

An Investigation on Design Criteria of Heat Exchangers by Using Tree Models of Machine Learning Methods

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ABSTRACT

Heat exchangers are essential in sectors such as chemical processing, automotive, and HVAC. Optimizing their design criteria is crucial for improving industrial efficiency. This study investigates tree-based machine learning models to identify the most suitable model for various heat exchanger design parameters. The XGBoost model provided over 96% prediction accuracy for heat transfer rate, safety, and reliability; AdaBoost achieved 94% accuracy for material selection and serviceability; and Random Forest (RF) reached 92% accuracy for cost and pumping power estimations. These findings suggest that tree-based models can effectively predict different criteria depending on data characteristics and accuracy needs. Utilizing such models offers a practical alternative to traditional numerical methods, especially for handling diverse dataset sizes. Future studies can leverage these techniques to develop more cost-effective, reliable, and energy-efficient heat exchangers.

Isı Değiştirici Tasarım Kriterlerinin Makine Öğrenmesi Ağaç Modelleri Kullanılarak İncelenmesi

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ÖZ

Isı değiştiriciler, kimyasal proses, otomotiv ve HVAC gibi sektörlerde kritik öneme sahip bileşenlerdir. Tasarım kriterlerinin optimize edilmesi, endüstriyel verimliliğin artırılmasında önemli bir rol oynar. Bu çalışmada, çeşitli ısı değiştirici tasarım parametreleri için en uygun modeli belirlemek amacıyla ağaç tabanlı makine öğrenmesi modelleri incelenmiştir. XGBoost modeli, ısı transfer hızı, güvenlik ve güvenilirlik için %96'nın üzerinde tahmin doğruluğu sağlamıştır. AdaBoost modeli, malzeme seçimi ve servis edilebilirlik için %94 doğruluk gösterirken; Random Forest (RF) modeli, maliyet ve pompalama gücü tahminlerinde %92 doğruluğa ulaşmıştır. Elde edilen sonuçlar, veri yapısına ve doğruluk gereksinimlerine bağlı olarak farklı kriterlerin etkin bir şekilde tahmin edilebildiğini göstermektedir. Bu tür modeller, geleneksel nümerik yöntemlere kıyasla farklı veri boyutlarıyla daha pratik bir çözüm sunarak gelecekte daha ekonomik, güvenilir ve enerji verimli ısı değiştiricilerin geliştirilmesine katkı sağlayabilir.

1. INTRODUCTION

Heat exchangers are essential thermal devices designed to transfer energy between two or more fluid streams at different temperatures while keeping them physically separated by a solid wall. Heat exchangers are extensively employed across industries (such as HVAC, power generation, etc.) with common applications including air conditioning units, LNG production facilities, vehicle radiators, food cooling systems, and aircraft thermal management, all of which continually evolve through technological advancements [1-3]. As the utilization of heat exchangers has become more widespread, studies on performance and efficiency have increasingly focused on various criteria such as thermophysical properties, design, and budget. Efficiency and effectiveness calculations are primarily based on classical methods such as the Effectiveness-NTU (ϵ -NTU) method and the Logarithmic Mean Temperature Difference (LMTD) method [4-7]. The effectiveness and efficiency of heat exchangers depends on parameters such as mass flow rate, surface area, heat transfer coefficient, and fluid properties [8,9]. These calculations are performed through experimental and numerical studies involving regression, classification, and correlation analysis for various parameters, materials, and operating conditions [10].

Although numerical solutions are employed when traditional methods fall short, the increasing complexity of problems significantly raises computational costs and processing time. Technological advancements have expanded the range of options available to engineers, enabling the precise design of heat exchangers based on factors such as heat transfer rate, cost, pumping power, and material properties [11]. In recent years, machine learning models have emerged as a valuable tool for analyzing heat exchanger performance by delivering precise predictions through the incorporation of elements such as parameter optimization, design refinement, learning algorithms, data quality, tree-based methods, hybrid approaches, input features, and system variables.

Supervised learning is a prevalent machine learning approach and serves as an essential tool in the design, operation, and optimization of heat exchanger systems. It is the primary method used for training neural networks and decision tree models. The two fundamental types of supervised learning are classification and regression [12,13]. The literature features various heat exchanger applications that employ different supervised learning techniques. Numerous studies have investigated a range of supervised learning models, including RVFL, SVM, GPR, KNN, ANN, and RF, from diverse analytical perspectives [14-17].

Several supervised learning techniques utilized in heat exchanger applications include Bayesian Regression (BR), Support Vector Machines (SVM), Tree-Based Models, and the K-Nearest Neighbors (KNN) algorithm and Supervised Neural Networks (SNN) [18].

Boosting algorithms (such as XGBoost, LightGBM, and CatBoost) transform multiple weak learners (tree structures) into a strong classifier. Random Forest is a widely used machine learning algorithm for classification and regression problems. Due to its suitability for hybrid approaches, it provides high prediction accuracy in applications such as fault diagnosis and thermal comfort analysis [19,20]. AdaBoost is a method based on ensemble learning algorithms, used to minimize errors in data analysis and enhance predictive performance. This approach demonstrates superior performance in areas such as data-driven energy consumption analysis, power usage forecasting, and improving resource efficiency [21,22]. XGBoost is a highly effective machine learning algorithm widely preferred for solving large-scale datasets and complex problems due to its high computational performance and flexible model architecture [23]. XGBoost is highly effective for fault detection, energy consumption prediction and environmental estimation in HVAC systems.

A review of the literature reveals that studies employing machine learning methods in heat exchanger applications can be broadly classified into two categories. The first group comprises investigations focusing on heat exchanger fluids (hot and cold fluids), while the second group examines flow characteristics and flow geometry. However, no study has been identified that specifically evaluates machine learning methods for analyzing heat exchanger design criteria.

Different from the literature, this study focuses on the application of machine learning methods in various types of heat exchangers and comparison of these methods for their design criteria. The study consists of three main sections. The first section provides a fundamental overview and classification of machine learning techniques, emphasizing their applications in heat exchanger systems. The second section

examines the key factors influencing model selection and includes tables that outline the variables affecting model performance across different types of heat exchangers. Finally, the third section presents recommendations for enhancing the implementation of machine learning in heat exchanger systems, drawing insights from existing literature and potential future research directions.

2. MATERIAL AND METHOD

Machine learning is generally classified into five main categories: supervised learning, unsupervised learning, reinforcement learning, and deep learning. AdaBoost, RF, XGBoost models are specifically categorized under tree models as shown in Figure 1.

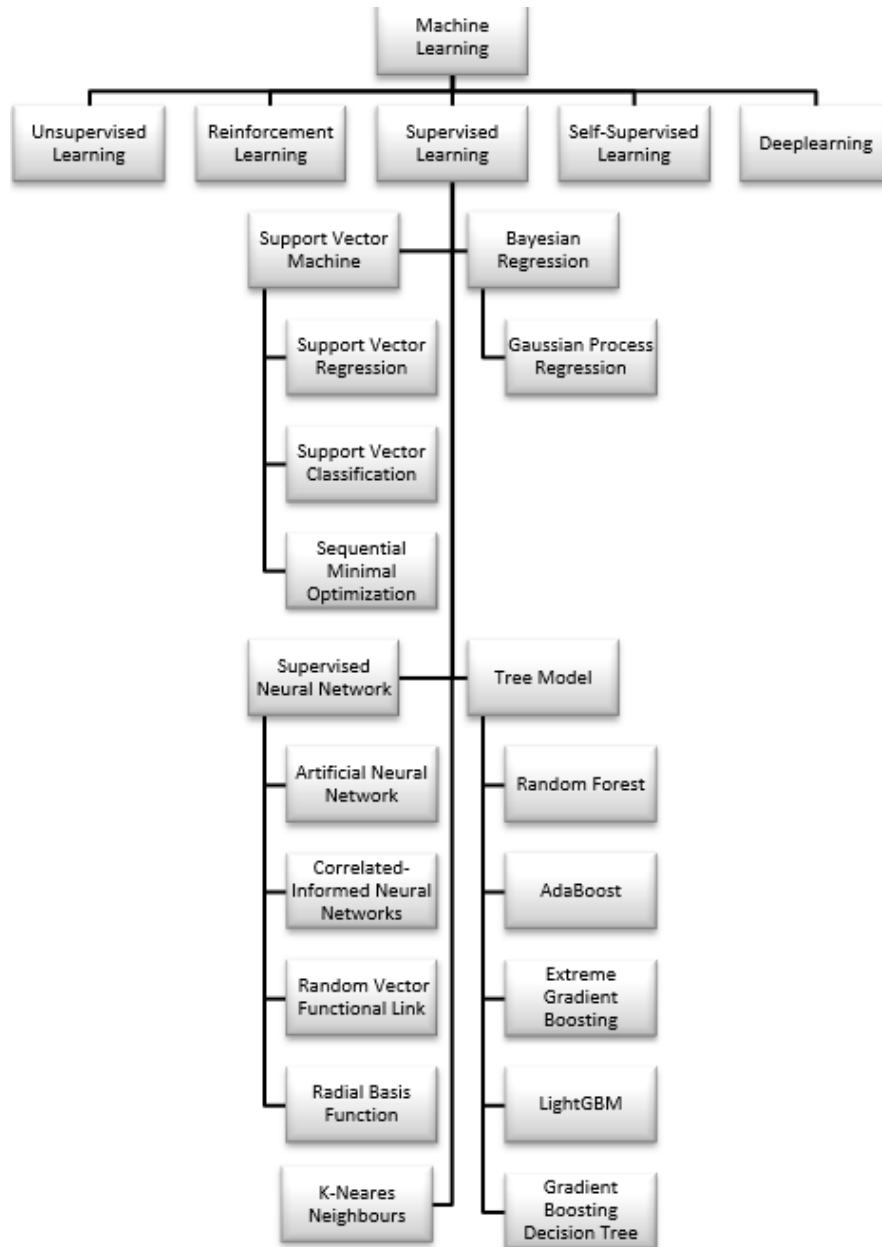


Figure 1. Hierarchical block list of machine learning models [24]

As shown in Table 1, XGBoost, AdaBoost, and Random Forest exhibit certain similarities and differences in terms of input/output structures, algorithm types, and intended use cases. Random Forest employs a learning method based on the aggregation of multiple decision trees to achieve accurate predictions. This model consists of a collection of diverse decision trees, each trained on a randomly selected subset of data

using the bootstrap method, thereby enhancing overall prediction accuracy. AdaBoost, as an ensemble learning method, iteratively updates the weights of misclassified instances by learning from their errors and forms a strong classifier through repeated adjustments. Its core principle is to combine multiple weak classifiers by assigning greater weight to those with higher accuracy, thereby improving overall model performance. This approach also enhances computational efficiency [25,26]. XGBoost, on the other hand, builds upon decision trees that make predictions by partitioning the dataset into segments. The objective function used to evaluate model performance is typically the mean squared error for regression problems, and the logarithmic loss for classification tasks [27].

In general, while machine learning models reduce computational load and provide time efficiency, they also have the potential to be utilized more effectively in specific problems.

Table 1. Comparison of tree learning methods

Machine learning approaches	Output type	Algorithm type	Purpose of use
Random forest	Classification/Regression	Bagging	Medium or big sized datasets
AdaBoost	Classification/Regression/	Boosting	Small or medium sized datasets
XGBoost	Classification/Regression/Ranking	Gradient boosting	Big data sets complex problems

3. RESULTS AND DISCUSSION

3.1. Machine Learning Models in Heat Exchanger Applications

In this section, existing studies on the application of machine learning models for determining heat exchanger design criteria are reviewed. Different tree-based models are compared across varying dataset sizes and evaluated based on RMSE, MAE, and R^2 performance metrics. Table 2 presents the selection criteria, input/output variables, and the best results reported in the literature for machine learning models applied to heat exchangers. In this context, dataset size emerges as the most critical factor in selecting appropriate tree-based models. The literature indicates that tree-based models are widely used in various applications, including energy consumption prediction, fault diagnosis, determination of thermophysical properties, and design optimization. Furthermore, it has been identified that tree models can be integrated with other machine learning techniques to form novel and more accurate hybrid models.

Table 2. Overview of machine learning applications for heat exchanger performance prediction in recent studies

Authors	Heat exchanger type	Type of machine learning	Selection Criteria	Input	Output	Results Value
[28]	HVAC system	SVM ANN XGBoost LightGBM	SVM, high performance in limited data and non-linear predictions ANN receives input and generates output using non-linear activation functions XGBoost and LightGBM are based on boosting theory. The study contains a small data set	Outdoor Temperature Humidity Indoor Temperature Setpoint, Hour of day	HVAC Power, Indoor Temperature	XGBoost as the highest accuracy result $R^2 = 0.978$ for Power $R^2 = 0.983$ for T
[29]	Liquid CPs	XGBoost	Well accuracy and performance in modelling complex processes and needs less training time. The study contains a small data set	Flow Path Diameter, Surface roughness, Mass flow rate	Heat Transfer Coefficient	63% of predictions within $\pm 10\%$ of true values. 90% of predictions within $\pm 20\%$ of true values.

Table 2. Continued

[30]	HVAC system	CNN-BiLSTM-XGBoost	CNN- BiLSTM will overcome the shortcomings of a single model XGBoost has higher accuracy and greater flexibility Total number of data used 88841	RH, DBT, WBT, T_{CHWR} , T_{CHWS} , T_{CWR} , T_{CWS} , f_{CHW} , f_{CW} , Q_c ,	RMSE MAE R^2 MAPE	CNN-BiLSTM - XGBoost RMSE = 5.785642 MAE = 2.942315 MAPE (%) = 2.436678 $R^2 = 0.9977$
[31]	Chiller	XGBoost SVM	Total number of data used 2460 XGBoost and SVM model perform well in nonlinear classification problems	TCI, TEI, TEO T_{sc} UA_c UA_e LMTD _c LMTD _e APPR _c APPR _e	CR Precision F1 score	Overall multi region XGBoost CR =95.83% F1 = 0.9824 Precision = 99.25%
[32]	Smart HVAC building system	XGBoost	A six-month dataset is collected. XGBoost has high sensitivity capability in hyperparameters	Temperature Humidity	RMSE MAPE	RMSE _{AVG,T} = 0.3 RMSE _{AVG,H} = 2.6 MAPE = 2.2342 %
[20]	HVAC system	HRF-SVM	A total of 2160 samples were collected for normal data. SVM performs well classification at low dimensional data. RF works well with large amounts of missing data and feature selection.	The most common 13 different types of faults	Precision F1 score Recall	HRF-SVM model diagnosed with higher accuracy at 98%
[33]	Heat Exchange Channels with bulges	GRNN RF	A total of 729 CFD simulation results were used	Bulge channel models in various heights	HTC	Both for GRNN and RF, $R^2 > 0.97$
[34]	Heat Exchanger	XGBoost SVR DTR	XGBoost performs well in structured/tabulated data scenarios and predictive modeling tasks. SVR performs the regression task with superior efficiency in non-linear models by determining the decision boundary of the model.	Size and volume, fraction of nanoparticles	RMSE MAE R^2	Best Result is XGBoost RMSE = 1.03880 MAE = 1.07911 $R^2 = 0.9142$
[35]	Double Pipe Heat Exchanger	RF CatBoost XGBoost	Random Forest improves prediction accuracy and reduces overfitting. The XGB algorithm is high-performance with its overfitting prevention approach.	Re, N, L	Nu, f, ε and NTU	Best Result for Test is CatBoost $R^2 = 0.9989$
[36]	Mini-Micro Channel	ANN RF AdaBoost XGBoost	A consolidated database of 4882 data points was used. Random Forest boosts accuracy and prevents overfitting. The Adaboost algorithm produces a sequence of weak classifiers based on the weight distribution.	Bd, Co, Fr _f , Fr _{fo} , Fr _g , Fr _{go} , Ga, Ka, Pr _f , Pr _g , Re _f , Re _{fo} , Re _g , Re _{go} , Su _f , Su _g , Su _{fo} , Su _{go} , We _f , We _{fo} , We _g , and We _{go}	Condensation of heat transfer coefficient	ANN and XGBoost models showed the best prediction accuracy.
[37]	Oscillating Heat Pipes	XGBoost	65 small-scale experimental data were used XGBoost performs well in modeling small datasets with the ability to prevent overfitting	Dimensionless numbers, heat flux, target temperature, and geometric parameters	RMSE MAE R^2	Best Result for Test is XGBoost RMSE = 167.78 MAPE (%) = 10.47 $R^2 = 0.07$

Table 2. Continued

[38]	Aircraft heat exchangers	NB KNN DT RF AdaBoost SVM	Naive Bayes performs fast and simple classification. KNN classifies based on similar data. Decision Tree provides easily interpretable decisions. Random Forest produces stable and accurate results. AdaBoost strengthens by learning from errors. SVM aims to make the most accurate separation.	Three types of fouling levels: No fouling, moderate fouling, severe fouling	Precision Recall F1-score Support	Best Result for Test is SVM Accuracy = 0.93
[39]	Ground-Coupled Heat Pump System	RF	360 months of experimental data. The RF model was preferred because it can easily adapt to complex, multi-dimensional data structures and preserves the possibility of generalization.	Borehole arrangement, Borehole depth, Borehole radius, Borehole number, Vertical spacing, Column spacing, Thermal conductivity coefficient, Nominal external diameter, U-tube spacing, Temperature, Thermal conductivity Circulating liquid parameter	Four types of heat transfer performance: Y1: Heat pump power consumption Y2: Total system power consumption Y3: The ratio of heat pump to the operating powers of heat pump Y4: The ratio of the heating capacity of heat pump to the total system	MAE MAPE RMSE

3.2. Evaluation of The Heat Exchanger Design Criteria for Different Tree Models

3.2.1. Heat Transfer Rate

Heat transfer rate stands as one of the fundamental determining factors in heat exchanger selection. Machine learning methods such as GRNN, RF, XGBoost, and AdaBoost demonstrate remarkable capability in predicting heat transfer coefficients on internal surfaces (e.g., plates and tubes) with both high accuracy and strong generalization performance. These computational approaches significantly reduce design optimization costs while offering substantial time savings in the selection process. Comparative analysis reveals that while the AdaBoost algorithm shows potential for achieving convergent predictions with relatively small datasets, it exhibits higher mean absolute error (MAE) values compared to other methods. In contrast, the XGBoost method has been shown to produce more accurate results when applied to larger datasets, demonstrating superior predictive performance in comprehensive evaluations.

3.2.2. Size and Weight

The compact size and low weight characteristics of heat exchangers significantly enhance their applicability in sectors such as aerospace and automotive, where stringent constraints on space and mass are paramount. The structural and working fluid materials employed across various heat exchanger types, in conjunction with intricate geometric configurations affecting surface area-to-volume ratios, directly influence these dimensional and mass-related design criteria. In this regard, the XGBoost machine learning algorithm, when integrated with autoencoders (AEs), exhibits superior predictive performance with respect to RMSE, MAE, and R² metrics. Moreover, when combined with other hybrid modeling approaches, it facilitates the accurate estimation of critical design parameters (most notably the Number of Transfer Units (NTU)) which play a central role in optimizing the size and weight of heat exchangers.

3.2.3. Cost

Budget constraints stand out as a fundamental criterion in the heat exchanger selection. The type of working fluid, material choice, design parameters, and application areas are among the key factors directly affecting the budget. The Random Forest algorithm enhances efficiency and reduces costs by making precise predictions regarding fouling accumulation, pressure, and temperature in medium-to-large datasets, thereby optimizing performance. Additionally, the AdaBoost algorithm improves fault detection accuracy in heat exchangers using small-to-medium datasets, and the resulting efficiency improvements directly impact system costs.

3.2.4. Pumping Power

Among the most critical factors affecting pump power are parameters such as temperature, flow rate, and system pressure. The Random Forest algorithm has demonstrated high accuracy and robust performance in predicting key parameters of heat pumps, including heating capacity, efficiency, thermal performance, and power consumption. This approach offers the advantage of effectively analyzing complex interactions between operational variables while maintaining computational efficiency compared to conventional methods.

3.2.5. Type

Shell-and-tube, compact, double-pipe, plate-and-frame, and regenerative heat exchangers are among the most widely preferred types in industry, depending on fluid thermophysical properties, operating pressure and temperature ranges, and system design constraints. The AdaBoost algorithm has been demonstrated to effectively predict heat exchanger thermophysical parameters and the Number of Transfer Units (NTU) - a key parameter related to size and weight - using data obtained from computational fluid dynamics (CFD) simulations. Particularly in cases involving limited datasets, AdaBoost's robust predictive performance provides a significant advantage for thermal system optimization and energy efficiency enhancement.

3.2.6. Safety and Reliability

The fluid's toxicity level, sealing condition, vibration and noise levels, along with the inlet/outlet fluid temperature and pressure constitute critical parameters for heat exchanger safety and reliability. The XGBoost algorithm, capable of producing highly accurate results on large datasets, emerges as an effective method for fault detection and diagnosis processes. Furthermore, it offers significant advantages in maintaining the system's desired thermal comfort level.

3.2.7. Ease of Servicing

The design of heat exchangers should facilitate in-situ cleaning procedures, and material selection should utilize corrosion-resistant materials such as stainless steel or titanium. Additionally, regular maintenance practices are essential to ensure long-term system durability and operational efficiency. The AdaBoost model enhances overall system efficiency by learning from previous errors to reduce prediction errors on new data, while enabling early fault detection based on corrosion data and predicting fouling formation.

3.2.8. Materials

In material selection, along with corrosion resistance, thermal conductivity and mechanical strength constitute important criteria. Therefore, materials such as copper, aluminum, stainless steel, and titanium are typically preferred. The XGBoost algorithm has been identified as an effective method for predicting thermophysical properties of fluids exposed to surface roughness - particularly parameters like heat transfer coefficient - due to its ability to provide high accuracy and efficiency with limited datasets.

3.3. Prospects for Tree Models in Heat Exchangers

In general, the utilization of machine learning models in heat exchangers can be categorized into six main areas:

- Optimization of performance and thermo-hydraulic modeling,
- Development of AI-assisted intelligent heat exchangers,
- Enhancement of energy efficiency and sustainability,
- Estimation of overall heat transfer coefficients,
- Detection and prevention of fouling,
- Prediction of the thermal properties of fluids.

Tree-based models such as Random Forest, AdaBoost, and XGBoost are increasingly employed in the analysis and optimization of heat exchangers. These methods demonstrate significant potential for predicting not only the energy transfer between fluids but also fluid-structure interactions and thermophysical properties of working fluids. Furthermore, these approaches enable enhancement of heat exchanger performance efficiency and more precise modeling of system operating conditions. Future developments are expected to integrate these models with other complementary approaches to achieve higher prediction accuracy for complex problems.

Through utilization of large datasets, optimal correlations between thermal and hydraulic properties can be established, facilitating the design of more efficient heat exchanger configurations. Decision tree-based models can analyze historical performance data to provide predictive insights for adapting to changing environmental and operational conditions. This capability allows for long-term improvement of system efficiency and more effective optimization of energy consumption.

4. CONCLUSIONS

In this study, heat exchanger design parameters were analyzed using various machine learning methods, and the most suitable machine learning approach for each parameter was identified. In conclusion,

- a. Considering the varying data density and accuracy requirements associated with tree-based models, it is concluded that different design criteria can be effectively analyzed under distinct application conditions: design parameters such as heat transfer rate, safety, and reliability are best addressed in applications requiring large datasets and high accuracy; pumping power can be effectively analyzed in cases involving large datasets but lower accuracy demands; cost, type, and material selection are more suitable for applications with smaller datasets and high precision needs; and ease of servicing can be efficiently evaluated in scenarios with both low data volume and low accuracy requirements.
- b. The application of tree-based machine learning methods in heat exchanger systems offers significant benefits in terms of improving energy efficiency, enabling early fault detection, facilitating maintenance processes, and reducing costs. These methods contribute to optimizing the performance of heat exchangers, thereby offering long-term advantages in sustainability and operational efficiency.

In the future, it is anticipated that by leveraging tree-based machine learning models, heat exchanger design parameters can be optimized in industrial applications to enable the development of more efficient systems. This may also facilitate the advancement of new materials and cooling fluids—such as metamaterials and nanofluids—and support the design and production of cost-effective, reliable, easy-to-maintain, and sustainable heat exchangers.

5. REFERENCES

1. Singh, A., Sahu, D. & Verma, O.P. (2023). Study on performance of working model of heat exchangers. *Materials Today: Proceedings*, 80, 8-13.
2. Thulukkanam, K. (2000). Heat exchanger design handbook. *CRC Press*.
3. Tang, G., Han, Y., Chen, H., Zhang, X. (2018). Design, fabrication and characterization of a mini heat exchanger for data centre cooling application. *2018 IEEE 20th Electronics Packaging Technology Conference (EPTC)*, 485-490.
4. Pardakhe, P.P.K., Samarth, P.A.B., Bhambere, V.L. & Rathod, P.P.H. (2019). A review on basics of heat exchanger. *International Research Journal of Engineering and Technology (IRJET)*, 6(10), 416-420.

5. Hassan, A.H., Martínez-Ballester, S. & González-Maciá, J. (2016). Two-dimensional numerical modeling for the air-side of minichannel evaporators accounting for partial dehumidification scenarios and tube-to-tube heat conduction. *International Journal of Refrigeration*, 67, 90-101.
6. Karaçaylı, İ., Şimşek, E., Altay, L. & Hepbaşlı, A. (2018). Experimental and analytical investigation of heat transfer coefficient of a water cooled condenser for different water flows and condensation pressures. *Çukurova Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi*, 33(2), 101-112.
7. Güneş, T., Şahin, M., & Kılıç, M. (2023). Investigation of the effect of different parameters of phase change materials on heat exchanger performance. *Çukurova Üniversitesi Mühendislik Fakültesi Dergisi*, 38(4), 1117-1128.
8. Fakheri, A. (2007). Heat exchanger efficiency. *J Heat Transfer* 129, 1268-1276.
9. Ala, M., Şahin, M. & Kılıç, M. (2024). Experimental investigation of the effect of different parameters on plate and frame heat exchanger effectiveness. *Çukurova Üniversitesi Mühendislik Fakültesi Dergisi* 39, 951-9.
10. Habib, G., Hussain, T., Kilic, M. & Ullah, A. (2024). Development of generalized correlations for predicting density and Specific heat of nanofluids for enhanced heat transfer. *Journal of Modern Nanotechnology*, 4(3), 1-10.
11. Ghajar, A. & Cengel, Y. (2020). Heat and mass transfer - fundamentals and applications. 6th Edition, McGraw-Hill Education, New York, NY.
12. Nasteski, V. (2017). An overview of the supervised machine learning methods. *Horizons. b*, 4(51-62), 56.
13. Sen, P.C., Hajra, M. & Ghosh, M. (2020). Supervised classification algorithms in machine learning: A survey and review. *In Emerging Technology in Modelling and Graphics: Proceedings of IEM Graph*, 99-111.
14. Ghalandari, M., Irandoost Shahrestani, M., Maleki, A., Safdari Shadloo, M. & El Haj Assad, M. (2021). Applications of intelligent methods in various types of heat exchangers: a review. *Journal of Thermal Analysis and Calorimetry*, 1-12.
15. Mudhsh, M., El-Said, E.M., Aseeri, A.O., Almodfer, R., Abd Elaziz, M., Elshamy, S.M. & Elsheikh, A.H. (2023). Modelling of thermo-hydraulic behavior of a helical heat exchanger using machine learning model and fire hawk optimizer. *Case Studies in Thermal Engineering*, 49, 103294.
16. Umamaheswari, K. & Madhumathi, R. (2024). Predicting crop yield based on stacking ensemble model in machine learning. *In 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*, 1831-1836, IEEE.
17. Traverso, T., Coletti, F., Magri, L., Karayiannis, T.G. & Matar, O.K. (2023). A machine learning approach to the prediction of heat-transfer coefficients in micro-channels. *arXiv preprint arXiv: 2305.18406*.
18. Zou, J., Hirokawa, T., An, J., Huang, L. & Camm, J. (2023). Recent advances in the applications of machine learning methods for heat exchanger modeling-a review. *Frontiers in Energy Research*, 11, 1294531.
19. Boutahri, Y. & Tilioua, A. (2024). Machine learning-based predictive model for thermal comfort and energy optimization in smart buildings. *Results in Engineering*, 22, 102148.
20. Tun, W., Wong, J.K.W. & Ling, S.H. (2021). Hybrid random forest and support vector machine modeling for HVAC fault detection and diagnosis. *Sensors*, 21(24), 8163.
21. Sun, L., Wei, Q., He, L. & Yin, Z. (2020). The prediction of building heating and ventilation energy consumption base on adaboost-bp algorithm. *In IOP Conference Series: Materials Science and Engineering (782)*, 3, 032008. IOP Publishing.
22. Bian, J., Wang, J. & Yece, Q. (2024). A novel study on power consumption of an HVAC system using CatBoost and AdaBoost algorithms combined with the metaheuristic algorithms. *Energy*, 302, 131841.
23. Chen, T. & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. *In Proceedings of the 22nd ACM Sigkdd International Conference on Knowledge Discovery and Data Mining*, 785-794.
24. de Giorgio, A., Cola, G. & Wang, L. (2023). Systematic review of class imbalance problems in manufacturing. *Journal of Manufacturing Systems*, 71, 620-644.
25. Freund, Y. & Schapire, R.E. (1996). Experiments with a new boosting algorithm. *Proceedings of the Thirteenth International Conference on International Conference on Machine Learning*, San Francisco, CA, USA: Morgan Kaufmann Publishers, 148-56.
26. de Giorgio, A., Cola, G. & Wang, L. (2023) Systematic review of class imbalance problems in manufacturing. *J Manuf Syst.*, 2023(71), 620-644.
27. Chen, T. & Guestrin, C. (2016). XGBoost. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, New York, NY, USA: ACM, 785-794.

28. Wang, H., Mai, D., Li, Q. & Ding, Z. (2024). Evaluating machine learning models for HVAC demand response: the impact of prediction accuracy on model predictive control performance. *Buildings*, 14.
29. Shaeri, M.R., Ellis, M.C. & Randriambololona, A.M. (2023). Xgboost-based model for prediction of heat transfer coefficients in liquid cold plates. In *ASTFE Digital Library*. Begel House Inc.
30. Luo, H. & Li, X. (2023). A hybrid model of CNN-BiLSTM and XGBoost for HVAC systems energy consumption prediction. In *2023 5th International Conference on Industrial Artificial Intelligence (IAI)*, 1-6. IEEE.
31. Zhang, S., Zhu, X., Anduv, B., Jin, X. & Du, Z. (2021). Fault detection and diagnosis for the screw chillers using multi-region XGBoost model. *Science and Technology for the Built Environment*, 27(5), 608-623.
32. Kaligambe, A., Fujita, G. & Tagami, K. (2022). Indoor room temperature and relative humidity estimation in a commercial building using the XGBoost machine learning algorithm. In *2022 IEEE PES/IAS PowerAfrica*, 1-5. IEEE.
33. Zheng, X., Yang, R., Wang, Q., Yan, Y., Zhang, Y., Fu, J. & Liu, Z. (2022). Comparison of GRNN and RF algorithms for predicting heat transfer coefficient in heat exchange channels with bulges. *Applied Thermal Engineering*, 217, 119263.
34. Godasiaei, S.H. & Chamkha, A.J. (2025). Advancing heat transfer modeling through machine learning: A focus on forced convection with nanoparticles. *Numerical Heat Transfer, Part A: Applications*, 86(10), 3409-3431.
35. Sammil, S. & Sridharan, M. (2024). Employing ensemble machine learning techniques for predicting the thermohydraulic performance of double pipe heat exchanger with and without turbulators. *Thermal Science and Engineering Progress*, 47, 102337.
36. Zhou, L., Garg, D., Qiu, Y., Kim, S.M., Mudawar, I. & Kharangate, C.R. (2020). Machine learning algorithms to predict flow condensation heat transfer coefficient in mini/micro-channel utilizing universal data. *International Journal of Heat and Mass Transfer*, 162, 120351.
37. Qian, N., Wang, X., Fu, Y., Zhao, Z., Xu, J. & Chen, J. (2020). Predicting heat transfer of oscillating heat pipes for machining processes based on extreme gradient boosting algorithm. *Applied Thermal Engineering*, 164, 114521.
38. Migliore, D.F., D'Alessio, G., Caggese, S., De Martin, A., Acerra, F., Sorli, M. & Fioriti, M. (2024). Comparative Analysis of Machine Learning Algorithms for Heat Exchangers Diagnosis in Electrified Aircraft. In *ICAS PROCEEDINGS. International Council of the Aeronautical Sciences*.
39. Zhuang, Z., Zhai, X., Ben, X., Wang, B. & Yuan, D. (2021). Accurately predicting heat transfer performance of ground-coupled heat pump system using improved autoregressive model. *PeerJ Computer Science*, 7, e482.

NOMENCLATURE

ANN	: Artificial Neural Network
BiLSTM	: Bidirectional Long Short-Term Memory
CFD	: Computational Fluid Dynamics
CNN	: Convolutional Neural Networks
DH	: District Heating
DC	: District Cooling
DT	: Decision Tree
GB	: Gradient Boosting
GRNN	: General Regression Neural Network
HTC	: Heat Transfer Coefficient
KNN	: K-Nearest Neighbour
ML	: Machine Learning
MLP	: Multilayer Perceptron
MRE	: Mean Relative Error
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percent Error
NB	: Naive Bayes
NTU	: Number of Transfer Unit
Nu	: Nusselt Number
Re	: Reynolds Number
RMSE	: Root Mean Square Error

RF	: Random Forest
RFR	: Random Forest Regression
RSLFN	: Random Single-Layer Feedforward Networks
RR	: Ridge Regression
R^2	: Coefficient of determination
SHAP	: SHapley Additive exPlanations
SMO	: Sequential Minimal Optimization
SVR	: Support Vector Regression
SVM	: Support Vector Machine
SVM-RBF	: Support Vector Machine -Radial Basis Function
XGBoost	: eXtreme Gradient Boosting

Greek Symbols

ε	: Effectiveness
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Subscripts

F	: Friction factor
N	: number of turbulators
L	: length of turbulators
Bd	: Bond Number
Co	: Convection number
Fr_f	: saturated liquid Froude number
Fr_{fo}	: liquid-only Froude number
Fr_g	: saturated vapor Froude number
Fr_{go}	: vapor-only Froude number
Ga	: Galileo number
Ka	: Kapitza number
Pr_f	: saturated liquid Prandtl number
Pr_g	: saturated vapor Prandtl number
Re_f	: saturated liquid Reynolds number
Re_{fo}	: liquid-only Reynolds number
Re_g	: saturated vapor Reynolds number
Re_{go}	: vapor-only Reynolds number
Su_f	: saturated liquid Suratman number
Su_g	: saturated vapor Suratman number
We_f	: saturated liquid Weber number
We_{fo}	: liquid-only Weber number
We_g	: saturated vapor Weber number
We_{go}	: vapor-only Weber number
RH	: relative humidity
DBT	: dry bulb temperature (outdoor)
WBT	: wet bulb temperature (outdoor)
T_{CHWR}	: chilled water temperature flowing into the chiller
T_{CHWS}	: chilled water temperature leaving the chiller
T_{CWR}	: condensate temperature flowing into the chiller
T_{CWS}	: condensate temperature leaving the chiller
f_{CHW}	: chilled water flow velocity into and out of the chiller
f_{CW}	: cooling water flow velocity into and out of the chiller
Q_C	: system Cooling Load

TCI	: Chilling water inlet temperature
TEI	: Chilled water inlet temperature
TEO	: Chilled water outlet temperature
T_{sc}	: Subcooled temperature
UA_c	: Overall heat conductance of condenser
UA_e	: Overall heat conductance of evaporator
$LMTD_c$: Logarithmic mean temperature difference of condenser
$LMTD_e$: Logarithmic mean temperature difference of evaporator
$APPR_c$: Approaching temperature difference of condenser