CFD-Based ANN Prediction of Fin Surface Nusselt Number for A Specific Laptop Heat Sink Design

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Abstract- Thermal performance prediction of compact heat sinks is important during early design stages of laptop cooling systems. While computational fluid dynamics (CFD) provides accurate evaluation of heat transfer behavior, repeated simulations are computationally intensive. In this study, a simple artificial neural network (ANN) model is developed as a surrogate tool to predict the surface-averaged Nusselt number of fins in a specific laptop heat sink design using CFD-generated data. A total of 30 data samples corresponding to six Reynolds numbers and five fin configurations were used for training and testing. Reynolds number and fin type were employed as input parameters, while the surface Nusselt number served as the output. The ANN was implemented using a single hidden-layer feedforward architecture. Model performance evaluated on the test dataset yielded a root mean square error (RMSE) of approximately 4.33 and a mean absolute percentage error (MAPE) of about 6.6%, indicating satisfactory predictive capability. The results demonstrate that the ANN successfully captures the relationship between Reynolds number, fin geometry, and convective heat transfer performance, providing a computationally efficient approach for preliminary thermal assessment of the specified heat sink configuration.

Keywords- Artificial neural network; CFD; Nusselt number; Heat sink; Reynolds number.

I. INTRODUCTION

Thermal management plays a crucial role in maintaining performance and reliability of modern laptop systems [1-2]. Increasing power densities and compact form factors demand efficient heat dissipation solutions within limited space constraints [3-4]. Finned heat sinks are commonly employed in laptop cooling modules due to their ability to enhance convective heat transfer by increasing surface area. The thermal performance of such systems can be evaluated using computational fluid dynamics (CFD), which provides detailed insight into flow and temperature distributions [5].

Although CFD simulations offer high accuracy, repeated numerical analysis for multiple operating conditions and geometric variations can be computationally expensive, particularly during early design stages. In such cases, surrogate modeling approaches can provide rapid performance estimation based on previously generated numerical data [6]. Artificial neural networks (ANN) are widely used data-driven tools capable of approximating nonlinear relationships between input and output parameters [7].

The present study focuses on developing a simple ANN-based surrogate model for predicting the surface-averaged Nusselt number of fins in a specific laptop heat sink design. The ANN is trained using CFD-generated data corresponding to multiple Reynolds numbers and fin configurations. The objective is not to replace detailed CFD simulations but to demonstrate a computationally efficient predictive framework for preliminary thermal assessment of the specified heat sink configuration.

II. CFD DATA AND HEAT SINK CONFIGURATION

A total of 30 data samples corresponding to six Reynolds numbers and five fin configurations were used in this study. The complete CFD dataset was previously published in [5] and is available as supplementary material. The dataset is reused here solely for ANN-based surrogate model development. The geometric layout of the heat sink remained unchanged across all cases, while only the fin geometry was varied to evaluate its influence on convective heat transfer performance.

Numerical simulations were performed under steady-state forced convection conditions using air as the working fluid. The governing equations of mass, momentum, and energy conservation were solved using the finite volume method [8]. To isolate the influence of flow conditions and fin geometry, all other operating parameters were kept constant throughout the simulations.

Six Reynolds numbers were considered, corresponding to increasing inlet airflow conditions representative of practical laptop cooling scenarios. For each Reynolds number, simulations were conducted for all five fin configurations, resulting in a total of 30 data samples. The surface-averaged Nusselt number evaluated over the fin surfaces was extracted from each simulation and used as the target output parameter for ANN training.

III. ANN MODEL DEVELOPMENT

A feedforward artificial neural network (ANN) was developed to predict the surface-averaged Nusselt number of fins using CFD-generated data. The ANN was implemented in MATLAB using a single hidden-layer architecture.

The input parameters to the network were Reynolds number and fin geometry type. The fin configurations were represented using integer encoding (1–5) to distinguish between the five geometries analyzed. The output parameter was the surface-averaged Nusselt number evaluated over the fin surfaces.

Prior to training, the dataset was normalized using a min–max scaling approach to ensure numerical stability and improve convergence behavior. The normalized dataset was divided into training (70%), validation (15%), and testing (15%) subsets. To ensure reproducibility of results, the random number generator seed was fixed before training.

The network consisted of one hidden layer with six neurons. A moderate network size was selected to avoid overfitting due to the limited dataset size (30 samples). The ANN was trained using the backpropagation algorithm until convergence was achieved.

Model performance was evaluated using root mean square error (RMSE) and mean absolute percentage error (MAPE) calculated on the test dataset. These metrics were used to assess the predictive capability of the ANN model for unseen data.

IV, RESULTS AND DISCUSSION

CFD-Based Thermal Performance Trend

Figure 1 illustrates the variation of surface-averaged Nusselt number with Reynolds number for the five fin configurations. As expected, the Nusselt number increases with increasing Reynolds number for all fin types due to enhanced convective heat transfer at higher flow rates. While all fin configurations exhibit similar overall trends, noticeable differences in magnitude are observed, indicating the influence of fin geometry on thermal performance. The monotonic increase in Nusselt number with Reynolds number confirms the physical consistency of the CFD dataset used for ANN training.
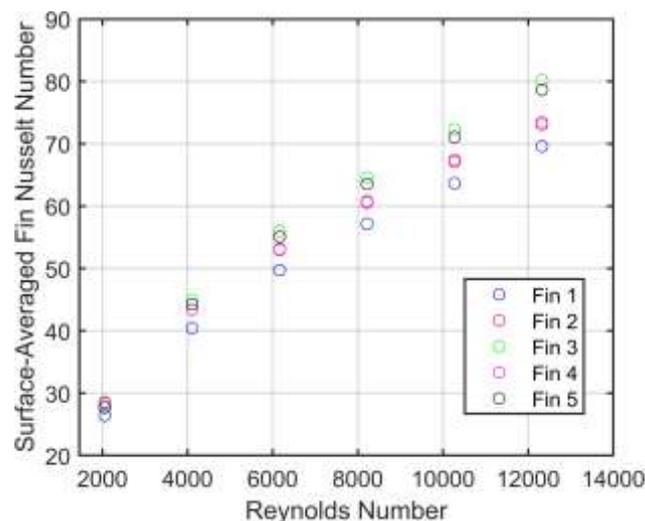

Figure 1: Surface-averaged fin Nusselt number versus Reynolds number for five fin configurations (CFD results).

ANN Prediction Performance

The predictive capability of the ANN model was evaluated by comparing ANN-predicted Nusselt numbers with CFD-derived values on the test dataset. Figure 2 presents the comparison between predicted and actual values along with the 45° reference line representing perfect agreement.
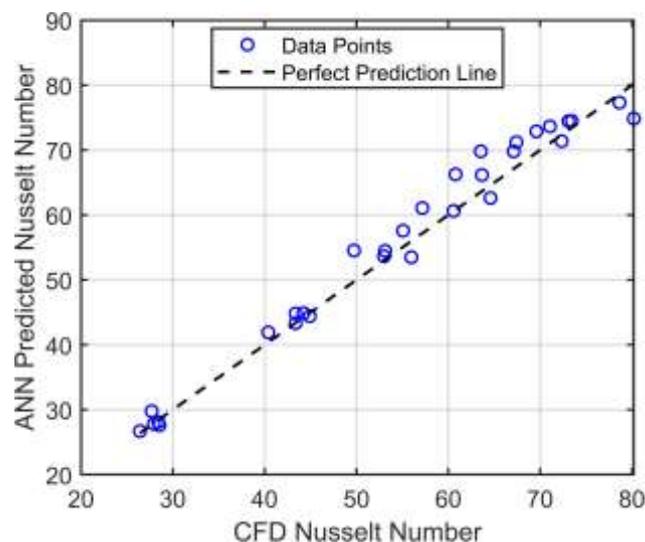

Figure 2: ANN-predicted versus CFD-derived surface-averaged fin Nusselt numbers (test data).

The ANN model demonstrated satisfactory predictive performance, yielding a root mean square error (RMSE) of approximately 4.33 and a mean absolute percentage error (MAPE) of about 6.6% on the test data. The predicted values closely follow the CFD results across the investigated Reynolds number range, indicating that the ANN successfully captured the nonlinear relationship between Reynolds number, fin geometry, and convective heat transfer behavior.

Minor deviations observed at higher Reynolds numbers may be attributed to increased nonlinearity in flow and heat transfer characteristics. Nevertheless, the overall prediction accuracy is adequate for preliminary thermal performance estimation of the specified heat sink configuration.

V, CONCLUSION

This study presented a CFD-based ANN model for predicting the surface-averaged Nusselt number of fins in a specific laptop heat sink design. CFD simulations were conducted for six Reynolds numbers and five fin configurations, resulting in a dataset of 30 samples used for ANN training and testing. Reynolds number and fin type were employed as input parameters, while the fin surface Nusselt number was used as the output.

The ANN model, implemented using a single hidden-layer feedforward architecture, demonstrated satisfactory predictive capability with a test-set RMSE of approximately 4.33 and a MAPE of about 6.6%. The results indicate that the ANN successfully captures the nonlinear relationship between flow conditions and fin geometry on convective heat transfer performance.

Although the proposed model is limited to the specific heat sink configuration and operating range considered, it provides a computationally efficient approach for preliminary thermal performance estimation. The study demonstrates the feasibility of combining CFD-generated data with simple ANN models for rapid prediction in early-stage heat sink assessment. The model is not intended to replace detailed CFD simulations but to serve as a rapid surrogate tool for preliminary evaluation.

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