# Deep Learning based Wind Speed Forecasting-A Review

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Abstract— Wind speed forecasting is the term used for predicting speed of wind to generate wind power. Deep learning, which is the subfield of machine learning and is used to implement on a large data sets and predictions made using deep learning with LSTM can increases the accuracy rate to the great extent. The combination of deep learning with LSTM can enhances the prediction rate as due to the property of LSTM of pattern remembrance for longer duration of time. This survey discusses the existing functionality measures of different approaches by partitioning them into various methodologies: models of very small time gap, small time gap, and longtime gap. All these approaches include certain models with various parameters, advantages and disadvantages are discussed. The focus of this survey is to present a better and efficient evaluation of various approaches to help the researcher to select best model out of all present models.

## Keywords—RNN, LSTM, Wind Speed Forecasting

# I. INTRODUCTION

Prediction of wind speed is just the estimation of power of wind and this forecasting is helpful in power generation .And also it is done so as to maintain the gap between power consumption and power production. Wind speed forecasting based learning techniques which uses the concept of deep learning with long short term memory (LSTM) deals with the wind speed predictions, so that it can be utilized more efficiently by the power generation authorities .These predictions are made so as to match the variations produced by wind due to its volatile nature. If these variations can be traced or we can say predicted down earlier than it can help out in continuous power supply and generation. Deep learning is a subfield of machine learning and can be implemented on large data sets to provide good and accurate results. Learning algorithms can be easily used and implemented in deep learning and introduction of LSTM deals with the prediction problems. LSTM proves to be of great importance due to its property of remembering certain patterns for longer durations. Various approaches for wind speed forecasting were developed but they have certain issues

regarding their performance and accuracy. Different approaches produces different results in changing of environment, conditions, wind parameters etc. and also utilization of individual model shows the confined nature. Different models with same parameters were providing the different results, and also the accuracy was not up to the mark. Also the result varies with the observations also i.e. whether it is very short, short, medium, long range forecasting. In order to solve these problem there is a need or to enhance the accuracy and performance the need of a more accurate model evolved and in this research work a new model is proposed using deep learning and LSTM (long short term memory). Deep learning models based on neural networks and it picks out the best feature to improve the performance and the property of pattern remembrance of LSTM for longer duration of time makes it a more reliable and efficient combined prediction models. Combination of deep learning methods and LSTM (long short term memory) can enhance the accuracy as well as can provide a better way of prediction. The survey paper is structured as follows: Description table for various wind speed approaches, wind speed horizons, comparison of wind speed forecasting models with various advantages and disadvantages.

## II. RELATED WORK

The mentioned table includes the various research work in the field of wind speed prediction and there main objective is included with the approaches involved.

Table 1. Realated work on various approaches of wind speed forecasting

| S.No | PAPER      | PUBLISHER  | YEAR | OBJECTIVE       |
|------|------------|------------|------|-----------------|
| 1    | Wind       | Ioannis G. | 2004 | This paper      |
|      | speed      | Damousis,  |      | focuses on the  |
|      | prediction | Minas C.   |      | fuzzy model for |
|      | using      | Alexiadis, |      | wind speed      |
|      | fuzzy      | John       |      | forecasting and |

|   | model to              | B.Theocharis                 |      | genetic algorithm                 |
|---|-----------------------|------------------------------|------|-----------------------------------|
|   | generate              | , and Petros                 |      | to train these                    |
|   | power                 | S.                           |      | models.                           |
|   | with<br>spatial       | Dokopoulos                   |      |                                   |
|   | correlation           |                              |      |                                   |
|   | [9]                   |                              |      |                                   |
| 2 | Recurrent             | Ioannis G.                   | 2006 | This method is                    |
|   | Neural<br>Network     | Damousis,<br>Minas C.        |      | used for problem of wind speed    |
|   | based                 | Alexiadis,                   |      | prediction based                  |
|   | wind                  | John                         |      | on weather                        |
|   | speed<br>prediction   | B.Theocharis<br>, and Petros |      | information using recurrent       |
|   | with large            | S.                           |      | neural networks.                  |
|   | time gap              | Dokopoulos                   |      |                                   |
|   | for power             |                              |      |                                   |
|   | generation.           |                              |      |                                   |
| 3 | Recursive             | T.G.                         | 2006 | To train the                      |
|   | Prediction            | Barbounis,                   |      | locally recurrent                 |
|   | Error                 | J.B.<br>Theocharis           |      | neural network                    |
|   | algorithm<br>for long | Theocharis                   |      | using RPE<br>algorithm by         |
|   | term                  |                              |      | reducing the                      |
|   | predictions           |                              |      | error into sub-                   |
|   | of wind and speed.    |                              |      | problem in order<br>to reduce the |
|   | [15]                  |                              |      | complexity.                       |
| 4 | Artificial            | Erasmo                       | 2009 | Different models                  |
|   | Neural<br>Networks    | Cadenas,<br>Wildfrido        |      | were developed<br>with different  |
|   | based                 | Rivera                       |      | layers but                        |
|   | prediction            |                              |      | simplest model                    |
|   | of wind               |                              |      | was best and                      |
|   | speed for<br>small    |                              |      | accurate.                         |
|   | variations            |                              |      |                                   |
|   | in time.[8]           | D: 1 C                       | 2000 | T. C 1                            |
| 5 | Fraction<br>ARIMA     | Rajesh G.<br>Kavasseri,      | 2009 | To forecast wind speeds on the    |
|   | models                | Krithika                     |      | day-ahead (24 h)                  |
|   | based                 | Seetharaman                  |      | and two-day-                      |
|   | wind<br>speed         |                              |      | ahead (48 h)<br>horizons. This    |
|   | prediction            |                              |      | paper focuses on                  |
|   | for power             |                              |      | persistence                       |
|   | [14]                  |                              |      | model to analyze                  |
|   |                       |                              |      | and compare the speed of wind.    |
| 6 | ARIMA-                | Erasmo                       | 2010 | To train the error                |
|   | ANN                   | Cadenas,                     |      | with the help of                  |
|   | models for<br>wind    | Wilfrido<br>Rivera           |      | ANN which is generated by         |
|   | speed                 | 1111014                      |      | ARIMA model                       |
|   | prediction            |                              |      | on hourly based                   |
|   | method<br>which is    |                              |      | time series data. To improve the  |
|   | the hybrid            |                              |      | accuracy of this                  |
|   | of both the           |                              |      | hybrid model by                   |
|   | techniques            |                              |      | reducing the mean square          |
|   | [11]                  |                              |      | mean square<br>error, mean        |
|   |                       |                              |      | absolute error.                   |
| 7 | Markov                | S.A.                         | 2011 | To develop                        |
|   | chain<br>model to     | Pourmousavi<br>Kani and      |      | ANN-MC wind speed forecasting     |
|   | predict the           | M.M.                         |      | model for few                     |
|   | speed of              | Ardehali                     |      | seconds                           |
|   | wind in a very short  |                              |      | prediction and pattern for very   |
|   |                       | I                            |      | Pattern 101 VOLY                  |

|    | time [1]  |  |      | small time period   |
|----|---|--|------|---|
| 8  | Bayesian<br>combinati   | Gong li, jing<br>shi, Junyi<br>Zhou  | 2011 | The paper includes the two step   |
|    | algorithm<br>and NN<br>models for<br>the<br>prediction<br>of wind<br>speed in<br>short term   | Zilou  |      | methodology on<br>Bayesian<br>algorithms for<br>wind speed<br>forecasting and it<br>also include<br>neural network<br>models                                |
| 9  | A new forecasting method which is based on Bayesian theory and structure break model to predict the speed of wind in a very short span of time series. Very short-term wind speed [2] | Yu Jiang<br>,Zhe Song,<br>Andrew<br>Kusiak "   | 2013 | To use the prior information about wind to improve the results of the time series model which are predicted as a set of values different from other models. |
| 10 | k-nearest<br>neighbour<br>hood<br>classificati<br>on model<br>for the<br>prediction<br>of wind<br>speed<br>having<br>parameters<br>in n –<br>tupled<br>input<br>space [4]             | Mehmet<br>Yesilbudak,<br>Seref<br>Sagiroglu,<br>Ilhami Colak                         | 2013 | The paper predicts the results on the basis of effect of various parameters on the wind speed and k-NN classification is used.                              |
| 11 | Hybrid model of seasonal adjustment method and the radial basis function neural networks which comprisin g wavelet transform technique to predict the wind speed in a short time      | Wenyu<br>Zhang, Jujie<br>Wang,<br>Jianzhou<br>Wang,<br>Zengbao<br>Zhao, Meng<br>Tian | 2013 | To combine the wavelet transforms seasonal adjustment methods for the better and efficient result.  |
| 12 | gap[10]<br>An   | Da liu,  | 2014 | The model   |
|    | -   |  |      |   |

|    | optimized model of wind speed forecasting with the combinati on of wavelet transform and support vector machines [6]   | Dongxiao<br>Niu<br>,HuiWang,<br>Leilei Fan  |      | proposed include wavelet transform, genetic algorithm and support vector machines and use of these together overcome the other models ,also two evolutionary algorithms were considered.    |
|----|--|---|------|---|
| 13 | Regression<br>tress<br>algorithms<br>to predict<br>the speed<br>of wind<br>for the<br>very short<br>time gap<br>[3]  | A. Tronsco,<br>S. Salcedo-<br>sanz, C.<br>Casanova-<br>Mateo, J.C.<br>Riquelmw,<br>L.Prieto | 2015 | This method includes the various types of regression tree in wind speed predictions. The objective is to check the performance of different regression tree models.                         |
| 14 | A Hybrid model comprisin g Support Vector Regression and Seasonal adjustment index using Elman recurrent neural network methods to predict the wind speed [12] | Jianzhou<br>Wang,<br>Shanshan<br>Qin,<br>Qingping<br>,China                                 | 2015 | To develop a hybrid model PLERNN with SVR, SIA and ERNN to improve the accuracy results.  |
| 15 | Optimized Least Squares Support Vector Machine are optimized by PSO algorithm to predict the speed of wind in a short time gap [18]                            | Youjun Yue<br>,Yan Zhao,<br>Hui Zhao<br>and Hongjun<br>Wang                                 | 2017 | In this paper the accuracy rate is tried to improve by combining approaches like Ensemble Empirical Mode Decomposition (EEMD) and Sample Entropy (SE) Also the optimisation is done by PSO. |
| 16 | Cross validation error method to minimize the number of training samples in order to   | Xin Zhao,<br>Haikun Wei,<br>Chi Zhang,<br>Kanjian<br>Zhang                                  | 2017 | The main objective is to reduce the training samples to reduce the training samples and thus enhancing accurate predictions.  |

| 17 | improve<br>the<br>accuracy<br>of wind<br>speed<br>prediction<br>[19]   | Thomas   | 2017 | In this course   |
|----|--|--|------|--|
| 17 | Back propagatio n Neural Networks residual correction to reduce the error of the model of wind speed predictions . [20]                                    | Zhang<br>Chenhong,<br>Wang<br>Penghui,<br>Zhao<br>Yuanhang<br>yagang | 2017 | In this approach<br>the time series<br>and Back<br>propagation<br>neural network is<br>combined for<br>correction and<br>better wind speed<br>prediction rate. |
| 18 | Convoluti on long short term memory network and WPC for wind speed prediction using deep learning approach [7]   | Hui liu,<br>Xiwie Mi,<br>Yanfei Li                                   | 2018 | To develop a combined model using WPD, CNN, and CNNLSTM ,all the techniques used have different task to achieve an produce a robust model                      |
| 19 | Lorenz disturbanc e based IPSO-BP Neural Network comprisin g PCA to pre- process the data and train the model using Error back propagatio n algorithm [18] | Yagang<br>Zhang, Bing<br>Chen, Yuan<br>Zhao, and<br>Guifang Pan      | 2018 | The main objective is to increase the accuracy rate by correcting the prediction value by the introduction of Lorenz distribution                              |
|    | l .  | l  |      | 1  |

# III. WIND SPEED HORIZONS

Very short term forecasting: ranging from few n second to 30 minutes and useful in immediate and regulation actions. Short term forecasting: ranging from 30 minutes to 6 hours ahead and is useful in load dispatch planning and operational security. Medium term forecasting: ranging from a day ahead useful in reserve requirements. Long term forecasting

ranging from 1 day to 1 week or more is useful in operational management and in optimizing the cost [21]. The detailed description of all these models are given below in Table 1, Table 2 and Table 3, Table 4 respectively.

In very short term model the approach ANN-MC (Artificial neural network-Markov chain) model [1] is used for the wind speed prediction, the model shows the reduction of MAPE, MPE and also certain uncertainties were reduced. The approach of Bayesian structural break model [2] shows certain set of values of wind speed and these set of values can be implemented in many applications but this model has low computing efficiency and small training samples. In the next approach local modes-based regression trees [3] the computation is done by comparing 8 regression tree algorithms, it shows small computational time but same function approximation is tough.

The model based on K-nearest neighbor classification [4] uses multi-tuple inputs and error rates were observed graphically ,model presented does not depend on data sets but the main drawback of this model was that if less number of parameters are used for prediction than it inappropriate results.

Kumar Ajay et al. (2017) [22] reviewed the different methodologies for document clustering using K-nearest neighbor classification and Artificial Neural Networks.

Kumar Ajay et al. (2017) [27] reviewed the different methodologies semantic similarity measures using semantic latent analysis.

In **short term model** the approach used Bayesian adaptive neural network model shows more accurate results as compared to the other models but sometimes is inconsistent too, the model comprising of wavelet transform, support vector machines provide stable model and removing fluctuations but uses only single parameter. Methods using smart deep learning model predicts better results for speed fluctuations but resource requirement is high. While in case of ANN (Artificial Neural Network) knowledge is gained from trained data but huge amount of data is required for this model. The fuzzy model is used in complex model but take longer time to train the data while on the other hand the hybrid model shows smaller error rate but requirement of previous knowledge is necessary.

Bali et al. (2018) [24] suggested the use of optimization technique for Rock Predication by using Artificial Neural Networks.

Kumar Ajay et al. (2018) [23] discussed the various methodologies for electricity load forecasting using Artificial Neural Networks and Machine Learning.

Bali et al. (2012) [25] suggested the use of optimization technique using goal programming approach.

Bali et al. (2014) [26] suggested the use of optimization technique for Optimal Component Selection.

In **Medium term model** the approach implemented such as ARIMA-ANN model in linear and non-linear time series but shows more accurate results if used separately. The

Hybrid model shows quite significant and generalized result but it is quite complex also.

In **Long term model** the local recurrent neural network used shows stability and require smaller computational and storage but the structure is quite complex. In case of F-ARIMA model structure is simple but huge data requirement and non-linear problem handling is tough. The model based on local recurrence neural network shows higher adaptability but good training procedure is required.

## IV. COMPARISON OF WIND SPEED FORECASTING MODELS

Table 2 describes the different models using different parameters, their advantages and disadvantages for very short term wind speed forecasting.

Table 2. Comparison of various approaches for very short term forecasting models

| AUTHORS  | MODELS   | PARAMET<br>ERS  | ADVANTA<br>GES  | DISADVAN<br>TAGES  |
|--|--|---|---|--|
| S.A.<br>Pourmousavi<br>kani,M.M.<br>Ardehali(201                           | ANN -MC Mod el[1]                              | Speed   | -Reduction of<br>uncertainties<br>and<br>calculation<br>time                        | -Overtraining and<br>exploration a<br>common problem   |
| Yu jiang,Zhe<br>song,Andrew<br>Kusiak(2013)                                | Baye<br>sian<br>struc<br>tural<br>mod<br>el[2] | Speed   | -prediction is<br>set of values<br>-numerous<br>results can be<br>obtained          | -ignorance of<br>structural breaks<br>can lead to more<br>errors and<br>unreliable results<br>-low efficiency and<br>small training<br>samples |
| A. Tronsco,S. Salcedo-sanz, C.Casanova-Mateo,J.C. Riquelmw, L.Prieto(2015) | Regression<br>treemodel[3]                     | atmosp<br>heric<br>pressur<br>e,<br>temper<br>ature<br>,solar<br>radiatio<br>n,<br>humidi<br>ty | -small computation time  - result can be interpreted easily in regression tree      | -approximation of same functions cannot be done  -global models have low computational cost than local models                                  |
| Mehmet<br>Yesilbudak,S<br>eref<br>Sagiroglu,IIh<br>ami<br>Colak(2013)      | K-<br>Near<br>est<br>mod<br>el[4]              | directio<br>n,<br>temper<br>ature,<br>atmosp<br>here,<br>pressur<br>e,<br>humidi<br>ty          | -model does<br>not dependent<br>on the data<br>set type<br>- multi<br>tuppled input | -shows<br>inappropriate results<br>with less parameters  |

The following Table 3 describes the various approaches used by the researchers to predict the wind speed for short term forecasting

TABLE 3. COMPARISON OF VARIOUS APPROACHES FOR SHORT TERM FORECASTING MODELS

| AUTHORS  | MODELS  | PARAMETERS                              | ADVANTAGES  | DISADVANTA<br>GES   |
|--|---|---|---|---|
| Gong li,jing<br>shi,Junyi<br>Zhou(2011)  | Bayesi<br>an<br>adaptiv<br>e –NN<br>model[<br>5]    | Speed                                   | -provide<br>reliable<br>,adaptive,<br>and<br>comparatively<br>accurate<br>result to NN          | NN is not consistent<br>in forecasting one<br>hour ahead results  |
| Da<br>liu,Dongxia<br>o<br>Niu,HuiWa<br>ng,Leilei<br>Fan(2014)                            | WT+S<br>VM+G<br>A [6]                               | Tempe<br>rature                         | -provide<br>stable model<br>-fluctuations<br>in wind is<br>eliminated by<br>WT                  | -using only single<br>parameter at a time<br>-deep quantitative<br>analysis is missed   |
| Hui<br>Liu,Xiwei<br>Mi,Yanfei<br>li(2018)  | Smart<br>deep<br>learnin<br>g<br>model[<br>7]       | Speed                                   | -Robust and<br>effective<br>model<br>-predict better<br>result for<br>fluctuations              | -more resources are<br>required for<br>computation  |
| Erasmo<br>Cadenas,W<br>ilfrido<br>Rivera(200<br>9)                                       | ANN<br>model<br>[8]                                 | Speed                                   | -gaining<br>knowledge<br>from training<br>data-<br>robustness-<br>error<br>tolerance is<br>high | -requirement of<br>large training data<br>sets<br>- careful analysis is<br>required<br>-great flexibility<br>leads to inconsistent<br>results |
| Ioannis G. Damousis, Minas C. Alexiadis,J ohn B.Theochar is,Petros S. Dokopoulo s(20004) | Fuzzy<br>model<br>[9]                               | Wind<br>speed<br>,wind<br>directio<br>n | -used where<br>system are<br>difficult to<br>model<br>-relatively<br>less complex               | -reduction in<br>performance where<br>terrain is complex<br>-longer training time<br>and cross correlation<br>of data is low                  |
| Wenyu<br>Zhang,Jujie<br>Wang,Jianz<br>hou<br>Wang,Zeng<br>bao<br>Zhao,Meng<br>Tian(2013) | Hybrid<br>model(<br>WTT+<br>SAM+<br>RBFN<br>N) [10] | Speed                                   | hybridizing results in smaller error rate  - better forecasting performance                     | -previous  Knowledge is required of various technologies  |

The Table 4 given below describes the various approaches used for wind speed prediction using medium term forecasting

TABLE 4. COMPARISON OF VARIOUS APPROACHES FOR SHORT TERM FORECASTING MODEL

| AUTHORS   | <i>ST</i> Э <b>дО</b> М            | PARAMETERS              | ADVANTAGES   | DISADVANTAGES   |
|---|------------------------------------|-------------------------|--|---|
| Erasmo<br>Cadenas,<br>Wilfrido<br>Rivera(201                    | ARIM<br>A-<br>ANN<br>model<br>[11] | Speed                   | high accuracy<br>in wind speed<br>-can be<br>implemented<br>in linear and<br>non-linear<br>time series | model shows high<br>accuracy rate<br>separately                     |
| Jianzhou<br>Wang,<br>Shanshan<br>Qin,<br>Qingping<br>,China(201 | Hybrid<br>model[<br>12]            | Speed,<br>directio<br>n | -high<br>generalisation<br>performance   | optimization is quite<br>complex<br>- takes longer<br>training time |

The Table 5 given below describes the various approaches used for wind speed prediction using long term forecasting.

Table 5. Comparison of various approaches for long term forecasting model

| AUTHORS   | MODELS                                     | PARAMETERS   | ADVANTAGES  | DISADVANTAGES  |
|---|--|--|---|--|
| Thanasis G. Barbounis, J ohn B. Theochar is, Minas C. Alexiadis, P etros S. Dokopoulo s(2006) | Local<br>recurre<br>nt NN<br>model<br>[13] | Speed<br>,directi<br>on,<br>pressur<br>e,<br>temper<br>ature | provide continuous stability during learning phase -smaller computational and storage requirement | -structure observed<br>to be complex one   |
| Rajesh G.<br>Kavasseri,<br>Krithika<br>Seetharama<br>n(2009)                                  | f-<br>ARIM<br>A<br>model<br>[14]           | Speed  | -structure is<br>quite basic<br>-useful in<br>time series<br>model                                | -non-linear problem<br>handling is tough<br>-large amount of<br>data requirement |

| T.G.<br>Barbounis,<br>J.B.<br>Theocharis(<br>2006) | Local recurre nce NN | Tempe<br>rature | -provide<br>stable model<br>-fluctuations<br>in wind is<br>eliminated by | -using only single<br>parameter at a time<br>-deep quantitative<br>analysis is missed |
|--|----------------------|-----------------|--|---|
|  | model [15]           |                 | eliminated by<br>WT  |   |

#### V. DISCUSSION

In the above mentioned models and techniques the main focus is on increasing the accuracy rate to a certain extent. But basically the accuracy rate vary with change in parameters and other environmental conditions. In most of the cases utilization of various environmental factors are not clear for the better prediction of wind speed or the used factors does not provide a enhanced way of wind speed prediction for better power generation. The use of variety of parameters (atmospheric pressure, temperature, velocity, relative humidity) together with various deep learning techniques can certainly provide better prediction results in wind speed forecasting.

## VII. CONCLUSION

After the detailed study of various researchers work the approaches for wind speed forecasting models has various limitations such as low efficiency, high computational cost, more resources requirement, high complexity and overtraining etc. so as to overcome certain problems which are not comprehensively achieved by the various prediction models the use of deep learning methods with LSTM (long short term memory) can result in the better prediction of wind speed for power generation. so it is necessary to develop a unique wind speed prediction model which have less error rate and produce better and more efficient result. Also these prediction can be of great use in various atmospheric activities predictions.

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