Heliyon 10 (2024) e39579

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Wind power prediction based on deep learning models: The case of Adama wind farm

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ARTICLE INFO

Keywords:
Wind power forecasting
Preprocessing
Renewable energy
Deep learning
Machine learning

ABSTRACT

Wind is a renewable energy source that is used to generate electricity. Wind power is one of the suitable solutions for global warming since it is free from pollution, doesn't cause greenhouse effects, and it is a natural source of energy. However, Wind power generation highly depends on weather conditions. It is very difficult to easily predict the amount of power generated from wind at a particular instant in time. Adama wind power farm is one of the wind farms in Ethiopia. There is no accurate and reliable forecasting model for the Adama wind farm that enables the forecasting of the power generated from the farm. The main objective of this research is to develop a wind power forecasting model for the Adama wind farm using deep learning techniques. Forecasting of wind power generation capacity involves appropriate modeling techniques that use past wind power generation data. The experiments have been conducted using Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU). To achieve the highest forecasting accuracy, four years of data (from 2016 to 2019), with 5-min intervals, have been collected with a total of 163,802 rows. For hyperparameter optimization grid search and random search techniques have been utilized. The performances of the proposed deep learning models were investigated error metrics, including Mean Absolute Errors (MAE) and the Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and R squared (R^2). Bi-LSTM outperforms the other two algorithms, scoring 0.644, 0.388, 0.769 and 0.978 MAE, MAPE, RMSE and R^2 values respectively. Such wind power forecasting helps energy planners and regional power providers to compute power production and energy generated from other sources.

1. Introduction

Energy has greater influence on the economic growth of both developing and developed countries. There has been a need to employ alternative energy sources, such as renewable energy, due to the shortage of fossil fuels and the constant rise in fuel prices in recent years, and most importantly its adverse environmental impacts. Renewable energy is energy that can be replenished within a human lifetime and does not harm the environment. Renewable energy includes all sustainable energy sources, such as hydropower, wind, solar, biomass, geothermal, wave, and tidal energies. To fulfill global climate change and emissions targets, meet demand for power,

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https://doi.org/10.1016/j.heliyon.2024.e39579
Received 11 October 2023; Received in revised form 14 October 2024; Accepted 17 October 2024
Available online 18 October 2024

Abbreviations

ANN	Artificial Neural Network
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLR	Multiple Linear Regression
NWP	Numerical Weather Prediction
OT-SVM	Orthogonal Test -Support Vector Machine
PR	Power Regression
RF	Random Forest
RMSE	Root Mean Squared Error
RT	Random Tree
SVM	Support Vector Machine
SVR	Support Vector Regression
WRF	Weather Research and forecast

and lower energy prices, the construction of wind power generators has increased significantly [1]. For instance, it has been reported that the total wind power generation capacity all over the world reached 623 GW in the year 2019, which accounts for 25 % and 6.7 % of total renewable energy sources and the total power generation respectively [2].

Wind power is one of the suitable solutions for global warming since it is free from pollution, doesn't cause greenhouse effects, and it is a natural source of energy. However, its dependency on weather conditions raises difficulties. It is very difficult to easily predict the amount of power generated from wind at a particular instant in time. To optimize the integration of wind power into current electrical systems, accurate and trustworthy wind power forecasting is required. Wind power generation is influenced by the wind's inconsistent, volatile, and intermittent character. The negative impacts can be minimized if the wind energy output is accurately predicted. Hence, wind power forecasting models have been extensively researched, and various state-of-the-art techniques have been identified over the years [3]. The outputs of Numerical weather Prediction (NWP) models are employed in many of the existing power forecast systems. The NWP model uses the current atmospheric weather condition to predict the future weather state. As a result, utilities employ a strategy in which the NWP model is included in all of their models [4].

Wind power forecasting techniques could be classified based on different criteria. Based on the time horizon, wind power prediction could be separated into two broad categories: short-term forecasting (from minutes to several days) and long-term forecasting (from several days to one year ahead) [5].

Other group of models are physical, statistical, and hybrid models [6–9]. The physical prediction model needs real-time and high-precision data which is extremely complex in terms of development, operation time and sensitivity to the errors [10] It is also known that as computation time increases error also increases. Ekanayake et al., 2021 [9] stated that Statistical prediction models are more appropriate for short-term wind power forecasting. Moreover, it has been also explained that the error becomes cumulative in long-term prediction [11]. There is also freedom of using Numerical Weather Prediction (NWP) in the statistical Approach while in the physical Prediction model is mandatory [12,13]. The hybrid prediction model combines physical methods and statistical methods. It uses weather forecasts and time series analysis [7,14]. Hybrid models are appropriate for forecasting wind energy from physical and statistical prediction methods with additional and combined features. Since it integrates information from different algorithms, many types of hybrid models have been constructed to predict wind power [7,8].

With the fast expansion of wind energy, it has been subjected to critical challenges. Wind resource is not constantly available and non-predictable; it is referred to as one the intermittent energy resources. Given the substantial environmental benefits, the output is restricted by the constant intermittency and unpredictable fluctuations of wind speed and other meteorological variables that entirely rely on the power of wind energy-producing systems chaotic and not unlike traditional energy sources. For this reason, wind power generation forecasting has received extensive consideration in research. The literature on wind power forecasting showed different approaches, models, and methodologies for wind speed and power forecasting.

A nonlinear and powerful advanced control approach called Economic Model-Predictive Control (EMPC) has been created to enhance the system's performance in a dynamic economy [15]. The model took into account power improvement and reduction in mechanical load. The researcher has reported that the effectiveness, dependability, and applicability of the suggested nonlinear EMPC technique were confirmed by three groups of simulations. A partial offline quasi-min-max fuzzy model-predictive control has been employed to examine the effect of wind speed variation on the turbine performance and control the pitch [16]. It has been reported that the online optimization problem is simplified as a partial offline optimization problem and resulted in more stable with less computational load. Moreover, a control strategy for large-scale wind farm has been developed using distributed economic model predictive technique by Ref. [17]. The technique integrated tracking of power and economic optimization of the farm into a single control system.

For the long-term prediction of wind power generation, a novel prediction model known as the EMD-based gray combined forecasting model has been developed [18]. AlShafeey & Csaki, 2024 [19] Clarified the development and verification of a dynamic hybrid model for wind energy forecasting that makes use of three machine learning algorithms: K-Nearest Neighbors, Support Vector

Machine, and Artificial Neural Network. The researcher disclosed that the hybrid model showed better predicting accuracy for both short-term energy projections at 15-min intervals over a day and long-term forecasts. A Normalized Mean Absolute Error (NMAE) of 5.54 % was noted. Recently, to improve the assessment of a site's wind power potential, a Copula-Deep Learning framework has been presented based on decision trees [20]. This framework makes use of the complex and non-linear connections among meteorological factors.

Deep learning algorithms have been used for wind power prediction. He et al., 2022 [21] proposed a wind power forecasting model called the Long Short-Term Memory (LSTM) model. Chandran et al., 2021 [22] proposed three deep-learning algorithms to forecast short-term wind power generation. Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN) were the machine algorithms used in this investigation and mean square error was used for performance measurement.

In order to effectively plan the power management, there is a need to exactly predict the available energy production at any instant of time as the demand for reliable energy becomes critical. As it could be seen from the literature, that different wind power forecasting works had been attempted using several approaches, statistical, physical and hybrid. However, wind power forecasting is weather dependent and difficult to develop general forecasting model for all locations. Due to the large dependency of wind energy on the geographical location and the non-availability of effective forecasting technique for wind farms in Ethiopia, developing wind power predicting model is required. Moreover, the fluctuation of overall power supply in Ethiopia is very critical which demands intervention to exactly estimate the available power from each source.

This research focuses on the Adama wind farm to forecast its power generation capacity by considering available climatic factors and historical power generation data. To predict the power production capacity of the wind farm, we need previous data to express future energy production. Wind power generation is influenced by the wind's inconsistent, volatile, and intermittent character as well as on overall weather condition. The negative impact of power can be minimized if the wind energy output is accurately predicted. A reliable forecasting system can help distribution system operators and power marketers to make better decisions in critical situations. Artificial intelligence approaches could forecast the wind power with reasonable accuracy, especially deep learning approaches are very essential to forecast wind power forecasting [23]. This study focuses on developing a wind power forecasting model for the Adama wind farm by using the latest deep learning algorithms, namely; LSTM, Bi-LSTM, and GRU.

The main contribution of our study on Developing Wind Power Generation Forecasting Model using Deep Learning approach are.

- Demonstrated the effectiveness of the suggested model, a comparison with deep learning forecasting techniques including LSTM, BiLSTM and GRU was conducted.
- Wind power generation dataset is collected and well preprocessed, which can be used as a reference point for upcoming studies on wind power forecasting.

2. Materials and methods

2.1. Study site description

The Adama Wind Farm II is located in Ethiopia's southeastern region, 95 km away from Addis Ababa and 7 km away from Adama

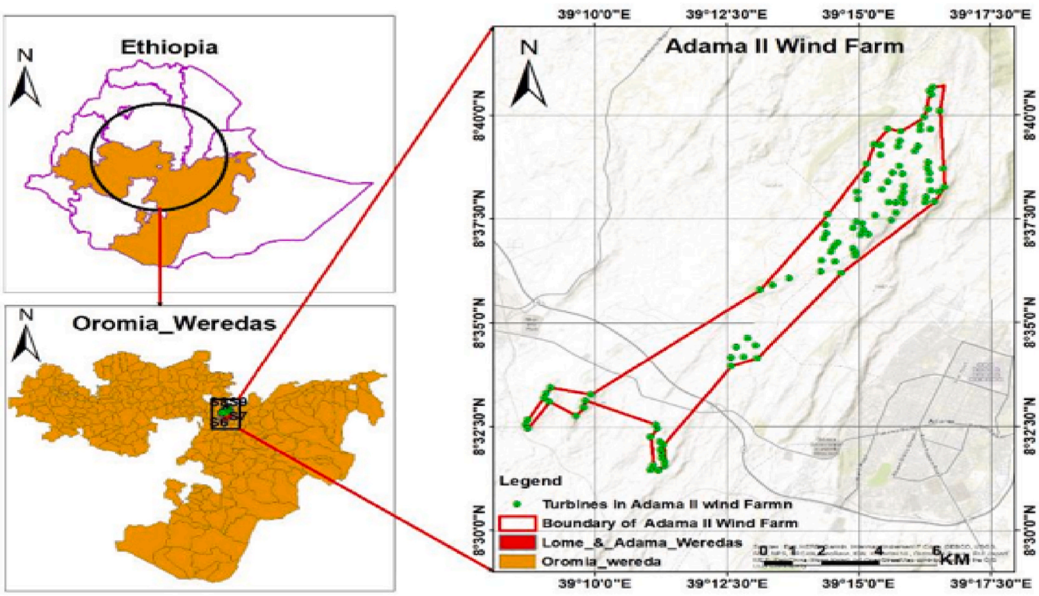

Fig. 1. Location of Adama wind farm (Debru et al., 2021).

town (see Fig. 1). The farm's center is situated in (8.5° North & 39.2° East), with an elevation range of 1741–2173 m. The site has good wind source and Adama wind farm II has a capacity of generating 153 MW power.

2.2. Methods

Dataset acquisition, dataset preprocessing, training and testing the model, Model development, and evaluation have been accomplished. The initial step in this work was to compile a list of wind power forecasting literature reviews and collect historical data from the wind farm. After collecting the data, preprocessing of the data have been conducted. The model was developed, trained, and evaluated after preprocessing the dataset. Since the data we used are time series data, time series sequence X of observations x_t with specific time stamp t, e.g., $X = [x_1, x_2, \ldots, x_t]$. or, to put it another way, $X_1, \ldots, t = X_{1:t}$, is a collection of data that is based on time variables.

Deep learning approaches, including the LSTM, Bi-LSTM, and GRU, were used to develop the proposed prediction model. Then, the best model has been selected on error based on metrics.

The architectural representation of the proposed wind power forecasting model (see Fig. 2) helps us to visualize the overall process of our research work that passes through to solve the desired problem. First, a total of four years of data starting from 2016 to 2019 have been collected. Such steps are taken by the suggested model to develop and forecast wind power. Before it is run through the algorithm, the data gathered from the Adama wind farm needs has been preprocessed. Using exploratory analysis and applying various Python modules to the dataset to change the date/time format, remove redundancy, abnormal values as well as missing data.

2.3. Dataset description and preprocessing

2.3.1. Dataset description

The dataset for this experiment is collected from the Adama wind farm that was recorded on the site by the farm as a case study. A

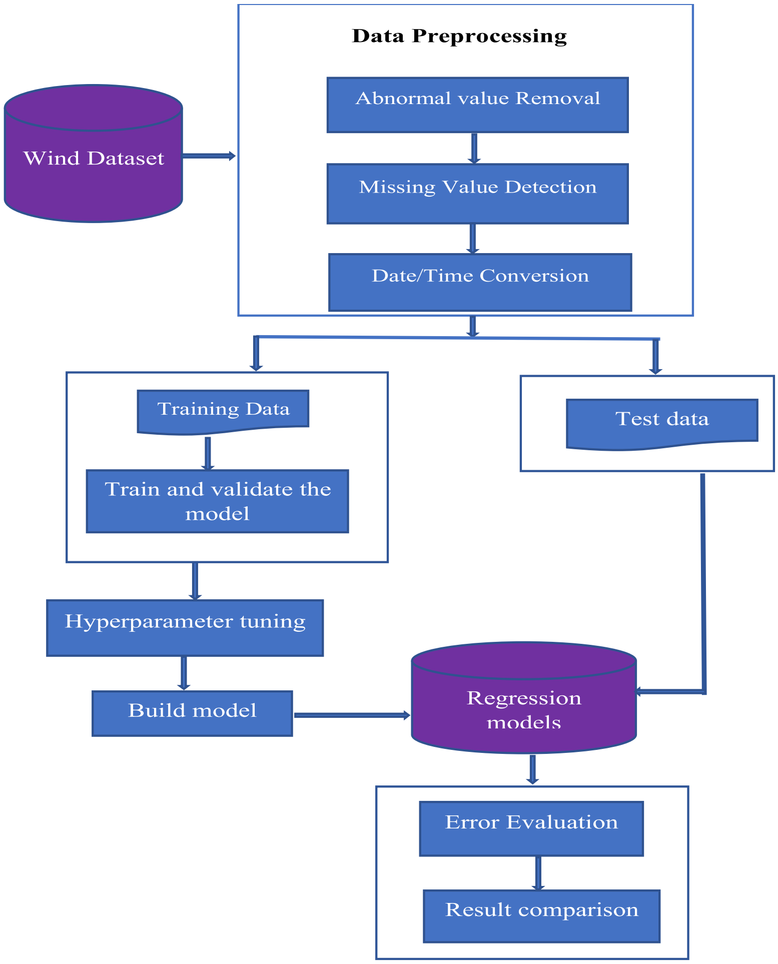

Fig. 2. Wind power forecasting model Architecture.

total of four years data were collected starting from 2016 to 2019. The dataset contains a total of 163,802 rows with a 5-min interval that was measured and recorded by the farm. Fig. 3 illustrates the wind power with respect to wind speed for a specified turbine parameter. From Fig. 3, it could be seen that the power output increases with wind speed until it reaches rated power. The rated power is the maximum power that a turbine could produce at safe working condition.

The associations between the datasets are plotted and displayed in Fig. 4. The associations between parameters power, wind speed, pitch angle, and wind direction are demonstrated in Fig. 4. It could be seen that the effects of these parameters on wind power. The variations of wind speed, power, and pitch angle with time is presented in Fig. 5. From Fig. 5, it could be demonstrated that the range and frequency of occurrence of the parameters described.

Fig. 6 demonstrates the pairwise correlation coefficients between the wind speed, pitch angle, wind direction, and wind power. It has been noted that a weak negative association between pitch angle and wind power but a strong positive relationship between wind speed and wind power. Generally, wind speed significantly affects the amount of wind power/energy to be generated.

2.4. Data preprocessing

It's quite unlikely that the raw data could be in a format that can be used by forecasting algorithms. Raw data mostly include missing values, abnormal data, and uneven scales between data. The data obtained from the wind farm typically includes a lot of outliers, noisy data, missing values, and redundancy values so it need to be preprocessed before conducting the actual experiments. To remove noises, redundancy, and missing value that can reduce model performance, preprocessing of dataset have been conducted. Exploratory analysis is critical for getting a sense of the many types of data, and their linkages, and identifying potential problems that need to be addressed in the next stage of preparation. Choosing the appropriate preprocessing methods to identify the missing data, noise reduction, and outlier detection has been considered as very vital step for getting quality preprocessed data. Hence, missing value detection and filling, abnormal value removal, and date/time conversion techniques have been used to preprocess the raw data.

Missing value detection: A linear interpolation which is a common method for imputation of missing values in time series data has been used for this research. The past and future data have been used to estimate the missing values using linear interpolation.

- **Abnormal value Removal:** Values that significantly vary from the patterns and trends of the other values in the time series are considered outliers in time series data. Hence, in this research outliers have been removed from wind power curve (see Fig. 7).
- Type 1: (normal). Fitting points on the power curve
- Type 2: (outlier). Points with little wind but a lot of production.
- Type 3: (outlier). Points with a high wind speed value but little productivity.

Date and time conversion: The date format of raw data was in different formats such as mm/dd/yy, dd/mm/yy, and yy/mm/dd, which is difficult to use directly to the algorithm. Similarly, raw data has been found with different time formats. To fit in to the model

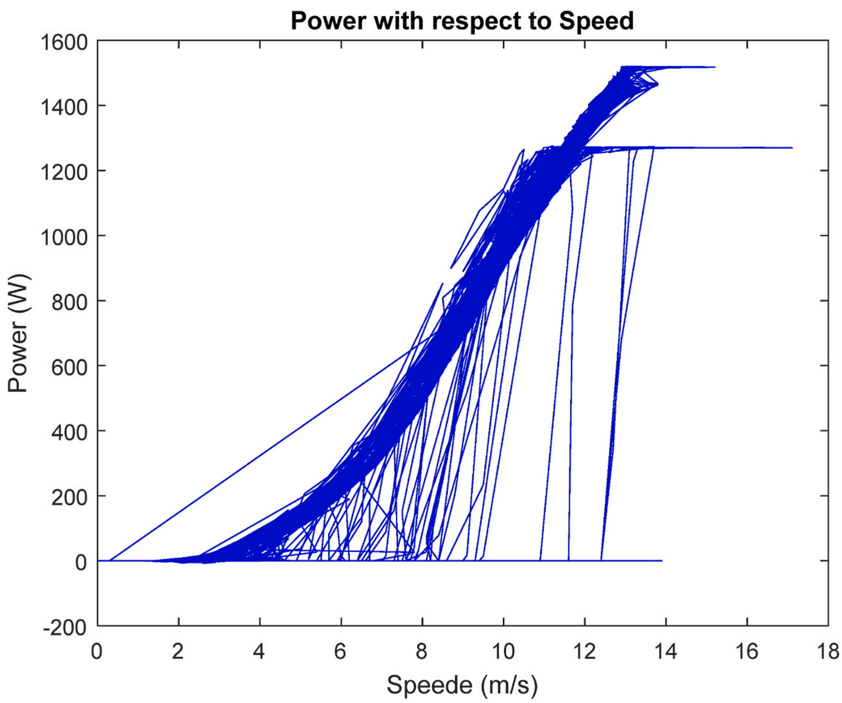

Fig. 3. Wind speed versus Power (One year data).

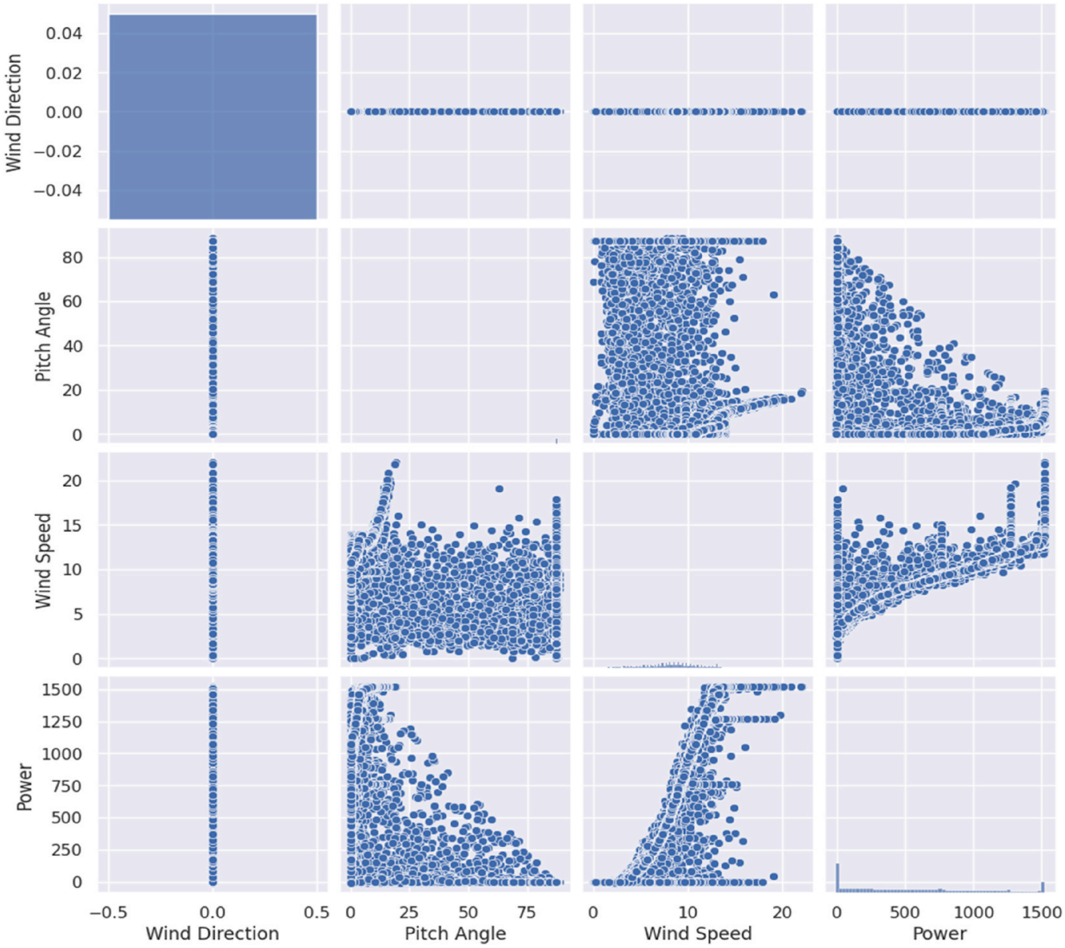

Fig. 4. Data visualization.

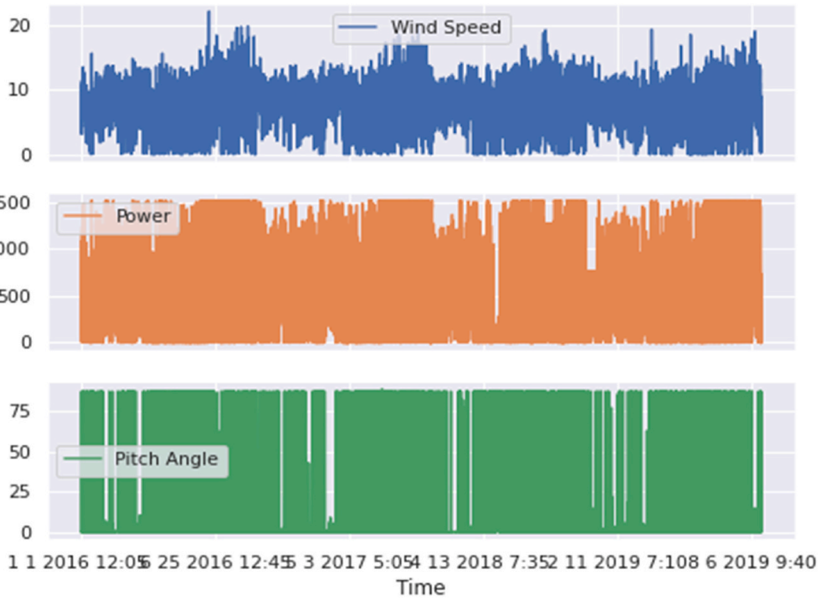

Fig. 5. Raw data correlation with time.

Fig. 6. Wind production auto-correlation.

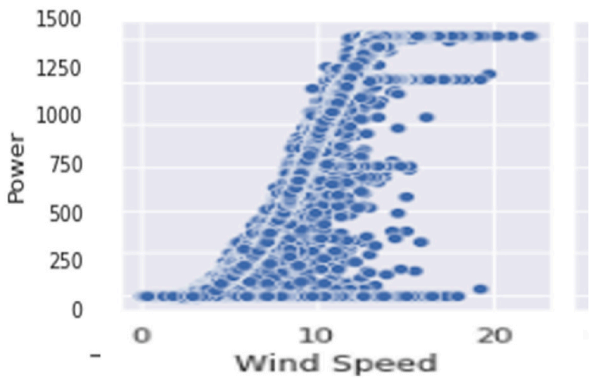

Fig. 7. Outliers in wind speed.

such formats have been converted to standard date time structure.

The preprocessed dataset has been used for the experiment with deep learning algorithms. Separate experiments are conducted using 80 % of the dataset for training, 10 % for validation, and 10 % for testing based on the recommendation given by Ref. [22].

2.5. Model performance evaluation metrics

As our model is a regression problem, the performance of the wind power generation forecasting model is measured using error-based metrics including Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) Root mean Squared error and R squared (R^2).

The MAE could be evaluated using Eq. (1):

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i^r - y_i^p| \tag{1}$$

Where y_i^r is the actual or real value wind power and y_i^p the predicted value of the wind power and n is the total number of samples.

The mean absolute percentage error (MAPE) is the most frequently used measure to anticipate error and could be computed using Eq (2):

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{y_i^r - y_i^p}{y_i^r}\right| \tag{2}$$

3. Result and discussion

In this section, the experimental results of the prediction model have been presented and discussed based on the objective of the study. The experiments are conducted using Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM) and

Gated Recurrent Unit (GRU) models. Grid search and random search methods were applied for hyperparameter tuning. While both grid search and random search are used to optimize machine learning models, their methods and levels of effectiveness are very different. Random search is typically more effective and scalable, whereas grid search is comprehensive and ensures examining all combinations, especially when working with vast and complex hyperparameter spaces. The results include preprocessed data set for four years, wind power forecast using the selected models and the associated errors for each model.

3.1. Hyper-parameter setup and tuning

An essential stage in machine learning model optimization is hyperparameter tuning. Hyper-parameters are used by the learning algorithm when it is learning but they are not part of the resulting model. Setting up a better deep learning model may be built with the help of optimal hyperparameter selection and setting, which can also shorten training times and eliminate pointless parameters. In order to optimize model performance, the optimal configuration must be chosen throughout the hyperparameter tuning phase. It has been reported that based on the level of fine-tuning, the Neural Network model's accuracy can range from 25 % to 90 % [24]. hyperparameters considered include; optimizer, dropouts, activation function, learning rate, number of epochs, and batch size. Over fitting is a common problem for neural networks. A dropout layer has been added to hidden layers of the RNN model for reducing such over fitting problems in training by sidestepping randomly selected neurons. The dropout rate of 0.1,0.2,0.3 were used and finally 0.1 is for each hidden layer of the recurrent neural network, because when we increase the size of the dropout rate the number of neurons that are deactivated increases which causes the model to fail to handle the dataset optimal features.

Tuning hyperparameters using grid search has been applied to improve forecasting results and reduce overfitting and underfitting of the model. A discrete grid is built within the defined hyperparameter limits, and grid search evaluates each possible combination within this grid to calculate performance measures. Random search has been applied to hyperparameter tuning to explore a broader range of configurations and potentially achieve optimal results.

3.2. Regression models

After the dataset was preprocessed, the next task was to train deep learning models for regression using the input data as well as forecasting wind power. For the regression of the wind data, models have been developed using deep learning algorithms; LSTM, Bi-LSTM, and GRU. All the three models have used different types/sizes of batch size, epochs, optimizer, learning rate, and dropouts. These techniques are receiving increased attention as a result of their suitability for wind power forecasting and their capacity to predict complex aspects without the need for expert involvement. Metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or Mean Absolute Percentage Error (MAPE) have been used to assess each experimental model's performance.

3.2.1. Building Long Short-Term Memory (LSTM) model

As it could be seen in Fig. 8, the training and validation loss of the LSTM model was higher at the initial stage of the training due to the newness of training data features for the model. As training goes on, both training and validation losses should ideally decline. This

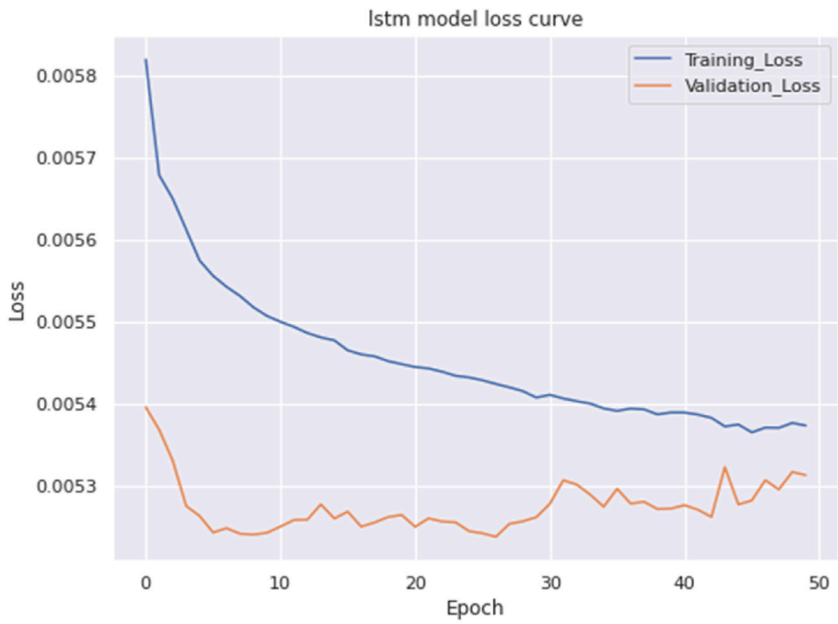

Fig. 8. LSTM model training and validation loss graph.

balance suggests that the model is generalizing well and learning efficiently. To sum up, monitoring both training and validation loss offers a thorough understanding of the model's functioning and helps to guarantee that it learns efficiently while making good generalizations to fresh data. Gradually the loss decreases when the model handles more features from the dataset. As shown in Fig. 8, the training and validation losses approach each other and become stabilized after 45 epoch, which suggests that the epoch size shall be above 45. From hyperparameter set up and tuning, it has been found that, an optimal hyperparameter setup by using grid search for LSTM has been found at batch size of 64 with 50 epochs using Adam as an optimizer, learning rate of 0.01, and dropout of 0.1. The performance of the model has been measured with the MAE and MAPE (using Eqs. (1) and (2)) and result of 0.645 and 0.398 have been reported respectively.

Evaluating the performance of LSTM networks for wind power prediction requires comparing the anticipated and real power levels. However, the first step is to train LSTM using historical wind power data before viewing the results. Fig. 9 depicts the power prediction using LSTM model through comparing the actual historical data and the predicted value. The forecasting number is seen to be quite close to the actual value. Most significantly, even after multiple spikes appear in the forecasting result, the forecasting values' errors are extremely low. The production of wind power is highly variable and dependent on a number of variables, such as the weather and the time of day. Because LSTM models are trained on historical wind speed and power generation data, they are able to handle this complexity with effectiveness. During, the comparison process repeated tuning of model has been conducted to match the actual data by varying the architecture, adding more features, and tweaking the hyperparameters.

3.2.2. Building bidirectional Long Short-Term Memory (Bi-LSTM) model

Fig. 10 demonstrates the loss graph for Bi-LSTM model. Bi-LSTM model is trained using the maximum input size of 50 in each forward and backward direction with 3 dense layers. An optimal hyperparameter setup by using grid search for Bi-LSTM has been found at batch size of 20 with 200 epochs using RMSprop as an optimizer, learning rate of 0.001, and dropout of 0.1. As it could be seen in Fig. 10, the loss decreases when the number of epochs increased similar to LSTM model. However, the training and validation losses approach each other and become stabilized after 100 epoch, which suggests that the epoch size shall be above 100 and its optimal epoch is taken as 200. So, we can conclude that the model gradually learned the features of our dataset and could be used for predicting the wind power with reasonable accuracy. Then, the performance of the model has been measured with the MAE and MAPE (applying Eqs. (1) and (2)) and result of 0.644 and 0.388 have been reported respectively.

Similar to LSTM network, Evaluating the performance of Bi-LSTM *n*etworks for wind power prediction requires comparing the anticipated and real power levels. The forecasted output power using the BiLSTM model is plotted by comparing the actual and the predicted power from the data set as shown in Fig. 11. The actual power and predicted power of the model are very close each other. Bi-LSTM networks, in contrast to LSTM networks, process data both forward (from the past to the future) and backward (from the future to the past). This enables them to make predictions based on the present time step while taking future context into account. As a result, Bi-STLM is better able to identify intricate patterns and relationships in the data for more effective management of long-term dependencies.

3.2.3. Building Gated Recurrent Unit (GRU) model

GRU educes the vanishing gradient issue, uses less memory than LSTM, is faster, has a straightforward design, and can handle long-term data [25]. The overall training and validation loss of the GRU model is summarized on Fig. 12. At the initial stage of the training, it seems that the training loss was higher than the validation loss due to the small validation data size than the training data size which

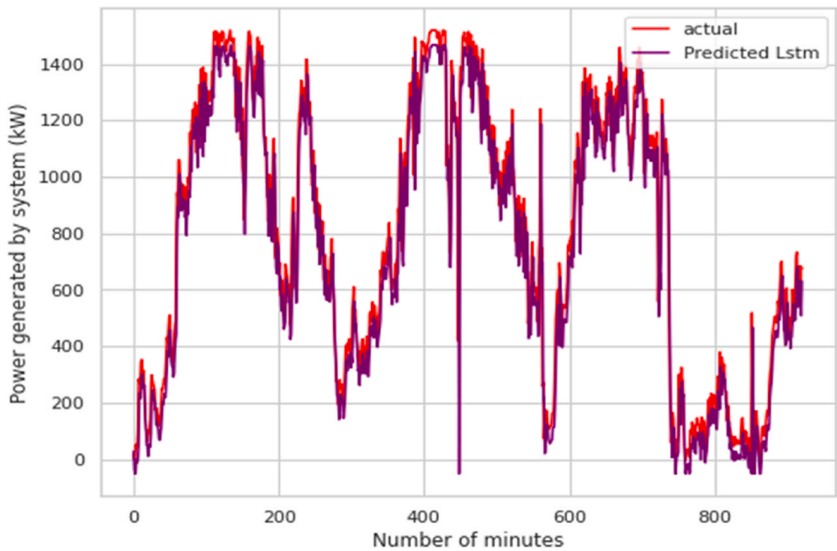

Fig. 9. LSTM model power prediction.

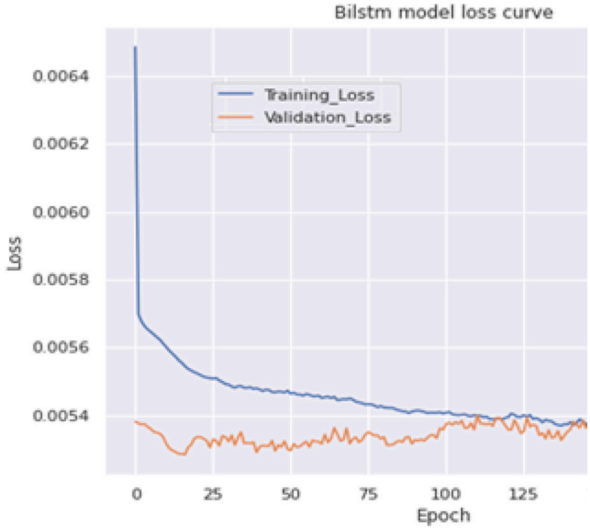

Fig. 10. BiLSTM and model training and validation loss graph.

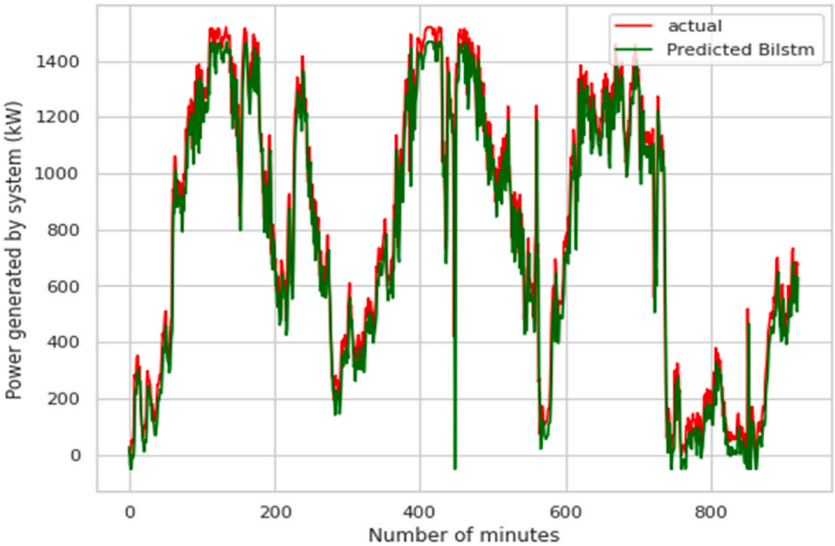

Fig. 11. BiLSTM model power prediction.

makes the model easily handle less complicated features of validation data. As it could be seen in Fig. 12, the training and validation losses approach each other and become stabilized around the epoch size of 140. An optimal hyperparameter setup for GRU has been found at batch size of 20 with 150 epochs using Adagrad as an optimizer, learning rate of 0.001, and dropout of 0.1. The performance of the model has been measured with the MAE and MAPE and result of 0.645 and 0.406 have been reported respectively.

To forecast wind power, the trained and validated model is put to the test using testing data. The wind power comparison between the actual and predicted using GRU model has been presented in Fig. 13. As could be seen in Fig. 13, the real and anticipated powers are quite similar to one another. In multi-step-ahead forecasting of wind power problems, it can be concluded that the GRU is a capable substitute for the LSTM, since it can reach a comparable forecasting accuracy with less computing time [26].

Table 1 depicts the model evaluations using MAE, MAPE, RMSE and R^2. Since wind power forecasting is a regression problem, we have used error-based metrics to gauge the variation between actual and predicted wind power. The evaluations indicate that the BiLSTM algorithm, due to its capability to process the wind power data in both forward and backward directions, has outperformed LSTM and GRU. Similar modeling of wind power output at two topographically distinct regions of Ethiopia was conducted using ERA5 data, and the performance metrics of MAE and RMSE were employed for evaluation by Ref. [27]. The researcher reported that respective hourly MAE and RMSE of 2.5 and 4.54 have been found for Adama II. This suggests that the current models have showed higher accuracy. Moreover, the research conducted on multi-step prediction of wind power using LSTM by Refs. [28,29] reported a

Fig. 12. Training and validation loss graph for GRU model.

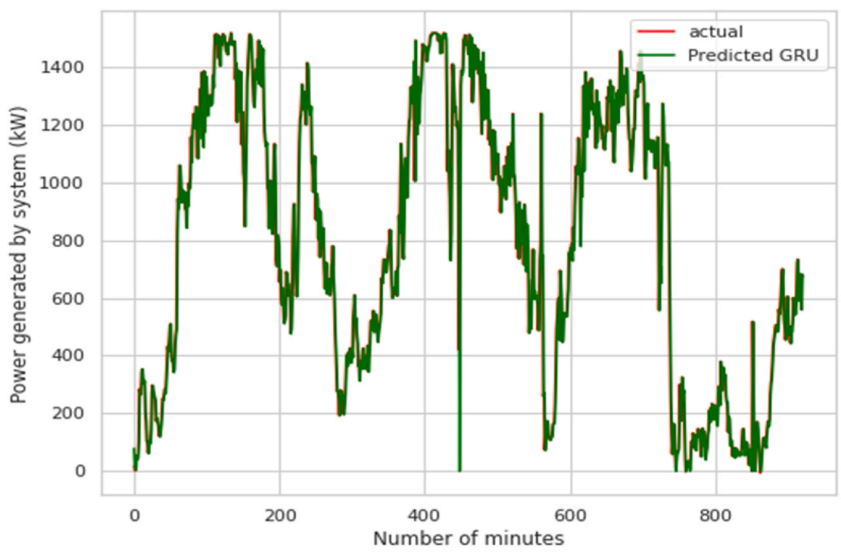

Fig. 13. GRU model power perdition.

Table 1
Performance comparison of the LST, BiLSTM and GRU algorithms.

Model	Performance metrics			
	MAE	MAPE	RMSE	R^2
LSTM	0.645	0.398	0.774	0.976
BiLSTM	0.644	0.388	0.769	0.978
GRU	0.645	0.406	0.775	0.977

RMSE value of 0.891 and 0.8643, respectively. The result suggests that the current model able to predict more accurately than the reported results.

4. Conclusion

Wind power is very intermittent and difficult to know the energy production capacity in the future. Moreover, the wind power is dependent on weather and environmental condition. This means it is difficult to adapt the forecasting model developed in other country. Hence, wind power forecasting is site dependent and necessary to develop appropriate model based on environmental and weather conditions of each site. In this work, we have designed wind power forecasting model using deep learning approach. This has a positive impact in supply and demand side energy planning and scheduling tasks as well as to maintain its energy resources. LSTM, Bi-LSTM, and GRU were used in our experiments. A total of 163,802 rows of data spanning from four years (2016–2019) have been used as input. Based on the forecasting experiment conducted, the following are summary of findings have been found.

- A comparison with deep learning forecasting techniques including LSTM, Bi-LSTM and GRU was conducted to demonstrate the effectiveness of the model. To prove its efficacy, sensitive and statistical analysis were also carried out.
- The R^2 value for all three models (LSTM, Bi-LSTM, and GRU) are all higher than 0.97, which shows very high level of predictive accuracies.
- The MAE and MAPE of the experimental LSTM model are found as 0.645 and 0.398 respectively.
- For Bi-LSTM model, MAE and MAPE are found as 0.644 and 0.388 respectively.
- For GRU model also MAE and MAPE of the experiment results 0.645 and 0.406 respectively.

Based on the model evaluations, all the three models achieved acceptable results. However, Bi-LSTM slightly outperforms the other two models and it shall be reproducible for further comparison. It is crucial to acknowledge certain constraints associated with our research. First, based on the unique features of the meteorological data and the wind power plant's location, the effectiveness of the deep learning models used may vary. Therefore, in order to evaluate the generalization of models, additional validation and testing across other datasets and geographical locations are required. Further research work has to be done to evaluate the effect of other climatic factors on the forecast accuracy of wind power. Moreover, the model shall be tested with other windfarms. The developed model could also be used to forecast the potential power production trend for the new wind farm analysis.

CRediT authorship contribution statement

Seblewongale Mezgebu Ayene: Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Abdulkerim Mohammed Yibre:** Writing – review & editing, Visualization, Validation, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to acknowledge Bahir Dar institute of technology and Adama wind farm.

Data availability

Data will be provided on request.

References

[1] M.A. Hossain, H.R. Pota, W. Issa, M.J. Hossain, Overview of AC microgrid controls with inverter-interfaced generations, Energies 10 (9) (2017) 1–27, https://doi.org/10.3390/en10091300.
[2] M.A. Hossain, R.K. Chakrabortty, S. Elsawah, M.J. Ryan, Very short-term forecasting of wind power generation using hybrid deep learning model, J. Clean. Prod. 296 (2021) 126564, https://doi.org/10.1016/j.jclepro.2021.126564.
[3] A.M. Foley, P.G. Leahy, A. Marvuglia, E.J. McKeogh, Current methods and advances in forecasting of wind power generation, Renew. Energy 37 (1) (2012) 1–8, https://doi.org/10.1016/j.renene.2011.05.033.
[4] G. Giebel, G. Kariniotakis, Wind Power Forecasting-A Review of the State of the Art, Elsevier Ltd, 2017, https://doi.org/10.1016/B978-0-08-100504-0.00003-2, 2007.
[5] H. Demolli, A. Sakir, A. Ecemis, M. Gokcek, Wind power forecasting based on daily wind speed data using machine learning algorithms, Energy Convers. Manag. 198 (July) (2019) 111823, https://doi.org/10.1016/j.enconman.2019.111823.
[6] A.-N. Buturache, S. Stancu, Wind energy prediction using machine learning, Low Carbon Econ. 12 (1) (2021) 1–21, https://doi.org/10.4236/lce.2021.121001.
[7] W.-Y. Chang, A literature review of wind forecasting methods, J. Power Energy Eng. 2 (4) (2014) 161–168, https://doi.org/10.4236/jpee.2014.24023.
[8] D.B. De Alencar, C. De Mattos Affonso, R.C.L. De Oliveira, J.L.M. Rodríguez, J.C. Leite, J.C.R. Filho, Different models for forecasting wind power generation: case study, Energies 10 (12) (2017), https://doi.org/10.3390/en10121976.

[9] P. Ekanayake, A.T. Peiris, J.M.J.W. Jayasinghe, U. Rathnayake, Development of wind power prediction models for pawan danavi wind farm in Sri Lanka, Math. Probl Eng. 2021 (2021), https://doi.org/10.1155/2021/4893713.
[10] D.D. Tung, T.H. Le, A statistical analysis of short-term wind power forecasting error distribution, Int. J. Appl. Eng. Res. 12 (10) (2017) 2306–2311.
[11] M.J. Cui, D.P. Ke, Y.Z. Sun, D. Gan, J. Zhang, B.M. Hodge, A scenario generation method for wind power ramp events forecasting, IEEE Power Energy Soc. Gen. Meet. 2015-Septe (2) (2015) 422–433, https://doi.org/10.1109/PESGM.2015.7285818.
[12] M.J. Ghadi, S.H. Gilani, H. Afrakhte, A. Baghramian, A novel heuristic method for wind farm power prediction: a case study, Int. J. Electr. Power Energy Syst. 63 (2014) 962–970, https://doi.org/10.1016/j.ijepes.2014.07.008.
[13] I. Okumus, A. Dinler, Current status of wind energy forecasting and a hybrid method for hourly predictions, Energy Convers. Manag. 123 (2016) 362–371, https://doi.org/10.1016/j.enconman.2016.06.053.
[14] X. Wang, P. Guo, X. Huang, A review of wind power forecasting models, Energy Proc. 12 (2011) 770–778, https://doi.org/10.1016/j.egypro.2011.10.103.
[15] X. Kong, L. Ma, X. Liu, M.A. Abdelbaky, Q. Wu, Wind turbine control using nonlinear economic model predictive control over all operating regions, Energies 13 (1) (2020) 1–21, https://doi.org/10.3390/en13010184.
[16] M.A. Abdelbaky, X. Liu, D. Jiang, Design and implementation of partial offline fuzzy model-predictive pitch controller for large-scale wind-turbines, Renew. Energy 145 (2020) 981–996, https://doi.org/10.1016/j.renene.2019.05.074.
[17] X. Kong, et al., Large-scale wind farm control using distributed economic model predictive scheme, Renew. Energy 181 (2022) 581–591, https://doi.org/10.1016/j.renene.2021.09.048.
[18] M. Ran, J. Huang, W. Qian, T. Zou, C. Ji, EMD-based gray combined forecasting model - application to long-term forecasting of wind power generation, Heliyon 9 (7) (2023) e18053, https://doi.org/10.1016/j.heliyon.2023.e18053.
[19] M. AlShafeey, C. Csaki, Adaptive machine learning for forecasting in wind energy: a dynamic, multi-algorithmic approach for short and long-term predictions, Heliyon 10 (15) (2024) e34807, https://doi.org/10.1016/j.heliyon.2024.e34807.
[20] K.N. Şahin, M. Sutcu, Probabilistic assessment of wind power plant energy potential through a copula-deep learning approach in decision trees, Heliyon 10 (7) (2024) e28270, https://doi.org/10.1016/j.heliyon.2024.e28270.
[21] B. He, et al., A combined model for short-term wind power forecasting based on the analysis of numerical weather prediction data, Energy Rep. 8 (2022) 929–939, https://doi.org/10.1016/j.egyr.2021.10.102.
[22] V. Chandran, et al., Wind power forecasting based on time series model using deep machine learning algorithms, Mater. Today Proc. 47 (xxxx) (2021) 115–126, https://doi.org/10.1016/j.matpr.2021.03.728.
[23] M. Santhosh, C. Venkaiah, D.M. Vinod Kumar, Current advances and approaches in wind speed and wind power forecasting for improved renewable energy integration: a review, Eng. Reports 2 (6) (2020) 1–20, https://doi.org/10.1002/eng2.12178.
[24] Md Riyad Hossain, Dr Douglas Timmer, Machine learning model optimization with hyper parameter tuning approach, Global J. Comput. Sci. Technol. 21 (2) (2021) 1, 1.
[25] C. Gu, H. Li, Review on deep learning research and applications in wind and wave energy, Energies 15 (4) (2022), https://doi.org/10.3390/en15041510.
[26] Z. Niu, Z. Yu, W. Tang, Q. Wu, M. Reformat, Wind power forecasting using attention-based gated recurrent unit network, Energy 196 (2020) 117081, https://doi.org/10.1016/j.energy.2020.117081.
[27] K.L. Nefabas, L. Söder, M. Mamo, J. Olauson, Modeling of ethiopian wind power production using era5 reanalysis data, Energies 14 (9) (2021) 1–17, https://doi.org/10.3390/en14092573.
[28] H. Shu, W. Song, Z. Song, H. Guo, C. Li, Y. Wang, Multistep short-term wind speed prediction with rank pooling and fast Fourier transformation, Wind Energy 27 (7) (2024) 667–694, https://doi.org/10.1002/we.2906.
[29] A.A. Mana, Winds of change: enhancing wind power generation forecasting with LSTM models and advanced techniques in a single turbine wind farm, Artif. Intell. Appl 00 (May 2023) (2024) 1–11, https://doi.org/10.47852/bonviewaia42021106.