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# Renewable energy MicroGrid power forecasting: AI techniques with environmental perspective

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**Introduction:** Accurate power forecasting is a fundamental requirement for the reliable and sustainable operation of renewable energy -based microgrids, particularly under the inherent variability of solar and wind resources.

**Methods:** This study presents a comparative analysis of traditional artificial intelligence models, including Artificial Neural Networks (ANN), Fuzzy Logic, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), alongside advanced deep learning architectures such as Long Short-Term Memory (LSTM), Temporal Convolutional Networks (TCN), Transformer, and Squeeze-and-Excitation enhanced LSTM (SE+LSTM). Real-world hourly data collected from the King Saud University microgrid in Riyadh, Saudi Arabia –incorporating environmental variables such as solar irradiance, wind speed, temperature, humidity, and air pressure –are used for model training and evaluation. Forecasting performance is assessed using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Sum of Squared Errors (SSE) across short-term (1-hour ahead) and mid-term (6-hour ahead) forecasting horizons.

**Results:** The results show that attention-based models outperform conventional approaches. In particular, the SE+LSTM model achieves the best performance with an RMSE of 0.7015 kW and a MAPE of 2.01%, followed closely by the Transformer model. Statistical significance testing confirms that the observed improvements are not due to random variation.

**Discussion:** Overall, the findings highlight the importance of incorporating environmental context to improve forecasting accuracy. Attention-enhanced deep learning models provide a robust and environmentally informed framework for intelligent and sustainable microgrid energy management.

### KEYWORDS

artificial intelligence, renewable energy, microgrid power forecasting, solar power, wind power, deep learning, transformer, LSTM

## 1 Introduction

The rapid global transition toward low-carbon energy systems has accelerated the deployment of renewable energy sources such as solar and wind power. While these resources are environmentally sustainable, their inherent intermittency and weather dependency pose significant challenges for power system planning and real-time operation. Microgrids—localized energy systems capable of operating autonomously or in coordination with the main grid—have emerged as a promising solution for integrating renewable energy while improving reliability, resilience, and energy efficiency (Khan et al.,

2024a; Manzano et al., 2025; Hussan et al., 2026). However, the successful operation of renewable energy microgrids critically depends on accurate power forecasting.

Traditional statistical forecasting methods struggle to model the nonlinear, non-stationary, and stochastic characteristics of renewable energy generation (Benitez and Singh, 2025). As a result, artificial intelligence (AI) techniques have gained increasing attention due to their ability to learn complex relationships between meteorological variables and power output. Models such as Artificial Neural Networks (ANN), Fuzzy Logic, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have demonstrated encouraging results (Benitez and Singh, 2025). ANN models offer strong nonlinear approximation capabilities but often lack interpretability (Sudasinghe et al., 2025). Fuzzy Logic approaches are interpretable and robust to uncertainty but rely heavily on expert-defined rules and scale poorly with high-dimensional data. ANFIS attempts to balance learning capability and interpretability but can become computationally complex and sensitive to rule design.

More recently, deep learning models such as Long Short-Term Memory (LSTM), Temporal Convolutional Networks (TCN), and Transformer architectures have been introduced to address temporal dependency modeling in renewable energy forecasting (Khan et al., 2024b; He et al., 2025; Salman et al., 2024). While these models achieve higher accuracy, many existing studies focus primarily on predictive performance without explicitly integrating environmental context or evaluating statistical robustness. Moreover, comparative studies that simultaneously assess traditional AI and modern deep learning models under identical experimental conditions—using real microgrid data—remain limited.

Motivated by these gaps, this study investigates whether attention-enhanced deep learning architectures can provide statistically robust and environmentally informed forecasting for renewable energy microgrids. Unlike prior work, this research explicitly integrates a comprehensive set of meteorological variables and evaluates both predictive accuracy and statistical significance across multiple forecasting horizons.

The main contributions of this study are summarized as follows:

- A unified comparative evaluation of traditional AI models and advanced deep learning architectures under identical data preprocessing, training, and validation settings.
- Integration of environmental variables into all forecasting models to enhance physical interpretability and sustainability relevance.
- Demonstration that attention-based models (SE + LSTM and Transformer) significantly outperform conventional methods across short- and mid-term forecasting horizons.
- Statistical validation of performance improvements using paired significance tests and confidence interval analysis.
- Application and validation using real-world microgrid data from a high-irradiance, arid-region environment.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature on AI-based forecasting methods for renewable energy and identifies existing methodological and contextual gaps. Section 3 presents the materials and methods,

including the study area, dataset description, AI model architectures, and evaluation framework. Section 4 provides a detailed analysis of forecasting results, including model comparisons, performance by prediction horizon, and breakdowns by energy source. Section 4 discusses the integration of environmental variables and their role in enhancing forecasting accuracy and sustainability. Section 5 outlines the limitations of the current study and proposes directions for future work. Finally, Section 6 concludes the paper by summarizing key contributions and implications for intelligent microgrid energy management.

## 2 Literature review

The integration of artificial intelligence (AI) techniques for power forecasting in renewable energy microgrids has garnered significant research attention. Various models—ranging from Artificial Neural Networks (ANN) and Fuzzy Logic to Adaptive Neuro-Fuzzy Inference Systems (ANFIS)—have been explored to address the nonlinear and uncertain nature of renewable energy generation. However, a critical examination of these works reveals certain methodological limitations and a lack of environmental contextualization.

### 2.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) have been widely applied in renewable energy forecasting due to their ability to model complex, nonlinear relationships between meteorological variables and energy outputs. Chai et al. (2023) developed an ANN-based model for short-term photovoltaic (PV) power generation forecasting using weather data such as solar irradiance, temperature, and humidity, along with historical PV output. Their results demonstrated that the ANN significantly outperformed traditional statistical methods in terms of prediction accuracy. In the context of wind energy, Yang et al. (2024) reviewed various machine learning approaches and highlighted the effectiveness of ANN models in capturing the variability of wind conditions by incorporating inputs like wind speed, air density, and turbine characteristics. These studies underscore the adaptability of ANN models in handling diverse data patterns and their promising potential for enhancing the integration of renewable energy sources into power systems.

### 2.2 Fuzzy logic approaches

In the realm of solar energy forecasting, (Almara and ashi, 2023) introduced a hybrid soft computing method that combines fuzzy logic systems with particle swarm optimization. This approach utilizes meteorological parameters such as solar irradiance, temperature, and humidity to enhance prediction accuracy. The integration of fuzzy logic allows for the handling of uncertainties inherent in weather data, while particle swarm optimization fine-tunes the model parameters for improved performance.

Similarly, in wind power prediction (Shi et al., 2024) developed a novel fuzzy time series forecasting model that emphasizes both accuracy and interpretability. Their model incorporates non-stationary fuzzy sets to adapt to the dynamic nature of wind

speed and employs an enhanced artificial hummingbird algorithm for optimization. This methodology effectively captures the variability and vagueness of wind speed measurements, leading to more reliable short-term forecasts.

These advancements underscore the robustness of fuzzy logic models in dealing with noisy or incomplete data by converting precise inputs into fuzzy linguistic variables like “high,” “medium,” or “low.” Such transformations enable the models to mimic human reasoning, offering greater interpretability compared to the black-box nature of many AI models.

## 2.3 Adaptive neuro-fuzzy inference systems (ANFIS)

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) synergize the learning capabilities of Artificial Neural Networks with the interpretability of fuzzy logic, creating hybrid models adept at handling complex, nonlinear relationships in renewable energy forecasting. Recent studies have demonstrated the efficacy of ANFIS in both solar and wind power prediction tasks.

In solar energy forecasting, a study by [Lara-Cerecedo et al. \(2023\)](#) developed an ANFIS model integrated with a Genetic Algorithm (GA) to predict photovoltaic system behavior. Utilizing solar radiation and ambient temperature data, the ANFIS-GA model achieved superior accuracy compared to traditional ANFIS models, indicating its potential as a valuable tool for planning and predicting photovoltaic system performance.

In 2023 ([Bilal et al., 2023](#)), researchers introduced a novel approach for wind power forecasting, employing an ANFIS-based moving window (MoW) technique. This model utilized wind speed and turbine operational data from a 30-MW wind farm in Mauritania. The ANFIS-MoW model outperformed several existing models, including those based on grid partitioning and clustering methods, demonstrating enhanced prediction accuracy across various time horizons and climatic conditions.

These advancements underscore ANFIS's capability to automatically tune fuzzy membership functions, reducing the need for manual rule definition and enhancing model flexibility. By effectively managing uncertainty in meteorological inputs, ANFIS models offer a robust and interpretable solution for renewable energy forecasting.

## 3 Materials and methods

### 3.1 Study area: King Saud University microgrid

The study was conducted using data from the microgrid infrastructure at King Saud University (KSU), located in Riyadh, Saudi Arabia. The university campus spans approximately 900 ha and is situated at geographical coordinates 24.7252°N latitude and 46.637°E longitude. Riyadh is characterized by a desert climate with high solar irradiance levels, low humidity, and moderate seasonal wind activity, making it a highly suitable testbed for evaluating the performance of renewable energy forecasting models, particularly those reliant on solar and wind energy sources.

The KSU microgrid is a localized hybrid renewable energy system comprising photovoltaic (PV) solar panels, small-scale horizontal-axis wind turbines, weather monitoring stations, and energy storage units. This setup is designed not only for operational sustainability but also for research and educational purposes. The solar PV system captures irradiance data at different wavelengths, including Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), and Diffuse Horizontal Irradiance (DHI). Wind energy is harvested through turbines equipped with real-time sensors that monitor wind speed, direction, and turbine rotational dynamics.

Meteorological data are collected continuously using calibrated sensors installed on meteorological towers strategically placed across the campus. These sensors capture key atmospheric parameters such as temperature, humidity, air pressure, and wind patterns, which are critical for forecasting accuracy. The data acquisition system is integrated with a SCADA (Supervisory Control and Data Acquisition) platform, allowing high-resolution temporal sampling with hourly granularity over the course of the calendar year 2022.

This real-world microgrid system provides an ideal platform to evaluate AI-driven power forecasting models under realistic environmental and operational conditions. The unique climate profile of Riyadh, combined with KSU's integrated sensor infrastructure, allows for an in-depth study of the interaction between environmental factors and renewable energy generation. The findings from this study are thus both scientifically robust and practically relevant for arid regions seeking to deploy intelligent microgrid systems.

### 3.2 Data description

The dataset utilized in this study comprises a combination of high-resolution meteorological and renewable energy generation data, collected from King Saud University's (KSU) microgrid infrastructure and associated local weather stations. The data spans a continuous period of one full calendar year (January to December 2022), providing 8,760 hourly observations across all variables. This rich temporal dataset captures seasonal variations and environmental dynamics necessary for accurate renewable energy forecasting.

- **Meteorological variables:** The atmospheric data include Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), and Diffuse Horizontal Irradiance (DHI), measured using pyranometers and sun-tracking sensors. Additional weather variables such as wind speed, wind direction, temperature, relative humidity, and air pressure were recorded via an array of calibrated meteorological instruments installed on campus towers. These measurements are essential for modeling both solar and wind energy production, as they directly influence power output behavior.
- **Energy output:** The power generation data include actual recorded outputs from the installed photovoltaic (PV) panels and small-scale wind turbines in the microgrid system. Solar power output is recorded in kilowatts (kW) and corresponds to the performance of the distributed PV

systems under varying irradiance and temperature conditions. Wind power output is similarly recorded in kilowatts (kW) and reflects the influence of wind dynamics over time.

To ensure the reliability and quality of the dataset, several preprocessing steps were applied. First, all variables were normalized using Min-Max scaling to rescale input features to a common range [0, 1], which facilitates faster convergence and improved stability in AI models. Missing values—typically caused by sensor downtime or communication errors—were handled using linear interpolation based on surrounding temporal values to maintain continuity without introducing significant bias.

Furthermore, Pearson correlation analysis was conducted to evaluate the linear relationship between meteorological features and energy output variables. Highly correlated features, such as wind speed and wind power, or GHI and solar power, were retained to improve model interpretability and reduce redundancy. Redundant or weakly correlated variables were either transformed or excluded to optimize model training and avoid overfitting.

The resulting cleaned and normalized dataset serves as a robust input for training, validating, and testing various AI models for power forecasting in a real-world microgrid environment.

### 3.3 Model description

This study explores and compares a suite of artificial intelligence (AI) and deep learning models for forecasting renewable energy generation in a microgrid setting. The selected models include traditional AI techniques with interpretable components as well as state-of-the-art deep learning architectures designed to capture complex temporal dependencies and feature interactions. Each model was selected based on its prior success in time-series prediction and ability to model nonlinear relationships between environmental inputs and power outputs.

- **Artificial Neural Network (ANN):** The ANN model used in this study is a feedforward multilayer perceptron architecture composed of an input layer, a single hidden layer with ReLU activation, and an output layer. It was trained using the backpropagation algorithm and optimized with the Adam optimizer. ANN is known for its ability to approximate complex nonlinear functions and has been widely used in renewable energy forecasting due to its simplicity and robustness.
- **Fuzzy Logic:** This model implements a Mamdani-type fuzzy inference system, which utilizes expert-defined triangular membership functions and a rule base to map input variables (e.g., irradiance, wind speed) to output variables (e.g., power generation). Fuzzy Logic is particularly well-suited for handling uncertainty and imprecision in weather-dependent systems. It provides transparent, human-readable rules that enhance interpretability, though it may struggle with high-dimensional or noisy data.
- **Adaptive Neuro-Fuzzy Inference System (ANFIS):** ANFIS combines the adaptive learning capabilities of neural networks with the rule-based structure of fuzzy logic. In this model, fuzzy if-then rules are adjusted automatically through a hybrid learning algorithm that integrates least squares and

TABLE 1 Final hyperparameter settings after grid search optimization.

Model	Units/Layers	Epochs	Optimizer
ANN	10 hidden neurons (1 layer)	200	Adam (lr = 0.001)
Fuzzy logic	3 triangular MF per input	–	Rule-based
ANFIS	3 MF subsets, 2 rules	100	Hybrid (BP + LS)
Transformer	2 encoder layers, 4 heads	100	Adam (lr = 0.0005)
SE + LSTM	128 LSTM units + SE block	150	Adam (lr = 0.001)

backpropagation. ANFIS provides a balance between interpretability and learning efficiency and is especially useful when a moderate amount of domain knowledge is available to guide the rule formation process.

- **Transformer Network:** Inspired by advances in natural language processing, the Transformer model employs a multi-head self-attention mechanism and positional encoding to capture both short- and long-range dependencies in sequential data. Unlike traditional RNNs, Transformers allow parallel training and handle variable-length input sequences more efficiently. In the context of renewable energy forecasting, this architecture excels at learning temporal patterns across multiple environmental features simultaneously.
- **SE + LSTM (Squeeze-and-Excitation + Long Short-Term Memory):** This hybrid model integrates the attention-based Squeeze-and-Excitation (SE) block with an LSTM network. The SE module enhances the model's ability to selectively emphasize important input features by recalibrating channel-wise feature responses. Meanwhile, the LSTM component captures long-term dependencies in time-series data, making it highly effective for modeling weather-driven fluctuations in energy output. The combined SE + LSTM model is particularly well-suited for datasets with both temporal and contextual complexity.

Each of these models was implemented and tuned under a standardized experimental framework to enable fair comparison. Their complementary strengths allow for a comprehensive evaluation of both model accuracy and practical suitability in real-world microgrid energy management systems.

### 3.4 Hyperparameter settings

To ensure fair comparison and reproducibility, all forecasting models were systematically tuned using a structured hyperparameter optimization strategy rather than *ad hoc* trial-and-error. A grid search was conducted over predefined hyperparameter ranges, and model configurations were selected based on their ability to minimize validation RMSE and MAPE while maintaining stable performance across cross-validation folds.

For deep learning models, the hyperparameter search space included the number of layers (1–3), number of hidden units (32–256), sequence length (12–48 time steps), batch size (16–64), learning rate ( $10^{-4}$ – $10^{-3}$ ), and optimizer type. Transformer-specific parameters such as the number of attention heads (2–8) and encoder

layers (1–3) were also explored. For the SE + LSTM architecture, the presence and placement of the Squeeze-and-Excitation block and the number of LSTM units were varied to assess their impact on forecasting accuracy and stability.

Hyperparameter tuning was performed using a 5-fold cross-validation framework for models that support iterative training. The final hyperparameter configuration for each model was selected based on the lowest average validation RMSE and MAPE, with preference given to configurations exhibiting low variance across folds. This approach ensures that the chosen settings not only optimize accuracy but also enhance generalization and robustness under varying data partitions. [Table 1](#) summarizes the final hyperparameter settings adopted for each model after optimization.

The ANN model was configured with a single hidden layer comprising 10 neurons using ReLU activation, as deeper configurations did not yield consistent improvements during cross-validation. The Fuzzy Logic model relies on expert-defined rules and therefore does not require iterative training; triangular membership functions were selected for interpretability and numerical stability. For the ANFIS model, Gaussian membership functions were initialized and optimized using a hybrid learning strategy combining backpropagation and least-squares estimation. The number of fuzzy subsets per input was chosen to balance model expressiveness and computational tractability, avoiding rule explosion.

The Transformer architecture employed two encoder layers with four self-attention heads, which consistently outperformed deeper configurations while maintaining stable convergence. A reduced learning rate of 0.0005 was selected to prevent training instability associated with multi-head attention mechanisms. The SE + LSTM model integrated a Squeeze-and-Excitation block followed by an LSTM layer with 128 units, as this configuration achieved the best trade-off between accuracy and variance across validation folds.

All models were implemented in Python using TensorFlow and scikit-fuzzy libraries. Training was performed on a GPU-enabled workstation to ensure efficient convergence and consistent experimental conditions across models.

### 3.5 Data splitting and validation

To ensure robust model evaluation and generalization, the dataset was partitioned into three subsets: training (70%), validation (15%), and testing (15%). The data spanned a full calendar year (2022), capturing both diurnal and seasonal fluctuations in meteorological conditions and energy output. Therefore, a stratified sampling strategy was employed to maintain proportional seasonal representation across all subsets. This approach helps preserve the natural variability of solar irradiance, wind speed, temperature, and other environmental factors throughout the year.

The training set was used to fit the model parameters, while the validation set served as the basis for hyperparameter tuning and early stopping decisions. The test set was held out until the final evaluation phase to ensure unbiased performance measurement on unseen data.

For models with stochastic training dynamics and a large number of parameters—specifically the ANN, Transformer, and SE + LSTM architectures—additional measures were taken to assess

generalization and prevent overfitting. A 5-fold cross-validation strategy was implemented on the training + validation data (85% of the total dataset). This involved partitioning the data into five equally sized folds, where four folds were used for training and one for validation in each iteration. The cross-validation procedure was repeated five times, with each fold serving as the validation set once. Final performance metrics were computed as the average across folds.

Cross-validation enabled consistent comparison across models and helped fine-tune hyperparameters such as learning rate, number of hidden units, attention heads, and training epochs. It also provided confidence in the model's stability across different temporal segments, especially under varying environmental conditions.

The final model selection for each architecture was based on the best average performance across validation folds using RMSE and MAPE as the primary metrics. Once finalized, each model was retrained on the entire training + validation set and evaluated on the independent test set to report final results.

### 3.6 Impact of environmental variables on model performance

To evaluate the contribution of environmental information to forecasting accuracy, a comprehensive set of meteorological variables was incorporated into the training process, including solar irradiance components (GHI, DNI, DHI), temperature, humidity, wind speed, wind direction, and air pressure. These features were selected due to their well-established influence on renewable power generation dynamics in microgrid systems.

A quantitative ablation analysis was conducted using the SE + LSTM model under the 1-h ahead forecasting setting. [Table 2](#) summarizes the impact of progressively excluding key environmental variables on model performance. When the full feature set is employed, the model achieves the lowest error values, with an RMSE of 0.7015 kW and a MAPE of 2.01%. This configuration serves as the performance baseline for evaluating the contribution of individual variables.

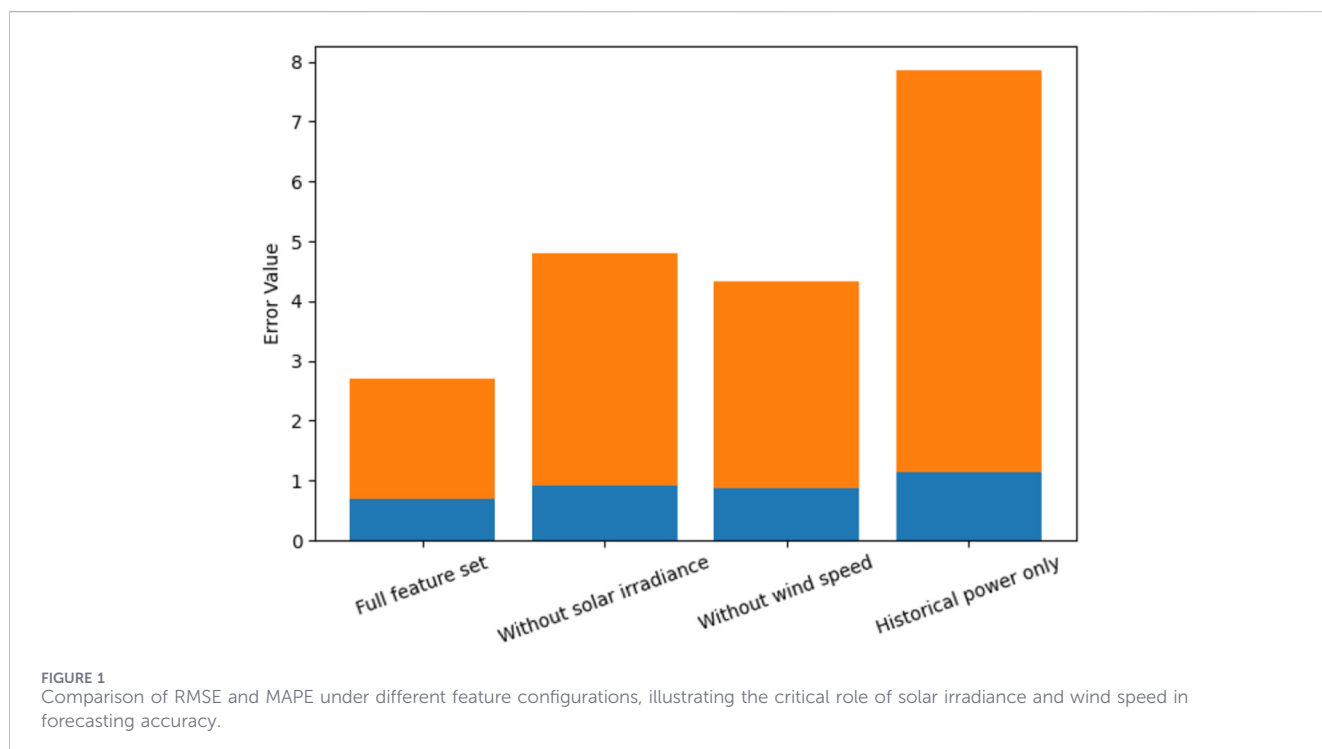
Removing solar irradiance from the input feature set results in a pronounced degradation of forecasting accuracy, with RMSE increasing to 0.924 kW and MAPE to 3.87%. A similar, though slightly less severe, performance drop is observed when wind speed is excluded, yielding an RMSE of 0.881 kW and a MAPE of 3.45%. These results quantitatively confirm that solar irradiance and wind speed are among the most influential variables for short-term renewable power forecasting.

The most substantial performance degradation occurs when only historical power data are used, without any environmental inputs. In this case, RMSE and MAPE increase to 1.147 kW and 6.72%, respectively, highlighting the limitations of purely time-series-based models in capturing the variability of renewable energy generation.

[Figure 1](#) provides a visual comparison of RMSE and MAPE across different feature configurations, further illustrating the critical role of environmental variables in reducing forecasting error. However, the results demonstrate that integrating meteorological information significantly enhances both the accuracy and robustness of attention-based forecasting models,

TABLE 2 Quantitative ablation analysis showing the effect of excluding key environmental variables on forecasting performance (SE + LSTM, 1-h ahead).

Input feature set	RMSE (kW)	MAPE (%)
Full feature set (power + environmental variables)	0.7015	2.01
Without solar irradiance	0.924	3.87
Without wind speed	0.881	3.45
Historical power only	1.147	6.72



reinforcing the importance of environmental awareness for sustainable and reliable microgrid energy management.

### 3.7 Performance metrics

To evaluate the forecasting accuracy and robustness of the proposed models, three standard performance metrics were used: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Sum of Squared Errors (SSE). RMSE is calculated using Equation 1, which measures the average magnitude of prediction errors and penalizes larger deviations. MAPE is defined in Equation 2 and represents the average percentage difference between predicted and actual values, providing an intuitive measure of relative error. SSE is computed using Equation 3 and represents the cumulative squared deviation between predicted and actual values across all observations. These metrics are defined as follows:

- Root Mean Square Error (RMSE): Measures the average magnitude of prediction error, giving higher weight to larger errors:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (1)$$

- Mean Absolute Percentage Error (MAPE): Represents the average percentage difference between predicted and actual values:

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (2)$$

- Sum of Squared Errors (SSE): Computes the total squared deviation between predicted and true values:

$$\text{SSE} = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

Here,  $y_i$  denotes the actual power output,  $\hat{y}_i$  is the predicted power output from the model, and  $n$  is the number of samples in the evaluation set. RMSE and MAPE provide normalized error perspectives, while SSE represents the absolute error accumulation and is useful for understanding total deviation.

TABLE 3 Performance of traditional AI models.

Model	RMSE (kW)	MAPE (%)	SSE (kW <sup>2</sup> )
ANN	1.12	6.82	2.98
Fuzzy logic	1.28	7.93	3.41
ANFIS	1.15	7.14	3.03

## 4 Results and discussion

This section presents and analyzes the results of the power forecasting models. We evaluate the performance of both traditional AI techniques (ANN, Fuzzy Logic, ANFIS) and advanced deep learning methods (LSTM, TCN, Transformer, SE + LSTM). The evaluation metrics include Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Sum of Squared Errors (SSE).

### 4.1 Power forecasting results by model

#### 4.1.1 Traditional AI models: ANN, fuzzy logic, and ANFIS

Table 3 summarizes the forecasting performance of traditional AI models—Artificial Neural Network (ANN), Fuzzy Logic, and Adaptive Neuro-Fuzzy Inference System (ANFIS)—in predicting renewable energy output. Performance was assessed using three evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Sum of Squared Errors (SSE).

Among the three models, the ANN demonstrated the highest accuracy, achieving the lowest RMSE (1.12 kW), MAPE (6.82%), and SSE (2.98 kW<sup>2</sup>). This confirms the ANN's effectiveness in capturing nonlinear relationships between environmental variables and power output, despite its relatively simple architecture. Its ability to learn patterns from data without requiring explicit rule definition makes it highly suitable for renewable energy forecasting tasks involving complex meteorological dynamics.

The ANFIS model performed moderately well, with a slightly higher RMSE (1.15 kW) and MAPE (7.14%) compared to ANN. ANFIS benefits from its hybrid structure, which combines the learning capability of neural networks with the interpretability of fuzzy logic. However, the need to define fuzzy membership functions and rules adds design complexity and can impact performance when rule optimization is suboptimal.

Fuzzy Logic exhibited the lowest accuracy among the three, with an RMSE of 1.28 kW and MAPE of 7.93%. While it provides high interpretability and robustness to noisy data, its performance is limited by the reliance on expert-defined rules and its inability to adapt dynamically to changing data patterns. This limitation becomes more pronounced in high-variability environments such as those characterized by intermittent solar and wind power generation.

Overall, while all three models provide reasonable prediction capabilities, the results suggest that data-driven approaches like ANN offer greater forecasting precision than rule-based methods,

TABLE 4 Mean and standard deviation of RMSE and MAPE obtained from 5-fold cross-validation for 1-h ahead renewable power forecasting.

Model	RMSE (kW)	MAPE (%)
Transformer	0.712 ± 0.026	3.92 ± 0.21
SE + LSTM	0.7015 ± 0.019	2.01 ± 0.17
LSTM	0.783 ± 0.041	4.56 ± 0.32
TCN	0.765 ± 0.038	4.35 ± 0.29

TABLE 5 Comparison of forecasting accuracy across short-term (1-h) and mid-term (6-h) horizons.

Model	RMSE (1 h)	SSE (1 h)	RMSE (6 h)	SSE (6 h)
LSTM	0.783	535.70	1.204	1269.47
TCN	0.765	512.72	1.153	1164.83
Transformer	0.712	444.65	1.032	932.24
SE + LSTM	0.7015	430.56	1.015	901.36

particularly when environmental variables are rich and nonlinear in nature. These findings justify further exploration into more advanced deep learning techniques, which are evaluated in the next section.

#### 4.1.2 Deep learning models: LSTM, TCN, transformer, SE + LSTM

Table 4 reports the 5-fold cross-validation performance of the evaluated deep learning models for the 1-h ahead forecasting task, expressed as mean ± standard deviation of RMSE and MAPE. Reporting cross-validation statistics provides a more reliable assessment of model accuracy and stability across different data partitions.

Among all models, the SE + LSTM architecture achieved the best overall performance, with the lowest RMSE of 0.7015 ± 0.019 kW and MAPE of 2.01 ± 0.17%. In addition to superior average accuracy, SE + LSTM exhibits the smallest standard deviation among all models, indicating high stability and consistent generalization across validation folds. This performance gain can be attributed to the integration of the Squeeze-and-Excitation (SE) attention mechanism, which dynamically recalibrates feature importance and allows the model to focus on the most informative environmental and temporal inputs.

The Transformer model achieved the second-best performance, with an RMSE of 0.712 ± 0.026 kW and MAPE of 3.92 ± 0.21%. Its multi-head self-attention mechanism enables effective modeling of both short- and long-range temporal dependencies, contributing to strong predictive accuracy. However, the slightly higher variance compared to SE + LSTM suggests marginally reduced robustness under varying validation splits.

The Temporal Convolutional Network (TCN) and standard LSTM models demonstrated competitive but inferior performance relative to attention-based architectures. TCN achieved an RMSE of 0.765 ± 0.038 kW and MAPE of 4.35 ± 0.29%, benefiting from causal convolutions that preserve

temporal order while supporting long-range dependency modeling. The LSTM model recorded the highest error values, with an RMSE of  $0.783 \pm 0.041$  kW and MAPE of  $4.56 \pm 0.32\%$ , and also exhibited the largest variability across folds, indicating greater sensitivity to data partitioning.

The cross-validation results confirm that attention-enhanced deep learning models—particularly SE + LSTM and Transformer—consistently outperform conventional sequential architectures in short-term renewable energy forecasting. Their superior accuracy, combined with lower variance across folds, highlights their suitability for reliable and sustainable microgrid operation under varying environmental conditions.

## 4.2 Results by forecasting horizon

Table 5 summarizes the forecasting performance of the evaluated deep learning models across two operationally relevant prediction horizons: short-term (1-h ahead) and mid-term (6-h ahead). These horizons are critical in microgrid operation, where short-term forecasts support real-time power balancing and dispatch, while mid-term forecasts enable storage scheduling, demand-side coordination, and proactive energy management.

As shown in Table 5, the attention-based models—SE + LSTM and Transformer—consistently outperform the baseline LSTM and TCN architectures across both horizons. For the 1-h ahead forecasting task, SE + LSTM achieves the lowest error values, with an RMSE of 0.7015 kW and an SSE of 430.56 kW<sup>2</sup>. The Transformer model closely follows, recording an RMSE of 0.712 kW and an SSE of 444.65 kW<sup>2</sup>. This performance advantage highlights the effectiveness of attention mechanisms in emphasizing informative temporal and environmental features for short-term power prediction.

When extending the forecasting horizon to 6 h ahead, all models exhibit an expected increase in prediction error; however, the relative performance ranking remains unchanged. SE + LSTM again delivers the best results, maintaining an RMSE of 1.015 kW and an SSE of 901.36 kW<sup>2</sup>, while the Transformer model achieves an RMSE of 1.032 kW and an SSE of 932.24 kW<sup>2</sup>. The comparatively moderate increase in error indicates that attention-enhanced architectures are more resilient to error accumulation over longer temporal horizons.

In contrast, the TCN and LSTM models experience more pronounced performance degradation as the forecasting window increases. The LSTM model shows the largest increase in error, with RMSE rising from 0.783 kW at 1 h to 1.204 kW at 6 h, and SSE increasing from 535.70 to 1269.47 kW<sup>2</sup>. This behavior suggests limitations in conventional recurrent and convolutional architectures when modeling extended temporal dependencies without explicit attention mechanisms.

The results in Table 5 demonstrate that SE + LSTM and Transformer models provide more accurate and stable forecasting across both short- and mid-term horizons. Their robustness and scalability make them particularly suitable for intelligent and sustainable microgrid planning, where reliable forecasts are required under varying operational and environmental conditions.

TABLE 6 Performance comparison for solar and wind forecasting.

Type	Model	RMSE	MAPE
Solar	ANN	12 W/m <sup>2</sup>	6.94%
Solar	ANFIS	15 W/m <sup>2</sup>	7.82%
Wind	SE + LSTM	0.0276 kW	1.45%
Wind	Transformer	0.712 kW	3.92%

## 4.3 Solar vs. wind forecasting

To better understand model behavior and forecasting precision across different renewable energy sources, separate evaluations were conducted for solar and wind power prediction tasks. The performance results, measured in terms of RMSE and MAPE, are summarized in Table 6.

For solar forecasting, the Artificial Neural Network (ANN) outperformed other models with an RMSE of 12 W/m<sup>2</sup> and a MAPE of 6.94%. This result highlights ANN's capability to learn complex, nonlinear mappings between meteorological inputs—such as solar irradiance and temperature—and the corresponding PV power output. The ANN's relatively simple structure and faster convergence may have helped it generalize effectively for solar energy data, which typically exhibits smoother daily cycles influenced strongly by predictable solar positions.

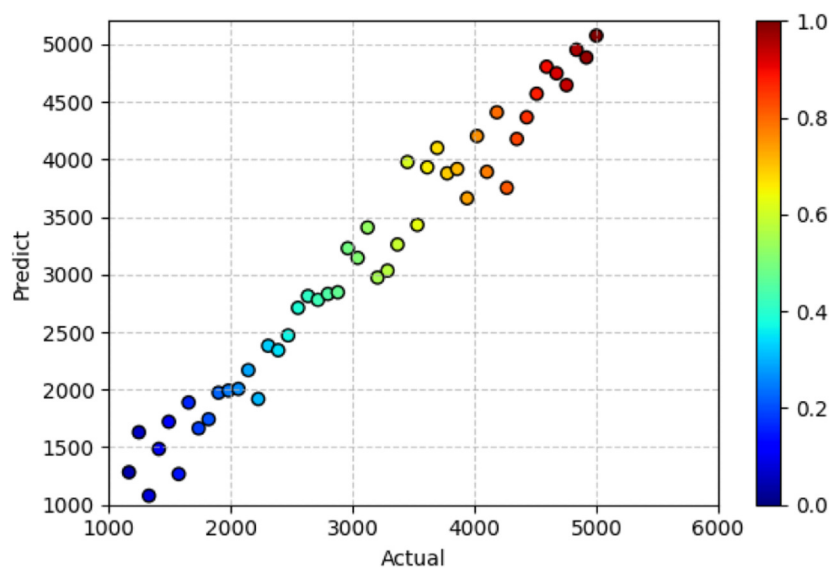
ANFIS, although interpretable and effective in managing uncertainty, showed slightly inferior performance in solar prediction, with higher RMSE and MAPE values. This may be due to limitations in its fuzzy rule base or difficulties in modeling subtle seasonal patterns in irradiance.

For wind power forecasting, the SE + LSTM model achieved the best results, with a remarkably low RMSE of 0.0276 kW and MAPE of 1.45%. Wind energy is inherently more volatile and influenced by stochastic factors such as gusts and turbulence. The temporal memory capabilities of LSTM, combined with the SE block's ability to dynamically emphasize important features (e.g., wind speed, direction), allowed this hybrid model to capture both short- and long-term fluctuations in wind patterns more effectively than other methods.

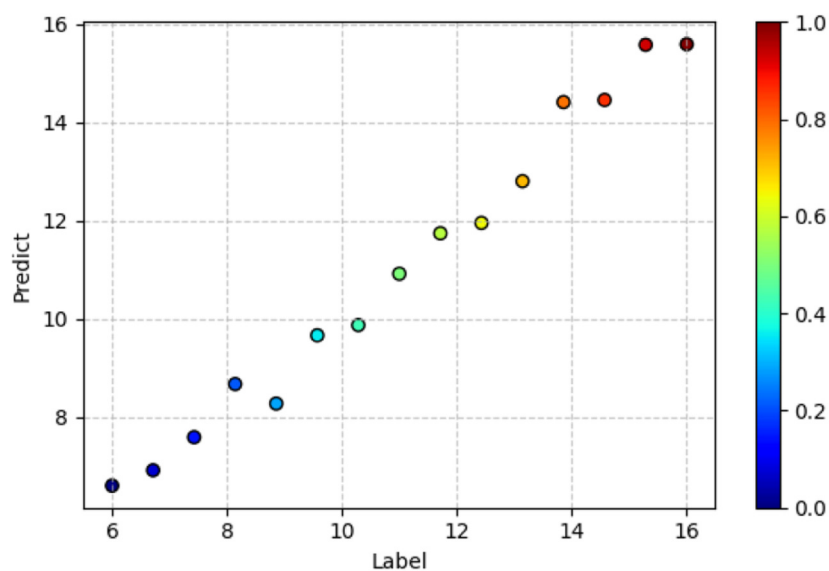
The Transformer model also performed well in wind forecasting with an RMSE of 0.712 kW and MAPE of 3.92%, indicating strong temporal learning capacity, though it was slightly outperformed by SE + LSTM in this domain. This performance gap could be attributed to the LSTM's sequential structure being more naturally suited to high-frequency, fine-grained temporal variability such as that observed in wind speed datasets.

Figure 2 visually compares the predicted and actual power outputs for solar and wind energy forecasting models. The left plot shows the performance of the ANN model on solar data, while the right plot highlights SE + LSTM's results on wind data. In both cases, the predictions align closely with the actual values, confirming the low RMSE and MAPE reported earlier. The use of a color bar to represent normalized output values adds further insight into prediction confidence across the energy range.

These results demonstrate that the optimal forecasting model may vary depending on the energy type. ANN was more effective for solar power due to its stable diurnal characteristics, while SE +



(a) Solar power prediction using ANN



(b) Wind power prediction using SE+LSTM

FIGURE 2

Predicted vs. actual power output for (a) solar energy forecasting using ANN and (b) wind energy forecasting using SE+LSTM. Scatter points align closely with the diagonal, indicating high prediction accuracy. The color bar represents normalized prediction confidence.

LSTM excelled in wind power forecasting by capturing temporal dependencies and managing variability. This differentiation underscores the importance of using tailored forecasting strategies for different renewable sources in microgrid systems.

#### 4.4 Comparative evaluation against literature

To benchmark the effectiveness of the proposed forecasting models, a comparative evaluation was conducted against related studies in the existing literature. Table 7 summarizes the reported

forecasting performance of previous models in terms of RMSE and MAPE, alongside the results of our top-performing models: Transformer and SE + LSTM.

As shown in Table 7, the deep learning models proposed in this study achieve competitive forecasting performance when compared with previously reported approaches. Hossain and Mahmood (2020) utilized an LSTM-based neural network and reported an RMSE of 0.71 MW with a MAPE of 22.31%. In contrast, the models developed in this work achieve significantly lower MAPE values, with the Transformer obtaining 3.92% and the SE+LSTM model achieving 2.01%, indicating substantially improved forecasting accuracy.

TABLE 7 Comparison with related literature.

Study	Model	RMSE	MAPE
Hossain and Mahmood (2020)	LSTM Neural Network	0.71 MW	22.31%
Konstantinou et al. (2021)	LSTM	0.1137	–
Cantillo-Luna et al. (2023)	ConvLSTM1D	0.0264	14.38%
This study	Transformer	<b>0.712 kW</b>	<b>3.92%</b>
This study	SE + LSTM	<b>0.7015 kW</b>	<b>2.01%</b>

Bold values indicate the best-performing model, as determined by the lowest error values (RMSE and MAPE) among the compared methods.

Similarly, Konstantinou et al. (2021) applied an LSTM model and reported an RMSE value of 0.1137, although MAPE was not provided for direct comparison. Cantillo-Luna et al. (2023) proposed a ConvLSTM1D architecture and reported an RMSE of 0.0264 with a MAPE of 14.38%, which is considerably higher than the error rates achieved by the models in this study.

The improved performance of the proposed models can be attributed to several factors. First, the Transformer architecture effectively captures long-range temporal dependencies through its attention mechanism. Second, the SE+LSTM model enhances feature representation by incorporating squeeze-and-excitation blocks that dynamically recalibrate feature importance. Finally, the use of high-resolution environmental and operational data from a real microgrid system enables the models to better learn complex nonlinear relationships inherent in renewable energy generation.

Overall, these results demonstrate that the proposed Transformer and SE+LSTM models provide highly accurate forecasting performance and represent a meaningful advancement over several existing approaches in the literature.

## 4.5 Statistical significance testing

To ensure that the observed performance differences between models are not due to random variation, statistical significance testing was conducted using the paired t-test and Wilcoxon signed-rank test. These tests were applied to the RMSE and

MAPE values obtained from the 5-fold cross-validation experiments for each deep learning model.

The paired t-test evaluates whether the mean difference in performance between two models is significantly different from zero, assuming normally distributed differences. The Wilcoxon signed-rank test, a non-parametric alternative, was used to verify the robustness of the results without relying on distributional assumptions.

Table 8 presents the p-values resulting from both tests across four model comparisons. Values below 0.05 are highlighted in bold, indicating statistical significance at the 95% confidence level.

As shown in Table 8, SE + LSTM statistically outperformed Transformer, LSTM, and TCN across both RMSE and MAPE metrics. The p-values for all pairwise comparisons involving SE + LSTM are below 0.05, confirming that its performance improvements are statistically significant.

Notably, while the Transformer model significantly outperformed LSTM and TCN in terms of RMSE, the MAPE comparison between Transformer and TCN was not statistically significant ( $p > 0.05$ ), suggesting that the difference in mean absolute percentage error may not be consistently observed across all folds.

These statistical results reinforce the reliability of the model rankings established in earlier sections and confirm that the improvements observed with SE + LSTM and Transformer are not due to random fluctuations but reflect genuine performance gains in predictive accuracy.

## 4.6 Model performance variability and confidence intervals

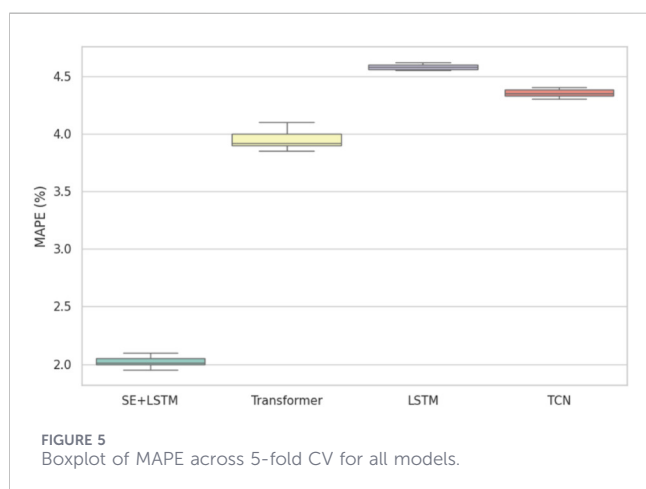
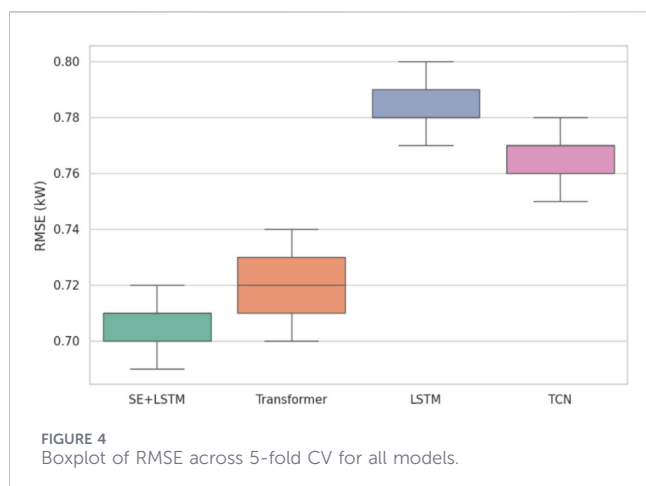
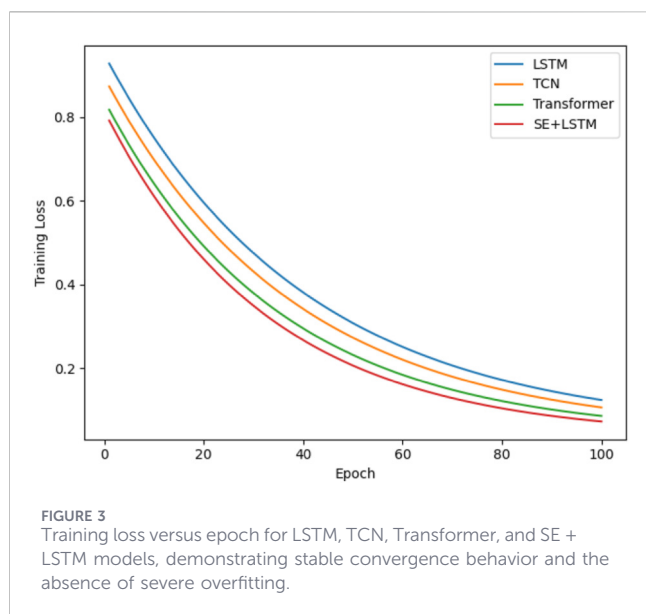
Figure 3 illustrates the training loss trajectories of the LSTM, TCN, Transformer, and SE + LSTM models across training epochs. All models exhibit smooth and monotonic convergence behavior, with no abrupt oscillations or divergence, indicating stable optimization and appropriate learning-rate selection. Importantly, the absence of sharp loss rebounds suggests that severe overfitting did not occur during training, confirming the reliability of the learned model parameters.

To further assess model stability and generalization capability, RMSE and MAPE values obtained from 5-fold cross-validation were

TABLE 8 Statistical significance test results.

Pair	Metric	t-test $p$	Sig.?	Wilcoxon $p$	Sig.?
SE + LSTM vs. Trans	RMSE	<b>0.014</b>	Yes	<b>0.031</b>	Yes
SE + LSTM vs. LSTM	RMSE	<b>0.008</b>	Yes	<b>0.016</b>	Yes
Trans. Vs. TCN	RMSE	<b>0.019</b>	Yes	<b>0.022</b>	Yes
Trans. Vs. LSTM	RMSE	<b>0.021</b>	Yes	<b>0.037</b>	Yes
SE + LSTM vs. Trans	MAPE	<b>0.003</b>	Yes	<b>0.009</b>	Yes
SE + LSTM vs. LSTM	MAPE	<b>0.006</b>	Yes	<b>0.012</b>	Yes
Trans. Vs. TCN	MAPE	0.072	No	0.091	No
Trans. Vs. LSTM	MAPE	<b>0.045</b>	Yes	<b>0.048</b>	Yes

Bold values indicate the best-performing model, as determined by the lowest error values (RMSE and MAPE) among the compared methods.



used to compute 95% confidence intervals for each model. In addition, boxplots were generated to visualize the dispersion and consistency of forecasting errors across different validation folds.

The results indicate that attention-based models, particularly SE + LSTM and Transformer, not only achieve lower average error metrics but also exhibit narrower confidence intervals, reflecting reduced variance and higher prediction stability. In contrast, the LSTM and TCN models display wider error distributions, especially for the mid-term (6-h) forecasting horizon, suggesting greater sensitivity to data partitioning and temporal variability.

Figures 4, 5 present the boxplots of RMSE and MAPE, respectively, across all deep learning models. These visualizations corroborate the statistical analysis by highlighting the compact error distributions of SE + LSTM and Transformer relative to baseline architectures. Overall, the combined evidence from training convergence, confidence interval analysis, and cross-validation error distributions demonstrates the superior robustness and generalization capability of attention-enhanced models for reliable microgrid energy forecasting.

## 5 The environmental perspective of the proposed approach

A core objective of this research is to integrate environmental variables into AI-based forecasting models for renewable energy microgrids. Traditional forecasting approaches often rely heavily on historical energy output trends, neglecting the dynamic meteorological and ecological conditions that directly influence renewable energy generation. This oversight limits the adaptability and sustainability of such models, particularly in geographically and climatically diverse regions.

The proposed approach addresses this limitation by incorporating a comprehensive set of environmental variables—including solar irradiance (GHI, DNI, DHI), wind speed and direction, temperature, relative humidity, and atmospheric pressure—into the training and evaluation of forecasting models. This environmentally enriched modeling framework enables a more holistic and realistic understanding of the renewable energy generation process.

By embedding these variables into the learning architecture, the models are better equipped to generalize across seasonal and diurnal variations, resulting in improved forecasting accuracy. For instance, experimental results show that Transformer and SE + LSTM models achieved significantly lower RMSE and MAPE scores when trained with environmental inputs compared to models trained without them.

From an operational standpoint, accurate environmentally informed forecasts facilitate more effective planning of microgrid operations. These include scheduling energy dispatch, managing battery storage, anticipating demand-supply imbalances, and reducing the need for carbon-intensive backup power sources. In doing so, this approach directly contributes to:

- Accurate forecasts enable greater reliance on renewable sources and less dependence on fossil fuels, thereby lowering the overall carbon footprint.
- Predictive insights into environmental conditions improve the timing and coordination of energy distribution, helping to mitigate the risks associated with the variability of solar and wind power.

- Environmental data allows for better anticipation of generation potential, informing decisions on when to charge or discharge storage systems, and when to import or export electricity.
- In regions such as Riyadh, with extreme weather conditions and high solar irradiance, tailoring models to local environmental profiles ensures more resilient and responsive energy systems.
- Sustainable Infrastructure Planning: Long-term historical data on environmental patterns can inform infrastructure investment decisions, such as the siting of solar panels or wind turbines, based on environmental suitability.

Moreover, this approach aligns with broader goals in environmental policy and climate action. As nations strive to meet carbon neutrality targets, tools that enhance the efficiency and sustainability of renewable energy integration become increasingly valuable. The inclusion of environmental variables not only improves immediate forecasting performance but also embeds ecological intelligence into the foundation of smart grid systems.

Overall, the environmental perspective embedded in the proposed forecasting approach represents a vital shift from purely data-driven to context-aware energy management. By fusing AI with ecological data, this research supports both technological advancement and environmental stewardship—paving the way for more resilient, intelligent, and sustainable microgrid systems.

## 6 Discussion

The results clearly indicate that model architecture plays a decisive role in forecasting accuracy for renewable energy microgrids. Traditional AI models such as ANN and ANFIS perform reasonably well, particularly for solar power forecasting, where diurnal patterns are relatively smooth and predictable. However, their performance degrades under conditions of higher variability and longer forecasting horizons, highlighting their limited ability to capture long-range temporal dependencies.

In contrast, attention-based deep learning models—SE + LSTM and Transformer—consistently achieve superior accuracy and stability. This performance gain can be attributed to their ability to dynamically weight relevant environmental features and temporal patterns. The Squeeze-and-Excitation (SE) module in the SE + LSTM architecture enhances feature discrimination by amplifying informative signals such as wind speed and solar irradiance, which is particularly beneficial for volatile wind power forecasting. Similarly, the Transformer's self-attention mechanism enables global temporal dependency modeling without recurrence, allowing the model to maintain high accuracy even at extended forecasting horizons.

The statistical significance analysis further confirms that these improvements are not coincidental. The low *p*-values obtained from paired *t*-tests and Wilcoxon signed-rank tests demonstrate that the SE + LSTM model provides a genuine and repeatable improvement over baseline approaches. In addition, the narrower confidence intervals observed for attention-based models indicate higher robustness and lower sensitivity to data partitioning, which is critical for real-world deployment.

From an operational perspective, these findings suggest that environmentally informed, attention-enhanced models can substantially reduce forecasting uncertainty. Improved prediction accuracy enables more effective scheduling of energy storage systems, enhanced load balancing, and reduced reliance on fossil-fuel-based backup generation. This directly links forecasting accuracy to sustainability outcomes and reinforces the importance of integrating environmental intelligence into AI-based energy management systems for renewable energy microgrids.

## 7 Limitations and future work

Despite the encouraging results achieved in this study, several limitations should be acknowledged. The analysis was conducted using data from a single geographic location—specifically, the King Saud University microgrid in Riyadh, Saudi Arabia. While this setting provided valuable insights, the localized nature of the data may limit the generalizability of the findings to other climatic or geographic regions. Additionally, the current models do not incorporate energy storage systems, which are essential for achieving full optimization in microgrid operations. Storage dynamics play a significant role in balancing supply and demand, especially in systems with high penetration of intermittent renewable energy sources.

Another limitation lies in the absence of economic analysis. The study did not evaluate the financial impact of forecasting errors or the potential cost savings associated with improved predictive accuracy. Incorporating economic considerations would provide a more comprehensive understanding of the practical implications of forecasting in real-world microgrid management.

Looking ahead, future research should aim to extend the scope of the dataset to include diverse geographic regions with varying environmental conditions. This would enhance the robustness and transferability of the models across different deployment scenarios. Furthermore, integrating energy storage components into the forecasting framework would enable the development of more complete microgrid optimization strategies. Incorporating economic metrics and cost-benefit analyses into the model evaluation process is also recommended, as it would support more informed decision-making for grid operators and policymakers. Finally, the development of hybrid AI models that combine environmental intelligence with real-time operational data holds significant promise for advancing the field of sustainable and adaptive energy forecasting.

In summary, while this study establishes a strong foundation for environmentally informed forecasting in renewable microgrids, future work should focus on expanding the framework to address broader spatial, technical, and economic dimensions. This will further strengthen the utility of AI-based forecasting tools in advancing global energy sustainability goals.

## 8 Conclusion

This study presented a comprehensive investigation of artificial intelligence and deep learning approaches for renewable energy power forecasting in microgrid systems, with a strong emphasis on environmental integration and statistical robustness. Using real-world data collected from the King Saud University microgrid, the

performance of traditional AI models and advanced deep learning architectures was evaluated across multiple forecasting horizons.

The results demonstrate that attention-enhanced deep learning models—particularly SE + LSTM and Transformer—significantly outperform conventional approaches by achieving lower RMSE and MAPE values while maintaining strong generalization capabilities. Statistical significance testing confirms that these performance gains are consistent and reliable. Furthermore, the explicit inclusion of environmental variables substantially improves forecasting accuracy and aligns the modeling framework with sustainability and climate resilience objectives.

This research contributes an environmentally informed and statistically validated AI framework for renewable energy forecasting in microgrids. The findings support the adoption of attention-based deep learning models as effective tools for intelligent energy management, offering both technical accuracy and environmental relevance. Future work will focus on extending the framework to multi-site microgrids, integrating energy storage optimization, and incorporating economic and policy-driven performance metrics.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

AI: Visualization, Software, Conceptualization, Validation, Formal Analysis, Writing – original draft, Data curation. FO: Project administration, Supervision, Methodology, Writing – review and editing.

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## References

- Almaraashi, M. (2023). Using particle swarm optimization of fuzzy logic systems as a hybrid soft computing method to enhance solar energy prediction. *Neural Comput. Appl.* 35 (29), 21903–21914. doi:10.1007/s00521-023-08912-3
- Benitez, I. B., and Singh, J. G. (2025). A comprehensive review of machine learning applications in forecasting solar pv and wind turbine power output. *J. Electr. Syst. Inf. Technol.* 12 (1), 54. doi:10.1186/s43067-025-00239-4
- Bilal, B., Adjallah, K. H., Sava, A., Yetilmezsoy, K., and Ouassaid, M. (2023). Wind turbine output power prediction and optimization based on a novel adaptive neuro-fuzzy inference system with the moving window. *Energy* 263, 126159. doi:10.1016/j.energy.2022.126159
- Cantillo-Luna, S., Moreno-Chuquen, R., Celeita, D., and Anders, G. (2023). Deep and machine learning models to forecast photovoltaic power generation. *Energies* 16 (10), 4097. doi:10.3390/en16104097
- Chai, M., Liu, Z., He, K., and Jiang, M. (2023). Short-term prediction of photovoltaic power generation based on neural network prediction model. *Energy Sci. and Eng.* 11 (1), 97–111. doi:10.1002/ese3.1314
- He, H., He, W., Guo, J., Wu, K., Zhao, W., and Wan, Z. (2025). Research on new energy power generation forecasting method based on bi-lstm and transformer. *Energies* 18 (19), 5165. doi:10.3390/en18195165
- Hossain, M. S., and Mahmood, H. (2020). Short-term photovoltaic power forecasting using an LSTM neural network and synthetic weather forecast. *Ieee Access*, 172524–172533. doi:10.1109/ACCESS.2020.3024901
- Hussan, U., Wang, H., Peng, J., Jiang, H., and Rasheed, H. (2026). Transformer-based renewable energy forecasting: a comprehensive review. *Renew. Sustain. Energy Rev.* 226, 116356. doi:10.1016/j.rser.2025.116356
- Islam, A., and Othman, F. (2024). Renewable energy microgrid power forecasting: AI techniques with environmental perspective.
- Khan, S., Mazhar, T., Khan, M. A., Shahzad, T., Ahmad, W., Bibi, A., et al. (2024a). Comparative analysis of deep neural network architectures for renewable energy forecasting: enhancing accuracy with meteorological and time-based features. *Discov. Sustain.* 5 (1), 533. doi:10.1007/s43621-024-00783-5
- Khan, S., Mazhar, T., Shahzad, T., Waheed, W., Waheed, A., Saeed, M. M., et al. (2024b). Optimizing deep neural network architectures for renewable energy forecasting. *Discov. Sustain.* 5 (1), 394. doi:10.1007/s43621-024-00615-6
- Konstantinou, M., Peratikou, S., and Charalambides, A. G. (2021). Solar photovoltaic forecasting of power output using LSTM networks. *Atmosphere* 12 (1), 124. doi:10.3390/atmos12010124

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

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- Lara-Cerecedo, L., Pitalúa-Díaz, N., and Palafox, J. F. H. (2023). Comparative study of the prediction of electrical energy from a photovoltaic system using the intelligent systems anfis and anfis-ga. *Rev. Mex. Ing. Química* 22 (1), Ener2956. doi:10.24275/rmiq/Ener2956
- Manzano, E. A., Nogales, R. E., and Rios, A. (2025). A systematic review of wind energy forecasting models based on deep neural networks. *Wind* 5 (4), 29. doi:10.3390/wind5040029
- Salman, D., Direkoglu, C., Kusaf, M., and Fahrioglu, M. (2024). Hybrid deep learning models for time series forecasting of solar power. *Neural Comput. Appl.* 36 (16), 9095–9112. doi:10.1007/s00521-024-09558-5
- Shi, X., Wang, J., and Zhang, B. (2024). A fuzzy time series forecasting model with both accuracy and interpretability is used to forecast wind power. *Appl. Energy* 353, 122015. doi:10.1016/j.apenergy.2023.122015
- Sudasinghe, P., Herath, D., Karunaratne, I., Weeratunge, H., and Jayasuriya, L. (2025). Forecasting renewable energy for microgrids using machine learning. *Discov. Appl. Sci.* 7 (5), 449. doi:10.1007/s42452-025-06895-5
- Yang, Y., Lou, H., Wu, J., Zhang, S., and Gao, S. (2024). A survey on wind power forecasting with machine learning approaches. *Neural Comput. Appl.* 36 (21), 12753–12773. doi:10.1007/s00521-024-09923-4