

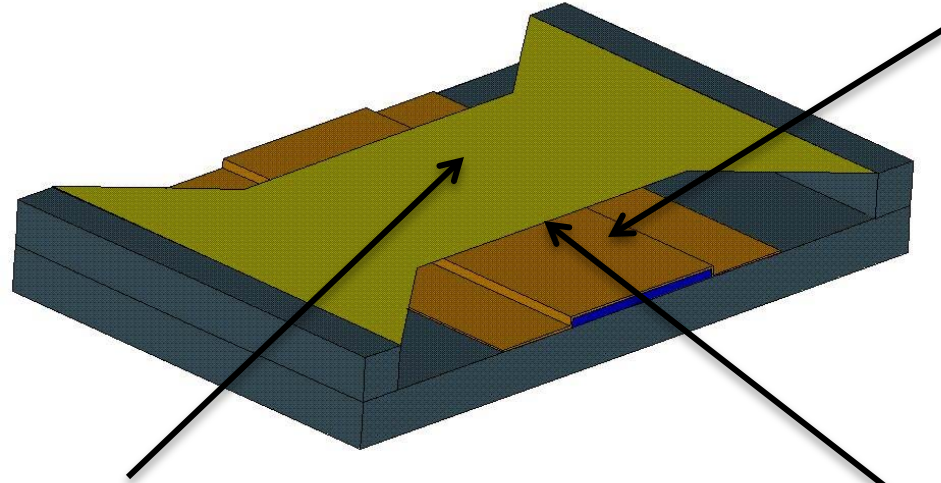


# Uncertainty quantification molecular dynamics simulations

Alejandro Strachan

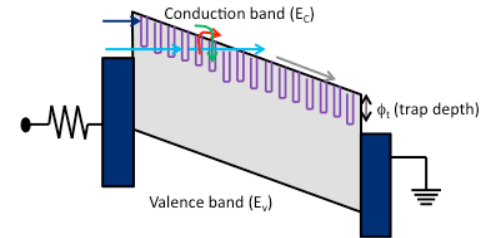
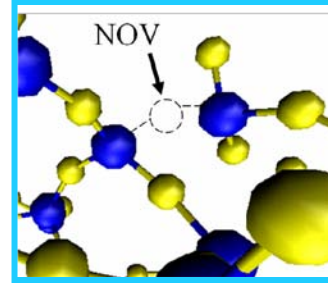
Materials Engineering, Purdue University

# Atomistic simulations in PRISM



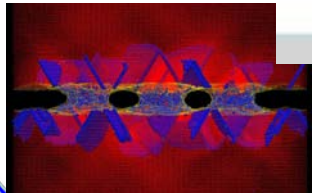
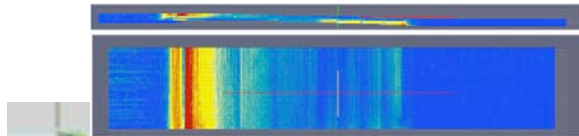
## Dielectric Charging

- Trapped charges cause uncontrollable changes in actuation voltage



## Solid mechanics

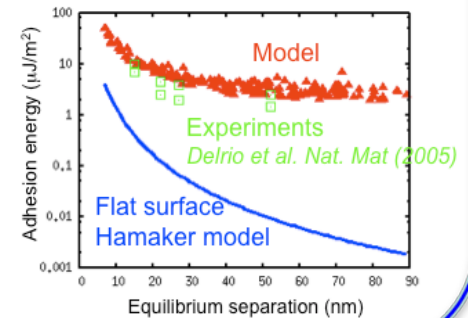
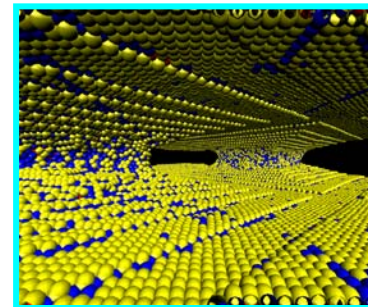
- Creep and stress relaxation, size effects



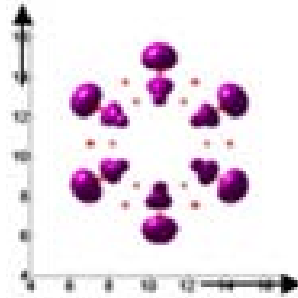
Defect properties:  
vacancies, dislocations,  
GBs

## Contact physics

- Surface interaction, adhesion & stiction
- Contact hardness & strength
- Sub-surface defects & surface chemistry



# Atomic level simulations of materials



Wave function of electrons

$$\psi(\{r_i\})$$

$$|\psi(\{r_i\})|^2$$

Probability density of finding electron 1 at  $r_1$ ,  
electron 2 at  $r_2$ , etc.

Wave function is obtained from the Schrodinger equation:

$$H(\{R_i\})\psi(\{r_i\};\{R_i\}) = E(\{R_i\})\psi(\{r_i\};\{R_i\})$$

# Molecular dynamics simulations

MD involves numerically solving Newton's equations of motion

$$\dot{R}_i = \frac{P_i}{M_i}$$

$$F_i = -\nabla_{R_i} E(\{R_i\})$$

$$\dot{P}_i = F_i$$

Ab initio MD (forces & energy from QM)

## MD with empirical potentials

Replace energy obtained from the Schrodinger equation  $E(\{R_i\})$  with an empirical function that approximates its behavior:

$$U_{FF}(\{R_i\}; \{C_i\})$$

Material specific force field parameters

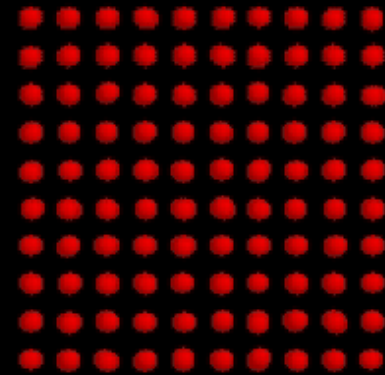
Atomic positions

# A simple MD run

Use stat mech to relate microscopic world to thermodynamical properties

Temperature ~ kinetic energy per DoF

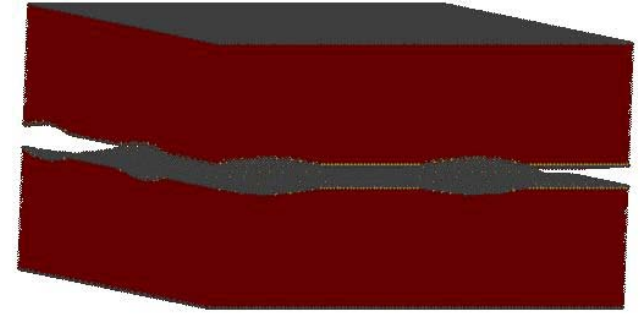
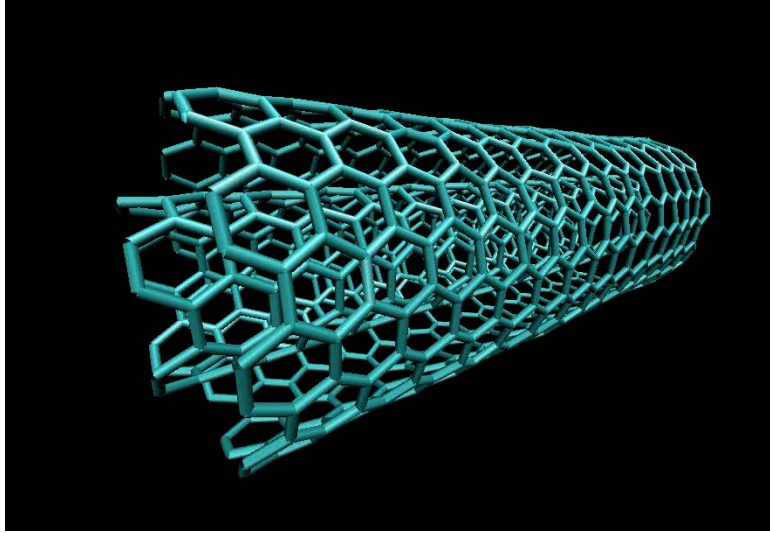
$$\langle K \rangle = \frac{3N}{2} kT$$



Stress tensor from the virial theorem

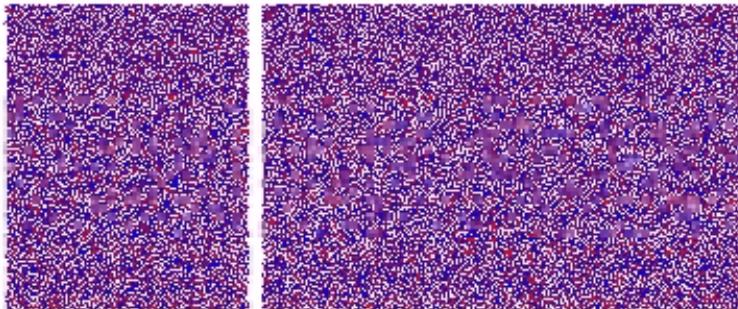
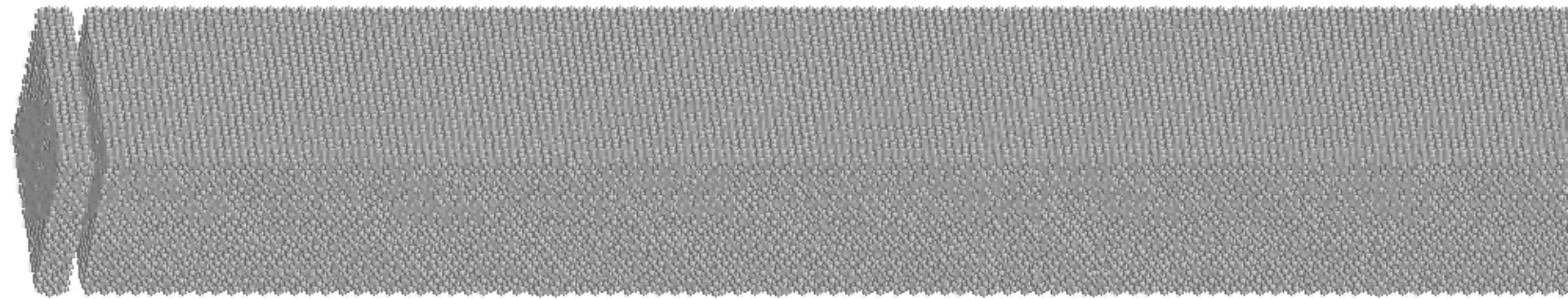
$$\sigma_{\alpha\beta} = \frac{1}{V} \sum_{i < j} F_{ij}^{\alpha} R_{ij}^{\beta} + \frac{1}{3V} \sum_i M_i \langle V_i^{\alpha} V_i^{\beta} \rangle$$

Contacts



Friction in CNTs

Shocks in molecular crystals



Spall failure



# Interatomic potentials and uncertainties in MD

## Newton's equations of motion

$$\dot{\mathbf{X}}_i = \frac{\mathbf{P}_i}{m_i}$$

$$\dot{\mathbf{P}}_i = \mathbf{F}_i$$

$$\mathbf{F}_i = -\nabla_{\mathbf{r}_i} U(\{\mathbf{r}_i\}; \{C_i\})$$

Force field form & parameters:  
Largest source of epistemic  
uncertainties in MD simulations



## Interatomic potential for fcc metals

Lennard Jones:

$$U(\{R_{ij}\}; \varepsilon, \sigma) = \sum_{i < j} 4\varepsilon \left[ \left( \frac{\sigma}{R_{ij}} \right)^{12} - \left( \frac{\sigma}{R_{ij}} \right)^6 \right]$$

Very simple, not appropriate for metals

EAM (Sutton Chen)

$$U(\{R_{ij}\}; \varepsilon, \sigma, c) = \sum_{i < j} \phi(R_{ij}) + \sum_i F(\rho_i)$$

$$\varepsilon \sum_i \left[ \sum_{j < i} \left( \frac{\sigma}{R_{ij}} \right)^{10} - c \sqrt{\sum_{j \neq i} \left( \frac{\sigma}{R_{ij}} \right)^5} \right]$$

How can we quantify this uncertainties?

# Force field parameterization and predictions

Find “optimal” FF parameter set in terms of a set of materials properties:

$M_i^{tar}$  Training set of experimental or *ab initio* properties

Error function to be minimized:

$$X(\{C_i\}) = \sum_i \frac{\left( \overbrace{M_i^{tar}}^{\text{Target value}} - \overbrace{M_i^{FF}(\{C_i\})}^{\text{FF prediction}} \right)^2}{2\sigma_i^2} w_i$$

Weight of property  $i$

Standard deviation

with respect to  $\{C_i\}$

# Example: force field for Nickel

Target properties from experiments  
(training set)

Lattice parameter:  $0.352 \pm 0.001 \text{ nm}$

Cohesive energy:  $-4.45 \pm 0.05 \text{ eV}$

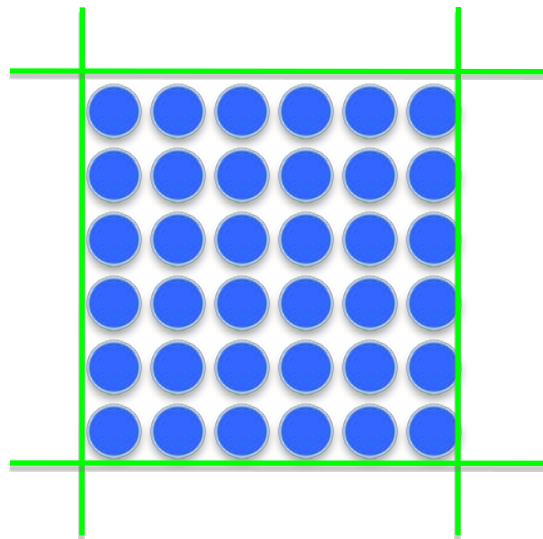
Bulk modulus:  $187 \pm 5 \text{ GPa}$

Surface energy:  $2.3 \pm 0.05 \text{ J/m}^2$

Prediction:

Vacancy formation energy:

Exp:  $1.55 - 1.85 \text{ eV}$



# Force field optimization via simulated annealing

Explore FF parameter space & optimize them via Monte Carlo

1. Start with initial guess for parameters

2. Generate new parameter set randomly from current set

$$\{C_i^{new}\} \leftarrow \{C_i + \delta_i\}$$

3. Compute change in cost function:

$$\Delta X = X(\{C_i\}) - X(\{C_i^{new}\})$$

4. If  $\Delta X$   $\left\{ \begin{array}{l} \leq 0: \text{ accept new FF parameter set } \{C_i\} \leftarrow \{C_i^{new}\} \\ > 0: \text{ accept new FF parameter set with probability: } p = \exp(-\Delta X / T) \end{array} \right.$

Metropolis Monte Carlo

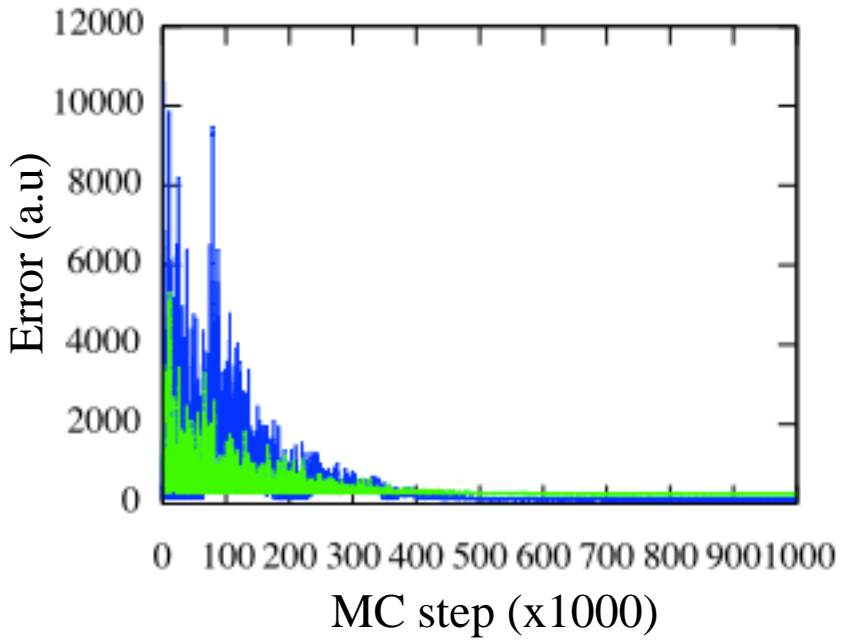
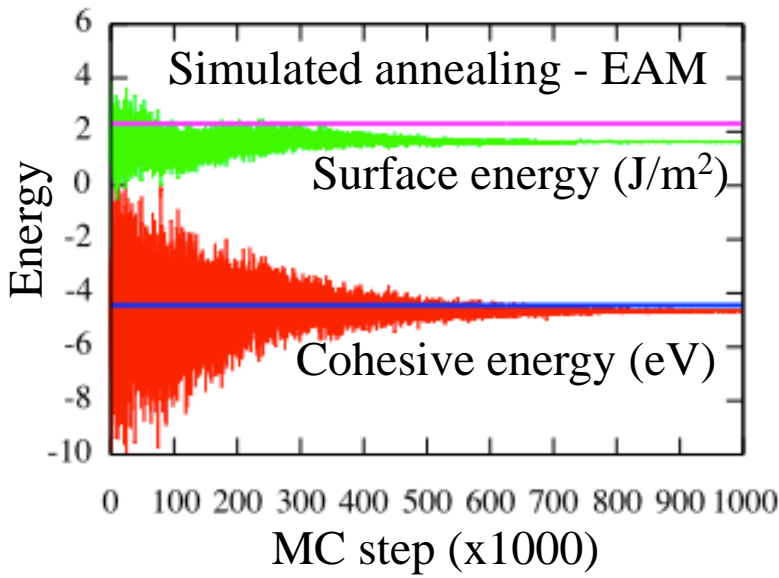
• Start at a high “temperature” (T) to explore parameter space

• Generates the canonical distribution:  $p(\{C_i\}) \propto \exp[-X(\{C_i\}) / T]$

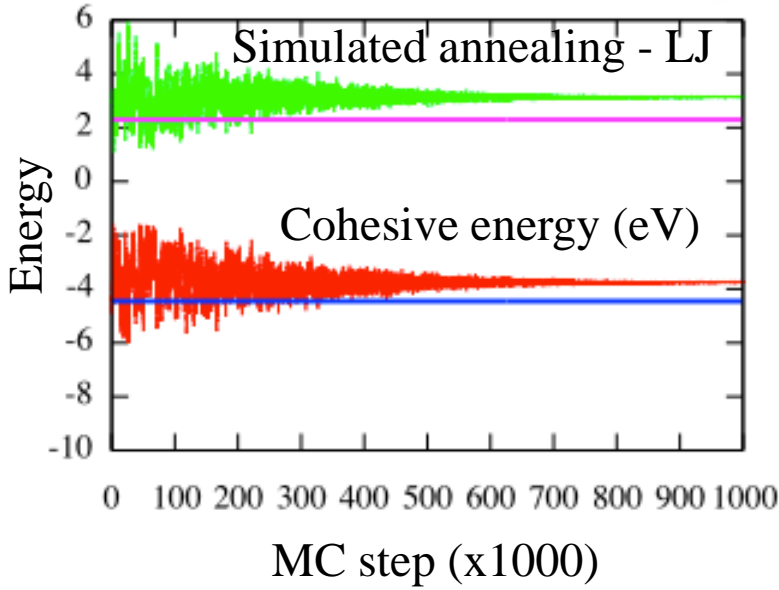
• Minimizes free energy:  $F = \langle X(\{C_i\}) \rangle - T S$

• “Cool down” system to obtain minimum E parameter set:  $\{C_i\}_{opt}$

# Simulated annealing: optimal FF



Decreasing temperature



Predictions by optimized potential:

- EAM: 1.35 eV
- LJ: 3.76 eV
- Experiments: 1.55-1.85 eV



# How to quantify uncertainties in $\{C_i\}$ ?

Assume training data in uncorrelated and each follow a normal distribution:

Probability of materials properties taking values  $\{M_i\}$  is:

$$\prod_i \exp \left[ - \left[ \frac{(M_i^{tar} - M_i)^2}{2\sigma_i^2} \right] \right]$$

Probability of FF parameter set  $\{C_i\}$  reproducing the training data:

$$P(\{C_i\}) \propto \prod_i \exp \left[ - \left[ \frac{(M_i^{tar} - M_i^{FF}(\{C_i\}))^2}{2\sigma_i^2} \right] \right]$$

Generate an ensemble of potentials with this distribution

# How to quantify uncertainties in $\{C_i\}$ ?

2. Generate new parameter set randomly from current set

$$\{C_i^{new}\} \leftarrow \{C_i + \delta_i\}$$

3. Compute change in cost function:

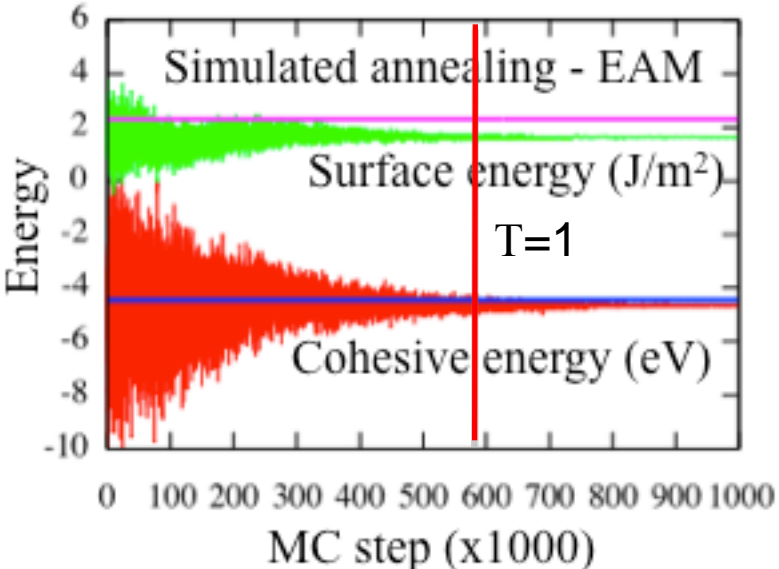
$$\Delta X = X(\{C_i\}) - X(\{C_i^{new}\})$$

4. If  $\Delta X$   $\begin{cases} \leq 0: \text{accept new FF parameter set } \{C_i\} \leftarrow \{C_i^{new}\} \\ > 0: \text{accept new FF parameter set with probability: } p = \exp(-\Delta X/T) \end{cases}$

Metropolis Monte Carlo

Produces parameters with probability

$$p(\{C_i\}) \propto \exp[-X(\{C_i\})/T]$$



Ensemble of FFs at  $T=1$  does not reproduce all the target properties

Increase  $T$  until all properties are described by the ensemble

Frederiksen et al.  
PRL, 93, 165501  
(2004)

# Quantifying uncertainties in $\{C_i\}$

$$P(\{C_i\}) \propto \prod_i \exp \left[ - \left[ \frac{(M_i^{tar} - M_i^{FF}(\{C_i\}))^2}{2\sigma_i^2} \right] / T \right]$$

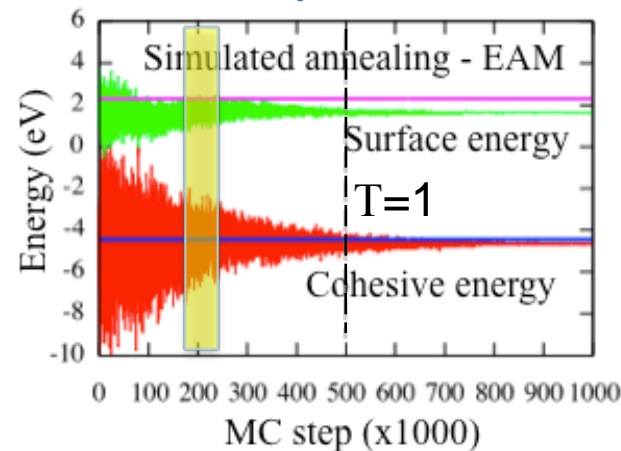
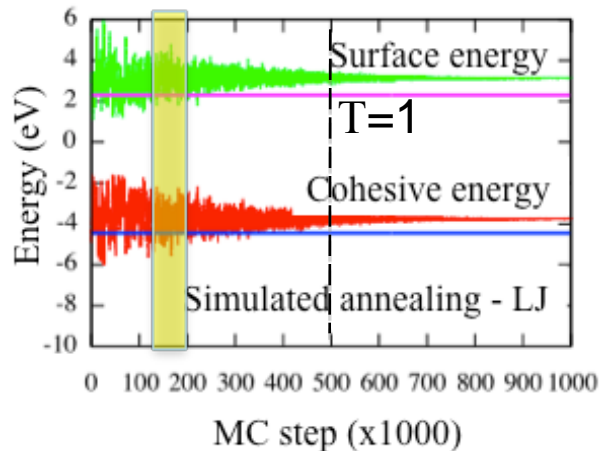
Ensemble of FF parameters for  $T=1$ : product of PDFs of target properties having values given by FF

Ensemble of FF parameters spans all properties including standard deviation

Ensemble of parameters does not describe all properties

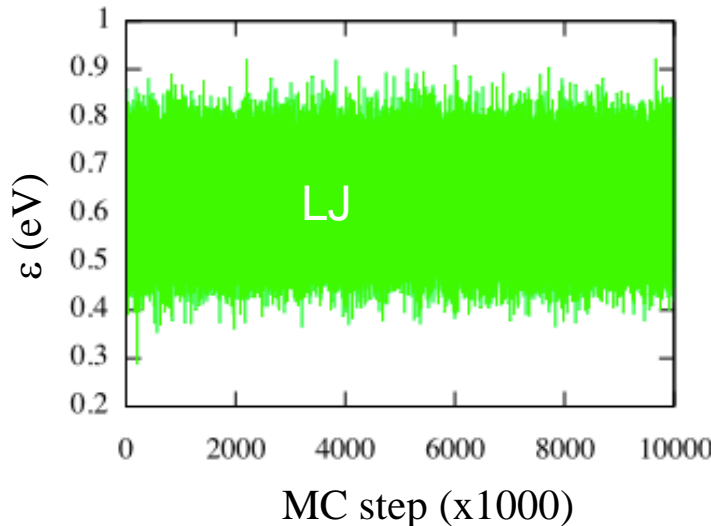
Done:  $T=1$

Increase temperature until all properties are described by ensemble

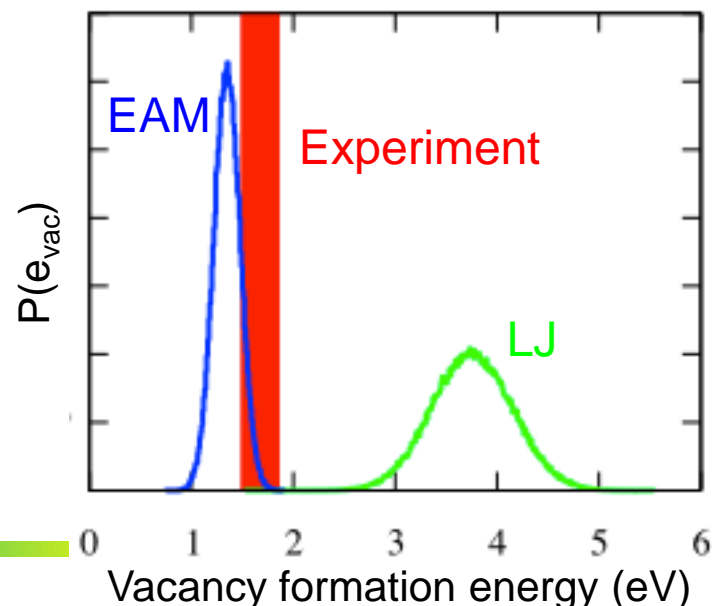


# Ensemble of FFs predictions

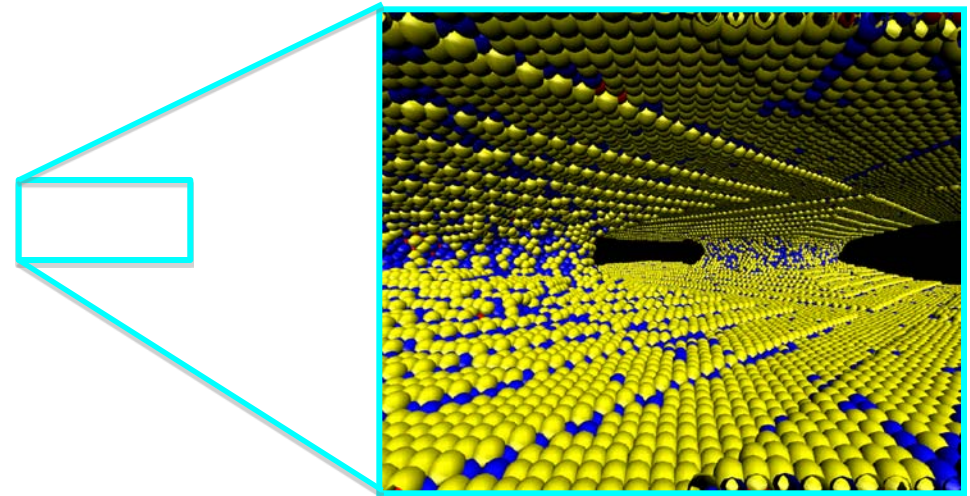
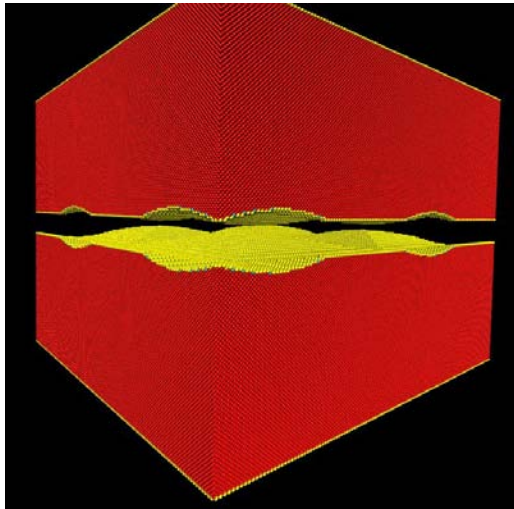
$\epsilon$  (eV)  
 EAM  
 MC step (x1000)



$$p(\{C_i\}) \propto \exp[-X(\{C_i\})/T] = \prod_i \exp\left[-\frac{(M_i^{FF}(\{C_i\}) - M_i^{tar})^2}{2\sigma_i^2}\right] / T$$



# Atomistic contact simulations



For a given surface asperity (distribution of heights and peak to peak separations)

- What is the minimum pull-out force as a function of applied closing force?
- What sub-surface defects are generated in metal and dielectric?



## Closing

Small contact area and large stress:  
Plastic deformation -> increase in  
contact area until stress equals the  
materials hardness



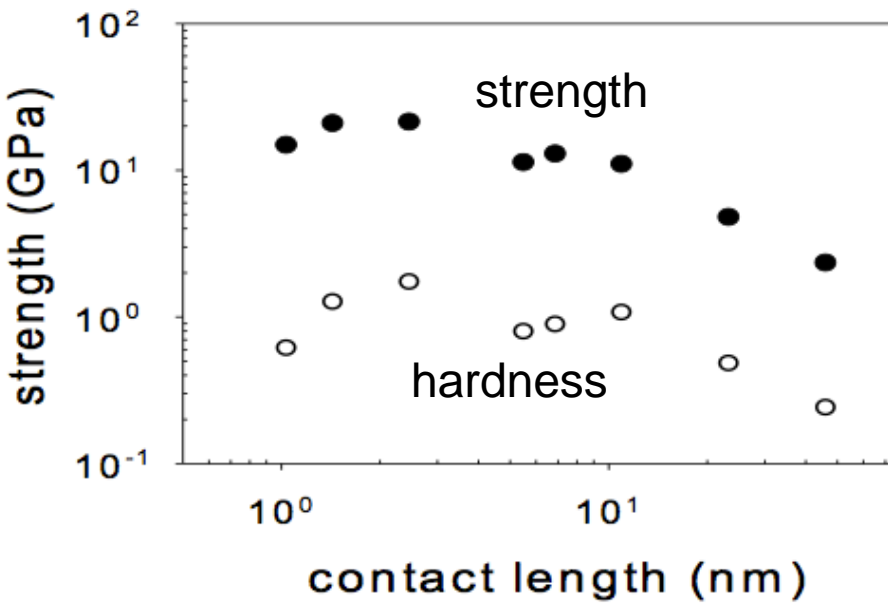
## Opening

Size dependent strength of bridges

# Initial UQ in large-scale MD

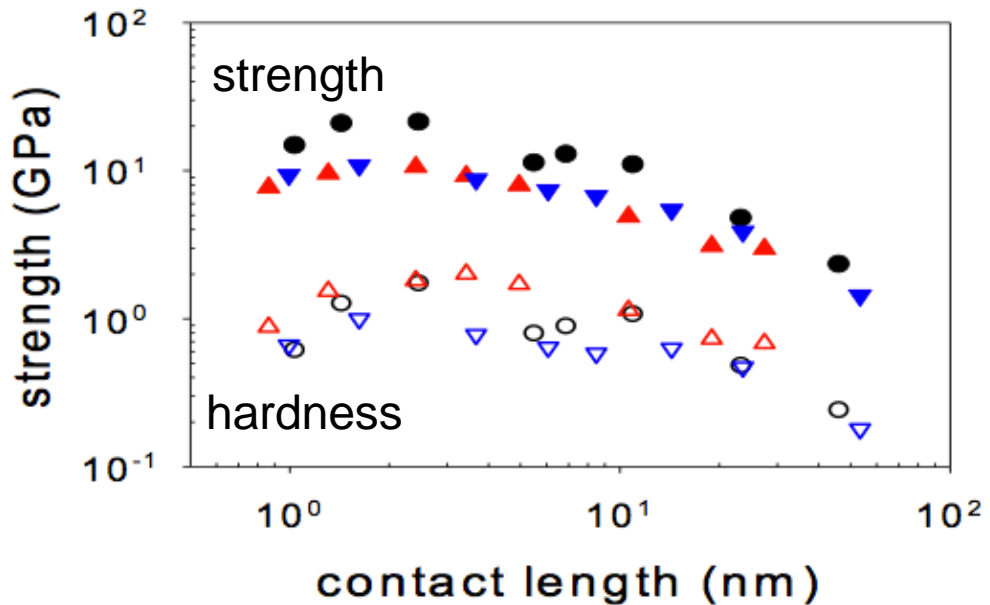
PDF of FF parameters is difficult to utilize for large-scale simulations

Current state-of-the-art FF results



• Force field overestimates binding

Decrease energy scales by 50%



• Initial UQ calculation leads to range properties

# Summary

## Uncertainties in force field parameters

- Monte Carlo procedure to generate an ensemble of FF parameters
  - PDF of parameter set associated with PDF of resulting properties
  - Ensemble describes all training set properties
- Overly simple FF → large variation in properties → uncertain prediction
- Future work
  - Correlated uncertainties in input data
  - Apply approach to PRISM device materials
  - Automatic model form uncertainty? Aidan Thompson @ SNL
  - *Ab initio* calculations – Peter Schultz @ SNL
- For large-scale MD simulations
  - Minimum-maximum approach as initial step
- Couple FF parameter uncertainty to other aleatoric uncertainties
- Propagate across scales