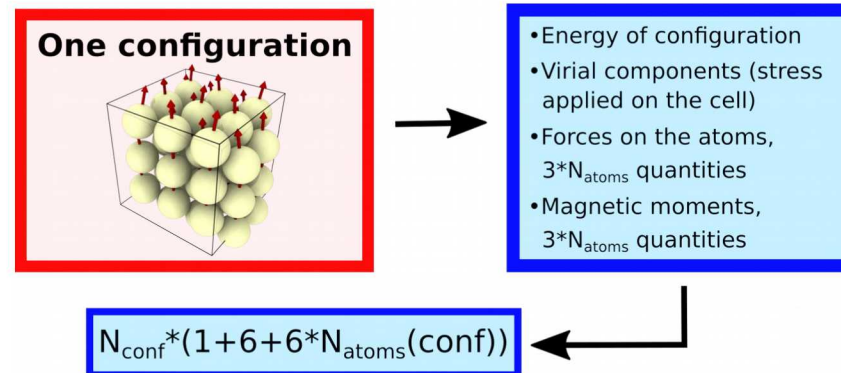
Subtracting magnetic PES

Training a ML-Interatomic potential

Running SD-MD simulations

Content of a database (DB) for machine-learning interatomic potential training

- ▶ We focus on **iron**:
 - ▶ Weak spin-orbit coupling, but...
 - ▶ Interesting spin-lattice coupling at high pressure,
 - ▶ Well-known and broadly studied.
- ▶ ML-IAP are trained on a DB of atomic configurations:



- ML inter-atomic potential reflects the configurations is in the DB:
 - ▶ The physical relevance of the configurations is fundamental.
 - ▶ Interatomic potential 'a la carte': configurations for a given range of validity.

- ▶ Example: if I need a potential simulating phonons and elastic constants only, I will only perform the corresponding ab initio calculations.

A framework for generating magneto-elastic PES for iron, using machine-learning interatomic potentials



Generating DB

Fitting a Spin Hamiltonian

Subtracting magnetic PES

Training a ML-Interatomic potential

Running SD-MD simulations

Generating a DB for machine-learning interatomic potential training

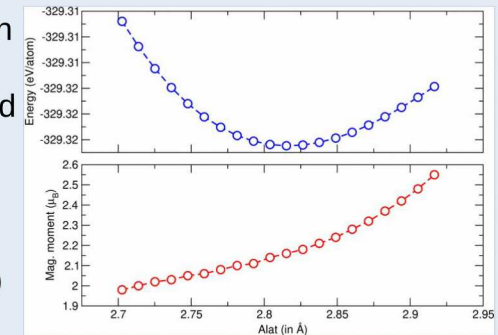
- ▶ Each configuration is the result of a self-consistent Density Functional Theory (DFT) calculation (performed with Quantum Espresso or VASP).



- ▶ Numerical verifications: k-points and PW cutoff convergence, number bands (when high smearing), energy convergence.
- ▶ Physics verifications: lattice constant, bulk modulus, Bohr magneton.
- ▶ Chosen DFT setup:
 - PBE pseudo-potential
 - Non-collinear and spin-orbit coupling
 - Smearing corresponding to 300K.
- ▶ Two sets of configurations generated.

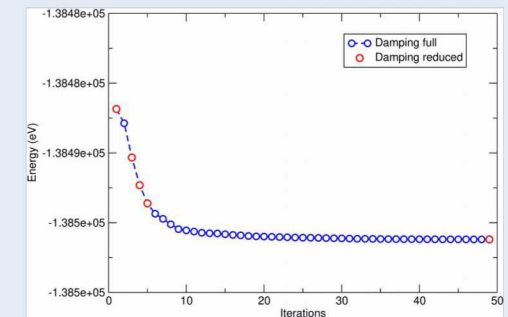
Equation of state configurations

- ▶ Lattice compression expansion ($\sim \pm 4\%$) on decorrelated 54 atom cells.
- ▶ Each run has 20 configurations.
- ▶ This group has 200 configurations.



DFT-MD configurations

- ▶ Performing DFT-MD runs on 128 atom cells.
- ▶ Decorrelated snapshots
- ▶ 40 configurations are stored.



A framework for generating magneto-elastic PES for iron, using machine-learning interatomic potentials



Generating DB

Fitting a Spin Hamiltonian

Subtracting magnetic PES

Training a ML-Interatomic potential

Running SD-MD simulations

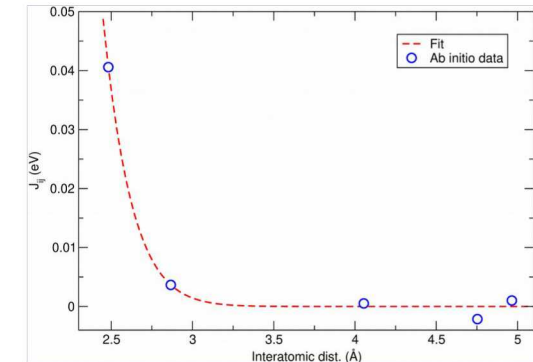
Fitting magnetic interactions on ab-initio results

- Objective: fitting an exchange interaction and a magnetic anisotropy on DFT calculations performed with the same setup as the DB generation.

- Parametrization of a Heisenberg exchange Hamiltonian:

$$H_{ex} = - \sum_{i,j}^N J_{ij}(r_{ij}) \mathbf{s}_i \cdot \mathbf{s}_j \quad \text{with} \quad J_{ij}(r_{ij}) = 4\alpha \left(\frac{r_{ij}}{\delta} \right)^2 \cos(\gamma r_{ij}) \exp \left(- \left(\frac{r_{ij}}{\delta} \right)^2 \right)$$

- For now, we are using the parametrization of a Heisenberg Hamiltonian formerly published.



- From this parametrized magnetic interaction, per-atom energy and mechanical forces for each atom of each configurations are computed and stored:

$$E_i = - \sum_j^{Neigh} J_{ij}(r_{ij}) \mathbf{s}_i \cdot \mathbf{s}_j \quad \mathbf{F}_i = \sum_j^{Neigh} \frac{d J_{ij}(r_{ij})}{d r_{ij}} (\mathbf{s}_i \cdot \mathbf{s}_j) \mathbf{e}_{ij}$$

A framework for generating magneto-elastic PES for iron, using machine-learning interatomic potentials



Generating DB

Subtracting the PES corresponding to the magnetic Hamiltonian

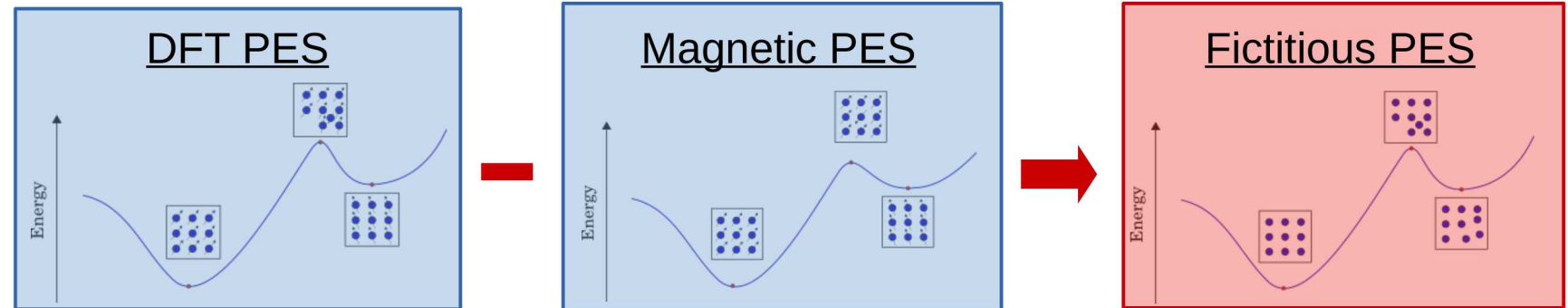
Fitting a Spin Hamiltonian

- ▶ The magnetic Hamiltonian is used as a reference potential.
- ▶ From each configuration, we subtract the energy, the mechanical forces (and, in principle, the virial components) generated by the parametrized spin Hamiltonian:

Subtracting magnetic PES

Training a ML-Interatomic potential

Running SD-MD simulations



- ▶ Generates a fictitious DB, on which we will train a ML-interatomic potential.

$$E_i^{Fic} = E_i^{DFT} - E_i^{Mag}$$
$$\mathbf{F}_i^{Fic} = \mathbf{F}_i^{DFT} - \mathbf{F}_i^{Mag}$$

A framework for generating magneto-elastic PES for iron, using machine-learning interatomic potentials



Generating DB

Fitting a Spin Hamiltonian

Subtracting magnetic PES

Training a ML-Interatomic potential

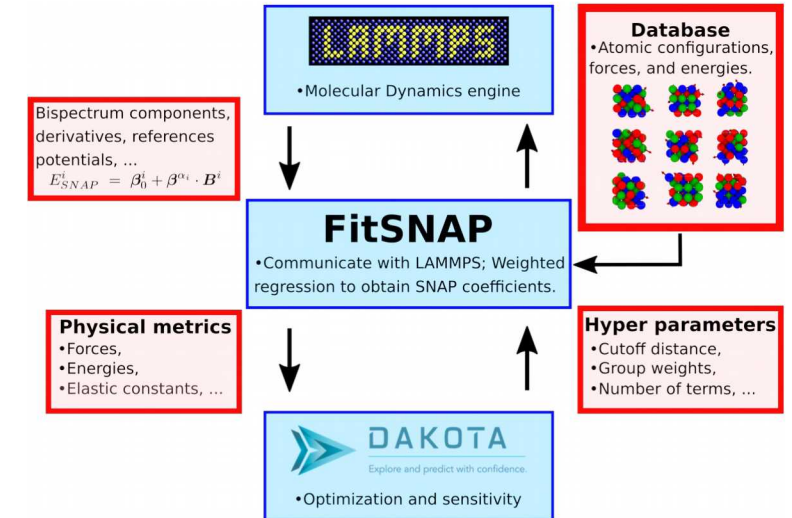
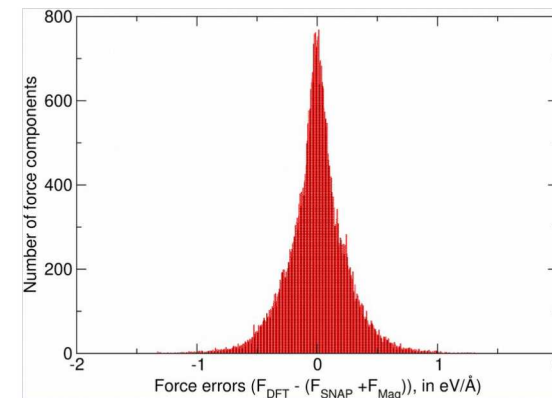
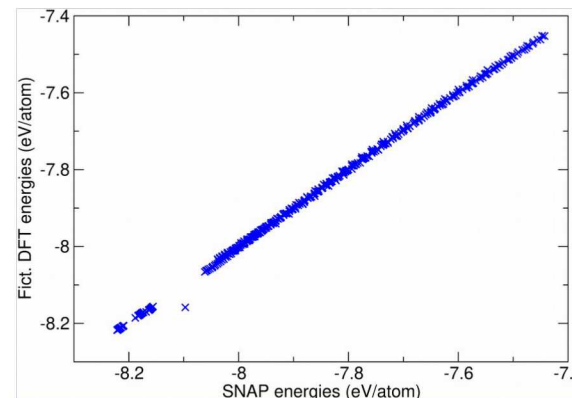
Running SD-MD simulations

Training a machine-learning interatomic potential on the fictitious PES

- ▶ Using the SNAP approach (developed at Sandia, implemented in LAMMPS).
- ▶ Energy and forces are expressed in terms of bispectrum components:

$$\left\{ \begin{array}{l} E_{SNAP}^i = \beta_0 + \boldsymbol{\beta} \cdot \mathbf{B}^i \\ \mathbf{F}_{SNAP}^j = -\boldsymbol{\beta} \cdot \sum_{i=1}^N \frac{\partial \mathbf{B}_i}{\partial \mathbf{r}_j} \end{array} \right.$$

- ▶ Training results, energy and force errors:



A framework for generating magneto-elastic PES for iron, using machine-learning interatomic potentials



Generating DB

Fitting a Spin Hamiltonian

Subtracting magnetic PES

Training a ML-Interatomic potential

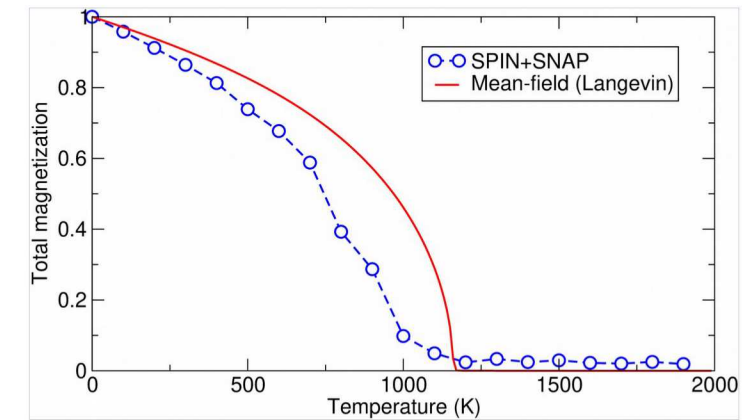
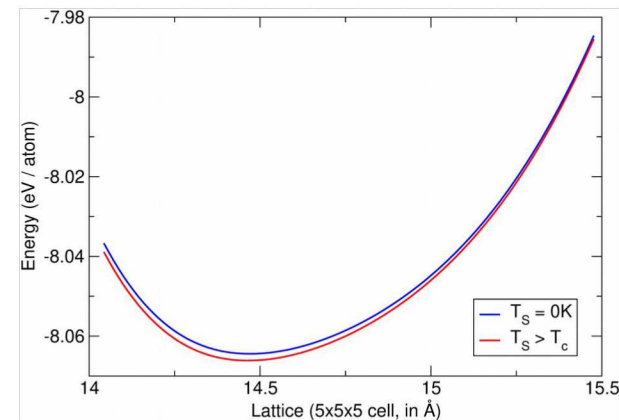
Running SD-MD simulations

Running SD-MD simulations

- ▶ Sum-up the contributions of the SNAP and Spin potentials:

$$\mathcal{H}_{sl} = \sum_i^N \frac{|\mathbf{p}_i|^2}{2m_i} + \sum_{i,j}^N V^{SNAP}(\mathbf{r}_{ij}) - \sum_{i,j}^N J_{ij}(r_{ij}) \mathbf{s}_i \cdot \mathbf{s}_j$$

- ▶ Tested minimization, NVE and NVT runs.
- ▶ Two calculation examples: EOS for two different spin temperatures, and Curie curve.



- ▶ Next test: influence of magnon-phonon scattering on the phonon dispersion.

Conclusions

10

Results:

- A new framework aiming at improving the accuracy of coupled spin and lattice simulations was developed.
- An initial DB of configurations was produced by DFT calculations (should work for phonons and elastic constants).
- We tested the framework on iron, and for simple SD-MD calculations.

Perspectives:

- ▶ Improving the potential's range of validity by adding more diverse configuration sets.
- ▶ Improving the spin model:
 - Accounting for the effects of the spin-orbit coupling, should lead a stronger S-L coupling.
 - Accounting for longitudinal spin fluctuations (very important for nickel, or for iron at higher pressure).

◆ Any suggestion welcome, feel free to contact us (jtrench@sandia.gov).

