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RESEARCH ARTICLE

A Comparative Deep Learning Approach for Short-Term Wind Power Generation Prediction

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ABSTRACT

Accurate wind power forecasting is essential for reliable renewable energy integration, grid stability, reserve scheduling, and wind farm operation because turbine output is highly variable and strongly influenced by meteorological conditions. However, forecasting wind power remains challenging due to the nonlinear relationship between weather variables and power generation, the temporal dependency of hourly observations, and the circular nature of wind direction data. This study aims to develop and compare deep learning models for predicting normalized wind turbine power output using a field-based hourly dataset collected from an operational wind energy site starting from January 2, 2017. The dataset includes temperature, relative humidity, dew point, wind speed at 10 m and 100 m, wind direction at 10 m and 100 m, wind gusts, and normalized turbine output. Five predictive models, namely LSTM, RNN, GRU, CNN, and Dense neural networks, were trained and evaluated after applying data preprocessing procedures, including missing-value handling, feature scaling, temporal alignment, and wind-direction transformation. Model performance was assessed using MSE, RMSE, MAE, MBE, correlation coefficient (r), coefficient of determination (R^2), RRMSE, NSE, and WI. The empirical results showed that recurrent architectures outperformed the CNN and Dense models, confirming the importance of temporal learning in hourly wind power forecasting. Among all models, LSTM achieved the best overall performance, with MSE = 0.0008, RMSE = 0.0282, MAE = 0.0106, MBE = -0.0006, $r = 0.9940$, $R^2 = 0.9880$, RRMSE = 0.0861, NSE = 0.9880, and WI = 0.9970. These findings demonstrate that LSTM can effectively capture nonlinear and sequential relationships between meteorological variables and turbine power generation, providing a reliable forecasting approach for operational wind energy management and supporting more stable integration of wind power into modern electricity systems.

Keywords: Wind power forecasting ▪ Deep learning ▪ Long Short-Term Memory (LSTM) ▪ Renewable energy prediction ▪ Time-series forecasting

1. INTRODUCTION

Wind energy is one of the most rapidly expanding renewable energy sources and plays an essential role in the transition toward low-carbon electricity systems [1, 2, 3]. As wind penetration increases in modern power systems, accurate wind power forecasting becomes increasingly important for grid stability, reserve scheduling, electricity market participation, and wind farm operational planning. Unlike conventional power generation, wind energy is highly variable because it depends directly on meteorological conditions, especially wind speed, wind direction, air temperature, humidity, dew point, and gust behavior. Therefore, wind power forecasting is not only a statistical prediction problem but also a practical operational requirement for improving the reliability and efficiency of renewable-energy-based power systems [4, 5].

The present study focuses on a real-world, field-based wind power dataset collected directly from an operational company site. The dataset contains hourly meteorological observations and turbine power generation records beginning on January 2, 2017. Unlike simulated or purely benchmark datasets, this dataset reflects actual operating conditions at a wind turbine installation, making it valuable for applied wind energy forecasting. The input variables include temperature at 2 m, relative humidity at 2 m, dew point at 2 m, wind speed at 10 m, wind speed at 100 m, wind direction at 10 m, wind direction at 100 m, and wind gusts. The prediction target is *Power*, which represents turbine output normalized between 0 and 1, where values closer to 1 indicate generation near the maximum potential output.

The motivation for this study arises from the need to understand how local meteorological conditions influence wind turbine power production. Wind power output is strongly affected by wind speed, wind direction, gust behavior, air-density-related variables, and temporal atmospheric patterns [6, 7]. Since the dataset provides hourly measurements at different heights, it enables the development of forecasting models capable of learning both near-surface and elevated wind behavior. This is particularly relevant because wind speed at higher altitudes, such as 100 m, is often more representative of turbine operating conditions than measurements taken closer to the ground [8, 9].

In this study, five deep learning models are evaluated for normalized wind power prediction: Long Short-Term Memory networks (LSTM), Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), and a Dense neural network. These models are selected because wind power forecasting is a nonlinear time-series regression problem. Recurrent architectures such as LSTM, RNN, and GRU are especially suitable for sequential data because they can learn temporal dependencies from previous hourly observations, while CNN and Dense models are included as comparative deep learning baselines. Forecasting wind power from field-based meteorological data involves several important challenges. First, the relationship between wind speed and power generation is highly nonlinear. At low wind speeds, turbines may generate little or no electricity; as wind speed increases, turbine output rises rapidly; and near rated operating conditions, power production may saturate. Because the target variable in this dataset is normalized between 0 and 1, the model must accurately estimate both low-generation and high-generation intervals. This requires a forecasting method capable of learning nonlinear operating regimes rather than relying on simple linear relationships [10, 11].

Second, the dataset contains meteorological variables measured at different heights, particularly *windspeed_10m* and *windspeed_100m*, as well as *winddirection_10m* and *winddirection_100m*. These variables may not contribute equally to forecasting accuracy. For instance, wind speed at 100 m may be more directly related to turbine output than wind speed at 10 m, while temperature, humidity, and dew point may influence power indirectly through atmospheric density and local weather conditions. Therefore, the model must learn the relative contribution of each predictor and distinguish highly informative variables from weak or redundant ones.

Third, wind direction presents a specific preprocessing challenge because it is a circular variable. A direction of 0° and a direction of 360° represent the same physical orientation, but if treated as ordinary numerical values, they appear artificially far apart. This can introduce discontinuity into the learning process and reduce model accuracy. Therefore, wind direction variables should be transformed using sine and cosine components, or converted into radians before trigonometric transformation. This representation preserves the circular nature of wind direction and provides a more suitable numerical form for regression-based learning models.

Fourth, the hourly structure of the dataset creates temporal dependency. Wind turbine output at a given hour is not independent of previous atmospheric conditions. Instead, it may be influenced by recent wind speed patterns, ramp events, gust fluctuations, and short-term persistence in local weather. This temporal structure explains why recurrent models such as LSTM, RNN, and GRU are expected to perform strongly. These architectures are designed to process sequential data and retain information from previous time steps, which is important for hourly wind power forecasting.

Finally, some models may capture temporal behavior more effectively than others. Dense neural networks can model nonlinear relationships among input variables, but they do not inherently preserve sequence information unless lagged features are explicitly engineered. CNN models may capture local patterns, but their effectiveness depends on how temporal windows are structured. Recurrent models, especially LSTM, are often more suitable for time-series forecasting because they are designed to learn dependencies across sequential observations. The main objective of this study is to develop and evaluate deep learning models for forecasting normalized wind turbine power output using hourly field-based meteorological data. The study focuses on predicting the *Power* variable from weather-related predictors collected at an operational wind energy site.

The specific objectives of this study are as follows:

- To preprocess the hourly meteorological dataset and prepare it for wind power forecasting, including scaling numerical variables and transforming circular wind-direction measurements into suitable sine and cosine representations.
- To evaluate five deep learning models, namely LSTM, RNN, GRU, CNN, and Dense neural networks, for normalized wind power prediction.
- To compare the ability of the selected models to capture nonlinear and temporal relationships between meteorological conditions and turbine output.

- To assess forecasting accuracy using a comprehensive set of regression metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), coefficient of determination (R^2), Relative Root Mean Squared Error (RRMSE), Nash–Sutcliffe Efficiency (NSE), and Willmott Index (WI).
- To identify the best-performing model for hourly wind power forecasting based on error minimization, goodness of fit, bias reduction, and agreement with observed turbine output.

Based on the experimental results, the LSTM model achieved the strongest overall forecasting performance, with MSE = 0.0008, RMSE = 0.0282, MAE = 0.0106, MBE = −0.0006, $r = 0.9940$, $R^2 = 0.9880$, RRMSE = 0.0861, NSE = 0.9880, and WI = 0.9970. These values indicate that LSTM produced highly accurate and nearly unbiased predictions of normalized turbine power output.

This study provides several contributions to wind power forecasting research. First, it presents a forecasting framework based on a real-world hourly dataset collected from an operational wind energy site. This is important because field-based datasets better represent the complexity of actual wind farm operation compared with purely simulated data. The dataset captures the interaction between meteorological conditions and turbine output under realistic environmental conditions.

Second, the study provides a comparative evaluation of five deep learning architectures for wind power forecasting: LSTM, RNN, GRU, CNN, and Dense neural networks. The results show that recurrent architectures outperform CNN and Dense models, confirming the importance of temporal modeling in hourly wind power prediction. Among all models, LSTM achieved the best performance, followed by RNN and GRU. This indicates that models capable of retaining sequential information are better suited to forecasting wind power from hourly meteorological observations.

Third, the study demonstrates the practical importance of model bias evaluation. Although several models achieved high correlation and R^2 values, their MBE values differed. LSTM produced an MBE of −0.0006, which is very close to zero and indicates almost unbiased forecasting. In contrast, GRU and Dense showed stronger positive bias, while CNN showed negative bias. This is important in wind energy applications because systematic overestimation or underestimation of power output can affect scheduling, reserve allocation, and operational decision-making.

Fourth, the study emphasizes the value of comprehensive evaluation. The LSTM model not only achieved the lowest error values but also obtained the highest goodness-of-fit and agreement metrics, including $R^2 = 0.9880$, NSE = 0.9880, and WI = 0.9970. These results demonstrate that LSTM accurately follows the observed variation in normalized turbine power output and provides reliable predictions across the hourly dataset.

Fifth, the study highlights the importance of wind-specific preprocessing, especially for wind-direction variables. Since wind direction is circular, representing it directly as a linear numerical value may reduce forecasting accuracy. Transforming wind direction into sine and cosine components helps preserve directional continuity and supports more physically meaningful learning.

The remainder of this paper is organized as follows. The next section describes the field-based wind power dataset, including the hourly meteorological variables, normalized turbine output, data collection process, and preprocessing procedures. Particular attention is given to the treatment of wind direction as a circular variable and the preparation of time-series samples for deep learning models. The following section presents the methodology, including the architecture and training process of the LSTM, RNN, GRU, CNN, and Dense models. It also describes the evaluation metrics used to compare model performance. The experimental results section reports and discusses the forecasting outcomes. The models are compared using MSE, RMSE, MAE, MBE, r, R^2, RRMSE, NSE, and WI. The results demonstrate that LSTM achieved the best overall performance, followed by RNN and GRU, while CNN and Dense models produced larger prediction errors.

The discussion section interprets the findings in relation to the temporal nature of wind power generation and the importance of meteorological predictors. It explains why recurrent models are more effective for this dataset and discusses the operational implications of low-error, low-bias wind power forecasting. Finally, the conclusion summarizes the major findings and suggests future research directions, including multi-step forecasting, feature selection, hyperparameter optimization, uncertainty quantification, explainable artificial intelligence, and extension of the framework to multiple wind farm locations.

2. LITERATURE REVIEW

The increasing global demand for electricity, combined with concerns regarding fossil fuel depletion, greenhouse gas emissions, and climate change, has accelerated the deployment of renewable energy systems worldwide. Among the various renewable energy resources, wind and solar energy are considered the most promising alternatives because of their environmental sustainability and abundance. However, the intermittent and stochastic behavior of renewable resources introduces major operational challenges for power systems, particularly in balancing electricity generation and demand. Consequently, accurate forecasting of renewable energy generation has become one of the most significant research areas in modern smart grid and energy management systems. Machine learning (ML) and deep learning (DL) approaches have emerged as effective tools for modeling the nonlinear and uncertain behavior of renewable energy systems due to their capability to learn hidden patterns from historical data.

One of the major research directions in renewable energy forecasting involves hybrid photovoltaic (PV)–wind systems. In this context, a comprehensive study investigated the prediction of power and energy generation in hybrid renewable energy systems using several machine learning models and seven influential weather parameters [12]. The study emphasized the importance of accurate forecasting in improving smart grid efficiency and enhancing renewable energy utilization. Historical hourly meteorological data were analyzed with and without feature manipulation techniques. Recursive Feature Elimination with Cross Validation (RFECV) was employed to identify the most significant weather variables affecting renewable energy output. Artificial Neural Network (ANN) regressors were also used to examine correlations among dataset features and identify meaningful patterns for statistical learning. The experimental findings demonstrated that feature selection substantially improved forecasting performance. Specifically, the linear regression model integrated with RFECV outperformed other machine learning models by achieving extremely low prediction errors and a coefficient of determination exceeding 99%. The study highlighted the importance of feature engineering and dimensionality reduction in renewable energy forecasting applications, particularly for improving computational efficiency and reducing model complexity.

In wind energy forecasting, deep learning techniques have received considerable attention because of their ability to model temporal dependencies within sequential datasets. A comparative study investigated several machine learning and deep learning architectures for short-term wind power prediction using historical wind energy production data [13]. The research considered meteorological input variables such as wind speed, wind direction, temperature, and pressure, alongside wind power output measurements. Multiple neural architectures were trained and evaluated, including baseline models, dense neural networks, convolutional neural networks (CNNs), Long Short-Term Memory (LSTM) networks, and Residual LSTM structures. The study demonstrated that recurrent architectures achieved superior forecasting accuracy compared with conventional feedforward methods. In particular, LSTM and Residual LSTM models produced the lowest mean absolute prediction errors because of their capability to preserve long-term temporal information and capture sequential dependencies within wind power time-series data. The authors concluded that deep recurrent learning models provide a promising direction for improving the operational planning and control of renewable energy systems.

The challenge of forecasting nonlinear and nonstationary wind speed signals has motivated researchers to develop hybrid decomposition-based prediction frameworks. One notable study proposed a hybrid prediction model integrating Variational Mode Decomposition (VMD), Elman neural networks, Radial Basis Function (RBF) networks, and Lorenz disturbance correction [14]. The VMD algorithm was first used to decompose nonstationary wind speed signals into several intrinsic mode functions (IMFs), thereby extracting stationary subcomponents with distinct characteristics. Sample entropy was further applied to determine the optimal number of decomposition modes. Subsequently, Elman neural networks were utilized to predict trend-related components due to their sensitivity to historical states, whereas RBF neural networks modeled stochastic components because of their strong nonlinear mapping capability. Finally, Lorenz disturbance equations were introduced to correct prediction errors associated with atmospheric fluctuations. Experimental evaluations using real-world wind farm data showed that the proposed hybrid framework significantly outperformed traditional neural network models. The study demonstrated that decomposition-based learning approaches can effectively reduce forecasting uncertainty by separating deterministic and stochastic behaviors within wind speed signals.

Besides deep learning methods, several studies have investigated classical machine learning approaches for wind speed forecasting. A comparative investigation examined Gaussian Process Regression (GPR), Bagged Trees (BTs), and Support Vector Regression (SVR) models for weekly wind speed prediction using meteorological data collected from multiple stations in Malaysia between 2000 and 2019 [15]. The study analyzed maximum, minimum, and average weekly wind speed forecasting scenarios. Results showed that average wind speed prediction yielded better accuracy than maximum and minimum forecasting tasks because average values exhibit lower variability. Among the evaluated models, Gaussian Process Regression consistently produced the lowest prediction errors for most meteorological stations. The probabilistic nature of GPR enabled better uncertainty representation and improved generalization capabilities compared with deterministic methods such as SVR. This research demonstrated that probabilistic machine learning frameworks can provide reliable renewable energy forecasting while maintaining acceptable computational efficiency.

Offshore wind energy forecasting has become important because offshore farms offer high generation potential and require accurate wind speed prediction for turbine selection and energy planning. In Taiwan, recurrent models such as LSTM, GRU, and stacked neural networks were used to assess offshore wind power potential under different locations, hub heights, rotor areas, and seasonal wind patterns, showing that forecasting can support practical turbine-selection decisions [16]. Broader ANN-based reviews also confirm that MLP, RNN, CNN, and LSTM models are widely used for short-term renewable energy forecasting because they can model complex temporal and spatial patterns in solar, wind, hydro, and hybrid systems [17].

Hybrid and optimization-based forecasting methods have also improved short-term renewable energy prediction. A Hybrid Variational Decomposition Model combined with IDGC optimization and RBF neural networks used SCADA and meteorological data to forecast wind power more accurately while reducing computational burden . Similarly, multi-source forecasting has been addressed through a hybrid CNN, attention-based LSTM, and autoregression framework, which captured correlations among solar PV, solar thermal, and wind generation and improved forecasting stability compared with standalone models [18].

Forecasting is closely connected to scheduling, grid stability, and operational efficiency. An optimized LSTM model was integrated with wind plant scheduling and SCADA-based maintenance planning to improve wind generation availability prediction and reduce operational costs [19]. Ensemble learning methods, including Boosted Trees, Random Forests, and Generalized Random Forests, also achieved strong wind power prediction performance, especially when lagged variables were included to represent temporal dependencies [20]. For long-term integrated systems, stochastic model predictive control supported hydro–wind–solar operation by combining probabilistic forecasting with rolling optimization and accounting for correlations among renewable resources [21].

Renewable energy forecasting has further been applied beyond conventional grid operation. In wind-powered reverse osmosis desalination, neural-network wind speed forecasting helped schedule modular RO units, reducing start-up and shutdown cycles and improving energy performance . The GMEE-WFED framework introduced a multilayer wind forecasting system involving turbine distribution, feature analysis, target shifting, and deep learning models, where GRU outperformed LSTM across different prediction horizons [22]. Offshore engineering studies also used bivariate ACER-based correction to improve extreme wind speed and wave height prediction by exploiting correlations between environmental variables [23].

Additional LSTM-based studies have shown that renewable energy forecasting accuracy depends strongly on resource behavior. Solar irradiance was predicted more accurately than wind speed because of its clearer daily cycle, while wind forecasting remained more variable due to stochastic wind conditions [24]. At the regional scale, spatial-temporal clustering with improved CNN and BILSTM networks improved wind farm cluster forecasting by learning both long-term spatial similarity and short-term fluctuation patterns among multiple wind farms [25].

Overall, the reviewed studies show that renewable energy forecasting has evolved from conventional machine learning models toward hybrid, deep learning, spatial-temporal, and optimization-integrated frameworks. Traditional methods remain useful for simpler forecasting tasks, but LSTM, GRU, CNN-LSTM, attention-based models, decomposition techniques, and ensemble learning provide stronger performance for nonlinear and uncertain renewable energy data. These approaches contribute to improved grid integration, operational scheduling, turbine selection, cost reduction, and sustainable energy management.

3. MATERIALS AND METHODS

A systematic workflow is essential for developing accurate and reliable deep learning models for wind power forecasting. Figure 1 illustrates the overall methodological framework adopted in this study, beginning with data preprocessing and progressing through model development, evaluation, and prediction analysis. The workflow includes several important stages such as wind dataset acquisition, handling missing values, data normalization, exploratory data analysis, train–test data splitting, implementation of deep learning architectures, and performance evaluation using statistical metrics. In addition to the workflow diagram, the figure also presents an actual versus predicted scatter plot, which visually demonstrates the predictive capability of the developed forecasting models.

As shown in Figure 1, the preprocessing stage plays a critical role in improving data quality and ensuring model stability by addressing incomplete observations and scaling the input variables appropriately. Following preprocessing, the dataset is divided into training and testing subsets using an 80%–20% ratio to evaluate model generalization performance. The processed data are then utilized for training deep learning models capable of learning complex nonlinear relationships and temporal dependencies within wind power data. The actual versus predicted scatter plot further demonstrates the effectiveness of the forecasting framework, where the majority of prediction points are closely aligned with the reference diagonal line, indicating strong agreement between observed and predicted power values. Minor deviations from the diagonal represent forecasting errors and variability that naturally occur in renewable energy systems due to atmospheric fluctuations. Overall, Figure 1 provides a comprehensive overview of the proposed forecasting methodology and highlights the predictive performance achieved by the developed deep learning approach.

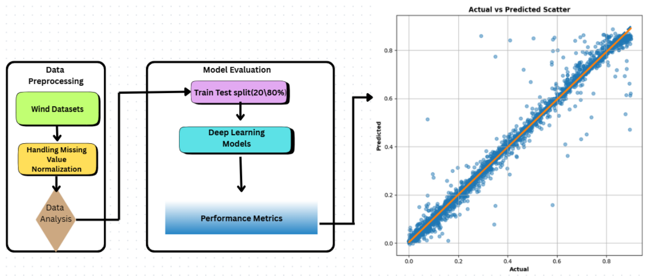

Figure 1. Overall workflow of the proposed wind power forecasting framework, including data preprocessing, deep learning model evaluation, and actual versus predicted power comparison.

3.1 Dataset Description

This study uses a field-based wind power generation dataset collected from an operational wind energy site. The dataset consists of hourly meteorological observations and corresponding turbine power output records. The observations begin on January 2, 2017, and provide a detailed representation of the relationship between local atmospheric conditions and wind turbine generation. Since the data were obtained from an actual operating site, they reflect practical environmental variability, turbine response behavior, and the nonlinear nature of wind energy production.

The main objective of using this dataset is to predict the normalized wind turbine power output based on meteorological variables measured at different heights above the surface. The target variable is *Power*, which represents turbine output normalized between 0 and 1. A value close to 0 indicates very low or no generation, whereas a value close to 1 indicates output near the maximum potential turbine generation. This normalized representation makes the forecasting task independent of the absolute rated capacity of the turbine and allows the model to focus on the relationship between weather conditions and relative power production.

The dataset includes ten variables: one temporal variable, eight meteorological input variables, and one target output variable. The meteorological predictors include temperature, relative humidity, dew point, wind speed, wind direction, and wind gusts. Wind speed and wind direction are measured at two different heights, namely 10 m and 100 m above the surface. This is important because wind characteristics vary vertically, and wind conditions closer to turbine hub height are generally more representative of actual turbine operating conditions than near-surface measurements. Table 1 summarizes the variables included in the dataset.

The input features have different physical meanings and measurement scales. For example, temperature and dew point are recorded in degrees Fahrenheit, relative humidity is expressed

Table 1. Description of the wind power generation dataset variables.

Variable	Unit/Range	Description
Time	Hour	Hour of the day when the reading was recorded.
temperature_2m	°F	Temperature measured at 2 m above the surface.
relativehumidity_2m	%	Relative humidity measured at 2 m above the surface.
dewpoint_2m	°F	Dew point temperature measured at 2 m above the surface.
windspeed_10m	m/s	Wind speed measured at 10 m above the surface.
windspeed_100m	m/s	Wind speed measured at 100 m above the surface.
winddirection_10m	0°–360°	Wind direction measured at 10 m above the surface.
winddirection_100m	0°–360°	Wind direction measured at 100 m above the surface.
windgusts_10m	m/s	Wind gust speed measured at 10 m above the surface.
Power	0–1	Normalized turbine power output.

as a percentage, while wind speed and wind gusts are measured in meters per second. Because deep learning models are sensitive to the scale of input variables, these features should be normalized or standardized before model training. Scaling also helps improve convergence speed and prevents variables with larger numerical ranges from dominating the learning process.

A specific characteristic of the dataset is the presence of wind direction variables measured in degrees from 0° to 360°. Wind direction is a circular variable because 0° and 360° represent the same physical direction. Treating wind direction as a conventional linear variable may introduce an artificial discontinuity, where two nearly identical directions appear numerically far apart. To overcome this issue, the wind direction variables can be converted into radians and transformed into sine and cosine components as follows:

$$\theta_{\text{rad}} = \theta_{\text{deg}} \times \frac{\pi}{180}$$

$$\text{WD}_{\text{sin}} = \sin(\theta_{\text{rad}})$$

$$\text{WD}_{\text{cos}} = \cos(\theta_{\text{rad}})$$

where θ_{deg} is the wind direction in degrees and θ_{rad} is the corresponding value in radians. This transformation preserves the circular structure of wind direction and allows the model to learn directional patterns more effectively.

The dataset also contains variables that may not contribute equally to forecasting performance. For instance, wind speed at 100 m may have a stronger relationship with turbine power output than some near-surface atmospheric variables, whereas temperature, humidity, and dew point may provide indirect information related to air density and local weather conditions. Therefore, all available variables are initially considered during model development, while their actual contribution is evaluated through model performance. This approach allows the forecasting models to learn relevant nonlinear relationships from the data without assuming in advance that all predictors have equal importance.

Overall, the dataset is suitable for hourly wind power forecasting because it combines time-dependent meteorological information with normalized turbine generation output. Its field-based nature makes it valuable for evaluating deep learning models under realistic operating conditions. In this study, the dataset is used to train and compare five predictive models, namely LSTM, RNN, GRU, CNN, and Dense neural networks, with the aim of identifying the most accurate model for normalized wind power prediction.

The relationships between meteorological variables and wind power generation are critical for understanding the operational behavior and variability of renewable energy systems. Figure 2 presents a comprehensive set of scatter plots illustrating the interaction between power output and several atmospheric parameters, including temperature at 2 meters, relative humidity, dew point, wind speed at different heights, wind direction, and wind gust speed. These visualizations provide important insights into the statistical distribution, variability, and dependency patterns between environmental conditions and generated power. In particular, wind speed variables measured at both 10 m and 100 m exhibit noticeable positive relationships with power output, reflecting the strong dependence of wind energy conversion on airflow intensity. Conversely, variables such as temperature, humidity, dew point, and wind direction demonstrate weaker or more dispersed relationships, indicating more complex or indirect influences on turbine performance. The figure therefore serves as an exploratory analysis tool for identifying influential features that may contribute to subsequent predictive modeling and wind power forecasting tasks.

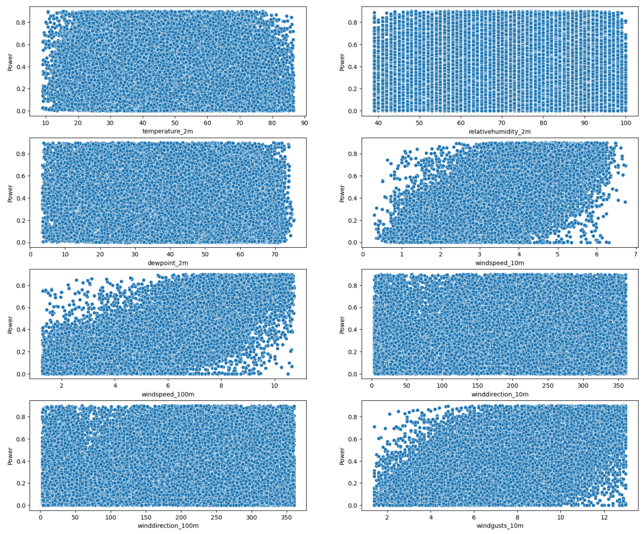

Figure 2. Scatter plot relationships between power output and meteorological variables including temperature, humidity, dew point, wind speed, wind direction, and wind gust speed measured at different heights.

To further investigate the nonlinear behavior and trend characteristics between atmospheric variables and wind power generation, smoothing-based visual analysis was performed using locally averaged regression patterns. Figure 3 illustrates the smoothed relationships between power output and several meteorological parameters, including temperature at 2 m, relative humidity, dew point temperature, wind speed at different heights, wind direction, and wind gust speed. Unlike conventional scatter plots, these smoothed curves reveal the underlying trend structures and gradual variations in power generation across changing environmental conditions while reducing the influence of noise and random fluctuations.

The figure demonstrates that wind speed variables, particularly at 10 m and 100 m heights, exhibit strong positive nonlinear relationships with generated power, confirming the dominant influence of wind intensity on turbine output. Similarly, wind gust speed shows a steadily increasing trend with power production, indicating that stronger gust conditions are generally associated with higher energy generation. In contrast, meteorological variables such as temperature, dew point, and relative humidity display comparatively weaker and more irregular trends, suggesting indirect or secondary effects on wind power behavior. Wind direction variables also reveal moderate cyclic variations, reflecting the directional dependency of airflow patterns and turbine orientation efficiency. Overall, Figure 3 provides an important exploratory interpretation of feature behavior and helps identify influential variables for subsequent machine learning and forecasting models in wind energy systems.

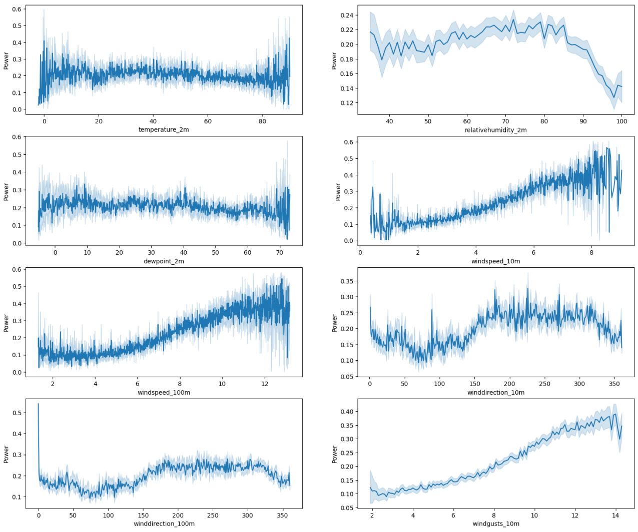

Figure 3. Smoothed relationships between wind power output and meteorological variables using locally averaged trend estimation.

Correlation analysis is an essential statistical technique for identifying the strength and direction of relationships among variables in wind energy datasets. Figure 4 presents the Pearson correlation coefficient matrix for the meteorological and temporal variables considered in this study, including temperature, relative humidity, dew point, wind speed, wind direction, wind gust speed, power output, year, and month. The heatmap visualization provides a compact representation of pairwise linear dependencies, enabling the identification of highly correlated features, potential multicollinearity issues, and influential predictors associated with wind power generation.

As illustrated in Figure 4, wind speed variables measured at both 10 m and 100 m heights exhibit strong positive correlations with power output, confirming the dominant contribution of wind velocity to energy generation. Wind gust speed also demonstrates a substantial positive relationship with power production, indicating that stronger atmospheric flow conditions generally lead to higher turbine output. Additionally, very high correlations are observed between temperature and dew point variables, as well as between wind direction measurements at different heights, reflecting the physical interdependence among atmospheric parameters. In contrast, variables such as relative humidity, year, and month show comparatively weak correlations with power output, suggesting limited direct linear influence. The correlation matrix therefore provides valuable preliminary insights for feature selection, dimensionality reduction, and the development of predictive machine learning models for wind power forecasting.

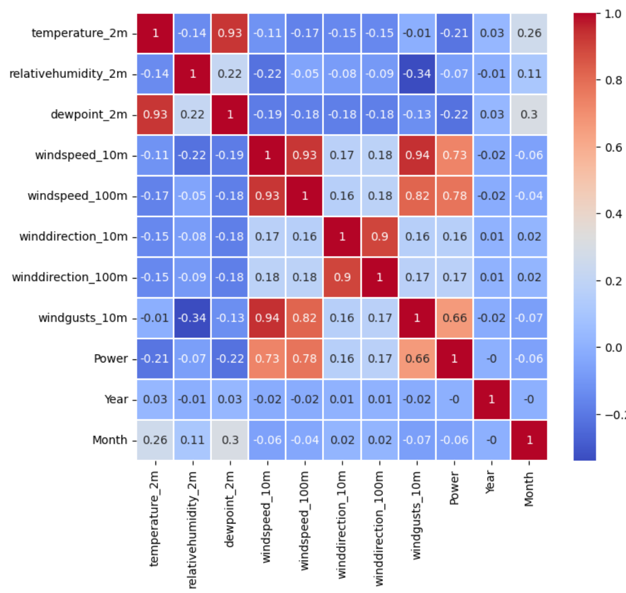

Figure 4. Pearson correlation coefficient heatmap showing the relationships among meteorological variables, temporal features, and wind power output.

Understanding the statistical distribution of meteorological and temporal variables is an important preliminary step in wind power data analysis, as it provides insights into data variability, seasonal behavior, skewness, and potential irregularities that may influence predictive modeling performance. Figure 5 presents the histogram distributions of the major variables used in this study, including temperature, relative humidity, dew point temperature, wind speed, wind direction, wind gust speed, power output, and temporal features such as year, month, and quarter. These histograms illustrate the frequency patterns and probability distributions of each feature across the observational dataset.

As shown in Figure 5, the meteorological variables exhibit diverse distributional characteristics. Wind speed variables measured at 10 m and 100 m heights display moderately skewed distributions concentrated around medium wind conditions, reflecting the typical operational range of atmospheric airflow observed during the study period. Wind gust speed also demonstrates a broader spread, indicating intermittent high-intensity wind events. Temperature and dew point variables reveal multimodal patterns, suggesting seasonal climatic variations throughout the recorded years. Relative humidity values are primarily concentrated in higher ranges, indicating generally humid atmospheric conditions. Additionally, wind direction variables exhibit cyclic directional distributions associated with dominant prevailing wind patterns. The power output distribution shows a higher frequency of lower and medium generation levels with comparatively fewer extreme high-power observations, which is common in wind energy production datasets due to fluctuating wind conditions. Temporal features such as month and quarter further confirm the balanced temporal coverage of the dataset. Overall, Figure 5 provides an informative overview of the statistical behavior of the dataset and supports subsequent feature engineering, normalization, and machine learning model development processes.

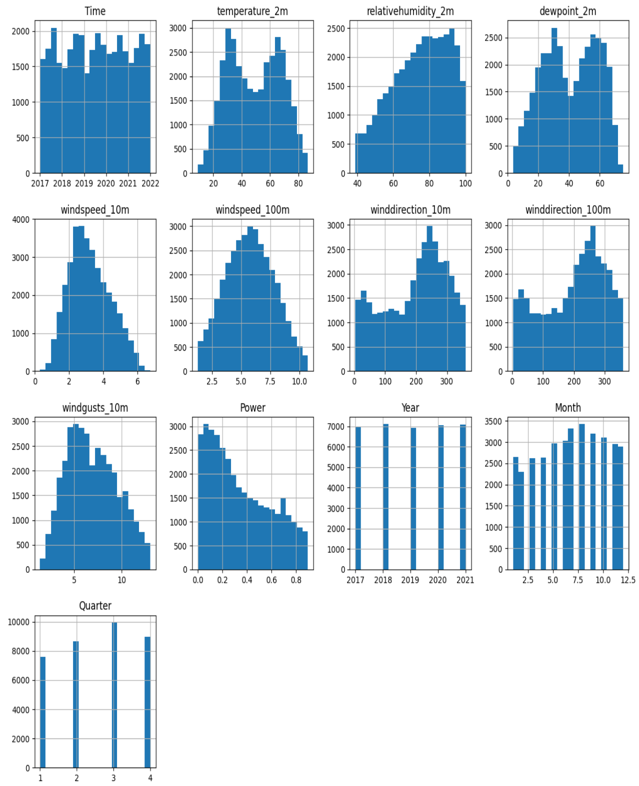

Figure 5. Histogram distributions of meteorological variables, wind characteristics, temporal features, and wind power output used in the study dataset.

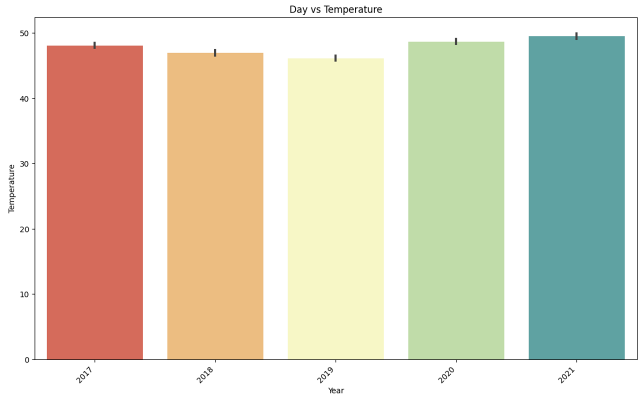

Figure 6. Average temperature comparison across different years with corresponding variability estimates represented by error bars.

Analyzing long-term temperature variations is important for understanding the climatic conditions that may influence wind energy generation and atmospheric behavior over time. Figure 6 illustrates the average temperature distribution across different years included in the study period, providing a comparative overview of annual thermal variations. The visualization highlights the mean temperature values together with variability estimates represented by the error bars, allowing a clearer interpretation of interannual fluctuations and statistical consistency within the dataset.

As observed in Figure 6, moderate variations in average temperature are present between the years 2017 and 2021. The year 2019 exhibits the lowest average temperature among the recorded periods, whereas 2021 demonstrates the highest average temperature level. The relatively small error margins indicate stable temperature observations with limited variability around the mean values for each year. These annual differences may reflect seasonal climatic changes, atmospheric circulation variability, and broader environmental conditions that can indirectly influence wind characteristics and power production patterns. Consequently, the figure provides useful temporal insights into the thermal behavior of the study environment and supports subsequent analyses involving meteorological trend assessment and renewable energy forecasting.

3.2 Data Preprocessing

Data preprocessing is an essential stage in wind power forecasting because the quality and consistency of the input data directly affect the performance of deep learning models. Since the dataset consists of hourly meteorological observations and normalized turbine power output, several preprocessing procedures were applied before model training. These procedures included handling missing and null values, scaling numerical variables, transforming wind direction features, and verifying temporal consistency across the dataset.

3.2.1 Handling Missing and Null Values

The dataset was initially examined to identify missing, null, duplicated, or inconsistent records. Missing values may occur in field-based wind energy datasets because of sensor malfunction, communication interruptions, turbine maintenance, or temporary failures in the data acquisition system. If such values are not treated properly, they may introduce noise into the learning process and reduce forecasting accuracy.

Continuous meteorological variables, including temperature, relative humidity, dew point, wind speed, and wind gusts, were inspected for missing observations. Short missing intervals were handled using interpolation because hourly atmospheric measurements usually change gradually over time. Longer missing intervals were excluded from the dataset to avoid introducing unreliable artificial patterns into the training data.

Special attention was given to the target variable, *Power*, because it represents the actual turbine output. Missing target values were not artificially reconstructed for large gaps, since inaccurate estimation of turbine output could bias the training process and affect model generalization.

The dataset was also checked for duplicated records and physically unrealistic values. For example, wind speed values cannot be negative, relative humidity should remain within the range of 0–100%, and normalized power output must remain between 0 and 1. Any inconsistent records detected during preprocessing were corrected when possible or removed from the dataset to ensure data reliability.

3.2.2 Normalization and Scaling of Input Features

The meteorological variables in the dataset have different units and numerical ranges. Temperature and dew point are measured in degrees Fahrenheit, humidity is represented as a percentage, while wind speed and wind gusts are measured in meters per second. Such variations in scale may negatively influence deep learning models because variables with larger numerical ranges can dominate the optimization process.

To overcome this issue, all continuous input variables were normalized before training. Feature scaling improves numerical stability, accelerates convergence during optimization, and ensures that all variables contribute more consistently to model learning. Min–max normalization was applied to transform the numerical variables into a common range between 0 and 1.

The scaling procedure was performed using only the training data to prevent data leakage. The same scaling parameters were then applied to the validation and testing subsets. This approach ensures that future information from the test data does not influence the training process.

The normalization process was applied to the following meteorological variables:

- *temperature_2m*
- *relativehumidity_2m*
- *dewpoint_2m*
- *windspeed_10m*
- *windspeed_100m*
- *windgusts_10m*

The target variable, *Power*, was already normalized between 0 and 1 and therefore did not require additional scaling. This representation expresses turbine output as a percentage of maximum potential generation and makes the forecasting task independent of the turbine's absolute rated capacity.

3.2.3 Wind Direction Transformation

Wind direction variables require special preprocessing because they are circular in nature. A direction of 0° and 360° represents the same physical orientation, although they appear numerically distant if treated as ordinary scalar values. This discontinuity may reduce forecasting accuracy and create difficulties for machine learning models.

To preserve the circular structure of wind direction, the variables *winddirection_10m* and *winddirection_100m* were transformed into sine and cosine components. This transformation converts each directional measurement into two continuous variables that better represent the physical relationship between angular positions.

The transformed wind direction variables provide a smoother and more meaningful representation for deep learning models. In addition, this preprocessing step improves the ability of the models to learn directional wind patterns associated with turbine power generation.

3.2.4 Temporal Alignment and Consistency Checks

Since the dataset consists of hourly observations, temporal alignment was performed to ensure that all meteorological measurements and turbine power outputs corresponded to the same time step. The *Time* variable was used to verify chronological consistency across the dataset.

The observations were sorted in ascending chronological order before model training. The hourly sequence was inspected to identify irregular intervals, missing timestamps, or inconsistent temporal ordering. Any detected temporal inconsistencies were corrected or removed to preserve the sequential structure of the data.

Temporal consistency is especially important for recurrent deep learning models such as LSTM, RNN, and GRU because these architectures learn patterns from sequential observations. Incorrect ordering or missing temporal relationships may significantly reduce forecasting performance.

To simulate realistic forecasting conditions, the dataset was divided chronologically into training and testing subsets rather than randomly shuffled. This approach ensures that the models are trained using past observations and evaluated on future unseen data, which better reflects real operational forecasting scenarios.

For sequence-based forecasting models, the processed data were converted into supervised learning samples using a sliding-window approach. In this method, a fixed number of previous hourly observations was used to predict the turbine power output at the next time step. This strategy allows the models to capture temporal dependencies between historical meteorological conditions and future wind power generation.

After completing all preprocessing procedures, the final dataset consisted of cleaned, normalized, temporally aligned, and model-ready input features. These processed data were subsequently used to train and evaluate the LSTM, RNN, GRU, CNN, and Dense neural network models under consistent experimental conditions.

3.3 Baseline Deep Learning and Machine Learning Models

The predictive modeling framework was designed to forecast normalized wind turbine power output using hourly meteorological observations collected from the operational wind energy site. Since wind power generation is influenced by nonlinear atmospheric behavior and temporal variations, different deep learning architectures were selected and compared. The selected models include Long Short-Term Memory networks (LSTM), Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), Dense neural networks, and Convolutional Neural Networks (CNN).

The selection of these models was motivated by the time-series nature of wind power forecasting. Wind turbine output at a given hour is not only affected by the current meteorological conditions but also by previous wind speed, wind gust, humidity, temperature, and wind direction patterns. Therefore, recurrent architectures such as LSTM, RNN, and GRU were included because they are specifically designed to learn sequential dependencies. In contrast, CNN and Dense models were used as comparative baseline models to evaluate whether local pattern extraction or direct nonlinear mapping can provide competitive forecasting accuracy.

The input to the models consisted of the preprocessed meteorological variables, including temperature, relative humidity, dew point, wind speed at 10 m and 100 m, transformed wind direction components, and wind gusts. The output variable was *Power*, representing normalized turbine power generation between 0 and 1. All models were trained under consistent experimental conditions to ensure a fair comparison.

3.3.1 Long Short-Term Memory Network

The Long Short-Term Memory network was selected as the main recurrent model because of its strong ability to capture long-term temporal dependencies in sequential data. Wind power generation often depends on previous atmospheric states, especially when wind speed changes gradually or when ramp events occur across consecutive hours. LSTM networks are well suited to this type of forecasting task because they use memory cells and gating mechanisms to retain important information while reducing the effect of irrelevant past inputs.

In the present study, the LSTM model was used to learn the temporal relationship between historical meteorological observations and normalized turbine output. Its ability to preserve useful information across time steps makes it particularly effective for hourly wind power forecasting. The experimental results confirmed this advantage, as LSTM achieved the best overall performance among all evaluated models, with the lowest prediction errors and the strongest agreement with observed power values.

3.3.2 Recurrent Neural Network

The Recurrent Neural Network was included as a baseline sequential model. RNNs are designed to process ordered data by maintaining information from previous time steps. This makes them suitable for time-series forecasting problems such as wind power prediction. In this study, the RNN model was used to evaluate whether a basic recurrent structure could capture the temporal behavior of the hourly meteorological dataset.

Although RNNs can model sequential dependencies, they may face limitations when learning long-term relationships because of vanishing-gradient problems. Nevertheless, the RNN model achieved strong forecasting performance in this study and ranked second after LSTM. This indicates that the hourly wind power dataset contains temporal patterns that can be effectively learned by recurrent architectures.

3.3.3 Gated Recurrent Unit

The Gated Recurrent Unit model was selected as another recurrent architecture for wind power forecasting. GRU is structurally simpler than LSTM but still uses gating mechanisms to control the flow of information through time. Because of this design, GRU can capture temporal dependencies while requiring fewer parameters than LSTM in many cases.

In this study, GRU was used to predict normalized turbine power output from sequential meteorological inputs. Its inclusion allows comparison between two advanced recurrent architectures: LSTM and GRU. The GRU model achieved high forecasting accuracy, although its performance was slightly lower than LSTM and RNN based on the reported error metrics. This suggests that GRU was able to learn the main temporal trends in the dataset but was less effective than LSTM in minimizing prediction error.

3.3.4 Dense Neural Network

The Dense neural network was used as a feedforward baseline model. Unlike recurrent models, Dense networks do not inherently process temporal sequences. Instead, they learn direct nonlinear relationships between input features and the target output. In this study, the Dense model was included to assess how well a standard neural network can predict wind power from meteorological variables without explicitly modeling sequential dependencies.

The Dense model can capture nonlinear interactions among predictors such as wind speed, temperature, humidity, dew point, and wind gusts. However, because it does not include memory-based mechanisms, it may be less capable of representing temporal persistence and hour-to-hour changes in wind conditions. The experimental results showed that the Dense model performed less accurately than the recurrent models, confirming the importance of temporal modeling in this forecasting task.

3.3.5 Convolutional Neural Network

The Convolutional Neural Network was included to evaluate the ability of convolutional structures to extract local patterns from the wind power time series. CNNs are commonly used for spatial and sequential pattern extraction because convolutional filters can identify local relationships within input windows. In the context of wind power forecasting, CNNs may detect short-term patterns in meteorological variables, such as sudden wind speed changes or local gust behavior.

In this study, the CNN model was applied as a comparative deep learning baseline. Although CNNs can capture local feature patterns, their ability to model longer temporal dependencies is limited compared with recurrent architectures unless additional temporal design strategies are used. The results showed that CNN produced larger forecasting errors than LSTM, RNN, and GRU, indicating that local pattern extraction alone was not sufficient to achieve the highest forecasting accuracy for this hourly wind power dataset.

Overall, the baseline modeling framework allows a fair comparison between recurrent and non-recurrent deep learning approaches. The results demonstrate that temporal modeling is essential for accurate wind power forecasting, with LSTM providing the most reliable predictions for the normalized turbine power output.

3.4 Evaluation Metrics

To evaluate the forecasting capability of the developed deep learning models, several statistical and regression-based evaluation metrics were employed. Since wind power forecasting is a nonlinear regression problem, relying on a single performance indicator may not provide a complete understanding of model behavior. Therefore, multiple metrics were used to assess forecasting accuracy, prediction stability, goodness of fit, model bias, and agreement between observed and predicted turbine power output.

The forecasting models evaluated in this study include LSTM, RNN, GRU, CNN, and Dense neural networks. Their performance was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), coefficient of determination (R^2), Relative Root Mean Squared Error (RRMSE), Nash–Sutcliffe Efficiency (NSE), and Willmott Index (WI). These metrics are widely used in renewable energy forecasting because they provide complementary information regarding model reliability and prediction quality.

MSE, RMSE, and MAE were used to quantify the magnitude of forecasting errors. Smaller values of these metrics indicate higher prediction accuracy and lower deviations between observed and predicted turbine power values. RMSE is particularly sensitive to large errors because it squares the prediction deviations before averaging, whereas MAE provides the average absolute forecasting error without emphasizing extreme values.

MBE was used to evaluate forecasting bias and determine whether the model tends to overestimate or underestimate turbine power output. Positive MBE values indicate overprediction, while negative values indicate underprediction.

The correlation coefficient (r) and coefficient of determination (R^2) were used to measure the strength of the relationship between observed and predicted values. Values closer to 1 indicate stronger predictive consistency and better explanatory capability of the forecasting models.

RRMSE was employed to evaluate the relative magnitude of forecasting errors with respect to the average observed values. Lower RRMSE values indicate better prediction accuracy relative to the scale of the dataset.

NSE was used to assess predictive skill by comparing model performance against the mean of the observed values. NSE values closer to 1 indicate highly accurate forecasting performance.

WI was adopted to evaluate the degree of agreement between observed and predicted turbine power outputs. Higher WI values indicate stronger agreement and greater model reliability.

Table 2 presents the mathematical formulations of all evaluation metrics used in this study.

Table 2. Evaluation metrics used for wind power forecasting performance assessment.

Metric	Equation
MSE	$\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert$
MBE	$\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)$
r	$\frac{\sum_{i=1}^{n}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2\sum_{i=1}^{n}(\hat{y}_i-\bar{\hat{y}})^2}}$
R^2	$1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$
RRMSE	$\frac{\text{RMSE}}{\bar{y}}$
NSE	$1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$
WI	$1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(\lvert\hat{y}_i-\bar{y}\rvert+\lvert y_i-\bar{y}\rvert)^2}$

These evaluation metrics were calculated for all forecasting models under identical experimental conditions to ensure fair comparison. The use of multiple statistical indicators provides a comprehensive assessment of forecasting performance and allows a more reliable comparison among the LSTM, RNN, GRU, CNN, and Dense models.

4. EMPIRICAL RESULTS

4.1 Baseline and Proposed Model Results

This section presents the empirical evaluation of the baseline and proposed deep learning models developed for hourly wind power forecasting. The objective of this experiment was to assess how effectively each model predicts the normalized turbine power output using the preprocessed meteorological variables collected from the operational wind energy site. Since the target variable, *Power*, is normalized between 0 and 1, lower error values indicate that the predicted turbine output is closer to the actual observed generation level.

The evaluated models include LSTM, RNN, GRU, Dense neural network, and CNN. These models were compared under the same experimental conditions using nine evaluation metrics: MSE, RMSE, MAE, MBE, correlation coefficient (r), coefficient of determination (R^2), RRMSE, NSE, and WI. The use of these metrics allows the results to be interpreted from different perspectives. Error-based metrics, such as MSE, RMSE, and MAE, measure the magnitude of prediction errors. MBE evaluates whether the model systematically overestimates or underestimates wind power output. Meanwhile, r, R^2, NSE, and WI assess the strength of association, goodness of fit, predictive efficiency, and agreement between observed and predicted values.

Table 3 presents the empirical results of all forecasting models. The results clearly show that recurrent neural network models achieved better forecasting performance than the non-recurrent models. In particular, LSTM obtained the best overall results across almost all metrics, followed by RNN and GRU. This confirms that temporal dependency modeling is highly important for hourly wind power forecasting, where current turbine output is influenced not only by current meteorological conditions but also by previous wind behavior and short-term atmospheric persistence.

Table 3. Empirical results of baseline and proposed forecasting models.

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
LSTM	0.0008	0.0282	0.0106	-0.0006	0.9940	0.9880	0.0861	0.9880	0.9970
RNN	0.0009	0.0303	0.0155	0.0043	0.9936	0.9862	0.0925	0.9862	0.9964
GRU	0.0011	0.0338	0.0223	0.0140	0.9938	0.9828	0.1032	0.9828	0.9955
Dense	0.0071	0.0842	0.0704	0.0485	0.9895	0.8931	0.2572	0.8931	0.9659
CNN	0.0072	0.0847	0.0593	-0.0225	0.9499	0.8919	0.2587	0.8919	0.9694

As shown in Table 3, the LSTM model achieved the strongest forecasting accuracy, with the lowest MSE value of 0.0008, RMSE of 0.0282, and MAE of 0.0106. These values indicate that the LSTM model produced the smallest prediction errors among all evaluated models. The very low RMSE and MAE values are especially important because the target variable is normalized; therefore, even small numerical improvements indicate meaningful gains in forecasting precision. The LSTM model also achieved an MBE value of -0.0006, which is very close to zero. This demonstrates that the model produced nearly unbiased predictions and did not show a strong tendency toward either overestimation or underestimation.

The high correlation coefficient of the LSTM model, with $r = 0.9940$, indicates a very strong relationship between the predicted and observed wind power values. In addition, the model achieved $R^2 = 0.9880$, meaning that it explained approximately 98.8% of the variance in the observed normalized turbine output. The NSE value of 0.9880 further confirms the high predictive efficiency of the LSTM model, while the WI value of 0.9970 indicates excellent agreement between observed and predicted values. These results demonstrate that LSTM is highly effective for modeling the nonlinear and temporal relationships between meteorological variables and wind turbine power generation.

The RNN model ranked second in overall performance. It achieved an MSE of 0.0009, RMSE of 0.0303, MAE of

0.0155, and R^2 of 0.9862. Although its performance was slightly lower than LSTM, the RNN model still produced highly accurate predictions. The strong results of the RNN model suggest that the dataset contains important sequential patterns that can be captured using recurrent learning mechanisms. However, compared with LSTM, the RNN model had slightly larger errors, which may be attributed to the limited ability of conventional RNNs to preserve long-term dependencies over extended time sequences.

The GRU model also achieved strong forecasting performance, with an MSE of 0.0011, RMSE of 0.0338, MAE of 0.0223, and R^2 of 0.9828. Its results were close to those of LSTM and RNN, confirming that gated recurrent architectures are well suited for wind power forecasting. However, the GRU model showed a higher MBE value of 0.0140, indicating a stronger tendency toward overestimating turbine output compared with LSTM and RNN. Although GRU is computationally efficient and capable of learning temporal patterns, its higher bias and error values suggest that it was slightly less effective than LSTM for this dataset.

In contrast, the Dense neural network and CNN models produced larger forecasting errors. The Dense model achieved an MSE of 0.0071, RMSE of 0.0842, MAE of 0.0704, and R^2 of 0.8931. Although these results indicate that the Dense model was able to capture part of the nonlinear relationship between meteorological predictors and wind power output, its performance was considerably weaker than the recurrent models. This is mainly because Dense networks do not explicitly model temporal dependencies unless lagged variables or sequence structures are manually introduced.

The CNN model obtained an MSE of 0.0072, RMSE of 0.0847, MAE of 0.0593, and R^2 of 0.8919. While CNNs can identify local patterns in input data, their performance in this experiment was lower than that of recurrent models. This suggests that local feature extraction alone was insufficient for accurately forecasting hourly wind power output. The CNN model also produced a negative MBE of -0.0225, indicating a tendency to underestimate turbine power generation. This underestimation may be problematic in operational contexts because it can lead to conservative scheduling and inefficient utilization of available wind energy.

Overall, the results confirm that recurrent-based architectures are more suitable for hourly wind power forecasting than Dense and CNN models. LSTM, RNN, and GRU all achieved high correlation, high R^2, high NSE, and high WI values, showing their ability to reproduce the observed behavior of turbine power output. Among these models, LSTM provided the most reliable and balanced performance because it achieved the lowest error values, the smallest bias, the highest R^2, the highest NSE, and the highest WI. Therefore, LSTM can be considered the most effective model for the proposed wind power forecasting framework.

From an operational perspective, the superior performance of LSTM is important because accurate wind power forecasting can improve grid scheduling, reduce reserve requirements, support energy trading decisions, and enhance wind farm management. Since wind generation is highly variable, forecasting models with low error and low bias are essential for reducing uncertainty in power system operation. The results of this study demonstrate that using temporal deep learning models, particularly LSTM, can provide accurate and reliable predictions of normalized turbine power output from field-based meteorological observations.

Comparative evaluation of deep learning models is essential for identifying the most effective architecture for wind power forecasting tasks. Figure 7 presents a radar chart comparison of several neural network models, including Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Dense Neural Network, and Convolutional Neural Network (CNN), using multiple statistical performance metrics. The selected evaluation criteria include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R^2), correlation coefficient (r), Nash–Sutcliffe Efficiency (NSE), and Willmott's Index (WI). This multidimensional visualization enables simultaneous assessment of predictive accuracy, error minimization, correlation strength, and model reliability within a unified framework.

As illustrated in Figure 7, the recurrent deep learning architectures, particularly LSTM and RNN, demonstrate consistently strong performance across most evaluation metrics, indicating their effectiveness in capturing temporal dependencies and nonlinear patterns in wind power data. The GRU model also exhibits competitive predictive capability with slightly lower metric values compared to LSTM and RNN. In contrast, the Dense and CNN models show comparatively weaker overall performance, suggesting limited effectiveness in modeling sequential temporal relationships within the dataset. The radar chart representation provides a comprehensive visual interpretation of model strengths and weaknesses, facilitating clearer comparative analysis of forecasting performance. Consequently, the figure supports the selection of the most suitable deep learning architecture for accurate and reliable wind power prediction applications.

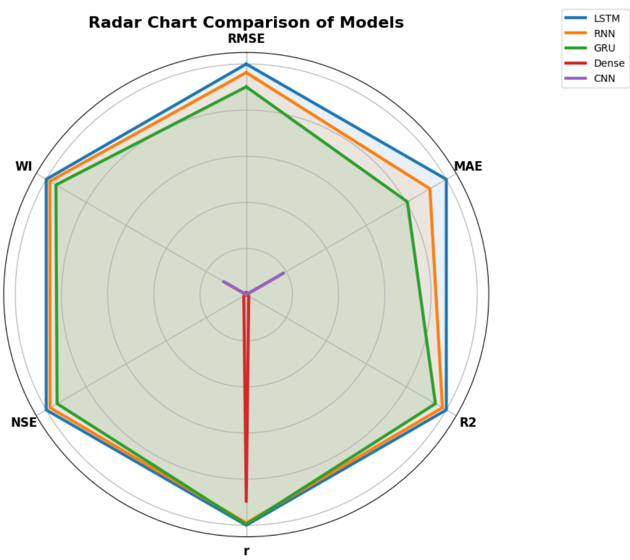

Figure 7. Radar chart comparison of deep learning models based on multiple forecasting performance metrics including RMSE, MAE, R^2, correlation coefficient (r), NSE, and WI.

The Taylor diagram is a widely used statistical visualization technique for evaluating and comparing the predictive performance of forecasting models by simultaneously representing correlation, standard deviation, and centered root mean square error within a single graphical framework. Figure 8 presents the Taylor diagram comparison of several deep learning models employed for wind power prediction, including Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Dense Neural Network, and Convolutional Neural Network (CNN). The diagram provides a concise yet comprehensive representation of how closely each model reproduces the statistical characteristics of the reference observations.

As illustrated in Figure 8, models positioned closer to the reference point indicate stronger predictive agreement with the observed wind power data. The angular displacement in the diagram reflects the correlation coefficient between predicted and observed values, while the radial distance represents the standard deviation associated with each model. Models with smaller deviations from the reference point generally demonstrate superior forecasting performance and better capability to capture the variability of the target signal. In this analysis, the recurrent architectures, particularly LSTM and RNN, appear closer to the reference observation compared with the Dense and CNN models, indicating higher correlation and improved representation of the observed data distribution. The Taylor diagram therefore offers an effective visual assessment of model reliability, accuracy, and variability reproduction, supporting the selection of the most suitable deep learning architecture for wind power forecasting applications.

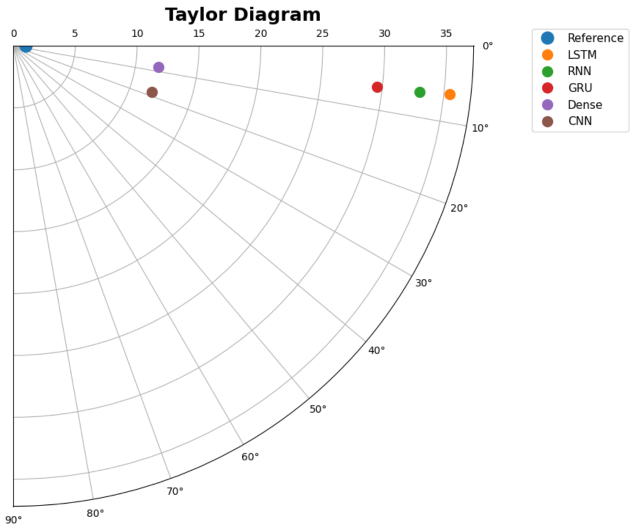

Figure 8. Taylor diagram comparing the statistical performance of deep learning models relative to the reference wind power observations.

Evaluating the balance between different forecasting error metrics is important for assessing the overall predictive quality and robustness of machine learning models in wind power forecasting applications. Figure 9 illustrates the trade-off relationship between Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for several deep learning architectures, including Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Dense Neural Network, and Convolutional Neural Network (CNN). The scatter-based visualization enables direct comparison of model accuracy by simultaneously examining the magnitude of average prediction errors and the sensitivity to larger forecasting deviations.

As shown in Figure 9, models positioned closer to the lower-left region of the plot exhibit superior predictive performance because they achieve lower RMSE and MAE values simultaneously. The LSTM model demonstrates the best overall forecasting capability, showing the smallest error values among all evaluated models, which indicates strong generalization performance and effective learning of temporal dependencies in wind power data. The RNN and GRU models also achieve relatively low error measures, confirming their suitability for sequential forecasting tasks. In contrast, the Dense and CNN models appear farther from the optimal region, reflecting comparatively higher prediction errors and reduced forecasting precision. The figure therefore provides a concise and intuitive representation of model efficiency, supporting the comparative evaluation and selection of the most reliable deep learning architecture for accurate wind power prediction.

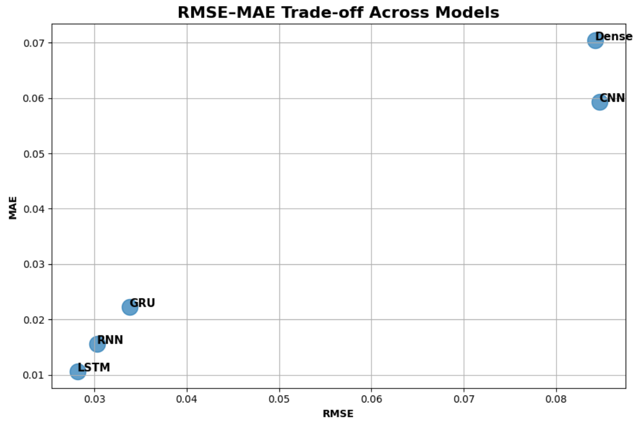

Figure 9. RMSE–MAE trade-off comparison among deep learning models used for wind power forecasting.

Root Mean Square Error (RMSE) is one of the most widely used statistical evaluation metrics for assessing the predictive accuracy of forecasting models, particularly in regression-based applications such as wind power prediction. RMSE measures the average magnitude of prediction errors while assigning greater emphasis to larger deviations, making it highly effective for evaluating model reliability and robustness. Figure 10 presents a comparative analysis of RMSE values obtained from several deep learning architectures, including Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Dense Neural Network, and Convolutional Neural Network (CNN). The figure provides a direct visual comparison of forecasting error magnitudes across the evaluated models.

As illustrated in Figure 10, the LSTM model achieves the lowest RMSE value among all examined architectures, indicating the highest prediction accuracy and strongest capability in capturing the temporal dynamics of wind power data. The RNN and GRU models also demonstrate relatively low RMSE values, confirming their effectiveness for sequential time-series forecasting tasks. In contrast, the Dense and CNN models exhibit substantially larger RMSE values, suggesting reduced forecasting precision and weaker adaptability to the nonlinear temporal dependencies present in the dataset. The noticeable performance gap between recurrent architectures and conventional feedforward or convolutional models highlights the importance of temporal memory mechanisms in wind power forecasting applications. Therefore, the figure provides important quantitative evidence supporting the superiority of recurrent deep learning approaches for accurate renewable energy prediction.

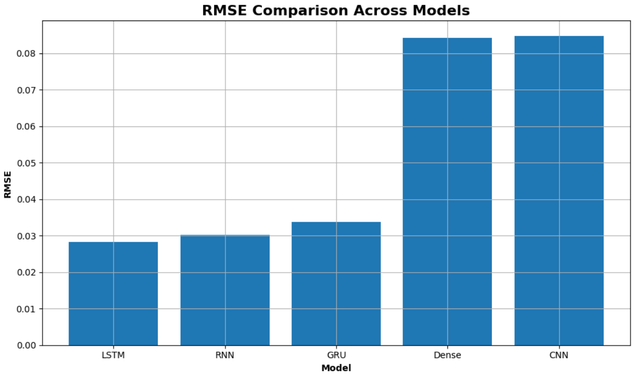

Figure 10. Comparison of RMSE values across different deep learning models used for wind power forecasting.

Comprehensive evaluation of forecasting models requires the simultaneous analysis of multiple statistical error metrics in order to assess prediction accuracy, robustness, and generalization capability. Figure 11 presents a comparative analysis of several deep learning architectures, including Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Dense Neural Network, and Convolutional Neural Network (CNN), using four widely adopted performance indicators: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Root Relative Mean Square Error (RRMSE). These metrics collectively provide a multidimensional assessment of forecasting quality by quantifying both average prediction deviations and sensitivity to larger errors.

As illustrated in Figure 11, the recurrent deep learning models, particularly LSTM and RNN, achieve substantially lower error values across all evaluation metrics compared with the Dense and CNN architectures. The LSTM model demonstrates the smallest MSE, RMSE, MAE, and RRMSE values, indicating superior predictive accuracy and enhanced capability in modeling the temporal dynamics and nonlinear dependencies present in wind power data. The GRU model also performs competitively, although with slightly higher error values than LSTM and RNN. In contrast, the Dense and CNN models exhibit considerably larger errors across all metrics, suggesting weaker forecasting precision and reduced effectiveness in capturing sequential patterns within the dataset. The grouped bar-chart visualization therefore provides a clear and interpretable comparison of model performance, supporting the conclusion that recurrent neural network-based architectures are more suitable for accurate and reliable wind power forecasting applications.

5. DISCUSSION

The experimental results demonstrate that deep learning models can effectively predict normalized wind turbine power output using hourly meteorological observations collected from the operational wind energy site. However, significant performance differences were observed among the evaluated architectures, particularly between recurrent and non-recurrent models. The results clearly indicate that models capable of learning temporal dependencies provide superior forecasting performance for hourly wind power generation.

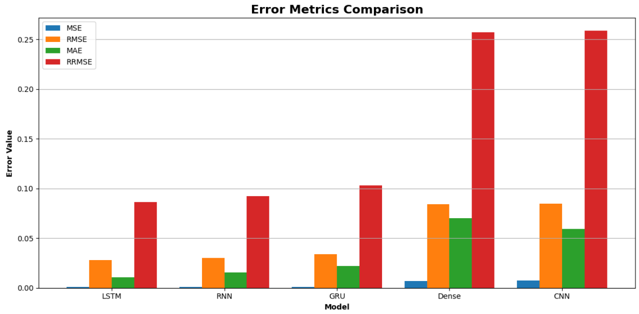

Figure 11. Comparison of forecasting error metrics across different deep learning models using MSE, RMSE, MAE, and RRMSE evaluation criteria.

Among all evaluated models, the LSTM model achieved the best overall performance. It obtained the lowest MSE, RMSE, and MAE values, together with the highest values of r, R^2, NSE, and WI. These results confirm that LSTM is highly effective for modeling nonlinear and time-dependent relationships between meteorological conditions and wind turbine output. The superior performance of LSTM can be attributed to its memory-cell structure and gating mechanisms, which enable the model to retain useful information across long temporal sequences while filtering irrelevant historical information.

Wind power generation is inherently sequential because turbine output at a given hour is strongly influenced by previous wind conditions, atmospheric persistence, and short-term fluctuations in wind behavior. Consequently, forecasting models that explicitly capture temporal relationships are expected to perform better than models that rely only on static feature relationships. The ability of LSTM to preserve long-term dependencies allowed it to better represent the dynamics of wind speed variation, wind gust behavior, and gradual atmospheric transitions within the hourly dataset.

The RNN and GRU models also achieved strong forecasting performance, confirming the importance of recurrent learning structures in wind power prediction. The RNN model ranked second after LSTM and produced very low forecasting errors. This suggests that the hourly meteorological observations contain sequential information that can be effectively captured using recurrent neural processing. However, the slightly weaker performance of RNN compared with LSTM may be associated with the vanishing-gradient problem that affects traditional recurrent architectures when learning long-term dependencies.

The GRU model also demonstrated high predictive capability, with performance metrics close to those of LSTM and RNN. GRU architectures are computationally simpler than LSTM because they use fewer gating components and require fewer trainable parameters. This makes GRU computationally efficient while still maintaining strong temporal learning capability. Nevertheless, the higher MAE and MBE values obtained by GRU indicate that it was slightly less effective than LSTM in minimizing prediction deviations and forecasting bias. This suggests that the more advanced memory management structure of LSTM may provide additional advantages when modeling highly dynamic wind power behavior.

In contrast, the Dense and CNN models achieved noticeably lower forecasting performance. Although these models were able to capture part of the nonlinear relationship between meteorological variables and turbine output, they lacked the ability to effectively model long-term temporal dependencies. The Dense neural network processes each input sample independently and therefore cannot naturally preserve sequential information unless additional temporal engineering techniques are introduced. As a result, its forecasting accuracy was significantly lower than that of recurrent architectures.

Similarly, the CNN model produced larger forecasting errors and lower agreement metrics compared with LSTM, RNN, and GRU. CNNs are generally effective at extracting local patterns from structured data through convolutional filters. In the context of wind power forecasting, CNNs may identify short-term fluctuations or localized relationships between meteorological variables. However, the present results suggest that local feature extraction alone is insufficient for accurately modeling the complex temporal dynamics of hourly wind power generation. The relatively low correlation coefficient and higher RRMSE values obtained by CNN further support this observation.

Another important finding concerns forecasting bias. The LSTM model achieved an MBE value very close to zero, indicating nearly unbiased predictions. In practical wind energy applications, minimizing forecasting bias is particularly important because systematic overestimation or underestimation may negatively affect power system operation, reserve allocation, and electricity market scheduling. Overestimating wind generation may result in insufficient reserve capacity, whereas underestimating generation may lead to conservative dispatch decisions and reduced utilization of available renewable energy resources. Therefore, the low bias observed in the LSTM model represents an important operational advantage.

The high values of R^2, NSE, and WI obtained by the recurrent models also demonstrate their strong ability to reproduce the observed variability in turbine power output. In particular, the LSTM model explained approximately 98.8% of the variance in the observed data, indicating that the selected meteorological predictors contain highly informative patterns for wind power forecasting when processed using suitable temporal architectures. The high WI values further indicate strong agreement between observed and predicted values across different operating conditions.

The preprocessing procedures applied in this study also contributed significantly to forecasting performance. Transforming wind direction variables into sine and cosine components helped preserve the circular structure of directional data and prevented discontinuities between 0° and 360°. This transformation likely improved the ability of the models to learn directional wind patterns associated with turbine generation behavior. Similarly, normalization of meteorological variables improved numerical stability during training and ensured consistent learning across features with different physical units and scales.

The results also highlight the importance of using real-world operational datasets for renewable energy forecasting research. Unlike simulated or benchmark datasets, field-based measurements contain realistic atmospheric variability, turbine response behavior, and environmental noise. Therefore, the forecasting performance observed in this study provides stronger practical relevance for real wind farm applications. The strong performance of recurrent models under these realistic conditions suggests that advanced temporal deep learning architectures can effectively support operational wind energy forecasting systems.

From an application perspective, accurate short-term wind power forecasting provides several operational and economic benefits. Improved forecasting accuracy can support grid stability, reduce balancing costs, optimize reserve scheduling, improve integration of renewable energy into electricity systems, and support energy market participation. Since renewable energy penetration continues to increase globally, reliable forecasting methods are becoming increasingly important for ensuring stable and efficient power system operation.

Despite the strong results obtained in this study, several limitations remain. The dataset represents a single operational site, and therefore the developed models may be partially site-dependent. Wind behavior, terrain characteristics, turbine specifications, and local atmospheric conditions may vary significantly between locations. Consequently, the generalization capability of the forecasting framework should be further investigated using multiple wind farms and geographically diverse datasets.

In addition, the present study focused on deterministic forecasting of normalized turbine output. Future research may extend the proposed framework toward probabilistic forecasting, uncertainty quantification, and multi-step ahead prediction. Integrating feature selection methods, attention mechanisms, transformer-based architectures, or optimization-based hyperparameter tuning may also further improve forecasting performance. Moreover, explainable artificial intelligence techniques could be incorporated to better understand the influence of individual meteorological variables on turbine power generation.

Overall, the discussion confirms that recurrent deep learning architectures, particularly LSTM, provide highly effective solutions for hourly wind power forecasting using field-based meteorological observations. The combination of low prediction error, low forecasting bias, strong goodness of fit, and high agreement with observed data demonstrates the suitability of LSTM for operational wind energy prediction tasks.

6. CONCLUSION AND FUTURE WORK

This study developed and evaluated a deep learning-based forecasting framework for predicting normalized wind turbine power output using hourly field-based meteorological observations. The dataset was collected from an operational wind energy site and included key atmospheric variables such as temperature, relative humidity, dew point, wind speed at 10 m and 100 m, wind direction at 10 m and 100 m, and wind gusts. The target variable, *Power*, represented turbine output normalized between 0 and 1, allowing the models to predict relative wind energy generation independently of the turbine rated capacity.

Several preprocessing procedures were applied to improve data quality and model reliability. Missing and inconsistent records were handled carefully, numerical meteorological variables were normalized, and wind direction variables were transformed to preserve their circular nature. Temporal alignment was also performed to ensure that hourly observations were chronologically consistent and suitable for sequence-based forecasting models.

Five predictive models were examined, namely LSTM, RNN, GRU, CNN, and Dense neural networks. The models were evaluated using a comprehensive set of statistical metrics, including MSE, RMSE, MAE, MBE, correlation coefficient (r), coefficient of determination (R^2), RRMSE, NSE, and WI. The empirical results showed that recurrent architectures outperformed the non-recurrent models, confirming the importance of temporal dependency modeling in hourly wind power forecasting.

Among all evaluated models, the LSTM model achieved the best overall forecasting performance. It obtained the lowest prediction errors, with MSE $= 0.0008$, RMSE $= 0.0282$, and MAE $= 0.0106$. It also achieved nearly unbiased forecasting with MBE $= -0.0006$, together with strong agreement and goodness-of-fit values, including $r = 0.9940$, $R^2 = 0.9880$, NSE $= 0.9880$, and WI $= 0.9970$. These findings indicate that LSTM was highly effective in capturing nonlinear and temporal relationships between meteorological conditions and wind turbine output.

The RNN and GRU models also demonstrated strong predictive performance, ranking second and third, respectively. However, their error values were slightly higher than those of LSTM. In contrast, the Dense and CNN models produced larger forecasting errors and lower agreement metrics, suggesting that models without strong temporal memory mechanisms are less suitable for this hourly wind power forecasting problem.

Overall, the results confirm that recurrent deep learning models, particularly LSTM, provide an effective and reliable solution for operational wind power forecasting. Accurate prediction of turbine power output can support wind farm management, grid stability, reserve scheduling, electricity market participation, and better integration of renewable energy into power systems.

Future work can extend the present study in several directions. First, the forecasting framework can be tested using data from multiple wind farm locations to evaluate model generalization under different terrain, climate, and turbine operating conditions. Second, multi-step-ahead forecasting can be investigated to support longer-term operational planning and grid scheduling. Third, feature selection techniques can be integrated to identify the most influential meteorological variables and reduce model complexity.

Future research may also explore advanced architectures such as attention-based recurrent models, transformer networks, hybrid CNN-LSTM models, and physics-informed deep learning approaches. In addition, metaheuristic optimization algorithms can be used to tune model hyperparameters and improve forecasting accuracy. Probabilistic forecasting and uncertainty quantification should also be considered to provide confidence intervals around predicted wind power output.

Finally, explainable artificial intelligence techniques can be incorporated to interpret model predictions and identify how variables such as wind speed, wind direction, gusts, humidity, and temperature influence turbine power generation. Such developments would improve model transparency and increase the practical value of deep learning-based wind power forecasting systems for real-world renewable energy applications.

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