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Artificial Neural Network to Predict Pressure Drops in Heat Sinks

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Abstract – In this study, pressure drop (ΔP) across air-cooled heat sinks (HSs) are predicted using an artificial neural network (ANN). A multilayer feed-forward ANN architecture with two hidden layers is developed. Backpropagation algorithm is used for training the network, and the accuracy of the network is evaluated by the root mean square error. The input data for training the neural network is prepared through three-dimensional simulation of air inside the channels of heat sinks using a computational fluid dynamics (CFD) approach. The developed ANN-based model in this study predicts ΔP with a high accuracy and within $\pm 7.9\%$ of the CFD-based data. The present study suggests that developing an ANN-based model with a high level of accuracy overcomes the limitations of physics-based correlations that their accuracy strongly depends on identifying and implementing key variables that affect the physics of a thermo-fluid phenomenon.

***Keywords*:** Heat sink; Machine learning; Artificial neural network; Pressure drop; CFD.

1. Introduction

Artificial neural networks (ANN), as a subset of machine learning, have been identified as excellent alternatives to experimental/computational techniques for modelling hydrothermal characteristics of engineering systems [1]. In this study, an ANN-based model is developed to predict pressure drop (ΔP) across air-cooled heat sinks (HSs) as shown in Fig.1. HSs have been widely used as primary thermal management solutions in a variety of applications due to their simplicity and low cost [2]. The channel's length, height, and width are shown by L, H, and W_{ch}, respectively, t_f is the fin thickness, the thickness at the base and top plate of the HS are t_b and t_t, respectively. It is assumed that the air properties remain constant, and flow is steady and remains in laminar regime with a Reynolds number (Re) below 2200.

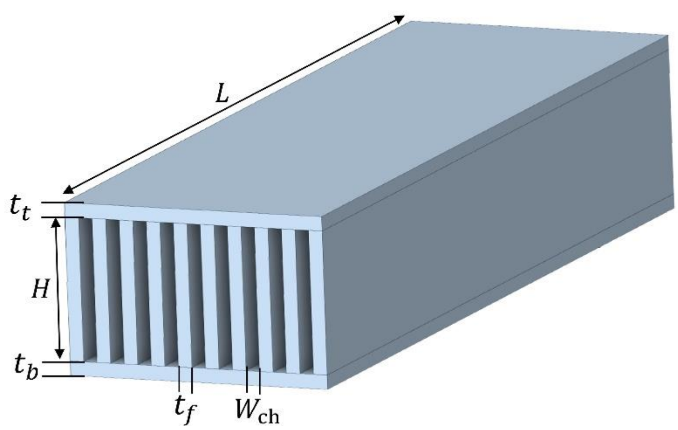

Fig. 1: Schematic of a heat sink.

Data preparation is the first step for training the neural network. In the present study, the input data are prepared through a computational fluid dynamics (CFD) analysis by simulating airflow inside channels of HSs. Six HSs with a fixed L and t_f at 100 mm and 1 mm, respectively, and 10 mm $\leq H \leq$ 25 mm and 1 mm $\leq W_{\mathrm{ch}} \leq$ 2.5 mm, are considered. For the simplicity, $t_b = t_t = 0$ for all HSs. Each HS is simulated at five Re. Because the flow is uniform and the configuration of the fin arrays is symmetrical, only one channel plus half of the fins is considered in the computational domain to save the simulation time [3]. The computational domain in the vertical dimension covers the HS's base to H. In the longitudinal direction, the computational domain covers three times and 10 times of L as the upstream and downstream, respectively, in addition to the HS's length. This is equivalent to locating the HS in a long duct. The ΔP corresponds to the pressure drop across the HS, which includes the effects of sudden contraction and sudden expansion losses. Ansys Fluent is used to solve the governing equations, as follows:

Continuity:
$$\nabla . \boldsymbol{u} = 0 \tag{1}$$
Momentum conservation:
$$(\boldsymbol{u}. \nabla)\rho\boldsymbol{u} = -\nabla p + \mu\nabla^2\boldsymbol{u} \tag{2}$$

where ρ, u, p, and μ are the fluid density, velocity, pressure, and viscosity, respectively. Re is calculated based on the channel hydraulic diameter (D_h), as $\text{Re} = \rho u D_h/\mu$. Training, testing, and validation are main parts of the ANN process [4]. Among 30 input data, 80% of them are selected randomly for training and validation. The remaining data are used for testing. The testing dataset does not participate in the training and is only used to evaluate the accuracy of the network to predict the true dataset after training [5]. A typical ANN structure consists of an input layer, hidden layers, and an output layer, which are connected to each other by neurons. To produce an output signal, a weighted sum of input signals to a neuron is passed through an activation function (f_n) [6]. Through an iterative process, weights are updated using gradient descent algorithms with a learning rate (η). The loss function corresponds the magnitude of the error between the predicted ΔP and simulated ΔP, and is defined by the mean absolute error (MAE). The accuracy of the neural network after training is evaluated by the root mean square error (RMSE). In this study, f_n is ReLU, and $\eta = 0.001$. Adam optimizer is used to improve training speed and accuracy for updating the weights [7]. Usually, a proper number of hidden layers and neurons are obtained by the trial-and-error method. Fig. 2 illustrates the multilayer feed-forward ANN architecture used in this study. The ANN architecture consists of one input layer, one output layer, and two hidden layers.

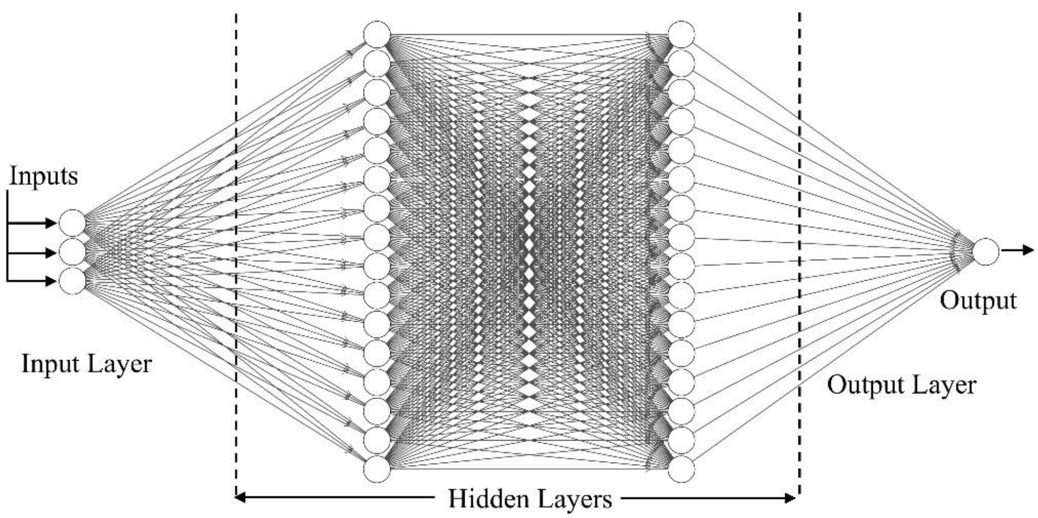

Fig. 2: Schematic of the ANN architecture used in the present study.

The input layer includes three neurons as inputs, which are H, W_{ch}, and Re. The output layer includes only one neuron that represents ΔP as the output. Each hidden layer consists of 16 neurons. Backpropagation (BP) algorithm is used for the training process. The present study is performed as the proof-of-concept to assess the capability of an ANN-based model to predict ΔP across HSs. For this reason, only a limited number of input data are prepared using a

CFD approach. Besides, since the accuracy of the simulation process is not the focus of this research, grid independence tests are not conducted; however, the simulations are performed using highly fine grid structures. After demonstrating the accuracy of an ANN-based model, more comprehensive models can be developed to predict hydrothermal characteristics of HSs subject to extensive design and operational parameters.

2. Results

Fig. 3 represents the corresponding MAE for training and validation processes at different number of epochs. Negligible changes in MAE beyond 100 epochs indicate the convergence of the training process at 100 epochs. After convergence of the training process, the accuracy of the neural network is assessed by using the testing dataset. Corresponding RMSE for the testing dataset was 0.02, which indicates the high accuracy of the ANN-based model in this study.

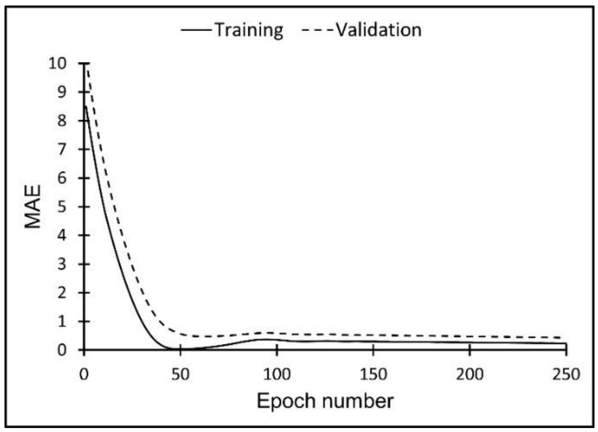

Fig. 3: MAE for the training and validation of dataset at different epochs.

Fig. 4 compares the predicted and simulated ΔP for six testing data.

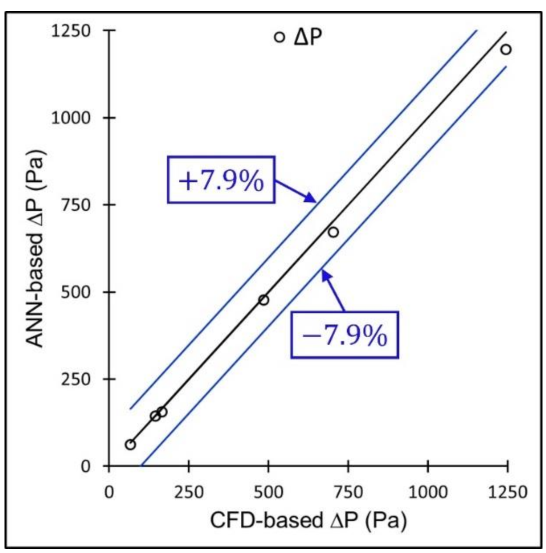

Fig. 4: Comparison between ANN-based (predicted) ΔP and CFD-based ΔP.

The difference between the predicted and simulated ΔP is calculated as $(\Delta P_{\mathrm{CFD}} - \Delta P_{\mathrm{ANN}})/\Delta P_{\mathrm{CFD}} \times 100$, which the index CFD and ANN stands for the CFD-based and ANN-based ΔP, respectively. The maximum difference between the predicted and simulated values is below 7.9%, which indicates the excellent accuracy of the developed ANN-based model in this study. By demonstrating the high capability of an ANN-based model to precisely predict ΔP across HSs, ANN can be used as a strong tool to design HSs in broad applications, as long as a large dataset of precise data is provided as the input.

3. Conclusion

An ANN-based model was developed to predict ΔP across air-cooled HSs operating in laminar flow. Since the focus of this research was to demonstrate the capability of the ANN model to predict ΔP, training process was performed using a limited number of input data obtained from CFD. It was found that the developed ANN model can predict ΔP with an excellent accuracy of below 7.9%. The present study suggests that if enough numbers of accurate data are prepared as the input, ANN-based models can be leveraged as excellent tools to design and/or optimize thermo-fluid systems. Another substantial advantage of an ANN-based model is its independency from physics-based variables that are generally required by correlations. The accuracy of a physics-based corelation strongly depends on identifying key parameters that affect a thermo-fluid phenomenon, otherwise the correlation is not sufficiently valid to predict the hydrothermal phenomenon. An ANN-based model, on the other hand, is based on the patterns that are prepared by the input data. As a result, as long as a large dataset of accurate input data is prepared for training the network, an ANN-based model predicts the hydrothermal characteristics with a high level of accuracy.

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