

Supplementary Materials: Lattice Thermal Conductivity Prediction using Symbolic Regression and Machine Learning

Christian Loftis¹, Kunpeng Yuan^{2,3}, Yong Zhao¹, Ming Hu^{* 2} , and Jianjun Hu^{* 1} 

¹ Department of Computer Science and Engineering, University of South Carolina, Columbia, SC, 29201 USA

² Department of Mechanical Engineering, University of South Carolina, Columbia, SC 29208, USA

³ Key Laboratory of Ocean Energy Utilization and Energy Conservation of Ministry of Education, School of Energy and Power Engineering, Dalian University of Technology, Dalian, 116024, China

* Correspondence: jianjunh@cse.sc.edu (J.H.); hu@sc.edu (M.H.);

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1. Noteworthy Formulae from Symbolic Regression Models

The Symbolic Regression models generated many formulae during the training phase. Most were uninteresting. While we elected only to include the best performing formulae in the main body of this work, it would be neglectful to omit several of the more physically interesting formulae that were found by the models. Below are some of the aforementioned interesting candidates, and their average MAE and R^2 scores across both the training and validation sets.

$$\kappa_L = 3.55 \cdot \sqrt{\frac{B}{(n_p)^2 \cdot \sqrt{H}}} \quad (1)$$

$$\kappa_L = \frac{B}{H \cdot n_p^2} \quad (2)$$

$$\kappa_L = \frac{E \cdot v}{n_p} \quad (3)$$

$$\kappa_L = \frac{B}{n_p^2} \quad (4)$$

$$\kappa_L = \frac{G^{\frac{2}{3}} \ln(2.60)}{\ln(|n_p|) H^{\frac{1}{9}}} \quad (5)$$

$$\kappa_L = \sqrt[6]{\frac{B^3 \cdot \sqrt[4]{e} \cdot \sqrt{\ln(0.45 \cdot |n|)}}{H}} \quad (6)$$

Formula	MAE	R^2
Slack-Berman	10.62	0.078
1	9.461	0.135
2	9.373	0.215
3	9.360	0.175
4	8.916	0.234
5	9.303	0.210
6	9.927	0.091

Table S1. Noteworthy formulae MAE & R^2