Solar Illumination And Wind Speed Prediction: The Relative Prospects and Potential outcomes

A. V. Pavan Kumar[1] **Alivelu M. Parimi[2]**
[1, 2] Department of EEE, BITS-Pilani, Hyderabad Campus, Jawahar Nagar,
Shamirpet, Hyderabad, T.S, India. (pawanrao82@gmail.com[1], alivelu@hyderabad.bits-pilani.ac.in[2])

K. Uma Rao[3]
[3]Department of EEE, R. V College of Engineering, Mysore Road,
Bengaluru, Karnataka, India. (drumarao@yahoo.co.in[3])

Abstract: *The Photovoltaic and wind are well-thought-out to be a clean source of power generation from Renewable Energy Sources (RES) without carbon emission which can relieve grid dependency. As we advance in both time and innovation, our vitality needs are ascending at an exponential level and henceforth we need to tap undependable sources of energy all the more proficiently. As the RES power are directly dependent on environmental conditions, the challenging task is to predict the power generation from them. Due to substantial increment in installation of PV and wind generation; prediction of power generation from these plays a vital role in having a better load control. The paper focuses on the prediction techniques to forecast solar illumination level and wind speed with the historical data of environmental conditions thereby power generated can be projected a day ahead. This task is achieved by statistical methods where large historical data of the environmental conditions of a particular location is collected. The data analyzed using Neural Network model, Regression Trees model, and multiple linear regression models. The results obtained are compared with the actual value available for validation.*

Key words: *solar illumination, NN model, regression trees model, wind speed, prediction, statistical analysis.*

1. Introduction

With the expansion in concern of curtail natural assets for power generation and keeping in mind the end goal to reduce the carbon emission alternate sources of power generation have emerged. The Renewable Energy Sources (RES) being a perfect and clean source of power generation that can relieve the load on conventional power generation. The RES such as Photovoltaic (PV), the wind, fuel cell, tidal, hydro, nuclear power etc. out of which the PV and wind power generation are more promising technologies of power generation. The solar and wind power are renewable in nature and are available at no cost. Harnessing power from these RES is a well-established technology and the penetration of PV and wind power generation into the grid is growing exponentially [1], [2]. PV and wind grid connected mode of generation is the most effective way to harness the power. The output power from the PV and wind power totally rely on the environmental conditions. Some sophisticated factors like non-linear nature of PV, randomness of wind variation has an impact on power generation. So, considering these practical difficulties it is difficult to have the knowledge of total power generation from RES very accurately which will cause the safety and synchronization problems with the power grid. In order to have a stable operation, the power from the PV and wind has to be predicated a day ahead in order to plan for a schedule operation. The varying nature of RES and its effect on power generating systems, considering the load demand variation has been considered for the study [3], [4] and a load management system was proposed by utilizing prediction methodology.

The prediction methodology can be classified into two types (i) Online and (ii) Off-line method. In the online method of prediction, no historical data is needed the prediction is based on the real-time prediction and in the off-line method the historical data of the resources are accumulated, analyzed and processed through software tools to predict the power generation [5]. The off-line method of prediction has gained more prominence as the weather monitoring and recording stations have a huge amount of historical data which can be processed through mathematical models and power characteristics [6]. The off-line computing techniques which were implemented to forecast wind speed and solar illumination in recent existences are Artificial Neural Network (ANN), Artificial Neuro-Fuzzy inference system (ANFIS), Grey Predication, Regression models, Multi vibrant regression method, Fuzzy Logic, Genetic algorithm [7]–[11]. This paper focuses on the off-line method of prediction of Wind speed and solar illumination to compute the total amount of power that can be scheduled a day ahead. The computing topologies developed based on Neural Network (NN), Regression Tree Model and multiple linear regression are adopted from the literature for the study. The historical data of wind speed and solar illumination are measured at

BITS-Pilani, Hyderabad campus.

2. Solar Illumination and Wind Speed Historical data

The real-time data of solar illumination and wind speed measured over a year are graphically represented in Fig. 1 – Fig. 8

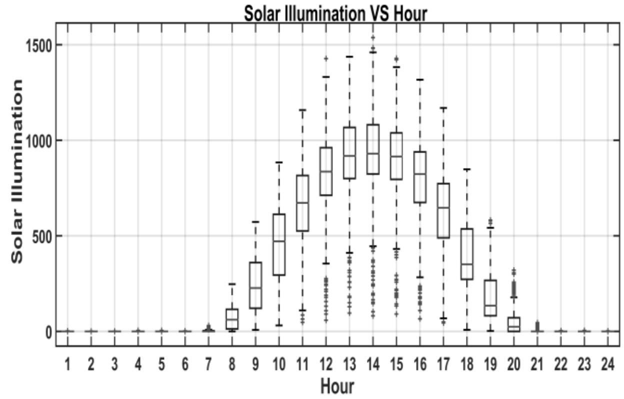

Fig. 1 Solar illumination measured over a day

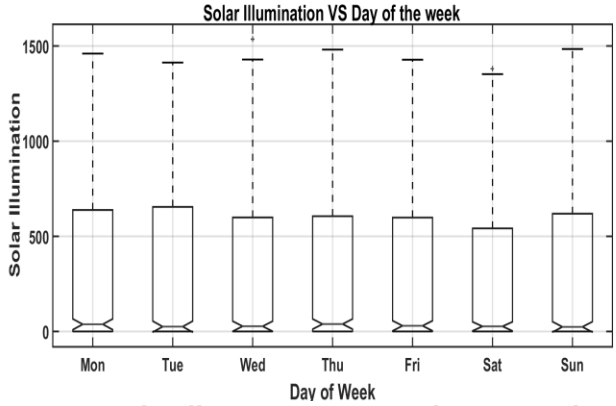

Fig. 2 Solar Illumination measured over a week

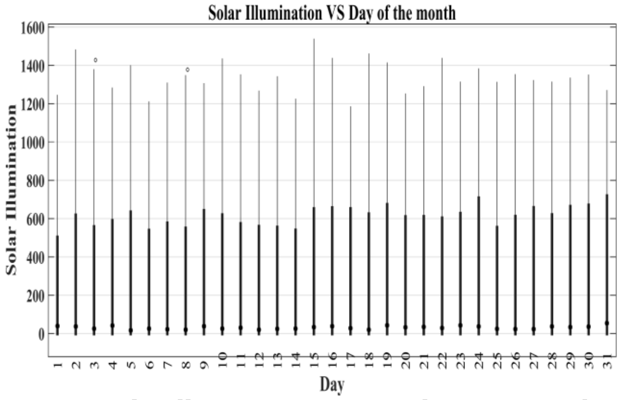

Fig. 3 Solar illumination measured over a month

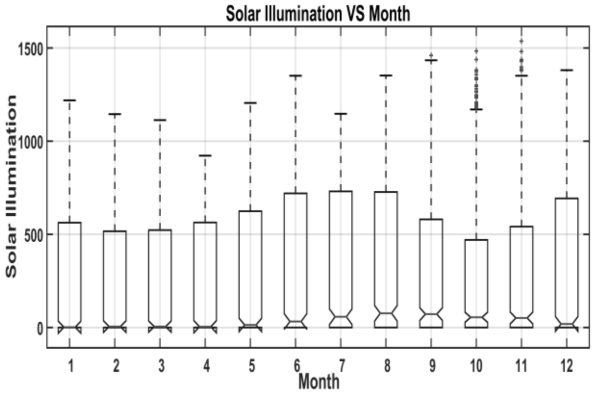

Fig. 4 Solar illumination measured over a year

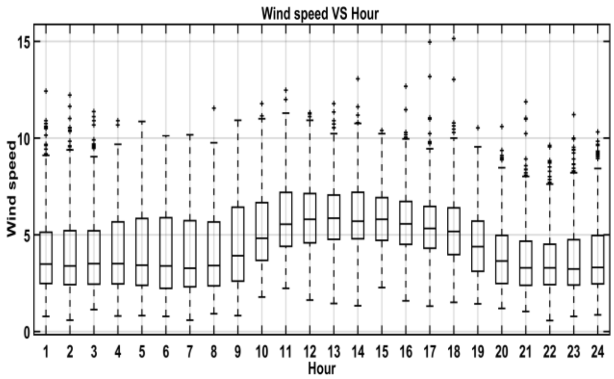

Fig. 5 Wind speed measured over a day

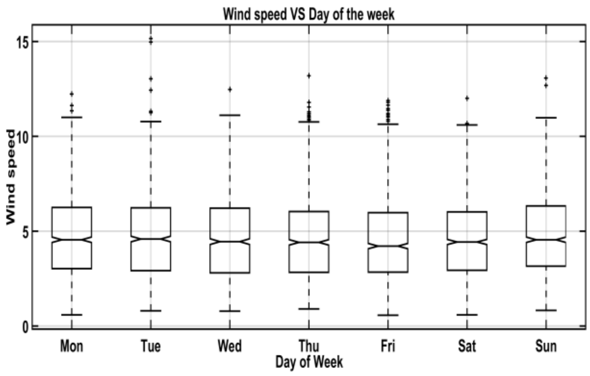

Fig. 6 Wind speed measured over a week

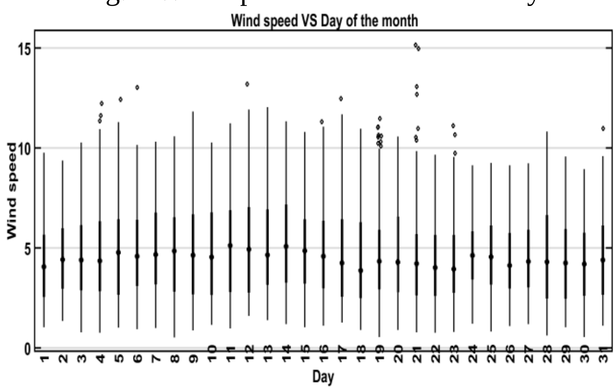

Fig. 7 Wind speed measured over a month

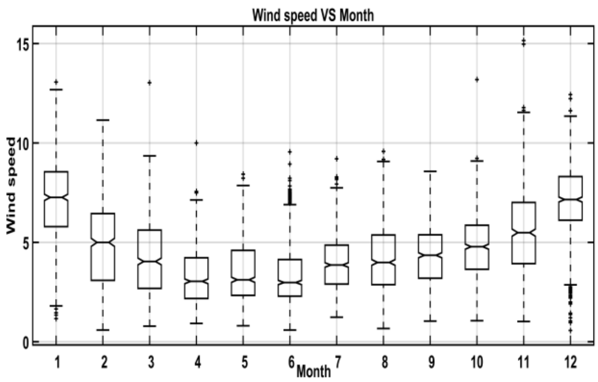

Fig. 8 Wind speed measured over a year

Figures. 1 - 4 shows the graphical representation of solar irradiation level measured over a year at the location. From the solar irradiation plot, it is clear that the location has a good solar energy with maximum solar irradiations level touching 1500 W/m^2 with average solar irradiation level around 600 W/m^2. Fig. 1 shows the graphical representation of hourly solar irradiance for the day it can be clinched that the location under consideration has a good solar irradiation level from 9 am to 6 pm with minimum irradiation of 400 W/m^2 and maximum value touching 1100 W/m^2.

Figures. 5 – 8 shows the graphical representation of wind speed measured over a year at the same location. It can be projected that the wind profile is quite good for low wind speed generation with average wind speed above 3 m/s and with the average maximum wind speed of 12 m/s. It can be clearly comprehended from Fig. 5 the hourly wind profile is quite good and from Fig. 7 that the monthly average is above 3 m/s and touching 5 m/s and maximum wind speed is between 8 m/s to 14 m/s

3. Prediction Methodology.

The prediction methodology of solar illumination and wind speed consists of different stages as shown in Fig. 9.

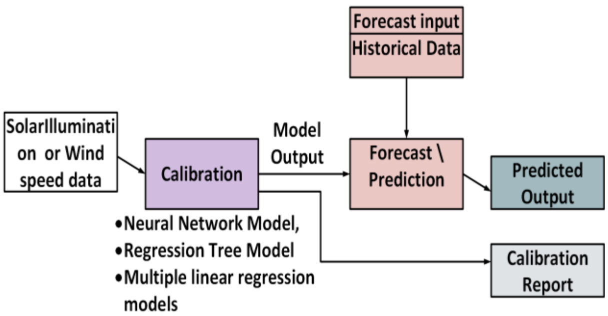

Fig.9 Block Diagram of Predictive model implementation procedure

The operation of the forecast methodology is divided into three steps

i) Acquiring and analyzing historical data,
ii) Selecting a model of calibration,
iii) Output the predicted data for a day ahead.

3.1 Neural Network Model for Prediction:

The Neural Network (NN) is a part of Artificial Intelligence (AI) that provides the flexibility to prediction model to solve complex mathematical computations. The NN model is based on the weight adjustment matrix for training the model as per historical data as shown in Figs. 1-8. Once the model is trained by adjusting weights according to the historical data it can be used to predict solar illumination or wind speed a day ahead. The schematic of NN model is shown in Fig. 10.

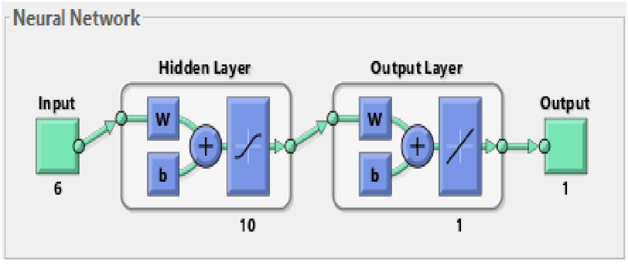

Fig. 10 Schematic of NN model developed

The Mean Absolute Percent Error (MAPE) for the forecasted Solar Illumination a day ahead is found to be 5.76 %, MAPE for historical solar illumination is 21.425% and execution time is 20 seconds for solar illumination prediction. MAPE for the forecasted wind speed of day ahead is found to be 14.099 %, MAPE for historical Wind speed is 28.242% and execution time is 18 seconds. The performance of the training is plotted in Fig. 11.

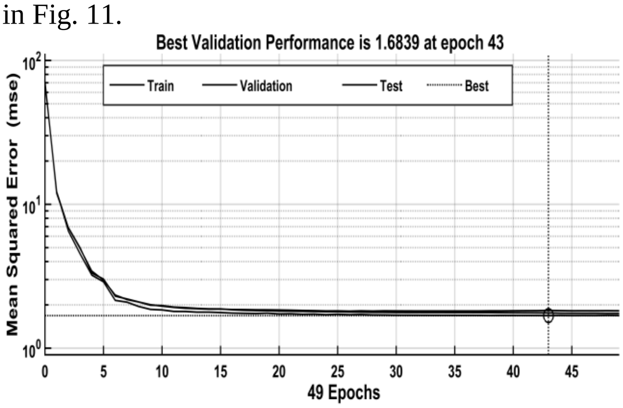

Fig. 11 Performance of NN model for prediction

The performance plot of NN model validates that the mean square error (mse) becomes minimum as a number of epochs increases as shown in Fig. 11. The epoch is one complete sweep of training, testing, and validation [12]. The test set error and validation set error have comparable characteristics and no major overfitting happens near epoch 43 where the best validation performance has taken place.

3.2 Regression Tree Model (RTM):

The solar illumination and wind speed prediction are achieved using Bagged Regression Tree (BRT) model. The BRT method of prediction is based on generating several versions of forecasted values and aggregating these values. These aggregated values are utilized to compute the final forecast output from the historical data. The several versions of forecasted values are made by forming bootstrap imitates of the learning set and utilizing imitates as a new learning set [13]. The computation technique of BRT is if each (y,

x) case is α be independently drawn from the probability distribution P. suppose y is numerical and $\varphi(x,\alpha)$ the predictor. Then the aggregated prediction is

$$\varphi_A(x,P)=E_\alpha \varphi(x,\alpha) \tag{1}$$

Considering Y, X to be random variables having the distribution P and independent of α. The average prediction error e in $\varphi(x,\alpha)$ is

$$e=E_\alpha E_{Y,X}\ (Y-\varphi(X,\alpha))^2 \tag{2}$$

The error in the aggregated predictor φ_A to be

$$e_A=E_{Y,X}\ (Y-\varphi_A(X,P))^2 \tag{3}$$

Using the inequality $(EZ)^2 \le EZ^2$ gives

$$e=EY^2-2EY\varphi_A+E_{Y,X}E_{\alpha\varphi^2}(X,\alpha) \tag{4}$$

$$\ge E(Y-\varphi_A)^2=e_A$$

Thus, ϕ_A has lower mse than ϕ. The value depends on how much unequal the two sides are [14]

$$[E_\alpha \varphi(x,\alpha)]^2 \le E_\alpha \varphi^2(x,\alpha) \tag{5}$$

The simulated MAPE for historical Wind speed is 11.470% and MAPE for the forecasted Wind speed of day ahead is 24.933%. MAPE for historical Solar Illumination is 39 % and MAPE for the forecasted Solar Illumination of the day ahead is 40.992%.

3.3 Multiple Linear Regression model:

The Multiple Linear Regression (MLR) model, is one of the prevalent, broadly used prediction technique for multivariable analysis and is used to implement a forecast model that can predict the solar illumination and wind speed. The mathematical representation of MLR is

$$X=a_0+a_1y_1+a_2y_2+.........+a_xy_x+E \tag{6}$$

where, X is the dependent variable, a_0, a_1, a_2 …. a_x are linear regression parameters that relate independent and dependent variables, E is the error [15].

The error between actual and predicted values is computed by

$$E=\left(\frac{H_{m\_avg}-H_c}{H_{m\_avg}}\right).100 \tag{7}$$

where, H_{m_avg} is the monthly average and H_c is the value of correlation. The mean square error is computed [16] as

$$mse=\frac{1}{n}\sum_{i=1}^{n}(H_{i,m\_avg}-H_{i,c}) \tag{8}$$

The simulated MAPE for historical Solar Illumination is 28.368%, MAPE for the forecasted Solar Illumination of the day ahead is 12.399%, MAPE for historical Wind speed is 29.879% and MAPE for the forecasted Wind speed of day ahead is 31.017%.

4. Prediction of Solar Illumination:

4.1 NN model based Prediction Results:

The long term and short term prediction of solar illumination are graphically represented in Fig. 12 and Fig. 13.

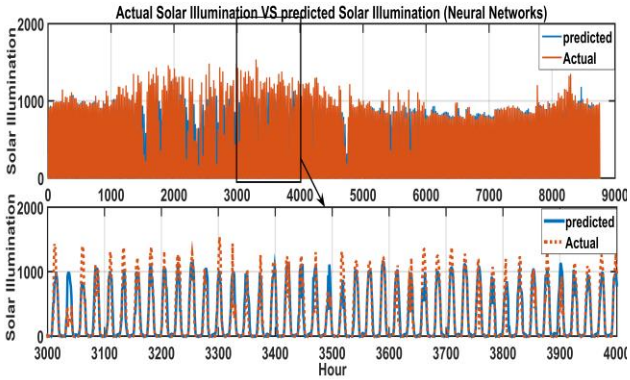

Fig. 12 Long-term Prediction of Solar Illumination

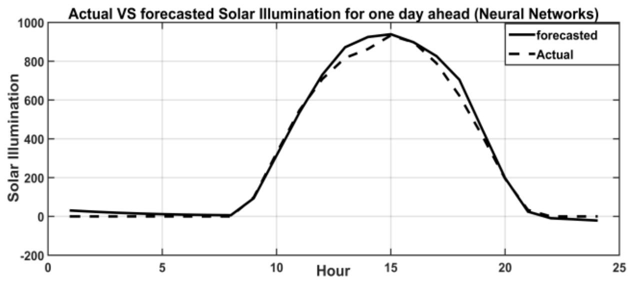

Fig. 13 A day ahead solar Illumination Prediction

From Fig. 12 and Fig. 13 it can be comprehended that the NN model of prediction has forecasted the solar illumination accurately. The long-term forecast of the historical data as shown in the Fig. 12 the predicted value duplicates the actual value with minimum deviation. The day ahead forecasts as shown in Fig. 13 the predicted value coincides with actual value with very small deviation.

4.2 RTM based Prediction Results:

Figure. 14 shows the long-term prediction of the solar illumination of historical data using RTM based prediction technique. It can be observed that the predicted value resembles the actual value of solar illumination. The technique has forecasted accurate values for long term prediction.

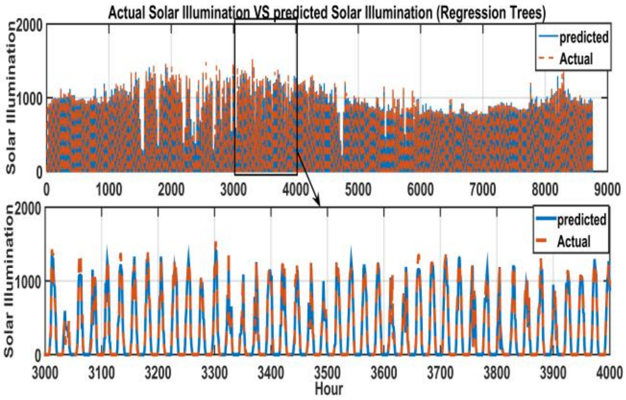

Fig. 14 Long-term prediction of solar illumination

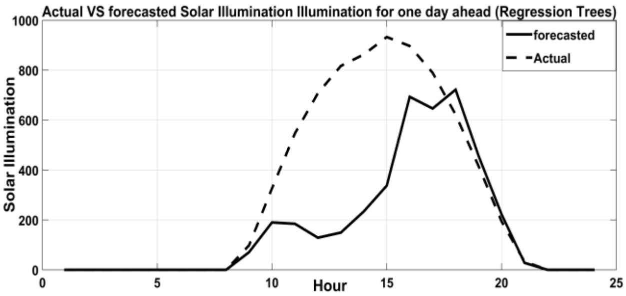

Fig. 15 A day ahead solar illumination forecast

Fig. 15 is the plot of a day ahead prediction of solar illumination. It can be comprehended that the RTM based prediction has accurate prediction long term prediction but has a deviation in short-term prediction.

4.3 MLR model based prediction Results:

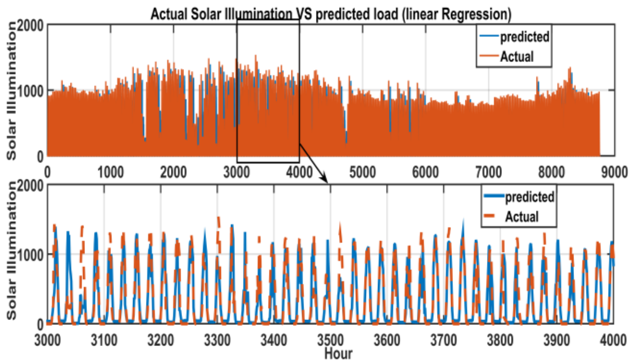

Fig. 16 Long-term prediction of solar illumination

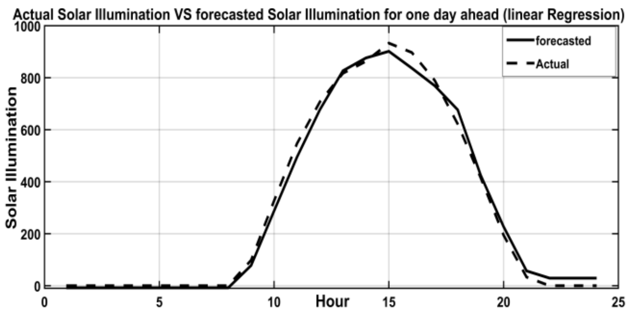

Fig. 17 A day ahead prediction of solar illumination

Figure. 16 shows the long-term prediction of the solar illumination of historical data using MLR model based prediction technique. It can be observed that the predicted value duplicates the actual value of solar illumination with minimum deviation. The technique has forecasted an accurately based on historical data. Fig. 17 exhibits accurate prediction results for a day ahead prediction. It can be comprehended that the MLR based prediction model has forecasted the long term and short term solar illumination accurately with minimum deviation from the actual value.

5. Prediction wind speed:

5.1 NN model based Prediction Results:

An NN model based long-term wind speed prediction of historical data and a day ahead forecast of wind speed is graphically represented in Fig. 18, Fig. 19.

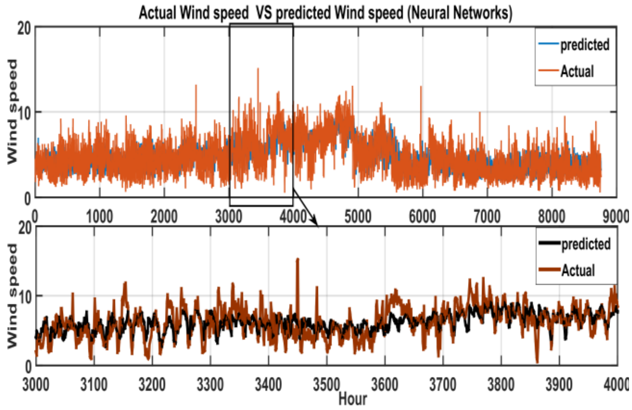

Fig. 18 Long-term wind speed prediction

From Fig. 18 the NN model based prediction has achieved accurate long-term prediction of historical data of wind speed.

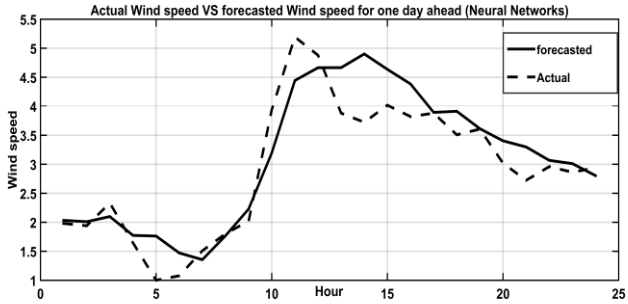

Fig. 19 A day ahead winds speed forecast

From Fig. 19 it can be comprehended that the NN-based prediction model has forecasted the day ahead wind speed accurately with a minimum deviation between predicted and actual values

5.2 RTM based Prediction Results:

An RTM based long-term wind speed prediction of historical data and a day ahead wind speed forecast is graphically shown in Fig. 20, Fig. 21. From Fig. 20 it can be comprehended that the RTM based prediction technique has accurately predicted long-term historical data of wind speed.

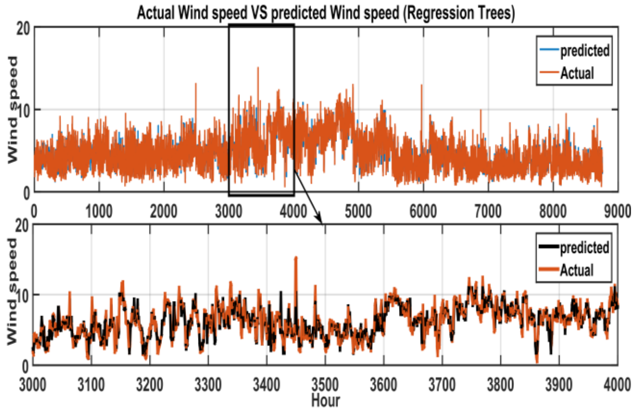

Fig. 20 Long-term wind speed prediction

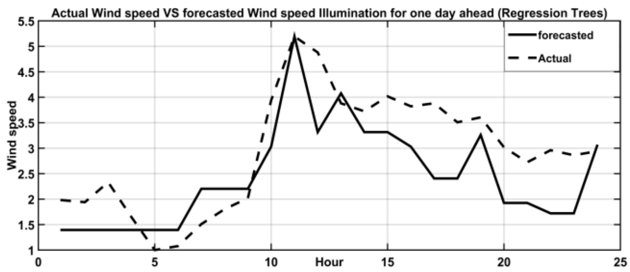

Fig. 21 A day ahead wind speed forecast

From Fig. 21 it can be observed that the forecasted of the day ahead wind speed resembles the actual wind speed with large deviation from actual value. The RTM has forecasted accurate long term wind speed but has deviation in short term prediction.

5.3 MLR model based Prediction Results:

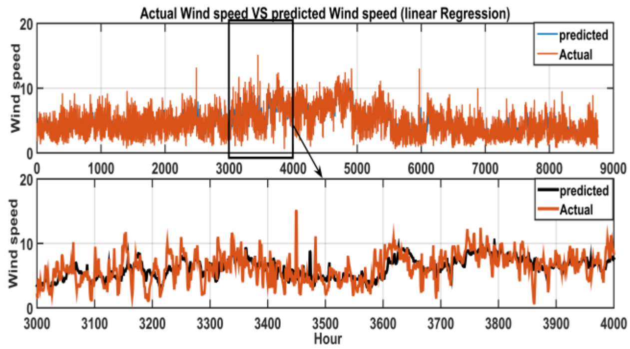

Fig. 22 Long-term wind speed prediction

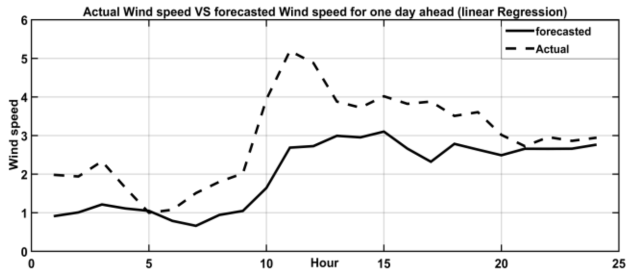

Fig. 23 A day ahead forecast of wind speed

An MLR based long-term wind speed prediction of historical data and a day ahead wind speed forecast is graphically shown in Fig. 22, Fig. 23. From Fig. 22 it can be comprehended that the MLR based prediction technique has accurately predicted long-term historical data of wind speed. From Fig. 23 it can be observed that the forecasted wind speed and actual wind speed has deviations. It can be comprehended that the MLR based prediction technique has accurate long-term wind speed prediction but has a deviation in short term wind speed prediction.

It can be concluded from the simulation study that the NN model based prediction technique has forecasted the solar illumination and wind speed very accurately with least MAPE value from the long term and short term forecast as compared with the RTM and MLR based prediction techniques.

6. PV and Wind Power Prediction:

From the prediction study, the Neural Network model is selected for predicting the power generated from PV and the wind-based generation a day ahead. A 10 kW PV and 10 kW wind power generation are considered to exhibit the power forecast.

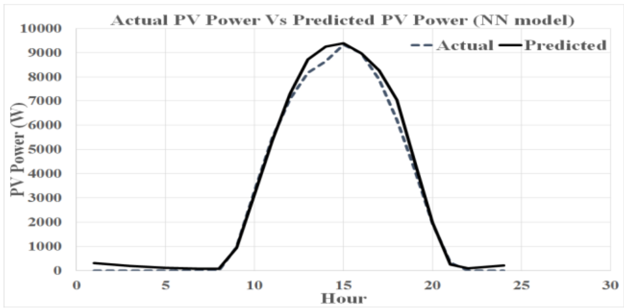

Fig. 24 a day ahead PV power forecast by NN model

The forecasted PV and wind power are graphically represented in Fig. 24 and Fig. 25. It can be comprehended that the NN-based prediction technique forecasts the power generated from PV and Wind accurately with a minimum deviation of predicted value from the actual value. A comparative analysis of MAPE is tabulated in Table 1 which demonstrates the performance of prediction techniques under consideration. The NN based model has demonstrated better performance as compared with the other prediction techniques considered.

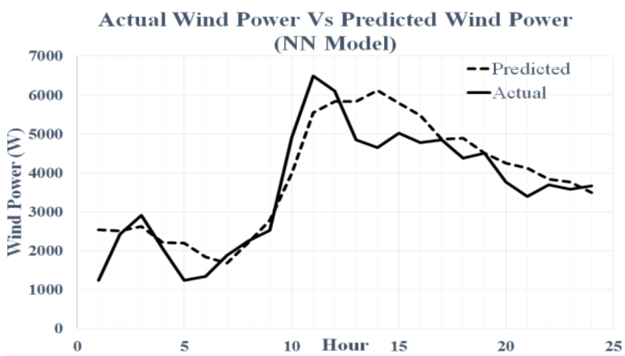

Fig. 25 a day ahead wind power forecast by NN model

Table 1. Comparison of Mean Absolute Percentage Error (MAPE)

Model	NN Model		RTM Model		MLR Model	
	Solar Illumination	Wind speed	Solar Illumination	Wind speed	Solar Illumination	Wind speed
MAPE for long term prediction	21.425%	28.242%	39%	11.470%	28.368%	29.829%
MAPE for a day ahead prediction	5.76%	14.099%	40.992%	24.933%	12.399%	31.017%

7. Conclusion:

Prediction of Solar illumination and Wind speed plays a vital role in RES power generation operating in grid connected mode or islanded mode of operation. Utilizing the prediction techniques to predict the amount of power that can be generated from RES a day ahead will add flexibility to the power generation system to schedule the power delivery for smooth operation and minimizing the grid stability problems.

The prediction is demonstrated using Neural Network model, Regression Tree model, and Multiple Linear Regression model techniques. From the simulation study, it can conclude that the NN-based prediction technique demonstrated more accurate results in terms of forecasting solar illumination and wind speed from historical data recorded at BITS-Pilani, Hyderabad campus. Out of the three models under consideration NN model has minimum Mean Absolute Percentage Error (MAPE) for both long term and a day ahead prediction of solar illumination and wind speed.

The NN model has forecasted accurate results for long term and a day ahead prediction for both Solar and Wind. Whereas, RTM and MLR prediction technique has forecasted accurate long-term solar illumination and wind speed prediction but could not forecast a day ahead prediction accurately. From this, it can be concluded that the NN model prediction has precise and accurate forecast.

Utilizing the NN model for a day ahead forecast of power that can be generated from a PV and Wind-based generation are analyzed. The forecasted power demonstrates accurate results as compared to the actual value.

Further, this model can be utilized for forecasting load demand in long term or short term prediction which helps the power system operation and control more flexible and can relieve stress on the conventional generation.

References

[1] A. V. P. Kumar, A. M. Parimi, and K. U. Rao,: *Implementation of MPPT control using fuzzy logic in solar-wind hybrid power system.* In: 2015 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES), 2015, pp. 1–5.

[2] R. K. G, V. Prema, and K. U. Rao. : *Multivariate Wind Power Forecast using Artificial Neural Network*. In: Global Humanitarian Technology Conference - South Asia Satellite (GHTC-SAS), 2014 IEEE, Trivandrum, 2014, pp. 159-163.

[3] D. Neves, M. C. Brito, and C. A. Silva. : *Impact of solar and wind forecast uncertainties on demand response of isolated microgrids*. In: Renewable Energy, 2016, vol. 87, pp. 1003–1015.

[4] R. Juban, H. Ohlsson, M. Maasoumy, L. Poirier, and J. Z. Kolter. : *A multiple quantile regression approach to the wind, solar, and price tracks of GEFCom2014*. In: International Journal of Forecast., 2016.

[5] Y. Yang and L. Dong. : *Short-term PV generation system direct power prediction model on wavelet neural network and weather type clustering*. In: Proc. - 2013 5th Int. Conf. Intell. Human-Machine Syst. Cybern. IHMSC 2013, vol. 1, pp. 207–211.

[6] Y. Li, J. Zhang, J. Xiao, and Y. Tan.: *Short-term Prediction of The Output Power of PV System Based on Improved Grey Prediction Model*. In: Proceedings of the 2014 International Conference on Advanced Mechatronic Systems, Kumamoto, pp. 547–551.

[7] N. N. Arjun, V. Prema, D. K. Kumar, P. Prashanth, V. S. Preekshit, and K. U. Rao. : *Multivariate regression models for prediction of wind speed*. In: Proceedings of International Conference of Data Science Engineering ICDSE, 2014, pp. 171–176.

[8] J. Zeng and W. Qiao.: *Short-term solar power prediction using an RBF neural network*. In: IEEE Power and Energy Society General Meeting, 2011 pp. 1-8.

[9] T. H. M. El-Fouly, E. F. El-Saadany, and M. M. A.

Salama.: *One day ahead prediction of wind speed and direction*. In: IEEE Transaction on Energy Conversion, 2008, vol. 23, no. 1, pp. 191–201.

[10] X. Yang, F. Jiang, and H. Liu.: *Short-Term Solar Radiation Prediction based on SVM with Similar Data.* In: 2nd IET Renewable Power Generation Conference (RPG 2013), 2013, pp. 1.11–1.11.

[11] A. Yona, T. Senjyu, T. Funabashi, and C.-H. Kim.: *Determination Method of Insolation Prediction With Fuzzy and Applying Neural Network for Long-Term Ahead PV Power Output Correction.* In: IEEE Transaction on Sustainable Energy, 2013, vol. 4, no. 2, pp. 527–533.

[12] B. Li, Y. Li, and X. Rong.: *Comparison of echo state network and extreme learning machine on nonlinear prediction*. In: Journal of Computation Information and System, 2011, vol. 7, no. 6, pp. 1863–1870.

[13] L. Breiman, J. Friedman, C. Stone, and R. Olshen. : *Classification and regression trees*. 1984.

[14] L. Breiman.: *Bagging predictors*. In: Machine Learning. 1996, vol. 24, no. 2, pp. 123–140.

[15] N. Akuagwu, E. Ejike, and A. Kalu.: *Estimation of Air Quality in Aba Urban, Nigeria Using the Multiple Linear Regression Technique*. In: journal of geography environment and earth science international., 2016, vol. 4, no. 2, pp. 1–6.

[16] O. Coulibaly and A. Ouedraogo.: *Correlation of Global Solar Radiation of Eight Synoptic Stations in Burkina Faso Based on Linear and Multiple Linear Regression Methods*," In: *Journal of Solar Energy*, 2016, vol. 2016, p. 9.