Short-Term Wind Power Forecasting Using R-LSTM

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Abstract - Renewable energies such as wind and solar begin receiving remarkable popularity in accordance with the energy demand, expeditious expansion of solar and wind energy generation involves acute forecasting of wind and solar power, so in past and recent years it has become an intensive research area. An accurate forecast of wind power to maintain an affordable, secure, and economical power supply is most significant. Numerous investigations and research have been performed in this area in recent years. This research article aims to develop a short-term wind power forecasting model to improve the accuracy of the prediction. Therefore, a novel approach based on LSTM (Long Short-Term Memory) is proposed to forecast from 1 to 6 hours ahead of wind power. A recursive strategy is used when predicting short-term wind power, unlike the conventional LSTM approach. The proposed model is implemented using historical generated wind power data for Gujarat state. A comparative analysis is performed between the proposed and existing approach presented in the literature, from the analysis, it is noted that the proposed R-LSTM (Rolling-LSTM) model outperformed with minimal error and better accuracy.

Keywords - Long-Short Term Memory (LSTM), Wind Energy, Short-Term Wind Power Forecasting, Deep Learning.

1. Introduction

Renewable energy is now becoming increasingly important as countries around the world seek to achieve carbon neutrality. Wind power generation increased by 10% globally in 2017. Denmark is the pioneer, with wind turbines providing 44 percent of its electricity. Among the most complicated aspects of depending on wind energy is its unpredictability. The grid must be balanced by power system operators. This implies that, in general, the amount of energy generated must equal the amount of energy consumed.

Wind energy production must be accurately predicted to plan when backup facilities must be triggered. Forecasting most accurately reduces costs by stopping these facilities from being activated unnecessarily. It also helps two methods to trade with each other. Another application for a more reliable forecasting model is locating suitable sites for new wind turbines. Knowing how often energy can be generated at a given location can help with spatial planning. [1]

Wind power is the prominent sustainable power source on the planet. Wind energy is being promising, considering it as the most secure, cleanest, and quickest developing sustainable power source in the on-going years. The constant increase in energy utilization has the capability of the generation of wind power gigantic. In an electrical grid, the infiltration of renewable energy is expanding around the world, for reliability and operation of the grid, and also for long-term energy planning and trading, the renewable energy forecasting with accurate results is more essential. Also, an exact wind power forecast can enhance the nature of the integration of wind power and will be helping to ensure the security of the power grid framework. The bottleneck of this kind of discharge-free energy is the inconstancy, unpredictability, and complex nature of wind speed [2].

Consequently, acceptance of sustainable renewable energy into electrical power blend can fill in as an elective source to provide for the constrained saves of petroleum products. [3] To saddle the energy content in a wind proficiently, it's of most extreme significance to precisely predict wind speed and generated power with the least acknowledged errors for security and financial matters of the utilization of wind power. Nonetheless, the undeniable irregularity and arbitrariness of wind speed value outcomes in the wind farm power output fluctuations, genuinely influencing the power quality. Accordingly, the exact forecast of wind power ahead of time can be enhancing the capacity of integration of wind power and upgrade the power systems consistency. Thus, it ends up important to assess diverse kinds of models utilized in the forecast of wind energy.

1.1 Importance of Short-term forecasting:

As reported by Colak et al. in [4], different forecasting horizons have been used for various purposes. Extremely short-term (seconds-30 minutes), short-term (30minutes-6 hours), medium-term (6hours-1day), and long-term (1day-1week) are indeed the four major time ranges for wind power forecasting [4]. Providing operators with ways to maintain that perhaps the turbine is not affected by high winds. The economic load dispatcher is focused on short-term forecasts. Identifying when additional power generation should be turned on or off.

Long-term forecasts are mostly used to plan repairs and maintenance, while medium-term forecasts are used to allow for energy trading. Models based on neural networks are the most popular for both ultra-short-term wind power forecasting and short-term. Their ability to work with nonlinear data is a huge plus.

Short-term forecasting covers a time horizon of 30 minutes to 6 hours ahead and it plays a key role in the scheduling, load following, and congestion management. The method aims at bringing the optimal, both scheduling and dispatch of the electricity for the subsequent day based on the data provided by the generators. In general, forecasting gives operational organizers to plan the generation of power and have the option to accomplish the grid. Without the visibility of RE power, ramp up/down steam-based generation would be difficult in a short time.

It generally prevents

- This leads to curtailment of wind power and moreover
- This leads to curtailment of loads
- Financial crisis

Perhaps the greatest concern related to coordinating a big volume of wind power data into the power grid system is the capacity to deal with large rises in the output of wind power. Distinctive geographic and time scales impact wind ramps events and there could be a combination of up ramps and down slopes with differing severity levels.

In this objective, we concentrate on forecasting short-term wind energy. The inbuilt inconsistency and changeability of wind power impose extraordinary difficulties upon numerous models. In this paper, a Rolling Long-Short Term Memory (R-LSTM) method is being proposed to increase the exactness of prediction for short-term wind energy forecasting. By using the proposed technique, from 15mins to 6 hours ahead power generation is forecasted based on the historical data of the past 6 hours generated actual power. Unlike the conventional LSTM method, a rolling strategy is introduced when forecasting the power of the wind. The key difference between the standard LSTM prediction approach and the Rolling LSTM approach are (i) The next day 24 hours is predicted in a recursive (multi-step) forecasting strategy by dividing into four periods and each period is to predict the nest 6hourws. (ii) The actual wind power generation of the previous period is included in the training data to learn the recent trends or patterns in wind power generation. (iii) The incorporation of actual data into LSTM model training data is repeated for 24 hours prediction (four periods).

To demonstrate the feasibility of the R-LSTM method, experiments are conducted with data collected from the National Institute of Wind Energy (NIWE). Concurrently, different metrics like Root Mean Square Error (RMSE), Average Relative Error (ARE), Mean Absolute Error (MAE) and Prediction Accuracy Rate (PAR) were chosen to compare the results of the R-LSTM method to existing methods like RARMA, XGBoost Regression, Random Forest Regression and Support Vector Regression. The numerical outcomes demonstrate that the R-LSTM strategy shows promising accuracy in wind energy forecasting. The neural network structures like LSTM which are temporally dependent can likewise be effectively reached out to model any temporal and time-series data.

2. Literature Review

2.1 Wind power forecasting

Numerous strategies on behalf of wind speed forecasting and wind power forecasting have been anticipated in different research studies. Though, they are commonly categorized into dual major groups: one is forecasting time horizon and another one is utilized, model. Given the forecasting perspective, the classification has been established on some literature surveys: the methods of forecasting renewable energy could be grouped into very short-term, short-term, medium-term, and long-term techniques as shown in Fig. 2.1. The change in forecasting horizon [5] suggested the succeeding classification dependent on various literature survey works:

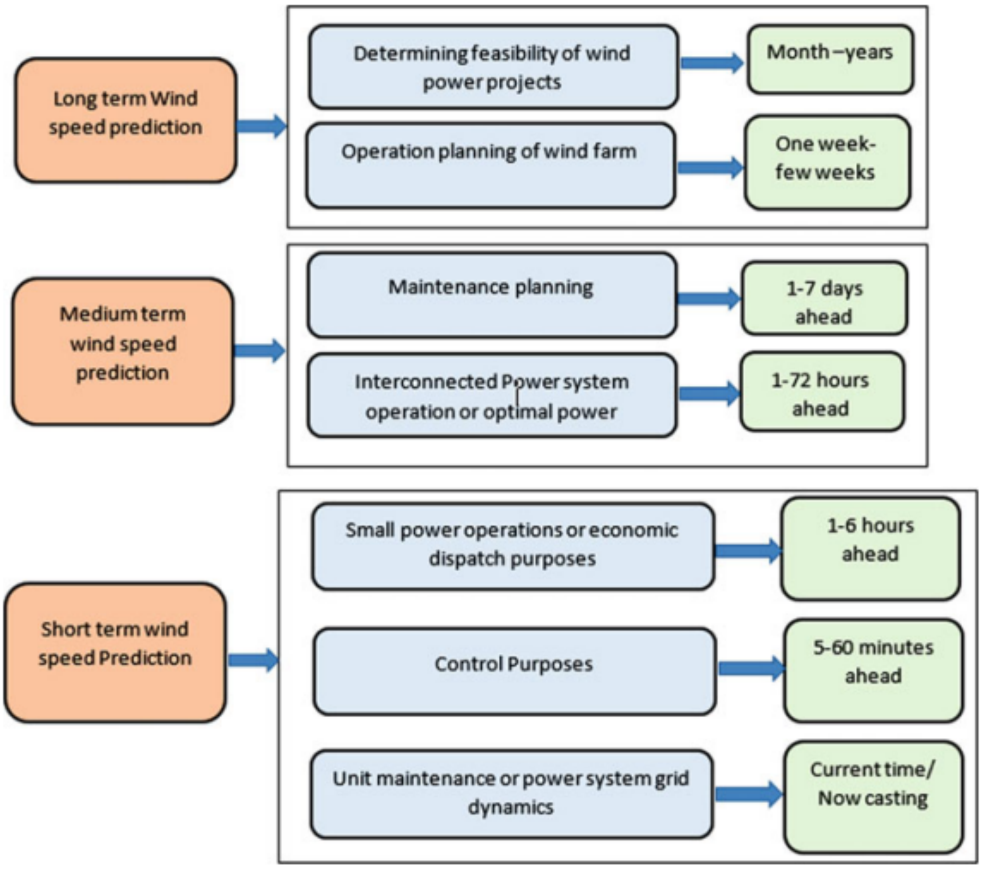

Fig. 2.1 Classification of wind power forecasting established on time horizon

- Ultra-short-term wind power forecasting: a few minutes ahead to one hour ahead forecasting.

- Short-term wind power forecasting: from one hour ahead to few hours ahead forecasting.

- Medium-term wind power forecasting: a few hours ahead to one week ahead forecasting.

- Long-term wind power forecasting: one week to one year ahead to more than one year ahead forecasting.

Recently, numerous researches on wind energy forecasting had been published. Though, the maximum of research focused on wind speed prediction at the same time as some researches targeted on wind energy generation forecasting techniques. The techniques of the above examinations can be categorized into 3 primary classes: techniques based on artificial intelligence, techniques based on time-series, and techniques based on time series and using artificial intelligence (a hybrid model). Most of these techniques are based on time-series for example, Autoregressive Moving Average Model (ARMA), Vector Auto-Regressive Model (VAR), and the Autoregressive Integrated Moving Average model (ARIMA). Furthermore, the categorizations of forecasting wind power techniques based on machine learning can be perceived concerning the applied technique as given below.

2.2 Short-Term Wind power forecasting:

Catalao J. P. S. et al. [6] recommended a novel hybrid method to forecast wind power for the short-term in Portugal. The proposed model is primarily considered as a combination of three systems namely, particle swarm optimization, wavelet transform, and adaptive network-driven fuzzy inference system. Nevertheless, the proposed (Normalized Mean Absolute Error) NMAE and MAPE (Mean Absolute Percentage Error) results tend to outperform the other similar approaches, wherein the average computational time has been acceptable. Moreover, the results of the proposed model substantiate the novelty and effectiveness of the proposed short-term forecasting of wind power in Portugal.

Catalao J. P. D. S. et al. [7] recommended a novel NNWT approach, which is a combination of both artificial neural networks and wavelet transform to predict the wind power for the short-term horizon in Portugal. The proposed approach leverages an average MAPE value of about 6.97% and outperforms the existing approaches like ARIMA and neural networks [NN] with less than 10 seconds of average computation time. The results of the proposed approach validate the effectiveness of wind power prediction for the short-term in Portugal.

Memarzadeh, G. A et al. [8] proposed a hybrid wind speed forecasting method based on 4 modules to boost the accurateness of short-term wind speed estimating: Wavelet transforms (WT), Crow search algorithm (CSA), mutual information (MI), entropy-based feature selection (FS) and Long Short Term Memory (LSTM) are used in deep learning time series prediction. The proposed wind speed forecasting strategy was tested using real-world data from Sotavento in Galicia, Spain, and Kerman in the Middle East, in the southeast of Iran. The numerical outcomes show that the projected approach is more efficient than any other current wind speed forecasting method.

Shahid, F. et al. [9] incorporated the new theory of wavenets using LSTM (WN-LSTM) for power forecast for several wind farms, with Morelet, Gaussian, Shannon and Ricker activation kernels, making it an exclusive hybrid method to complement the primary use of the deep learning model for diminishing wavelet and gradient transformations for the non - linear mapping. For short-term wind power prediction, the proposed technique, WN-LSTM, is applied on 7 wind farms in Europe and evaluated using standard output metrics for example mean absolute error (MAE) as well mean absolute percentage error (MAPE). When the findings are being compared to well-fixed current techniques, MAE shows a percentage increase of up to 30%. To ensure the model's effectiveness and robustness, it is run several times independently. Furthermore, using ANOVA (Analysis of Variance) -based Fisher's and Tukey's tests, the interval forecast is supplemented to quantitatively define the ambiguity as evolving intervals and variance between expected and real power is likely 0.02 at a 95 percent confidence level.

Srivastava, T. et al. [10] recommended a software-based computing model that can accurately predict future demand. The current forecasting technique employs linear methods namely Autoregressive Integrated Moving Average Model (ARIMA), Moving Average (MA), and Auto Regression (AR), as well as non-linear algorithms such as Neural Networks, AutoRegressive Conditional Heteroskedasticity (ARCH) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH). Since wind energy is so important in the renewable energy field. So, using three neural network-based models, RNN (Recurrent Neural Network), Gradient Boosting Machine (GBM), and LSTM, we must predict the power produced from wind turbines with wind velocity, and then determine which is better based on the output parameters values.

Syu, Y.D. et al. [11] presented a 15-minutes wind speed forecast model established using recurrent neural network (RNN) named gated recurrent unit (GRU). One designed anemometer is placed for the first six months to collect wind speed data, which is then fed to GRU model which generate data for the following three phases of 15 minutes interval ahead of time. Lastly, the root mean square error and mean absolute error are used to assess the prediction model's accuracy, and the outcomes are contrasted to those achieved with plain standard RNN and LSTM model. The efficiency of GRU technique is greater than the other two approaches, as shown by the assessment metrics.

Duan J. et al. [12] proposed a perfect short-term improves the wind power hybrid forecasting model based on such a Correntropy-enhanced Long Short-Term Memory (LSTM), which incorporates Sample Entropy (SE) and improved variational mode decomposition (IVMD). The IVMD is being used to disintegrate the initial wind power data, with Maximal Correntropy Criterion (MCC) defining the variable K as in IVMD, and SE reconstructs the disintegrated subseries to enhance prediction efficiency. After that, the MCC has been used to supplement the MSE mostly in traditional LSTM network, yielding an innovative robust hybrid model for predicting wind power. After this, four analyses were carried utilizing actual data from the 2 wind farms of China at various sample intervals that evaluate the efficiency of the suggested procedure, with the outcomes showing that it outperforms most traditional methods.

Sun Z. et al. [13] used prediction technique for the short-term wind energy, the hybrid model combining Convolutional Long short memory network (ConvLSTM), variational mode decomposition (VMD), and error analysis. The VMD method disintegrates the wind power input into the ensemble of different frequency components, and then procures a novel framework integrating the convolutional layer into an LSTM network, that is capable of extracting the spatiotemporal features of each subseries as an initial forecasting engine. By consolidating all of predicted subsignals, initial forecasting findings are achieved. LSTM modeling the pattern in deviation series of the initial forecasting outcome is being used to better fine-tune the unsteady characteristics inside the actual wind power series. Ultimately, the overall forecasting solution is achieved by incorporating the predicting deviation series data and initial results. The final outcome, when contrasted to traditional approaches, the proposed system efficiently achieves good prediction performance for complicated wind power sequence.

Toubeau J.F. et al. [14] introduced advanced Long Short Term Memory (LSTM) network architectures and validate them in practice. Second, various strategies for recalibrating the method while their practical uses are examined in terms of continually improve the prediction method. This technique consists of modifying the parameters of neural networks based on new knowledge revealed over time, rather than retraining the model after scratch with the entire dataset (which is time-consuming). Finally, the financial savings resulting from improved forecast accuracy are calculated. The results of the Belgian case study explain that a premium model recalibration will increase forecast consistency while lowering the system's assessment costs.

Amjady N. et al. [15] considered wind power as a non-linear multivariate function that allows hyperplane singularities and spatial inhomogeneities. Moreover, ridgelets are considered as an effective basic set to construct such a function. With this in consideration, this research work [15] forecasts the wind power using RNN that incorporates ridge as initiation function for the nodes present in the hidden layer. To train the recommended forecast engine and determine the freely available parameters, this article suggested a novel stochastic search technique called NDE. The proposed NDE has less computational complexity and requires only a limited number of samples for the training and validation phase. Nevertheless, the proposed model can be widely searched and analyze the solutions from various research directions that increase the possibilities for finding a global optimum value for the training challenges. The competence of the proposed strategy would be helping in forecast wind power according to the power systems and single wind farms. Furthermore, this research work has extensively illustrated the forecasting of wind speed.

Carpinone, A. et al. [16] proposed a novel forecasting method by utilizing the discrete time-based Markov chain model, to obtain an easier way to estimate the distribution of wind power. The proposed model establishes a time series analysis on wind power to easily estimate the distributions of wind power within a short term and also without including any type of restrictive assumptions. This research work has analytically described the first and second-order Markov chain model. To conclude, the proposed method is illustrated and applied over real-time wind power data.

Zeng, J. et al. [17] proposed Support Vector Machine (SVM) driven regression tool. Moreover, by simulating this proposed model, it has leveraged various conclusions. Firstly, the final result value predicted and obtained by the SVM model matches the expectant values along with exceptional precision, and also the results obtained are almost in-line with the expected variations. Secondly, when compared the proposed SVM model with the RBF-neural network-driven model and persistence model, SVM has significantly enhanced the forecasting of wind power in the short-term by achieving greater than 26% with a predictive horizon of about 16 hours. Thirdly, the proposed SVM model is considered an effective tool to boost the accuracy in forecasting wind power, when compared with the existing diligence model. Despite the hype, by the increasing predictive horizon accordingly, the data history has become very less correlated. This makes the proposed model gradually fail in coping up with the wind power variations. Henceforth, to forecast 24h wind power, it may either require additional meteorological variables like pressure, temperature, etc., which can be combined with NWP to boost the accuracy of forecasting the wind power.

Osorio, G.J. et al. [18] proposed a new methodology called Hybrid Evolutionary Adaptive [HEA] methodology, to analyze the predictions on wind power forecast in the novel Portuguese system for a short term viz. 3 hours ahead by including 15-minutes interval, which has integrated the characteristics from the WT model to leverage the filtering effect to handle the non-stationary sets; EPSO model to incorporate evolutionary optimization characteristics; ANFIS model to deploy the adaptive architecture; MI model to select the preferred input data and enhance the robustness of the proposed methodology. To implement a transparent and clear-cut comparative study, this research work has considered indistinguishable test cases utilized by other similar methodologies by neglecting the exogenic variables. The results obtained from the proposed HEA method have been observed as more effective and accurate by reducing the uncertainties associated with forecasting wind power. The proposed method has obtained a MAPE value of 3.75% along with average error variance and NRMSE of about 0.0013 and 2.66% respectively. The proposed HEA method has reduced computational complexity by displaying the results of wind power forecast within 40sec/iteration by leveraging compromising results on accuracy and computation complexity in real-time applications.

Nielsen, T.S. et al. [19] described some statistical methods that have been considered in the ANEMOS project to forecast wind power for the short-term. This whole procedure includes different steps, which include the downscale from the refereed MET forecast to actual wind power farm, wind power curves obtained from the wind farm, dynamic models to predict the wind speed/power, uncertainty estimation, and finally the up scaling methods to estimate the overall regional production by considering a less number of wind farms for reference. Moreover, all those steps are described in this research work.

Venayagamoorthy, G.K. et al. [20] has proposed a novel and effective hybrid WNF method to predict wind power for short term horizon. Since the penetration of wind power increases unprecedently in power systems, it becomes increasingly important to consider the accurate and authentic prediction of wind performance and its corresponding electric energy generation. The proposed method has obtained an average MAPE of about 5.99% along with an average computational time of less than 1 min, which tends to outperform the other existing approaches like ARIMA, NNWT, persistence, and NN approaches.

Abdoos, A.A., et al. [21] have proposed a novel forecaster for wind power by utilizing intelligent and hybrid pattern recognition technology. As VMD is generally considered an effective signal processing technology, this research work has utilized it for performing time-series decomposition on the generated wind power. In order to, enhance the simplification and interpretation ability of the forecasting device and diminish the memory requirements, the proposed method removes the non-informative data by utilizing a GSO-driven feature selection model. Further, to explore the relationship between the desired output and exemplar patterns, Extreme Learning Machine (ELM) has been used. Further, a cross-validation method has been applied to acquire an optimal structure of the forecast engine and estimate the performance of the proposed method by analyzing various selected features and decomposition mode. From the simulation outcomes, it has been marked that the forecast model with a total of ten decomposition types and nominated 20 features have leveraged fewer forecasting mistakes. The best performance of the projected model is appraised for both 1 hour and 10-minute intervals. By implementing the proposed model on historical wind power data obtained from twelve different wind farms, it has been evident that the proposed model tends to leverage a better performance based on processing speed and prediction accuracy.

Xu, Q. et al. [22] introduced NWP-data adjustment models to predict wind power for short-term horizons. Here, the proposed model has been implemented to identify and cluster the errors present in NWP by utilizing the different data mining techniques and further the raw and unusual NWP data are attuned before sending it to the Wind Power Forecasting (WPF) engine. Nevertheless, from the simulation outcomes of the projected method, it has been evident that the model has significantly reduced the overall Wind Forecasting (WFO) error. Despite the hype, there also exist some challenges for the proposed work. Firstly, the substantial explanation and the reason behind various error patterns are unclear. Secondly, an exclusively data-driven resolution without the appropriate model description is not adequate to assure the generalization of the proposed algorithm, and also the threshold of AWPF selection can only be determined through the neural network module. Henceforth the proposed method requires more robust and adaptive criteria for its application in real-time.

Ayadi, F et al. [23] lists the advantages and disadvantages of integrating renewable resources, as well as the various control strategies that enable this integration. Considering the current energy shortage, renewable energy have also been identified as the primary source of future energy production. As a result, current research focuses on integrating renewable energy sources into another smart grid to facilitate optimal energy management.

Saidi, A., et al. [24] discussed the significance of binomial Energy in managing power flows. This paper proposed and develop a different fuzzy logic - based energy management system this purpose. The SIMULINK-MATLAB environment has been used to develop and test a robust simulator design for the proposed PV-Wind hybrid power system. A series of experiments are performed out with actual data utilizing meteorological data found in the Adrar region, and the results have been compared to a calculated practicable load demand pattern. The simulation results demonstrate that the "coupled approach" outperforms traditional management strategies by a significant margin.

Dolara, A. et al. [25] presented the creation of prediction methods for wind farm producibility with only 24 hours. The goal is to use feed forward artificial neural networks to get reliable wind power projections. Various prediction models are made in particular, and the best architecture for every one of them is determined through a simulation model, which involves changing the artificial neural network's key variables. The obtained outcomes are compared to forecasts produced by numerical weather prediction models (NWP).

Aguilar, S. et al. [26] offered a new approach to generating wind energy forecasts by creating a complete probability-based forecast only for wind power for each wind speed predicted by time series methods for each lead time - Using Double Seasonal Holt Winters and conditional density kernel estimation. There has been a lot of research done on this subject, with most of it deviating through point forecasts to wind speed, which generates the associated energy level forecast using the windfarm power curve. The uncertainty related to wind speed is not taken into account by such approaches. The approach was put to the test with real data from a wind farm in Brazil, and the results were very positive.

Harrouz, A. et al. [27] There are several renewable sources of energy available around the world that can be used to generate electrical energy from environmental sources. Wind energy, in particular, is playing an increasingly important role due to its viability and reliability. Since wind energy is a renewable resource, the productivity of a wind farm is highly dependent on the weather. Predicting the output is the most critical aspect of achieving optimal efficiency. This situation allows for more effective joint development of various energy sources while preventing over-cost and increased production. Three separate wind patterns are designed and simulated in this paper, with the full and accurate models being chosen.

Banna, H.U. et al. [28] discussed the effects of a huge volume of wind power infeed on the turbine oscillatory stabilization are discussed. The types of wind turbine generators currently used in wind farms, the best place for wind farms in the integrated power grid, efficient optimum wind power dispatch, and the degree of tie-line congestion have all been extensively investigated. Using MATLAB/Simulink, Kundur's two-area network model was used to analyze the described effects on the overall framework. The damping properties of wind farms are critically dependent on the location of integration in the grid and the optimum wind energy disposal, according to some of the main findings. Increased wind energy penetration increases the damping of inter-area oscillations in general. Furthermore, stress reduction on the poor tie lines increases the oscillation's inter-area mode.

3. Methodology

Short-term prediction (predicting the horizon is 6 hours ahead) has significance for real-time power grid scheduling, according to research messages from wind power plants. Thus, in this aim, attention is paid to the short-term prediction under this incentive, and LSTM methods are adopted. Rolling LSTM (R-LSTM) is proposed to increase accuracy. This goal of the research is structured as follows. In sections 3.1 and 3.2, the LSTM model for wind power prediction is given. The numerical experiment is then performed in section 3.3 to validate the R-LSTM technique's feasibility. Lastly, in section 4, we draw results and conclusions.

3.1. Wind Power Prediction using LSTM method

LSTM is modified version of RNN built on the time series based data and an exceptional kind of recurrent neural system that decides how to rely upon data for an interval of a long time. Moreover, it can forecast and deal with more threatening issues that exist in data like many intervals and delays range in the time series data. LSTM has been initially established by the authors Hochreiter and Schmidhuber [29] and further enriched by the author Graves et al. [30]. It has gained important evolution and it is being used widely. Based on previous studies, the LSTM wind power prediction technique will be given in this section and a Rolling LSTM (R-LSTM) will be put forward to increase the accurateness of the prediction.

3.2 LSTM Methods

The models of Long Short-Term Memory are tremendously efficient time series methods. It is possible to predict an arbitrary number of potential movements. There are 5 essential components in an LSTM module (or cell) that enable the same to model together short-term and long-term data. For implementing time series models, Tensor Flow delivers a sub API (is called RNN API). The LSTM cell is shown in Fig. 3.1.

Cell State (ct): It illustrates the cell's internal memory that retains both short-term and long-term memories.

Hidden State (ht): This is the estimated w.r.t. recent input, former hidden state, and recent cell input of output state information that you ultimately use to forecast the prices of the upcoming stock market. Moreover, to make the next prediction, the hidden state may decide to either recover the short-term or long-term or both types of memory would be stored into the cell state.

Input Gate (it): Decide how much data flows into the cell state from the current input.

Forget Gate (ft): Decide how much information flows into the present cell state from the current input and the previous cell state.

Output Gate (ot): Decide how much data flows into the hidden state from the current cell state, hence LSTM could pick neither long-term nor short-term memories.

A LSTM cell is shown below:

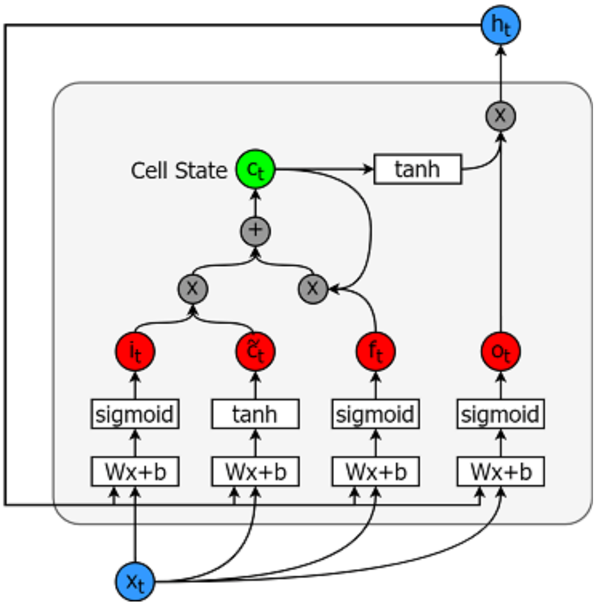

Fig. 3.1 LSTM Cell Structure

The equations are as follows for measuring each of these entities.

$$i_t = \sigma (W_{ix}X_t + W_{ih}\, h_{t-1} + b_i) \quad (3.1)$$

$$\tilde{C}\_t = \sigma (W\_cxx\_t + W\_chh_{t-1} + b_c) \quad (3.2)$$

$$f\_t = \sigma (W\_fxx\_t + W\_fhh_{t-1} + b_f) \quad (3.3)$$

$$C_t = f\_tc\_t - 1 + i_t\tilde{C}_t \quad (3.4)$$

$$o\_t = \sigma (W\_oxx\_t + W\_ohh_{t-1} + b_o) \quad (3.5)$$

$$h_t = o_t \tanh(C_t) \quad (3.6)$$

3.2 Rolling Prediction LSTM:

The steps involved in the short-term wind energy prediction using rolling LSTM as shown in Fig. 3.2 are as follows:

Step 1:

The one-year historical generated wind power from the selected substation (in MWs) is selected for LSTM model training.

Step 2:

The outliers in the training data have been removed using some sequential data quality check procedures such as constant value test, minimum, and maximum physical limit test, and missing value test. Once the data quality checks are completed on training data the missing values has been replaced using the mean values of previous four timestamps.

The pre-processed training data is passed to the model construction to make LSTM learn the patterns in the historical data.

Step 3:

If the last intraday update is less than 6 hours the actual power generation data from the selected substation is included in the training data to make the LSTM model learn new patterns. The intraday forecast schedule is updated.

Step 4:

The forecasted output solar power is compared with actual values of generated power for the substation to evaluate the accuracy of the forecasting model.

Step 5:

The standard comparison matrices such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean square Error (RMSE), and Accuracy are used to evaluate the predicted output power values with actual generation values. The flowchart of the proposed forecast model algorithm is shown in Fig. 3.2.

It is simple to operate the conventional LSTM method and can reliably predict the future value if the series is a stationary operation. However, for grid demand, the wind power can often be reduced, and also, the wind power is unreliable, leading to lower prediction accuracy. The rolling technique implemented in predictive control is used to enhance the precision of prediction. To advance wind power forecast accuracy, an R-LSTM model is proposed for this aim. As follows, the rolling strategy is defined. When we forecast the wind power meant for the following 6 hours, the forecasting model is reformulated again after six hours of prediction ends, where the real power generation data is applied to the training data.

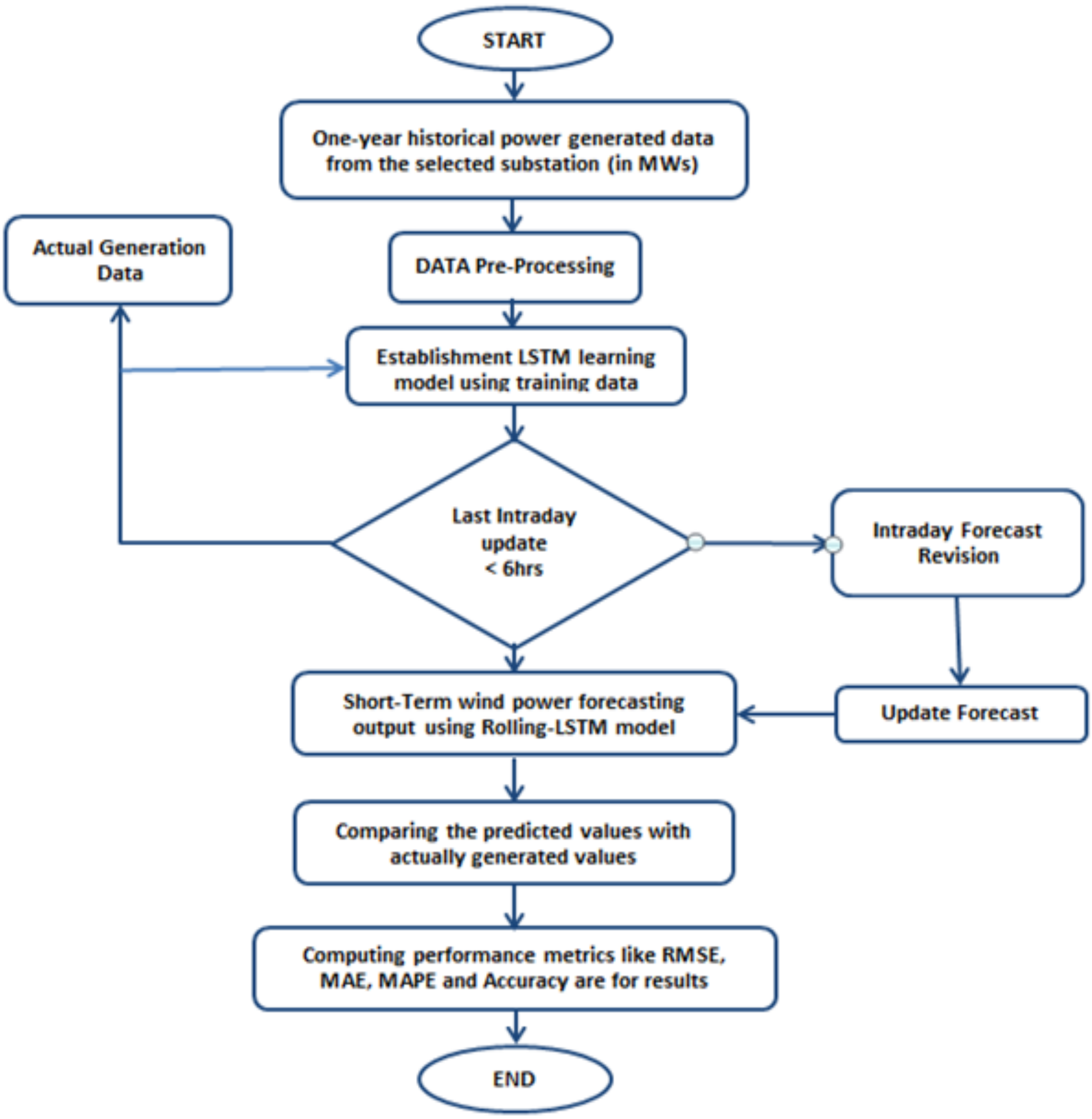

Fig. 3.2 R-LSTM Flowchart

3.3 Numerical experiments:

3.3.1 Dataset Description

The historical data of time series of wind power, produced each 15 minutes range timestamp, are warehoused and collected in the central server system of the National Institute of Wind Energy (NIWE), to validate and estimate the proposed forecasting technique of wind power.

The dataset of the substation with the entire rated installed capacity of 5480 MW wind power from the state of Gujarat is utilized. The dataset comprises 1,13,377 data points of wind power, which are chosen arbitrarily from 2015 to the 2018 year as empirical samples. From the empirical samples, the prior 1, 13,280 data of wind power are used to train the recommended R-LSTM technique. To test the proposed technique, 96 data points of the dataset were utilized. Finally, for model validation, the resulting 96 rows (24 hours with 15 minutes time period) of time series of actual generation power data are used to forecasting intraday. The statistical indices of the wind energy time series dataset are given in Table3.1.

Table 3.1 Scientific Wind Power Time Series Dataset's Statistic Justifications.

Dataset (MW)	No. of Samples	Min.	Max.	Mean.	Median.	Std. Dev.
Total	113376	0	3636.583	820.408	643.031	657.774
Training	113280	0	3636.583	819.186	642.428	656.559
Test	96	1658.98	3151.431	2263.212	2045.259	485.488

To validate the developed forecasting model the data from April 1st to 30th, 2018, and also from May 1st to 31st 2018 is used as training data. The April 30th and May 31st data are used as test data to validate the proposed R-LSTM forecasting model and the time between collecting data is 15 minutes. We pay more attention to the short-term forecast of wind power in this objective, which means that we estimate the next 6 hours of wind power. We choose April and May data to conduct the experiments, respectively, to demonstrate the validity of the procedure. We use the data from the last day as the test data for each month, and from the previous days for model training.

Simultaneously, the test data is split into four time periods, including six-hour data. Thus, four numerical experiment period groups are performed for each month. Table 3.2 shows the collection of the training and testing results. It is noteworthy that while performing the second cycle experiment (Period 2), the first period's actual power generation data is placed into LSTM model training data, and so on.

Table 3.2. Description of the training and test dataset used to short-term wind power forecasting.

<table>
<tr><th colspan="6">Selection of the Test and Training Data</th></tr>
<tr><td rowspan="2">Month</td><td rowspan="2">Training Data</td><td colspan="4">Test Data</td></tr>
<tr><td>Period_1</td><td>Period_2</td><td>Period_3</td><td>Period_4</td></tr>
<tr><td rowspan="2">4</td><td rowspan="2">1-30</td><td colspan="4">April 30th</td></tr>
<tr><td>0:00-05:45</td><td>06:00-11:45</td><td>12:00-17:45</td><td>18:00-23:45</td></tr>
<tr><td rowspan="2">5</td><td rowspan="2">1-31</td><td colspan="4">May 31st</td></tr>
<tr><td>0:00-05:45</td><td>06:00-11:45</td><td>12:00-17:45</td><td>18:00-23:45</td></tr>
</table>

3.3.2 Prediction Evaluation

To compare the prediction effect of the R-LSTM, with other conventional models such as ARMA, XGBoost, RFRegressor, and the actual power of substation. The execution performance of the projected method for wind power forecasting is generally assessed by various statistical error metrics viz. Prediction Accuracy Rate (PAR), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and as well as Mean Absolute Error (MAE) are utilized. The basic wind power assessment approach is PAR. It is also used to measure the expected accuracy rate by forecasting wind power. These formulas are described, respectively, as Equations 3.7 to 3.10.

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - p_i)^2} \tag{3.7}$$

$$MAPE\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - p_i|}{y_i}\ X\ 100 \tag{3.8}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - p_i| \tag{3.9}$$

$$PAR\ (\%) = \left(1 - \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - p_i}{Cap}\right)^2}\right)X100 \tag{3.10}$$

Where, y_i and p_i are the real and projected wind power, e_i = y_i −p_i, i = 1, •••, N, N = 24 is the total number of predicted values, and Cap = 5480MW is the total installed capacity of the Wind Farm examined.

In general, the best forecasting model will have the smaller value of RMSE, MAPE, and MAE, the better the precision of the forecast. At the same time, the bigger the PAR, the greater the precision of the forecast. To assess if a prediction approach is feasible, the forecast of wind power is also established on PAR. In particular, the proposed model is successful when PAR is > 80 percentage.

4. Results and Discussion

The numerical experiments have been carried out using the above-mentioned proposed methodology for the selected dataset. The LSTM network model is built using the Keras model from the TensorFlow environment. The neuron dimensions used within the network used for an input layer are 4, a hidden layer is 5, and an output layer is 1. The cumulative numeral of epochs is set to 100, the training rate is set to 0.1, and the training precision rate is set to 0.00004. By considering the first group of April month data as an example, the forecasting results of period 1 are unsteady and it's not matching with actual power generation. The period1 forecasting results of R-LSTM and its comparison with other regression models are shown in Fig. 4.1.

The implementation of Period2 is made by injecting the actual power generation data of period1 timestamp values into the training data of the forecasting model. The model was able to learn the new generation pattern or trend and improved its prediction results when compared to period1. This difference can be easily depicted in Fig. 4.2. The same methodology is adopted in successive periods such as Period3 and Period4. The comparison results are also detailed in the Fig. from 4.3 to 4.4. The overall 24hrs full day forecasting results are also given in graph Fig. 4.5, to get clear insights of how the model is learning pattern using this recursive forecasting strategy and its compared with the best regression and statistical models like ARMA, XGBoost, RFRegressor. From the literature study, the top best regression models have been chosen for performance evaluation based on their RMSE score. The regression model with lesser error has been selected and also the proposed technique is compared using the actual power generation data of the selected state.

The statistical results of performance metrics such as MAE, MAPE, RMSE, and PAR are given for all the forecasting models and all the periods are tabulated in the Tables from 4.1 to 4.4. The following gives the concrete analysis:

From Table 4.1., while comparing the RMSE, MAE, MAPE, and PAR value the Proposed R-LSTM forecasting model shows better results when compared to ARMA, XGBoost, and RF regressor models. The R-LSTM model is still having 85.18 MW deviations when compared to actual generation and the RMSE of 104.24 tends to be higher. The proposed model still needs to be improved further to achieve better results.

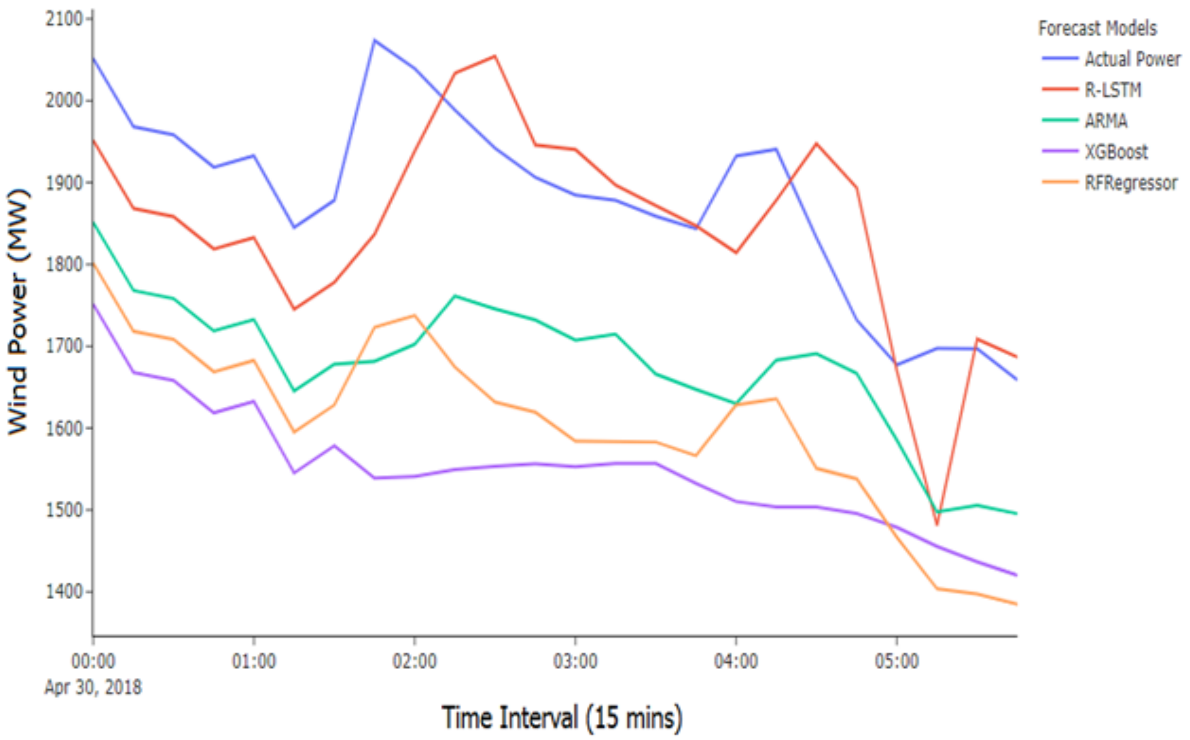

Fig. 4.1 The Forecasting Results of Period1 (00.00 – 05.45)

To advance the prediction performance of recommended LSTM model, the recursive forecasting strategy has been proposed and the actual generation data of the previous period is injected into training data of the model for the successive intraday revision every 6 hours. From Tables 4.2. to 4.4 it's evident that the proposed model is improving prediction values and thereby reducing the error values.

The final evaluation result for one-day prediction using this recursive strategy is detailed in Table 4.5. The proposed R-LSTM model reduced the MAE error from 85.18MW to 50.18MW, the RMSE error from 104.24MW to 67.77MW, and the PAR percentage increased from 98.10% to 98.76%. The installed capacity of the selected dataset is 5480MW so even the minimal increase in error value will lead to more deviation in the time series blocks of the forecasting schedule.

Table 4.1. Comparison of the Period 1 Index of Prediction Evaluation

(a) The 1st time period - Evaluation index				
MODELS	**MAE (MW)**	**MAPE (%)**	**RMSE (MW)**	**PAR (%)**
R-LSTM	**85.18**	**2.1**	**104.24**	**98.10**
ARMA	202.90	4.2	213.63	96.10
XGBOOST	330.87	6.6	340.81	93.78
RFREGRESSOR	276.05	5.7	278.16	94.92

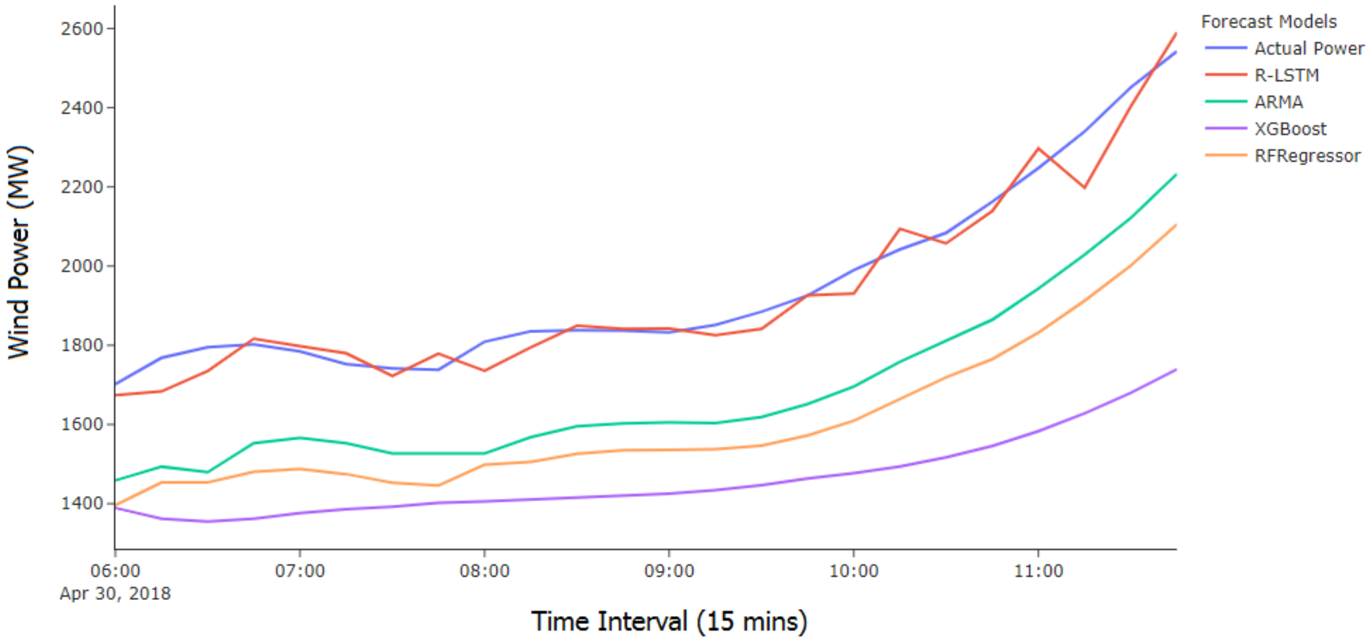

Fig. 4.2 The Forecasting Results of Period2 (06.00 – 11.45)

Table 4.2. Comparison of the Period 2 Index of Prediction Evaluation

(b) The 2nd time period - Evaluation index				
MODELS	**MAE (MW)**	**MAPE (%)**	**RMSE (MW)**	**PAR (%)**
R-LSTM	**39.55**	**1.8**	**24.89**	**99.09**
ARMA	265.52	5.2	133.97	95.11
XGBOOST	485.24	9.3	251.65	90.82
RFREGRESSOR	343.58	6.2	173.61	93.66

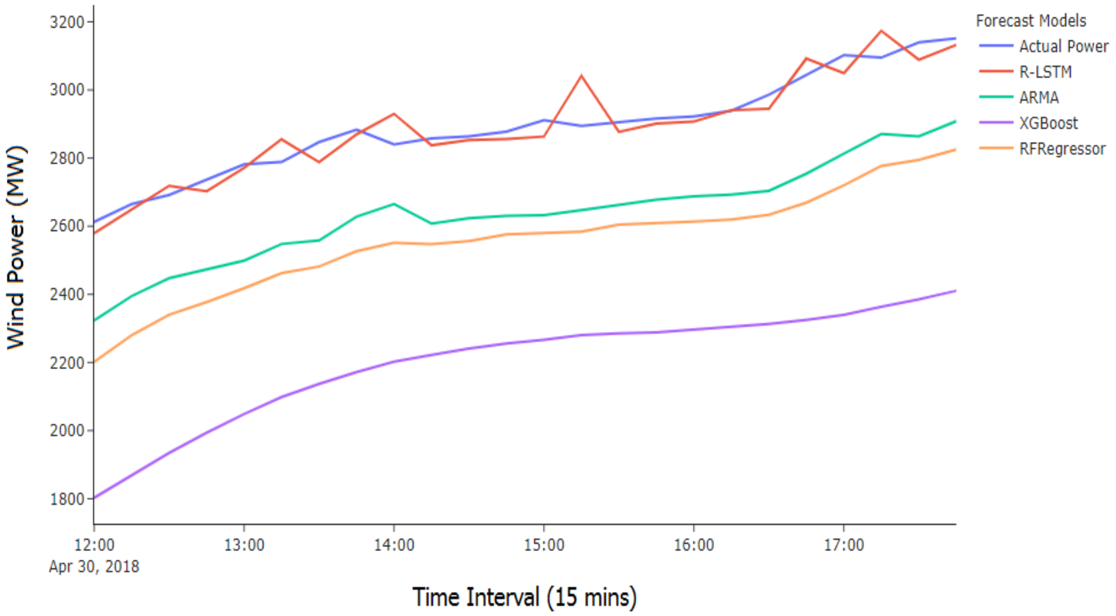

Fig. 4.3 The Forecasting Results of Period3 (12.00 – 17.45)

Table 4.3. Comparison of the Period 3 Index of Prediction Evaluation

(c) The 3rd time period - Evaluation index				
MODELS	**MAE (MW)**	**MAPE (%)**	**RMSE (MW)**	**PAR (%)**
R-LSTM	**39.47**	**1.6**	**25.32**	**99.08**
ARMA	255.63	5.1	128.48	95.31
XGBOOST	692.34	13.2	347.50	87.32
RFREGRESSOR	337.60	6.5	169.53	93.81

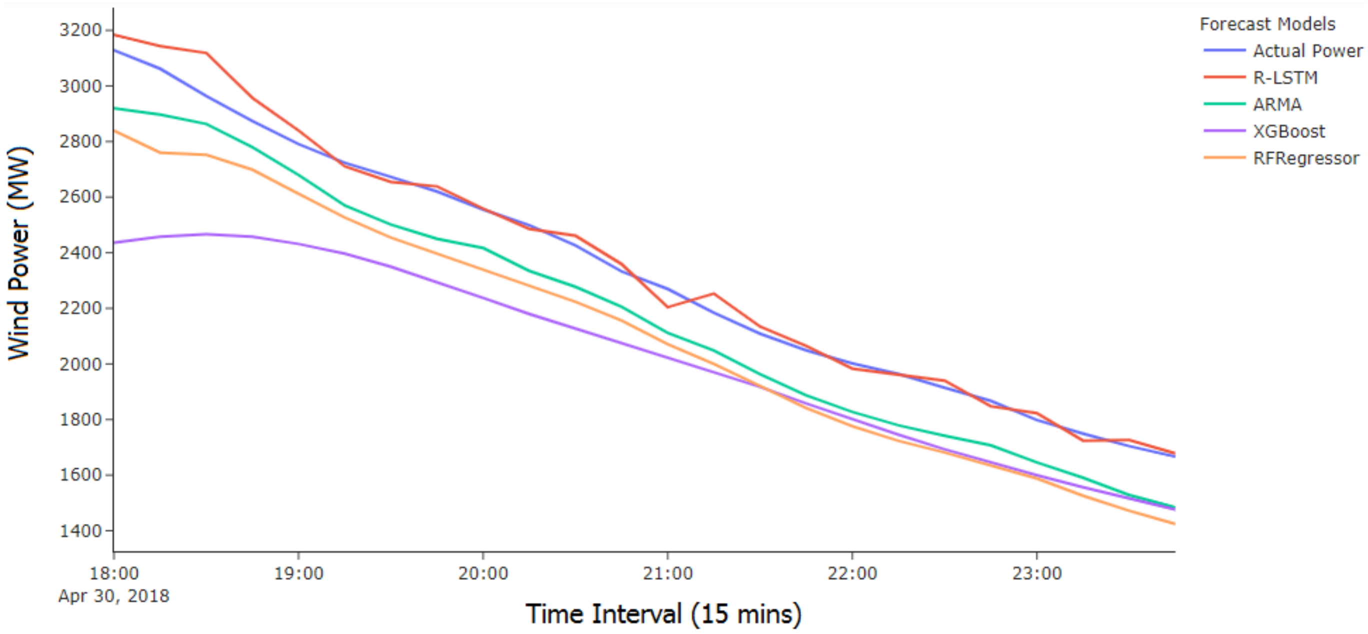

Fig. 4.4 The Forecasting Results of Period4 (18.00 – 23.45)

Table 4.4. Comparison of the Period 4 Index of Prediction Evaluation

(d) The 4th time period - Evaluation index				
MODELS	**MAE (MW)**	**MAPE (%)**	**RMSE (MW)**	**PAR (%)**
R-LSTM	**36.51**	**1.4**	**24.81**	**99.09**
ARMA	154.74	3.2	78.48	97.14
XGBOOST	300.29	5.8	163.93	94.02
RFREGRESSOR	217.69	4.6	109.91	95.99

Table 4.5. Statistical performance metrics results attained using Short-Term Predicting for the dataset.

The One-Day Time Period Evaluation Index				
MODELS	**MAE (MW)**	**MAPE (%)**	**RMSE (MW)**	**PAR (%)**
R-LSTM	**50.18**	**1.2**	**67.77**	**98.76**
ARMA	219.7	4.3	228.09	95.84
XGBOOST	452.18	8.5	489.9	91.06
RFREGRESSOR	293.73	5.6	300.5	94.52

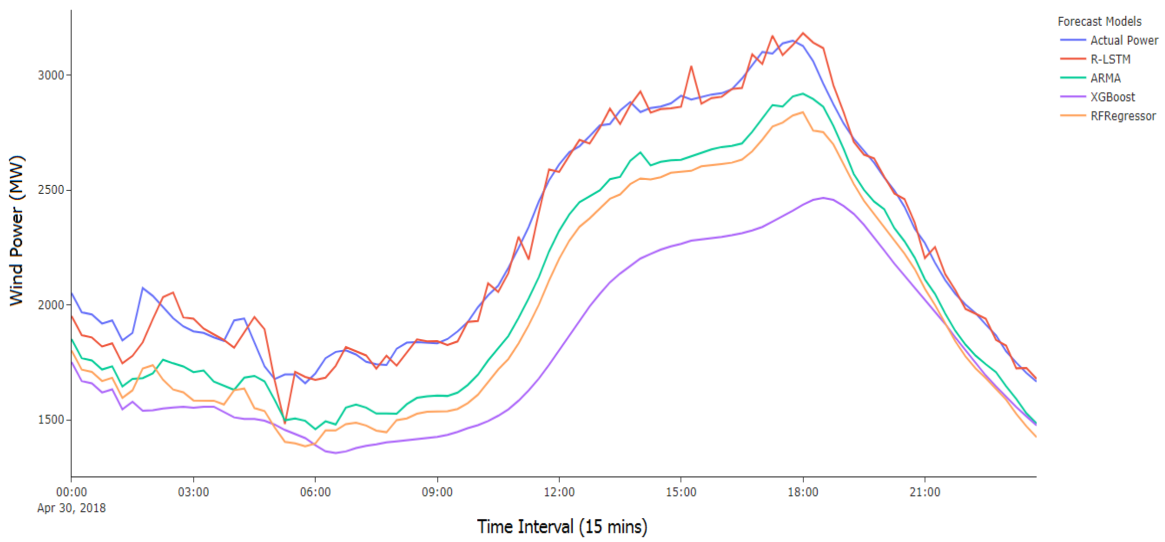

Fig. 4.5. Results of Short Term Wind Power Forecasting of Proposed R-LSTM Model with Other Conventional Models.

5. Conclusion

In short-term Wind Power Forecasting, improving the precision of wind power prediction is important. Therefore, a new methodology for wind power forecasting is being proposed to boost the accuracy of prediction in this objective, based on LSTM. A recursive strategy is applied when predicting wind strength, unlike the conventional LSTM approach. It can be inferred from the previous numerical analysis that, compared to other models and findings of wind energy forecasting method used by the WPP (wind power prediction), R-LSTM has higher prediction accuracy. It can be shown, however, that there is a delay in the outcome of the R-LSTM prediction. Therefore, the explanation for the delay may be explored and the delay can be removed in future work. Besides, after further data collected (more than a year) in the future study, we will take the periodicity into account and carry on the medium as well as the long-term prediction of wind power.

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