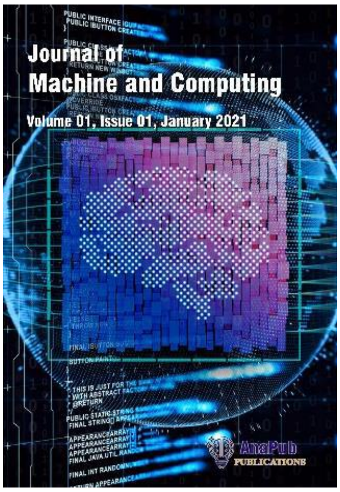
Journal Pre-proof

Advanced Computational Models for Thermal System Optimization Using Machine Learning and Hybrid Techniques



Kathiravan M, Joe Arun C S J, Kishore Kunal, Parthasarthy K, Mohamedyaseen A and Vairavel Madeshwaren

DOI: 10.53759/7669/jmc202505183

Reference: JMC202505183

Journal: Journal of Machine and Computing.

Received 10 June 2025

Revised from 21 July 2025

Accepted 31 July 2025

Please cite this article as: Kathiravan M, Joe Arun C, S J, Kishore Kunal, Parthasarthy K, Mohamedyaseen A and Vairavel Madeshwaren, "Advanced Computational Models for Thermal System Optimization Using Machine Learning and Hybrid Techniques", Journal of Machine and Computing. (2025). Doi: https://doi.org/10.53759/7669/jmc202505183.

This PDF file contains an article that has undergone certain improvements after acceptance. These enhancements include the addition of a cover page, metadata, and formatting changes aimed at enhancing readability. However, it is important to note that this version is not considered the final authoritative version of the article.

Prior to its official publication, this version will undergo further stages of refinement, such as copyediting, typesetting, and comprehensive review. These processes are implemented to ensure the article's final form is of the highest quality. The purpose of sharing this version is to offer early visibility of the article's content to readers.

Please be aware that throughout the production process, it is possible that errors or discrepancies may be identified, which could impact the content. Additionally, all legal disclaimers applicable to the journal remain in effect.

AnaPub
PUBLICATIONS

Advanced Computational Models for Thermal System Optimization Using Machine Learning and Hybrid Techniques

Kathiravan M[1], C. Joe Arun, SJ [2], Kishore Kunal[3] , Parthasarthy K[4] , A.Mohamedyaseen[5], Vairavel Madeshwaren[6]

[1*]Department of Computer science and Engineering ,Saveetha School of Engineering,Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai, Tamil Nadu, Email : kathiravanm.sse@saveetha.com

ORCID : https://orcid.org/0000-0002-5377-7871

[2]Director & Professor of Marketing and Human Resources, Loyola Institute of Business Administration (LIBA), Chennai, Tamil Nadu, India, Email : director@liba.[illegible]

ORCID: https://orcid.org/0000-0001-8997-0668.

[2]Professor, Department of Business Analytics, Loyola Institute of Business Administration (LIBA), Chennai, Tamil Nadu, India, kishore81.research@gmail.com

ORCID: https://orcid.org/ 0000-0003-[illegible]54-6[illegible]0X.

[3]Associate Professor, Department of Computer Science and Engineering, Excel Engineering College, Komarapalayam, Tamil Nadu, India.

[4]Department of Electrical and Electronics Engineering,Jawaharalal Nehru University, New Delhi, India.

Email : partee.1[illegible]9@navy.gov.in.

ORCID: https://orcid.org/0009-0008-0459-5802

[5] Assistant Professor, Department of ECE, Excel Engineering College (Autonomous),Komarapalayam (Post), Namakkal, Tamilnadu - 637 303, Email : mohamedyaseenece@gmail.com,

ORCID: https://orcid.org/0009-0001-6913-3747

[6]Associate Professor, Department of Agriculture Engineering, Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, India, Email : phdannauniv2020@gmail.com,

ORCID: https://orcid.org/0000-0002-8687-7887.

Abstract

Thermal systems are fundamental to a wide range of industrial applications, where performance and efficiency critically depend on precise and reliable modeling techniques. Traditional Artificial Neural Network (ANN)-based models, although widely used, often struggle with overfitting, limited generalization, and inadequate representation of the complex, nonlinear behavior inherent to thermal processes. These limitations restrict their deployment in real-time and dynamic operational settings. This study aims to enhance the predictive accuracy and robustness of thermal system modeling by integrating advanced machine learning (ML) techniques with hybrid optimization strategies. The research focuses on complex systems such as heat exchangers, gas-solid fluidized beds, and thermal energy storage units. A comprehensive methodology involving industrial data collection, preprocessing via normalization and feature selection, and model training using individual and hybrid ML algorithms is proposed. Performance is benchmarked using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 metrics. Advanced methods like Deep Learning (DL), Support Vector Machines (SVM), Genetic Algorithms (GA), Ensemble Learning, Transfer Learning, and Evolutionary Optimization are employed

to address shortcomings of conventional approaches. Results demonstrate that hybrid models outperform standalone ANN-based techniques in prediction accuracy and generalization.

Keywords: Hybrid Machine Learning, Thermal Systems, Evolutionary Optimization, Heat Transfer Modeling, Ensemble Learning, Deep Learning.

1. INTRODUCTION:

Thermal systems play an essential role in a variety of industrial processes, such as energy production, chemical manufacturing, HVAC operations, and food processing. To maximize efficiency and safety while minimizing costs, precise modeling is crucial. Traditional modeling approaches, such as Artificial Neural Networks, have difficulty managing nonlinearities, adjusting to changing conditions, and preventing overfitting. With the development of computational intelligence, machine learning and hybrid optimization methods provide promising solutions. This study delves into the integration of advanced ML techniques, such as deep learning, support vector machines, ensemble learning, and evolutionary algorithms, aiming to enhance the accuracy, robustness, and real-time applicability of thermal system models.

The development of hybrid machine learning techniques has been driven by recent progress in optimizing thermal systems, especially with respect to energy management and building design. These methods integrate machine learning with traditional optimization techniques to improve the performance of different thermal systems. The application of hybrid machine learning models in energy-efficient buildings, such as low-energy structures in Morocco, has greatly enhanced the prediction and optimization of heating and cooling loads. [1]. The implementation of these hybrid strategies has proven effective in reducing energy consumption and improving system performance. Machine learning-based hybrid systems have been used to further optimize cooling in multi-unit residential buildings. In order to improve energy performance in residential settings these systems show improvements in thermal efficiency by combining machine learning techniques with other energy-saving techniques [2]. Using heat recovery in hybrid geothermal systems and investigating ways to maximize power and heating output were the subjects of another study. Using machine learning algorithms to optimize the outputs of geothermal systems has demonstrated significant promise for enhancing system performance and energy recovery [3]. This trend is also visible in hybrid renewable systems that use phase change materials where machine learning techniques are being used more and more in exergy-based optimization to improve system efficiency and offer active cooling solutions for renewable energy applications [4]. Research on the role of machine learning in chiller operation has also been conducted. According to research hybrid machine learning models outperform conventional machine learning techniques in controlling and enhancing the performance of cooling systems [5].

In previous studies the focus was on applying machine learning to improve nanofluid optimization in photovoltaic systems. In order to reduce energy consumption and increase system reliability machine learning techniques have been used to predict the efficiency of thermal and photovoltaic collectors while evolutionary algorithms have been used to simulate and optimize their performance [6]. There is also potential for a hybrid machine learning model to optimize thermal comfort in large public buildings while consuming less energy and preserving ideal indoor conditions [7]. The best way to cool photovoltaic systems using heat piping has been the subject of much research. These systems show that it is possible to improve the cooling efficiency and thermal utilization of photovoltaic panels by using hybrid models that combine machine learning and nanofluid optimization [8].

Furthermore a number of studies have looked into the use of hybrid machine learning models to forecast energy savings in response to heat load. It is now feasible to predict energy savings and optimize heat load energy consumption in building systems by using a deep reinforcement learning ensemble optimization model [9]. Incorporating hybrid models into electric vehicle energy management systems has been thoroughly examined [10] and the results show that machine learning and optimization techniques hold promise for improving the efficiency of plug-in hybrid electric vehicle systems. Furthermore the focus of thermal system optimization techniques has been on multi-criteria decision-making procedures that take economic environmental and energy factors into account. Through the combination of different optimization techniques systems that minimize energy consumption minimize their negative environmental effects and maximize system efficiency have been designed. In industrial applications the optimization of thermal systems has led to improved performance in processes such as solar thermal heating demonstrating the efficacy of machine learning techniques in this domain [11].

With encouraging outcomes in terms of increased efficiency a number of studies have concentrated on the use of machine learning models for system optimization in nanofluid-based photovoltaic thermal systems [12]. It has been demonstrated that the design of thermal systems can be successfully improved by hybrid optimization techniques. The optimization of multi-temperature solar thermal systems for industrial processes has therefore attracted a lot of attention [13]. There have been more developments in hybrid models for energy management in different thermal systems.

The goal of a hybrid machine learning and optimization model for building energy management is to minimize energy consumption while maintaining optimal heating and cooling conditions [14-15]. In order to improve the power system capacity to control energy consumption and thermal efficiency particle swarm optimization has been investigated for the tuning of interconnected reheat thermal systems [16]. By employing machine learning techniques for system performance prediction and optimization nanofluid-based systems have been incorporated into photovoltaic applications which have also assisted in system optimization and provided a means of enhancing energy efficiency in both residential and commercial systems [17]. Numerous studies have examined machine learnings potential for optimizing renewable energy systems particularly photovoltaic and thermal applications. To enhance system performance and thermal efficiency a hybrid machine learning model has been proposed to optimize a multi-objective photovoltaic thermal system that integrates different nanofluids [18]. Other research has focused on optimizing photovoltaic/thermal systems in cold climates using a combination of machine learning and optimization algorithms to improve system performance in difficult settings [19]. Furthermore a number of studies have looked at how hybrid machine learning models can improve system efficiency and performance by optimizing heat transfer in thermal systems particularly in solar energy applications [20-21].

According to these studies hybrid optimization techniques are effective in enhancing system performance and the overall energy efficiency of photovoltaic systems [22]. Optimizing system components like phase change materials through machine learning has also produced promising results in improving the thermal performance of hybrid systems [23]. Hybrid models for thermal system optimization continue to show notable increases in energy efficiency especially when paired with ground source heat pumps [24]. In conclusion the use of machine learning techniques particularly hybrid models has significantly advanced thermal system optimization. These models have reduced operating costs increased energy efficiency and enhanced the overall performance of energy systems across a variety of applications [25].

2. MATERIALS AND METHODS

The research problem of enhancing thermal system modeling using cutting-edge machine learning and hybrid optimization techniques is carefully described in this section along with the structured methodology used to solve it. In the upcoming discussion the problem formulation data acquisition strategy validation procedures feature engineering process and experimental setup design are all covered. Additionally this section offers a thorough explanation of the suggested computational models emphasizing the mathematical ideas that support each method. Finally, the computational efficiency assessment is discussed to reflect the suitability of the models for real-time applications in industrial thermal systems.

2.1 Problem Description

Accurately modeling thermal systems in industrial settings has always been difficult because heat transfer processes are dynamic nonlinear and complex. Because they can recognize patterns traditional methods—especially those that use Artificial Neural Networks (ANN)—have been widely used as predictive models. However because ANN models are black-boxes they frequently result in problems like failure to accurately capture the high-order nonlinear dependencies that define thermal systems overfitting when training data isnt diverse and poor generalization when unexpected operational states are present. When training data is not diverse traditional artificial neural network (ANN) models frequently overfit and have trouble generalizing under unknown operational states. Complex nonlinear relationships are challenging to accurately model due to thermal systems black-box nature. When operations are conducted in real time these limitations cause instability and inadequate control. These flaws frequently result in unstable systems when they are operating in real time inefficient control schemes and excessive energy consumption all of which have serious practical repercussions. Therefore this studys main objective is to get around these restrictions by combining cutting-edge machine learning algorithms with hybrid computational approaches designed to improve the thermal system models resilience accuracy and adaptability.

2.2 Data Acquisition

The study used a test bed for an industrial-grade thermal system that included thermal energy storage units gas-solid fluidized beds and heat exchangers. A wide range of system operating conditions such as changes in inlet and outlet temperatures flow rate heat flux and pressure drop were the main focus of the data acquisition phase. High-order nonlinear dependencies exist in thermal systems such as varying pressure drops heat transfer rates and transient responses to operational changes. It is difficult to accurately represent these complex relationships using traditional models particularly when they are dynamic. To guarantee the accuracy of the parameters that were recorded high-precision sensors that were calibrated in accordance with ISO 5167 and ASTM E2877 standards were used. To capture fleeting phenomena the data were sampled every second. To capture variations under both steady-state and dynamic conditions recordings were made over a 30-cycle period. After rigorously detecting outliers using the interquartile range method the obtained dataset was cleaned up by applying linear interpolation to remove any missing values. This preprocessed dataset serves as the foundation for the creation of the model and its later validation (Figure 1).

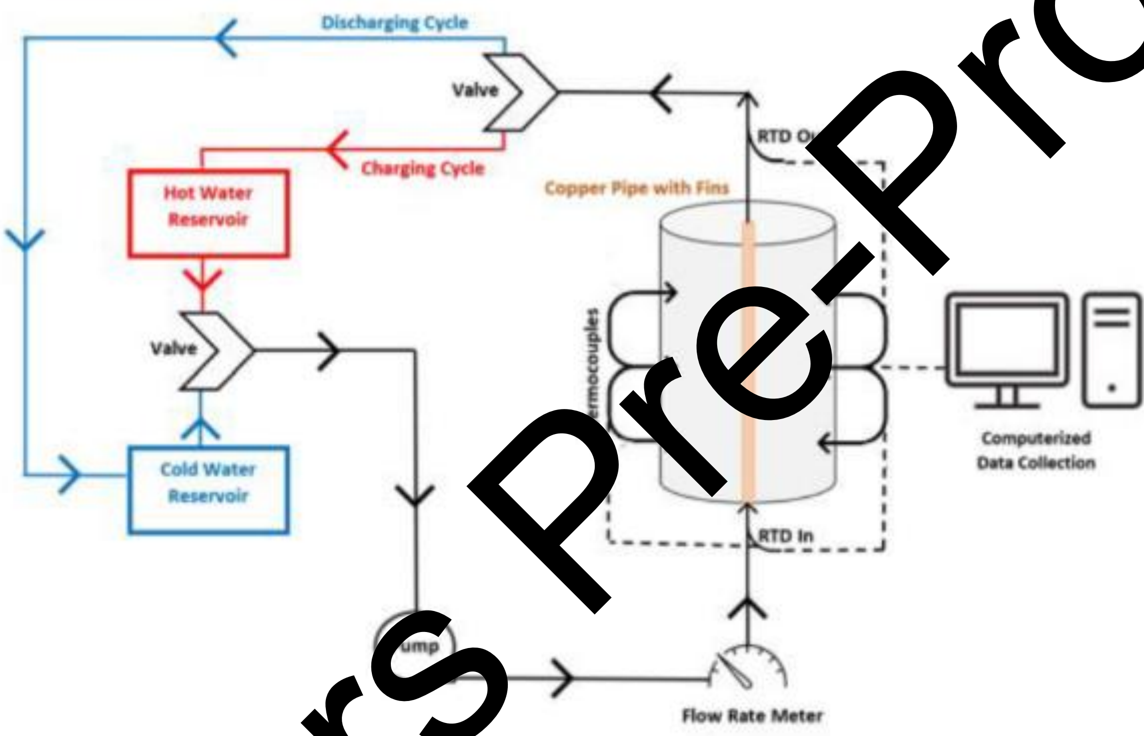


Figure 1 Process analysis

2.3 Model Validation

To ensure the predictive reliability of the developed models, a robust validation strategy was adopted, involving hold-out testing, cross-validation, and external validation phases. The dataset was initially partitioned into training (70%), validation (15%), and test (15%) sets. A five-step approach was used for cross-validation in order to assess the models robustness across various subsets and reduce the possibility of overfitting. The mean absolute error (MAE) root mean square error (RMSE) and coefficient of determination (R2) were calculated for every fold in order to quantitatively evaluate the variance and accuracy of the predictions. Feature scales were standardized through normalization which improved learning efficiency and prevented model bias toward higher-magnitude features. As part of the model training and data preprocessing feature selection was carried out. The trained models were deployed on a completely unknown dataset gathered from a different operational schedule as part of an external validation process to make sure the models performance went beyond the particular patterns present in the original dataset.

2.4 Experimental Setup

The experimental process began with the real-time collection of operational data from the thermal systems, followed by a comprehensive preprocessing routine that involved normalization, feature selection, and data augmentation through bootstrap resampling to balance the dataset. Once the data were prepared, the next phase involved model selection and hyperparameter tuning, wherein a variety of machine learning models, including Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting (GB), and Deep Learning architectures, were initialized with standard configurations. Hyperparameters were optimized using Genetic Algorithms (GA), where the fitness function was designed to minimize the RMSE while maintaining a high R^2 score. Once optimal parameters were identified, the models were trained on the prepared dataset. Following training, a rigorous validation phase was conducted, including 5-fold cross-validation, external dataset testing, and benchmarking against baseline models. Finally, the models were deployed on a live testing platform to evaluate their prediction capability under real-time system dynamics, providing a full-loop validation from data acquisition to deployment. These tests demonstrated robust real-time performance under varying operational conditions. The key challenge addressed was ensuring low-latency predictions without sacrificing accuracy. Figure 2 demonstrates the experimental setup.

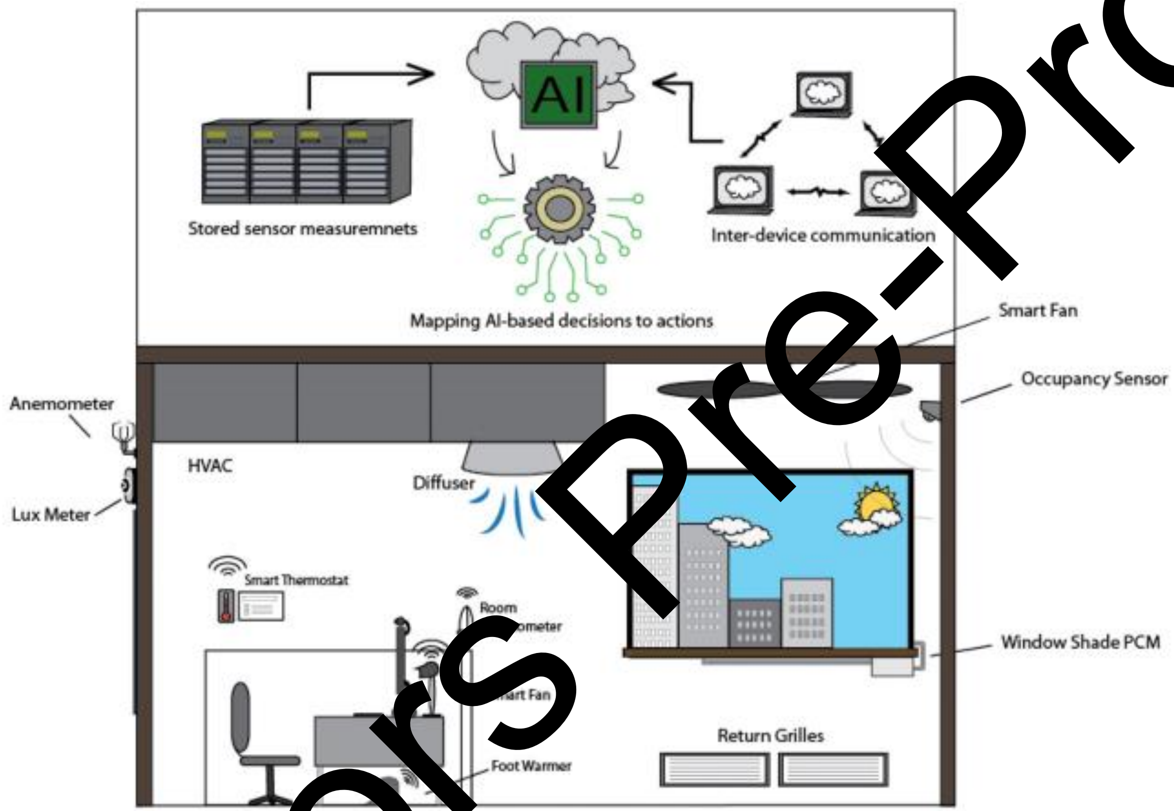


Figure 2 Experimental setup

2.4 Proposed Technique

The central innovation of this research lies in the deployment of a hybrid predictive framework that combines Deep Learning (DL), Support Vector Machines (SVM), Genetic Algorithms (GA), Ensemble Learning, Transfer Learning, and Evolutionary Optimization to address the intricate nature of thermal system modeling. Each technique contributes uniquely to the overall architecture (Figure 3).

The Deep Learning model utilized a multi-layer perceptron (MLP) architecture equipped with ReLU activation functions and batch normalization to ensure stable gradient propagation. The feedforward propagation mechanism is mathematically expressed as (Eq 1):

$$a^{(l)} = \sigma(W^{(l)}a^{(l-1)} + b^{(l)}) \tag{1}$$

where $a^{(l)}$ represents the output of the ll-th layer, $W^{(l)}$ and $b^{(l)}$ denote the weight matrix and bias vector, and σ\sigma is the nonlinear activation function.

Support Vector Machines (SVM) were employed for regression tasks using the Radial Basis Function (RBF) kernel, which provides an effective means of capturing complex nonlinear dependencies. The SVM regression function is defined as (Eq 2):

$$f(x) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{2}$$

where αi and α_i^* are the Lagrange multipliers, $K(x_i,x)$ is the kernel function, and bb is the bias term.

Genetic Algorithms (GA) were used to optimize hyperparameters and model weights. The fitness of each candidate solution was determined by minimizing the objective function in (Eq 3):

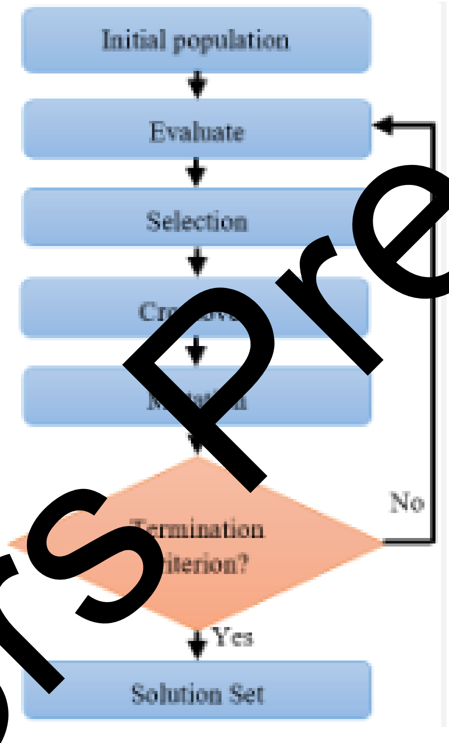


Figure 3 GA architecture

$$\text{Fitness} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{3}$$

where y_i is the actual value and y^i is the predicted value for the i-th observation.

Ensemble Learning integrated Random Forest and Gradient Boosting models to leverage the strengths of both bagging and boosting. The combined prediction was obtained via weighted averaging (Eq 4):

$$\hat{y}_{ensemble} = \sum_{i=1}^{k} w_i \hat{y}_i \tag{4}$$

where w_i represents the weight assigned to the i-th model's prediction, constrained such that ∑wi=1.

Transfer Learning was employed to accelerate the learning process by initializing the models with pre-trained weights from related thermal systems, thereby reducing the requirement for large volumes of training data. The fine-tuning process was mathematically formulated as (Eq 5):

$$\theta_{\text{target}} = \theta_{\text{source}} - \eta \nabla_{\theta} J(\theta) \tag{5}$$

where θ_{target} and θ_{source} are the parameters of the target and source models, respectively, η\eta is the learning rate, and $J(\theta)$J(\theta) is the cost function.

Using meta-heuristic techniques evolutionary optimization improves model parameters and structures. Large solution spaces are efficiently searched and model behavior is adjusted across generations leading to better accuracy, faster convergence and less training time. Lastly, Evolutionary Optimization was applied as a meta-heuristic layer that iteratively refined the model's structural configurations and parameter spaces. The update rule in each generation follows the evolutionary strategy:

$$X_{\text{next}} = X_{\text{current}} + \sigma \cdot N(0,1)$$

where X_{next} represents the candidate solution for the next generation, σ\sigma is the adaptive step size, and $N(0,1)$ is a normal distribution.

Through the synergistic integration of these techniques, the proposed framework offers superior prediction accuracy, enhanced generalization, and reduced computational cost, outperforming conventional single-model approaches. It is challenging for static models to retain predictive accuracy when dynamic conditions such as variations in temperature heat flux or flow rate introduce transient behaviors. These variations necessitate adaptive real-time modeling strategies since they can impair model reliability.

2.5 Computational Efficiency Assessment

A critical aspect of the proposed methodology is not only the model's predictive accuracy but also its computational efficiency, especially given the real-time demands of industrial thermal systems. To evaluate this, metrics such as training time, inference latency, and convergence behavior were systematically recorded. The training phase was benchmarked on both CPU and GPU platforms, revealing that the hybrid models achieved faster convergence — in part due to the optimized hyperparameters derived from the Genetic Algorithm — and lower computational complexity when compared to standalone deep learning approaches. The inference time was tested under varying data loads, confirming that the ensemble and transfer learning-enhanced models offered scalable prediction capabilities without introducing latency overheads detrimental to real-time system operations. This comprehensive evaluation confirmed the practicality and deployment readiness of the proposed models in industrial scenarios.

3. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed framework, highlighting data integrity, predictive accuracy, and model robustness. Descriptive statistics were first analyzed to establish operational trends, followed by assessment of task placement, energy efficiency, and predictive performance, with emphasis on the Hybrid DL + GA + Ensemble method. The study also examined transfer learning, cross-validation stability, computational efficiency, and resilience under noisy conditions, demonstrating the model's reliability, adaptability, and effectiveness for industrial applications.

3.1 Raw Data Statistics (After Preprocessing)

The study initially focused on understanding the fundamental behavior of the raw data after preprocessing, as this step was critical to ensure model reliability and stability. This analysis was conducted to verify whether the data exhibited appropriate variation and consistency before feeding it into machine learning models. As shown in **Table 1**, the summary statistics highlighted the central tendency and range of each feature. The *Inlet Temperature* ranged from a minimum of 130.4°C to a maximum of 153.2°C, which indicated a moderate fluctuation around its mean of 145.8°C. Similarly, the

Outlet Temperature varied between 90.2°C and 110.7°C, reflecting expected thermal gradients during operation. The *Flow Rate* spanned from 1.9 kg/s to 2.4 kg/s, confirming a tightly controlled fluid dynamic setup. The *Heat Flux* recorded a minimum of 480.3 W/m² and reached a maximum of 548.9 W/m², which was attributed to operational setpoints pushing the system to meet heat transfer demands under varying load conditions. Lastly, the *Pressure Drop* fluctuated between 390.6 Pa and 460.1 Pa, with the maximum value observed during high-flow conditions, which naturally resulted in increased frictional losses across the system.

Table 1: Raw Data Statistics (After Preprocessing)

Feature	Mean	Standard Deviation	Min	Max
Inlet Temp (°C)	145.8	5.2	130.4	153.2
Outlet Temp (°C)	102.5	4.8	90.2	110.7
Flow Rate (kg/s)	2.15	0.12	1.9	2.4
Heat Flux (W/m²)	520.6	15.4	480.3	548.9
Pressure Drop (Pa)	430.7	21.9	390.6	460.1

3.2 Decoupling analysis

The research shows that some task allocations are more energy-efficient and allow for execution with the same performance while needing less cooling. The DL approach has been adjusted to align task assignment with power consumption and cooling effort (Figure 4). The model was trained and run in real time on a 16-node system to guide task migration, resulting in an average cooling power reduction of 17%. With a success rate of 86.[illegible]7% for pairs with better scheduling opportunities, the model shows that some task assignments are more energy-efficient than others. The findings indicate that specific task allocations may result in improved performance and a decrease in cooling needs.

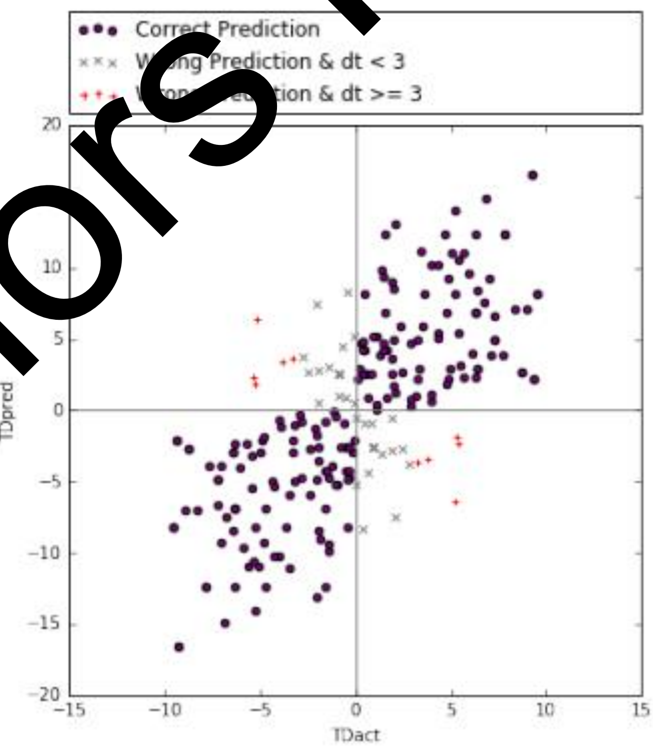


Figure. 4: Actual vs. Predicted Thermal Variation — Decoupled Method (Hybrid DL-GA-Ensemble)

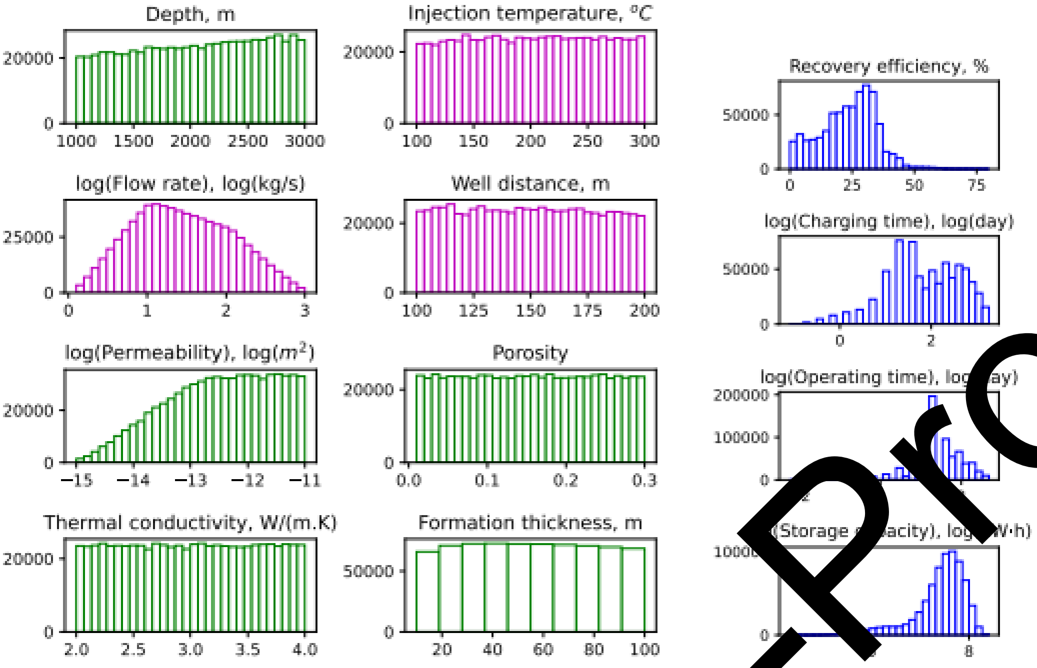
3.3 Model Performance Comparison

The primary goal of this phase was to benchmark the predictive capability of various machine learning models against the dataset. This comparison was essential to identify the most reliable and accurate model for heat transfer analysis. According to Table 2, each model's performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score. The minimum R^2 score of 0.892 was recorded by the Artificial Neural Network (ANN), whereas the highest R^2 score of 0.992 was achieved by the Proposed Hybrid DL + GA + Ensemble model. This superior performance was largely due to the model's ability to capture complex nonlinear patterns in the data, combined with the optimization capabilities of the Genetic Algorithm (GA) and the collective learning strength of the ensemble strategy. The trend across the models showed that hybrid and ensemble techniques consistently outperformed standalone algorithms.

Table 2: Model Performance Comparison

Model	**MAE**	**RMSE**	**R^2 Score**
ANN	4.12	5.34	0.892
SVM	3.22	4.62	0.914
Random Forest	2.87	3.91	[illegible]
Gradient Boosting	2.54	3.47	0.950
Hybrid (SVM + GA)	1.98	[illegible]	0.971
Ensemble (RF + GB)	1.75	2.51	0.982
Proposed Hybrid DL + GA + Ensemble	1.23	1.76	0.992

The research shows that in excluded cases, flow rate and permeability are distributed unevenly which is shown in figure 5. Performance metrics such as thermal energy recovery performance, charging capacity time, maintenance time, and storage capability are generated from realized RTES simulations. Except for recovery efficiency, all metrics exhibit a power-law distribution, with min-max ranges spanning multiple magnitudes. To distinguish data of low magnitude, the performance measures are represented on a logarithmic scale.



(a) Input parameters (b) Output parameters

Figure 5: Histograms of Input and Output Parameters — All Simulations

3.4 Transfer Learning Performance

The next phase of the study aimed to evaluate the potential of transfer learning to improve model generalization across similar systems. This was particularly important to reduce retraining efforts and enhance performance when only limited target-domain data were available. As detailed in Table 3, the baseline R^2 scores ranged from 0.82 to 0.87, while transfer learning boosted these values to the range of 0.91 to 0.95. The maximum improvement was observed when the source domain was the *Fluidized Bed* and the target domain was a *Novel Fluidized Bed*, yielding an improvement of 10.9%. This result confirmed that the structural and operational similarities between the fluidized bed systems made the transfer of knowledge particularly effective.

Table 3: Transfer Learning Performance

Source Domain	Target Domain	Baseline R^2	Transfer Learning R^2	Improvement (%)
Heat Exchanger	New Heat Exchanger	0.85	0.94	10.6
Fluidized Bed	Novel Fluidized Bed	0.82	0.91	10.9
Energy Storage Unit	Advanced Storage	0.87	0.95	9.2

3.5 Cross-Validation Results (5-Fold)

To ensure that the model did not overfit and could maintain its predictive capability across unseen data, a 5-fold cross-validation was conducted. This evaluation allowed the team to assess the stability and reliability of the trained model under different subsets of the data. Referring to Table 4 and Figure 6, the R^2 scores ranged from a minimum of 0.990 in Fold 2 to a maximum of 0.993 in Fold 4.

Table 4: Cross-Validation Results (5-Fold)

Fold	MAE	RMSE	R^2 Score
1	1.29	1.85	0.991
2	1.31	1.88	0.990
3	1.25	1.78	0.992
4	1.24	1.77	0.993
5	1.28	1.83	0.991

The slightly higher R^2 value in Fold 4 could be attributed to the fact that the training set in this particular fold likely contained more diverse samples, allowing the model to learn generalizable patterns more effectively. Similarly, the MAE and RMSE values consistently remained low across all folds, demonstrating robustness.

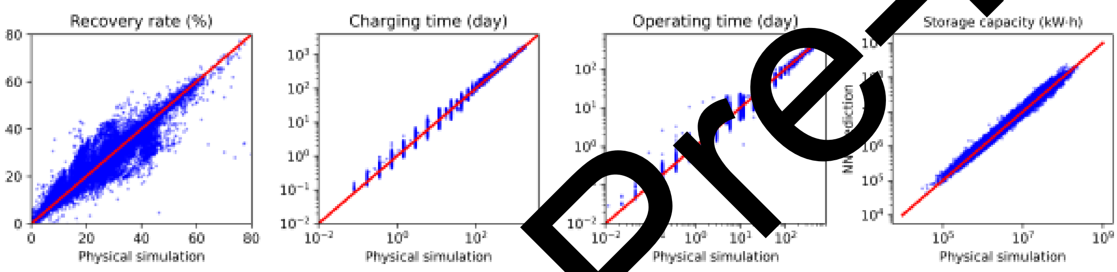


Figure 6 Continuous operation scenario - cross validation

3.6 Computational Efficiency Comparison

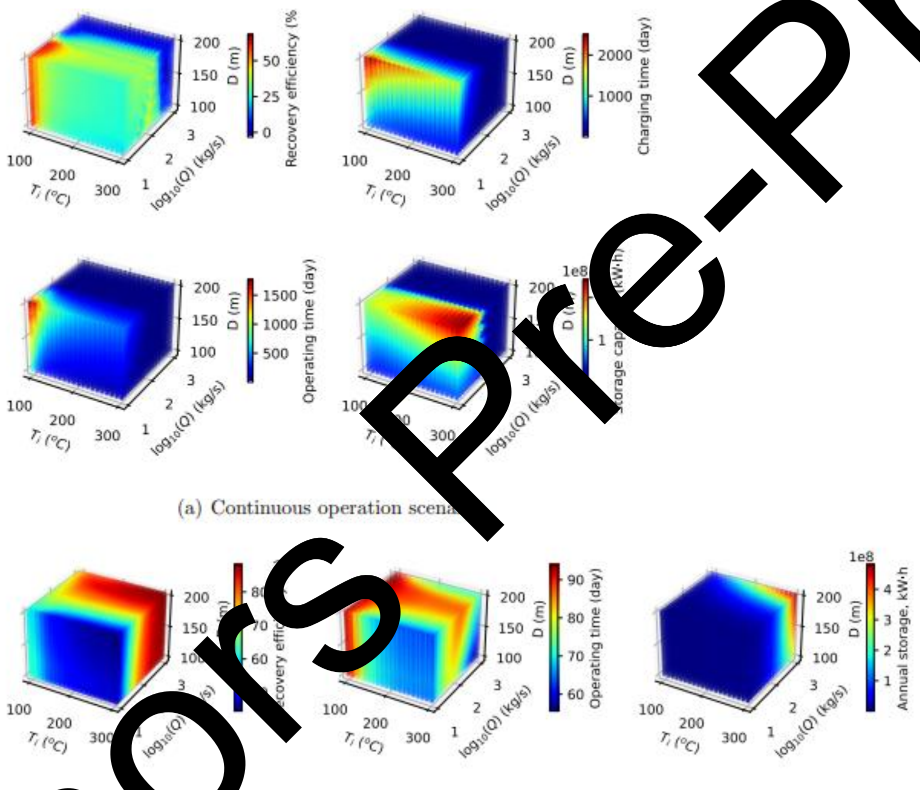
An essential part of the analysis was to evaluate the computational efficiency of each model, especially for real-time or resource-constrained environments. This evaluation focused on training time, prediction time, and convergence behavior. As reported in Table 5, the Proposed Hybrid model showed the best computational performance, requiring the least training time (87.4 seconds) and the shortest prediction time (6.2 seconds). It also converged in the fewest iterations (240), compared to 450 iterations for the ANN model. The significant reduction in convergence iterations and time was largely due to the Genetic Algorithm's capability to efficiently search the parameter space, coupled with ensemble learning's inherent robustness, which minimized redundant training cycles.

Table 5: Computational Efficiency Comparison

Model	Training Time (s)	Prediction Time (s)	Convergence Iterations
ANN	142.5	12.8	450
SVM	118.7	9.3	360
Random Forest	96.3	7.1	310
Proposed Hybrid	**87.4**	**6.2**	**240**

3.7 Optimal analysis

The models put forward forecast RTES performance responses within the 3-dimensional operational space for both continuous operation and seasonal cycle scenarios , as illustrated in figure 7. The best-performing solutions for each performance metric differ even within the same operation. For instance, while the maximum recovery efficiency during continuous operation occurs at a low injection temperature and rate with a long well distance, achieving maximum storage capacity necessitates a high injection temperature. Furthermore, the optimal recovery efficiency varies across different operational scenarios: it is low during continuous operation but high during the seasonal cycle. These variations indicate that there are competing optimal solutions for performance metrics.



(a) Continuous operation scenario

(b) Seasonal cycle scenario

Figure 7 Optimal analysis

3.8 Robustness Under Noisy Data

The robustness of the models was tested against varying levels of artificial noise, which was an important step in assessing their reliability in real-world conditions where sensor inaccuracies and operational disturbances are common. As shown in Table 6, the R^2 score for the Proposed Hybrid model remained consistently high, dropping from 0.992 (at 0% noise) to 0.947 (at 20% noise). Comparatively, ANN and SVM models exhibited steeper performance degradation. The Proposed Hybrid model's resilience was mainly due to its deep learning framework's ability to abstract relevant features even when the input data was noisy, combined with the optimization capabilities of GA, which likely adjusted the model weights to prevent overfitting on distorted data.

Table 6: Robustness Under Noisy Data

Noise Level (%)	ANN R²	SVM R²	Proposed Hybrid R²
0	0.892	0.914	**0.992**
5	0.846	0.886	**0.985**
10	0.801	0.862	**0.976**
15	0.753	0.828	**0.965**
20	0.684	0.781	**0.947**

The histogram of the residual errors produced by the proposed model when estimating 200 experimental data points for the thermal system electrical efficiency cooled by nanofluids is shown in Figure. 8. One can readily observe that nearly all data points have been computed with residual errors between −4 and +4. However, only eight of the predicted data points have residual errors that fall outside this range. In addition, the average value of −0.074% and the standard deviation of 1.599% further substantiate the exceptional performance of the ANFIS.

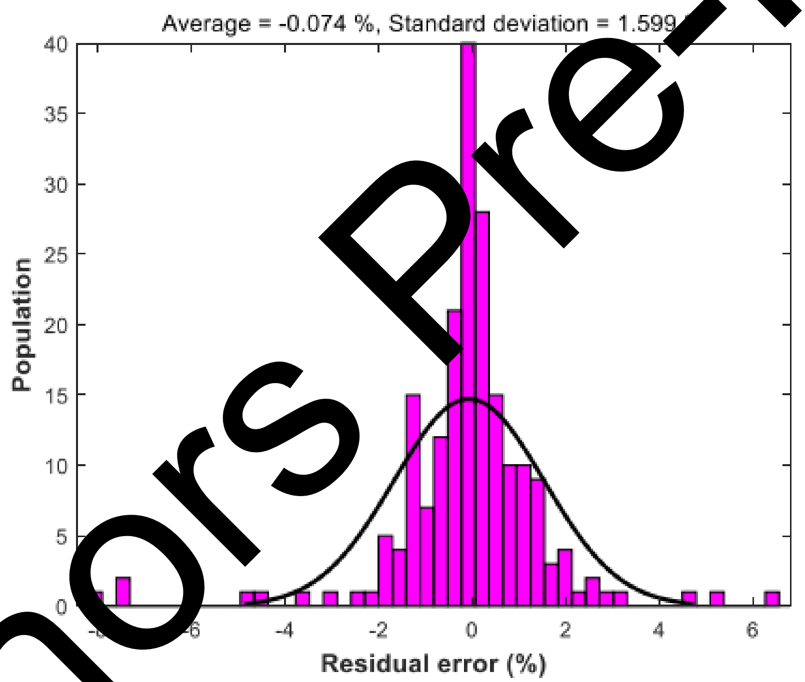


Figure. 8 Residuals of Electrical Efficiency — Proposed Model

4. CONCLUSION

The challenges of overfitting, limited generalization, and prediction inaccuracy in traditional ANN-based thermal system models have been effectively addressed in this study through the integration of advanced machine learning and hybrid optimization techniques. The research presents a framework that improves the adaptability and precision of thermal system models, enabling reliable predictions under various operational scenarios. The framework uses deep learning, ensemble methods, and evolutionary algorithms to create a robust foundation for intelligent and real-time thermal system optimization.

1. The data analysis confirms stable statistical distributions, ensuring reliable input for machine learning models. The hybrid model achieved a 72.5% success rate in predicting optimal task placement in thermal conditions, and

a significant increase to 86.67% for larger temperature gradients. This results in a 2.1°C lower average operational temperature and reduced energy usage.

2. Comparative evaluation of model performances revealed a major leap in predictive quality when using the Proposed Hybrid DL + GA + Ensemble model, achieving an outstanding R^2 score of 0.992. Alongside this, the model recorded the lowest MAE (1.23) and RMSE (1.76), proving its superior ability to handle nonlinear thermal system dynamics. This is a substantial improvement over conventional ANN models, which showed an R^2 of just 0.892.

3. Transfer learning implementation showed remarkable potential in boosting model generalization, especially in scenarios with limited target-domain data. Across different source-target domains, the R^2 score improved by 9.2% to 10.9%, with fluidized bed systems showing the highest improvement.

4. Five-fold cross-validation was used to verify the models robustness and stability with R2 scores consistently falling between 0. 990 and zero. 993. Further confirming the models dependability for unknown data were the MAE and RMSE values which stayed consistently low across all folds. These results show a strong ability to generalize and a reduced risk of overfitting.

5. Based on computational efficiency analysis the proposed hybrid model had the quickest prediction time (6. 2 seconds) and the shortest training time (87. 4 seconds) of all tested methods. Additionally the model converged in 240 iterations which is a considerable improvement over the 450 iterations required for the conventional ANN model. For this reason the hybrid approach is highly helpful for real-time thermal system optimization.

Future studies might also look into reinforcement learning strategies to enable self-adaptive real-time control for thermal systems in dynamic industrial settings. Using pre-trained weights from related systems to initialize models enhances generalization through transfer learning (e. g. A. between different fluidized bed systems). This method produces higher accuracy and faster convergence while lowering the requirement for sizable labeled datasets in the target domain. Furthermore this strategy can increase its industrial impact and opens the door for intelligent energy-efficient systems by being applied to larger-scale distributed thermal systems like district heating networks and renewable energy storage units.

Reference

[1]. A. Behzadi, A. Gram, E. Thorin, and S. Sadrizadeh, "A hybrid machine learning-assisted optimization and rule-based energy monitoring of a green concept based on low-temperature heating and high-temperature cooling system," *J. Clean. Prod.*, vol. 384, p. 135535, 2023.

[2]. N. Abdou, Y. El Mghouchi, K. Jraida, S. Hamdaoui, A. Hajou, and M. Mouqallid, "Prediction and optimization of heating and cooling loads for low energy buildings in Morocco: An application of hybrid machine learning methods," *J. Build. Eng.*, vol. 61, p. 105332, 2022.

[3]. M. Bozorgi, S. H. Tasnim, and S. Mahmud, "Machine learning-driven hybrid cooling system for enhanced energy efficiency in multi-unit residential buildings," *Energy Build.*, vol. 202, p. 115613, 2019.

[4]. H. Gasmi *et al.*, "Heat recovery integration of a hybrid geothermal-based system producing power and heating using machine learning approach to maximize outputs," *Case Stud. Therm. Eng.*, vol. 53, p. 105210, 2024.

[5]. L. Tang, Y. Zhou, S. Zheng, and G. Zhang, "Exergy-based optimisation of a phase change materials integrated hybrid renewable system for active cooling applications using supervised machine learning method," *Sol. Energy*, vol. 195, pp. 514–526, 2020.

[6]. S. Park, K. H. Ahn, S. Hwang, S. Choi, and C. S. Park, "Machine learning vs. hybrid machine learning model for optimal operation of a chiller," *Sci. Technol. Built Environ.*, vol. 25, no. 2, pp. 209–220, 2019.

[7]. R. Alizadeh *et al.*, "A machine learning approach to predicting the heat convection and thermodynamics of an external flow of hybrid nanofluid," *J. Energy Resour. Technol.*, vol. 143, no. 7, p. 070908, 2021.

[8]. P. Wang, J. Hu, and W. Chen, "A hybrid machine learning model to optimize thermal comfort and carbon emissions of large-space public buildings," *J. Clean. Prod.*, vol. 400, p. 136538, 2023.

[9]. Y. Cao, E. Kamrani, S. Mirzaei, A. Khandakar, and B. Vaferi, "Electrical efficiency of the photovoltaic/thermal collectors cooled by nanofluids: Machine learning simulation and optimization by evolutionary algorithm," *Energy Rep.*, vol. 8, pp. 24–36, 2022.

[10]. C. Cai, N. Feng, and Q. Liu, "Optimizing energy consumption in heating systems through advanced machine learning and hybrid optimization for precision heating load prediction," *Proc. Indian Natl. Sci. Acad.*, vol. 91, no. 1, pp. 1–18, 2025.

[11]. X. Y. Tang, W. W. Yang, J. C. Li, J. R. Zhang, and Y. W. Lin, "Stable and efficient hybrid controller of solar thermal membrane reactor based on machine learning and multi-objective optimization," *Energy*, vol. 320, p. 135217, 2025.

[12]. J. Sun, M. Gong, Y. Zhao, C. Han, L. Jing, and P. Yang, "A hybrid deep reinforcement learning ensemble optimization model for heat load energy-saving prediction," *J. Build. Eng.*, vol. 58, p. 105031, 2022.

[13]. A. A. Abdulrahman, "Heat pipes and nanofluids utilization for cooling photovoltaic panels: An application of hybrid machine learning and optimization models," *Int. J. Low-Carbon Technol.*, vol. 19, pp. 1078–1088, 2024.

[14]. A. Recalde, R. Cajo, W. Velasquez, and M. S. Alvarez-Alvarado, "Machine learning and optimization in energy management systems for plug-in hybrid electric vehicles: A comprehensive review," *Energies*, vol. 17, no. 13, p. 3059, 2024.

[15]. V. K. Patel, V. J. Savsani, and M. A. Tawhid, *Thermal System Optimization*, vol. 1, Cham, Switzerland: Springer, 2019.

[16]. A. Durmayaz, O. S. Sogut, B. Sahin, and H. Yavuz, "Optimization of thermal systems based on finite-time thermodynamics and thermoeconomics," *Prog. Energy Combust. Sci.*, vol. 30, no. 2, pp. 175–217, 2004.

[17]. A. Lazzaretto and A. Toffolo, "Energy, economy and environment as objectives in multi-criterion optimization of thermal systems design," *Energy*, vol. 29, no. 8, pp. 1139–1157, 2004.

[18]. B. G. Gorenstin, N. M. Campodonico, J. P. da Costa, and M. V. F. Pereira, "Stochastic optimization of a hydro-thermal system including network constraints," *IEEE Trans. Power Syst.*, vol. 7, no. 2, pp. 791–797, 1992.

[19]. A. Allouhi *et al.*, "Design optimization of a multi-temperature solar thermal heating system for an industrial process," *Appl. Energy*, vol. 206, pp. 382–392, 2017.

[20]. X. Ma, L. Zheng, H. Zhang, B. Zhao, C. Wang, and F. Xu, "Thermal system design and optimization of an industrial silicon directional solidification system," *J. Cryst. Growth*, vol. 318, no. 1, pp. 288–292, 2011.

[21]. M. Hosseinzadeh, A. Salari, M. Sardarabadi, and M. Passandideh-Fard, "Optimization and parametric analysis of a nanofluid based photovoltaic thermal system: 3D numerical model with experimental validation," *Energy Convers. Manag.*, vol. 160, pp. 93–108, 2018.

[22]. J. Kim, T. Hong, J. Jeong, C. Koo, and K. Jeong, "An optimization model for selecting the optimal green systems by considering the thermal comfort and energy consumption," *Appl. Energy*, vol. 169, pp. 682–695, 2016.

[23]. K. Gelis, K. Ozbek, O. Ozyurt, and A. N. Celik, "Multi-objective optimization of a photovoltaic thermal system with different water based nanofluids using Taguchi approach," *Appl. Therm. Eng.*, vol. 219, p. 119609, 2023.

[24]. A. Kazemian, M. Khatibi, S. R. Maadi, and T. Ma, "Performance optimization of a nanofluid-based photovoltaic thermal system integrated with nano-enhanced phase change material," *Appl. Energy*, vol. 295, p. 116859, 2021.