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LSTM Deep Learning Techniques for Wind Power Generation Forecasting

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ABSTRACT

Wind power generation forecasting is crucial for the optimal integration of renewable energy sources into power systems. Traditional forecasting methods often struggle to accurately predict wind energy production due to the complex and nonlinear relationships between wind speed, weather parameters, and power output. In recent years, deep learning techniques have emerged as promising alternatives for wind power forecasting. This paper presents a review of the deep learning technique for wind power forecasting with a special focus on Long Short-Term Memory (LSTM) networks for short-term wind energy production prediction. This paper demonstrates the effectiveness of LSTM networks in capturing temporal dependencies in wind data and improving forecast accuracy. The study provides high accuracy prediction to improve the integration of wind energy into power systems and reduce energy costs.

1. Introduction

Wind energy is an important component of the shift to more sustainable energy systems, providing a renewable and ecologically beneficial alternative to traditional fossil fuel-based power generation [1]. However, the variable and intermittent nature of wind presents considerable issues for power system managers, needing precise forecasting of wind energy generation [2]. Traditional forecasting methods, such as statistical and physical models, frequently fail to capture the intricate dynamics of wind behavior, yielding unsatisfactory results [3].

Deep learning techniques, a subset of machine learning approaches inspired by the structure and function of the human brain, are increasingly popular in a variety of sectors, including wind power generation forecasts. Among deep learning architectures, LSTM networks have demonstrated potential in capturing long-term dependencies in sequential data, making them ideal for time series forecasting tasks like wind power prediction [4]. The purpose of this work is to discuss the most recent advances in LSTM-based approaches for forecasting wind power generation and provide insights into their efficacy and prospective applications [5]. Recent advances in wind power generation forecasting, notably the use of LSTM deep learning techniques, highlight the importance of this field in incorporating renewable energy into the power grid [6]. Scholars have worked extensively to improve forecasting models' accuracy and dependability, with major contributions by Zhao et al. [7] and Li et al. [8], who proposed hybrid and attention-based LSTM models, respectively.

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Sørensen et al. [9] and Liu et al. [10] highlight the importance of understanding the link between model complexity, data availability, and forecasting accuracy. Traditional forecasting methods frequently fail to capture complicated wind data correlations, spurring the use of deep learning systems such as LSTMs, which automatically learn non-linear relationships without requiring manual feature engineering [11].

LSTMs avoid standard recurrent neural network constraints, such as the vanishing gradient problem, and can learn long-term dependencies in wind data [12, 13]. Despite its promise, LSTMs require a lot of high-quality data to train effectively [14].

The importance of wind power forecasting in renewable energy integration is demonstrated by studies on storage technologies and deployment restrictions [14, 15]. Recent research, including work by Taylor and McSharry [16], Liu et al. [17], and Chen et al. [18], has demonstrated the efficiency of LSTM networks in collecting wind data temporal patterns.

To summarize, recent advances in LSTM networks show great potential for improving wind power generation forecasting accuracy and facilitating the transition to a sustainable energy future, despite persistent hurdles. This article is organized as follows. In Chapter 2, preliminary information regarding LSTM and its architecture is provided. In Chapter 3, data was analyzed to estimate wind power using LSTM. Initially, wind turbine data was studied. The projected and actual values were compared using one-day consumption data. In Section 4, the simulation and prediction outcomes are assessed.

2. Long Short-Term Memory (LSTM) Architecture

LSTM is a type of recurrent neural network (RNN) architecture specifically designed to address the vanishing gradient problem and capture long-term dependencies in sequential data [19]. Unlike traditional RNNs, LSTM networks incorporate memory cells and gates to selectively retain and forget information over time, allowing them to effectively learn and remember patterns in time-series data. The key components of an LSTM unit include the input gate, forget gate, memory cell, and output gate, each serving a unique role in processing sequential inputs and updating the network's internal state [20]. By learning to maintain and update memory over extended time periods.

- Cell State: Known as the "memory," it flows horizontally through the network, preserving information across time steps and aiding in learning and retaining information over long sequences.
- Forget Gate: Implemented as a sigmoid layer, it determines which information in the cell state to discard based on the previous hidden state and current input, allowing for selective retention or forgetting.
- Input Gate: Composed of a sigmoid layer for deciding which new information to store in the cell state and a tanh layer for generating new candidate values to add to the cell state, facilitating the incorporation of relevant new information.
- Output Gate: This sigmoid layer determines which information from the cell state to output, considering the current input and previous hidden state, thus regulating the flow of information to the next time step.
- Hidden State (Output): Also termed the output state, it carries information from one time step to the next, calculated based on the cell state and input using the output gate, thereby influencing subsequent predictions and computations.

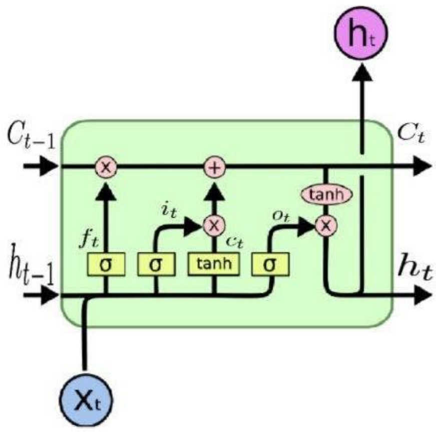

Figure 1 Architecture of LSTM Model

LSTM networks excel in tasks such as natural language processing, speech recognition, time series prediction, and more. Their ability to handle long-range dependencies and mitigate the vanishing gradient problem makes them a popular choice for modeling sequential data with complex temporal dynamics.

3. Material and Method

3.1. Case Study: LSTM-Based Wind Power Forecasting

This study investigates how well LSTM networks can predict wind power generation. Referencing Salihi and Danismaz's [21], it utilizes SCADA data from the Penmanshiel Wind Farm (UK) acquired from Zenodo. The data covers a period from 2020 to mid-2021, including wind speed, direction, temperature and power (KW). Before using the data to train the LSTM model, crucial preprocessing steps were taken cleaning to ensure data quality, selecting relevant features, and normalization for efficient training.

Table 1 Wind Turbine Data Set

	Wind speed (m/s)	Wind direction (°)	Power(kW)	Temperature (°C)
count	49603	49603	49603	49603
mean	7.87723	196.869	744.691	16.7376
std	4.36993	82.9756	733.142	3.54051
min	0.16917	0.00588183	-14.9246	8
25%	4.68003	151.43	94.4476	14
50%	6.93356	208.875	461.654	16
75%	10.2398	253.425	1382.31	19
max	25.7975	359.989	2076.73	28.9583

Table 1 Presented is a summary table detailing data statistic derived from wind turbine measurements. Across the observation period, 49,603 readings were gathered encompassing wind speed, wind direction, power output, and hub temperature. Notably, the average wind speed stood at 7.88 meters per second, exhibiting a standard deviation of 4.37 meters per second, indicative of the varied wind conditions experienced. Likewise, the average power output registered at 744.69 kW, with a considerable standard deviation of 733.14 kW, suggesting notable fluctuations in power generation. Wind direction data also demonstrated substantial variability, with an average of 196.87 degrees and a standard deviation of 82.98 degrees. Furthermore, the average hub temperature was recorded at 16.74 degrees Celsius, accompanied by a standard deviation of 3.54 degrees Celsius.

3.2. Exploratory Data Analysis

Exploratory Data Analysis (EDA) is pivotal in the development of LSTM models for wind power generation. EDA provides researchers with crucial insights into the wind power dataset's characteristics and patterns, informing the design and optimization of LSTM architectures. By analyzing features such as wind speed, direction, and temperature, EDA helps identify relationships with power output. Additionally, EDA detects outliers, missing values, and anomalies, which can significantly impact model performance. Understanding the data distribution and dynamics facilitates informed decisions on data preprocessing, feature selection, and model hyperparameter tuning. This comprehensive approach enhances the accuracy and robustness of LSTM models for wind power generation forecasting, making EDA a fundamental step in constructing effective predictive models to leverage wind energy resources fully.

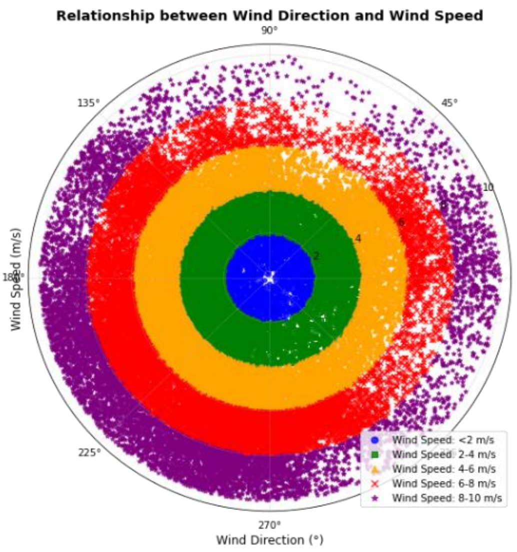

Figure 2 Relationship between wind direction and wind speed

Figure 2, depicts the wind direction and wind speed relationship, revealing that the weakest winds emanated from the East, as indicated by darker shades, while the strongest winds originated from the West. This visual representation should be regarded as a momentary depiction of the wind conditions at the specified location and time. Wind characteristics can significantly differ across various locations and timeframes. Factors such as time of day, season, and weather conditions can lead to variations in wind direction and velocity.

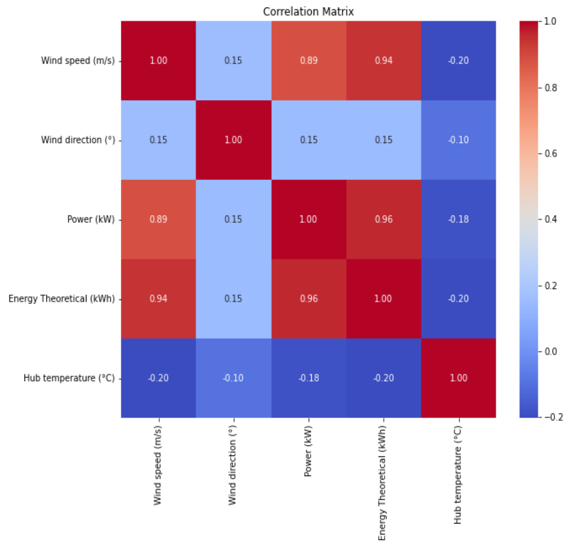

Figure 3 Correlation matrix

In Figure 3, a correlation matrix displays linear relationships among wind power generation variables such as wind speed, direction, power output, theoretical energy production, and hub temperature. Correlation coefficients, ranging from -1 to +1, are represented by shades, with darker tones signifying stronger correlations. For instance, a darker shade between wind speed and power suggests a positive correlation, indicating that higher wind speeds correspond to. This correlation matrix is crucial for informing the wind power generation LSTM model by elucidating the relationships among various factors influencing power generation. It helps understand relationships among factors like wind speed, direction, and temperature affecting power output. This analysis facilitates model training by prioritizing the learning of influential variables and potentially streamlining the input feature selection process. Additionally, the matrix aids in detecting unexpected relationships that may indicate technical issues or data inaccuracies within the wind turbine system. It serves as a valuable starting point for understanding the data, guiding model development, and improving forecasting accuracy for wind power generation.

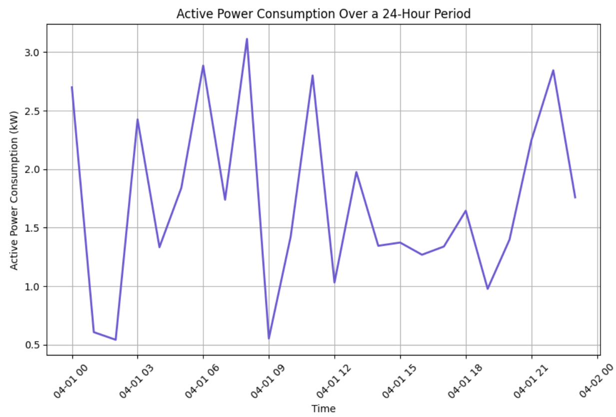

Figure 4 power consumption (in kW) of a household over a 24-hour period

The chart displays active power consumption over a 24-hour period. The X-axis represents time (hours of the day), while the Y-axis shows the active power consumption in kilowatts (kW). The fluctuations in the graph illustrate how power consumption changes throughout the day.

At the beginning of the day, power consumption is low, around 0.5 kW. It then increases in the early morning hours, reaching up to approximately 3.0 kW, which could correspond to people waking up and starting to use electrical appliances. Following this, there is a decrease in consumption during the mid-morning and an increase again in the afternoon.

Midday consumption levels are relatively low, with the lowest point being around 1.0 kW. Consumption rises again towards the evening, likely when people return home and begin using various electrical devices. Towards midnight, consumption starts to decline once more.

Overall, the graph indicates typical fluctuations in power consumption throughout the day and reflects changes tied to different levels of activity during various times.

This data holds significance for wind power generation for various reasons. Firstly, it aids in predicting electricity demand, assisting wind farm operators in planning operations to meet peak demand periods. In essence, understanding the fluctuations in active power consumption throughout the day is crucial for wind power generation. It facilitates demand prediction and informs the development of LSTM algorithms, empowering operators to optimize generation strategies and meet consumer needs effectively.

3.3. Model Configurations

The LSTM model employs a layered architecture. Each layer contains LSTM units that process sequences of historical data. These sequences include wind speed, direction, temperature, and other relevant weather factors. By processing these sequences, the model learns the intricate relationships between the variables and aims to generate accurate predictions of future wind power generation.

3.4. Result And Experiment

This work evaluates the LSTM model's performance in wind power forecasting using two established error metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics are presented within an evaluation matrix, providing a quantitative assessment of the model's accuracy.

MAE: Represents the average absolute difference between predicted (Pi) and actual wind power values (Oi), as (n) is the sample size, indicating the average magnitude of the model's errors. Lower MAE signifies better forecasts, as they are closer to the actual values [19].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(Oi - Pi)^2 \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Oi - Pi)^2} \qquad (2)$$

RMSE: As shown in the equation (2), the RMSE is calculated by squaring the error between the observed value (Oi) and the projected value (Pi) and then averaging the results. This metric penalizes larger errors more heavily compared to MAE [20]. Like MAE, lower RMSE suggests superior model performance [19].

In wind power generation LSTM models, MAE and RMSE serve as crucial metrics for evaluating model performance, these metrics are vital for assessing the LSTM model's ability to forecast wind power generation accurately, essential for efficient energy planning. Ultimately, MAE and RMSE quantitatively assess the accuracy and precision of wind power generation forecasts, enabling informed decision-making and supporting the transition to sustainable energy systems.

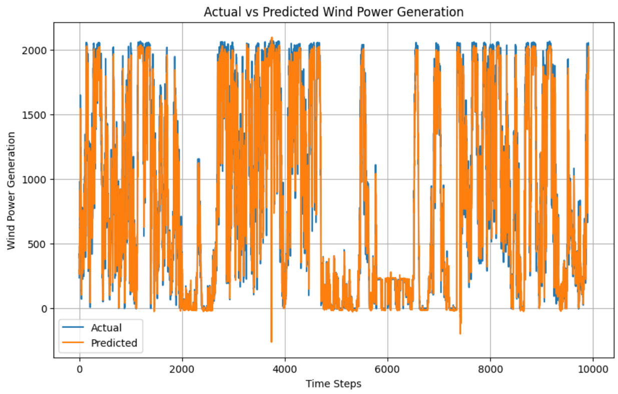

Figure 5 True values and Predicted values

Figure 5 displays a comparison between predicted and actual power generation.

The graph illustrates the wind power generation over a period, with each data point representing measurements taken hourly. The x-axis denotes the time steps, representing consecutive hours, while the y-axis indicates the wind power generation in kilowatts.

The graph displays the predicted and actual wind power generation values for one day. Notably, the predicted values consistently appear higher than the actual values across the entire time. This discrepancy suggests that the model overestimated wind power generation.

In certain instances, particularly noticeable in specific segments of the graph, there exists a substantial difference between the predicted and actual values. This indicates areas where the model's predictions deviate significantly from the observed data. Overall, the graph indicates that the model's performance in predicting wind power generation requires improvement. It suggests that the current model may not accurately capture the dynamics of wind power generation over time.

Furthermore, the result indicates that this model is better in predicting short-term wind power generation compared to longer-term predictions.

Table 2 shows the results of the model prediction in 24 hours.

	Actual Values	Predicted Values	MSE	RMSE	MAE
0	233.884967	294.378845	26994.798083	164.300938	102.279917
1	389.535538	260.284515	26994.798083	164.300938	102.279917
2	421.667401	405.193237	26994.798083	164.300938	102.279917
3	383.933072	417.644806	26994.798083	164.300938	102.279917
4	483.707760	384.408752	26994.798083	164.300938	102.279917
5	406.767236	476.337952	26994.798083	164.300938	102.279917
6	455.113559	406.248016	26994.798083	164.300938	102.279917
7	423.971927	459.741699	26994.798083	164.300938	102.279917
8	621.902557	425.773376	26994.798083	164.300938	102.279917
9	511.364365	609.265869	26994.798083	164.300938	102.279917
10	434.775117	508.870209	26994.798083	164.300938	102.279917
11	515.069096	454.939941	26994.798083	164.300938	102.279917
12	647.580460	522.117615	26994.798083	164.300938	102.279917
13	901.831228	632.385254	26994.798083	164.300938	102.279917
14	980.685708	851.631409	26994.798083	164.300938	102.279917
15	822.039872	912.124084	26994.798083	164.300938	102.279917
16	680.807493	791.598694	26994.798083	164.300938	102.279917
17	742.926449	701.770325	26994.798083	164.300938	102.279917
18	635.265433	759.528503	26994.798083	164.300938	102.279917
19	657.915340	653.927856	26994.798083	164.300938	102.279917
20	614.263058	683.931885	26994.798083	164.300938	102.279917
21	1008.143827	637.953064	26994.798083	164.300938	102.279917
22	1647.814246	984.621765	26994.798083	164.300938	102.279917
23	1172.860598	1543.394043	26994.798083	164.300938	102.279917

4. Conclusion

This case study demonstrates the effectiveness of Long Short-Term Memory (LSTM) neural networks in wind power generation forecasting. LSTM's strength lies in its ability to capture long-term dependencies within wind data, leading to accurate predictions of future wind power output. This capability is crucial for efficiently integrating wind energy into the power grid, as it allows for better planning and management of renewable energy sources. The findings suggest that LSTM can significantly improve wind power forecasting methods, especially when dealing with larger datasets. Furthermore, its robust pattern recognition capability makes LSTM a valuable tool for organizations seeking to optimize both wind power generation and utilization. By leveraging LSTM, these organizations can make more informed decisions regarding wind energy production and integration into the grid.

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