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EFFICIENT DEEP LEARNING TECHNIQUES FOR SHORT-TERM WIND POWER FORECASTING

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ABSTRACT

Wind power is playing an increasingly important role in present power grids due to innovative advancements in wind energy generation. Wind power and wind speed should always be accurately predicted in order to assess wind power for power system operation and planning properly. Due to the advancement of AI technologies, Deep learning, in particular, is increasingly being used in wind energy forecasting because of its outstanding capacity to handle complicated nonlinear challenges. The aim of this paper is to forecast the wind power, speed, and direction for a given historical wind data using two deep learning techniques; long short-term memory (LSTM) and gated recurrent unit (GRU). The experiment results show that GRU outperforms LSTM for a small number of epochs, but when epochs increase to a larger number, the behavior of both techniques is nearly equal, with a preference for LSTM with a mean square error of 0.03 %.

INDEX TERMS- Wind power, forecasting, deep learning, gated recurrent unit, long short-term memory, wind speed, wind direction, and machine learning.

1. INTRODUCTION

Wind energy is a significant source of clean energy and a viable alternative to fossil fuels. Concerns about global warming and other environmental issues as well as the diminishing supply and decreasing quality of oil and gas, have all led to the rising interest in renewable resource globally. Predictions of wind speed and power that are both precise and accurate are the most important and important factors in making the right and most efficient operational decisions in the wind energy industry. Wind energy and forecasting are critical components of planning, controlling, and monitoring of smart wind energy systems[1].

Interconnecting wind energy to the grid imports high benefits in term of economic and environmental aspects. Wind energy, on the other hand, can cause severe complications in sustaining a safe and stable power source Because of the way the wind moves and changes the environment [2]. Wind power forecasting is a crucial part of enhancing the dependability and efficiency of the power system.. Wind farm placement, management, and control may all be improved by using this information. It can also serve as a foundation for executing power market transactions and connecting to distributed grids.[3].

It's impossible to program wind energy since it's a random and intermittent source of electricity that can alter dramatically even in the short term [4]. As a result, estimating and correctly predicting the amount of wind energy available at any particular time is challenging. This fluctuation complicates the operation of power systems. As a result, its potential energy production must be estimated or forecasted. Based on current and

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historical data, a wind energy prediction tool is built to anticipate what could happen in the future [4].

Renewable and pollution-free wind power is attracting increasing attention as a source of electricity generation. The intermittent nature of wind power's energy output provides issues for the safety and stability of electric power networks on a large scale. Because of this, wind speed and power forecasts have become more important in system dispatch planning in order to minimize wind power variations.. Result of advances in artificial intelligence, particularly deep learning, forecasting of wind speed and power are becoming increasingly dependent on deep learning-based models because of their greater capacity to handle complicated nonlinear situations [5].

2. RESEARCH CONTRIBUTIONS

Micro grids, smart buildings, and smart houses can't function without wind energy; it's a major source of electricity generation. As a result of its unpredictability and limited predictability, wind power is an intermittent power source. This has a substantial influence on the safety, stability, and dependability of large grid-integrated wind energy systems..

Predicting future wind power accurately is one of the potential solutions to the above barriers. Lowering operational costs and enhancing wind power profitability and competitiveness will also be aided by the capacity to predict the future. This paper can help researchers by providing information about the recent deep learning techniques to be used for wind energy forecasting's, such as gated recurrent unit (GRU) modeling and long short-term memory (LSTM) modeling.

3. WIND POWER FORECASTING TECHNIQUES

Wind-power forecasting has been conceived, planned, and implemented in a variety of ways. They can be classified into multiple groups according to various categorization criteria, as illustrated in Fig. 1.

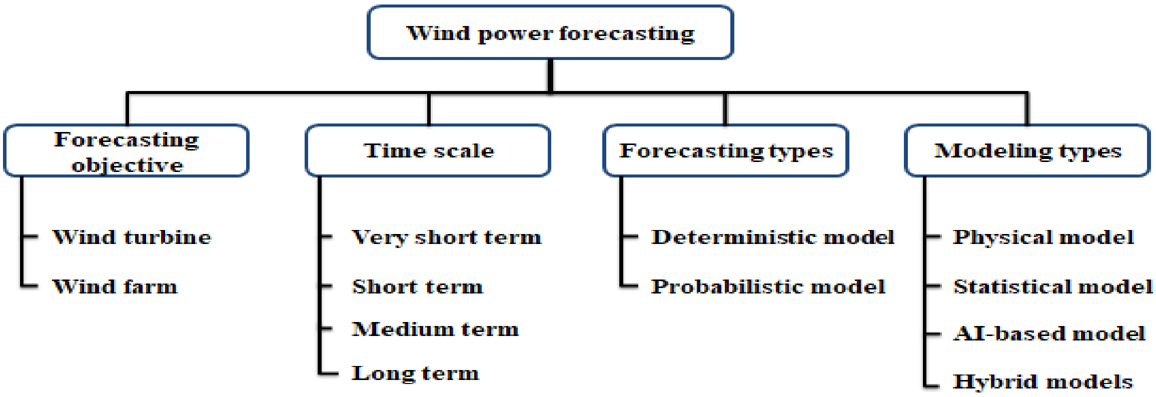

FIG. 1. WIND POWER FORECASTING CLASSIFICATION.

We may divide models into two categories according to their forecasting objectives: wind turbine and wind farm wind energy prediction[6], [7]. a single wind turbines power output. Wind turbine data from a large number of turbines may be used to anticipate the total energy production of a wind farm. However, this method is far more difficult.

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Wind power prediction systems can be categorized based on their timescales: There are four types of time horizons: short-term (within the next 30 minutes), medium-term (within the next six hours), and long-term (more than six hours up to one day or longer) (one day to one week and more ahead)[8]. Useful in turbine control and load-monitoring, short-term and medium-term predictions are used for unit commitment planning, while long-term forecasts are used to identify the ideal time to carry out maintenance.[9]. Moreover, based on the type of prediction made, wind forecast models may be divided into deterministic and probabilistic types. [10]. Due to the complexity of the situation, deterministic models that provide just point wind power forecasts are limited in their forecasting performance and frequently generate inadequate forecasts with obvious mistakes. Probabilistic models, which frequently provide decision-makers with more insight than point predictions, can express uncertainty in terms of forecast intervals[11].

Based on the differences in modeling philosophy, Four types of forecasting models exist, physical models, traditional statistical models, AI-based models, and a combination of the three (hybrid). In this case, we're talking about physical models, e.g., weather researcher forecasting (WRF)[12] and numerical weather prediction (NWP)[13], which typically take a variety of meteorological parameters into account. Some of the most common traditional statistical models are the autoregressive integrated moving average (ARIMA)[14], the autoregressive moving average (ARMA)[15], and the fractional-ARIMA (f-ARIMA)[16]. Because it is a time series model that may be used to quantify the linear fluctuations in wind power at various locations, it differs from physical techniques. In general, forecasts in wind power forecasting perform well, especially in short and medium-term time frames.

Artificial Intelligence (AI) models have also been widely employed in wind power forecasting due to advancements in computer science. There are many techniques used in wind power forecasting, such as; support vector machine (SVM)[17], [18], extreme learning machine (ELM)[19], fuzzy logic method, back propagation neural network (BPNN)[20], multi-layer perception (MLP)[21], long short-term memory (LSTM)[22], convolution neural network (CNN)[23], gated recurrent unit (GRU)[24] and recurrent neural network (RNN)[25].

By integrating multiple types of the above models can build the Hybrid models to interpret various aspects of wind power volatility. Based on their hybrid techniques, hybrid prediction models are classified into two types in the literature: weight-based models and stacking-based models. The estimates of one or maybe more base models are typically regarded as features by stacking-based forecasting models, which are then merged with another higher-level model[26]. With regards to the weighted prediction model, they can be constructed using a diverse set of forecasters[27].

The structure of various prediction methods has a considerable impact on their effectiveness, thus, many researchers utilize various forms of intelligent optimization strategies to identify the best configurations of various wind power forecasting models.

4. LONG SHORT TERM MEMMORY

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LSTM has been formulated to solve the conventional RNN's long-term dependence issue since learning about the connections becomes increasingly difficult as the distance between relevant inputs increases. It is a variant of the RNN model that is defined by the presence of a cell state[28].The LSTM consists of three gates: input gate, forget, and output gate. The sigmoid layer and point wise multiplication are used to control the significance of each gate. Fig.2 illustrates the architecture of the LSTM.

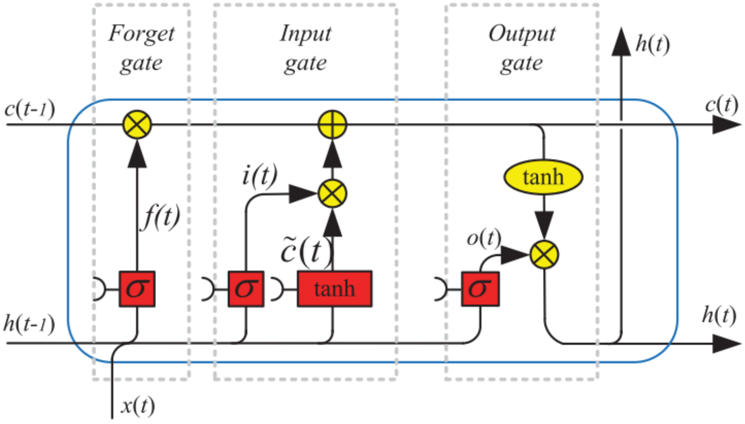

FIG.2. LSTM ARCHITECTURE[28].

The LSTM cells can be mathematically described as follows using the connections illustrated in Fig.2[28]:

$$f_t = \sigma\left(W_{fh}h_{t-1} + W_{fx}x_t + b_f\right) \quad (1)$$

$$i_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \quad (2)$$

$$\tilde{c}_t = \tanh(W_{\tilde{c}h}h_{t-1} + W_{\tilde{c}x}x_t + b_{\tilde{c}}) \quad (3)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \quad (4)$$

$$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \quad (5)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (6)$$

Wherex_t, h_t, and o_t represent the input data, the recurrent, and the output data of each cell at time t, in sequence,$f_t$represent the forget gate, $c_t$donates the LSTM's cell state,W_i, $W_{\tilde{c}}$, and W_o represent the network weights,the operator '·' used for the multiplication of two point wise vectors and b is the bias.

As the cell state is updated, the input gate determines which new information can be recorded in the cell state and which data can be produced depending on the cell state. The forget gate has the ability to determine what information is discarded from the current cell state. Once the forget gate, f_t, has a value of 1, and it retains this data; when it has a value of 0, it discards all information.

According to the findings, the forget and output gates are the most critical components, and removing any of them results in severe performance reductions across the network. In addition, the list of parameters and the computational cost may be lowered without significantly impacting network performance by changing the connected input

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and forget gate.. Due to its significant capability, LSTM has been the focal point of deep learning, and its used to a variety of tasks [28].

5. GATED RECURRENT UNIT

The LSTM cell has a greater ability for learning than the typical recurrent cell. The additional factors, however, increase the amount of computational load used. The gated recurrent unit (GRU) was developed. Fig.3 illustrates the architecture of the GRU.

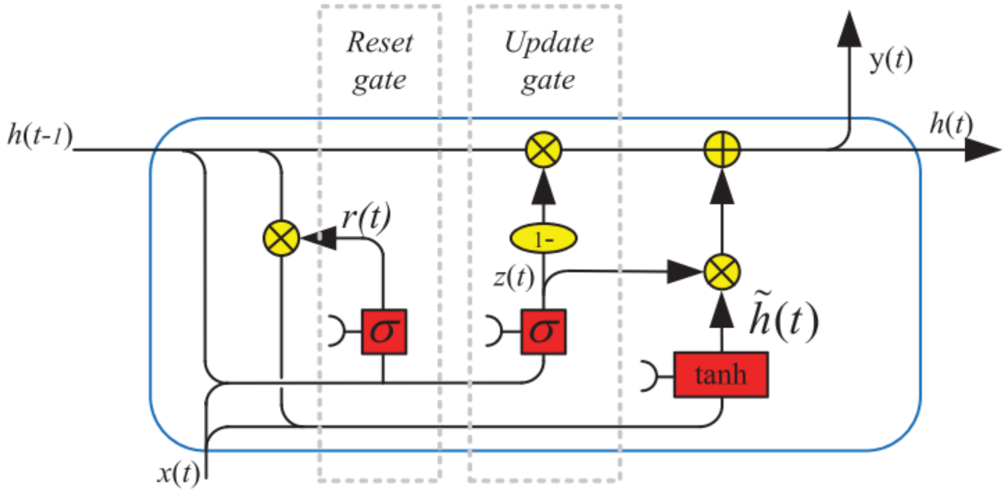

FIG.3. GRU ARCHITECTURE [28].

The mathematical formulas for the GRU cell are as follows, based on Figure 3, which represents the information bellow[28]:

$$r_t = \sigma(W_{rh}h_{t-1} + W_{rx}x_t + b_r) \quad (7)$$

$$z_t = \sigma(W_{zh}h_{t-1} + W_{zx}x_t + b_z) \quad (8)$$

$$\tilde{h}_t = \tanh(W_{\tilde{h}h}(r_t \cdot h_{t-1}) + W_{\tilde{h}x}x_t + b_z) \quad (9)$$

$$h_t = (1 - z_t) \cdot h_{t-1} \quad (10)$$

To minimize the number of arguments, the GRU cell incorporates the LSTM cell's forget and input gates as an update gate. There are only two gates in the GRU cell: an update gate and a reset gate. Which resulted to; it is possible to save a single gating signal and its associated parameters. The GRU is essentially LSTM with the addition of a forget gate. Due to the absence of one gate, the single GRU cell is less powerful than the LSTM in its entirety.

6. WORK STRUCTURE

The physical model of this study is explained in Fig.4. Moreover, the overall work structure of this study is described in Fig. 5. The procedure of the study is explained as steps in detail below:

Step1: Preprocessing the data: Since the GRU and LSTM networks are sensitive to the scale of the input data. A normalization process is required to ensure that all data is consistent. [0, 1].

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Step2: Training the GRU/ LSTM model: For training, eighty percent of the newly reframed data is used, while twenty percent is used for validation testing. Predetermined training sets are utilized for the GRU/LSTM model to be trained.

Step3: Forecasting with GRU/ LSTM model the goal is to predict future wind power speed and direction rates based on past processing dynamics. The data for the future can be found in the testing set developed in step 2. Testing inputs must therefore be iteratively revised to reflect their predicted value each time.

It is, therefore possible to apply the optimum GRU/LSTM model to acquire the matching testing set's findings. Once the output data has been de-normalized, the final results may be achieved.

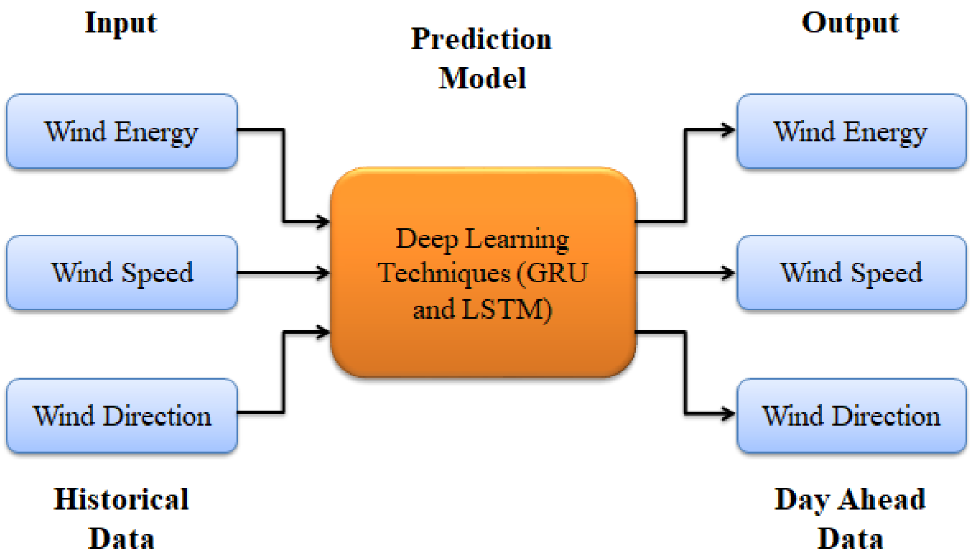

FIG.4. DAY AHEAD WIND ENERGY PREDICTION PHYSICAL MODEL.

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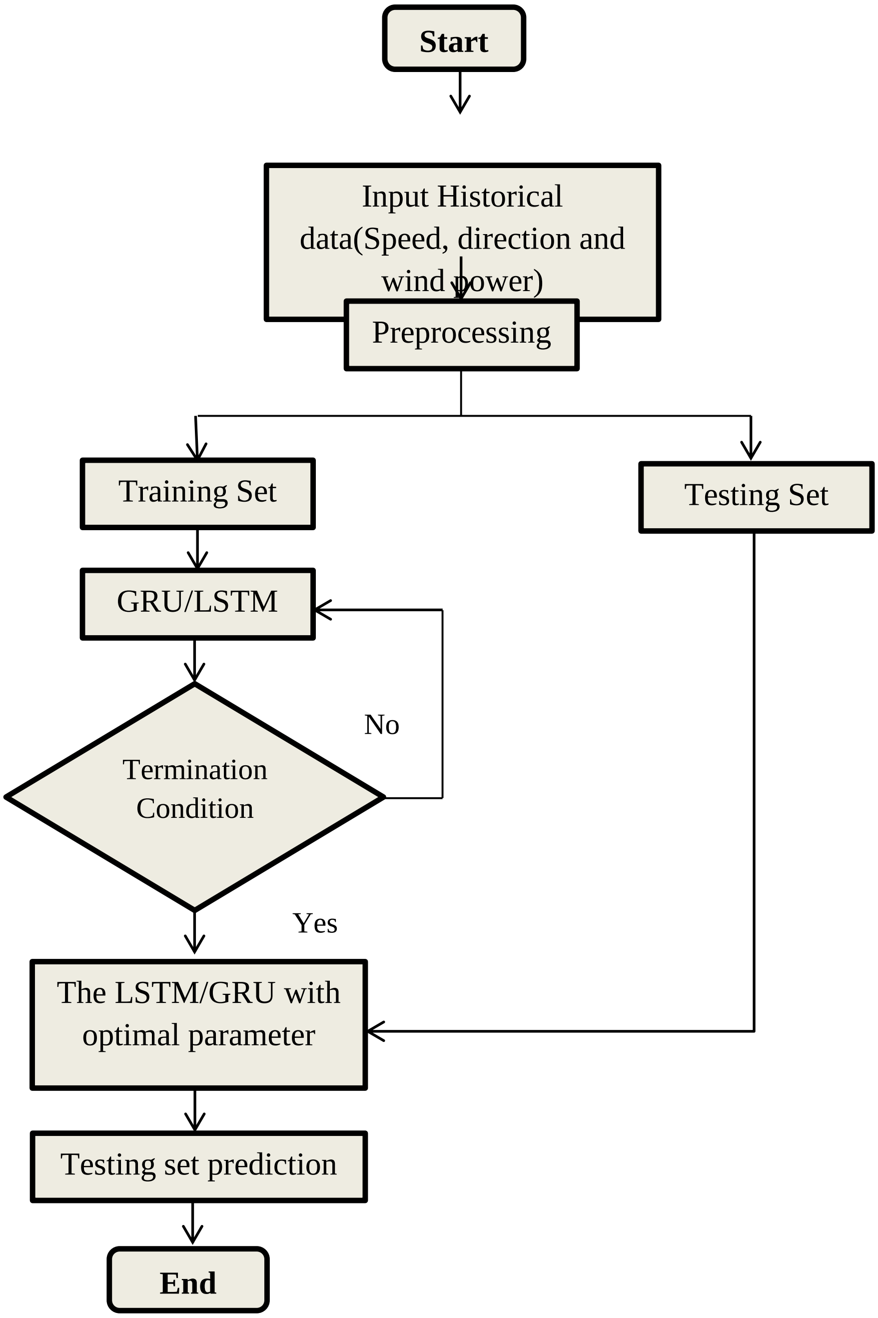

FIG.5 THE WORKFLOW OF THE PROPOSED APPROACH.

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7. CASE STUDY

The data were collected from the Sotavento wind farm which is used in this study. The Sotavento wind farm is located In Spain, Galicia (43.354377 +N, 7.881213+ W, m.a.s.l.). It has a total capacity of 17.56 MW and is made up of 24 turbines. The historical wind energy, direction, and speed output of this wind farm's 24 wind turbines with a 10-minute resolution in 2016 can be collected. As a result, each variable receives 144 sets of datasets per day [29]. Figures (6-8) illustrate the wind energy, speed, and direction performance within one year, respectively.

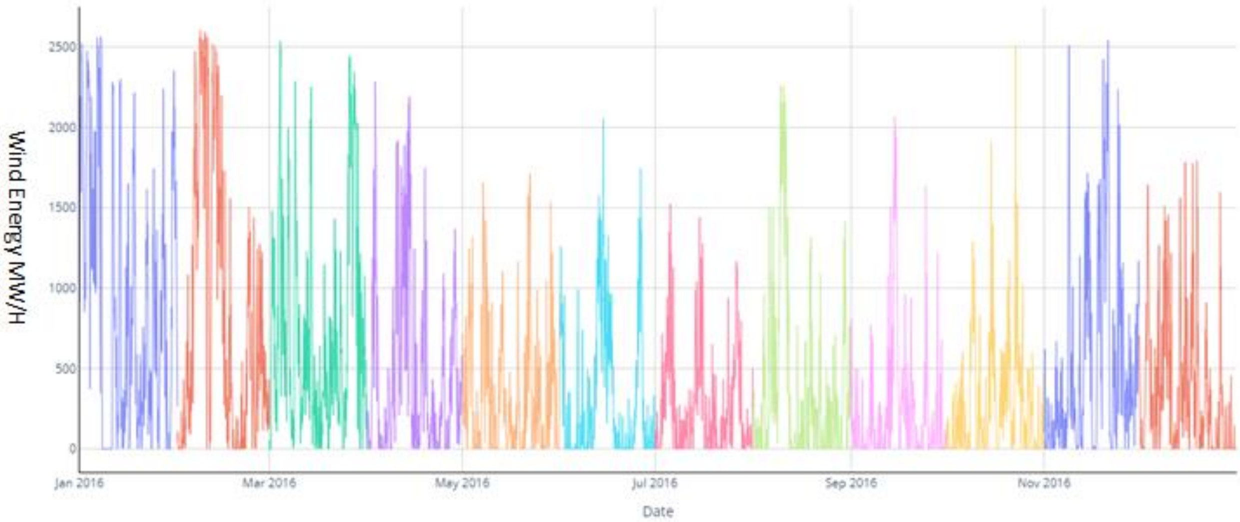

FIG.6. WIND ENERGY PERFORMANCE IN ONE YEAR.

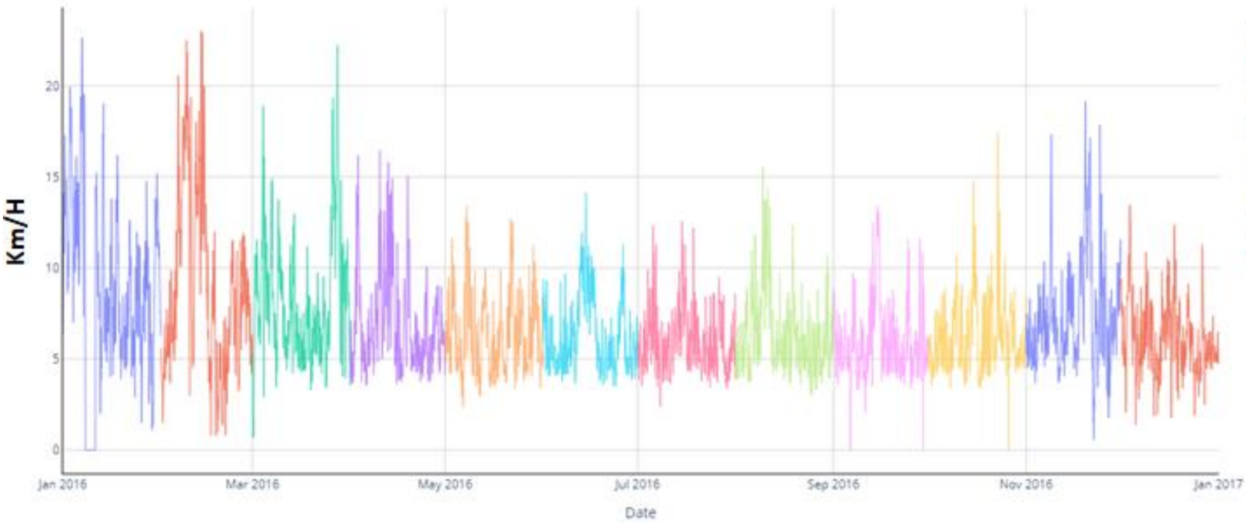

FIG.7. WIND SPEED PERFORMANCE IN ONE YEAR.

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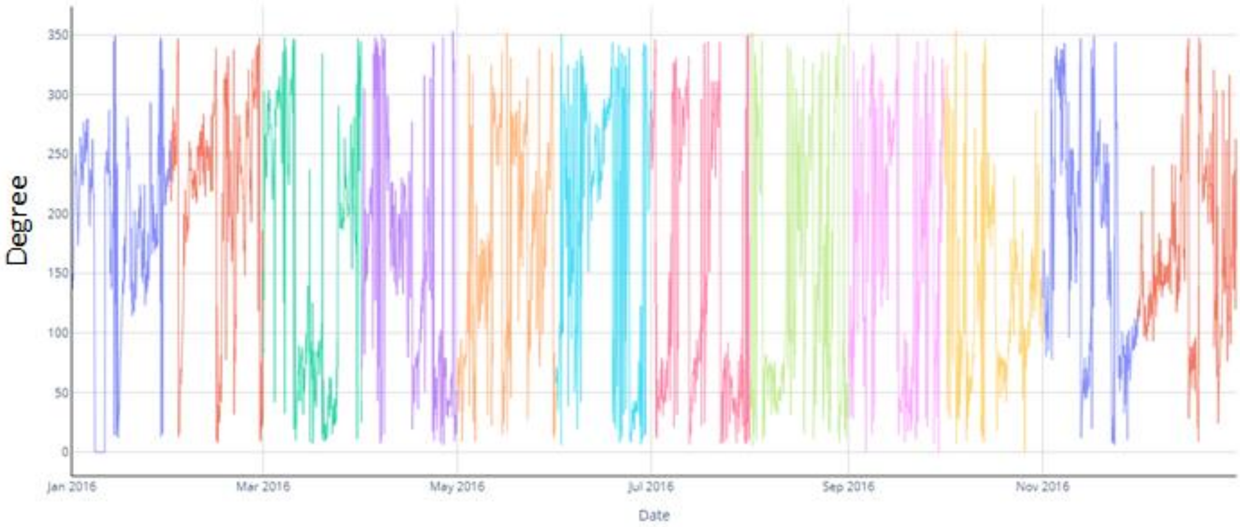

FIG.8.WIND DIRECTION PERFORMANCE IN ONE YEAR.

Seasonal variations in wind speed and direction are clearly evident. In spring, the wind speed varies more widely than in any other season. In the spring, the predominant wind direction in the southwest, while in the summer, strong winds come from all directions. In the fall and winter, the Low-speed wind blows from the northeast and east, with the former being the most prevalent direction.

8. RESULTS AND DISCUSSIONS

After applying the proposed forecasting techniques (GRU and LSTM) in the mentioned case study, the results show that in terms of mean squared error (MSE) and mean absolute error (MAE), the GRU outperforms LSTM when the number of epochs less than 500. However, in the case of having a higher number of epochs, both algorithms perform very closely with preference to LSTM in some cases. Tables (1-3) show the prediction results in terms of wind energy, speed, and direction.

Since the loss function of an LSTM and GRU model with fixed architecture varies with the training process, the number of epochs has an impact on their performance. Tables (1-3) show the results, respectively. The proposed models' loss function for the real-world case is high before the 500th epoch, indicating that the model is not yet well trained. The model should only be used to anticipate once the loss function has stabilized. Excessive training, on the other hand, may result in an overfitting issue, lowering reliability.

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TABLE.1: WIND ENERGY PREDICTION RESULTS.

No. of Epochs	GRU Evaluation of Training Data			LSTM Evaluation of Training Data		
	Loss	Mean Squared Error	Mean Absolute Error	Loss	Mean Squared Error	Mean Absolute Error
10	6.35	6.35	16.8	6.32	6.32	17.03
50	5.01	5.01	15.32	5.85	5.85	16.24
100	2.98	2.98	11.15	4.3	4.3	14.31
500	0.18	0.18	3.01	0.52	0.52	4.52
1000	0.1	0.1	2.28	0.1	0.1	2.24
5000	0.05	0.05	1.51	0.03	0.03	1.07

TABLE.2: WIND SPEED PREDICTION RESULTS.

No. of Epochs	GRU Evaluation of Training Data			LSTM Evaluation of Training Data		
	Loss	Mean Squared Error	Mean Absolute Error	Loss	Mean Squared Error	Mean Absolute Error
10	2.77	2.77	11.49	2.7	2.7	11.43
50	2.55	2.55	11.2	2.6	2.6	11.2
100	2.03	2.03	10.3	2.39	2.39	11.06
500	0.17	0.17	3.03	0.16	0.16	2.98
1000	0.04	0.04	1.63	0.13	0.13	2.24
5000	0.01	0.01	0.9	0.01	0.01	0.55

TABLE.3: WIND DIRECTION PREDICTION RESULTS.

No. of Epochs	GRU Evaluation of Training Data			LSTM Evaluation of Training Data		
	Loss	Mean Squared Error	Mean Absolute Error	Loss	Mean Squared Error	Mean Absolute Error
10	9.07	9.07	18.24	9.08	9.08	18.65
50	7.01	7.01	16.39	7.38	7.38	16.74
100	4.77	4.77	13.28	5.75	5.75	14.25
500	1.54	1.54	6.35	0.24	0.24	3.3
1000	0.05	0.05	1.61	0.37	0.37	3.63
5000	0.02	0.02	0.85	0.02	0.02	0.9

The testing set is by far the most important for the model validation since the testing set's results are what is really wanted. As a result, the testing set's results are examined further. The MSE and MAE of the two methods are graphically illustrated in Fig. 9 and 10, respectively. As shown, while the number of epochs increases, the performance of both algorithms works identically. However, for the first 500 epochs GRU outperforms the LSTM.

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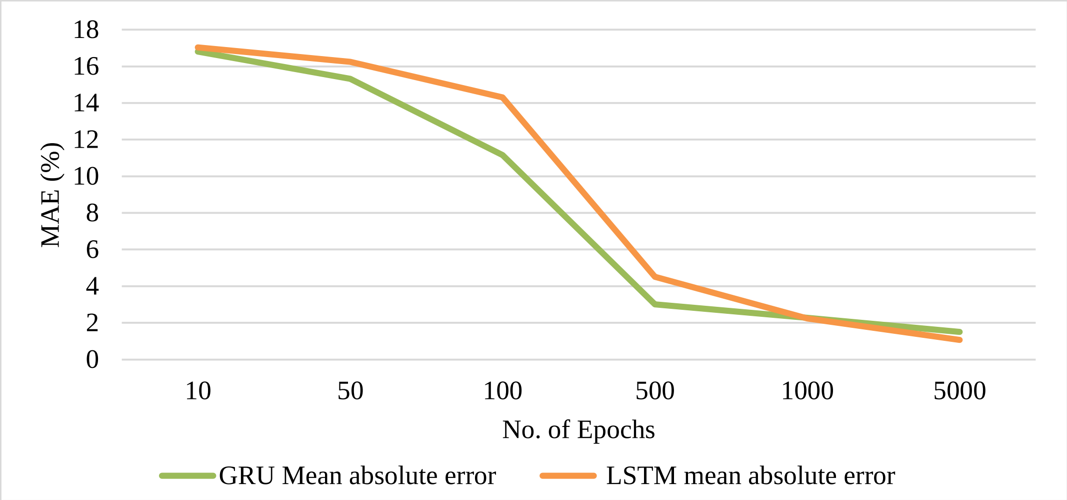

FIG.9. GRU AND LSTM FORECASTING MAE.

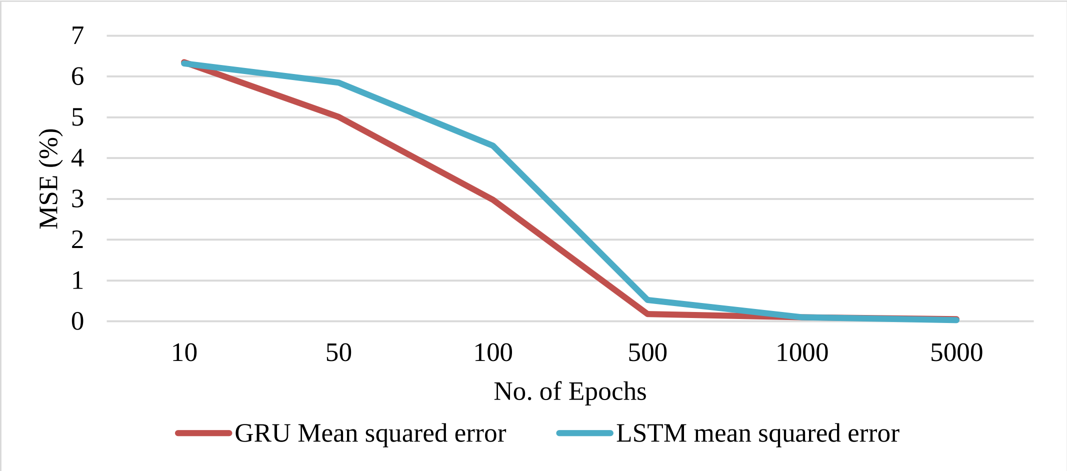

FIG.10. GRU AND LSTM FORECASTING MSE.

9. CONCLUSION

The wind is considered to be a promising source of energy currently, and it's attracting a lot of attention from all over the world. Wind energy is beneficial to the conservation of worldwide natural resources. Wind power, on the other hand, is uncontrollable, and inner instability keeps the usage rate low. The ability to accurately predict wind power and wind speed have become increasingly important in the pursuit of renewable energy sources.

In this study, wind power, speed, and direction historical data for one year were used to predict the short-term performance of wind power. Two common deep learning techniques were used; GRU and LSTM. The results show that for a low number of epochs, GRU outperforms the performance of LSTM; however, when the number of epochs increases, the performance of both techniques is almost the same, with a preference for LSTM with MSE of 0.03%.

REFERENCES

1) M. Ahmadi and M. Khashei, "Current status of hybrid structures in wind forecasting," *Eng. Appl. Artif. Intell.*, vol. 99, no. December 2020, p. 104133, 2021.
2) H. Demolli, A. S. Dokuz, A. Ecemis, and M. Gokcek, "Wind power forecasting based on daily wind speed data using machine learning algorithms," *Energy Convers. Manag.*, vol. 198, no. March, p. 111823, 2019.
3) B. Xiong, L. Lou, X. Meng, X. Wang, H. Ma, and Z. Wang, "Short-term wind power forecasting based on Attention Mechanism and Deep Learning," *Electr. Power Syst. Res.*, vol. 206, no. January, p. 107776, 2022.
4) J. Maldonado-Correa, J. C. Solano, and M. Rojas-Moncayo, "Wind power forecasting: A systematic literature review," *Wind Eng.*, vol. 45, no. 2, pp. 413–426, 2021.
5) Y. Wang, R. Zou, F. Liu, L. Zhang, and Q. Liu, "A review of wind speed and power forecasting with deep neural networks," *Appl. Energy*, vol. 304, no. April, p. 117766, 2021.
6) Y. Wang, Q. Hu, D. Srinivasan, and Z. Wang, "Wind Power Curve Modeling and Wind Power Forecasting With Inconsistent Data," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 16–25, 2019.
7) J. Zhang, J. Yan, D. Infield, Y. Liu, and F. sang Lien, "Short-term forecasting and uncertainty analysis of wind turbine power based on long short-term memory network and Gaussian mixture model," *Appl. Energy*, vol. 241, no. March, pp. 229–244, 2019.
8) H. Liu and C. Chen, "Data processing strategies in wind energy forecasting models and applications: A comprehensive review," *Appl. Energy*, vol. 249, no. April, pp. 392–408, 2019.
9) W. Zhao, Y. M. Wei, and Z. Su, "One day ahead wind speed forecasting: A resampling-based approach," *Appl. Energy*, vol. 178, pp. 886–901, 2016.
10) H. Liu, C. Chen, X. Lv, X. Wu, and M. Liu, "Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods," *Energy Convers. Manag.*, vol. 195, no. May, pp. 328–345, 2019.
11) X. Yuan, C. Chen, M. Jiang, and Y. Yuan, "Prediction interval of wind power using parameter optimized Beta distribution based LSTM model," *Appl. Soft Comput. J.*, vol. 82, p. 105550, 2019.
12) C. Wu, K. Luo, Q. Wang, and J. Fan, "Simulated potential wind power sensitivity to the planetary boundary layer parameterizations combined with various topography datasets in the weather research and forecasting model," *Energy*, vol. 239, p. 122047, 2022.
13) S. Hu *et al.*, "Hybrid forecasting method for wind power integrating spatial correlation and corrected numerical weather prediction," *Appl. Energy*, vol. 293, no. March, p. 116951, 2021.
14) W. Zhang, Z. Lin, and X. Liu, "Short-term offshore wind power forecasting - A hybrid model based on Discrete Wavelet Transform (DWT), Seasonal Autoregressive Integrated Moving Average (SARIMA), and deep-learning-based Long Short-Term Memory (LSTM)," *Renew. Energy*, vol. 185, pp. 611–628, 2022.
15) U. Zaman, H. Teimourzadeh, E. H. Sangani, X. Liang, and C. Y. Chung, "Wind Speed Forecasting Using ARMA and Neural Network Models," *2021 IEEE Electr. Power Energy Conf. EPEC 2021*, pp. 243–248, 2021.
16) H. Hu, L. Wang, and R. Tao, "Wind speed forecasting based on variational mode decomposition and improved echo state network," *Renew. Energy*, vol. 164, pp. 729–751, 2021.
17) L. L. Li, X. Zhao, M. L. Tseng, and R. R. Tan, "Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm," *J. Clean. Prod.*, vol. 242, p. 118447, 2020.
18) D. Salman and M. Kusaf, "Short-term unit commitment by using machine learning to cover the uncertainty of wind power forecasting," *Sustain.*, vol. 13, no. 24, 2021.
19) L. Tan, J. Han, and H. Zhang, "Ultra-Short-Term Wind Power Prediction by Salp Swarm Algorithm-Based Optimizing Extreme Learning Machine," *IEEE Access*, vol. 8, pp. 44470–44484, 2020.
20) R. Jiao, X. Huang, X. Ma, L. Han, and W. Tian, "A Model Combining Stacked Auto Encoder and Back Propagation Algorithm for Short-Term Wind Power Forecasting," *IEEE Access*, vol. 6, pp. 17851–17858, 2018.
21) Y. Li *et al.*, "Weather Forecasting Using Ensemble of Spatial-Temporal Attention Network and Multi-Layer Perceptron," *Asia-Pacific J. Atmos. Sci.*, vol. 57, no. 3, pp. 533–546, 2021.
22) L. Han, H. Jing, R. Zhang, and Z. Gao, "Wind power forecast based on improved Long Short Term Memory network," *Energy*, vol. 189, p. 116300, 2019.
23) C. Yildiz, H. Acikgoz, D. Korkmaz, and U. Budak, "An improved residual-based convolutional

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neural network for very short-term wind power forecasting," *Energy Convers. Manag.*, vol. 228, no. August 2020, p. 113731, 2021.
24) Z. Niu, Z. Yu, W. Tang, Q. Wu, and M. Reformat, "Wind power forecasting using attention-based gated recurrent unit network," *Energy*, vol. 196, p. 117081, 2020.
25) D. Salman, M. Kusaf, and Y. K. Elmi, "Using Recurrent Neural Network to Forecast Day and Year Ahead Performance of Load Demand: A Case Study of France," *2021 10th Int. Conf. Power Sci. Eng. ICPSE 2021*, pp. 23–27, 2021.
26) S. Cui, Y. Yin, D. Wang, Z. Li, and Y. Wang, "A stacking-based ensemble learning method for earthquake casualty prediction," *Appl. Soft Comput.*, vol. 101, p. 107038, 2021.
27) C. Wang, S. Zhang, L. Xiao, and T. Fu, "Wind speed forecasting based on multi-objective grey wolf optimisation algorithm, weighted information criterion, and wind energy conversion system: A case study in Eastern China," *Energy Convers. Manag.*, vol. 243, no. March, p. 114402, 2021.
28) Y. Yu, X. Si, C. Hu, and J. Zhang, "A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures," *Neural Comput.*, vol. 31, no. 7, pp. 1235–1270, Jul. 2019.
29) Y. Zhang, Y. Li, and G. Zhang, "Short-term wind power forecasting approach based on Seq2Seq model using NWP data," *Energy*, vol. 213, p. 118371, 2020.