Proceedings of the 8th World Congress on Mechanical, Chemical, and Material Engineering (MCM'22)
Prague, Czech Republic – July 31, 2022 - August 02, 2022
Paper No. HTFF 138
DOI: 10.11159/htff22.138

Application of Machine Learning to Predict Thermal Performances of Heat Sinks

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Abstract - In the present study, the capabilities of two machine learning (ML) regression methods, support vector regression (SVR) and kernel ridge regression (KRR), to predict heat transfer coefficients (HTCs) in air-cooled heat sinks (HSs) are evaluated. Within the laminar regime, HSs with different geometrical parameters and at five different Reynolds numbers are considered for the simulations. Since the focus of the present study is the proof-of-concept, the ML-based models are developed using limited numbers of input data. The input data are prepared by solving three-dimensional equations of continuity, momentum, and energy inside the channels of HSs. Results indicate that both SVR and KRR predict HTCs with excellent accuracy and within $\pm 1.9\%$ of simulated values. The present study suggests that both SVR and KRR are promising design tools to predict hydrothermal performances of thermal systems using sufficiently large and accurate input data. Such precise ML-based models will be excellent alternatives to expensive experimental and computational efforts that are required to develop physics-based correlations for predicting hydrothermal performances of engineering systems.

***Keywords*:** Machine learning; Support vector regression; Kernel ridge regression; Air-cooled heat sink; Heat transfer coefficient; CFD.

1. Introduction

Machine learning (ML), as a subset of artificial intelligence, is a powerful data-driven method that allows computers to learn from a training dataset to predict new data [1, 2]. Accurate ML-based models overcome the challenges of expensive experimental and computational techniques for developing physics-based models [3]. Different mathematics-based algorithms in ML such as artificial neural network (ANN) [4], support vector regression (SVR) [5], and kernel ridge regression (KRR) [6] have been widely used for regression and classification analysis. However, selecting appropriate ML techniques to predict hydrothermal performances of engineering systems highly depends on understanding the capabilities of the individual ML methods and algorithms. As a result, comparing the effectiveness of different ML techniques to predict thermo-fluid characteristics of engineering systems is essential to understand the capabilities of individual ML techniques. In the present study, two different ML regression methods, support vector regression (SVR) and kernel ridge regression (KRR), are used to predict heat transfer coefficients (HTCs) in air-cooled heat sinks (HSs). SVR is a powerful ML algorithm for problems involving limited samples [7], and KRR is an efficient method when a nonlinear fit is desired [8].

Input data preparation is an essential step to develop a ML-based model. The input data are divided into training and testing datasets. The training dataset is used to train the ML's model using the input-output patterns of the dataset, and the testing dataset is used to test the accuracy of the model after training. In the present study, the input data are provided through three-dimensional simulations of laminar flow and heat transfer inside channels of air-cooled HSs. Air-cooled HSs, schematically shown in Fig. 1, consist of a series of parallel rectangular cross-sectional channels. These cooling systems are among the most widely used thermal management solutions due to their simplicity and low-cost manufacturing [9]. The channel's length, height, and width are represented by L, H, and W_{ch} respectively in Fig. 1, and t_f, t_b, and t_t, are the fin thickness, the base thickness, and the thickness of the top plate, respectively. For the input data preparation, six HSs with $30\ \mathrm{mm} \leq H \leq 40\ \mathrm{mm}$ and $2.5\ \mathrm{mm} \leq W_{\mathrm{ch}} \leq 5\ \mathrm{mm}$, and fixed values of $L = 200\ \mathrm{mm}$, $t_f = 1\ \mathrm{mm}$, and $t_b = t_t = 0$ are considered. The thermal performance of each HS is described by HTC. The hydraulic diameter of the channel is used to determine Reynolds number (Re). Simulations are performed for each HS in a laminar flow with five different Re, up to $\mathrm{Re} = 2200$. The training dataset is selected randomly from 83% of the input data; the remaining data are the testing dataset.

Both the training and network accuracy are evaluated by the mean absolute error (MAE). Since the present study is performed for the purpose of proof-of-concept, the ML-based models are developed using limited numbers of input data. When the accuracies of ML's algorithms are demonstrated, an extensive range of design and operational parameters for engineering systems like HSs can be prepared as input data to develop comprehensive ML-based models to predict hydrothermal performances of systems. Table 1 lists the parameters used for the ML regression methods in this study.

Due to the uniform flow and symmetry of the configuration of fin arrays in the HSs, only one channel plus half of the fins is considered in the computational domain. In the vertical dimension, the computational domain covers the HS's base to the fin height. In the longitudinal direction, the computational domain covers three times and ten times of L as the upstream and downstream, respectively, in addition to the HS's length. The governing equations by assuming a steady, laminar, and incompressible flow, as well as constant properties for the fluid (i.e., air) and the solid (i.e., aluminium) are as follows:

Continuity:
$$\nabla.\boldsymbol{u} = 0 \quad (1)$$
Momentum conservation:
$$(\boldsymbol{u}.\nabla)\rho\boldsymbol{u} = -\nabla p + \mu\nabla^2\boldsymbol{u} \quad (2)$$
Energy conservation (fluid):
$$\boldsymbol{u}.\nabla T_f = \frac{\lambda}{\rho c_p}\nabla^2 T_f \quad (3)$$
Energy conservation (solid):
$$\nabla^2 T_s = 0 \quad (4)$$

where ρ, u, p, μ, λ, c_p, and T_f are the fluid density, velocity, pressure, viscosity, thermal conductivity, specific heat, and temperature, respectively, and T_s is the temperature of the solid. Airflow rates and temperature (22°C) are set at the inlet. Zero axial gradients for all the variables are imposed at the outlet. The remaining surfaces are walls with a no-slip boundary condition. A fixed temperature of 50°C is set at the base of heat sink to represent the heat source. At the interface of fluid and solid, the conjugate problem of Fourier's steady-state heat conduction equation with convection in the fluid are solved, simultaneously [10]. The remaining surfaces are insulated. Although all the simulations are performed using sufficiently fine grid structures, grid independence tests are not conducted because the purpose of this research is not verifying the accuracy of CFD analysis but evaluating the capabilities of ML's techniques to predict CFD-based HTCs. Ansys Fluent is used to solve the governing equations.

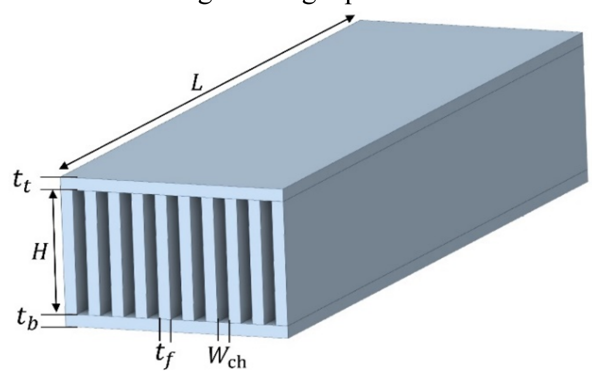

Fig. 1: Schematic of the heat sink.

Table 1: Parameters of the ML regression models in this study.

Model	**Hyperparameters**
SVR	Kernel: RBF; $C = 20$; $\varepsilon = 0.001$; $\gamma = 0.615$
KRR	Kernel: RBF; $\alpha = 1 \times 10^{-6}$; $\gamma = 0.0127$

2. Results

Corresponding MAE for the testing dataset is lower than 0.13 and 0.14 for the SRV and KRR models, respectively, which indicates the high accuracy of the ML-based models in this study. Figs. 2 and 3 compare the predicted and simulated simulated HTCs obtained by SVR and KRR methods, respectively. The difference between the predicted and simulated HTC HTC is calculated as $(\mathrm{HTC}_{\mathrm{CFD}} - \mathrm{HTC}_{\mathrm{ML}})/\mathrm{HTC}_{\mathrm{CFD}} \times 100$, which the indices CFD and ML stand for the CFD-based and and ML-based HTCs, respectively. Both SVR and KRR predict HTCs with excellent accuracy and within $\pm 1.4\%$ and $\pm 1.9\%$ of simulated values, respectively. Such high accuracy suggests that SVR and KRR are promising design tools for HSs, as well as excellent alternatives to experimental and computational efforts to predict thermal performances of HSs if enough numbers of accurate data points are provided as inputs.

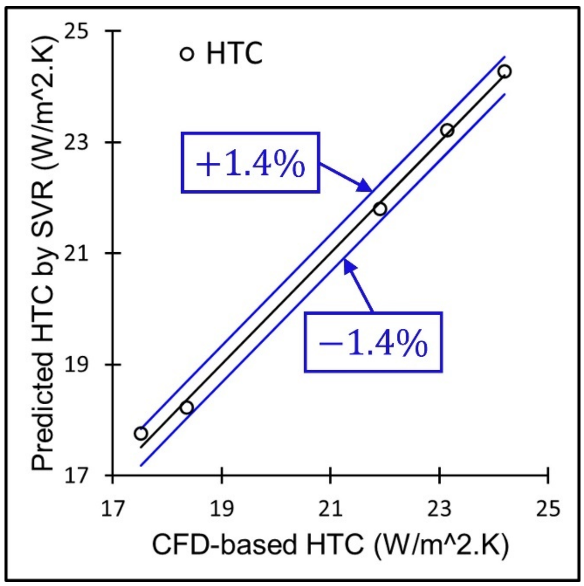

Fig. 2: Comparison between predicted HTC by SVR approach and CFD-based HTC.

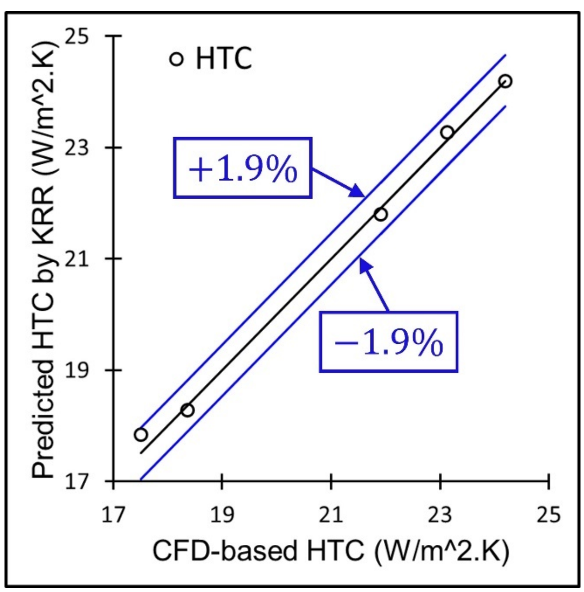

Fig. 3: Comparison between predicted HTC by KRR approach and CFD-based HTC.

3. Conclusion

Two ML-based models using SVR and KRR methods were developed to predict HTCs of air-cooled HSs operating within a laminar flow. The input data were provided through three-dimensional CFD analysis. Since the purpose of this was the proof-of-concept to demonstrate the capabilities of ML-based techniques to predict thermal performances of the models were developed using limited numbers of input data. Both ML-based techniques predicted the simulated with excellent accuracy and within $\pm 1.9\%$ of CFD-based values. A remarkable advantage of an accurate ML-based model is its independency from variables that are required by physics-based correlations to describe hydrothermal performances of engineering systems. A ML-based model is developed through a training process and using input-output patterns of input dataset. As a result, if large numbers of input-output performance data of an engineering system within a sufficiently wide range of design and operational parameters are provided as the input dataset, the developed ML-based models can predict the hydrothermal performances of the system independent from key parameters that affect the thermo-fluid physics of the problem.

Acknowledgements

This research is supported by the National Science Foundation-CREST Award (Contract #HRD-1914751) and the Department of Energy/National Nuclear Security Agency (DE-FOA-0003945).

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