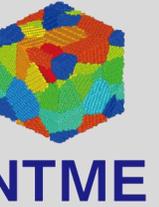




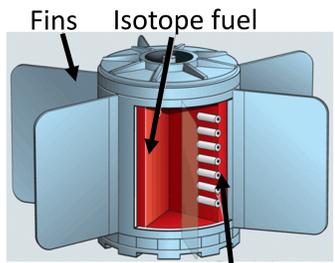
# Machine Learning Assisted Prediction of Aperiodic Superlattice Structures with Ultralow Lattice Thermal Conductivity for NASA's Radioisotope Thermoelectric Generators

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## Why do we need efficient thermoelectric (TE) devices?



Thermoelectric converter

Mars rover

Radioisotope thermoelectric generator (RTG)

- NASA Applications:** RTG is the primary power source of most of NASA's deep space missions. The poor efficiency of TE materials is one significant limiting factor for such RTGs.
- Energy Recycling:** Around 70% of the consumed energy is wasted in the form of low-grade heat. Thermoelectric devices can generate usable electricity from the waste heat.
- Cooler or Refrigerator:** Thermoelectric coolers are noise free, do not need working fluids, and occupy less space. Thermoelectric materials are used for cooling small-scale devices.

## Towards better thermoelectric materials

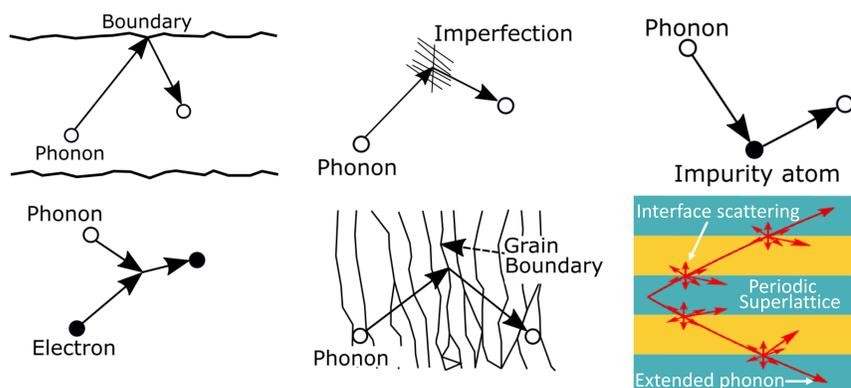
- Figure of merit ( $ZT$ ) of thermoelectric materials

$$ZT = \frac{\sigma S^2 T}{\kappa_e + \kappa_L}$$

$\sigma$  = Electrical conductivity  
 $S$  = Seebeck coefficient  
 $T$  = Temperature  
 $\kappa$  = Thermal conductivity

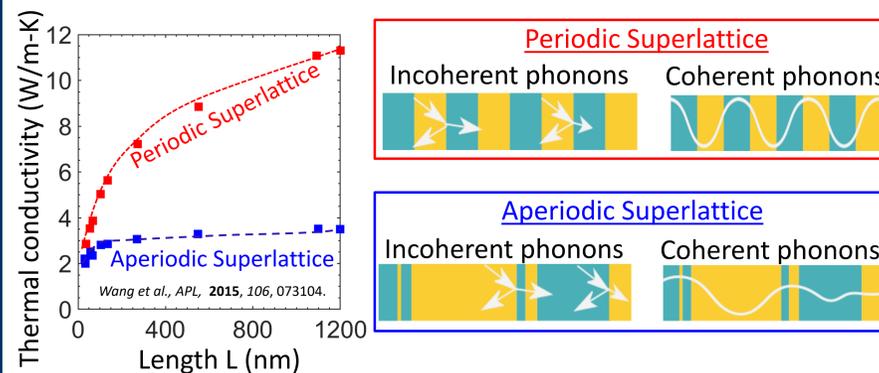
Electronic thermal conductivity  $\kappa_e$   
 Lattice thermal conductivity  $\kappa_L$

- Minimizing the lattice thermal conductivity while retaining good electrical conduction is essential for developing high-ZT thermoelectric materials.
- Several scattering strategies are used for reducing  $\kappa_L$ .....



- These scattering mechanisms are well studied and the outcome tends to be saturated. We need new strategies to further reduce  $\kappa_L$ .

## Aperiodic superlattice structures exhibit significantly lower thermal conductivity than periodic superlattice



Aperiodic Superlattice (ASLs) localize the coherent phonon transport and therefore, exhibit lower thermal conductivity than superlattice structure

## Objective of this work

- Correlate the randomness and thermal conductivity of ASLs
- Achieve optimized ASLs through machine learning
- Further reduction of ASL thermal conductivity through rational doping

## Molecular dynamics (MD) simulations

A (40 g/mol) B (90 g/mol)

Periodic Superlattice (PSL)

Aperiodic Superlattice (ASL)

Gradient Superlattice (GSL)

Setup of MD simulations

Hot bath Cold bath

Fixed boundaries

Lennard-Jones potential

$$\Phi_{ij} = 4\epsilon \left[ \left( \frac{\sigma}{r_{ij}} \right)^{12} - \left( \frac{\sigma}{r_{ij}} \right)^6 \right]$$

$\epsilon = 0.1664$  eV and  $\sigma = 0.34$  nm

Conceptual materials for computational efficiency

LAMMPS package

Non-equilibrium molecular dynamics simulations

$\kappa_L$  is calculated as

$$\kappa_L = \frac{JL}{A_c(T_h - T_c)}$$

## Quantification of randomness in aperiodic superlattice (ASL)

- We identified a few disorder parameters to correlate the randomness with  $\kappa_L$  of ASLs obtained through molecular dynamics simulations

- Thickness based randomization index

$$R_d = \sqrt{\frac{\sum_{i=2}^N [(d_{A,i} - d_{A,i-1})^2 + (d_{B,i} - d_{B,i-1})^2]}{N}}$$

- Period based randomization index

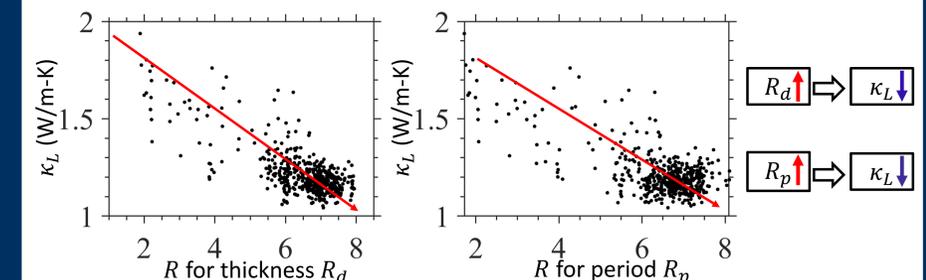
$$R_p = \sqrt{\frac{\sum_{i=2}^N [(d_{A,i} + d_{B,i})^2 + (d_{A,i-1} + d_{B,i-1})^2]}{N}}$$

- Standard deviation

$$\delta = \sqrt{\frac{\sum_{i=1}^N [(d_{A,i} - d)^2 + (d_{B,i} - d)^2]}{2N}}$$

Higher  $R_d, R_p, \delta$  should result in lower  $\kappa_L$

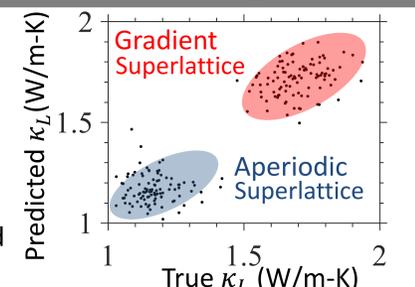
## Randomness index and lattice thermal conductivity ( $\kappa_L$ ) relation



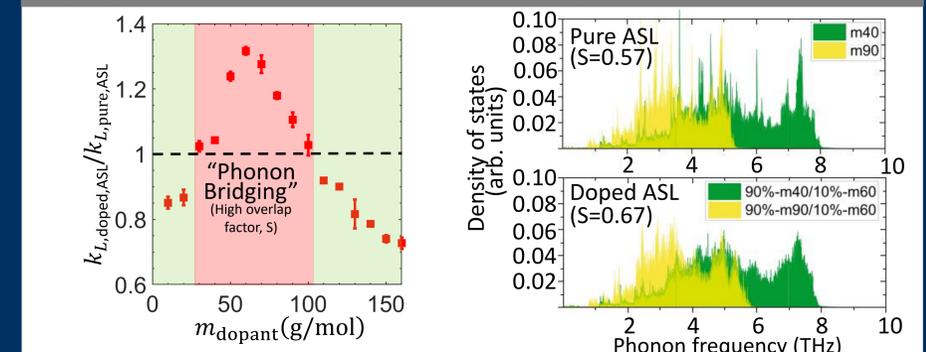
- We still could not find the best ASL configuration. Machine learning can aid us for the same.

## Machine learning prediction of thermal conductivity

- Neural network
- Training data (3200 structures)
- Testing data (200 structures)
- Python packages
- Features: Thickness sequence,  $R_p, R_d$ , and  $\delta$ .
- Machine learning model predicted  $\kappa_L$  are compared with true- $\kappa_L$



## Doping reduces the thermal conductivity of ASLs even further



- Recommendations:  $m_{dopant} \gg m_{A,B(ASL)}$  or  $m_{dopant} \ll m_{A,B(ASL)}$

## Conclusions

- We have identified several key features for machine learning to predict thermal conductivity of multilayer structures.
- We have demonstrated that rational doping can reduce the thermal conductivity of aperiodic superlattice structures even further

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## References

- Chakraborty, P; Liu, Y; Ma, T; Guo, X; Cao, L; Hu, R; Wang, Y. Quenching thermal transport in aperiodic superlattice: a molecular dynamics and machine learning study. Applied Materials and Interfaces 2020.