

Investigating Wind Speed Forecasting for Grid-Connected Renewable Energy Systems Using LSTM and A Day Ahead Chaining

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Abstract

Insufficient access and unreliable grid service are among emerging communities' most significant challenges. Consequently, these communities rely on fossil fuel-based technologies to provide for their electrical needs, resulting in substantial socioeconomic implications for society. Accurate and reliable wind speed forecasting is essential for effectively using wind energy, a Renewable Energy Source (RES) with considerable developing potential. Forecasting wind speed (FWS) is essential for the safe and effective operation of the power grid. Despite considerable study on various processing and validation methodologies, its application to realistic forecasting remains problematic due to the substantial influence of newly acquired data on the outcomes of the initial fragmented sub-sequences. A Long Short-Term Memory (LSTM) neural network-based model for wind speed prediction, validated by the A Day Ahead Chaining (ADAC) approach, has been proposed to address this problem. A FWS model using LSTM has been developed, ADAC has been implemented for validation, and a comparison study has been conducted to identify a superior methodology for application on bigger datasets, enhancing accuracy and forecasting efficiency. The proposed model emphasizes real-time data characterized by abrupt transitions and dependence on the wind speed.

Keywords: Renewable Energy Source, LSTM, A Day Ahead Chaining, Grid Service, Wind Speed.

Introduction

Due to the warnings about global warming and heightened environmental issues associated with fossil fuel use in energy production, wind power facilities have emerged as more appealing economically and ecologically options compared to energy production from fossil fuels (Albatran et al., 2020). The fluctuating characteristics of wind electricity have limited the integration of wind power facilities into generating systems. Furthermore, elevating wind power integration in power networks above certain thresholds poses significant security challenges. The fluctuation of wind energy necessitates supplementary functional primary reserves, elevating the structure's operating costs and posing a possible risk to its dependability (Amroune, 2022). Distributions of likelihood functions, such as the Weibull distribution, are often used to quantify wind speed at wind farm locations over extended durations, including seasons and years.

In (Marouani et al., 2022), wind velocity was included in the optimum energy flow (OEF) framework. The framework accounts for the risk of overestimating the available wind energy during the distribution period, imposing an extra cost on the wind farm owner. The potential underestimation of wind energy is considered an extra cost for generating reserves, which is included in the model. Many parameters, including the scale component, the shape parameter for the distribution operation, the savings cost, and the associated penalty charge, significantly influence the outcomes of the financial shipping.

The authors in (Huang et al., 2017) suggested a probabilistic wind energy prediction technique including three stages. A query-based, simultaneous support vector modeling approach with improved harmonization has been applied to FWS. The precision of the devised approach depends on a learning stage for the created models. The predictive phases of the system exhibit a complex and extended iterative approach, enhancing its suitability for long-term FWS. Nevertheless, the findings indicate comparable convergence using more straightforward approaches. A sophisticated FWS model, introduced in (Jawad et al., 2018) using an evolutionary algorithm-based, artificial neural network, has been employed for wind and load estimation. Integrated meteorological and load estimation was conducted to enhance the dependability of the prediction model. The technique emphasized long-term forecasting, making it appropriate for planning rather than operational phases. This modeling depends on recurrent learning stages that need prolonged execution durations.

Recurrent neural networks (RNNs) have a superior architecture for time series analysis in meteorological forecasting data. The work adheres to this methodology but utilizes an advanced technology known as LSTM, an innovative variant of RNN. Compared to traditional RNNs, LSTM more effectively addresses the issue of gradient vanishing and comprehensively captures regular and long-term dependencies in a series of information (Cai et al., 2023). Studies indicate that it outperforms a conventional RNN in discerning the connections within a complex time series structure. LSTM networks have been widely used in the domain of FWS because of their superiority in managing time series data.

This paper presents the primary contributions as follows:

- A hybrid forecasting and verification approach is offered, using the measured data from a wind turbine at a power station alongside a comparison study of wind energy data over time.
- LSTM network-based FWS model has been presented.
- The verification has been conducted with ADAC. The test dataset assessed the chosen model with the ADAC cross-validation technique.

Proposed Method

The essential elements of wind velocity forecasting with LSTM are data cleaning, normalization, pre-processing (sampling), partitioning, model development, evaluation, and forecasting. The wind velocity data was first formulated as a non-negative real matrix A of dimensions $(P \times TS)$, where P represents the total number of wind velocity observation stations, and TS denotes the number of discrete time slots observed. Each block in the wind velocity information matrix represents a location where wind velocity has been recorded within a specified timeframe.

Wind velocity forecasts may be produced using historical time-series data. $X(j, k)$ represents the dimensions of the $P \times TS$ circulation matrix, whereas $x_{-}(p, t)$ signifies the wind velocity estimate for row p and column ts . To predict the wind velocity at time t in the future, a series of prior wind velocity data $(x_{-}(p, t - 1), x_{-}(p, t - 2), x_{-}(p, t - 3), \dots, x_{-}(p, t - n))$ is used. The LSTM-based wind velocity prediction model assumes that the wind velocity at a

designated location in the t-slot is estimated; thus, the model's inputs are supplied, and its output is the predicted value $(\hat{x}_t)$ of the wind velocity at this site over a specified timeframe.

Preparation and pre-processing of wind speed data: The data must be resampled, either by downsampling or upsampling, to align with the time-frequency wind velocity and data forecasting requirements. All data fields in the pre-processed dataset must be populated if applicable. The wind speed data has been imputed with null values using the K-Nearest Neighbors (KNN) machine learning approach.

Data normalization: The wind velocity data is normalized using the scope normalization method, resulting in data points that range from 0 to 1.

Data partitioning: A simple cross-validation method divides the wind velocity data into training and testing phases after pre-processing and normalization. The wind velocity data series remains constant. Fourfold cross-validation has been applied to partition the data into training and testing datasets for the LSTM wind velocity forecasting model's training and prediction, respectively.

Develop a model for LSTM forecasting of wind velocities: Define the configurations for an LSTM neural network, including the sampling interval, protocol stack count, number of perceptrons, dropout rates, learning rate, return value dimensions, hidden state size, activation functions, block size, and epoch count settings.

Construct the network: Adjust the parameters for the optimization technique, defect evaluation metrics, training documentation, and the LSTM wind speed prediction model. **Examine the network:** The framework effectively utilizes the training sample data, evaluates the loss of the developed forecasting model, and modifies the model features to enhance its predictive capability.

Forecast and evaluation: Utilize the enhanced FWS algorithms to generate predictions; thereafter, evaluate the accuracy by juxtaposing the results with the actual data.

Cross-validation Using the ADAC Methodology

Cross-validation is an essential procedure for evaluating the efficacy of predictive models. It is used to guarantee the model's generalization and to estimate the model parameters accurately. When machine learning methodologies are used on time series data, the predictive strategy accounts for the temporal dependencies of the results. To maintain the order of information acquisition, the primary objective is to inhibit using potential knowledge for predicting historical facts. No significant effects of the interconnections within the data can be identified by standard k-fold cross-validation.

Results and Discussion

Three error analysis metrics—Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)—are used to assess the accuracy of the LSTM-based FWS. Fig. 2 delineates the performance assessment of an LSTM model used for FWS at three distinct wind power stations. The performance measures include MAE, RMSE, and MAPE. Station 2 has superior forecasting performance, shown by the lowest error metrics (MAE: 0.32, RMSE: 0.011, MAPE: 0.29), signifying enhanced prediction accuracy and reliability.

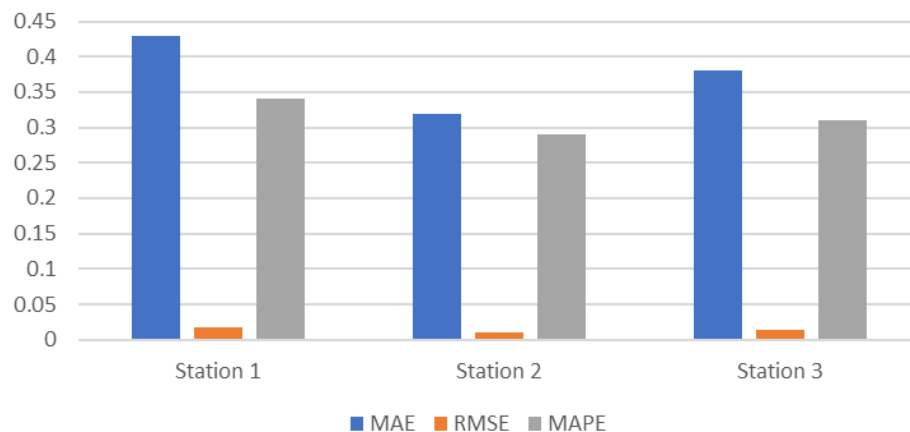


Fig. 1: Error Analysis of LSTM-based FWS

Conversely, Station 1 has comparatively elevated errors (MAE: 0.43, RMSE: 0.017, MAPE: 0.34), indicating somewhat worse predictive accuracy relative to the other stations. Station 3 has a median position with modest error values. The findings underscore the reliability of the LSTM-based model in FWS, with significant accuracy variations potentially affected by site-specific environmental or operational factors.

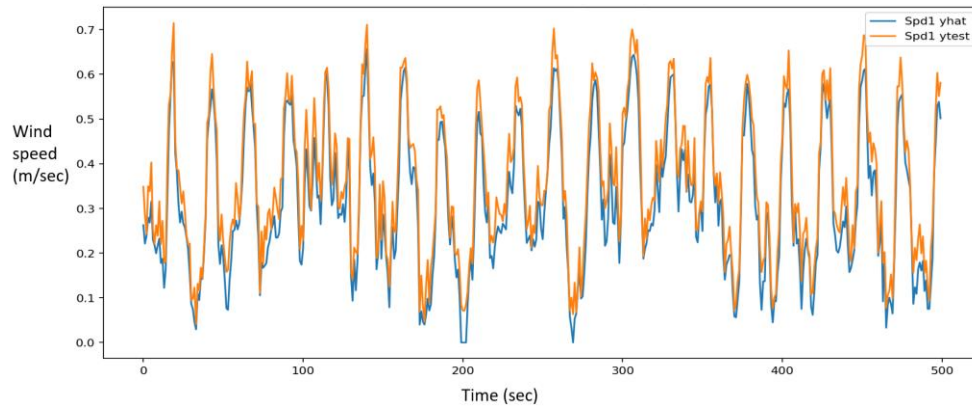


Fig. 2: Temporal Comparison Between the FWS Values and the Actual Observed Values

Fig. 2 illustrates a temporal comparison between the FWS values (Spd1 yhat) and the actual observed values (Spd1 ytest). The depicted curves demonstrate a robust correlation between the projected and actual data over the whole duration, signifying the model's exceptional precision in projecting wind speeds at a 50-meter hub height. Despite modest discrepancies, especially at peak variations, the forecasted values typically align with the trend and amplitude of the actual data. The strong association indicates that the used prediction model—presumably a time-series deep learning method—is efficient and dependable for estimating wind speed, essential for enhancing energy production and operational planning in wind power facilities.

Conclusion

Forecasting wind speed (FWS) is crucial for the secure and efficient functioning of the electrical grid. Despite extensive research on diverse processing and validation approaches, their application to realistic forecasting remains challenging owing to the significant impact of freshly obtained data on the results of the original fragmented subsequences. A model based on LSTM neural networks for wind speed prediction, verified using the ADAC method, has been presented to tackle this issue. A FWS model using LSTM has been built, ADAC has been used for validation, and a comparative analysis has been performed to ascertain a superior approach. Station 1 has comparatively elevated errors (MAE: 0.43, RMSE: 0.017, MAPE: 0.34), indicating somewhat worse predictive accuracy relative to the other stations. Station 3 has a median position with modest error values.

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