

A machine learning–based surrogate model for estimating the air-side friction factor in plain finned-tube heat exchangers with staggered arrangement

Sayed Ehsan Alavi*

Faculty of Engineering, ShohadayeHoveizeh Campus of Technology, Shahid Chamran University of Ahvaz, Dasht-eAzadegan, Iran.

*Corresponding author: e.alavi@scu.ac.ir

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Abstract

Accurate determination of the friction factor in finned-tube heat exchangers through experimental and numerical methods entails substantial costs and significant computational effort. Therefore, the development of an alternative approach for rapid and precise estimation is essential. In this study, the air-side friction factor of a plain finned-tube heat exchanger with a staggered arrangement is estimated with high accuracy using machine learning techniques, including Bagging, M5P, M5Rules and REPT. A large dataset comprising 1,149 observations, extracted from various reliable sources, is employed for training and testing the developed models. Fin pitch, transverse tube pitch, longitudinal tube pitch, and Reynolds number are considered as input parameters, while the air-side friction factor is defined as the target variable. The results indicate that the Bagging method achieves the highest accuracy among the investigated models, with correlation coefficients of 0.9983 and 0.9968 for the training and testing datasets, respectively. The mean absolute error (MAE) and root mean square error (RMSE) for this method are 0.0003 and 0.0004 for the training data, and 0.0004 and 0.0006 for the testing data, respectively, demonstrating the very low prediction error and high reliability of this approach in estimating the friction factor.

Keywords: Finned-tube heat exchanger; friction factor; machine learning; surrogate model; staggered arrangement.

1. Introduction

Heat exchangers are widely employed in power plants, petrochemical industries, refrigeration systems, and air-conditioning applications. Consequently, numerous studies have been conducted on these systems. Some studies have focused on the investigation of irreversibilities, with parameters such as entransy, exergy, and entropy being extensively analyzed [1, 2]. Liu et al. [3] conducted a numerical investigation on heat transfer enhancement in a corrugated finned-tube heat exchanger. In their study, computational fluid dynamics (CFD) was employed to simulate the effects of fin geometric parameters on heat transfer. The results indicated that the wavelength had no significant effect on the heat transfer coefficient, whereas the symmetric wave configuration led to a considerable reduction in pressure drop. Furthermore, the proposed modifications to the fin geometry resulted in a 34.2% increase in heat transfer. Liang et al. [4] investigated heat transfer and exergy enhancement in finned-tube heat exchangers using a novel vortex generator. In this study, the effects

of different vortex-generator geometries on temperature distribution, friction factor, and pressure drop were also examined. The results demonstrated that the rectangular vortex generators with inclination angles of 60° and 90° produced the highest temperature differences and pressure drops, respectively.

This study develops a machine-learning model based on a large dataset comprising 1,149 observations to predict the air-side friction factor of a plain finned-tube heat exchanger with a staggered arrangement across all flow regimes with very high accuracy. To this end, four machine-learning methods, namely Bagging, M5P, M5Rules, and REPT, are investigated and comparatively evaluated. Ultimately, the best-performing and most accurate model is identified and introduced as the proposed model of the study. The developed model can serve as an efficient and accurate alternative to the existing experimental and computational approaches currently employed in industry. Owing to its high generalizability, the proposed model can function as a robust and reliable tool for processing new industrial data and accurately

predicting the friction factor.

2. Modeling and Data Analysis

Finned-tube heat exchangers are among the most widely used types of heat exchangers in industrial applications. In these heat exchangers, the fluid with a higher heat transfer coefficient flows inside the tubes, while the fluid with a lower heat transfer coefficient, typically air or gas, passes over the fins. Figure 1 illustrates the plain finned-tube heat exchanger with a staggered arrangement investigated in the present study.

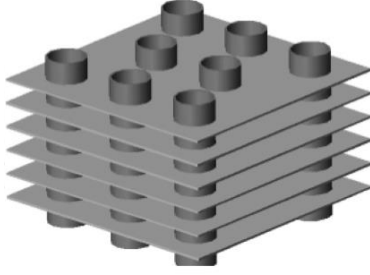


Figure 1. Staggered plain finned-tube heat exchanger.

The air-side friction factor in finned-tube heat exchangers is defined using Equation (1).

$$f = \frac{(P_{in} - P)}{1/2 \rho u_{in}^2} \frac{H}{4L} \quad (1)$$

In Equation (1), P , u , and ρ denote the pressure, velocity, and density of the fluid, respectively.

3. Machine Learning Methods

This study investigates the predictive capabilities of four machine-learning techniques, namely Bagging, M5P, REPT, and M5Rules, for predicting the friction factor of finned-tube heat exchangers. Each approach is comprehensively evaluated in terms of prediction accuracy and real-world applicability within the scope of the present study. The advantages and limitations of each method in predicting the friction factor are thoroughly examined.

The criteria used to evaluate the performance of the models developed in this study include the correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE). These metrics are defined as follows [5]:

$$R = \frac{\sum_{i=1}^N (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}} \quad (2)$$

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^N (y_i - x_i)^2 \right)^{0.5} \quad (3)$$

$$MAE(\%) = \left(\frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - x_i}{y_i} \right| \right) \quad (4)$$

In the above equations, x_i , $\bar{x}$, y_i , $\bar{y}$, and N denote the predicted value, mean predicted value, actual value, mean actual value, and total number of data points, respectively. In addition, r represents the Pearson correlation coefficient.

4. Results

The dataset was randomly divided to apply the Bagging, M5P, REPT, and M5Rules machine-learning techniques for friction factor prediction, with an 80:20 ratio allocated to the training and testing datasets, respectively.

Figure 2 presents the scatter plots for the different techniques, comparing the predicted and actual friction factor values for the training and testing datasets. In these plots, the actual values are shown along the horizontal axis, while the predicted values are plotted along the vertical axis. A higher and more accurate predictive capability is reflected by a closer clustering of the data points around the diagonal line, $y=x$. The Bagging method demonstrates a highly robust and accurate learned model, as evidenced by the excellent agreement between the predicted values and the actual measurements. Among the investigated techniques, the Bagging approach exhibits superior accuracy, with the data points showing a closer fit to the ideal line compared with the other techniques. In each plot, the dashed lines represent the $\pm 20\%$ deviation limits, indicating the degree of inaccuracy in the predicted friction factor values. Examination of the results reveals that the predictions obtained by all methods, except REPT, fall within these limits. It can also be observed that the data points generated by the Bagging method are more closely distributed around the 45° line. Therefore, Bagging provides the most accurate predictions among the methods evaluated in this study, followed by M5Rules, which ranks second. The REPT method exhibits the weakest performance in predicting the friction factor. Furthermore, evaluation of the friction factor predictions obtained using the different methods clearly indicates that the proposed Bagging-based model produces no outlier predictions in either the training or testing datasets. In other words, no data points deviate substantially from the line of best fit. The model demonstrates remarkable accuracy in predicting both low and high values of the actual friction factor. Consequently, these findings indicate that the proposed model possesses a high degree of generalizability.

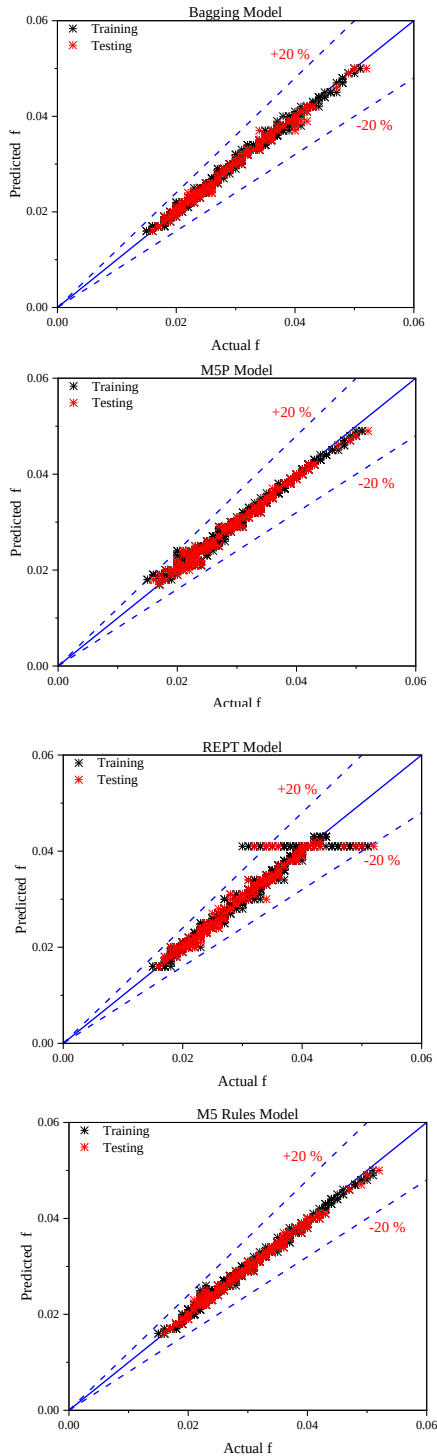


Figure 2. Scatter plot of the training and testing data of different methods.

Figure 3 presents the friction factor prediction results for the training and testing datasets. The evaluation metrics employed in this study include the correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE). These metrics are presented for models trained using different methods, thereby facilitating a comparative assessment of their predictive performance. The results of the investigated methods indicate that all three methods achieve very

high accuracy with very low error rates. A comparison of the results obtained from the different models shows that the Bagging model exhibits the best performance for the training dataset, with a correlation coefficient, mean absolute error, and root mean square error of 0.9995, 0.0002, and 0.0002, respectively. During the testing phase, this method also provided highly accurate predictions of the friction factor, achieving a correlation coefficient of 0.9978, an MAE of 0.0004, and an RMSE of 0.0005. Therefore, the Bagging method can be considered a reliable approach for predicting the friction factor in industrial applications involving staggered finned-tube heat exchangers and can potentially serve as an alternative to experimental and numerical methods. The M5Rules, M5P, and REPT methods ranked second, third, and fourth, respectively. The inferior performance of the REPT algorithm compared with the other methods can be attributed to its modeling structure, which is based on a single decision tree with error-based pruning. Owing to its piecewise structure and lack of capability to fit linear or nonlinear relationships within the tree nodes, this method has limited ability to approximate the continuous and highly nonlinear behavior of the friction factor in heat exchangers. Furthermore, REPT is highly dependent on the manner in which the data are partitioned and is sensitive to noise present in experimental thermohydraulic data, which generally results in higher variance.

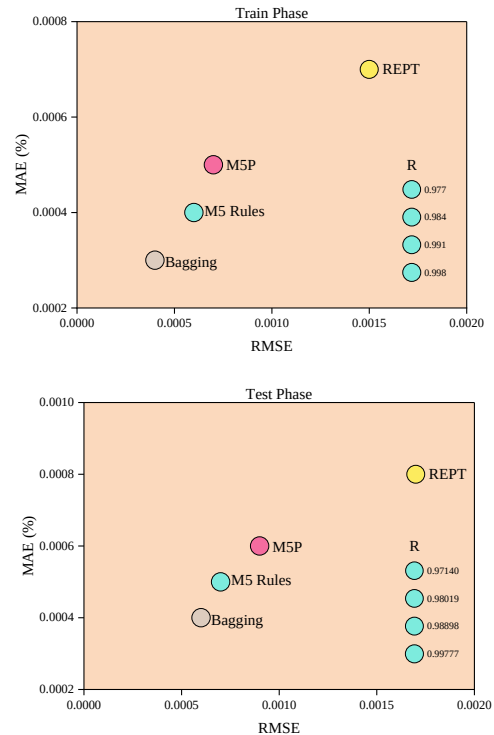


Figure 3. Performance evaluation of different methods.

5. Conclusion

In this study, the air-side friction factor of staggered finned-tube heat exchangers was estimated using various machine-learning methods. The Bagging, M5P, REPT, and M5Rules machine-learning techniques were trained using a dataset comprising 1,149 observations. The friction factor was selected as the output parameter, while the longitudinal tube pitch, transverse tube pitch, fin pitch, and Reynolds number were considered as the input variables influencing the friction factor. The main findings of the study are summarized as follows:

- The analysis of the effects of different features on the target variable revealed that, across all three flow regimes—laminar, transitional, and turbulent—the Reynolds number had the greatest influence on the friction factor. The second most influential parameter varied among the different flow regimes. In the laminar flow regime, fin pitch was the most influential parameter, whereas in the transitional flow regime, transverse tube pitch exhibited the greatest influence. In the turbulent flow regime, the longitudinal tube pitch, transverse tube pitch, and fin pitch had approximately equal effects on the friction factor.
- For the training dataset, the Bagging model demonstrated the best performance, achieving a correlation coefficient of 0.9983. The M5Rules, M5P, and REPT methods ranked second, third, and fourth, respectively, with correlation coefficients of 0.9979, 0.9954, and 0.9773.

- For the testing dataset, the Bagging method demonstrated a very high capability for predicting the friction factor, achieving a correlation coefficient of 0.9978. The M5Rules, M5P, and REPT methods also exhibited acceptable performance, with correlation coefficients of 0.9967, 0.9939, and 0.9714, respectively.
- Accurate determination of the friction factor using costly, time-consuming, and computationally intensive experimental and numerical methods is challenging. Therefore, the data-driven approach proposed in the present study, which can rapidly and accurately predict the friction factor across different flow regimes, appears to be a powerful and useful tool for industrial applications.

6. References

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