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Neural Network-based Performance Prediction of Heat Pipe and Loop Heat Pipe Heat Exchangers: A State-of-the-Art Review

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Abstract

As the demand for compact and high-efficiency thermal management systems intensifies, Heat Pipes (HPs) and Loop Heat Pipes (LHPs) have emerged as vital solutions due to their passive operation and superior heat transfer characteristics. However, accurately predicting their performance across varying operating conditions remains a formidable challenge. This review explores the transformative role of Artificial Neural Networks (ANNs) in modeling these complex systems, offering a data-driven alternative to conventional empirical and numerical methods. It critically evaluates diverse ANN architectures, training strategies, and hybrid approaches- including physics- informed models- that bridge the gap between physical laws and predictive analytics. The findings reveal that ANNs not only enhance prediction accuracy but also significantly reduce computational burden, making them ideal for real-time optimization in next-generation thermal systems. This study also outlines current challenges and paves the way for future research that combines domain knowledge with AI to revolutionize thermal engineering design and control.

Major Findings: *This study shows that Artificial Neural Networks (ANNs) effectively predict the nonlinear performance of heat pipes and loop heat pipes with higher accuracy than traditional methods. Integrating physics-informed and hybrid models enhances prediction reliability and physical consistency. ANN approaches also reduce experimental and computational costs, enabling real-time thermal system optimization.*

Keywords: *Artificial Intelligence, ANN, Data-Driven Modeling, Heat Pipe, Heat Transfer, Loop Heat Pipe, Neural Networks, Performance Prediction, Thermal Management, Thermal Resistance*

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1.0 Introduction

Heat pipes and loop heat pipes are efficient heat transfer devices utilizing phase change and capillary action to move heat from one location to another with minimal temperature drop. However, predicting their performance under varying conditions remains complex due to factors like working fluid properties, wick structure, heat input, and orientation. Artificial Neural Networks (ANNs), inspired by the human brain's learning mechanism, have demonstrated high accuracy in handling non-linear, multivariate data. This review explores the integration of ANNs in modeling and predicting HP and LHP performance metrics such as thermal resistance, heat transport capacity, and startup behavior.

Heat exchangers, pivotal components in numerous engineering applications, facilitate the transfer of thermal energy between two or more fluids[1]. Among the diverse array of heat exchanger technologies, heat pipes and loop heat pipes stand out due to their exceptional thermal performance and passive operation as explained in Figure 1[2]. Heat pipes exhibit remarkable heat transfer capabilities, often surpassing those of conventional solid conductors by several orders of magnitude, making them suitable for applications demanding efficient heat dissipation over considerable distances[2]. The operational advantages of heat pipes have spurred rapid technological advancements, leading to their widespread adoption in diverse engineering systems[3]. This review delves into the realm of employing neural networks for predicting the performance of heat pipe and loop heat pipe heat exchangers, elucidating the current state-of-the-art and highlighting future research directions[4].

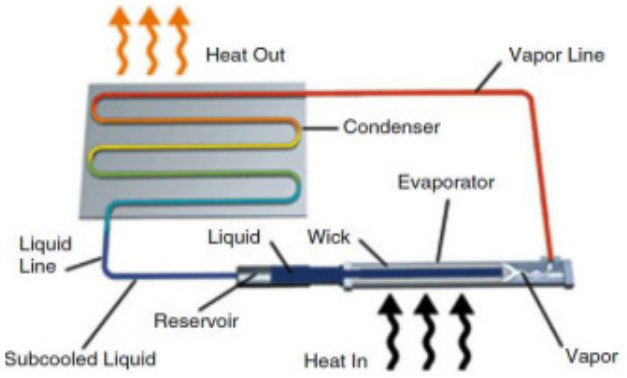


Figure 1. Schematic of loop heat pipe[2].

The integration of artificial intelligence and machine learning techniques into thermal engineering has opened new avenues for optimizing and predicting the behavior of complex systems. This review focuses on how neural networks are specifically applied to predict the performance of heat pipes and loop heat pipes, critical components in thermal management systems[5]. Unlike deterministic models, machine learning algorithms are valuable when detailed knowledge is unavailable, so exploration of machine learning algorithms has increased for heat transfer applications explained in Figure 2[6].

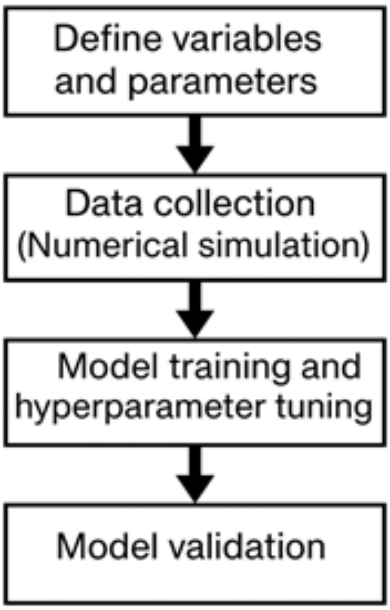


Figure 2. Flow chart of ML process[6].

1.1 Why Neural Networks?

1.1.1 Nonlinear Modeling

HP or LHP behavior is influenced by multiple interdependent parameters; ANNs can map these relations effectively. ANNs possess the inherent capability to approximate any continuous function, rendering them adept at capturing the intricate non-linear relationships governing heat transfer phenomena within HP or LHPs.

1.1.2 Adaptive Learning

NN models can be trained on experimental or simulation data, improving accuracy as more data becomes available. The adaptive learning capabilities of ANNs enable continuous refinement and improvement of predictive accuracy as new experimental or simulation data becomes incorporated into the training process.

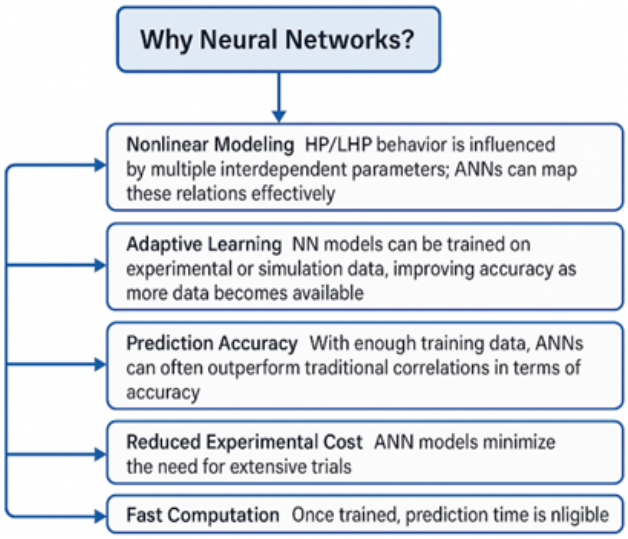


Figure 3. Key advantages of using neural networks for modeling heat pipe and loop heat pipe behaviour.

1.1.3 Prediction Accuracy

With enough training data, ANNs can often outperform traditional correlations in terms of accuracy. The recent developments in heat pipe technology include diverse types such as thermal diodes, variable conductance heat pipes and pulsating heat pipes[7,8]. The effectiveness of heat pipes is attributed to the latent heat of phase change of the working fluid during condensation and evaporation, which significantly surpasses the sensible heat capacity[8]. Furthermore, heat pipes are classified into 3 distinct sections based on their operational principles: The evaporator section, where heat absorption occurs; the condenser section, where heat is dissipated to the cooling medium; and the adiabatic section, which connects the evaporator and condenser sections, facilitating vapor transfer[9]. Neural networks offer a distinct advantage in handling the intricate relationships between design parameters, operating conditions, and performance metrics, making them well-suited for modeling heat pipe behavior[10]. Neural networks have found extensive use in various fields, including pattern detection, data interpretation, and function approximation. ANNs are employed because of their efficiency, generalization, and simplicity[11]. ANN is a machine-learning technology that analyzes complex data to find patterns that can be used to make predictions and decisions[12]. They can handle non-linear relationships and learn from data without explicit physical equations. Artificial neural networks are computational models inspired by the structure and function of biological neural networks[13]. ANNs can be applied to classification, pattern recognition, and data analysis[14].

1.1.4 Reduced Experimental Cost

ANN models minimize the need for extensive trials. In recent years, ANNs have emerged as powerful tools for prediction and simulation in diverse fields of science and engineering[15]. ANNs are extensively employed in analyzing intricate relationships between input and output variables, encompassing energy efficiency investigations[16]. ANNs serve as a data-driven technique that has gained widespread adoption for forecasting water resource variables over the last decade[17]. ANNs are relatively accurate when used for short-term predictions; despite global climate change research favoring the effects of interactions as the basis of study and the preference for long-term experimental research[18]. ANNs are capable of modeling complex nonlinear relationships between variables[19]. ANNs derive knowledge by identifying patterns and relationships in data and learn through experience rather than explicit programming[14,20]. Some ANN models can be considered as extensions of statistical models, some are closely connected to statistical modeling, while others pose difficult problems[14]. Inspired by the biological neuron system, artificial neural networks have been utilized to construct nonlinear models between independent and dependent variables, mimicking the learning of the biological neuron system[21]. Artificial neural networks represent a paradigm shift in computational methodologies, drawing inspiration from the intricate architecture and functionality of biological neural networks[22]. An ANN is a system made of connected artificial neurons[23]. The interconnected neurons work together to solve specific problems[24]. The

network of neurons and synapses stores the knowledge in a "distributed" manner[25].

1.1.5 Fast Computation

Once trained, prediction time is negligible. There is an increase in the convergence of simulation models together with ANN's due to the increase in size of data sets, with the potential to improve data evaluation and analysis[26]. ANN is known for its capacity to approximate complex and continuous functions with high precision, irrespective of the complexity inherent in the process being modelled[27]. This is because it can adjust the interconnections among a large number of internal nodes to process complex information within the system[28]. This adaptability and predictive power make ANNs a valuable tool for optimizing HP and LHP designs. Artificial neural networks present a paradigm shift in the prediction and optimization of complex engineering systems, offering a departure from traditional physics-based modeling approaches[29]. ANNs stand out for their capacity to discern intricate patterns and relationships within data, without the necessity of explicitly defined mathematical equations[30]. This capability is particularly advantageous when dealing with systems characterized by nonlinearity, multiple variables, and intricate interactions, such as heat pipes and loop heat pipes. By training on vast datasets of experimental or simulated data, ANNs can effectively learn the underlying behavior of these systems and make accurate predictions regarding their performance under varying conditions[31]. The use of neural networks can enhance the efficiency of technological processes, contributing to cost reduction and time savings[32]. Ann's ability to be continuously updated with minimal resources makes them attractive for real-time control scenarios[33]. They are trained through a network of interconnected nodes, each applying a nonlinear function to recognize input features by adjusting the weights of inputs[34]. This learning process allows the ANN to adapt to the underlying patterns in the data and make predictions or decisions based on the learned representations. Figure 3 represents key advantages of using neural networks for modeling heat pipe and loop heat pipe behavior.

The aim of this paper is to critically review and evaluate the application of Artificial Neural Networks (ANNs) for predicting the performance of Heat Pipes (HPs) and Loop Heat Pipes (LHPs), highlighting their effectiveness in modeling nonlinear thermal behavior, reducing experimental and computational efforts, and enhancing real-time optimization of thermal management systems.

2.0 Literature Review

The application of machine learning techniques in fluid mechanics has shown remarkable success, offering the potential to replace traditional numerical simulations with faster and more efficient alternatives[35]. The fusion of physics-based models with deep learning models through a physics-guided machine learning framework enables leveraging interpretable physics-based models with deep learning[36]. Physics-informed machine learning integrates theoretical laws as informative priors into the model, introducing inductive biases that guide the training process towards the most physically plausible model[37]. These methods leverage inductive biases based on the underlying physics laws, directly coding them into the network[38]. This methodology has been shown to improve the generalization capability, reduce the sample complexity, and enable predictions even in unseen regions[39]. The ability to incorporate established physics and conservation laws into the training process offers better generalization and accuracy[36,40,41].

Integrating machine learning with physics-based modeling can be achieved through various methodologies, including the development of physics-guided machine learning models and hybrid physics-machine learning frameworks[40,42]. These hybrid approaches aim to leverage the strengths of both physics-based models and machine learning algorithms to improve the prediction of complex dynamical systems[40]. Physics-based approaches are interpretable and can be extrapolated beyond the observed data, while machine learning algorithms can discover unknown patterns from the data[43]. The combination of machine learning with traditional fluid simulations can lead to improvements in both accuracy and speed, even in scenarios that deviate significantly from the training data[44]. The ongoing research aims to integrate machine learning and data-driven techniques in the field of fluid dynamics[45]. The integration of machine learning and data-driven techniques in the field of fluid dynamics can lead to improvements in both

accuracy and speed[46]. One such hybrid approach involves combining a physics-based full-order model with a data-driven reduced-order model to form an integrated framework[47].

The versatility of hybrid approaches is highlighted by their categorization into serial, parallel, or complex schemes, allowing for the combination of physics-driven and data-driven models to harness their respective advantages[48]. The serial approach uses the output of a data-driven model to act as the input to a physics-driven model, while the parallel approach runs both simultaneously, using their outputs in a combined way[49]. By integrating domain knowledge into machine learning models, it becomes possible to account for missing physics and improve the accuracy of predictions. One way to accomplish this is by incorporating a long short-term memory-based correction term into the predictive model to account for hidden physics[50].

The integration of physical insights through the addition of specific features at intermediate layers of the neural network architecture can enhance the learning process[51]. Machine learning can also be employed to refine the results of physical and mathematical models by addressing uncertainties that are difficult to describe analytically[52]. For example, one can construct a hybrid prediction scheme by combining a knowledge-based approach with a machine learning approach to improve performance and feasibility[53]. Hybrid models can be used to leverage machine learning to improve the efficiency and accuracy of simulations of fluid flows[47]. The integration of machine learning with simulation can be achieved from either machine learning or a simulation perspective[54].

2.1 Literature Review of ANN Applications in HP and LHP

The use of artificial neural networks to predict the thermal performance of heat pipes and loop heat pipes represents a significant advancement in heat transfer technology[55]. Artificial neural networks have emerged as a powerful tool for predicting the thermal performance of heat pipes and loop heat pipes, offering a data-driven approach that complements traditional analytical and

Table 1. ML and ANN applications in fluid mechanics and heat pipes

Topic	Summary	Reference
Application of ML in fluid mechanics	ML techniques offer faster alternatives to numerical simulations.	35
Physics-guided machine learning	Combines interpretable physics-based models with deep learning for better prediction.	36
Physics-informed ML	Incorporates physics laws as inductive biases to guide training towards plausible models.	37,38
Advantages of physics integration	Enhances generalization, reduces sample complexity, and improves accuracy.	39,36,40,41
Hybrid modeling approaches	Uses physics-guided and hybrid frameworks for predicting complex systems.	40,42
Benefits of combining physics and ML	Leverages interpretability of physics models and pattern recognition of ML.	43,44,45,46
Full-order + Reduced-Order models	Combines full-order physics models with data-driven reduced models.	47

Hybrid categorization	Hybrid models categorized as serial, parallel, or complex based on data-physics interaction.	48,49
Hidden physics correction	LSTM correction terms used to integrate domain knowledge and handle missing physics.	50
Enhanced NN learning	Physical insights added to NN intermediate layers improve learning.	51
Uncertainty refinement	ML helps refine mathematical model predictions under uncertain conditions.	52
Hybrid prediction scheme	Combines knowledge-based and ML approaches for improved prediction.	53,54
ANN in heat pipe prediction	ANNs predict thermal performance of HP and LHP effectively.	55
Hybrid empirical-bayesian ANN	Combines data fitting and prior knowledge to enhance model robustness.	56
ANN applications	Used in biomedicine, chemistry, and materials for classification and prediction.	55,57
Multi-layer perceptron	Widely used ANN model for diverse research domains.	58
ANN with fuzzy logic and wavelets	Enhances accuracy and data interpretation using integrated techniques.	59
Backpropagation in ANN	Key algorithm for optimizing ANN prediction performance.	60,61
ANN generalization	Learns from data to generalize in unseen scenarios for complex simulations.	62,14

numerical methods. The performance of a hybrid empirical- Bayesian artificial neural network model depends on both its fit to observed data and its sensitivity compared to prior knowledge of the system's behavior[56]. Incorporating prior knowledge during ANN training helps enhance the model's accuracy, efficiency, and robustness. Incorporating prior knowledge during ANN training helps enhance the model's accuracy, efficiency, and robustness.

The application of artificial neural networks in diverse fields, including biomedicine, chemistry, and material science, showcases the broad applicability of this machine learning technique[55]. The use of neural networks extends to various applications, including modeling, classification, pattern recognition, and prediction[57]. Multi-layer perceptron, characterized by its extensive use as a machine learning algorithm, has been employed across various research domains[58]. The development of artificial neural networks has been marked by the integration of fuzzy logic and wavelet analysis to improve data interpretation and model accuracy[59]. The algorithm adjusts the connectivity between layers using an error back propagation algorithm to perform prediction and estimation tasks[60].

The back-propagation algorithm is widely used in training artificial neural networks, reflecting its effectiveness in optimizing network performance[61]. Artificial neural networks can learn from data and generalize to new, unseen conditions, making them invaluable for simulating complex systems where traditional methods fall short[14,62]. Table 1 represents ML and ANN applications in fluid mechanics and heat pipes.

3.0 Neural Networks in Heat Exchanger Analysis

Neural networks, inspired by the biological structure of the human brain, have emerged as powerful tools for modeling intricate relationships in complex systems[63]. The applications of neural networks span various engineering disciplines, including heat transfer, where they have been successfully employed for performance prediction, optimization, and control of heat exchangers. Neural networks have demonstrated their ability to model the complex thermal behavior of heat exchangers and can be successfully applied with accuracy in areas like heat pumps coupled with refrigeration and air-conditioning systems[64]. The capability of neural networks to learn from data and generalize to unseen scenarios makes them particularly well-suited for handling the nonlinear and multi-parameter dependencies inherent in heat pipe and loop heat pipe operation. One of the compelling applications of neural networks lies in temperature estimation, where they have shown superior approximation capabilities compared to methods like Kriging and capacitor models, especially when dealing with the non-linear relationships between temperature sources and targets[65]. The efficacy of neural networks in such applications is heavily influenced by the quality and quantity of training data, network architecture, and the selection of appropriate training algorithms, highlighting the need for meticulous consideration of these factors during model development. Traditional numerical solvers, while effective, often lack the flexibility to adapt to variations in parameters such as initial and boundary conditions, permeability, and source terms, necessitating retraining for each alteration[66].

The application of machine learning extends to fluid dynamics, encompassing turbulence modeling, flow estimation, and optimization of flow control designs, revealing the ability of these techniques to accurately model intricate input-output relationships within nonlinear fluid flows. The Figure 4 illustrates a supervised machine learning framework for fluid flow analysis, where direct numerical simulation data is used to train neural networks for tasks like force estimation, flow reconstruction, and super-resolution.

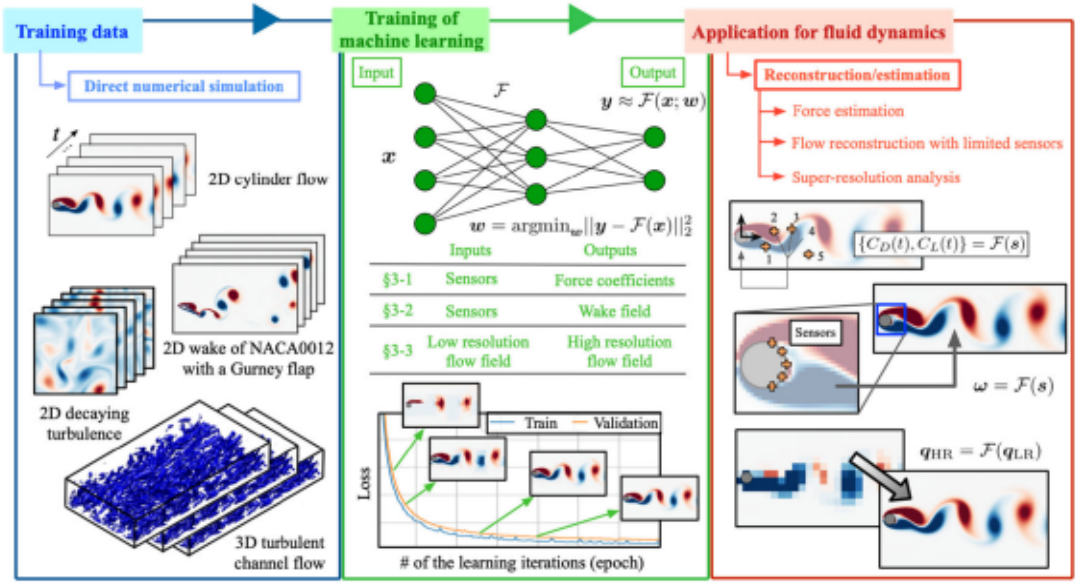


Figure 4. Overview of supervised machine learning problems for fluid flows[67].

It highlights the mapping from low-resolution or sensor data to high-resolution flow fields using trained models[67].

The capability of neural networks to accelerate computational fluid dynamics simulations is particularly noteworthy, where they can either directly solve the governing equations or act as surrogate models to approximate the solutions obtained from traditional numerical methods. The integration of physics-informed neural networks into scientific computing has further revolutionized the field, enabling the solution of partial differential equations with limited data by leveraging automatic differentiation to incorporate established physics and conservation laws into the training process[66,68]. The benefits of incorporating physics into neural network training extend to enhanced generalization and accuracy, demonstrating the importance of integrating established physical principles into the learning process.

Neural networks have demonstrated exceptional potential in analyzing and optimizing heat exchanger performance, particularly for complex systems such as heat pipes and loop heat pipes. Their ability to model nonlinear and multi-parameter dependencies without the need for explicit physical equations makes them highly effective for thermal behavior prediction, control, and real-time analysis. Compared to traditional numerical solvers, ANNs offer greater flexibility and adaptability, especially when dealing with parameter variations and limited data scenarios. The integration of physics-informed neural networks further enhances their accuracy and consistency by embedding fundamental physical laws into the learning process. As a result, neural networks provide a robust framework for advancing the design, monitoring, and predictive capabilities of modern heat exchanger systems.

4.0 Challenges and Future Directions

Despite the promising advancements in neural network-based performance prediction of heat pipes and loop heat pipes, several challenges remain. One significant obstacle is the limited availability of comprehensive experimental datasets for training and validating neural network models. The development of robust and generalizable models necessitates large datasets that span a wide range of operating conditions, geometric parameters, and fluid properties. The ability of neural networks to model intricate relationships makes them valuable for reducing the reliance on computationally intensive methods and overcoming the limitations of traditional numerical simulations[69]. Moving forward, future research endeavors should focus on addressing these challenges and exploring new avenues for enhancing the accuracy, reliability, and applicability of neural network-based performance prediction models for heat pipes and loop heat pipes. The integration of neural networks with computational fluid dynamics simulations also presents opportunities for developing hybrid modeling approaches that leverage the strengths of both methodologies[70].

The versatility of neural networks has been showcased through various applications, including turbulence closure modeling, spatio-temporal super-resolution, state-estimation, and nonlinear model order reduction[36]. The application of physics-informed neural networks extends to solving complex problems, such as the prediction of pressure drop in multiphase flow within pipes, by integrating physical laws into the neural network architecture. Inaccurate predictions from extrapolation adversely affect the trustworthiness of neural networks for scientific applications, and embedding the known physics to enhance the generalizability is a challenge and opportunity for data-driven algorithm developments[36]. By incorporating physical principles into deep learning models, it is possible to improve not only prediction accuracy but, more importantly, physical consistency[71]. This fusion of physical understanding with machine learning techniques offers new routes for building reliable and physically consistent models across a range of scientific and engineering applications[72].

The integration of domain knowledge into the design and learning of machine learning models is crucial for bridging the gap between physics-based models and data mining models[73]. Traditional numerical simulation runs can be computationally expensive and time-consuming, driving the development of machine learning-based methods as faster alternatives[74]. The development

Table 2. Challenges and opportunities in neural network-based prediction for heat pipes and loop heat pipes

Topic	Summary	Reference
Data availability challenge	Limited experimental datasets hinder the training and validation of robust neural network models.	69
Need for diverse datasets	Robust models require data covering diverse operating conditions, geometries, and fluids.	69
Reduction of computational burden	NNs can reduce reliance on intensive numerical simulations, offering faster predictions.	69
Hybrid modeling opportunities	Combining NNs with CFD allows leveraging strengths of both methods.	70
NN versatility in applications	Used in turbulence modeling, super-resolution, state-estimation, and model order reduction.	36
Physics-informed neural networks (PINNs)	Solves complex problems like multiphase flow pressure drop using physical laws.	36
Generalizability challenge	Extrapolation issues affect trust; embedding physics can improve generalization.	36
Improved physical consistency	Incorporating physical laws enhances model accuracy and consistency.	71,72
Bridging physics and ML models	Domain knowledge integration helps link physics-based and data-driven approaches.	73
Simulation cost motivation	High simulation costs motivate the shift to ML-based prediction methods.	74
Development of PINNs	PINNs blend data-driven methods with physical laws for complex problem-solving.	75
Physics-enhanced features	Approximate physics provide intermediate features to improve statistical model performance.	51
Hybrid model workflow	ML models can act as post-processors for physics-based model outputs.	76
Standardization of hybrid methods	Organizing hybrid modeling methods is the key to unlocking full potential.	77
Emergence of hybrid modeling	Combining physics and data-driven methods is a growing field with evolving standards.	78
Importance of prior knowledge	Embedding prior knowledge into ANN improves model robustness and efficiency.	79
ANN architecture	ANNs consist of input, hidden, and output layers for complex pattern recognition.	80

of physics-informed neural networks represents a significant step towards incorporating physical understanding into machine learning models[75]. Physics-informed neural networks offer a way to tackle complex scientific and engineering problems by combining the strengths of both data-driven and physics-based approaches.

Data-driven models can be enhanced by incorporating approximate physics to provide intermediate features to statistical models, bridging the gap between simplified theories and more accurate models[51]. This is often done by feeding a data-driven model with the outputs of a process-based model, allowing the data-driven model to act as a post-processor within a hybrid modelling workflow[76]. However, it is crucial to meticulously organize and standardize the methods of combining machine learning and model-based approaches to fully harness the potential of hybrid models[77]. Hybrid modeling, which combines physics-based and data-driven approaches, is a relatively new field of research that is still evolving[78].

The integration of prior knowledge into artificial neural networks is crucial for enhancing model accuracy, efficiency, and robustness[79]. Artificial neural networks use multiple layers of nodes, or artificial neurons, to recognize patterns and make decisions with greater accuracy than traditional machine learning methods[80]. The architecture of neural networks includes an input layer, hidden layers, and an output layer. Table 2 represents challenges and opportunities in neural network-based prediction for heat pipes and loop heat pipes.

While Artificial Neural Networks (ANNs) have shown great promise in predicting the performance of heat pipes and loop heat pipes, several challenges persist that limit their full potential. The primary obstacle remains the scarcity of comprehensive and diverse experimental datasets necessary for training robust, generalizable models. Furthermore, the extrapolation capability of neural networks is often limited, raising concerns about reliability in unseen scenarios. To overcome these limitations, future research must focus on integrating domain-specific knowledge, such as physical laws and boundary conditions, into neural network architectures through hybrid and physics-informed approaches. Standardizing methods for combining machine learning with traditional simulations and ensuring physical consistency in predictions will be crucial. These advancements will pave the way for the development of more accurate, interpretable, and scalable ANN models for complex thermal systems in real-world applications.

5.0 Discussion

Artificial neural networks are inspired by the structure and function of biological neural networks and are used to make predictions or decisions without being explicitly programmed for specific tasks[81]. Artificial neural networks are inspired by the structure and function of biological neural networks and are used to make predictions or decisions without being explicitly programmed for specific tasks. Artificial neural networks, inspired by the biological neural networks in the brain, are connectionist models that map inputs to outputs[82]. The artificial neural network is implemented by developing a computational learning algorithm that does not need to program all the rules since it is able to build up its own rules of behavior through what we usually refer to as "experience"[83]. Artificial neural networks models have the ability to address a wide range of challenges, including function approximation, classification, time series prediction, and pattern recognition[84]. The human brain's ability to perform complex, nonlinear, and parallel processing inspires the development of artificial neural networks, which aim to replicate these capabilities in computational systems[83]. Since the first neural model by McCulloch and Pitts there have been developed hundreds of different models considered as artificial neural networks[85].

Artificial neural networks are capable of mapping, modeling, and classifying non-linear systems[86]. Artificial neural networks learn by adjusting the connections between neurons in response to training data, gradually improving their performance on a specific task[87]. These networks are structured as weighted directed graphs, where nodes represent neurons and arcs represent connections carrying information, with weights denoting the importance of each connection[88]. ANNs have a layered structure composed of interconnected neurons, which interact with each other to perform a given task[89]. The back propagation algorithm, which fine-tunes the network to produce the desired output, is often used to

train the network using a sample of known input/output relationships[90].

Cooling with PCM (Phase Change Material) was found to exhibit significantly higher cooling performance under high power operation as compared to conventional methods such as convection and heat pipes[91]. The silicon and copper-based PCBs (with nine sectional components) with different flow rates were used to conduct the simulation, and the results show that the copper substrates were proved to be beneficial in cooling component temperatures down. At a 5 m/s airflow and the temperature within the range of 30-47° C, IC cooling could be enhanced at a 2 m/s lower airflow demand by between 1.50 and 11.12° C[92]. Of the materials considered in mini channel PCM systems, n-Eicosane was the most efficient in terms of heat transfer, reducing the temperature from 53.234° C to 51.520° C compared to only 0.5° C and 1.35° C reduction in the case of paraffin wax and ATP 78, respectively[93]. More recent studies have extended to minijet impingement, nanofluids, water cooling methods, and promoting devices such as twisted tape inserts[94-99]. More extensive research include electronic cooling applications, biodiesel systems, solar thermal collector, substrate cooling, aerodynamics and intelligent systems such as the fuzzy logic control systems[100-108]. Further technological progress includes cooling in windmills, surface modification properties, locations for HVACR systems, vehicular thermal protection safety and adsorptives approach[109-123]. Applications can be found in the steel plate, welded joint, curved structure, PCM-enhanced IC cooling system and fuel additive optimization[124-132]. In addition, Multi-Type Phase Change (MTPC) materials were presented for better IC heat transfer, deep learning was applied for detecting surface defects in geology, and geometric optimization was performed to improve the thermal characteristics of the micro channel heat sinks. Emissions control and solid particle reduction, reduced emissions with biodiesel blends and catalytic reactors, the use of trapezoidal ducts with delta-wing vortex generators, more effective than rectangular in solar collectors for sustainable thermal energy storage systems[133-139].

Another related work addressed the problems of shaft failure in industrial paddle mixers and another improvement of thermal management for portable electronic devices with PCM[140]. FEA was also used to optimise the design of the mixer shaft to improve performance[141]. Heat transfer enhancement was also analyzed with the help of perforated twisted tape inserts[142]. Artificial intelligence was also praised for its ability to mitigate the ecological footprints of mining. Dynamic response of a vibratory bowl feeder with the use of a paddle shaft system was studied by means of numerical simulation[143-145].

6.0 Conclusion

ANNs have been applied successfully to solve numerous and complex problems. ANN models, as a result of their black-box nature, are unable to offer explicit equations that correlate input and output variables, which is an important drawback. In this paper, it is shown that ANN approaches yield more realistic results compared to the empirical correlations. Therefore, computational fluid dynamics simulations are needed for the accurate prediction of heat transfer characteristics in complex geometries. The training process of ANNs usually involves optimization techniques such as gradient descent to minimize the difference between the predicted and actual outputs. The universal approximation theorem suggests that ANNs can approximate any continuous function, making them suitable for a wide range of applications. One advantage of ANNs is their capability to automatically learn complex relationships from data, eliminating the need for manual feature engineering. The success of ANNs depends on several factors, including network architecture, training data quality, and hyperparameter selection. Artificial neural networks are used as universal function approximators to model complex relationships between input and output variables. These networks are trained using the back-propagation algorithm, which adjusts the weights of the connections between neurons to minimize the prediction error. The values of these weight factors between the neurons are adjusted during the training process, either from external information or by the neurons themselves in response to input signals. This adjustment is crucial to the learning and memory capabilities of ANNs. The use of neural networks for predicting the thermal performance of heat pipes and loop heat pipes presents a promising shift from traditional methods. With advancements in AI and data availability, ANN models offer a fast, accurate, and flexible

alternative for the design and real-time optimization of thermal systems. Continued research in this domain will lead to more robust, interpretable, and generalizable models for a wide array of thermal management applications.

7.0 References

1. Mangrulkar CK, Dhoble AS, Chamoli S, Gupta A, Gawande VB. Recent advancement in heat transfer and fluid flow characteristics in cross flow heat exchangers. Renew Sustain Energy Rev. 2019; 113:109220. https://doi.org/10.1016/j.rser.2019.06.027
2. Girishkumar V. Advancements in heat pipe science and technology. IJEAST. 2020; 5(4):375-382. https://doi.org/10.33564/ijeast.2020.v05i04.059
3. Abdullahi B, Al-Dadah R, Mahmoud S. Thermosyphon heat pipe technology. IntechOpen. 2019. https://doi.org/10.5772/intechopen.85410
4. Faghri A. Review and advances in heat pipe science and technology. J Heat Transf. 2012; 134(12):123001. https://doi.org/10.1115/1.4007407
5. Prabir B, Safwan MM, Saikat M, Mandal P. Modelling of artificial neural network to control the cooling rate of a laboratory scale run-out table. MATEC Web Conf. 2020; 306(03004):1-5. https://doi.org/10.1051/matecconf/202030603004
6. Kwon B, Ejaz F, Hwang LK. Machine learning for heat transfer correlations. Int Commun Heat Mass Transf. 2020; 116:104694. https://doi.org/10.1016/j.icheatmasstransfer.2020.104694
7. Riffat S, Ma X. Recent developments in heat pipe technology and applications: A review. IJLCT. 2007; 2(2):162-177. https://doi.org/10.1093/ijlct/2.2.162
8. Chan CW, Siqueiros E, Chin JL, Royapoor M, Roskilly AP. Heat utilisation technologies: A critical review of heat pipes. Renew Sustain Energy Rev. 2015; 50:615-627. https://doi.org/10.1016/j.rser.2015.05.028
9. Yu Y, An G, Wang L. Major applications of heat pipe and its advances coupled with sorption system: A review. Front Energy. 2019; 13(1):172-184. https://doi.org/10.1007/s11708-019-0610-6
10. Faroughi SA, Pawar N, Fernandes C, Das S, Kalantari NK, Mahjour SK. Physics-guided, physics-informed, and physics-encoded neural networks in scientific computing. arXiv. 2022. https://arxiv.org/abs/2211.07377
11. Aghbashlo M, Hosseinpour S, Mujumdar AS. Application of Artificial Neural Networks (ANNs) in drying technology: A comprehensive review. Dry Technol. 2015; 33(12):1397-1462. https://doi.org/10.1080/07373937.2015.1036288
12. Dhumal AR, Kulkarni AP, Ambhore NH. A comprehensive review on thermal management of electronic devices. J Eng Appl Sci. 2023; 70(1). https://doi.org/10.1186/s44147-023-00309-2
13. Palmi K, Kubinski W, Darnowski P. Prediction of the evolution of the nuclear reactor core parameters using artificial neural network. arXiv. 2023. https://arxiv.org/abs/2304.10337
14. Basheer IA, Hajmeer M. Artificial neural networks: fundamentals, computing, design, and application. J Microbiol Methods. 2025; 43(1):3-31. https://doi.org/10.1016/s0167-7012(00)00201-3
15. Tan Z, Qin Z, Zhang Q, Liu Y, Liu F. Prediction and process analysis of tensile properties of sinter-hardened alloy steel by artificial neural network. Metals. 2022; 12(3):381. https://doi.org/10.3390/met12030381
16. Obuch SK, Piotrowska B, Starzec M. Gaining CO_2 reduction insights with SHAP: Analyzing a shower heat exchanger with artificial neural networks. Energies. 2025; 18(8):1904. https://doi.org/10.3390/en18081904
17. Wunsch A, Liesch T, Broda S. Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (NARX). J Hydrol. 2018; 567:743-758. https://doi.org/10.1016/j.jhydrol.2018.01.045
18. Liu Z, Peng C, Xiang W, Dalun T, Deng X, Zhao M. Application of artificial neural networks in global climate change and ecological research: An overview. Chin Sci Bull. 2010; 55(34):3853-3863. Available from: https://doi.org/10.1007/s11434-010-4183-3
19. Barbedo JGA. A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. Drones. 2019; 3(2):40. https://doi.org/10.3390/drones3020040
20. Rathi NK, Rathi N. An application of ANN for modeling and optimisation of process parameters of manufacturing process: A review. IJEAST. 2020; 4(12):127-134. https://doi.org/10.33564/ijeast.2020.v04i12.017
21. Zhang Y, Ma J, Liang S, Li X, Li M. An evaluation of eight machine learning regression algorithms for forest aboveground biomass estimation from multiple satellite data products. Remote Sens. 2020; 12(24):4015. https://doi.org/10.3390/rs12244015

22. Zhao Z, Meng FR, Yang Q, Zhu H. Using artificial neural networks to produce high-resolution soil property maps. Advanced Applications for Artificial Neural Networks. InTech eBooks. 2017. https://doi.org/10.5772/intechopen.70705
23. Eckart L, Eckart S, Enke M. A brief comparative study of the potentialities and limitations of machine-learning algorithms and statistical techniques. E3S Web Conf. 2021; 266:2001. https://doi.org/10.1051/e3sconf/202126602001
24. Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D. Deep neural networks based recognition of plant diseases by leaf image classification. Comput Intell Neurosci. 2016. https://doi.org/10.1155/2016/3289801
25. Cavalieri S, Maccarrone P, Pinto R. Parametric *vs.* neural network models for the estimation of production costs: A case study in the automotive industry. Int J Prod Econ. 2003; 91(2):165-177. https://doi.org/10.1016/j.ijpe.2003.08.005
26. Mawson VJ, Hughes BR. Deep learning techniques for energy forecasting and condition monitoring in the manufacturing sector. Energy Build. 2020; 217:109966. https://doi.org/10.1016/j.enbuild.2020.109966
27. Khashei M, Bijari M. A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. Appl Soft Comput. 2010; 11(2):2664-2675. https://doi.org/10.1016/j.asoc.2010.10.015
28. Cheng Q, Chunhong Z, Qianglin L. Development and application of random forest regression soft sensor model for treating domestic wastewater in a sequencing batch reactor. Sci Rep. 2023; 13(9149). https://doi.org/10.1038/s41598-023-36333-8
29. Liu Y, Jiang X. Towards predictive maintenance of a heavy-duty gas turbine a new hybrid intelligent methodology for performance simulation. Annual Conference of the PHM Society. 2022; 14(1). https://doi.org/10.36001/phmconf.2022.v14i1.3148
30. Tavakoli R, Najafi M, Sharifara A. Artificial neural networks and adaptive neuro-fuzzy models for prediction of remaining useful life. arXiv. 2019. https://arxiv.org/abs/1909.02115
31. Raj KH, Sharma RS, Srivastava S, Patvardhan C. Modeling of manufacturing processes with ANNs for intelligent manufacturing. Int J Mach Tools Manuf. 2000; 40(6):851-868. https://doi.org/10.1016/s0890-6955(99)00094-2
32. Wrobel J, Kulawik A. Prediction of the superficial heat source parameters for TIG heating process using FEM and ANN modeling. Entropy. 2019; 21(10):954. https://doi.org/10.3390/e21100954
33. El-Din AG, Smith DW, El-Din MG. Application of artificial neural networks in wastewater treatment. J Environ Eng Sci. 2004; 3(1):S81-S95. https://doi.org/10.1139/s03-067
34. Kadauw AAA. Neural network optimization of mechanical properties of ABS-like photopolymer utilizing Stereolithography (SLA) 3D printing. J Manuf Mater Process. 2025; 9(4):116. https://doi.org/10.3390/jmmp9040116
35. Brunton SL. Applying machine learning to study fluid mechanics. Acta Mech Sin. 2021; 37(12):1718-1726. https://doi.org/10.1007/s10409-021-01143-6
36. Pawar S, San O, Nair A, Rasheed A, Kvamsdal T. Model fusion with physics-guided machine learning. arXiv. 2021. http://export.arxiv.org/pdf/2104.04574
37. Latrach A, Malki ML, Morales M, Mehana M, Rabiei M. A critical review of physics-informed machine learning applications in subsurface energy systems. Geoenergy Sci Eng. Elsevier. 2024; 239:212938. https://doi.org/10.1016/j.geoen.2024.212938
38. Gokhale G, Claessens B, Develder C. Physics informed neural networks for control oriented thermal modeling of buildings. Appl Energy. 2022; 314:118852. https://doi.org/10.1016/j.apenergy.2022.118852
39. Hao Z, Liu S, Zhang Y, Ying C, Feng Y, Su H, Zhu J. Physics-informed machine learning: A survey on problems, methods and applications. arXiv. 2022. https://arxiv.org/abs/2211.08064
40. Willard J, Jia X, Xu S, Steinbach M, Kumar V. Integrating physics-based modeling with machine learning: A survey. 2020; 1(1). https://doi.org/10.1145/1122445.1122456
41. Ba Y, Zhao G, Kadambi A. Blending diverse physical priors with neural networks. arXiv. 2019. https://arxiv.org/abs/1910.00201
42. Willard J, Jia X, Xu S, Steinbach M, Kumar V. Integrating scientific knowledge with machine learning for engineering and environmental systems. ACM Comput Surv. 2022; 55(4):1-37. https://doi.org/10.1145/3514228
43. Pawar S, Ahmed SE, San O, Rasheed A. Data-driven recovery of hidden physics in reduced order modeling of fluid flows. Physics of Fluids. 2020; 32:036602. https://doi.org/10.1063/5.0002051

44. Kochkov D, Smith JA, Alieva A, Wang M, Brenner MP, Hoyer S. Machine learning-accelerated computational fluid dynamics. PNAS. 2021; 118(21):e2101784118. https://doi.org/10.1073/pnas.2101784118
45. Brunton SL, Hemati MS, Taira K. Special issue on machine learning and data-driven methods in fluid dynamics. Theor Comput Fluid Dyn. 2020; 34(4):333-337. https://doi.org/10.1007/s00162-020-00542-y
46. Brenner MP, Eldredge JD, Freund JB. Perspective on machine learning for advancing fluid mechanics. Phys Rev Fluids. 2019; 4(10). https://doi.org/10.1103/physrevfluids.4.100501
47. Ahmed SE, San O, Kara K, Younis R, Rasheed A. Interface learning in zonal multifidelity simulations of fluid flows with a hybrid analysis and modeling framework. arXiv. 2020.
48. Xu Q, Shi Y, Bamber J, Tuo Y, Ludwig R, Zhu XX. Physics-aware machine learning revolutionizes scientific paradigm for machine learning and process-based hydrology. arXiv. 2023. https://arxiv.org/abs/2310.05227
49. Zhao K, Xue J, Meng X, Li G, Wu M. Learning residual model of model predictive control *via* random forests for autonomous driving. arXiv. 2023. https://arxiv.org/abs/2304.04366
50. Pawar S, San O, Rasheed A, Navon IM. A nonintrusive hybrid neural-physics modeling of incomplete dynamical systems: Lorenz equations. arXiv. 2021. https://arxiv.org/abs/2104.00114
51. Pawar S, San O, Aksoylu B, Rasheed A, Kvamsdal T. Physics guided machine learning using simplified theories. Phys Fluids. 2021; 33(1):011701. https://doi.org/10.1063/5.0038929
52. Zotkin O, Osokina A, Simonov M, Alla A, Sharifov AR. A novel approach to refinment reservoir proxy model using machine-learning techniques. SPE Annual Caspian Technical Conference. 2019. https://doi.org/10.2118/198411-ms
53. Pathak J, Wikner A, Fussell R, Chandra S, Hunt BR, Girvan M, Ott E. Hybrid forecasting of chaotic processes: Using machine learning in conjunction with a knowledge-based model. Chaos. 2018; 28(4):041101. https://doi.org/10.1063/1.5028373
54. Rueden L von, Mayer S, Sifa R, Bauckhage C, Garcke J. Combining machine learning and simulation to a hybrid modelling approach: Current and future directions. LNISA. 2020; 12080: pp. 548. https://doi.org/10.1007/978-3-030-44584-3_43
55. Tsai HF, Podder S, Chen PY. Microsystem advances through integration with artificial intelligence. Micromachines. 2023; 14(4):826. https://doi.org/10.3390/mi14040826
56. Rath JS, Hutton PH, Chen L, Roy SB. A hybrid empirical-bayesian artificial neural network model of salinity in the San Francisco Bay-Delta estuary. Environ Model Softw. 2017; 93:193-208. https://doi.org/10.1016/j.envsoft.2017.03.022
57. Abiodun OI, Jantan A, Omolara AE, Dada KV, Mohamed N, Arshad H. State-of-the-art in artificial neural network applications: A survey. Heliyon. 2018; 4(11):e00938. https://doi.org/10.1016/j.heliyon.2018.e00938
58. Badu NKAA, Missah YM, Amekudzi LK, Najim U, Twum F, Ahene E. Rainfall prediction using machine learning algorithms for the various ecological zones of Ghana. IEEE Access. 2021; 10:5069. https://doi.org/10.1109/access.2021.3139312
59. Huang Y. Advances in artificial neural networks-methodological development and application. Algorithms. 2009; 2(3):973-1007. https://doi.org/10.3390/algor2030973
60. Park SH, Jung HS, Lee S, Yoo HS, Cho NW, Lee MJ. A trend analysis of development projects in South Korea during 2007-2016 using a multi-layer perceptron based artificial neural network. Appl Sci. 2021; 11(15):7133. https://doi.org/10.3390/app11157133
61. Liu S, Chang R, Zuo J, Webber R, Xiong F, Dong N. Application of artificial neural networks in construction management: Current status and future directions. Appl Sci. 2021; 11(20):9616. https://doi.org/10.3390/app11209616
62. Tomar PS, Singh V, Rathod T. Rainfall simulation using ANN based Multilayer Perceptron (MLP) and Multiple Linear Regression (MLR) technique for Bhopal, Madhya Pradesh. IJRASET. 2021; 9(VII):1069. https://doi.org/10.22214/ijraset.2021.36470
63. Sridharan M. Applications of artificial intelligence techniques in heat exchanger systems. Advanced Analytic and Control Techniques for Thermal Systems with Heat Exchangers. Elsevier. 2020: pp. 325-334. https://doi.org/10.1016/b978-0-12-819422-5.00015-3
64. Singh RK, Ahmad SN, Priyadarshi N, Rahman O, Bhoi AK. Waste heat energy utilization in refrigeration and air-conditioning. IOP Conf Ser Mater Sci Eng. 2018; 402:12060. https://doi.org/10.1088/1757-899x/402/1/012060

65. Melis RB, McCarthy U, Garcia LR, Hierro JG, Robla JI. New trends in cold chain monitoring applications- A review. Food Control. 2018; 86:170-182. https://doi.org/10.1016/j.foodcont.2017.11.022
66. Diab W, Chaabi O, Alkobaisi S, Awotunde AA, Kobaisi MA. Learning generic solutions for multiphase transport in porous media *via* the flux functions operator. Adv Water Resour. 2023; 183:104609. https://doi.org/10.1016/j.advwatres.2023.104609
67. Fukami K, Fukagata K, Taira K. Assessment of supervised machine learning methods for fluid flows. Theore Comput Fluid Dyn. 2020; 34(4):497-519. https://doi.org/10.1007/s00162-020-00518-y
68. Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys. 2018; 378:686-707. https://doi.org/10.1016/j.jcp.2018.10.045
69. Tanyu DN, Ning J, Freudenberg T, Heilenkotter N, Rademacher A, Iben U, Maass P. Deep learning methods for partial differential equations and related parameter identification problems. arXiv. 2022. https://arxiv.org/abs/2212.03130
70. Huynh MTT, Truong TQ, Doan TN, Huynh TN, Nguyen T, Nguyen V, Nguyen YQ. Prediction of flow field in a solar chimney using ANFIS technique. IOP Conf Ser Mater Sci Eng. 2021; 1109(1):12067. https://doi.org/10.1088/1757-899x/1109/1/012067
71. Wang R, Kashinath K, Mustafa M, Albert A, Yu R. Towards physics-informed deep learning for turbulent flow prediction. 2020; 1457-1466. https://doi.org/10.1145/3394486.3403198
72. Pawar S, San O, Nair A, Rasheed A, Kvamsdal T. Model fusion with physics-guided machine learning: Projection-based reduced-order modeling. Physics of Fluids. 2021; 33(6):067123. https://doi.org/10.1063/5.0053349
73. Muralidhar N, Bu J, Cao Z, He L, Ramakrishnan N, Tafti DK, Karpatne A. Physics-guided design and learning of neural networks for predicting drag force on particle suspensions in moving fluids. arXiv. 2019. https://arxiv.org/abs/1911.04240
74. Wen G, Li Z, Azizzadenesheli K, Anandkumar A, Benson S. U-FNO- An enhanced Fourier neural operator-based deep-learning model for multiphase flow. arXiv. 2021. https://arxiv.org/abs/2109.03697
75. Bihlo A, Popovych RO. Physics-informed neural networks for the shallow-water equations on the sphere. J Comput Phys. 2022; 456:111024. Available from: https://doi.org/10.1016/j.jcp.2022.111024
76. Yu Q, Tolson BA, Shen H, Han M, Mai J, Lin J. Enhancing long short-term memory (LSTM)- based streamflow prediction with a spatially distributed approach. Hydrology and earth system sciences. 2024; 28(9):2107. https://doi.org/10.5194/hess-28-2107-2024
77. Rai R, Sahu CK. Driven by data or derived through physics? A review of hybrid physics guided machine learning techniques with Cyber-Physical System (CPS) focus. IEEE Access. 2020; 8:71050-71073. https://doi.org/10.1109/access.2020.2987324
78. Erge O, Oort EV. Combining physics-based and data-driven modeling for pressure prediction in well construction. Proc Python Sci Conf. 2020; 125. https://doi.org/10.25080/majora-342d178e-011
79. Koksal ES, Aydın E. Physics informed piecewise linear neural networks for process optimization. Comput Chem Eng. 2023; 174:108244. https://doi.org/10.1016/j.compchemeng.2023.108244
80. Artsi Y, Sorin V, Glicksberg BS, Nadkarni GN, Klang E. Advancing clinical practice: The potential of multimodal technology in modern medicine. J Clin Med. 2024; 13(20):6246. https://doi.org/10.3390/jcm13206246
81. Kaal WA. AI governance *via* web3 reputation system. SSRN. 2024. https://doi.org/10.2139/ssrn.4941807
82. Bangi MSF, Kwon JS. Deep hybrid modeling of chemical process: Application to hydraulic fracturing. Comput Chem Eng. 2019; 134:106696. https://doi.org/10.1016/j.compchemeng.2019.106696
83. Lopez OAM, Lopez AM, Crossa J. Fundamentals of artificial neural networks and deep learning. 2022: pp. 379. https://doi.org/10.1007/978-3-030-89010-0_10
84. Sager C, Janiesch C, Zschech P. A survey of image labelling for computer vision applications. J Bus Anal. 2021; 4(2):91-110. https://doi.org/10.1080/25732 34x.2021.1908861
85. Macukow B. Neural networks- State of art, brief history, basic models and architecture. LNISA. 2016; 9842: pp. 3-14. https://doi.org/10.1007/978-3-319-45378-1_1
86. Ali MT, Abed BH. The proposition of three approaching ways to implement tan-sigmoid activation function in FPGA. J Eng Technol. 2022; 40(2):311. https://doi.org/10.30684/etj.v40i2.2160

87. Zhao H, Luo Y. An O(N) sorting algorithm: Machine learning sort. arXiv. 2018. https://arxiv.org/abs/1805.04272
88. Mata GF, Montero EM. Using a convolutional siamese network for image-based plant species identification with small datasets. Biomimetics. 2020; 5(1):8. https://doi.org/10.3390/biomimetics5010008
89. Tang R, Donato LD, Besinovic N, Flammini F, Goverde RMP, Lin Z, Liu R, Tang T, Vittorini V, Wang Z. A literature review of artificial intelligence applications in railway systems. Transp Res Part C Emerg Technol. 2022; 140:103679. https://doi.org/10.1016/j.trc.2022.103679
90. Song H, Choi H. Forecasting stock market indices using the recurrent neural network based hybrid models: CNN-LSTM, GRU-CNN, and ensemble models. Appl Sci. 2023; 13(7):4644. https://doi.org/10.3390/app13074644
91. Kurhade A, Talele V, Rao TV, Chandak A, Mathew VK. Computational study of PCM cooling for electronic circuit of smart-phone. Mater Today Proc. 2021; 47(11):3171-3176. https://doi.org/10.1016/j.matpr.2021.06.284
92. Kurhade AS, Amruth E, Joshi PS, Kondhalkar GE, Jadhav PA, Murali G, Mahajan RG, Waware SY. Enhancing flat-plate solar collector efficiency: A numerical study. JMMF. 2025; 73(4):1065-1076. https://doi.org/10.18311/jmmf/2025/48249
93. Kurhade AS, Murali G. Thermal control of IC chips using phase change material: A CFD investigation. Int J Mod Phys C. 2022; 33(12):2250159. https://doi.org/10.1142/s0129183122501595
94. Kurhade AS, Murali G, Rao TV. CFD approach for thermal management to enhance the reliability of IC chips. Int J Eng Trends Technol. 2022; 71(3):65-72. https://doi.org/10.14445/22315381/ijett-v71i3p208
95. Waware SY, Kore SS, Kurhade AS, Patil SP. Innovative heat transfer enhancement in tubular heat exchanger: An experimental investigation with minijet impingement. J Adv Res Fluid Mech Therm Sci. 2014; 116(2). https://doi.org/10.37934/arfmts.116.2.5158
96. Kurhade AS, Biradar R, Yadav RS, Patil P, Kardekar NB, Waware SY, Munde KH, Nimbalkar AG, Murali G. Predictive placement of IC chips using ANN-GA approach for efficient thermal cooling. J Adv Res Fluid Mech Therm Sc. 2024; 118(2):137-140. https://doi.org/10.37934/arfmts.118.2.137147
97. Waware SY, Chougule SM, Yadav RS, Biradar R, Patil P, *et al*. A comprehensive evaluation of recent studies investigating nanofluids utilization in heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024; 119(2):160-172. https://doi.org/10.37934/arfmts.119.2.160172
98. Upadhe SN, Mhamane SC, Kurhade AS, Bapat PV, Dhavale DB, Kore LJ. Water saving and hygienic faucet for public places in developing countries. Techno-Societal 2018. Springer International Publishing. 2020: pp. 617-624. https://doi.org/10.1007/978-3-030-16848-3_56
99. Sidhappa KA, Hande SS, Patil MS, Mask MV. Heat transfer enhancement by using twisted tape inserts with circular holes in forced convection. IJIERT. 2016; 3(3):1-7.
100. Kurhade AS, Kardekar NB, Bhambare PS, Waware SY, Yadav RS, Pawar P, Kirpekar S. A comprehensive review of electronic cooling technologies in harsh field environments: obstacles, progress, and prospects. J Mines Met Fuels. 2024; 72 (6): 557-579. https://doi.org/10.18311/jmmf/2024/45212
101. Kurhade AS, Waware SY, Bhambare PS, Biradar R, Yadav RS, Patil VN. A comprehensive study on *Calophyllum inophyllum* biodiesel and dimethyl carbonate blends: Performance optimization and emission control in diesel engines. J Mines Met Fuels. 2024; 72(5):499-507. https://doi.org/10.18311/jmmf/2024/45188
102. Kurhade AS, Waware SY, Munde KH, Biradar R, Yadav RS, Patil P, Patil VN, Dalvi SA. Performance of solar collector using recycled aluminium cans for drying. J Mines Met Fuels. 2024; 72(5):455-461. https://doi.org/10.18311/jmmf/2024/44643
103. Kurhade AS, Siraskar GD, Bhambare PS, Dixit SM, Waware SY. Numerical investigation on the influence of substrate board thermal conductivity on electronic component temperature regulation. J Adv Res Numer Heat Trans. 2024; 23(1):28-37. https://doi.org/10.37934/arnht.23.1.2837
104. Kurhade AS, Siraskar GD, Kondhalkar GE, Darade MM, Yadav RS, Biradar R, Waware SY, Charwad GA. Optimizing aerofoil design: A comprehensive analysis of aerodynamic efficiency through CFD simulations and wind tunnel experiments. J Mines Met Fuels. 2024; 72(7):713-724. https://doi.org/10.18311/jmmf/2024/45361
105. Kurhade AS, Siraskar GD, Darade MM, Dhumal JR, Kardile CS, Biradar R, Patil SP, Waware SY. Predicting

heat transfer enhancement with twisted tape inserts using fuzzy logic techniques in heat exchangers. J Mines Met Fuels. 2024; 72(7):743-750. https://doi.org/10.18311/jmmf/2024/45348
106. Kurhade AS, Kadam AA, Biradar R, Bhambare PS, Gadekar T, Patil P, Yadav RS, Waware SY. Experimental investigation of heat transfer from symmetric and asymmetric IC Chips mounted on the SMPS board with and without PCM. J Adv Res Fluid Mech Therm Sci. 2024; 121(1):137-140. https://doi.org/10.37934/arfmts.121.1.137147
107. Patil P, Kardekar N, Yadav R, Kurhade A, Kamble D. Nanofluids: An experimental study for MQL grinding. J Mines Met Fuels. 2023; 71(12):2751-2756.
108. Patil P, Kardekar N, Yadav R, Kurhade A, Kamble D. Al_2O_3 nanofluids: An experimental study for MQL grinding. J Mines Met Fuels. 2023; 72(12):2751-2756. https://doi.org/10.18311/jmmf/2023/41766
109. Kurhade AS, Bhambare PS, Desai VP, Murali G, Yadav RS, *et al*. Investigating the effect of heat transfer influenced by applying wavy corrugated twisted tape inserts in double pipe heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024; 122(2):146-155. https://doi.org/10.37934/arfmts.122.2.146155
110. Kurhade AS, Murali G, Jadhav PA, Bhambare PS, Waware SY, Gadekar T, Yadav RS, Biradar R, Patil P. Performance analysis of corrugated twisted tape inserts for heat transfer augmentation. J Adv Res Fluid Mech Therm Sci. 2024; 121(2):192-200. https://doi.org/10.37934/arfmts.121.2.192200
111. Kurhade AS, Dange MM, Nalawade DB. Effect of wavy (corrugated) twisted tape inserts on heat transfer in a double pipe heat exchanger. IJIERT. 2015; 2(1):1-8.
112. Kurhade AS, Gadekar T, Siraskar GD, Jawalkar SS, Biradar R, Kadam AA, *et al*. Thermal performance analysis of electronic components on different substrate materials. J Mines Met Fuels. 2024; 72(10):1093-1098. https://doi.org/10.18311/jmmf/2024/45569
113. Kurhade AS, Siraskar GD, Jawalkar SS, Gadekar T, Bhambare PS, Biradar R, Yadav RS, Waware SY, Mali CN. The impact of circular holes in twisted tape inserts on forced convection heat transfer. J Mines Met Fuels. 2024; 72(9):1005-1012. https://doi.org/10.18311/jmmf/2024/45505
114. Kurhade AS, Darade MM, Siraskar GD, Biradar R, Mahajan RG, Kardile CS, Waware SY, Yadav RS. State-of-the-art cooling solutions for electronic devices operating in harsh conditions. J Mines Met Fuels. 2024; 72(8):843-861. https://doi.org/10.18311/jmmf/2024/45374
115. Kurhade AS, Warke P, Maniyar K, Bhambare PS, Waware SY, Deshpande S, Harsur S, Ingle M, Kolhe P, Patil PA, Jadhav P. The wind rose analysis of temperature variation with sensor implantation technique for a wind turbine. J Adv Res Fluid Mech Therm Sci. 2024; 122(1):1-8. https://doi.org/10.37934/arfmts.122.1.118
116. Kurhade AS, Siraskar GD, Bhambare PS, Keloth D, Kaithari SM, Waware SY. Enhancing smartphone circuit cooling: A computational study of PCM integration. J Adv Res Numer Heat Trans. 2024; 27(1):132-145. https://doi.org/10.37934/arnht.27.1.132145
117. Yadav RS, Gadekar T, Gundage V, Patil P, Patil A, Patil P, Patil A, Sutar R, Kurhade AS. Numerical and experimental investigation of the effect of overlapping angle on strength and deformation of curved plate joined using arc welding process. J Mines Met Fuels. 2024; 72(10):1059-1066. https://doi.org/10.18311/jmmf/2024/45697
118. Yadav RS, Nimbalkar A, Gadekar T, Patil P, Patil VN, Gholap AB, Kurhade AS, Dhumal JR, Waware SY. Comparison of experimental and numerical investigation of mono-composite and metal leaf spring. J Mines Met Fuels. 2024; 72(8):815-827. https://doi.org/10.18311/jmmf/2024/45325
119. Deshpande SV, Pawar RS, Keche AJ, Kurhade A. Absolute time surface finish measurement of stepped holding shaft by automatic system. J Adv Manuf Sys. 2025.
120. Kurhade AS, Siraskar GD, Bhambare PS, Murali G, Deshpande SV, Warke PS, Waware SY. Simulation and analysis of heat transfer in counter-flow helical double-pipe heat exchangers using CFD. Int J Mod Phys C. 2025. https://doi.org/10.1142/s0129183125500433
121. Parkar A, Yadav RS, Chopade R, Dhavase N, Dhumal JR, Mankar SP, Patil S, Ghuge K, Giri B, Kurhade AS. Automating the two-dimensional design of Heating, Ventilation, Air Conditioning, and Refrigeration (HVACR) ducts using computer programming language: An algorithmic approach. J Mines Met Fuels. 2025; 73(1):211-220. https://doi.org/10.18311/jmmf/2025/47335
122. Kurhade AS, Siraskar GD, Darade MM, Murali G, Katkar TR, Patil SP, Charwad GA, Waware SY, Yadav RS. Enhancement in heat transfer with nanofluids in double-pipe heat exchangers. J Mines Met Fuels.

2025; 73(1):165-172. https://doi.org/10.18311/jmmf/2025/47225
123. Kurhade AS, Chougule SM, Kharat PV, Kondhalkar GE, Murali G, Raut PN, Charwad GA, Waware SY, Yadav RS. Integrated approach to enhance vehicle safety: A novel bumper design with energy-absorbing mechanisms. J Mines Met Fuels. 2025; 73(1):27-35. https://doi.org/10.18311/jmmf/2025/47168
124. Raut PN, Dolas AS, Chougule SM, Darade MM, Murali G, Waware SY, Kurhade AS. Green adsorbents for heavy metal removal: A study on zinc ion uptake by *Tinospora cordifolia* biocarbon. J Mines Met Fuels. 2025; 73(1):21-25. https://doi.org/10.18311/jmmf/2025/47121
125. Yadav R, Nimbalkar A, Kirpekar S, Patil PJ, Dalvi SA, Jadhav PA, Kurhade AS, Wakchaure GN. Effect of transformed-induced plasticity steel plate thickness on ultimate tensile strength of butt welded joint using Nd: YAG laser. Int J Veh Struct Syst. 2024; 16(6). https://doi.org/10.4273/ijvss.16.6.08
126. Yadav RS, Gandhi P, Veeranjaneyulu K, Gaji R, Kirpekar S, Pawar D, Khairnar YS, Patil S, Kurhade AS, Patil SP. Influence of plate thickness on the mechanical behaviour of mild steel curved plates: An experimental study. J Mines Met Fuels. 2024; 72(12):1319-1327. https://doi.org/10.18311/jmmf/2024/46253
127. Kurhade AS, Bhambare PS, Siraskar GD, Dixit MS, Waware SY, *et al*. Computational study on thermal management of IC chips with phase change materials. *J Adv Res Numer Heat Transf*. 2024; 26(1). https://doi.org/10.37934/arnht.26.1.3443
128. Kurhade MA, Dange MM, Nalawade DB. Fuzzy logic modeling of heat transfer in a double pipe heat exchanger with wavy (corrugated) twisted tape inserts. IJIERT. 2015; 2(1):1-8.
129. Kurhade AS, Siraskar GD, Raut PN, Dolas AS, Murali G, Dalvi SA, Waware SY, Yadav RS. Investigating the impact of oxygenated additives on exhaust emissions from unleaded gasoline vehicles. J Mines Met Fuels. 2025; 73(2):333-344. https://doi.org/10.18311/jmmf/2025/47410
130. Purandare P, Yadav RS, Nema AA, Kulkarni A, Kirpekar S, Giri B, Patil PA, Jagdale M, Kurhade AS. Comparative study of helical coil, spiral coil and conical coil (900) heat exchanger for single phase fluid flow. J Mines Met Fuels. 2025; 73(2):377-384. https://doi.org/10.18311/jmmf/2025/47396
131. Kurhade AS, Siraskar GD, Dalvi SA, Kharat PV, Jadhav NA, Shelkande VD, Murali G, Waware SY, Yadav RS. Passive cooling of EV batteries using phase change material: A simulation study. J Mines Met Fuels. 2025; 73(2):447-454. https://doi.org/10.18311/jmmf/2025/47368
132. Kurhade AS, Kharat PV, Chougule SM, Darade MM, Karad MM, Murali G, Charwad GA, Waware SY, Yadav RS. Harnessing the power of plastic waste: A sustainable approach to fuel production. J Mines Met Fuels. 2025; 73(2):467-473. https://doi.org/10.18311/jmmf/2025/47354
133. Kurhade AS, Siraskar GD, Deshmukh MT, Patil PA, Chaudhari SS, Kadam AA, Dolas AS, Mahajan RG, Waware SY, Yadav RS. Impact of PCM on heat dissipation from IC chips. J Mines Met Fuels. 2025; 73(3). https://doi.org/10.18311/jmmf/2025/47522
134. Ramani P, Reji V, Kumar VS, Murali G, Kurhade AS. Deep learning-based detection and classification of Moss and Crack damage in rock structures for geo-mechanical preservation. J Mines Met Fuels. 2025; 73(3). https://doi.org/10.18311/jmmf/2025/47760
135. Chippalkatti S, Chekuri RBR, Ohol SS, Shinde NM, Barmavatu P, Shelkande VD, Murali G, Kurhade AS. Enhancing heat transfer in micro-channel heat sinks through geometrical optimization. J Mines Met Fuels. 2025; 73(3). https://doi.org/10.18311/jmmf/2025/47773
136. Kurhade AS, Siraskar GD, Chekuri RB, Murali G, Pawar P, Patil AR, Waware SY, Yadav RS. Biodiesel blends: A sustainable solution for diesel engine performance improvement. J Mines Met Fuels. 2025; 73(3). https://doi.org/10.18311/jmmf/2025/47628
137. Kurhade AS, Bhavani P, Patil SA, Kolhalkar NR, Chalapathi KS, Patil PA, Waware SY. Mitigating environmental impact: A study on the performance and emissions of a diesel engine fueled with biodiesel blend. JMMF. 2025; 73(4):981-989. https://doi.org/10.18311/jmmf/2025/47669
138. Wakchaure GN, Vijayarao P, Jadhav TA, Bhamare YM, Jagtap A, Gaji R, Chavan Patil AS, Kamble SD, Jagtap SV, Yadav RS, Kurhade AS. Performance evaluation of Trapezoidal ducts with Delta-wing vortex generators: An experimental investigation. J Mines Met Fuels. 2025; 73(4):991-1003. https://doi.org/10.18311/jmmf/2025/48202
139. Wakchaure GN, Jagtap SV, Gandhi P, Patil ASC, Kandharkar S, Kokare NN, Bhamare YM, Kamble SD, Jadhav A, Yadav RS, Kurhade AS. Heat transfer characteristics of Trapezoidal duct using Delta-wing

vortex generators. J Mines Met Fuels. 2025; 73(4):1053-1056. https://doi.org/10.18311/jmmf/2025/48335

140. Chougule SM, Murali G, Kurhade AS. Failure investigation of the driving shaft in an industrial paddle mixer. J Mines Met Fuels. 2025; 73(5):1247-1256. https://doi.org/10.18311/jmmf/2025/48627
141. Kurhade AS, Sugumaran S, Kolhalkar NR, Karad MM, Mahajan RG, Shinde NM, Dalvi SA, Waware SY. Thermal management of mobile devices *via* PCM. J Mines Met Fuels . 2025; 73(5):1313-1320. https://doi.org/10.18311/jmmf/2025/48437
142. Chougule SM, Murali G, Kurhade AS. Finite element analysis and design optimization of a paddle mixer shaft. J Mines Met Fuels. 2025; 73(5):1343-1354. https://doi.org/10.18311/jmmf/2025/48664
143. Waware SY, Ahire PP, Napate K, Biradar R, Patil SP, Kore SS, Kurhade AS. Advancements in heat transfer enhancement using perforated twisted tapes: A comprehensive review. J Mines Met Fuels. 2025; 73(5):1355-1363. https://doi.org/10.18311/jmmf/2025/48438
144. Patil Y, Tatiya M, Dharmadhikari DD, Shahakar M, Patil SK, Mahajan RG, Kurhade AS. The role of AI in reducing environmental impact in the mining sector. J Mines Met Fuels. 2025; 73(5):1365-1378.
145. Chougule SM, Murali G, Kurhade AS. Dynamic simulation and performance evaluation of vibratory bowl feeders integrated with paddle shaft mechanisms. Adv Sci Technol Res J. 2025; 19(7):179-196. https://doi.org/10.12913/22998624/203873