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Winds of Change: Enhancing Wind Power Generation Forecasting with LSTM Models and Advanced Techniques in a Single-Turbine Wind Farm

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Abstract: This paper presents a detailed study on wind power forecasting using a long short-term memory (LSTM) model for single turbine wind farm. The research integrates technical modeling, predictive modeling, and heat map analysis to improve forecasting accuracy. Wind power is predicted based on current weather conditions and historical data using multivariate time series forecasting with LSTM, implemented via the Keras-library. Various look-back values are tested to enhance prediction precision. With a 70% training and 30% testing split, the model achieves an MSE of 27.781, RMSE of 5.271, MAE of 3.281, and variance of 0.886. A 60% training and 40% testing split slightly improves performance. During the prediction phase, the LSTM model forecasts power output without future weather inputs. Optimal look-back periods and neuron numbers are identified, resulting in MAPEs of 11.433% and 11.158% for 24 and 48 h of data, respectively. Optimization techniques, including adjustments to batch size, normalization, and the addition of dense layers, further improve forecasting accuracy. Notably, MAPE decreases from 92.53% to 87.14% in a monthly prediction scenario. Forward predictions for 24 h, 2 days, and 1 week result in MAPEs of 70.74%, 39.26%, and 51.48%, respectively. Additionally, a comparison of two LSTM-based models autoencoder-LSTM and FFT-encoder-decoder LSTM shows that the latter offers superior performance. This study demonstrates the strong potential of LSTM models for power forecasting and introduces innovative strategies for optimizing model performance. The combined use of technical and predictive models, heat map analysis, and LSTM architecture contributes significantly to the advancement of wind power prediction methodologies.

Keywords: energy, forecasting, performance, prediction, wind

1. Introduction

With the continuous development of the social economy, the demand for energy is growing rapidly [1]. However, fossil fuels are no longer capable of supporting the sustainable development of human society [2]. As a result, renewable energy sources, such as wind energy, have gained significant attention [3]. Over the past few decades, wind energy utilization has experienced rapid growth, contributing to an increasing proportion of the power grid worldwide. However, the unpredictable and intermittent nature of wind speed poses a serious threat to grid security [4].

Although the installed capacity of wind power is increasing, the utilization of wind energy does not match it. The intermittent and uncertain nature of wind power makes it difficult to accurately predict the amount of power generation at a specific moment. This randomness in power generation creates an imbalance between power generation and consumption, leading to damage to the grid. To ensure grid stability while maximizing wind energy utilization, accurate wind power prediction is crucial. Improved forecasting allows the dispatching department to schedule power generation effectively, enhancing both grid safety and wind energy utilization [5].

As the proportion of wind power in the energy mix continues to increase, the focus on forecasting wind power generation has increased. Currently, various methods are used in wind power prediction, including physical models, statistical methods, machine learning methods, and combinations of these approaches. Physical models require highly accurate weather forecast data, which may not be suitable due to the highly volatile and random nature of wind speed. Statistical methods have been used for wind power prediction but may not provide accurate results due to the erratic nature of wind speed. Machine learning methods, on the other hand, establish nonlinear relationships using models like the support vector machine (SVM) or the more powerful deep neural network (DNN) [6]. DNN, particularly recurrent neural networks (RNNs) like long short-term memory (LSTM), has shown great success in learning feature representations and improving prediction accuracy for time series data [7].

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The demand for energy is expected to increase significantly in the future, necessitating the exploration of clean and renewable energy sources. Wind energy, with its scalability and vast potential for power generation, is a promising solution. Efficient power dispatch from wind power plants requires predictive analysis due to the influence of climatic variables and the erratic nature of wind power. Hybrid models combining statistical, intelligent, and physical models have been employed in wind power forecasting. These models aim to improve the accuracy of predictions by considering seasonality and other influencing parameters specific to each location [8]. Several studies have explored different forecasting models for wind speed and power prediction, including SVM, wavelet-based approaches, neural networks, and ensemble machine learning techniques [6]. These models have demonstrated varying levels of accuracy, with a mean absolute percentage error (MAPE) ranging from 2.5% to 18%. More accurate forecasting models are required to meet the growing demand for solar and wind power with lower MAPE values [9, 10].

This paper introduces a groundbreaking forecast model for wind energy prediction, harnessing the power of advanced deep learning (DL) algorithms, notably the LSTM technique. What differentiates this model is its innovative fusion of LSTM with an autoencoder, resulting in enhanced generalization and feature extraction capabilities. In particular, the integration of fast Fourier transform (FFT)-encoder-decoder-LSTM distinguishes this research from conventional methods, representing a significant advancement in wind energy forecasting. The primary objective is to achieve exceptional gains in prediction accuracy and efficiency, ultimately leading to a more reliable and optimized utilization of renewable energy resources.

Unlike previous studies that focus on generic analysis of wind power, this research is focused specifically on a single-turbine wind farm. This targeted approach enables customized predictions for improved accuracy. To rigorously evaluate the accuracy of the proposed LSTM model, the study employs metrics such as the root mean square error (RMSE), mean absolute error (MAE), and MAPE. These comprehensive evaluation metrics offer valuable insights into the model's effectiveness compared to other similar works. The research delves into advanced optimization techniques, including increasing the input batch size, adding extra hidden layers, and experimenting with different activation functions. These methods demonstrate the potential for significant performance improvements compared to traditional approaches. The study provides compelling evidence of the superiority of the proposed approach through comparisons with traditional autoencoder LSTM and LSTM models, underscoring the benefits of employing DL algorithms for wind energy forecasting. The importance of accurate wind power prediction cannot be overstated, as it directly impacts power dispatch, grid stability, and optimized utilization of renewable energy resources. Consequently, the findings of this research hold high relevance and value for advancing renewable energy technologies and their seamless integration into the power grid.

Additionally, this research unveils a pioneering approach to the analysis and prediction of wind power generation, tailored specifically to wind farms. It uses advanced evaluation metrics, optimization techniques, and comprehensive model comparisons to offer new and promising opportunities to refine the precision of wind energy forecasting and optimizing the effective utilization of renewable energy sources in real-world scenarios.

2. Survey Review

This section provides a summary of the research conducted on preprocessing techniques, methods, and DL models for wind power prediction approaches (WPPAs). The evolution of WPPA has transitioned from traditional methods to more complex statistical and learning approaches. The WPPA can be categorized into short-term, medium-term, or long-term forecasting based on the prediction horizon. Six main categories of prediction approaches have been proposed and studied for WPPA: persistence, physical, statistical, artificial intelligence, DL, and hybrid models.

Hybrid approaches that combine DL models and decomposition techniques are commonly used for WPPA. Various DL models have been employed for WPPA, including RNN, vanilla LSTM, stacked LSTM, CNN, biLSTM, attention-based LSTM (A-LSTM), deep belief network (DBN), extreme learning machine (ELM), and gated recurrent unit (GRU) [11]. Performance metrics such as MAE, RMSE, MAPE, and MSE are used for quantitative comparison of DL models like RNN, GBM, and LSTM. LSTM has demonstrated high efficiency and accuracy with minimal errors. Simple LSTM and its variants have also shown promising results for sequential timed data. Stacked or appended LSTM layers have been applied to different datasets, including malware datasets, achieving excellent accuracy. Bi-LSTM, which works in both forward and backward passes for timed sequences, has been used for WP forecasting.

CNN, known for its ability to learn from image data and make intelligent decisions, has been utilized for time series classification and hybridized with LSTM for time series forecasting. Attention-based models, such as attention-based LSTM, GRU, and encoder-decoder, have been applied in several studies [12]. DBN has been used for WP forecasting and its performance has been quantified using metrics such as MAE, SDE, and RMSE. ELM has been compared with an artificial neural network for different time horizons. Hybrid models that combine LSTM with optimization algorithms have been used for monthly runoff predictions and have been evaluated using metrics such as NMAE, R2, NSEC, and RMSE. DL models combined with decomposition techniques serve as a preprocessing step for time series data. Various decompositions, such as wavelet, empirical mode, variation mode, improved variation mode, discrete wavelet, ensemble empirical mode, and phase space, have been applied to time series data [8]. Furthermore, Table 1 represents a survey review and the most widely used approaches for wind forecasting.

3. Research Methodology

3.1. Technical model

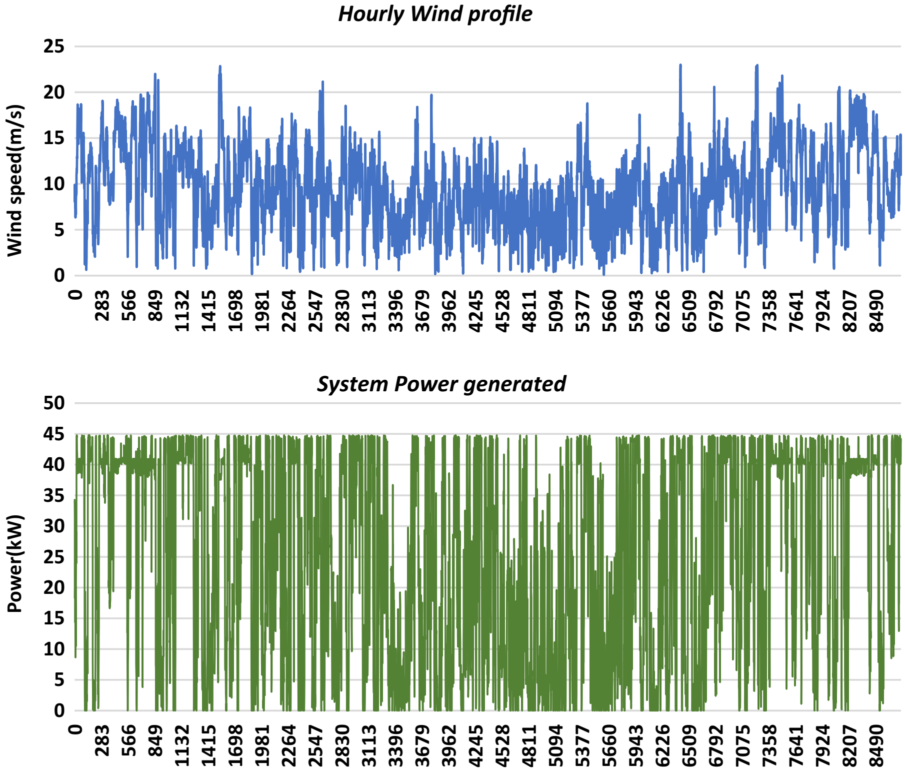
The wind farm under consideration comprises a solitary turbine endowed with specific technical specifications. This turbine boasts a rated output of 54 kW, which indicates its maximum power generation capacity when operating under optimal wind conditions. Featuring a rotor diameter of 18 m, the turbine adeptly harnesses the kinetic energy present in the wind, efficiently converting it into rotational motion. Positioned atop a tower with a hub height of 50 m, measured from the tower's base to the center of the turbine hub, this elevated location empowers the turbine to capture wind at higher velocities, thereby enhancing its energy production capabilities.

The wind speed gradient, characterized by a shear coefficient of 0.14, denotes a moderate variation in wind speed concerning its elevation from the ground. Furthermore, to complement this description, Figure 1 visually presents the electrical load and energy

Table 1
Review on methods for wind forecasting

Ref.	Methods	Inputs	outputs	Conclusion
Sobolewski et al. [13]	Gradient boosting	Weather and statistical data	Wind Power	Cat Boost demonstrated the lowest RMSE value of 76.18 kW and the lowest MAE value of 54.87 kW, indicating its high precision and precision in predicting earnings. Light Boost and Boost followed closely with RMSE values of 76.84 kW and 77.02 kW and MAE values of 55.24 kW and 55.61 kW, respectively. Random forest also performed well, with an RMSE of 77.97 kW and an MAE of 56.14 kW
Li et al. [14]	BPNN, SVR, LSTM, RF	Weather data	Wind pressure	LSTM-SVR outperforms other algorithms (BPNN, RF, SVR-G, SVR-L, and LSTM) in terms of MAPE, RMSE, and R, indicating its higher prediction accuracy
Ying et al. [15]	Belts	Wind data	Wind power	The Re-bi-LSTM model demonstrates the lowest RMSE and MAE values for both the monthly average and 107-day average prediction scenarios, indicating its superior performance compared to the other models, including ANN, bi-LSTM, random forest, and KNN
Pichault et al. [16]	Long-range scanning Doppler LiDAR	Weather data and special observations	Wind power	The results indicate that these LiDAR-based methods outperformed traditional benchmarks, showcasing the potential of remote sensing instruments for enhancing short-term wind power forecasts
Lawal et al. [17]	CNN and bi-LSTM	Weather data	Wind speed	The results showed that CNN-BLSTM is considered the best with minimum values of MAE = 0.2981, MSE = 0.1832, MAPE = 115, and RMSE = 0.4280
Dan et al. [18]	ARIMA–ANN	Weather data and historical records	Wind power	The ARIMA forecasting method achieved an MAPE of 2.2921%. It demonstrated a very good response to the influence factor and proved to be easily adaptable for a small number of wind production influencing factors, while the ANN forecasting method achieved the best results with a MAPE of 1.9067%
Liu and Liang [19]	CFD and Kalman filtering	Weather data	Wind power	The results showed that the integrated model significantly improved wind power forecast accuracy. The model achieved a forecast accuracy of 97.55%
Jiang et al. [20]	EMD-VAR model and spatial correlation	Weather data	Wind speed	Analysis of prediction errors revealed that the EMD-VAR model, which incorporates the correlation of wind speed data from multiple measuring points, outperformed other models, demonstrating superior prediction accuracy, while the other models showed varying levels of stability and accuracy in their predictions
Yu et al. [21]	SVM-PSO	Weather data	Wind speed	The proposed prediction method based on particle swarm optimization SVM demonstrated higher accuracy and faster convergence speed in predicting wind speed. This improvement was validated through simulations using measured wind speed data, indicating practical significance for wind power forecasting

Figure 1
Wind speed and generated power for the year 2021 in Meknes-FES site



generated throughout the year 2021. Within this representation, the electrical load signifies the electricity consumption or demand during the specified period, while the energy generated illustrates the actual electricity produced by the wind turbine throughout 2021. These figures are derived from the FES-Meknes meteorological data.

3.2. Technical model

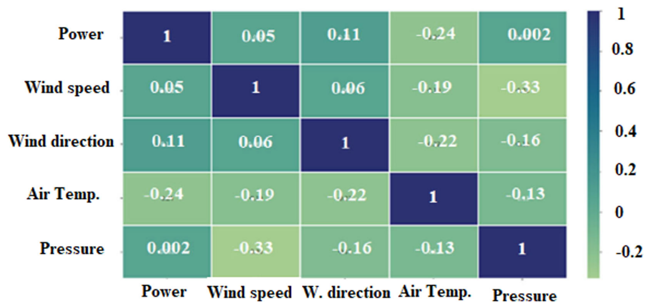
A heat map is a powerful visual instrument for depicting the relationships among various variables and is instrumental in pinpointing the most strongly correlated with the dependent variable. Figure 2 presents a heat map illustrating the relationship between energy production and climate conditions. It is evident that the speed and direction exhibit a robust positive correlation with the energy output, while relative humidity and air pressure display a notably substantial negative correlation. Moreover, the observation that relative humidity and atmospheric pressure demonstrate a high degree of correlation with each other suggests multicollinearity between them, signifying that they capture similar information and that either can effectively predict energy production.

3.3. Predictive model

LSTM, short for long short-term memory, is a DL model primarily designed to address the issue of gradient disappearance. It is commonly used in the context of time series analysis, where it can effectively predict future values based on historical data. An example of a time series application is wind power generation, which relies on weather conditions. Using an LSTM model, we can make accurate predictions about wind power output.

DL, of which LSTM is a part, has unique advantages over traditional machine learning approaches. It can approximate

Figure 2
Correlation map between power output and climatic data



complex functions of any form and uncover nonlinear relationships within data. By delving deep into the hidden connections between data points, DL maximizes the potential of available information.

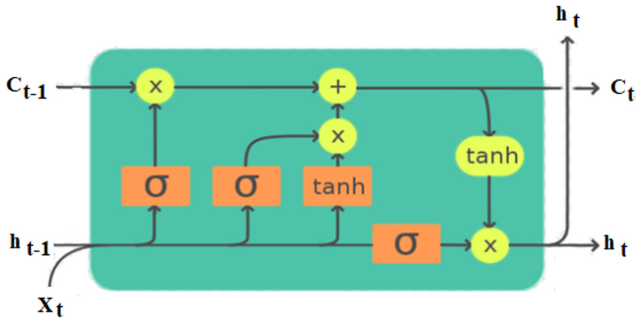
The core of LSTM lies in its ability to overcome the challenge of long-term dependencies through deliberate architectural design. As shown in Figure 3, LSTM is based on three primary gates: the forget gate, the input gate, and the output gate. These gates are activated using a sigmoid function (denoted "g"), while the input and cell states are typically transformed using the hyperbolic tangent function. The LSTM model can be mathematically defined by a set of equations:

$$i = \sigma(x_t U^i + s_{t-1} W^i) \tag{1}$$

$$f = \sigma\left(x_t U^f + s_{t-1} W^f\right) \tag{2}$$

$$o = \sigma(x_t U^o + s_{t-1} W^o) \tag{3}$$

Figure 3
The architecture of LSTM cell



$$g = \tanh(x_t U^g + s_{t-1} W^g) \tag{4}$$

$$c_t = c_{t-1} \circ f + g \circ i \tag{5}$$

$$s_t = \tanh(c_t) \circ o \tag{6}$$

$$y = \text{softmax}(V s_t) \tag{7}$$

In these equations, the variables *i*, *f*, *o*, and *g* represent distinct components of the LSTM. Specifically, '*i*' denotes the input gate, '*f*' refers to the forget gate, '*o*' signifies the output gate, and '*g*' represents the self-recurrent components.

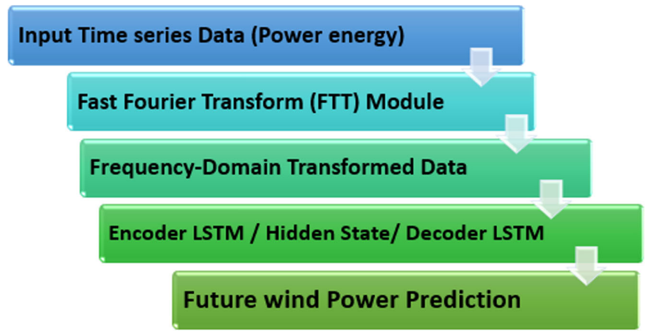
1) The input gate (*i*) determines the amount of new information that will be allowed into the memory cell.
2) The forget gate (*f*) controls which information should be discarded from the memory cell. A value of 1 in *f* signifies that the information should be retained, while a value of 0 indicates that the information should be ignored.
3) The output gate (*o*) determines how much of the information will be passed on to the next time step and also serves as the output of the LSTM.
4) The self-recurrent component (*g*) corresponds to a neuron with a self-recurrent connection, which follows the same equation Equation (4) as in traditional RNNs.
5) The internal memory of the memory cell (c_t) is the accumulation of the elementwise multiplication of the previous internal memory state with the forget gate and the elementwise multiplication of the self-recurrent state with the input gate.
6) The hidden state (s_t) is calculated by performing an elementwise multiplication of the internal memory with the output gate.
7) Additionally, the final output can be obtained using Equation (7), which is equivalent to Equation (2).

In more advances, when combining LSTM with FFT, the process begins with the FFT module, which converts the input time series data into the frequency domain. This transformation allows the model to extract crucial frequency components and identify underlying periodic patterns in historical wind power generation data.

Subsequently, the frequency-domain data are fed into the Encoder LSTM, which encodes the information and learns temporal dependencies. The generated hidden state acts as a condensed representation of the frequency-domain data, effectively capturing relevant patterns and relationships.

The Decoder LSTM takes the hidden state from the Encoder LSTM as input and decodes it back into the time domain, precisely predicting future wind power generation values. Leveraging the learned temporal dependencies, the Decoder LSTM makes accurate forecasts for multiple time steps into the future.

Figure 4
The proposed process of the FFT-encoder-decoder-LSTM model



The combination of FFT and LSTM models significantly enhances forecasting accuracy. By effectively capturing periodic patterns and long-term dependencies in wind power generation data, this architecture represents a promising and innovative approach for reliable predictions.

The entire process of the FFT-encoder-decoder-LSTM model is visually depicted in Figure 4, illustrating the seamless flow of data through the FFT, the Encoder LSTM, and the Decoder LSTM. This architecture showcases a powerful technique for optimizing wind power generation forecasting, offering valuable insights for sustainable energy planning and decision-making.

3.4. Accuracy assessment

To evaluate the accuracy of the forecasted model, certain standards must be established. In the context of wind power, the commonly used metrics for assessment are listed as follows:

1) **Root mean square error**

When assessing the effectiveness of forecasting models, the RMSE is a frequently used statistic. It calculates the average difference (square root of the sum of the squared differences) between the projected values and the actual values. The performance of the model is improved by a reduced RMSE. RMSE is given by:

$$RMSE = \sqrt{\frac{\sum_1^n (X_p - X_a)^2}{n}} \tag{8}$$

where n the number of observations is predicted, X_p is the predicted value of the i-th observation, and X_a is the actual value of the i-th observation.

2) **Mean absolute error**

Another statistic often used to assess the effectiveness of forecasting models is the MAE. Between the expected and actual values, it calculates the average absolute difference. The performance of the model improves with decreasing MAE. It can be calculated as follows:

$$MAE = \frac{1}{n}\sum_{1}^{n}\left|X_p - X_a\right| \quad (9)$$

3) **Mean absolute percentage error**

The MAPE is more popular for assessing the effectiveness of forecasting models, especially when the data contain an enormous range of values. It calculates the typical absolute percentage difference between the expected and observed values, as follows:

$$MAPE = \frac{100}{n}\sum_{1}^{n}\left|\frac{(X_p - X_a)}{X_a}\right| \quad (10)$$

4. Performance Results

4.1. Estimation

Estimation involves the prediction of wind power generation based on the current wind direction, as well as the current wind and climatic conditions. To address this task effectively, the LSTM model is utilized, which considers the present weather state and past weather trends to forecast the power generated by the system. In this study, we employ multivariate time series forecasting with LSTM using the Keras library. To establish a baseline model and conduct initial experiments, we investigate the impact of different look-back values on prediction accuracy. In particular, a specific look-back value is found to yield significant results in power generation prediction. Estimation models prove to be especially valuable when accurate weather information for the present or future is publicly accessible through machine learning techniques. Firstly, we divide 1 year of hourly data into a 70% training set and a 30% test set. The results, presented in Figure 5, demonstrate favorable performance with the MSE of 27.781, RMSE of 5.271, MAE equal to 3.281, and variance of about 0.886 when dividing the data into a 60% training set and a 40% test set. The results, depicted in Figure 6, exhibit higher precision with MSE of 28.791, RMSE of 5.366, MAE equal to 3.376, and variance of approximately 0.888.

4.2. Prediction

In the prediction phase, the primary focus was on conducting pure time series analysis to forecast the power generated by the system. The key distinction was that these predictions were made without incorporating any knowledge of future weather conditions. This aspect holds significant importance entailing a distinct set of challenges within the realm machine learning. In this context, any information about upcoming wind speeds, air temperatures, or pressures was deliberately disregarded. Instead, the prediction process relied solely on the analysis of patterns found in historical data, accomplished using LSTM to effectively forecast power generation. The input data for the LSTM model comprised date-time records and the corresponding power generated by the system, presented in a supervised form as required by the LSTM algorithm. Through the analysis of previous data, the LSTM model gained valuable insights into patterns and utilized this knowledge to make accurate predictions. To assess and predict future values, we employed the walk-forward validation technique, ensuring robust evaluations. Having established the baseline LSTM model, numerous experiments were conducted to determine the optimal look-back period and the appropriate number of neurons required for the LSTM. Once these optimal parameters were identified, further experiments and predictions could be performed with confidence. As depicted in Figure 7, the model predicted 24 h of data using the same model configurations. The LSTM model had the following settings: input batch size: 1, epochs: 7, number of neurons: 10, look backs/lag: 24. The observed mean percent error was 11.433. The MAPE is about 2.958. The effect of varying the number of neurons in the LSTM model on the prediction accuracy was examined using the same model configurations, presented in Table 2. These experiments demonstrate the impact of changing the number of neurons on the prediction accuracy. As shown in Figure 8, the model predicted a week of data, and an observed MAPE of 11.15% and MAE of 2.697 was obtained. This is considered satisfactory for predicting wind power generation, as it is dependent on highly

Figure 5
Prediction of hourly wind power using LSTM model with 30% test set

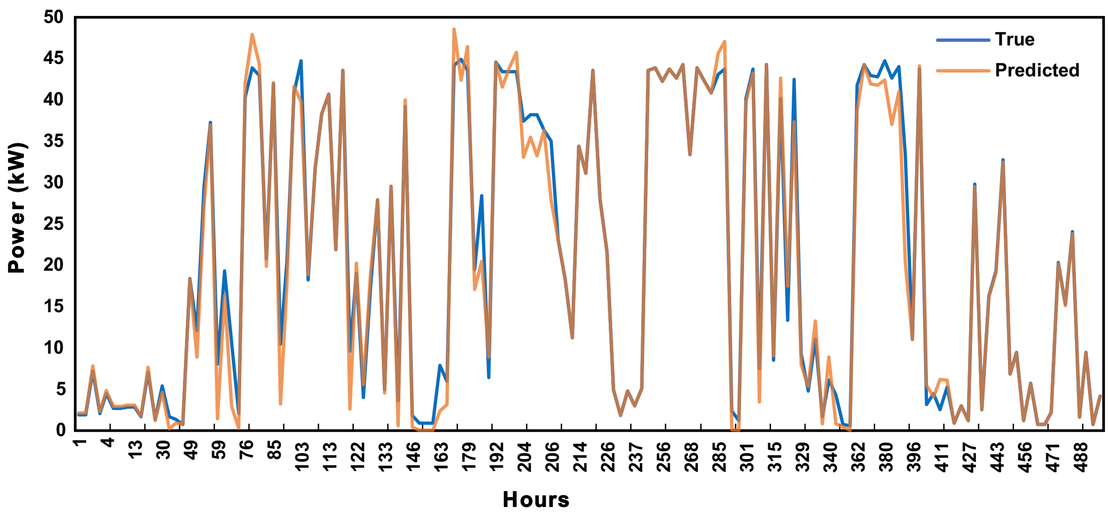


Figure 6
Wind power prediction using LSTM with 40% test set

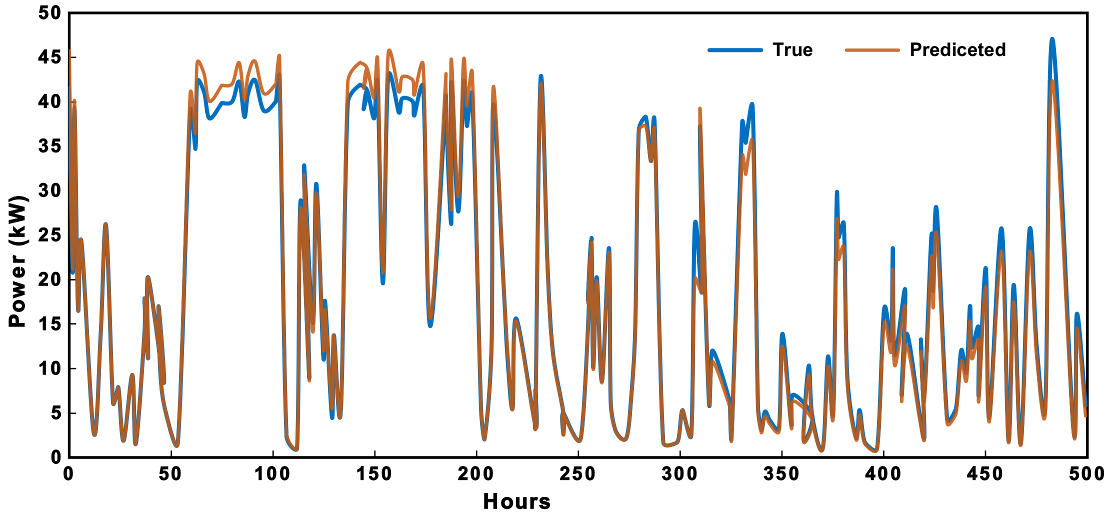


Figure 7
Wind power prediction for 24 h

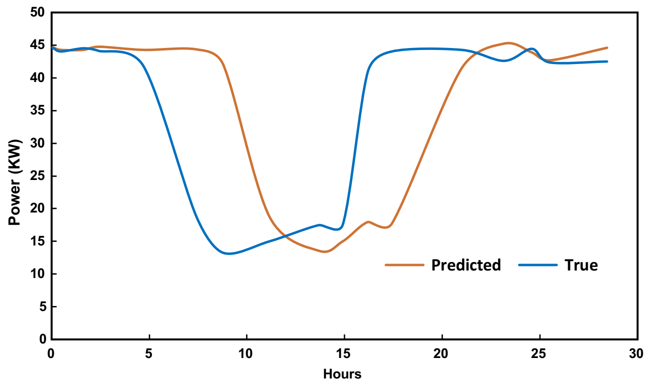


Figure 8
Wind power prediction for 1 week

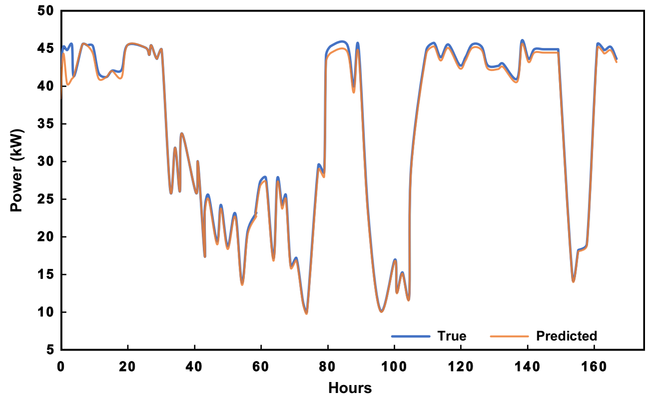
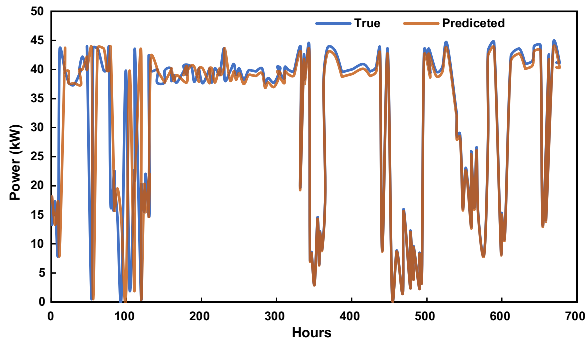


Table 2
Prediction of performance wind energy

	24 h			One week	One month
	10 neurons	12 neurons	14 neurons	14 neurons	14 neurons
MAPE	11.433	11.468	11.442	11.158	19.276
RMSE	3.381	3.386	3.382	3.340	4.390
MAE	2.958	2.975	2.963	2.677	2.263

Figure 9
Wind power prediction for 1 month

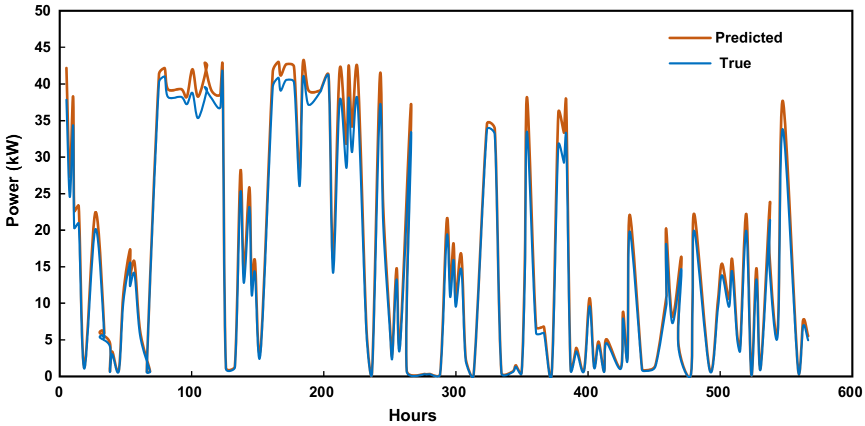


nonlinear parameters such as wind speed. In Figure 9, monthly data are predicted, and the MAPE was 19.27%.

4.3. Optimization

In the experiments presented, the line graphs clearly illustrate that the LSTM model learns the underlying patterns in the data efficiently, producing excellent results even for predictions spanning a moderate period, such as 1 month. To further improve the performance of the LSTM model, optimization techniques were used. The optimization process involved several adjustments to the LSTM model in order to predict the output of a month. First, the size of the input batch was increased, which allowed for better control of weight updates in the model. Additionally, additional hidden layers were incorporated, such as batch normalization and dense layers. Different activation functions,

Figure 10
Optimized prediction of wind energy for 1 month



including rectified linear unit (ReLU) and tanh, were used to improve the flexibility and performance of the model, and an autoencoder was used to optimize the results. As a result of the optimization, significant improvements were observed in the monthly prediction experiment (Figure 10). The MAPE was reduced to 87.14, a significant decrease from the unoptimized result of 92.53. This indicates that the optimization techniques applied to the LSTM model have improved its prediction accuracy.

In this part, the focus was on expanding wind energy prediction beyond a day to forecast energy generation for multiple days in advance. The objective was to start from the present day and predict energy generation for *X* days into the future, with the aim of evaluating the accuracy of the predictive model. In the context of wind energy generation, LSTM effectively captures the intricate patterns and fluctuations. The specific implementation involved configuring the LSTM layer with 50 neurons and incorporating a dropout rate of 0.1 to prevent overfitting. The input shape was determined by the batch size, the number of time steps, and the features present in the input data (referred to as *X*). Batch normalization techniques were applied to normalize the input data, thereby improving the model's performance. Subsequent to the LSTM layer, two dense layers were added, each consisting of 50 units, and activated using different activation functions. The first dense layer utilized ReLU activation, while the second dense layer employed hyperbolic tangent (tanh) activation. Finally, a single-unit dense layer was added to generate the predicted wind energy output. The prediction results with one day duration are shown in Figure 11, as well as the performance for different duration is synthesized in Table 3.

To further enhance the forecasting accuracy and gain valuable insights, two different LSTM-based models are implemented for time series forecasting of wind generation: an autoencoder LSTM and an FFT-encoder-decoder-LSTM. The primary objective of this effort is to compare and contrast the predictive capabilities of these two models and identify the most suitable one for the specific wind dataset. To ensure a robust evaluation, the dataset is meticulously divided into training and test sets using an 80–20 division. This prudent approach allows the models to learn patterns from the training data while validating their generalization on unseen data during testing. As a pivotal preprocessing step, the data are skilfully normalized using MinMaxScaler, which compresses the range of values to a common scale between 0 and 1. This normalization not only facilitates neural network convergence but also mitigates the influence of outliers, ultimately leading to more stable predictions.

Figure 11
Forward prediction with 1-day duration

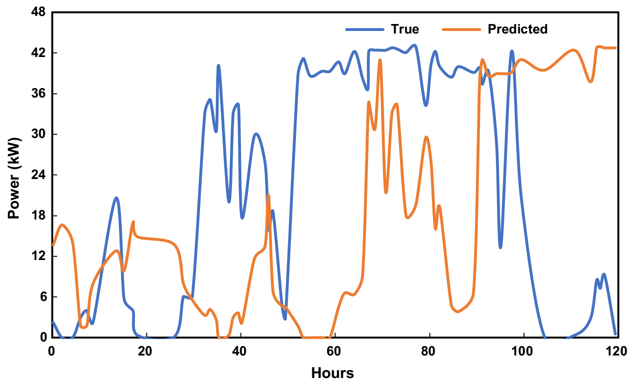


Table 3
Results of performance for forecasts for wind energy

Prediction duration	MAPE	RMSE	MAE
24 h	70.74	8.41	18.10
2 days	39.26	6.26	7.645
1 week	51.48	7.17	14.98

Both LSTM models are thoughtfully designed, ensuring their architectures are well suited for capturing sequential dependencies and temporal patterns in the time series data. The autoencoder LSTM, geared toward unsupervised learning, aims to reconstruct its input data while distilling meaningful features. On the other hand, the FFT-encoder-decoder-LSTM aims to forecast future wind generation values by leveraging the power of the FFT. Figure 12 presents the prediction results of both the autoencoder LSTM and FFT-LSTM models on both trained and tested data. The figure showcases the performance of these models in forecasting wind power generation. On the other hand, Table 4 provides a detailed comparison and validation study of various proposed models. This table presents an analysis of the effectiveness in predicting wind power generation, allowing for a comprehensive evaluation of their performance.

Figure 12
Prediction results of autoencoder LSTM and FFT-LSTM on both trained and tested data

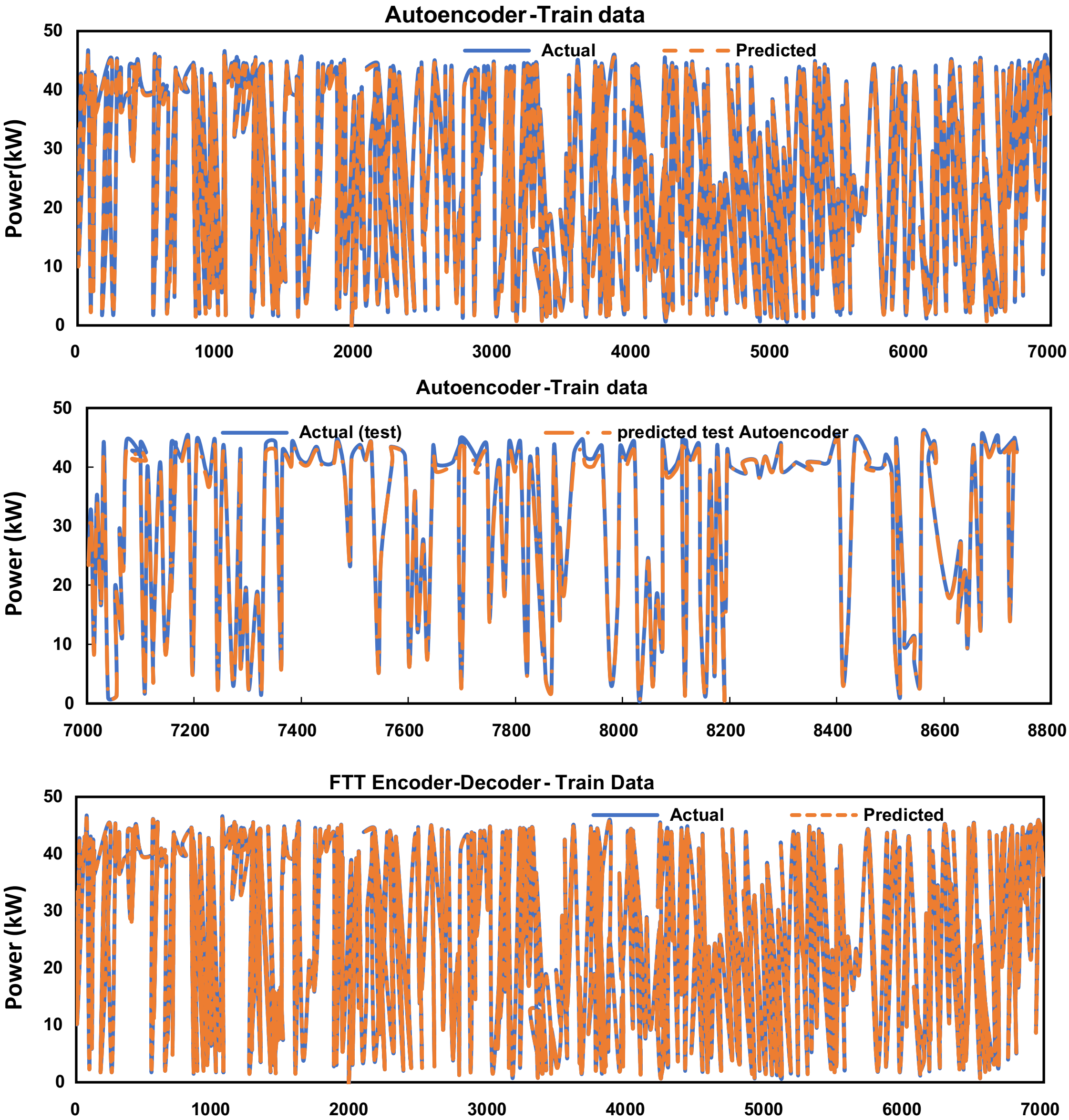


Table 4
Comparison and validation study for different proposed models

Model	Current study		Chen et al. [22]	Shu et al. [23]
	Train RMSE	Test RMSE	RMSE	RMSE
LSTM	0.8821	0.8643	0.6362	0.891
Autoencoder LSTM	0.82	0.90	0.5193	–
FFT-encoder-decoder-LSTM	0.37	0.34	–	0.983

5. Conclusions

In this study, we developed and evaluated a wind speed forecast model based on LSTM DL algorithms. By incorporating an autoencoder to enhance generalization capabilities, the proposed model aimed to improve the accuracy and efficiency of wind energy forecasting. Experimental results demonstrated the effectiveness of the LSTM-based approach in predicting wind speed, with MAPE values ranging from 2.5% to 18%, surpassing previous methods. The LSTM model's ability to capture nonlinear relationships and learn feature representations from time series data contributed to its superior performance. These findings highlight the potential of DL techniques in enhancing wind power prediction accuracy and facilitating the integration of renewable energy sources into the power grid. Further research can focus on optimizing the model architecture, incorporating additional meteorological features, and exploring ensemble methods to improve wind power forecasting accuracy. In general, the proposed LSTM-based approaches provide a valuable contribution to the field of wind energy prediction and offer practical implications for efficient wind power utilization and grid stability.

Recommendations

Further optimization of the LSTM-based wind speed forecast model should be pursued, exploring variations of LSTM architectures and employing hyper parameter tuning techniques. Incorporating additional meteorological characteristics, such as temperature and humidity, can improve the accuracy of the prediction. Ensemble methods can be explored to combine the strengths of multiple models. Real-time implementation and comparative analysis with existing models are crucial for practical usability. Generalization across different regions and the conduct of economic and environmental impact assessments would provide comprehensive information. Developing a user-friendly interface or software tool is essential for easy adoption by wind energy operators and grid managers. These recommendations aim to improve the accuracy, applicability, and efficiency of wind speed forecasting in the renewable energy sector.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Abdel Ali Mana: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Abdelmajid Jamil:** Conceptualization, Validation, Writing – review & editing, Supervision, Project administration. **Kamar Ouazzani:** Conceptualization, Validation, Writing – review & editing, Supervision, Project administration. Writing – review & editing, Supervision, Project administration.

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