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Artificial Neural Network Models to Predict Heat Transfer Coefficients and Pressure Drops in Cold Plates with Surface Roughness

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Abstract **–** In the present study, artificial neural network (ANN) models are developed to predict heat transfer coefficient (h) and pressure drop (ΔP) in cold plates (CPs) with surface roughness operating in turbulent flow. Roughness sizes range from zero (smooth surface) to 0.5 mm, and Reynolds numbers vary from 3,170 to 10,560. The RNG $k-\varepsilon$ model is used to simulate turbulent flow. Input data for the ANN models are prepared by simulating three-dimensional steady state turbulent flow and heat transfer inside the CPs. Separate multilayer neural networks are selected to predict h and ΔP. Both ANN architectures include two hidden layers with 1,024 neurons in each layer. The accuracy of the training process and the neural network is assessed by the mean absolute error. Both ANN models show excellent predictions as the predicted h and ΔP are within $\pm 1.2\%$ and $\pm 2.6\%$ of the simulated values, respectively. Since roughness is an inevitable consequence of additive manufacturing, the present study suggests that accurate ANN-based models can be used as promising design tools for optimizing additively manufactured CPs. While roughness improves heat transfer, it leads to a higher pressure drop. As a result, accurate ANN models can be used to design additively manufactured cooling systems with an optimized range of roughness to improve heat transfer while operating within the allowed pressure drop and pumping power.

Keywords**:** Artificial neural network; Cold plate; Surface roughness; Heat transfer coefficient; Pressure drop.

1. Introduction

Artificial neural network (ANN) has received growing attention in broad ranges of thermal-fluid sciences due to its ability to learn and adapt to changing conditions [1]. An ANN model consists of multiple interconnected nodes (called neurons) within multiple layers [2]. Three types of layers exist within the ANN model: input, hidden, and output layers. The input layer is the first layer in which inputs are received, and the output layer is the last layer where output parameters are generated. The number of neurons in the input and output layers are the same as the number of input and output parameters, respectively [3]. Hidden layers are intermediate layers between the input and the output layers and are used to transfer the information within the network [4]. Each neuron is associated with weights and a bias. The collected input dataset is divided into three parts: training, validation, and testing. The neural network learns the input-output patterns from the training dataset, the validation dataset is used to assess the trained performance, and the testing dataset is used to evaluate the accuracy of network after training [5]. The mathematical model for a neuron in an ANN is shown in Fig. 1 [6]:

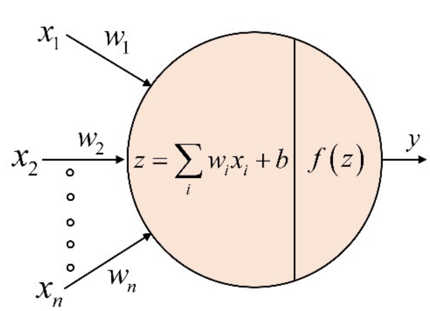

Fig. 1: Schematics of mathematical model for a single neuron.

where x_i is the ith input, w_i is the specific weight of x_i, and b is a constant bias. The net input is then passed through an activation function (f) to generate the output y. In this study, ANN models are developed to predict heat transfer coefficient (h) and pressure drop (ΔP) in cold plates (CPs) with surface roughness. The input data is generated from three-dimensional simulation of steady state turbulent flow and heat transfer inside the CPs. The CPs (shown in Fig. 2) consist of an aluminium plate with a square cross-sectional area and length of $1.5\ \text{mm} \times 1.5\ \text{mm}$ and 50 mm, respectively. At the square cross section, a circular cross-sectional flow path with a 1.0 mm diameter is implemented along the length of CP.

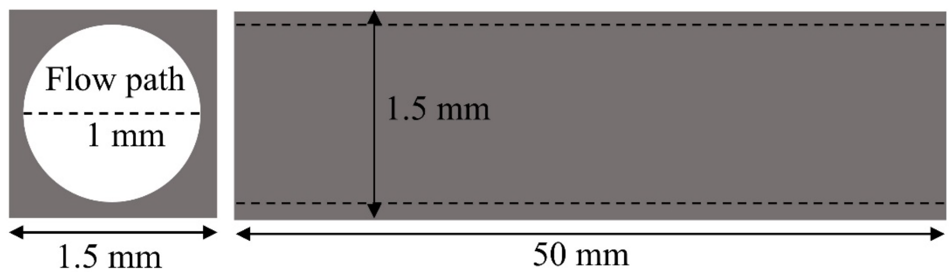

Fig. 2: Schematic of the cold plate.

The RNG $k - \varepsilon$ model is used to simulate turbulent flow. Detailed explanations about the governing equations and turbulent model were provided in [7] and are omitted here for brevity. The input data covers six roughness heights from zero (smooth surface) to 0.5 mm, and eight flow rates for each roughness size with Reynolds numbers (Re) ranging from 3,170 to 10,560. Re is defined based on the flow path diameter. Water flow rate and temperature $(20°\text{C})$ 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. One of the surfaces of the CP is subjected to a constant heat flux equivalent to 50 W. On the interface of the fluid and solid, a conjugate heat conduction equation with convection in the fluid are solved simultaneously [8]. The rest of the surfaces are adiabatic. Although the simulations are performed using sufficiently fine grid structures, grid independence tests are not conducted because the purpose of this research is not to verify the accuracy of CFD analysis. The governing equations are solved using Ansys Fluent. The roughness size is set at the interface of fluid and solid in Ansys Fluent as the boundary condition.

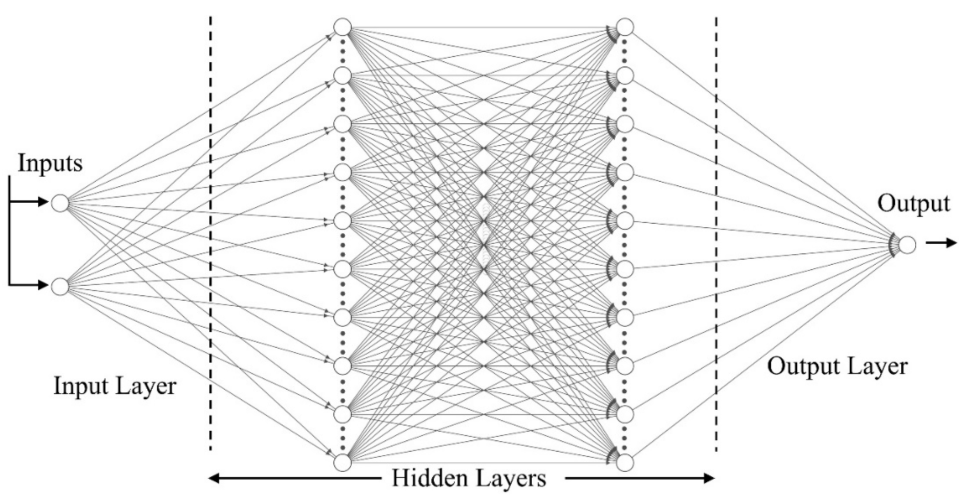

Fig. 3: Schematic of the ANN architecture used in the present study.

Among the prepared input data, 90% are chosen randomly for training and validation, and the remaining 10% are used for testing. The accuracy of training, validation, and the neural network (i.e., testing) is evaluated by the mean absolute error (MAE). ReLU is selected as the activation function because of its effectiveness. For the training process, the backpropagation algorithm is employed. Adam optimizer is implemented to improve training speed and accuracy for updating the weights. The learning rate for updating the weights is equal to 0.01. Fig. 3 illustrates the ANN architectures in the present study. The same architecture is used for both ANN models. The input layer has two neurons defined as roughness height and flow rate. Both architectures also contain two hidden layers with 1,024 neurons. The single output neuron in the output layer is h and ΔP for the ANN model that predicts h and ΔP, respectively.

2. Results

Corresponding MAE for training and validation processes at different number of epochs are illustrated in Fig. 4.

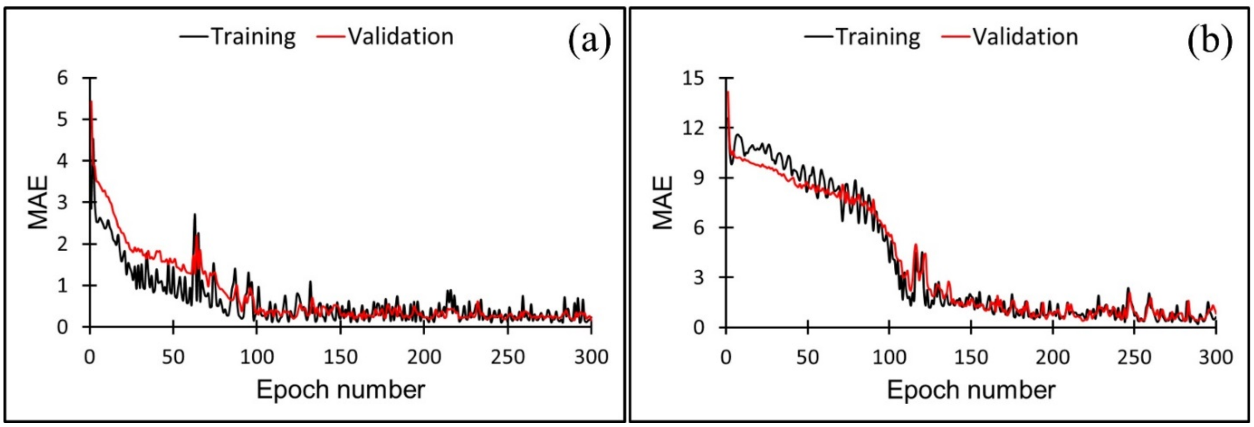

Fig. 4: MAE for the training and validation of dataset at different epochs: (a) heat transfer coefficient; (b) pressure drop.

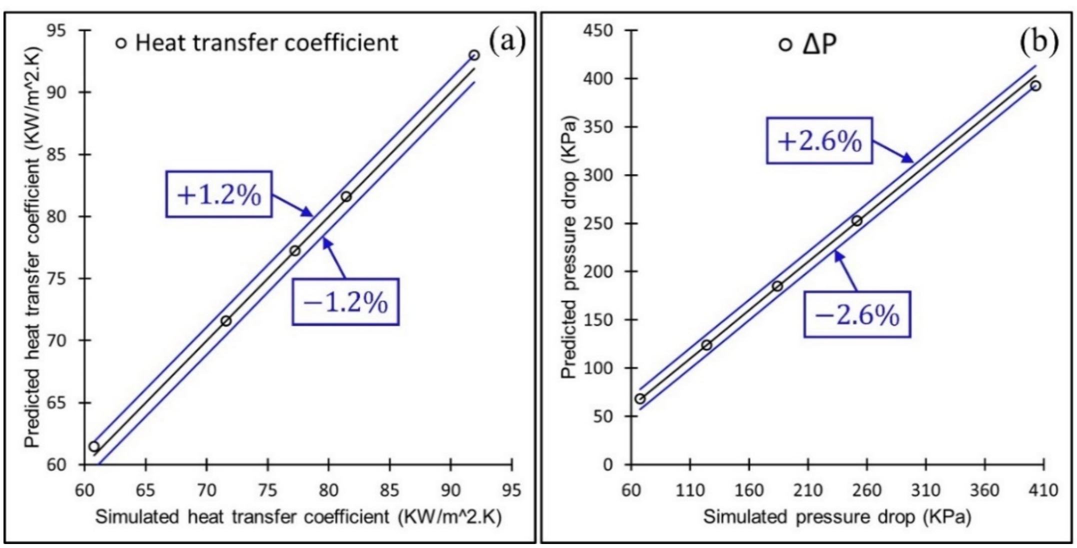

Fig. 5: Comparison between predicted and simulated values: (a) heat transfer coefficient; (b) pressure drop.

The training is converged at 150 epochs due to negligible changes in MAE beyond 150 epochs. After convergence of the training process, the testing dataset is used to evaluate the accuracy of the neural network. The MAE of the neural networks used to predict h and ΔP is below 0.11 and 0.33, respectively, which indicates a high level of accuracy of the ANN models in this study. Fig. 5 compares the predicted and simulated values for the testing dataset. The difference between the predicted and simulated values is calculated as $(Y_{\mathrm{ANN}} - Y_{\mathrm{CFD}})/Y_{\mathrm{CFD}} \times 100$, where Y represents either h or ΔP, and the index CFD and ANN stands for the simulated and predicted values, respectively. The maximum difference between the predicted and simulated h, and that of the predicted and simulated ΔP is below 1.2% and 2.6%, respectively, which indicates excellent accuracy of the developed ANN models in this study to predict hydrothermal performances of CPs with surface roughness. Although the performances of ANN models increase when providing large numbers of input data within wide ranges of operating conditions and design parameters, the ANN models in this study are developed with a limited number of input data because this work is only a proof-of-concept. Since the capability of ANN models to predict hydrothermal performances of CPs with surface roughness are demonstrated, comprehensive ANN models can be developed by providing an extensive range of design and operational parameters as input data.

3. Conclusion

ANN-based models were developed to predict hydrothermal performances of CPs with surface roughness operating in turbulent flows. The input data was generated through three-dimensional simulations of steady state fluid flow and heat transfer in CPs. Accurate models developed in this study suggest that ANN models are promising design tools to predict and optimize performances of thermal systems with the advantage of independency from key parameters that are required by physics-based correlations. The present study provides good insight for optimizing hydrothermal performances of additively manufactured CPs because roughness is an inevitable consequence of additive manufacturing. While roughness enhances heat transfer, it increases ΔP. Accurate ANN-based models will be able to optimize additively manufactured thermal management systems for enhancement of heat transfer and operation within allowed ΔP and, in turn, pumping power, which is a key design parameter of an active cooling system such that its increase may hinder using the cooling system regardless of the system's capability to improve heat transfer [9].

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References

[1] R. Al-Jarrah, F. M. AL-Oqla, "A novel integrated BPNN/SNN artificial neural network for predicting the mechanical performance of green fibers for better composite manufacturing," *Compos. Struct.*, vol. 289, p. 115475, 2022.

[2] A. Poro, S. Sarabi, S. Zamanpour, et al., "Investigation of the orbital period and mass relations for W UMa-type contact systems," *MNRAS*, vol. 510, pp. 5315-5329, 2022.

[3] G. Ren, A. Chuttar, D. Banerjee, "Exploring efficacy of machine learning (artificial neural networks) for enhancing reliability of thermal energy storage platforms utilizing phase change materials," *Int. J. Heat Mass Transfer*, vol. 189, p. 122628, 2022.

[4] M. Uzair, N. Jamil, "Effects of hidden layers on the efficiency of neural networks," in *2020 IEEE 23rd International Multitopic Conference (INMIC). IEEE*, 2020, pp. 1-6.

[5] X. Cheng, F. Ren, Z. Gao, L. Zhu, Z. Huang, "Synergistic effect analysis on sooting tendency based on soot-specialized artificial neural network algorithm with experimental and numerical validation," *Fuel*, vol. 315, p. 122538, 2022.

[6] P. Liu, R. Kandasamy, T. N. Wong, "Experimental study and application of an artificial neural network (ANN) model on pulsed spray cooling heat transfer on a vertical surface," *Exp. Therm. Fluid Sci.*, vol. 123, p. 110347, 2021.

[7] M. R. Shaeri, M. Yaghoubi, K. Jafarpur, "Heat transfer analysis of lateral perforated fin heat sinks," *Appl. Energy*, vol. 86, pp. 2019-2029, 2009.

[8] M. R. Shaeri, T. C. Jen, "The effects of perforation sizes on laminar heat transfer characteristics of an array of perforated fins," *Energy Convers. Manage.*, vol. 64, pp. 328-334, 2012.

[9] M. R. Shaeri, R. W. Bonner, "Lightweight and high-performance air-cooled heat sinks," in *Proceedings of the 34th Thermal Measurement, Modeling & Management Symposium (SEMI-THERM)*, 2018, pp. 224-227.