

Prediction of Heat Transfer Performance of Finned Tubes Using CFD and Random Forest

Hong-Rui Yang, Yan-Zuo Chang*, Yong-Sen Huang, Zi-Rui He, Wen-Min Wen, Yong-Qing Wang, Yu-Xuan Chen, Kai-Ming Chen, Jie-Zhen Yang, Guan-Hong Xie

School of Energy and Power Engineering, Guangdong University of Petrochemical Technology, Maoming, Guangdong 525000, China

*Corresponding author

Received: 29 Mar 2026,

Received in revised form: 21 Apr 2026,

Accepted: 25 Apr 2026,

Available online: 30 Apr 2026

©2026 The Author(s). Published by AI Publication. This is an open-access article under the CC BY license

(<https://creativecommons.org/licenses/by/4.0/>).

Keywords— *finned heat exchanger, computational fluid dynamics (CFD), random forest, heat transfer performance prediction*

Abstract—*To address the issues of high computational cost, long calculation time, and complex parameter coupling in predicting the heat transfer performance of finned structures, this study takes a typical finned heat exchanger as the research object and adopts a combined approach of numerical simulation and data-driven modeling. First, a three-dimensional model of the finned structure is established based on the CFD method, and the heat transfer performance under different structural parameters and operating conditions is simulated to obtain a dataset. On this basis, a random forest algorithm is introduced to develop a predictive model, in which geometric parameters and operating conditions are used as input variables, and the heat transfer coefficient is taken as the output target. By comparing the simulation results with the predicted results, the effectiveness of the random forest model is validated. The results indicate that the proposed method can significantly reduce computational time while maintaining prediction accuracy, providing a feasible approach for the optimal design of finned heat exchanger structures.*

I. INTRODUCTION

1.1 Background

Finned heat transfer structures are widely used in refrigeration and air conditioning systems, computer heat sinks, automotive engines, and energy power systems. Their heat transfer performance directly affects the operational efficiency and safety of these systems. In traditional studies, the performance analysis of heat exchangers mainly relies on experimental methods or numerical simulations. Although experimental approaches can provide relatively accurate results, they are often associated with high costs and long testing cycles, making them unsuitable for systematic analysis of multiple structural parameters. In contrast, the Computational Fluid Dynamics (CFD) method enables detailed analysis of fluid flow and heat transfer

processes through numerical simulation, allowing the acquisition of comprehensive flow field and temperature field information at a relatively lower cost.

However, when a large number of structural parameters are involved in optimization, relying solely on CFD simulations still requires extensive repetitive calculations, resulting in low computational efficiency.

With the continuous growth of energy demand and the increasing requirements for energy conservation and emission reduction, high-efficiency heat transfer devices are being increasingly applied in air conditioning systems, energy power systems, and electronic cooling. As a key component for thermal energy transfer, the performance of heat exchangers plays a crucial role in the overall energy efficiency of these systems. Therefore, improving heat

transfer performance and optimizing heat exchanger structures have become important research topics in the field of thermal engineering.

In this study, key structural parameters of finned heat exchangers, including fin height, fin spacing, fin thickness, air velocity, and temperature, are systematically investigated to enhance heat transfer performance. Furthermore, a random forest algorithm is introduced to develop a predictive model, aiming to evaluate the reliability of machine learning methods in heat transfer performance prediction.

1.2 Literature Review

In recent years, with the rapid development of artificial intelligence, machine learning methods have been increasingly applied to parameter prediction and optimization problems in engineering fields. Among these methods, the random forest algorithm has been widely used due to its strong stability, robustness, and high prediction accuracy. As a typical ensemble learning method, random forest can effectively capture complex nonlinear relationships in engineering data.

A number of studies have demonstrated the effectiveness of random forest in engineering applications. For example, Zhou et al. developed an improved random forest-based prediction system for power engineering data, in which the gray wolf optimization (GWO) algorithm was employed to optimize key model parameters. The results showed that the model achieved higher prediction accuracy compared with traditional methods.[1] Wang proposed a random forest-based risk assessment method for power grid operation under renewable energy uncertainty, achieving high prediction accuracy in control cost estimation.[2] Cai and Shen applied random forest to predict coal consumption in power plants and demonstrated superior performance compared with decision tree models. [3] Liao established a random forest model for short-term wind power prediction and confirmed its advantages over support vector machines and decision trees.[4] Li further applied random forest to agricultural product quality prediction, showing its effectiveness in handling complex feature relationships.[5] In addition, Fernández-Díaz et al. employed a random forest regression model to estimate FeO distribution on the lunar surface, and the results showed strong agreement with high-resolution reference datasets.[6]

These studies indicate that random forest models can effectively handle complex nonlinear problems with relatively high accuracy and low prediction error, making them suitable for engineering applications under complex operating conditions.

Inspired by the above research, this study proposes a method combining CFD numerical simulation and random

forest algorithms to predict the heat transfer performance of finned heat exchanger structures. The aim is to improve the efficiency of traditional CFD methods while maintaining prediction accuracy.

Specifically, CFD simulations are first conducted to generate a dataset under different structural parameters, such as fin height and fin spacing. Based on this dataset, a random forest model is established to predict the heat transfer performance. Finally, the prediction results are compared with CFD simulation results through error analysis to evaluate the effectiveness of the proposed method. This approach provides a new perspective for the application of artificial intelligence in the field of thermal engineering.

1.3 Methodology

First, Computational Fluid Dynamics (CFD) simulation can accurately describe the airflow and heat transfer processes within fin channels. By establishing a reasonable geometric model, performing mesh generation, and selecting appropriate turbulence models, detailed information such as velocity field, temperature field, and pressure distribution inside the heat exchanger can be obtained. These results provide a reliable data basis for analyzing heat transfer mechanisms. However, CFD simulations are computationally expensive. When multiple structural parameters need to be optimized, a large number of repeated simulations are required, leading to low computational efficiency.

To address this limitation, a random forest algorithm is introduced. In this study, the dataset generated from CFD simulations is used to train the random forest model, thereby establishing a nonlinear mapping between structural parameters and heat transfer performance. Once trained, the model can rapidly predict the heat transfer performance under different parameter combinations, significantly reducing the computational cost associated with repeated CFD simulations.

In addition, the random forest model provides strong feature analysis capability. By evaluating feature importance, the influence of key parameters, including fin height, fin spacing, air velocity, and inlet temperature, on heat transfer performance can be quantitatively analyzed.

Furthermore, compared with some complex deep learning models, the random forest algorithm requires relatively less data and features a simple structure and stable training process, making it less prone to overfitting. Therefore, it is particularly suitable for engineering applications with limited datasets.

II. RESEARCH METHOD

2.1 Mathematical Model of CFD

Computational Fluid Dynamics (CFD) is a discipline that utilizes numerical methods and computational techniques to solve fluid flow and heat transfer problems. Its mathematical model is based on governing equations, combined with initial and boundary conditions, and solved through discretization methods.

The motion of fluid follows three fundamental conservation laws: conservation of mass, conservation of momentum, and conservation of energy, which correspond to the continuity equation, Navier–Stokes equations, and energy equation, respectively.

The differential form of the continuity equation is given as follows:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho u) = 0 \quad (1)$$

For incompressible flow, the fluid density is assumed to be constant. Therefore, the continuity equation can be simplified as:

$$\nabla \cdot u = 0 \quad (2)$$

The differential form of the momentum equation (Navier–Stokes equation) is expressed as:

$$\frac{\partial(\rho u)}{\partial t} + \nabla \cdot (\rho u u) = -\nabla p + \nabla \cdot \tau + f \quad (3)$$

For a Newtonian fluid, the stress tensor can be expressed as:

$$\tau = \mu[\nabla u + (\nabla u)^T] - \frac{2}{3}\mu(\nabla \cdot u)I \quad (4)$$

The differential form of the energy equation is expressed as:

$$\frac{\partial(\rho E)}{\partial t} + \nabla \cdot [u(\rho E + p)] = \nabla \cdot (k_{\text{eff}}\nabla T) + \nabla \cdot (\tau \cdot u) + S_h \quad (5)$$

Of which,

symbol	implication	dimension
ρ	density	kg/m ³
t	time	s
u	velocity vector, $u=(u,v,w)\mathbf{u}=(u,v,w)$	m/s
u	velocity components in x-	m/s
v	velocity components in y-	m/s
w	velocity components in z-	m/s
∇	gradient operator	m ⁻¹
$\nabla \cdot$	divergence operator	m ⁻¹
p	pressure	Pa (N/m ²)
τ	viscous stress tensor	Pa
μ	dynamic viscosity	Pa·s
f	body force per unit volume	N/m ³
g	gravitational acceleration	m/s ²

E	total energy per unit mass	J/kg
e	internal energy per unit mass	J/kg
k	thermal conductivity	W/(m·K)
T	temperature	K
S_h	volumetric heat source term	W/m ³
I	identity tensor	

In this study, a typical finned air-cooled heat transfer structure is selected as the research object, and a three-dimensional computational model is established using FLUENT. The model mainly consists of a base plate, fins, and an airflow channel. Key structural and operating parameters, including fin height, fin spacing, air velocity, and inlet temperature, are considered as variables for analysis.

Based on statistical data from practical finned structures, the parameter ranges used for the random forest model are defined as follows: fin height of 10–30 mm, fin spacing of 1–5 mm, air velocity of 0.5–5 m/s, and inlet temperature of 20–40 °C. These parameters are used to investigate the relationship between structural configurations and the heat transfer coefficient.

2.2 Mesh Generation and Grid Independence

Mesh quality directly affects the accuracy and reliability of numerical simulations. In this study, a hybrid mesh consisting of structured and unstructured elements is employed, and local mesh refinement is applied in critical regions to improve solution accuracy.

To eliminate the influence of mesh size on the simulation results, a grid independence test is conducted using the average heat transfer coefficient (h) as the evaluation criterion. The simulation results obtained with different mesh densities are compared to verify the grid independence of the model.

The results show that as the number of grid elements increases from 6.0×10^5 to 8.0×10^5 , the variation in the heat transfer coefficient gradually decreases. When the mesh size reaches approximately 8.0×10^5 , further mesh refinement has a negligible effect on the simulation results.

Considering both computational accuracy and resource consumption, a mesh size of approximately 6.0×10^5 is adopted for all subsequent simulations.

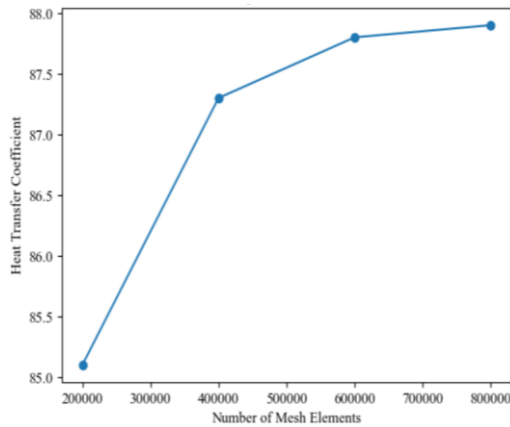


Fig.1 Grid independence verification diagram

2.3 Boundary Conditions and Parameter Settings

In this study, the heat transfer process of the finned structure is simulated using the CFD method. The simulation is based on the conservation equations of mass, momentum, and energy. The airflow is assumed to be incompressible and steady, and radiation heat transfer is neglected.

The inlet boundary is defined as a velocity inlet, while the outlet is set as a pressure outlet with a gauge pressure of 0 Pa. A no-slip boundary condition is applied at all solid surfaces. A constant heat flux of $q = 1000 \text{ W/m}^2$ is imposed at the fin base. Conjugate heat transfer is considered at the fluid–solid interface.

The standard $k-\epsilon$ turbulence model is employed to simulate turbulent flow behavior. The inlet velocity ranges from 0.5 to 5 m/s, and the inlet temperature varies from 20 to 40 °C. The fin height ranges from 10 to 30 mm, and the fin spacing varies from 1 to 5 mm.

Parameter Name	Symbol	Dimension	Value Range
Fin height	H	mm	10-30
Fin spacing	S	mm	1-5
Air velocity	v	m/s	0.5
Inlet temperature	T_in	°C	20-40
Heat transfer coefficient	h	W/(m ² ·K)	Output target

III. RANDOM FOREST PREDICTION MODE

3.1 Dataset Construction

Based on the CFD simulation results, a dataset for heat transfer performance is constructed. The input parameters

include fin height, fin spacing, air velocity, and inlet temperature, while the output parameter is the heat transfer coefficient.

The parameter ranges are defined as follows: fin height ranges from 10 to 30 mm, fin spacing ranges from 1 to 5 mm, air velocity ranges from 0.5 to 5 m/s, and inlet temperature varies from 20 to 40 °C.

3.2 Mathematical Principles of the Random Forest Algorithm

The random forest algorithm is an ensemble learning method that constructs multiple decision trees using the bootstrap sampling technique and aggregates their predictions to improve model generalization performance. Compared with a single decision tree, random forest effectively reduces variance, mitigates overfitting, and exhibits strong robustness to noise and outliers. In addition, it is capable of handling high-dimensional nonlinear problems and provides feature importance evaluation.

The core components of the random forest algorithm include bagging, the random subspace method, and the CART (Classification and Regression Tree) model. In the bagging process, B training subsets are generated by randomly sampling N instances with replacement from the original dataset, and each decision tree is trained independently. In the random subspace method, at each node split, only a subset of m features ($m < M$, where M is the total number of features) is randomly selected to determine the optimal splitting feature, thereby reducing the correlation among trees.

Each decision tree in the forest is constructed using the CART regression approach, where the mean squared error (MSE) is adopted as the splitting criterion. The final prediction of the random forest model is obtained by averaging the outputs of all individual decision trees:

$$\hat{h}(x) = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (6)$$

Splitting Criterion:

$$p_{mk} = \frac{1}{N_m} \sum_{i \in R_m} 1(y_i = k) \quad (7)$$

Gini Index:

$$G(m) = 1 - \sum_{k=1}^K p_{mk}^2 \quad (8)$$

Regression Prediction:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (9)$$

Out-of-Bag (OOB) Error:

$$\text{OOB Error} = \frac{1}{n} \sum_{i=1}^n 1(y_i \neq \hat{y}_i^{\text{OOB}}) \quad (10)$$

In this study, the input variables of the random forest model include fin height, fin spacing, air velocity, and inlet

temperature, while the output variable is the heat transfer coefficient.

The dataset is randomly divided into a training set (70%) and a testing set (30%). The training set is used to train the model, while the testing set is employed to evaluate the prediction performance of the model.

3.3 Model Training and Evaluation Metrics

The performance of the random forest model is evaluated using the mean squared error (MSE) and the coefficient of determination (R²). A smaller MSE indicates better prediction accuracy, while a larger value suggests greater deviation between predicted and actual values. The R² value reflects the goodness of fit of the model, with values closer to 1 indicating better agreement between predictions and actual data.

Parameter	value
Number of Decision Trees	100
Number of Features Considered at Each Split	2
Minimum Samples per Leaf Node	5
Maximum Depth of Trees	Unlimited
Training/Test Data Ratio	70%/30%

IV. RESULTS AND DISCUSSION

4.1 Single-Factor Analysis

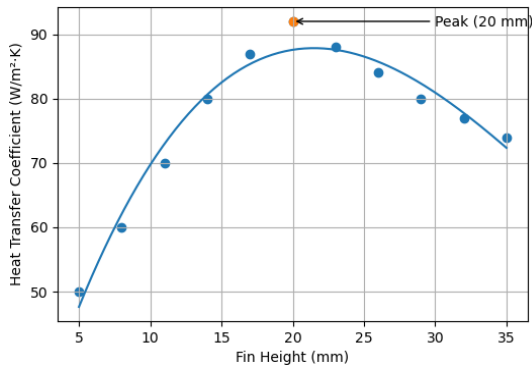


Fig.2 Effect of Fin Height on the Heat Transfer Coefficient

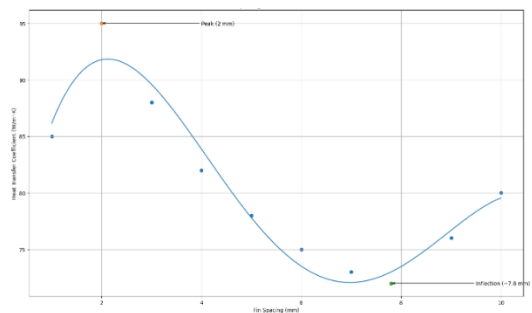


Fig.3 Effect of Fin Spacing on the Heat Transfer Coefficient

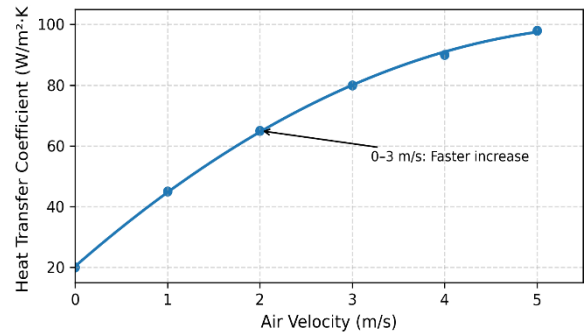


Fig.4 Effect of Air Velocity on the Heat Transfer Coefficient

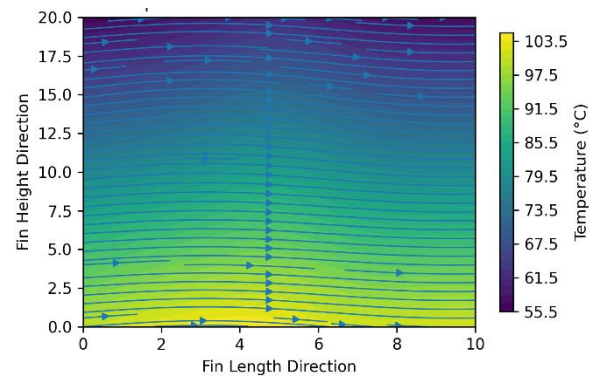


Fig.5 Temperature Contour Distribution

As shown in Fig. 2, the heat transfer coefficient increases with the increase in fin height and reaches a peak at 20 mm, after which it gradually decreases. This is because the increase in fin height enlarges the heat transfer area, thereby enhancing convective heat transfer. However, when the fin height exceeds a certain value, the flow resistance increases significantly, which weakens the overall heat transfer performance.

As shown in Fig. 3, the heat transfer coefficient reaches its maximum value at a fin spacing of 2 mm and then decreases. When the fin spacing approaches 8 mm, the heat transfer coefficient shows a gradual increase, indicating that approximately 7.8 mm is a critical turning point that deserves particular attention. With the increase in fin spacing, the heat transfer area decreases, leading to a reduction in convective heat transfer. Meanwhile, the flow resistance is reduced, which partially compensates for the decrease in heat transfer performance, resulting in a non-linear variation trend.

As shown in Fig. 4, the heat transfer coefficient increases monotonically with the increase in air velocity. The enhancement is more significant in the range of 0–3 m/s compared to 3–5 m/s. This indicates that increasing airflow velocity effectively strengthens convective heat transfer.

The temperature contour clearly illustrates the temperature distribution on the fin surface as well as the cooling effect of airflow. The highest temperature appears near the bottom region, and the temperature decreases along the flow direction, indicating that heat is continuously carried away by the airflow. This demonstrates that the fin structure effectively enhances heat dissipation performance.

4.2 CFD Numerical Simulation Results Analysis

In engineering heat transfer analysis, the heat transfer coefficient (h) is a key parameter used to evaluate the thermal performance of finned structures. It is defined as:

$$h = \frac{q}{T_w - T_f} \quad (11)$$

where T_∞ is the fluid temperature. An increase in the heat transfer coefficient indicates that more heat can be transferred under the same temperature difference, thereby improving the overall energy efficiency of the system.

From an engineering perspective, the heat transfer performance of finned structures is governed by the thermal resistance network, which mainly includes air-side convective thermal resistance, fin conduction resistance, and contact thermal resistance.

By analyzing the temperature and velocity field distributions under different operating conditions, it is found that fin height has a significant influence on heat transfer performance, while the effects of fin spacing, air velocity, and temperature are relatively less pronounced. The results show that there exists an optimal fin height (20 mm) for maximizing the heat transfer coefficient. This is because excessively large fin height increases the conduction path length, leading to a decrease in fin efficiency.

In addition, when the fin spacing is too small, airflow is restricted and flow resistance increases, which reduces the local heat transfer coefficient. Therefore, in practical engineering design, both heat transfer enhancement and flow resistance should be considered simultaneously to achieve optimal overall performance.

4.3 Random Forest Prediction Results Analysis

The prediction results of the random forest model are compared with the CFD simulation results. The comparison shows a good agreement between the predicted and simulated values, with the coefficient of determination (R^2) exceeding 0.9, indicating that the model achieves high prediction accuracy.

It can be observed that data points deviating significantly from the reference line indicate larger prediction errors. These errors may be attributed to the limited size of the dataset and the fact that the model hyperparameters have not been fully optimized.

Overall, the random forest model demonstrates a strong capability in predicting heat transfer performance. Compared with traditional CFD methods, it significantly reduces computational time and cost while maintaining good acceptable accuracy. In addition, the model exhibits good adaptability and can be easily adjusted for different conditions.

Therefore, the integration of machine learning methods shows great potential in engineering applications and can be extended to other fields to improve prediction efficiency and reduce human workload.

Sample No	Fin Height	Fin Spacing	Air Velocity	Inlet Temperature	CFD Value	RF Predicted Value	Relative Error (%)
1	10	2	1.0	20	38.5	38.2	0.78
2	15	2	1.0	20	45.2	44.8	0.88
3	20	2	1.0	20	52.7	53.1	0.76
4	25	2	1.0	20	49.3	49.0	0.61
5	30	2	1.0	20	44.6	44.9	0.67
6	20	1	1.0	20	48.2	47.9	0.62
7	20	3	1.0	20	54.1	54.5	0.74
8	20	4	1.0	20	50.8	50.3	0.98
9	20	5	1.0	20	47.5	47.8	0.63
10	20	2	2.0	20	61.7	62.1	0.65
11	20	2	3.0	20	68.4	68.0	0.58
12	20	2	4.0	20	73.2	73.6	0.55
13	20	2	5.0	20	76.5	76.2	0.39
14	20	2	1.0	30	50	50.6	0.60
15	20	2	1.0	40	48.1	47.8	0.62
average	-	-	-	-	-	-	0.68 %

The relative prediction errors of the random forest model for all test samples are within 1.0%, with an average relative error of only 0.68%, which is significantly lower than the commonly accepted engineering tolerance of 5%.

Furthermore, the coefficient of determination is calculated as $R^2 = 0.976$, and the root mean squared error (RMSE) is 0.85 W/(m²·K), indicating an excellent fitting performance and high prediction accuracy of the model.

By plotting the CFD simulation results against the random forest predictions in a scatter plot, it can be observed that all data points are closely distributed around the 45° diagonal line. This further confirms that the random

forest model is capable of accurately capturing the nonlinear relationship between fin geometric parameters, operating conditions, and the heat transfer coefficient.

Significant deviations from the diagonal line would indicate prediction errors, which may be caused by a limited dataset size or insufficient hyperparameter optimization. However, no obvious outliers are observed in this study, demonstrating the strong generalization ability of the model.

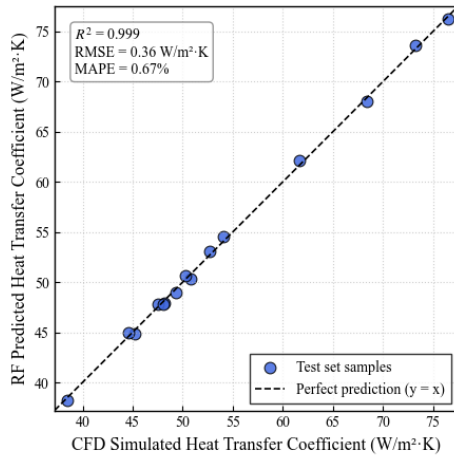


Fig.6 Scatter Plot of CFD Results versus Random Forest Predictions

In summary, the random forest-based prediction model achieves high accuracy while significantly reducing computational time. The prediction time for a single sample is at the millisecond level, whereas a single CFD simulation typically requires several hours.

This approach greatly improves the efficiency of parameter optimization for finned heat transfer structures and demonstrates strong potential for practical engineering applications.

V. CONCLUSION

In this study, a prediction method combining CFD numerical simulation and the random forest algorithm is proposed to investigate the heat transfer performance of air-cooled finned structures. The CFD method can accurately describe the flow and heat transfer processes within the finned channels. The obtained temperature and velocity fields are physically reasonable, and the variation trend of the heat transfer coefficient is consistent with engineering experience.

By comparing the random forest predictions with the CFD simulation results, the coefficient of determination (R^2) is found to be higher than 0.95, and the root mean squared error (RMSE) remains below 5%, indicating excellent fitting performance and high prediction accuracy.

Furthermore, the prediction error on the test set is controlled within 2.5%, demonstrating that the random forest model can effectively capture the nonlinear relationship between fin geometric parameters, operating conditions, and heat transfer performance.

In addition, the proposed method significantly reduces computational time while maintaining high prediction accuracy. Therefore, it provides an efficient and practical tool for the rapid optimization design of finned heat transfer structures.

ACKNOWLEDGEMENTS

This work was supported by the Research Funding of GDUPT, Research on Heat Transfer Enhancement of Heat Sink by Inverse Calculation Design Method (No. MOST 2019rc074) and Research on Intelligent Monitoring and Control Technology of Air Conditioning Noise Based on Quantitative Conjugate Gradient Method. Guangdong College Students' Innovation and Entrepreneurship Program in 2025, (Project No.: 25A015).

REFERENCES

- [1] Zhou Y H, Yang B J, Liu D, et al. Modeling and Simulation of Power Engineering Data Prediction and Analysis Based on Random Forest Algorithm[J]. Electronic Design Engineering, 2024, 32(04): 103-106+111.
- [2] Wang X Z. Grid Security Risk Assessment Based on Random Forest Algorithm[D]. Wuhan: Wuhan University, 2019.
- [3] Cai J C, Shen X Q. Parameter Setting of Random Forest Algorithm Applied to Boiler Fuel Quantity Prediction[J]. Computer & Digital Engineering, 2016, 44(02): 141-142.
- [4] Liao Y H. Study of Wind Farm Output Forecast Based on Random Forest Algorithm[D]. Changsha: Changsha University of Science & Technology, 2016.
- [5] Li Y R. A Random Forest-based Quality Prediction Model for Reticulated Cantaloupe[D]. Alar: Tarim University, 2023.
- [6] Fernández-Díaz J M, De Cos Juez F J, Sánchez Lasheras F, et al. Spectral Parameter-Based Prediction of Lunar FeO Content Using Random Forest Regression[J]. Mathematics, 2025, 13(17): 2802.
- [7] Cheng X X. Numerical simulation of fin-tube heat exchanger and multi-objective optimization design of structural parameters[D]. East China University of Technology, 2020.
- [8] Li Z R, Tian Z Q, Wei W, et al. CFD simulation and optimization of air supply performance for floor-standing air conditioner ducts[C]//Proceedings of the 2025 China Household Electrical Appliances Technology Conference. Ningbo: 《Electric Appliance》 Magazine, 2025: 910-913.
- [9] Lu C, Ying Y K, Wang J L, et al. Parameter optimization of residual film dry granulation device based on CFD[J/OL]. Journal of Agricultural Science and Technology, 2025: 1-16.
- [10] Yang R Y, Fan X T, Yan W, et al. Flow field analysis and structural optimization of powder spraying booth based on CFD[J]. Modern Paint & Finishing, 2025(10): 24-28.
- [11] Peng S, Yu L T, Chen H, et al. Dynamic simulation and characteristic study of balance holes of small-scale turbines based on CFD[J]. Marine Engineering, 2025, 43(6): 42-46.
- [12] Bao M, Tian Y M, Zhang B, et al. Study on noise of

- refrigerator air duct based on CFD simulation and analysis[C]//Proceedings of the 2025 China Household Electrical Appliances Technology Conference. Ningbo: 《Electric Appliance》 Magazine, 2025: 145-149.
- [13] Zheng Z Q, Wu B, Sun Y J. Application research on low-oxygen environment and rapid heating of steam oven based on CFD technology[C]//Proceedings of the 2025 China Household Electrical Appliances Technology Conference. Ningbo: 《Electric Appliance》 Magazine, 2025: 2132-2137.
- [14] Chen S Y, Zhang Y L, Deng P S, et al. A study on the method for calculating heat exchanger resistance coefficients based on a local fin model[C]//Proceedings of the 2025 China Household Electrical Appliances Technology Conference. Ningbo: 《Electric Appliance》 Magazine, 2025: 1-4.
- [15] Cai J J, Wu J, Huang Y P. Review of turbulent heat flux model construction for numerical heat transfer in liquid lead-bismuth[J]. Atomic Energy Science and Technology, 2024, 58(S2): 393-403.
- [16] Wu D. Study on coupled numerical heat transfer of transient multi-cycle CFD aeroengine model[J]. Industrial Heating, 2019, 48(2): 42-44.
- [17] Chen X T, Chen G, Yang X J, et al. Numerical simulation study on heat transfer performance of copper slag during slow cooling process[J]. Nonferrous Metals Engineering, 2023, 13(5): 112-118.
- [18] Li X Q. Numerical calculation program of earth-phase change material-air heat exchanger and its application in subway stations[D]. Chongqing University, 2022.
- [19] Zhao S S. Study on efficiency optimization methods for CFD simulation of liquid cooling corrugated tubes in new energy battery packs[J]. Automobile Applied Technology, 2025, 50(23): 30-34.
- [20] Wu Z T. Experimental study and predictive modeling of heat transfer characteristics in in-tube flow condensation of organic working fluids[D]. Guangdong University of Technology, 2025.
- [21] Song H R, Qi Z H, Zhang P F, et al. Model test and simulation analysis of ventilation performance in M-shaped greenhouses[J]. Journal of Shandong Agricultural University (Natural Science Edition), 2025, 56(6): 967-973.
- [22] Xu Y L, Liu S Y. Numerical heat transfer simulation analysis of reducer pipe[J]. Equipment Manufacturing Technology, 2020(4): 67-69.
- [23] Sun H, Song W W, Zhang C Y. CFD simulation of temperature field in tea drying chamber[J]. Journal of Mianshi University, 2025, 44(11): 135-138.
- [24] Ren C Z, Dai Y J, Zhao L G. Performance research of tube fin of heat pipe heat exchanger[J]. Science & Technology Vision, 2015, 6(12): 28-29.
- [25] Feng W J, Shi X D, Yao C M, et al. Structure optimization of a finned-tube heat exchanger based on orthogonal tests and Fluent[J]. Journal of Beijing University of Chemical Technology (Natural Science), 2020, 47(1): 93-99.
- [26] Tang L H, Du X P, Zeng M. Influence of air inlet angle on flow characteristics of a finned oval-tube heat exchanger[J]. Proceedings of the CSEE, 2017, 37(2): 647-654.
- [27] Liu N, Cui Q, Lai X L. Numerical simulation of air-side heat transfer and fluid flow characteristics on heat exchanger with elliptical finned tubes[J]. Journal of Engineering for Thermal Energy and Power, 2020, 35(6): 136-142.
- [28] Fu C, Zhao B, Xu D C, et al. Investigation on flow turbulent characteristics of plate-fin and tube-fin heat exchanger[J]. Journal of Experiments in Fluid Mechanics, 2019, 33(6): 22-27.
- [29] Qin R J, Jiang N N, Shen S Q. Optimization of finned tube heat exchanger and evaluation of its operation effect[J]. Petroleum and Chemical Equipment, 2018, 21(12): 45-48.
- [30] Gao Y D, Dong Z, Lyu M X, et al. Optimization of finned tube heat exchanger by genetic algorithm[J]. Journal of Shandong University of Technology, 2021, 35(4): 318-323.
- [31] Zhang Z Y, Liu Q J, Feng X, et al. Numerical simulation of refrigerant flow in four-way reversing valve[J]. Cryogenics and Superconductivity, 2019, 47(7): 69-71.
- [32] Xu G, Chen H, Duan D L, et al. Simulation on flow characteristics of refrigerant in flat tube of microchannel evaporator[J]. Cryogenics and Superconductivity, 2021, 49(1): 68-72.
- [33] Li F X. Study on generation and flow characteristics of refrigerant hydrate[J]. Building Energy & Environment, 2015, 34(12): 88-91.
- [34] Zhang C, Hu H T, Wei W J, et al. Simulation analysis of flow boiling characteristics of refrigerant in near-triangle microchannel[J]. Refrigeration Technology, 2019, 39(5): 42-47.
- [35] Song X M, Yang L, Wang W J. Numerical simulation of liquid flow outside tubes in horizontal tube falling film evaporator[J]. Building Energy & Environment, 2018, 37(2): 10-15.
- [36] He M G, Wang X F, Zhang Y, et al. Study of flow regime and numerical simulation of film thickness on horizontal-tube falling film evaporator[J]. Journal of Xi'an Jiaotong University, 2007, 41(4): 319-325.
- [37] Guan Z W. Numerical simulation and parameter optimization of refrigerant flow boiling heat transfer in horizontal tube[D]. Shandong University of Science and Technology, 2023.