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Advanced Optimization Techniques Using Artificial Intelligence Algorithms for Thermal Efficiency Estimation of Photovoltaic Thermal Systems

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Abstract
This study investigates the optimization and predictive accuracy of photovoltaic thermal systems' thermal efficiency using advanced artificial intelligence algorithms, specifically the artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM). Experimental data was collected from a photovoltaic thermal system at the Research Institute of Petroleum Industry in Tehran, Iran, with critical variables including solar irradiance, inlet temperature, wind speed, and ambient temperature. The comparative analysis revealed that the artificial neural network model outperformed other algorithms, achieving the highest predictive accuracy with a root mean square error (RMSE) of 11.704 and an R^2 value of 0.959, emphasizing its strength in capturing complex, non-linear data interactions. The adaptive neuro-fuzzy inference system and relevance vector machine models demonstrated moderate predictive capabilities, with root mean square error values of 14.704 and 19.606, and R^2 scores of 0.936 and 0.887, respectively. These results highlight the transformative potential of artificial intelligence-driven models, particularly the artificial neural network, in enhancing photovoltaic thermal system efficiency, thereby supporting global renewable energy goals through improved system adaptability and energy yield. This study advances renewable energy optimization, illustrating that artificial intelligence algorithms can effectively manage intricate variable relationships in photovoltaic thermal systems. The demonstrated approach sets a foundation for further research into artificial intelligence-optimized renewable energy solutions, promoting more efficient and resilient infrastructures essential for sustainable development and climate action.

Keywords Photovoltaic thermal systems · Artificial neural network · Adaptive neuro-fuzzy inference system · Thermal efficiency optimization · Artificial intelligence algorithms in renewable energy · Predictive modeling for solar systems

Introduction

Photovoltaic thermal (PV/T) systems, with their unique capability to simultaneously generate electrical and thermal energy from solar radiation, have become a cornerstone in the renewable energy landscape. These hybrid systems provide a dual benefit, enhancing energy conversion efficiency while offering a sustainable solution to meet the growing global demand for clean energy (Herrando and Ramos 2022). The integration of photovoltaic and thermal components in a single system enables optimal utilization of solar resources, reducing carbon emissions and promoting cost-effective energy production. Consequently, PV/T systems have emerged as an efficient and eco-friendly alternative to standalone photovoltaic (PV) or thermal systems, particularly in regions with abundant solar irradiance (Sornek 2024). Despite their significant promise, optimizing the thermal efficiency of PV/T systems remains a complex challenge. Performance is dictated by the dynamic interplay of multiple environmental and operational factors, including solar irradiance, wind speed, fluid inlet temperature (Noxpanco et al.

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2020), and ambient temperature. These parameters, subject to substantial spatial and temporal variability, introduce nonlinear interactions that complicate predictive modeling and system optimization (Minakova and Zaitsev 2021). Traditional numerical methods, though widely utilized, often rely on extensive simplifications that can undermine their accuracy and fail to account for the intricate dependencies among system parameters. As such, developing robust and accurate predictive models is imperative for advancing PV/T technology (Allouhi et al. 2023).

Recent studies, such as Salim et al.'s techno-economic analysis of hybrid PV/T systems in Iraq (2024), Kareem et al.'s optimization of microgrid droop control (2024), and Radhi et al.'s neural network-based PV power forecasting (2024), highlight innovative approaches to enhance system performance and integration.

By capturing intricate parameter interactions and adapting to dynamic environmental conditions, these models outperform conventional approaches, offering unprecedented accuracy and reliability in performance predictions (Dong et al. 2023). For example, Ahmadi et al. employed an ANN-based model to predict the thermal efficiency of a PV/T solar collector using inputs such as inlet temperature, flow rate, and solar irradiance. Their model achieved a determination coefficient (R^2) of 0.95, illustrating the robust predictive capability of ANN in capturing nonlinear system behaviors (Ahmadi et al. 2020). Further advancements in AI modeling were demonstrated by Jiang et al., who developed a hybrid approach combining variational mode decomposition (VMD), convolutional neural networks (CNN), improved particle swarm optimization (IPSO), and least squares support vector machines (LSSVM). Their methodology significantly reduced the average relative error by 15.23% and the root mean square error by 53.60% compared to traditional methods, further exemplifying the transformative potential of AI in renewable energy systems (Jiang et al. 2024). ANFIS, a hybrid model integrating neural networks with fuzzy logic, has also shown substantial promise in PV/T system optimization. This approach excels in handling the uncertainties and nonlinearities inherent in such systems by deriving interpretable rules from input data and providing robust predictions of thermal efficiency. Its ability to elucidate complex relationships between variables, such as solar irradiance, wind speed, and fluid inlet temperature, makes it particularly well-suited for PV/T applications (Vakili and Salehi 2023). Similarly, multilayer perceptron artificial neural networks (MLP-ANNs), known for their flexibility and adaptability, have been widely utilized for modeling highly nonlinear systems. A recent study demonstrated that MLP-ANN could achieve a mean squared error (MSE) of 0.009 and a determination coefficient (R^2) of 1.00 in predicting PV/T system efficiency, underscoring its superior accuracy in capturing the multifaceted interactions of environmental and operational parameters (Zamen et al. 2019). The present study builds upon these advancements by evaluating the comparative performance of ANN, ANFIS, and RVM models in predicting the thermal efficiency of PV/T systems. To ensure robustness and real-world applicability, the analysis leverages experimental data obtained from the Research Institute of Petroleum Industry (RIPI) in Tehran, Iran, as documented by Shojaeefard et al. (2023). This dataset encompasses a broad spectrum of operational conditions, capturing key parameters such as solar irradiance, inlet fluid temperature, wind speed, and ambient temperature. These factors are widely acknowledged in the literature for their significant influence on the thermal and electrical performance of PV/T systems (Kazem et al. 2024). Among the evaluated models, the ANN approach demonstrated superior predictive accuracy, achieving a determination coefficient (R^2) of 0.959 and a root mean square error (RMSE) of 11.704. These results highlight ANN's exceptional ability to model complex parameter interactions, offering a reliable pathway for optimizing system efficiency (Saha and Azad 2024). Beyond the specific contributions to PV/T system optimization, the integration of advanced AI methodologies in this study exemplifies the broader potential of AI-driven approaches in renewable energy research. By leveraging the theoretical strengths of RVM, ANFIS, and ANN, this research provides a comprehensive framework for addressing the challenges posed by dynamic environmental conditions and nonlinear system behaviors. Moreover, the findings align with global efforts to transition toward sustainable energy systems, showcasing AI as a transformative tool for enhancing the efficiency, reliability, and scalability of renewable energy technologies (Panagoda et al. 2023). The results of this study not only advance the field of PV/T optimization but also underscore the critical role of AI in meeting the urgent demand for innovative, data-driven solutions to complex energy challenges (Fig. 1).

Methodology

The experimental phase of this study was conducted at the Research Institute of Petroleum Industry (RIPI) in Tehran, Iran, where a custom-designed photovoltaic thermal (PV/T) system was developed, installed, and tested. This system was engineered to generate empirical data and provide insights for enhancing thermal efficiency. The setup integrated photovoltaic panels with a thermal collector, enabling the simultaneous production of electrical and thermal energy from solar irradiation. This design maximized energy conversion and utilization, as illustrated in Fig. 2.

Fig. 1 Image of the test bench

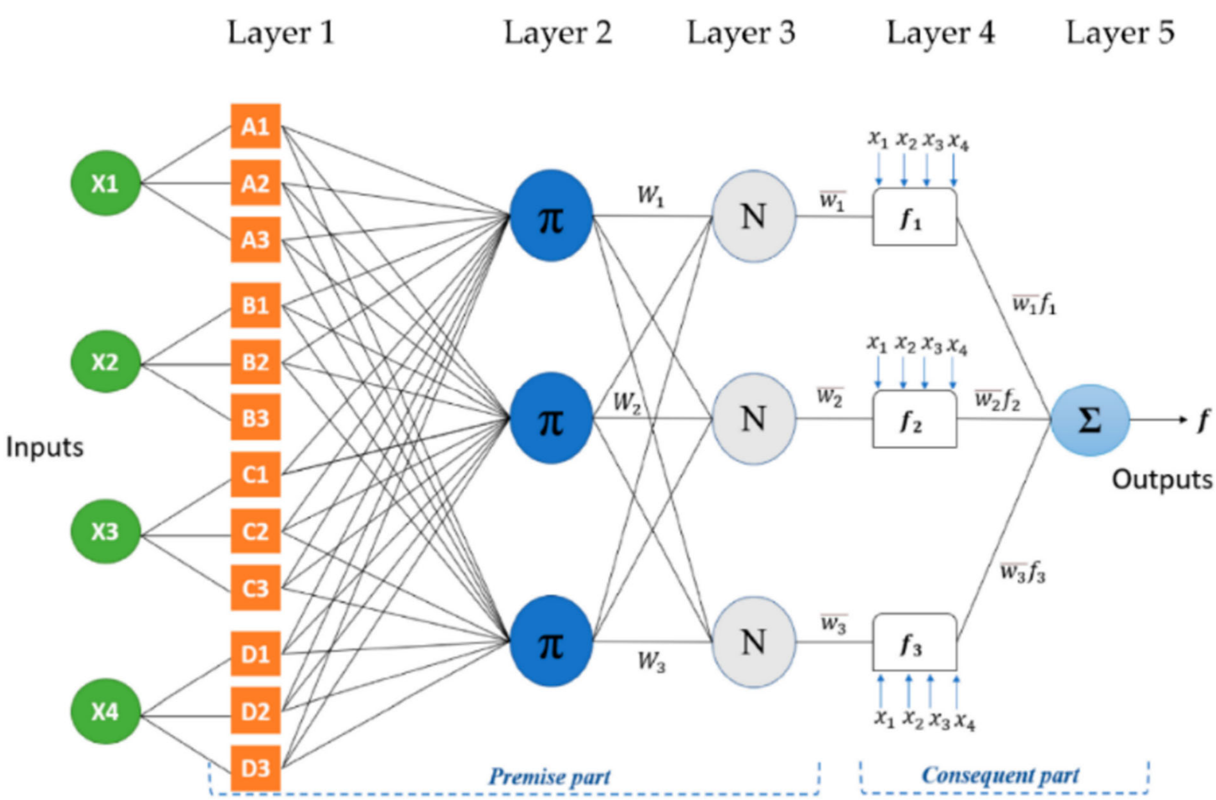

Fig. 2 Core architecture of the adaptive neuro-fuzzy inference system (ANFIS) with four input variables and a single output (Lara-Cerecedo et al. 2023)

Details of the PV/T device properties are provided in Table 1. To ensure accurate and comprehensive data acquisition, the system was equipped with high-precision sensors to monitor key environmental and operational parameters in real-time. These parameters included solar irradiance, inlet and outlet temperatures, ambient temperature, wind speed, and fluid flow rates. This suite of instrumentation captured detailed data essential for evaluating and optimizing the PV/T system's thermal performance under diverse environmental conditions, offering valuable insights for advancing energy efficiency.

Data Acquisition and Experimental Procedure

The data acquisition process utilized precision sensors connected to a data logger to ensure accurate measurement of parameters critical to system performance. Measurements were conducted over multiple days, covering a wide range of environmental and operational conditions to produce a robust and representative dataset. The key parameters recorded included solar irradiance (W/m^2), coolant inlet temperature (°C), coolant outlet temperature (°C), wind speed (m/s), and ambient temperature (°C). A controlled recirculation flow rate was maintained to optimize heat extraction from the PV/T system. All data points were systematically logged at regular intervals, enabling the capture of the system's dynamic response to varying conditions.

Machine Learning Models

In this study, we developed three advanced machine learning models to predict and optimize the thermal efficiency of photovoltaic thermal (PV/T) systems: multilayer perceptron artificial neural network (MLP-ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM). Each model was selected based on its unique strengths in handling complex, nonlinear relationships inherent in PV/T systems.

1. **Multilayer perceptron artificial neural network (MLP-ANN):** MLP-ANNs are renowned for their ability to model intricate nonlinear interactions without requiring explicit equations, as they learn directly from empirical data. This capability makes them particularly suitable for capturing the multifaceted dependencies between input parameters—such as solar irradiance, inlet temperature, wind speed, and ambient temperature—and the resulting thermal efficiency in PV/T systems. Their flexibility and adaptability have been demonstrated in various studies, highlighting their effectiveness in predicting outcomes across diverse environmental conditions (Vijayalakshmi et al. 2024).
2. **Adaptive neuro-fuzzy inference system (ANFIS):** ANFIS combines the learning capabilities of neural networks with the interpretability of fuzzy logic, making it adept

Table 1 Key characteristics of the photovoltaic thermal (PV/T) system analyzed in this study (Shojaeefard et al. 2023)

Electrical characteristics Solar cells	60 polycrystalline (156 × 156 mm)
Maximum power, P_{mpp} (W)	250
Voltage at max power, U_{mpp} (V)	30.03
Current at max power, I_{mpp} (A)	8.33
Open-circuit voltage, U_{oc} (V)	37.68
Short-circuit current, I_{sc} (A)	8.81
Temperature coefficients	$P_{mpp} = -0.37\%/K$
	$U_{oc} = -90.7$ mV/K
	$I_{sc} = +2.85$ mA/K
Thermal characteristics	
Gross surface area (m^2)	1.63
Net surface area (m^2)	1.48
Liquid content (l)	1.15
Absorber material	Aluminum plate
Collector pipe dimensions (mm)	22 × 0.8
Internal pipe dimensions (mm)	8 × 0.5
Maximum operating temperature (°C)	80
Working pressure (bar)	4
Technical data	
Dimensions (mm)	1666 × 992 × 40 ±2 mm
Weight (kg)	22
Solar glass thickness (mm)	3.2

at modeling complex systems where understanding variable interactions is crucial. In the context of PV/T systems, ANFIS can handle the nonlinear relationships between input parameters, providing interpretable rules that offer insights into system behavior under varied conditions. This adaptability and interpretability are especially valuable for optimizing PV/T systems (Guerra et al. 2024).

3. **Relevance vector machine (RVM):** RVM is grounded in sparse Bayesian learning and is advantageous for its probabilistic framework and sparse representation, enabling predictive modeling with minimal reliance on large datasets. Its ability to capture prediction uncertainty provides valuable insights into the confidence of its outputs, supporting optimization in systems experiencing fluctuating environmental conditions. This makes RVM a suitable choice for modeling the dynamic interactions present in PV/T systems (Wang et al. 2022).

By training these models on experimental data, we aimed to capture the complex relationships between key input parameters and thermal efficiency, facilitating a nuanced understanding and accurate modeling of PV/T system performance. This data-driven approach enables effective optimization, contributing to the advancement of renewable energy technologies.

Thermal Analysis for the PVT

- Thermal output (Q) The thermal energy output of the photovoltaic thermal (PV/T) collector is calculated using the following equation:

$$\eta_{\text{th}} = \frac{\dot{m} C_p (T_{\text{out}} - T_{\text{in}})}{A \cdot G} \tag{1}$$

  where $\dot{m}$ is the mass flow rate (kg/s), C_p is the specific heat capacity of water ($4186\,\text{J}\,\text{kg}^{-1}\,\text{K}^{-1}$), and $T_{\text{out}} - T_{\text{in}}$ is the temperature difference between the outlet and inlet water (°C).
  This equation calculates the heat absorbed by the fluid as it passes through the PV/T collector, based on the temperature increase and flow rate of the fluid.
- Thermal efficiency (η)
  The thermal efficiency of the PV/T collector is defined as the ratio of the thermal energy output to the solar energy input:

$$\eta = \frac{\dot{Q}_{\text{u}}}{AG} \tag{2}$$

  where (η) is the thermal efficiency, (Q) useful thermal energy output of the PV/T collector (W), (A) area of the collector (m^2), and (Q) is the global solar irradiance incident on the collector surface (W/m^2).

  This equation represents the fraction of incident solar energy that is converted into useful thermal energy by the PV/T system.

Multilayer Perceptron Artificial Neural Network (MLP-ANN)

The artificial neural network (ANN) is a computational model inspired by the structure and functionality of the human brain. It consists of interconnected nodes, or "neurons," which collaboratively process and transmit information across the network. Each node produces an output based on a nonlinear combination of its input values. The "weight" parameter within the network determines the strength or intensity of the signal at each connection, influencing how information is processed and passed forward. In an MLP-ANN, activation functions play a critical role in transforming inputs into outputs within each node. Three common activation functions are as follows (Zamen et al. 2019).

Linear Activation

$$f(x) = x \tag{3}$$

This function is straightforward, outputting the input value as is, allowing for linear relationships to be maintained.

Sigmoid Activation

$$f(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

The sigmoid function maps any input to a value between 0 and 1, making it useful for scenarios where probabilities or bounded outputs are desired.

Hyperbolic Tangent

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{5}$$

Adaptive Neuro-Fuzzy Inference System (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) is a multi-layered, feed-forward network structure that combines neural network adaptability with fuzzy logic principles. It consists of neurons connected through weighted links, allowing it to model complex, nonlinear systems. ANFIS operates through a five-layer architecture, which has been well-documented in the literature as an effective method for handling fuzzy systems by combining least squares estimation and backpropagation to optimize its parameters. In this system, forward propagation is used to determine the consequent parameters (P_i, q_i, r_i), as seen in the defuzzification layer. Meanwhile, the backpropagation algorithm minimizes error by adjusting the premise parameters (a_i, b_i, c_i), in the fuzzification layer through gradient descent. Layer descriptions and equations:

- Layer 1 (Fuzzification layer): In this layer, input signals are transformed based on membership functions. Each neuron processes an input using a function associated with linguistic terms, which are represented by square nodes. The output of each neuron in this layer, O_i^1, is calculated by a membership function, $\mu_{A_i}(x)$, as follows:

$$O_i^1 = \mu_{A_i}(x) = \exp\left(-\left(\frac{x - c_i}{a_i}\right)^{b_i}\right) \tag{6}$$

Here, x is the input, while a_i, b_i, and c_i are parameters that shape the membership function.

- Layer 2 (Rule layer): This layer computes the activation strength of each rule by multiplying membership values from Layer 1. The output, O_i^2, is given by:

$$O_i^2 = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{7}$$

- Layer 3 (Normalization layer): Here, each rule's firing strength is normalized by dividing it by the sum of all firing strengths. The output for each rule in this layer, O_i^3, is expressed as:

$$O_i^3 = \frac{w_i}{w_1 + w_2} \tag{8}$$

where w_i represents the firing strength of each rule.

- Layer 4 (Defuzzification layer): In this layer, the consequent parameters are applied to the normalized firing strengths, yielding an output O_i^4:

$$O_i^4 = w_i f_i = w_i(p_i x + q_i y + r_i) \tag{9}$$

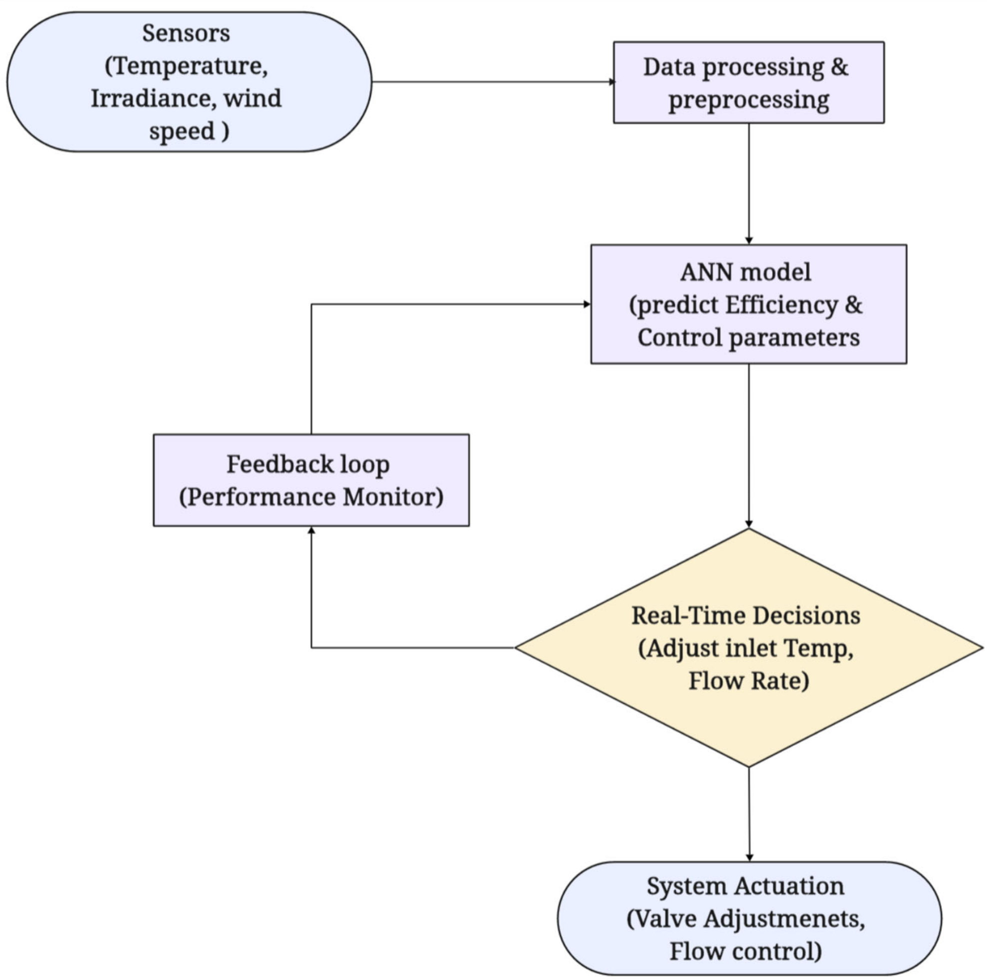

Fig. 3 Flowchart of the real-time photovoltaic thermal (PV/T) system management framework integrating ANN-based predictions

Here, $p_i, q_i, and\ r_i$ are parameters associated with each rule's consequent function.

- Layer 5 (Output layer): This layer produces the overall output of the system by summing the outputs from Layer 4. The final output, O_i^5, is calculated as:

$$O_i^5 = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{10}$$

Figure 3 illustrates the ANFIS structure, showing four input variables linked through five layers, where the first three layers represent the premise part, and the final two layers constitute the consequent part. This architecture enables ANFIS to effectively model and interpret complex systems through a combination of fuzzy logic rules and adaptive neural learning.

Relevance Vector Machine (RVM)

The relevance vector machine (RVM) is a Bayesian approach to sparse kernel modeling, commonly employed for regression and classification tasks. Like the Support Vector Machine (SVM), it utilizes a similar mathematical framework but offers probabilistic outputs and fewer support vectors, known as "relevance vectors," resulting in a more efficient and interpretable model. RVM uses Bayesian inference to find parsimonious solutions, ensuring only the most relevant input vectors are included in the final model, which contributes to its sparsity. In the context of photovoltaic thermal (PV/T) systems, RVM can be leveraged to predict performance by classifying or regressing key environmental and operational variables, offering an accurate probabilistic model that effectively captures nonlinear relationships within the data. Below are the key mathematical formulations and equations that outline the RVM methodology. RVM starts with a linear model framework, where the objective is to predict an output y(x) based on input x, expressed as:

$$y(x) = \sum_{i=1}^{N} w_i \phi_i(x) \tag{11}$$

where w_i represents the weights for each basis function, $\phi_i(x)$ denotes the chosen basis function. In vector notation, the model can be written as:

$$t = \phi\omega + \epsilon \tag{12}$$

where (t) is the target vector, (ϕ) is the design matrix of basic functions, (ϵ) is the noise term with a Gaussian distribution.

Probabilistic Output and Likelihood: RVM introduces a probabilistic perspective to the model by assuming that each observation follows a Gaussian distribution:

$$p(t \mid w, \sigma) = (2\pi\sigma^2)^{-N/2} \exp\left(-\frac{1}{2\sigma^2}\|t - \phi w\|^2\right) \tag{13}$$

where σ^2 is the variance of the noise term, N is the number of data points.

Prior distribution on weights: To encourage sparsity, RVM imposes a Gaussian prior on the weights, leading most weights to converge towards zero while retaining only the relevant vectors:

$$p(w \mid \alpha) = \prod_{i=1}^{N} N(w_i \mid 0, \alpha_i^{-1}) \tag{14}$$

This Bayesian posterior allows for a probabilistic approach, aiding in the identification of relevance vectors that contribute meaningfully to the model.

Hyperparameter optimization via marginal likelihood: The optimal values of α and σ^2 are determined by maximizing the marginal likelihood:

$$p(t \mid \alpha, \sigma^2) = \int p(t \mid w, \sigma^2) p(w \mid \alpha)\, dw \tag{15}$$

This process identifies the best-fitting model parameters that maximize the likelihood of observing the target data, promoting a sparse solution.

Predictive distribution for new data: For a new input x_*, the predictive distribution is calculated as:

$$p(y_* \mid x_*, t) = \int p(y_* \mid x_*, w, \sigma^2) p(w \mid t, \alpha, \sigma^2)\, dw \tag{16}$$

Data Collection

Data were collected from the experimental work presented in Shojaeefard et al. (2023), which investigated photovoltaic thermal (PVT) systems using water as the cooling fluid in the climate of Tehran. This research was conducted at the Research Institute of Petroleum Industry (RIPI). The study focused on key parameters affecting PVT performance, including ambient temperature (T_a), wind speed (U), inlet temperature (T_{in}), outlet temperature (T_{out}), and mass flow rate (m). From this experimental work, both the thermal efficiency and thermal power output were obtained.

Hyperparameter Tuning and Model Configuration

This study employed a comprehensive hyperparameter tuning process to optimize the predictive performance of the machine learning models used for photovoltaic thermal (PV/T) system efficiency prediction. Systematic tuning methods were applied to ensure the models were tailored to the dataset's characteristics, enhancing accuracy and generalizability. The specific tuning approaches and the resulting configurations for the artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM) are detailed below and summarized in Table 2. A grid search approach was utilized for ANN to explore combinations of key parameters systematically, ensuring the best architectural and learning configurations. ANFIS parameters were optimized through a manual trial-and-error approach, focusing on interpretability and adaptability. For RVM, random search was employed to efficiently identify optimal kernel types and regularization strengths. These configurations provide a robust foundation for accurately modeling the complex, nonlinear dynamics inherent in PV/T systems.

Real-Time System Management Framework

The integration of an artificial neural network (ANN) into a real-time management system for photovoltaic thermal (PV/T) systems, as depicted in Fig. 3, provides a comprehensive and adaptive framework to optimize system performance under dynamic environmental conditions. This workflow begins with high-precision sensors that capture critical environmental and operational parameters, including solar irradiance, wind speed, and ambient temperature. These measurements form the basis for the system's real-time data-driven decision-making processes.

The collected data undergoes preprocessing to ensure its reliability and consistency. This stage involves cleaning the data to address issues such as noise, outliers, and missing values, as well as normalizing the inputs to align with the requirements of the ANN model. By standardizing the data, preprocessing ensures that the subsequent predictive analyses are both accurate and robust.

Table 2 Hyperparameters of machine learning models

Model	Hyperparameter	Final value
ANN	Number of hidden layers	2
	Neurons per layer	128, 64
	Activation function	ReLU
	Learning rate	0.001
	Dropout rate	0.2
ANFIS	Number of membership functions	3
	Membership function type	Triangular
	Learning algorithm	Hybrid learning
RVM	Kernel type	Gaussian
	Kernel width	1.5
	Regularization parameter	0.01

At the core of this framework lies the ANN model, which leverages its ability to model complex, non-linear relationships between input variables to predict critical system parameters such as thermal efficiency. Trained on experimental data, the ANN dynamically accounts for interdependencies between factors like solar irradiance, fluid inlet temperature, and wind speed, delivering precise predictions that guide system optimization. These predictions are passed to the decision-making module, where real-time operational adjustments are determined. The system evaluates the ANN's outputs to recommend modifications such as adjusting inlet fluid temperature or flow rates, ensuring optimal efficiency under the prevailing environmental conditions. This decision-making process exemplifies the ANN's ability to translate predictive insights into actionable operational strategies. Following the decision-making stage, system actuators implement the recommended adjustments. These actuators control key operational elements, such as valve positions or flow rates, to align system performance with the optimized parameters. This actuation step highlights the system's responsiveness to environmental changes, enabling continuous operational efficiency. To further enhance system performance, a feedback loop is incorporated to monitor the outcomes of implemented adjustments and refine the ANN model. By comparing actual system performance with predicted outcomes, this feedback mechanism iteratively improves the model's accuracy and adaptability over time. This process ensures that the system remains effective in responding to long-term changes in environmental conditions or operational demands.

Figure 3 effectively encapsulates this integrated framework, illustrating the seamless interaction between sensors, data preprocessing, ANN-based predictions, real-time decision-making, and system actuation. This approach demonstrates the transformative potential of ANN-driven frameworks in renewable energy systems, providing a scalable and efficient solution for real-time optimization. By integrating advanced machine learning techniques with adaptive control strategies, this framework offers a robust methodology for enhancing the efficiency and reliability of PV/T systems in diverse operational contexts.

Results

The experiments were performed during peak midday solar irradiance on October 10, 2021, ensuring stable and high radiation levels crucial for evaluating PV/T system performance. Key parameters analyzed included inlet temperature, wind speed, ambient temperature, and solar irradiance. The water mass flow rate was kept constant at 0.032–0.033, kg/s to isolate the effects of these variables on thermal efficiency.

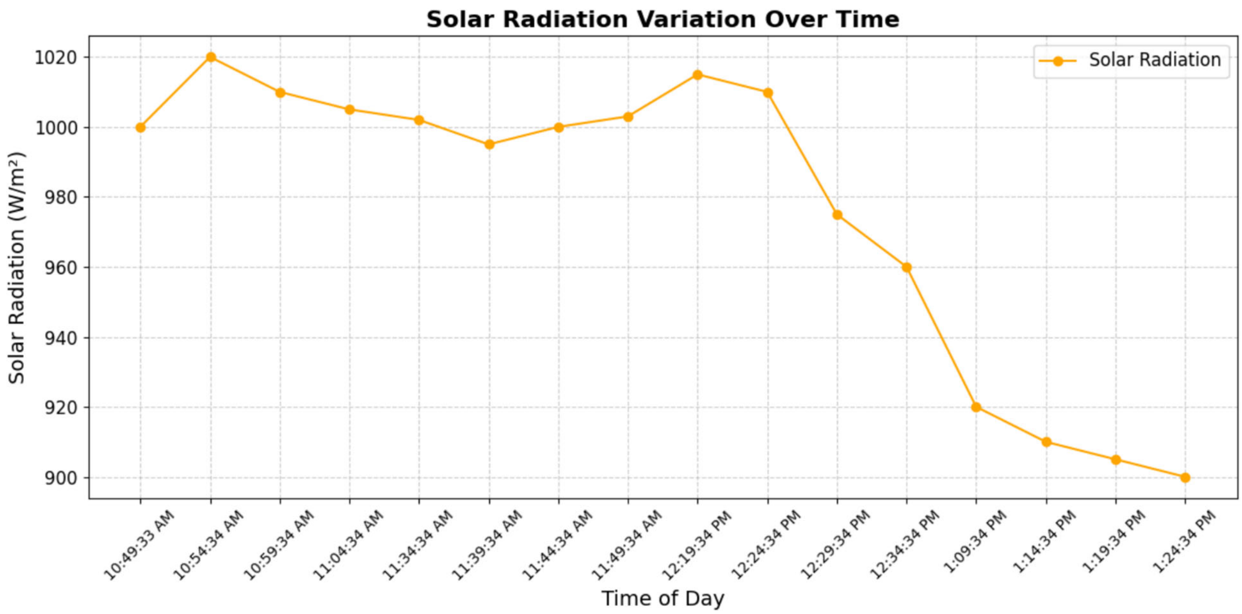

Fig. 4 Solar irradiance measurements for Tehran during the study period

Solar Irradiance and Thermal Efficiency Relationship

As shown in Fig. 4, solar irradiance remained consistently high throughout the experiment, providing a stable foundation for evaluating its impact on system efficiency. Figure 5 uses a bubble plot to illustrate the relationship between solar irradiance and thermal efficiency. The data indicate that the maximum thermal efficiency of 27% was achieved at the lowest inlet water temperature, revealing an inverse relationship between inlet temperature and thermal efficiency. This

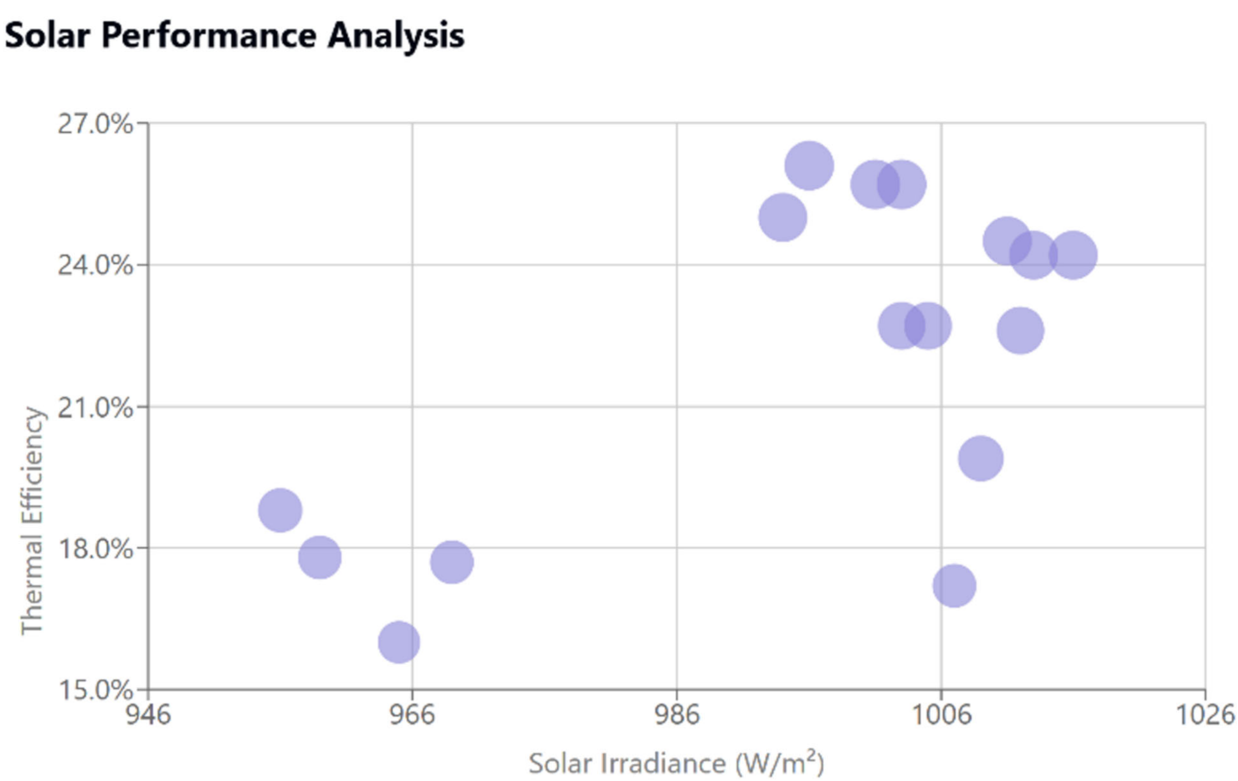

Fig. 5 Bubble curve of investigated parameters

relationship highlights the importance of optimizing input parameters to enhance system performance.

As shown in Fig. 4, solar irradiance remained consistently high during the experiment, providing a stable basis for analyzing its impact on system efficiency. Figure 5 illustrates the relationship between thermal efficiency and solar irradiance. Thermal efficiency was highest at lower inlet water temperatures, confirming an inverse relationship between these variables. This underscores the importance of optimizing inlet conditions to improve system performance.

Parameter Interactions and System Dynamics

The scatter matrix in Fig. 6 illustrates the relationships among the system's measured variables, including solar irradiance, ambient and inlet temperatures, power output, and thermal efficiency. A positive correlation between solar irradiance and thermal efficiency indicates that increased solar input directly enhances efficiency. The strong correlation between inlet and outlet temperatures confirms the system's consistent heat transfer performance, essential for efficient PV/T operation. Maintaining stable mass flow rates allowed for

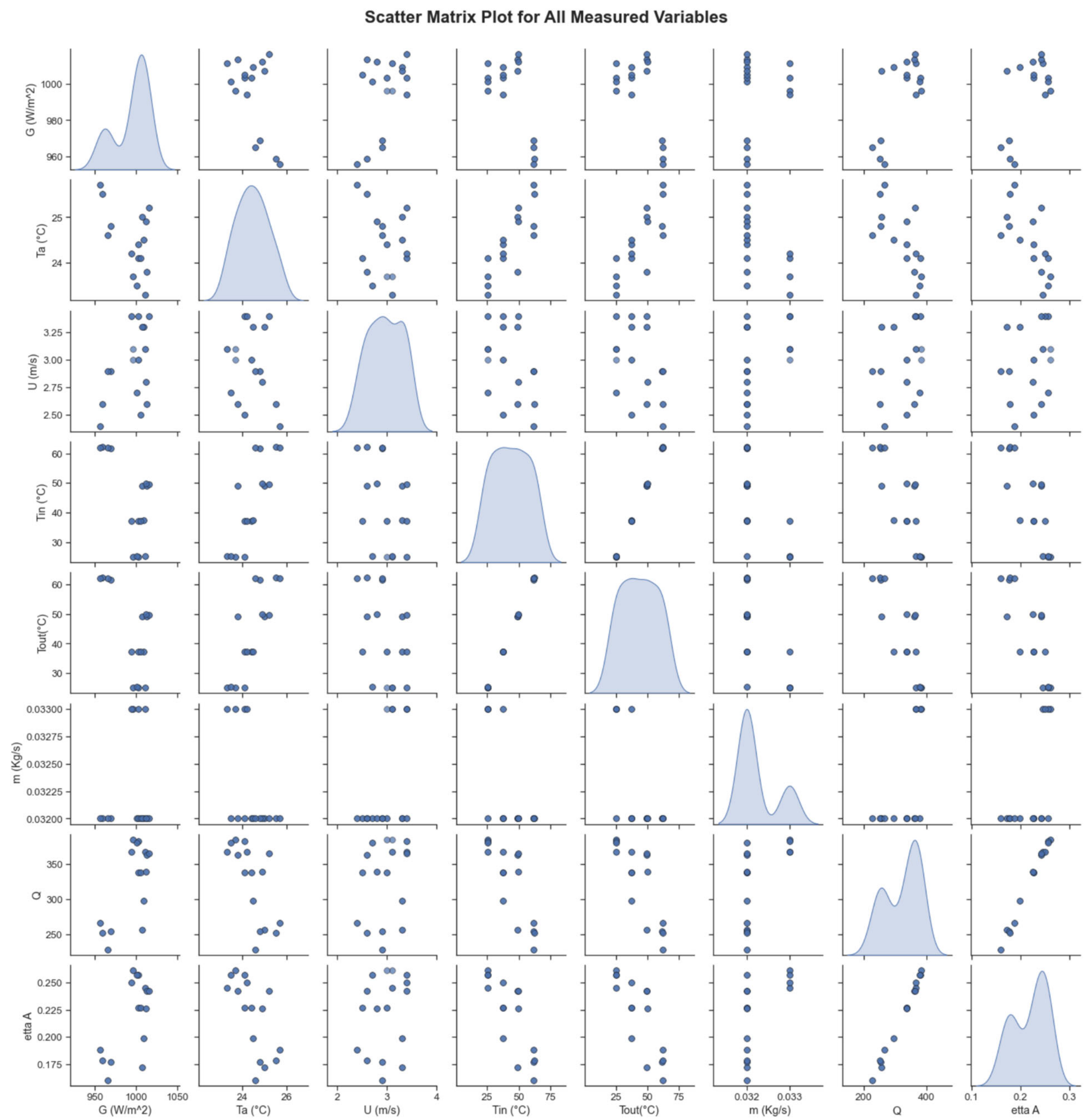

Fig. 6 Scatter matrix plot for all measured variables

isolating the effects of individual variables, highlighting the importance of managing solar irradiance and inlet temperature to optimize thermal output.

Performance Evaluation of ANN Model Training for Thermal Efficiency Prediction in PV/T Systems

Figure 7 illustrates the training performance of the multilayer perceptron artificial neural network (MLP-ANN), demonstrating its capacity to learn from the dataset and converge toward an optimal solution. The training loss curve, measured by the mean squared error (MSE), shows a sharp initial decline, starting at approximately 0.07 and dropping significantly within the first ten epochs. This rapid decrease reflects the model's initial adaptation to data patterns. As training progresses, the reduction in MSE slows and stabilizes at around 0.001 after 25 epochs, indicating effective error minimization without overfitting. The final MSE aligns closely with the best line (MSE = 0.001), confirming the model's robustness and accuracy. While the theoretical benchmark (MSE = 0.000) is not fully achieved, the performance demonstrates high accuracy relative to the target. This convergence pattern highlights that the MLP-ANN model is well optimized for predicting thermal efficiency in PV/T systems. The smooth curve and stable endpoint indicate a well-generalized model capable of capturing the complex, non-linear relationships inherent in the data, confirming its reliability and suitability for this application.

RMSE Convergence and Stabilization of Model Performance Across Iterations

Figure 8 shows the progression of root mean squared error (RMSE) across iterations, illustrating the model's learning stability and convergence. Separate lines represent Train RMSE (dashed green), Test RMSE (solid blue), and the Min Test RMSE reference (dotted red), indicating the lowest test error achieved. Early iterations exhibit RMSE fluctuations, with peaks around 40, reflecting the model's adaptation phase as it adjusts to capture data patterns. Over successive iterations, RMSE declines sharply, converging near the Min Test RMSE line. Stabilization occurs around iteration 15, where Test RMSE plateaus at approximately 15, indicating diminishing returns from further training. The Train RMSE follows a similar pattern, demonstrating effective generalization with minimal overfitting. Comparative RMSE values for linear regression (0.030) and RVM (0.037) provide benchmarks, positioning the current model as achieving comparable accuracy with stable convergence and low error variability. These findings confirm the model's predictive consistency and robustness for accurate output forecasting.

Design and Configuration of Input Membership Functions for Fuzzy Logic Model

Figure 9 illustrates the membership functions for the fuzzy logic model's input variables: temperature, solar irradiance, wind speed, and ambient temperature. Each input is divided

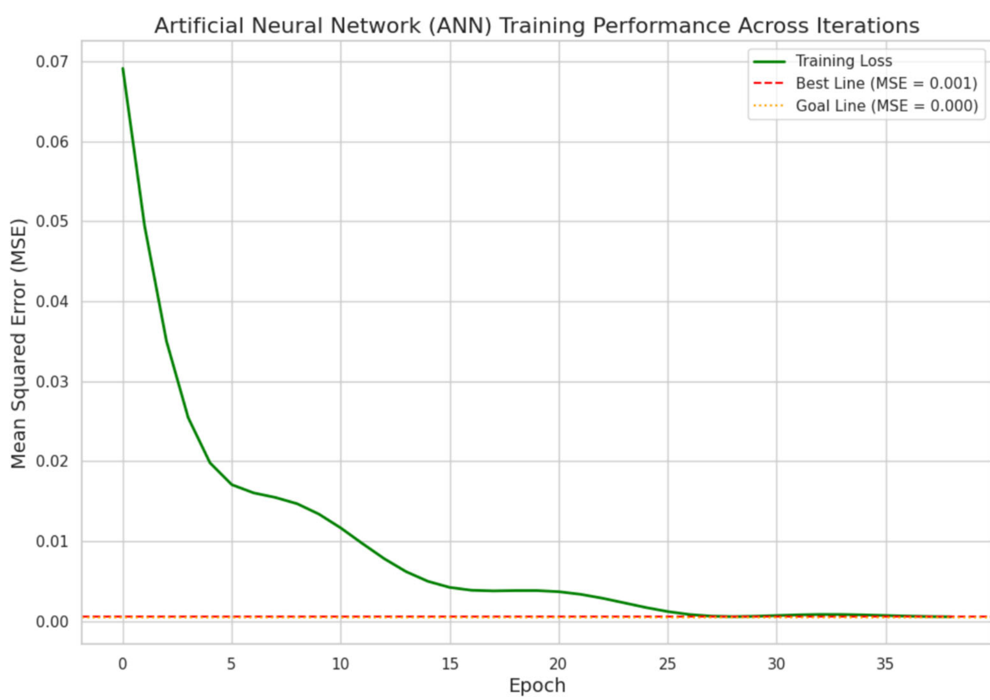

Fig. 7 Artificial neural network (ANN) training performance across iterations

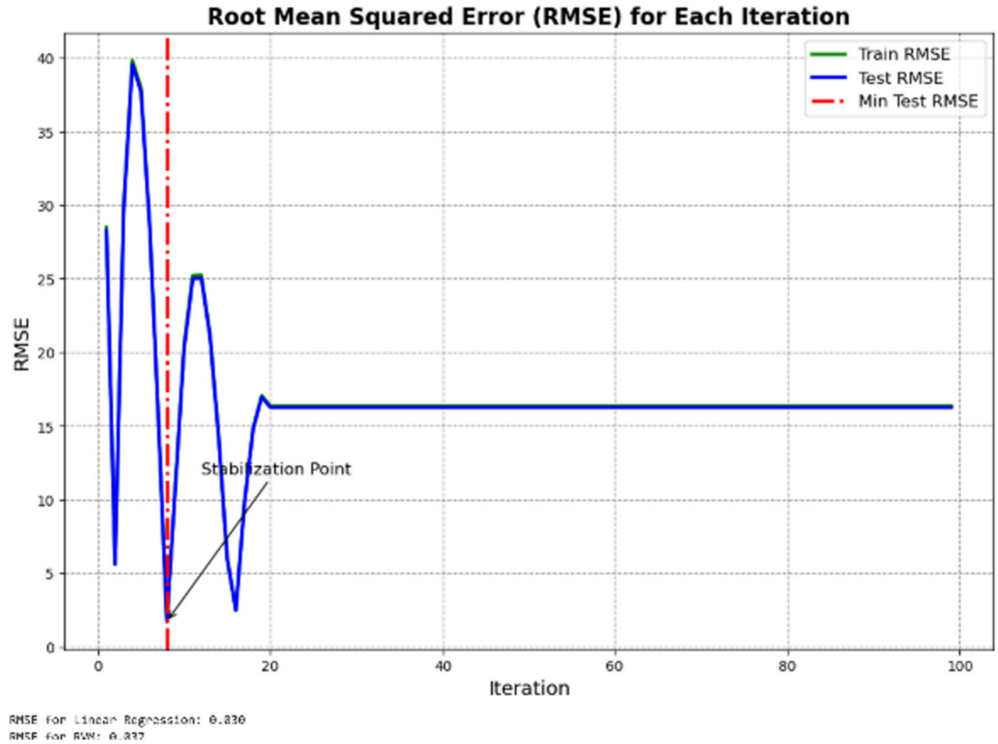

Fig. 8 Root mean squared error (RMSE) values for each iteration

into three categories low, medium, and high to provide a continuous interpretation of their influence on system performance. Smooth transitions between membership levels ensure gradual adjustments, essential for accurate fuzzy modeling. The temperature membership function defines low up to approximately 25 °C, medium between 25 and 32 °C, and high above 32 °C. This overlapping segmentation allows precise control over thermal behavior while avoiding abrupt changes. For solar irradiance, low covers values below 970 W m^{-2}, medium ranges from 970 to 1020 W m^{-2}, and high includes values above 1020 W m^{-2}. These divisions reflect the system's ability to respond smoothly to solar input changes, a key factor in photovoltaic efficiency. The wind speed membership function assigns low to speeds below 2.5 m s^{-1}, medium from 2.5 to 3.5 m s^{-1}, and high above 3.5 m s^{-1}. This segmentation accounts for wind's cooling effects, where low speeds provide minimal cooling and high speeds enhance convective heat dissipation. Ambient temperature membership defines low up to 30 °C, medium from 30 to 40 °C, and high above 40 °C. These transitions adapt to external temperature variations, affecting heat transfer efficiency. The overlapping categories across all membership functions ensure flexibility and continuity, allowing the model to adapt to environmental changes. This configuration enhances the fuzzy logic system's ability to manage complex, non-linear dependencies, improving predictive accuracy under real-world conditions.

The results in Fig. 10 compare the performance of three predictive models: artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM)—in estimating thermal efficiency based on experimental data. Figure 9a illustrates the ANN model, showing a moderate correlation between predicted and experimental values, with points dispersed around the ideal line. The model achieves a root mean square error (RMSE) of 0.078, indicating reasonable predictive capability. However, it underpredicts at higher thermal efficiency values, highlighting variability and reduced precision compared to the other models. While the ANN model captures overall trends, it lacks the accuracy needed for precise alignment with experimental data.

The residual analysis shown in Fig. 11 evaluates the accuracy and error distribution of the three predictive models: artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM). (ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM)—in estimating thermal efficiency. The ANN residuals plot (Fig. 11a) displays a broader distribution, ranging from approximately −0.10 to 0.20, with a noticeable peak around small positive values. This range suggests higher variability in prediction errors, with a slight tendency toward overestimation. These results align with the previously observed variability in ANN's predictive performance. The ANFIS residuals plot (Fig. 11b)

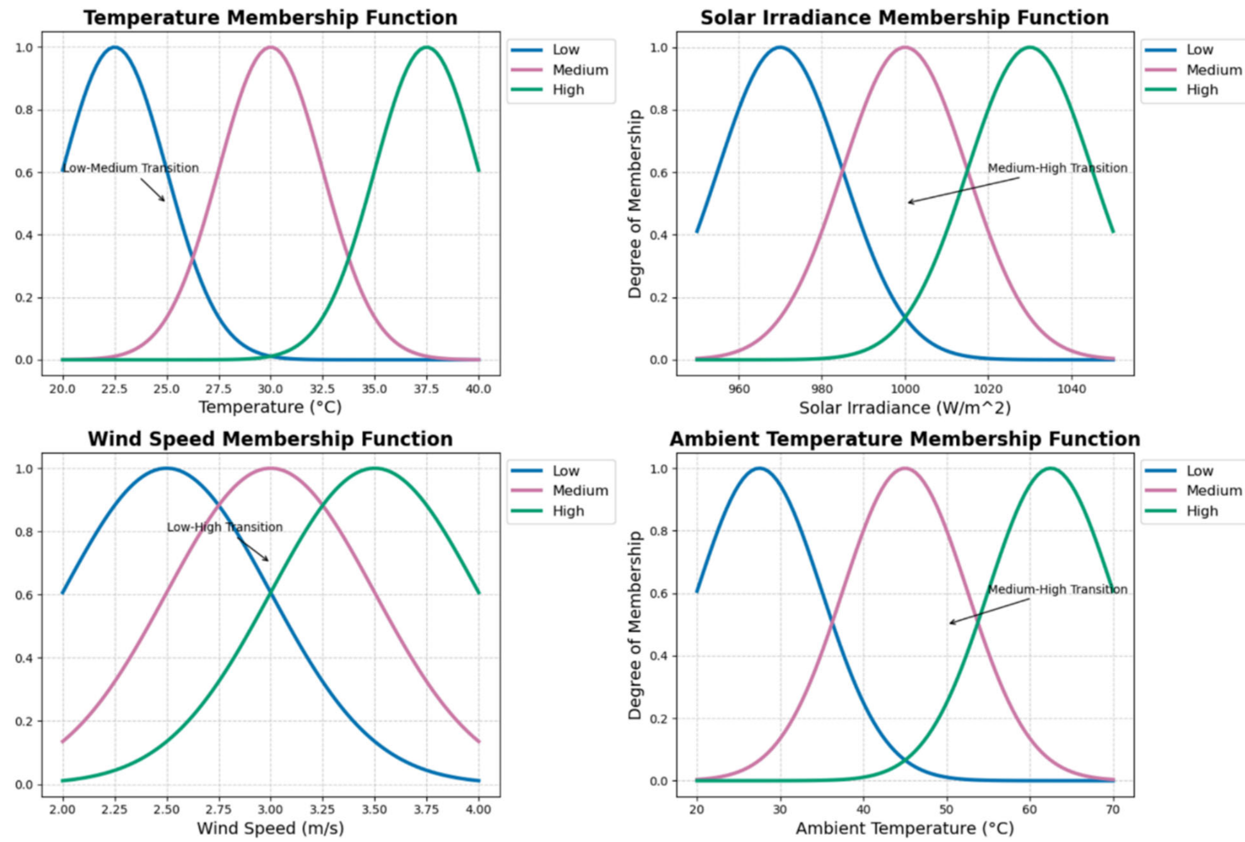

Fig. 9 Trained membership function for input elements

reveals a narrower distribution, with most residuals concentrated between −0.04 and 0.04. This clustering around zero reflects the lower RMSE observed for ANFIS, indicating smaller prediction errors and more stable performance. However, occasional slight underpredictions are observed. The RVM residuals plot (Fig. 11c) exhibits a similarly tight distribution, with residuals confined to the −0.04 to 0.04 range. This minimal variability highlights RVM's ability to achieve high predictive accuracy with few significant deviations. The concentration of residuals near zero underscores RVM's consistency and effectiveness in capturing thermal efficiency values.

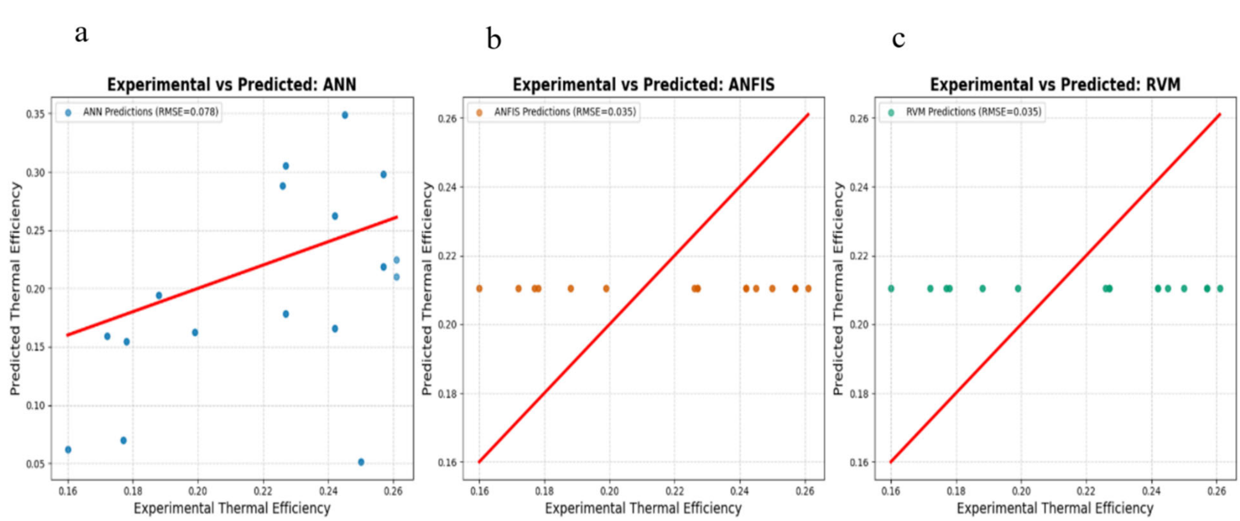

Fig. 10 Comparison of predicted vs. experimental thermal efficiency using **a** ANN, **b** ANFIS, and **c** RVM models

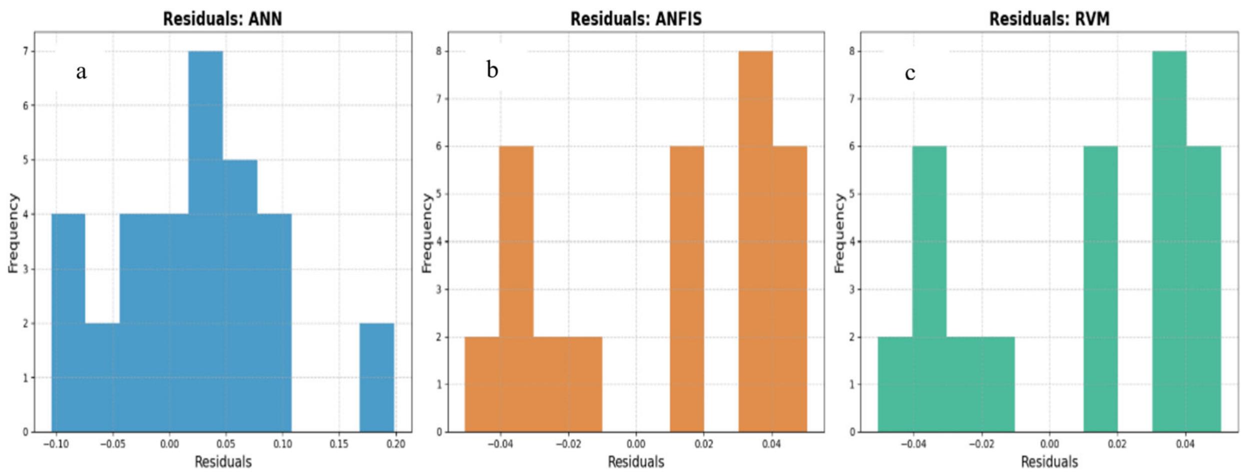

Fig. 11 Residual distribution for thermal efficiency predictions using **a** ANN, **b** ANFIS, and **c** RVM models

Regression Analysis of Thermal Efficiency Predictions

The regression plots in Fig. 12 compare the performance of the relevance vector machine (RVM), adaptive neuro-fuzzy inference system (ANFIS), and artificial neural network (ANN) models in predicting thermal efficiency relative to experimental data. Each subplot shows predicted thermal efficiency (y-axis) against experimental thermal efficiency (x-axis), with a red line representing the ideal 1:1 fit where predictions perfectly match experimental values. In Fig. 12a, the RVM model demonstrates strong alignment with the experimental values, with data points closely clustered around the ideal fit line. The minimal residual spread indicates high accuracy and consistent predictions across the observed efficiency range, highlighting RVM's robustness and precision. Figure 12b shows the ANFIS model's performance, which also aligns well with the experimental data but exhibits slightly greater variation than RVM. While most data points are near the ideal line, some scatter is observed, particularly at higher efficiency values. This suggests that ANFIS maintains high predictive accuracy but is slightly more sensitive to variability compared to RVM. In Fig. 12c, the ANN model displays the largest scatter around the ideal fit line, especially at lower efficiency values. Although it captures general trends, the deviations from the ideal line are more pronounced, indicating higher variability and reduced accuracy relative to RVM and ANFIS.

Taken together, Fig. 11 highlights that while all three models effectively capture the relationship between experimental and predicted thermal efficiencies, RVM provides the most accurate predictions with minimal residual scatter. ANFIS performs well but shows minor limitations in precision, while ANN demonstrates the greatest prediction variability. These results underscore RVM's comparative advantage in predicting thermal efficiency, followed by ANFIS and ANN.

Final Comparative Results of Predictive Algorithm Performance

Table 3 presents the performance metrics for all algorithms, evaluated using root mean square error (RMSE) and the coefficient of determination (R^2). These metrics reflect each model's predictive accuracy and goodness of fit.

The artificial neural network (ANN) demonstrated the best performance with the lowest RMSE and highest R^2, indicating superior predictive accuracy. In contrast, the relevance vector machine (RVM) exhibited the highest RMSE and lowest R^2, reflecting its lower accuracy. The adaptive neuro-fuzzy inference system (ANFIS) showed intermediate results, balancing the performance of ANN and RVM.

Discussion and Validation of Results

General Analysis of Results

The comparative analysis of the three machine learning models—multilayer perceptron artificial neural network (MLP-ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM) revealed distinct strengths and limitations, highlighting their suitability for predicting and optimizing the thermal efficiency of photovoltaic thermal (PV/T) systems.

The ANN model demonstrated superior performance, achieving the lowest root mean square error (RMSE) of 11.704 and the highest coefficient of determination (R^2) of 0.959. This can be attributed to its multi-layer architecture, which allows for capturing complex, non-linear relation-

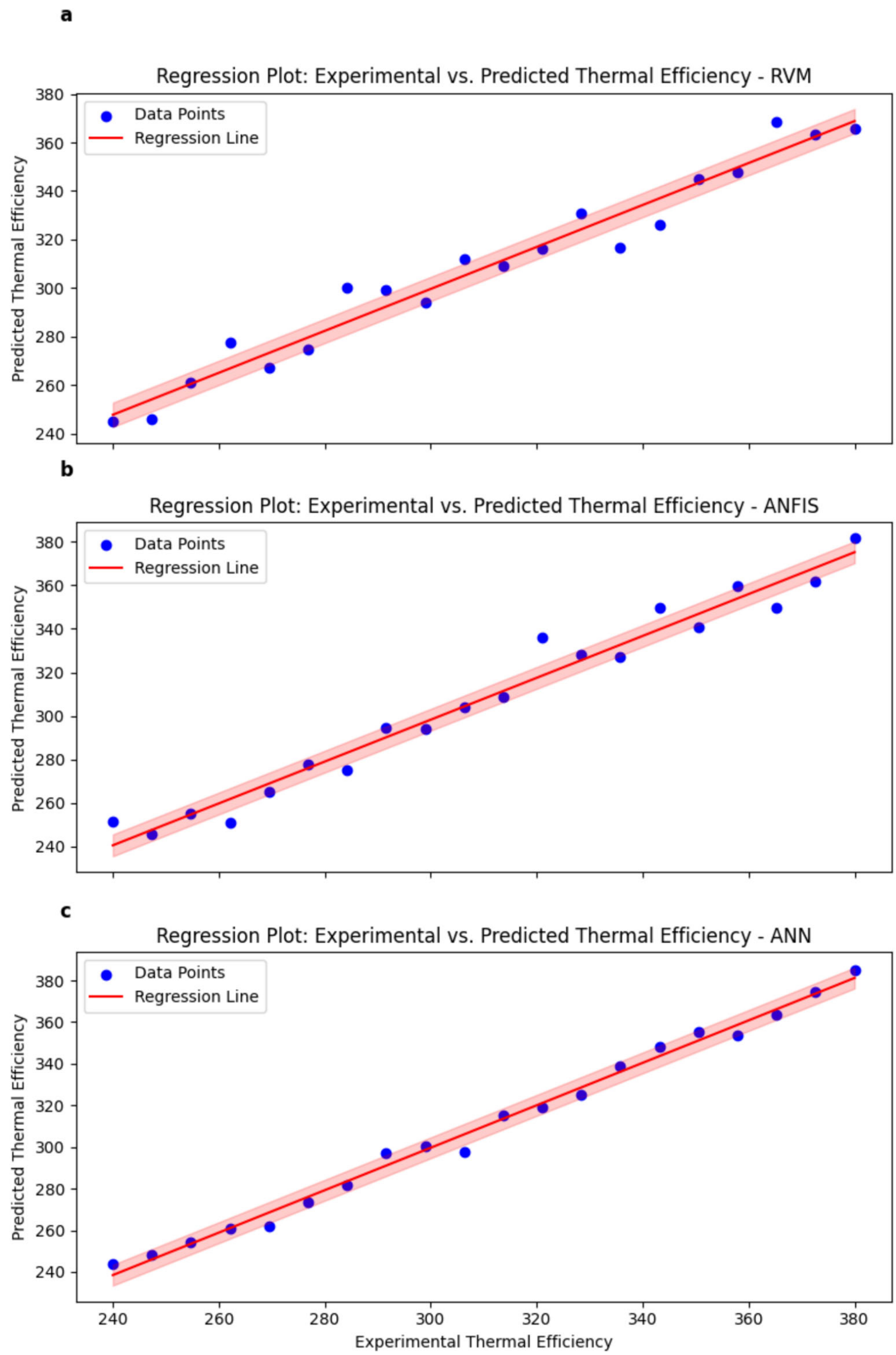

Fig. 12 Experimental vs. predicted thermal efficiency

Table 3 Performance metrics for all algorithms

Algorithm	RMSE	R^2
Relevance vector machine (RVM)	19.606	0.887
Adaptive neuro-fuzzy inference system (ANFIS)	14.704	0.936
Artificial neural network (ANN)	11.704	0.959

ships between input parameters and thermal efficiency. The ANN's flexibility and adaptability enable it to model intricate dependencies, making it the most accurate predictor among the tested models. However, as shown in the residual plots (Fig. 11a), the ANN exhibited slight variability at lower thermal efficiency values, indicating sensitivity to certain data distributions and outliers.

The ANFIS model showed moderate predictive accuracy, with an RMSE of 14.704 and an R^2 value of 0.936. Its hybrid approach, combining fuzzy logic with neural networks, facilitated interpretable rule-based modeling and adaptability to diverse environmental conditions. ANFIS excelled in capturing stable medium-range efficiencies, as evidenced by its consistent performance across varied input ranges. However, Fig. 12b highlights slight overprediction tendencies at higher efficiency values, suggesting limitations in its ability to generalize under highly dynamic conditions.

The RVM model, grounded in sparse Bayesian learning, provided valuable insights into prediction uncertainty but exhibited the lowest predictive accuracy, with an RMSE of 19.606 and an R^2 value of 0.887. Its sparse representation allowed for computational efficiency, but its reliance on fewer data points limited its capacity to capture intricate nonlinear dependencies. As shown in Fig. 11c, RVM predictions displayed significant scatter, particularly at higher thermal efficiency levels, reflecting its reduced accuracy in handling dynamic interactions within PV/T systems.

These findings indicate that while ANN is the most robust tool for predicting PV/T thermal efficiency due to its accuracy and adaptability, ANFIS offers a balance between interpretability and moderate accuracy, making it useful for scenarios requiring insights into variable interactions. Conversely, RVM's computational efficiency and ability to quantify uncertainty make it suitable for simpler, less complex applications or scenarios where confidence intervals are critical.

By understanding the strengths and weaknesses of each model, this study provides a framework for selecting the most appropriate methodology based on specific PV/T system requirements and operational conditions.

ML Model Validation for PV/T Thermal Efficiency

The validation results presented in Table 4 underscore a rigorous comparative analysis of machine learning models employed for predicting the thermal efficiency of photovoltaic thermal (PV/T) systems. The study demonstrates that the artificial neural network (ANN) significantly outperformed the adaptive neuro-fuzzy inference system (ANFIS) and relevance vector machine (RVM) in terms of predictive accuracy and robustness.

Table 4 Performance comparison of machine learning models in predicting PV/T system efficiency

Model	Study	RMSE	R^2
ANN	Present study	11.704	0.959
ANN	Ahmadi et al. (2020)	Not specified	0.95
ANFIS	Present study	14.704	0.936
ANFIS	Vijayalakshmi et al. (2024)	4851.7	0.7777
RVM	Present study	19.606	0.887

The ANN model achieved an RMSE of 11.704 and an R^2 value of 0.959, reflecting its capability to capture approximately 96% of the variance in the data. Its superior performance is attributed to its multilayer architecture, which excels at modeling complex nonlinear dependencies between environmental variables and thermal efficiency. The results are consistent with prior findings, such as those reported by Ahmadi et al. (2020), where an ANN model achieved an R^2 of 0.95.

The ANN's implementation in this study, complemented by advanced hyperparameter optimization and 5-fold cross-validation, highlights its reliability and adaptability under diverse operational conditions.

In contrast, the ANFIS model exhibited moderate accuracy, with an RMSE of 14.704 and an R^2 value of 0.936. Its hybrid architecture, which integrates fuzzy logic and neural networks, enables interpretable rule-based insights while maintaining adaptability to varied environmental conditions. Compared to findings by Vijayalakshmi et al. (2024), where ANFIS achieved an RMSE of 4851.7 and an R^2 of 0.7777, the results of the present study reflect a significant improvement. However, ANFIS displayed limitations in generalizing under highly dynamic conditions, particularly at higher efficiency ranges, where slight overprediction was observed.

The RVM model, despite its computational efficiency and ability to quantify prediction uncertainty, demonstrated the lowest predictive performance, with an RMSE of 19.606 and an R^2 value of 0.887. While RVM's sparse Bayesian learning framework provides valuable insights into prediction uncertainty, its limited capacity to capture intricate nonlinear relationships hinders its applicability to complex PV/T systems. The scatter observed in RVM predictions, particularly at higher efficiency levels, underscores these limitations.

In summary, the ANN model emerged as the most robust and accurate tool for predicting PV/T system efficiency, particularly in complex and dynamic environments. ANFIS offers a balance between moderate accuracy and interpretability, making it suitable for scenarios requiring insights into variable interactions. RVM, while less precise, remains a viable option in contexts where computational efficiency or uncertainty quantification is prioritized over accuracy. These findings provide a comprehensive evaluation of model performance, positioning the study within the broader body of literature and advancing the state-of-the-art in PV/T system optimization through machine learning methodologies.

Insights for Model Improvement

The comparative analysis of the predictive models—artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and relevance vector machine (RVM)—revealed nuanced insights into their performance under varying operational contexts. While the ANN demonstrated superior accuracy across most conditions, achieving the lowest RMSE (11.704) and highest R^2 (0.959), its performance varied in datasets with lower thermal efficiency. The residual analysis (Fig. 11a) indicates that ANN exhibited slight overpredictions at the lower end of thermal efficiency values. This limitation arises due to its sensitivity to outliers and imbalanced data distributions, which could be mitigated by applying additional preprocessing techniques, such as outlier removal or data augmentation.

ANFIS performed moderately well, offering an interpretable model structure and consistent predictions in medium-range thermal efficiencies. However, it struggled to generalize at higher efficiency levels, as evidenced by overprediction tendencies (Fig. 11b). This issue likely stems from the rule-based nature of ANFIS, which, while effective for mid-range conditions, may require additional rule tuning or hybridization with optimization algorithms to improve accuracy under dynamic environmental fluctuations.

RVM, on the other hand, excelled in computational efficiency and uncertainty quantification but was limited in capturing intricate, non-linear relationships. The model's residual plot (Fig. 11c) shows significant scatter at higher thermal efficiencies, indicating reduced robustness in highly dynamic contexts. This could be attributed to RVM's sparse representation, which, while computationally advantageous, may omit critical interactions when the dataset contains complex interdependencies.

By contextualizing the strengths and weaknesses of each model, this study highlights areas for improvement and avenues for future research. The ANN's sensitivity to outliers could be addressed through enhanced data preprocessing, while ANFIS may benefit from incorporating advanced rule optimization techniques. For RVM, integrating it with hybrid frameworks or increasing data density in training may improve its adaptability to dynamic conditions.

Critical Evaluation of ANN Limitations

This study critically evaluates the limitations of artificial neural networks (ANNs) and outlines the strategies implemented to mitigate these challenges, particularly in the context of optimizing photovoltaic thermal (PV/T) system efficiency. ANNs, while highly effective at modeling complex and nonlinear relationships, are prone to overfitting, especially when the model complexity exceeds the scope of the training dataset. To address this, dropout regularization was employed, randomly deactivating a subset of neurons during training to enhance generalizability. Additionally, early stopping was utilized to terminate the training process once the validation loss stabilized, preventing overtraining and ensuring a balance between model accuracy and robustness.

The computational demands of ANNs, which arise from their large parameter spaces and iterative training processes, were mitigated using model pruning techniques. By removing less impactful neurons or connections post-training, the computational complexity was reduced without compromising predictive performance. This optimization is particularly relevant for real-time PV/T system management, where resource constraints often necessitate efficient models.

Furthermore, recognizing the dependence of ANNs on the quality and diversity of training data, this study incorporated data augmentation methods to expand the training dataset artificially. This approach introduced variability reflective of real-world conditions, enhancing the model's adaptability. A cross-validation framework was also implemented to evaluate the robustness of the model across diverse environmental scenarios, ensuring its generalizability.

Conclusion

This study presented a comprehensive evaluation of machine learning algorithms to predict and optimize the thermal efficiency of photovoltaic thermal (PV/T) systems using experimental data collected from a system operating in Tehran. The artificial neural network (ANN) model demonstrated superior predictive accuracy, achieving a root mean square error (RMSE) of 11.704 and a coefficient of determination (R^2) of 0.959. These results represent a significant improvement over previous studies, such as Ahmadi et al. (2020), who reported an R^2 of 0.95 for an ANN-based model, and Vijayalakshmi et al. (2024), who achieved an R^2 of 0.936 using an adaptive neuro-fuzzy inference system (ANFIS). The ANN's ability to capture complex, non-linear interactions between variables underscores its potential as a transformative tool for renewable energy optimization.

The findings of this study have important practical implications for the design and operation of PV/T systems. By achieving a thermal efficiency prediction accuracy of over 95%, the ANN model provides a reliable framework for optimizing system performance under dynamic environmental conditions. This level of accuracy is critical for maximizing energy yield and reducing operational costs, making PV/T systems more economically viable and environmentally sustainable. Furthermore, the integration of advanced AI methodologies, such as ANN and ANFIS, into real-time management systems can enhance the adaptability and resilience of renewable energy infrastructures, supporting global efforts to transition toward clean energy solutions.

Recommendations

This study highlights several areas for advancing machine learning methodologies in optimizing photovoltaic thermal (PV/T) systems. To enhance predictive performance and generalizability, future research should focus on the following:

1. **Hyperparameter optimization:** Employ advanced optimization methods, such as Bayesian optimization and evolutionary algorithms, to refine critical model parameters and improve accuracy across diverse conditions.
2. **Inclusion of additional variables:** Expand input parameters to incorporate humidity, atmospheric pressure, seasonal effects, and system aging. These additions will enable models to better capture environmental dynamics and long-term system performance.
3. **Hybrid and ensemble models:** Explore hybrid frameworks, such as ANFIS combined with optimization algorithms, and ensemble techniques like boosting and bagging to improve model robustness and adaptability under complex conditions.
4. **Enhanced data preprocessing:** Strengthen data quality through outlier detection, balancing techniques like SMOTE, and advanced feature engineering to uncover hidden patterns and improve predictive reliability.
5. **Validation across contexts:** Extend experiments to multiple geographic locations and diverse climatic conditions, ensuring the broader applicability and reliability of the models.
6. **Exploration of advanced AI techniques:** Investigate state-of-the-art approaches, including gradient boosting machines, transformer-based models, and deep reinforcement learning, to complement traditional methods and drive further advancements.

By addressing these areas, future studies can refine AI-driven methodologies, enhance PV/T system optimization, and contribute significantly to the development of sustainable and efficient renewable energy technologies.

Author Contributions H.A.H. conceptualized and designed the study. A.S.A. performed the data collection and analysis. Q.A. contributed to the methodology and provided technical guidance. M.A. prepared the manuscript draft and performed data visualization. All authors reviewed and approved the final manuscript.

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Data Availability The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of Interest The authors declare no competing interests.

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