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Multi Step Ahead Wind Speed Forecasting Using Long Short Term Memory Recurrent Neural Network

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ABSTRACT: *This paper proposes a multi-step ahead wind speed forecasting approach utilizing Long Short Term Memory Recurrent Neural Network – LSTMRNN (a deep learning technique). Accurate wind speed forecasting is the prerequisite to harvest maximum power from windmills. Proper forecasting of wind speed directly impacts the generation, demand management and unit commitment of windmills. In this research, one year's historical dataset consisting of wind speed, relative humidity and temperature of thirty minutes interval has been considered to train the proposed LSTMRNN model. The model's performance has been evaluated by Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The performance of the proposed model has also been compared with another machine learning model called Convolutional Neural Network – CNN. The results show that the proposed model can forecast wind speed with much better accuracy in comparison with CNN.*

KEYWORDS: Machine Learning, Wind Speed Forecast, LSTMRNN, RMSE, MAE, MAPE, CNN, Deep learning and windmill.

1. Introduction

To achieve the goals of sustainable development, it is a must to develop and extract energy from renewable resources rather than conventional energy sources like fossils (oil, gas and coal) and so on, which are declining day by day. There are also issues like price hike of fuels, CDM (Clean Development Mechanism), change in climate, insufficient and unreliable supply of power in developing countries etc. (Hu & Chen, 2018) To keep pace with the development on this 21stcentury, the demand of energy is increasing locally as well as globally; which is forcing us towards a crisis of global energy. To maintain the development in a sustainable way, we must be concerned about the environmental issue.

Using the energy from fossils and non-renewable sources are polluting the environment and it also is the reason for global warming (Liu, Mi, & Li, 2018). On the contrary, wind and the other renewable resources of energy are sustainable and spotless alternatives to the conventional sources of energy, which would reduce the dependency on fossil fuels. Among the available alternative resources of energy, wind is available throughout the 24 hours. Besides, the low operating cost to extract energy from wind has made it one of the most expedient and active renewable energy sources. Again, it is also considered as one of the most cost-effective and environment responsive sources of energy (Yu, Li, & Zhang, 2017). At the same time as the cost of energy conversions form wind approaching the conventional powerplants so it has a huge potential to compete with the traditional plants. As it is eco-friendly, generation of power from wind is increasing rapidly across the countries of the globe and it has a growth rate of 28% per year (Varanasi & Tripathi, 2017). Wind power generation is playing a vibrant role amongst the low-carbon technologies and it holds all the potential to meet the goals of sustainable energy stream. Besides, it can contribute to the micro-grids which eventually leads to the infrastructure of smart grid (Cadenas & Rivera, 2010; Dokur, Kurban, & Ceyhan, 2016; Grigonytė & Butkevičiūtė, 2016; Lei, Shiyan, Chuanwen, Hongling, & Yan, 2009).

There are many challenges in harvesting power from wind energy. The first and most challenging one is, it's stochastic and irregular nature in terms of speed and direction. It is a great hinder towards the reliable performance of managing and controlling wind power and in way towards penetrating the wind energy at large a scale. The irregularity of wind speed insecure the stability and security of the system; which influences the power quality of the wind farm (Liu et al., 2018). It also affects the security of grid and market economics. A well secured electric power system always ensures the equilibrium between demand and supply of power. So, when a power system tries to adopt or integrate a renewable source of energy like wind which is stochastic in nature, it makes the system more complex and challenging in terms of operation or control or management. To sort these issues several factors like improvements in forecasting model to lessen error, moderation in the conventional plants, enhanced storage system or management of load in a better way etc. can be addressed.

As we can't control nature so it's not possible to control the wind speed as per our requirement. However, we can forecast the wind speed in advance to efficiently manage and coordinate the generation of power from the wind farms. Therefore, the development of a suitable model to forecast wind speed in a proper way can greatly influence the conversion and management of energy from

wind energy resource. In addition, a proper forecast will help in reducing the cost and growing the revenue from the electricity market (Foley, Leahy, Marvuglia, & McKeogh, 2012). However, forecasting the wind speed is considerably tough as the wind shows unstable and random characteristics (speed, direction etc.). As a result, a vast attention and effort have been given by many research centers and universities that deals with environment and energy, to develop and improve different forecasting techniques to accurately predict the wind speed in various scales (short, medium or long term) which will permit the operators to schedule and maintain generations as well as the other aspects of operation (Sainath, Vinyals, Senior, & Sak, 2015).

There are many forecasting methods found in literature. The forecasting approaches are therefore categorized into the statistical method (ARMA, ARIMA) (Grigonytė & Butkevičiūtė, 2016) physical method (NWP) (Meng, Ge, Yin, & Chen, 2016), deep learning (AI – neural networks) (Foley et al., 2012; Mori & Okura, 2017; Varanasi & Tripathi, 2017; Wang, Wang, Li, Peng, & Liu, 2016)and hybrid (grouping of NNs or NN with additional approaches) (Cadenas & Rivera, 2010; Dobbs, Elgindy, Hodge, & Florita, 2017; Hu & Chen, 2018; Kumar, Goomer, & Singh, 2018).

Hiroyuki Mori (Mori & Okura, 2017) has proposed an ANN based two staged (RBFN with S-transform) wind speed forecasting method with around 93% accuracy with real time wind speed data in Japan. Jyothi Varanasi (Varanasi & Tripathi, 2017) has implemented a NARX Artificial neural network to predict wind speed with MAPE around 2.3%. Emrah DOKUR (Dokur et al., 2016) proposed a hybrid EMD-ANN (Empirical Mode Decomposition Artificial Neural Networks) for wind speed forecasting with MSE as the accuracy index. It found MSE = 0.0879 for predicting wind speed of around 111 samples. T.G. Barbounis and J.B. Theocharis employed an online learning algorithm with a locally recurrent neural network (Barbounis & Theocharis, 2006) to predict long term wind speed of four different locations in Handras. The best forecasted wind speed had a correlation factor of 0.8533 in the northside and the MAE was 2.2779 m/s.Hu and Liang developed an LSTM based neural network model for accurate & stable forecasting of wind speed in Inner Mongolia, China (Hu & Chen, 2018). The model was developed for

both ten-minute and one-hour ahead forecasting. The test performance displayed an improved accuracy for 10 min. ahead forecasting. The performance for 10-min ahead forecasting was – MAE= 2.00, RMSE = 2.016, MAPE = 1.842, R = 1.952 and for one- hour ahead the performance was - MAE = 2.482, RMSE = 2.287, MAPE = 2.484, R = 2.186.

Yong Chen (Yu et al., 2017) has applied a CNN model along with some baseline and evaluation metrics model to forecast the wind speed data collected from Texas National Wind Institute. The model's performance is evaluated by MAE, RMSE and some other index. The convolutional neural network was used to forecast wind speed for summer and sprig season. The performance of summer was MAE = 1.1060, RMSE = 1.5456; while the performance of spring was MAE = 1.1100, RMSE = 1.5373.

The main contribution of the paper is to conquer the inconvenience of linear mutual models. The proposed model is developed to investigate and utilize the imbedded information of wind speed time series for wind speed anticipating by LSTM network.

2. Data Collection and Cleansing

This research has utilized 12 months historic dataset consisting of wind speed (m/s), temperature (0 C) and relative humidity (%), collected from Asian Institute of Technology's meteorology station. The raw data has consisted of 5 minutes interval and then those data have been converted to 30 minutes interval for the proposed LSTMRNN model. The half hourly averaged data are represented in fig. 1.

The statistical parameters of the data are presented in table I. The collected data are of different range. As a result, the data with higher values will have a great impact on the data of lower values. To avoid this problem the collected data are normalized using the equation 1.

$$y = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

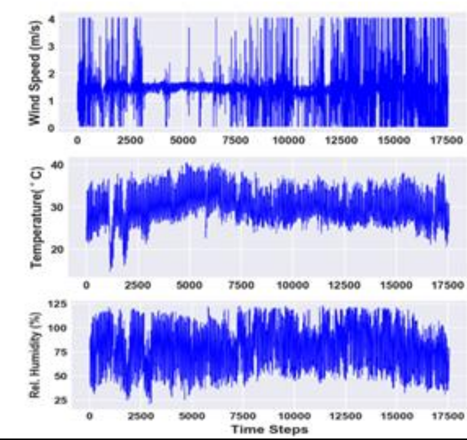

Figure 1: Collected data with 30 min. intervals

3. LSTMRNN Architecture

Table I: Statistical parameter of the collected data

Parameter		Value
Wind Speed (ms^{-1})	Min	0.04
	Max	4.05
	Mean	1.42
Temperature (^{0}C)	Min	14.7
	Max	40.47
	Mean	29.83
Relative Humidity (%)	Min	20.84
	Max	123.05
	Mean	80.94

This research proposes a LSTMRNN model that is suitable in predicting wind speed in six steps ahead. The architecture of the proposed model is presented in figure 2. The model contains two hidden layers along with an input, a fully connected layer that leads to the output layer.

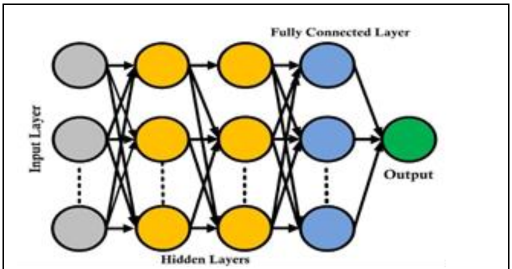

Figure 2: LSTMRNN structure

4. Recurrent Neural Network

RNN – Recurrent Neural Network is a type of ANN – Artificial Neural Network that is usually utilized for the prediction of time series. It utilizes the feedback provided by one or more units of its network as input in selecting the succeeding output (Cao, Ewing, & Thompson, 2012). The layers of the network perform necessary operations and yield specific output as directed and then pass the information to the next layer as an input (J. Kumar, Goomer, & Singh, 2018). Recurrent neural networks behavior can be expressed by the following two equations (Salman et al., 2018):

In hidden layer:

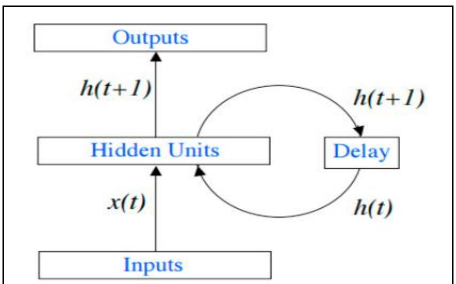

Figure 3: Unfolded RNN

$$h(t+1) = f_H\left(W_{IH}x(t) + W_{HH}h(t)\right) \qquad (2)$$

In output layer:

Where,

$$y\left(t+1\right) = f_0\left(W_{H0}h\left(t+1\right)\right) \qquad (3)$$

x (t) is the input time series and y (t) is output; WIH, WHH, WHO are the weight metrics; fH is the activation function of hidden layer while fO is for the output layer. h(t) is known as context unit of dynamical system.

5. Long Short-Term Memory Network

LSTM is explicitly a subfield of the recurrent neural network (RNN) architecture (Salman et al., 2018). It is very useful type of model when the gap between the past information and the required future values are at large scale. The specialty of LSTM network is its memory block in the hidden layers(Sainath et al., 2015). In the memory blocks, it has specific memory cells (fig. 4) that store the networks temporal states which is the basic reason this type of network are good at storing long term information. The gates inside the memory block are of three categories, namely (Salman et al., 2018)

- Input gate: It handles the flow of inputs towards the memory cell.
- Output gate: It controls the output stream of cell activations toward the remaining network.
- Forget gate: It forgets or resets the cells memory. It also scales the internal state of the cell.

Considering a sequence of input x = (x1…xT)for an LSTM network and the network computes the sequences of output y = (y1…yT), by deterring the network activation units by following equations.

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \qquad (4)$$

$$Z_t = \tanh\left(W_Z x_t + U_Z h_{t-1} + b_Z\right) \qquad (5)$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \qquad (6)$$

$$C_t = i_t Z_t + f_t C_{t-1} \qquad (7)$$

$$O_t = \sigma\left(W_0 x_t + U_0 h_{t-1} + V_0 C_t + b_0\right) \qquad (8)$$

$$h_t = O_t \tanh\left(C_t\right) \qquad (9)$$

Where,

x = input signal; y = output signal; i, o, f represents the input, output and gate signal respectively; h stands for the recurrent signal; W, b are the weight and bias metrics respectively; O represents the output gate activation vector; σ (sigmoid) and tanh are activation functions.

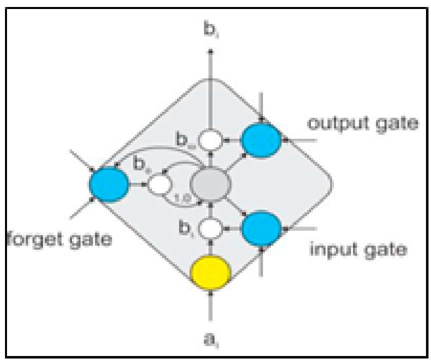

Figure 4: Memory cell of LSTM unit

The block diagram of the propose LSTMRNN is presented in figure 5.

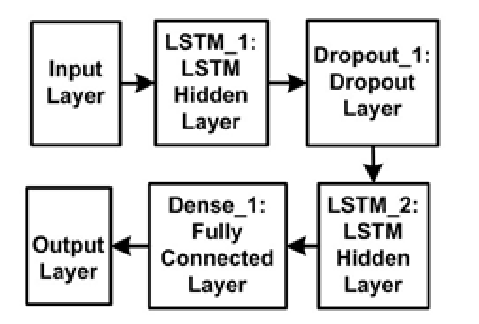

Figure 5: LSTMRNN block diagram

6. Accuracy measurement

There are many accuracy indexes found in the literature to evaluate the performance of prediction models. In this research, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are considered to evaluate the proposed model's performance.

These accuracy indexes are mathematically illustrated below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - y_i^{'} | \qquad (10)$$

$$RMES = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - y_i^{'})^2} \qquad (11)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{| y_i - y_i^{'} |}{y_i} \times 100\% \qquad (12)$$

7. Experimental Results:

Table II: Experimental Scenario			
Total data	Training data	Validation data	Test data
17500	14875 (85%)	1750 (10%)	875 (5%)

In this research, the model has been trained with 85% (14875 samples) of the total collected data

Table II: List of inputs	
Input Variable	Description
X_0	Wind Speed (m/s)
X_1	Temperature (^{0}C)
X_2	Relative Humidity (%)
X_3 - X_{12}	Lagged Series

(17500 samples). The rest 15% of the data used validation and test (10% and 5% respectively). The model was trained with three input variables wind speed, temperature and relative humidity along with a lagged series of previous 10 samples. The experimental scenario and the list of inputs are tabulated in table II & IV respectively.

Table IV: Performance comparison of the model

Steps Ahead	MAE		MAPE		RMSE	
	CNN	LSTM	CNN	LSTM	CNN	LSTM
1	0.30	0.28	7.25	2.00	0.78	0.57
2	0.39	0.35	8.32	3.06	0.81	0.69
3	0.54	0.40	10.03	3.89	0.96	0.74
4	0.59	0.44	10.42	4.34	1.81	0.76
5	0.62	0.47	11.98	4.87	1.83	0.76
6	0.64	0.51	12.73	5.66	2.54	0.79

Figure 6 represents the performance of the proposed model in predicting wind speed up to six steps ahead. It shows that at the first step the model predicts almost accurately while the

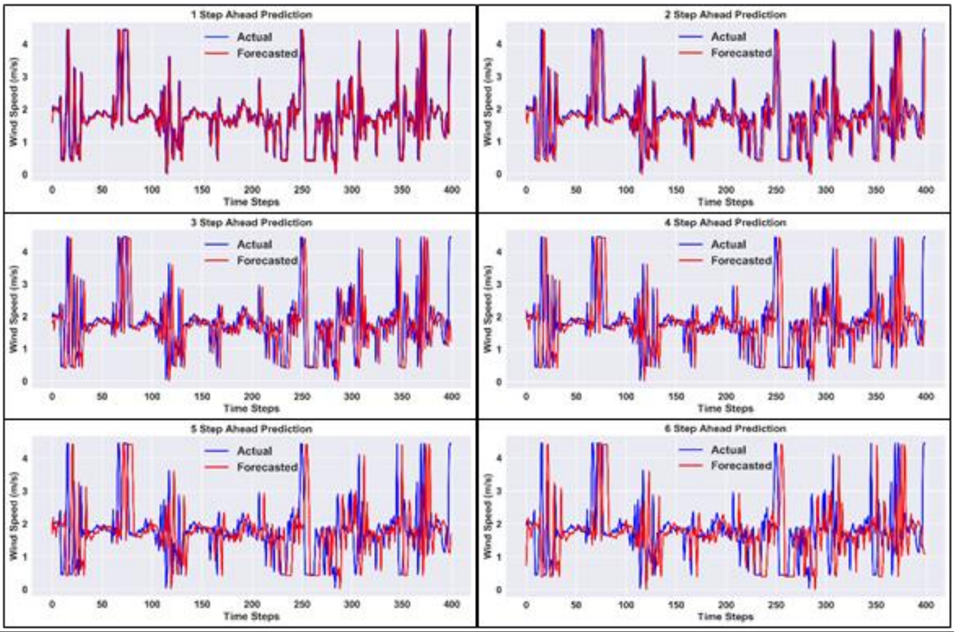

Figure: 6 Actual versus predicted wind speed

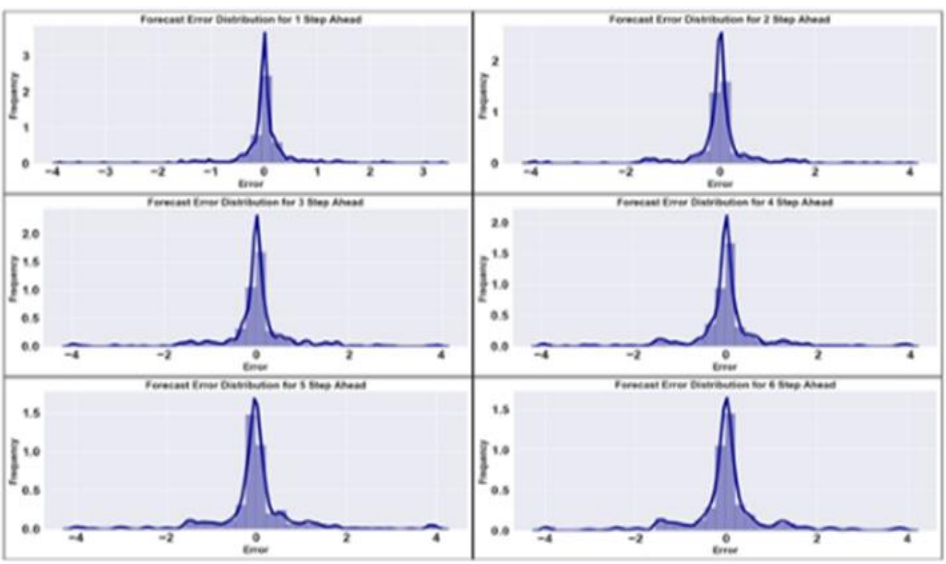

Figure 7: Error distribution of the proposed model

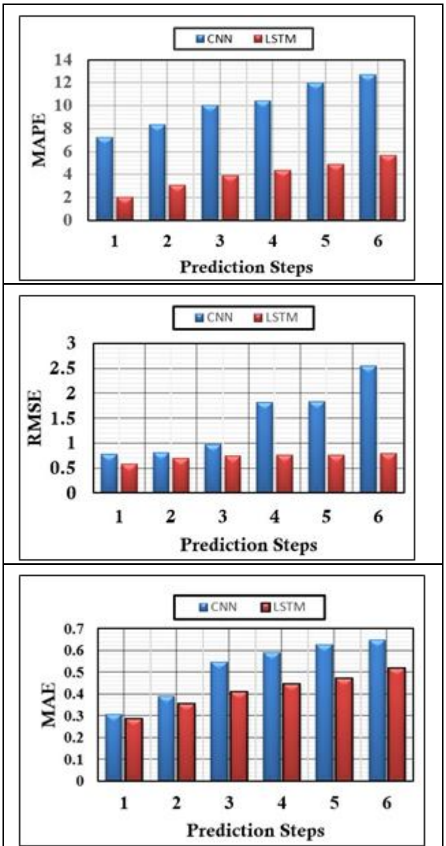

Figure 8: Comparison of performance

performance degrades as the time horizon of the forecast increases. The error distribution and error line curve are also represented in figure 7 and figure 8 respectively. The error distribution curve shows that during the earlier prediction horizon the error mean value is almost zero which proves the model's accuracy in successfully predicting the wind speed.

The error line curve shows very narrow fluctuation that proves the proposed model's acceptability. However, there are some sharp spikes in the error chart that has occurred due to

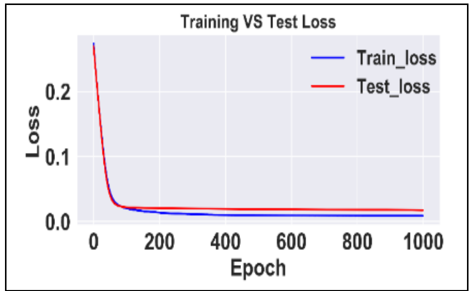

Fig.9. Training VS Testing loss of the proposed model

the sudden change in the actual wind speed value. Table III shows the performances of the proposed model. It also represents the comparison of performance with the CNN model. It shows that the proposed model performed better in every accuracy index in comparison with the CNN model. The model's training performance is depicted in figure 9.

8. Conclusion

Due to a vital role in the power system that incorporates wind power to a considerable scale, wind speed forecasting models are attracting huge attention. Specially, the forecasting approaches that are capable of providing more useful information about the intermittency or associated risk in wind speed has real appeal to the system operators. The proposed LSTMRNN model has successfully predicted the wind speed with 98% accuracy at first steps. The RMSE and MAE error of the proposed model is also very low. So, it can be concluded that the proposed model is effective in forecasting wind speed at a multi-scale level. The comparison is also presented in figure 7, where, the accuracy indexes are compared for both the models. It shows that the proposed LSTMRNN model can provide around 98% accuracy during the first prediction horizon. However, the accuracy drops at around 94% during the sixth prediction steps.

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