Chapter 6

Short-term and Long-term Prediction of Solar illumination and Wind speed profile for the location

6.1 Introduction

In this chapter the real-time data of Solar illumination and Wind speed recorded at BITS-Pilani, Hyderabad campus is utilized for Predicting the expected profile of solar illumination and wind speed in short term and long term period. Which can be further utilized to predict amount of power that can be harnessed from PV-Wind hybrid power system.

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, the 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 [250, 251] 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 [252]. 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 [253]. 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 [254–258]. 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.

6.2 Prediction Methodology

The prediction methodology of solar illumination and wind speed consists of different stages as shown in Figure 6.1 The operation of the forecast methodology is divided into three steps i) Acquiring and analyzing historical data,

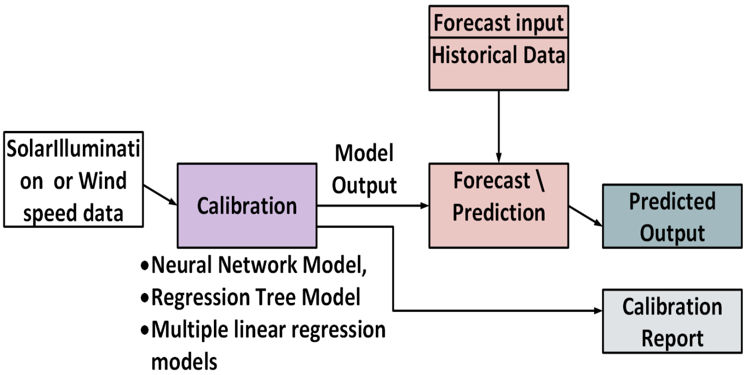

FIGURE 6.1: Block Diagram of Predictive model implementation procedure

ii) Selecting a model of calibration,

iii) Output the predicted data for a day ahead.

6.2.1 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 Figures 5.11 - 5.18. 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 Figure 6.2.

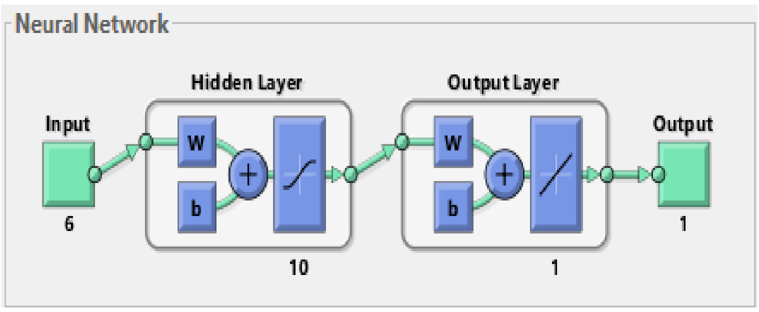

FIGURE 6.2: Schematic of NN model developed

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 Figure 6.3.

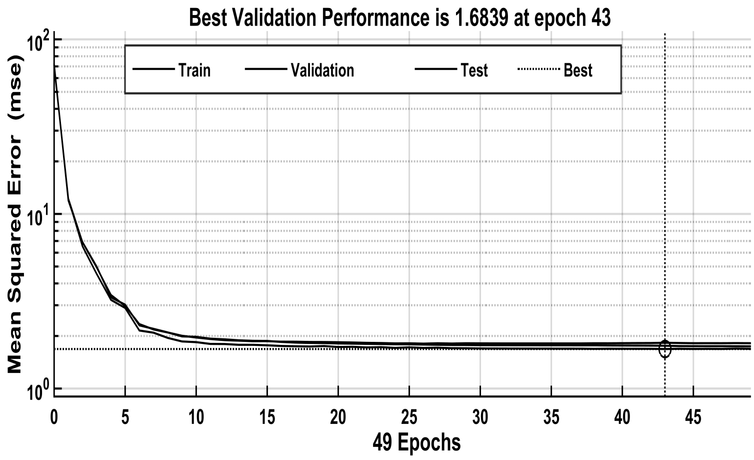

FIGURE 6.3: Performance of NN model for prediction

The performance plot of NN model validates that the mean square error (mse) becomes minimum as a number of epochs increases as shown in Figure 6.3. The epoch is one complete sweep of training, testing, and validation [259]. The test set error and validation set error have comparable characteristics and no major over fitting happens near epoch 43 where the best validation performance has taken place.

6.2.2 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 [260]. The computation technique of BRT is if each (y, x) case is be independently drawn from the probability distribution P. suppose y is numerical and $\phi(x,\alpha)$ the predictor. Then the aggregated prediction is (6.1)

$$\phi_A(x,P) = E_\alpha \phi(x,\alpha) \tag{6.1}$$

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

$$e = E_{\alpha} E_{Y,X} (Y - \phi(X,\alpha))^2 \tag{6.2}$$

The error in the aggregated predictor ϕ_A to be

$$e = E_{Y,X} (Y - \varepsilon \phi_A(X,P))^2 \tag{6.3}$$

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

$$e = EY^2 - 2EY\phi_A + E_{Y,X} E_{\alpha\phi^2}(X,\alpha) \geqslant E(Y - \phi_A)^2 = e_A \tag{6.4}$$

Thus, ϕ_A has lower mse than . The value depends on how much unequal the two sides are [261]

$$[E_{\alpha}\phi(x,\alpha)]^2 \leq E_{\alpha}\phi^2(x,\alpha) \tag{6.5}$$

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%.

6.2.3 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

$$X = a_0 + a_1 y_1 + a_2 y_2 + ... + a_x y_x + E \tag{6.6}$$

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 [262]. The error between actual and predicted values is computed by

$$E = \left[\frac{H_{m\_avg} - H_c}{H_{m\_avg}}\right].100 \tag{6.7}$$

where, H_{m_avg} is the monthly average and H_c is the value of correlation. The mean square error is computed [263] as

$$mse = \frac{1}{n}\sum_{i=1}^{n}(H_{i,m\_avg} - H_{i,c}) \tag{6.8}$$

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

6.3 Prediction of Solar Illumination

6.3.1 NN model based Prediction Results

The long term and short term prediction of solar illumination are graphically represented in Figure 6.4 and Figure 6.5

From Figure 6.4 and Figure 6.5 it can be comprehended that the NN model of prediction has fore-casted the solar illumination accurately. The long-term forecast of the historical data as shown in the Figure 6.4 the predicted value duplicates the actual value with minimum deviation. The day ahead forecasts as shown in Figure 6.5 the predicted value coincides with actual value with very small deviation.

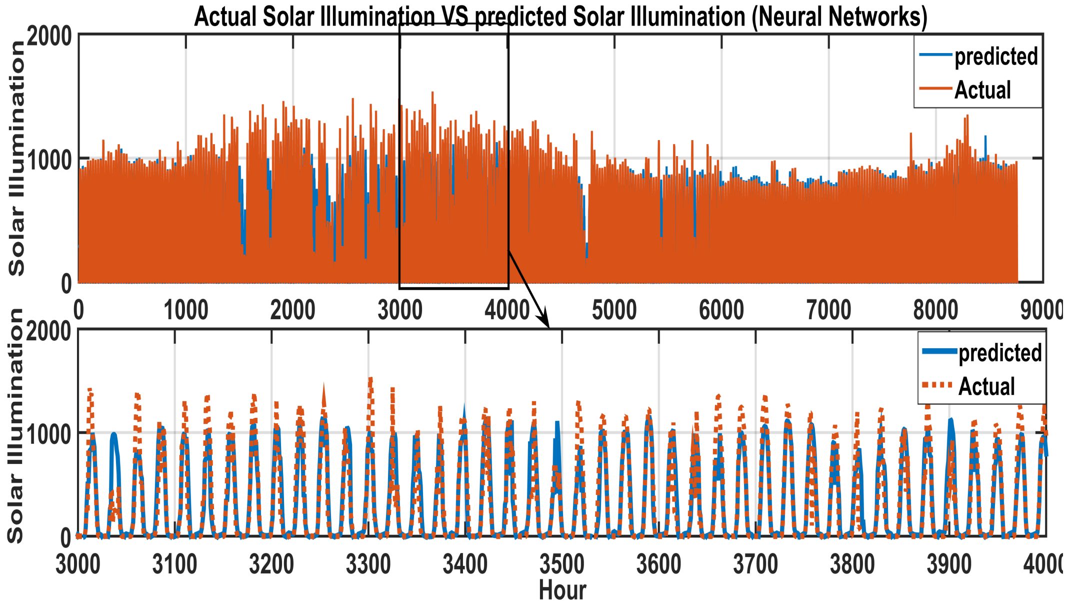

FIGURE 6.4: Long-term Prediction of Solar Illumination

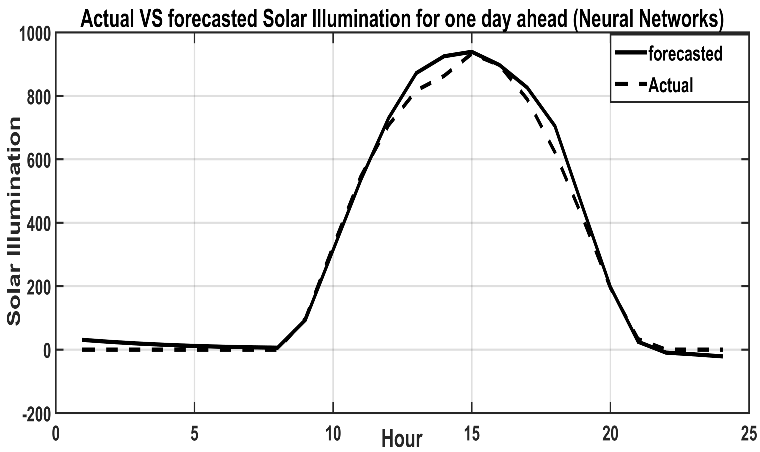

FIGURE 6.5: A day ahead solar Illumination Prediction

6.3.2 RTM based Prediction Results

Figure 6.6 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.

Figure 6.7 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.

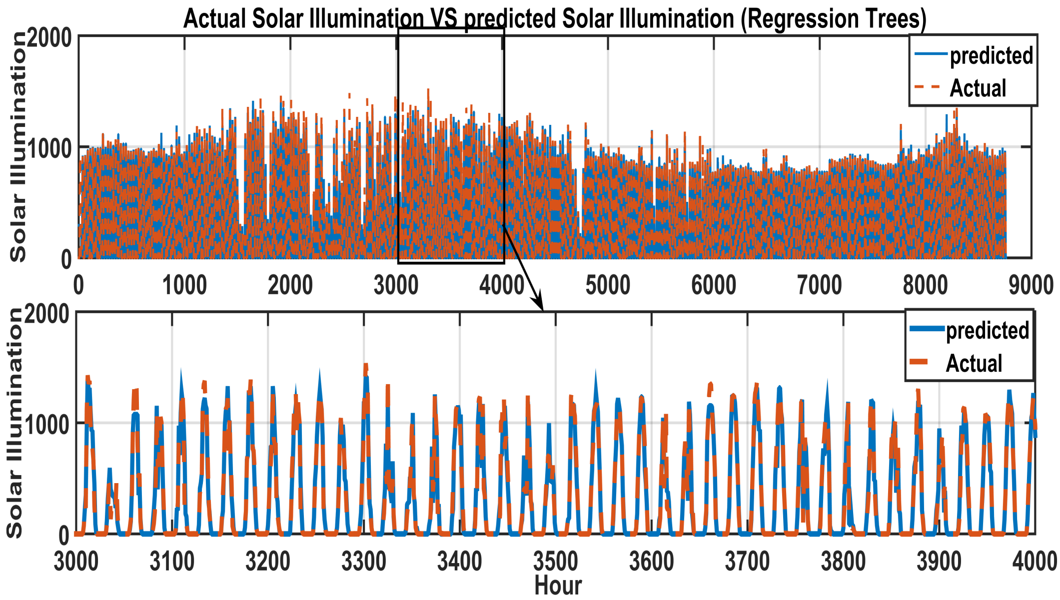

FIGURE 6.6: Long-term Prediction of Solar Illumination

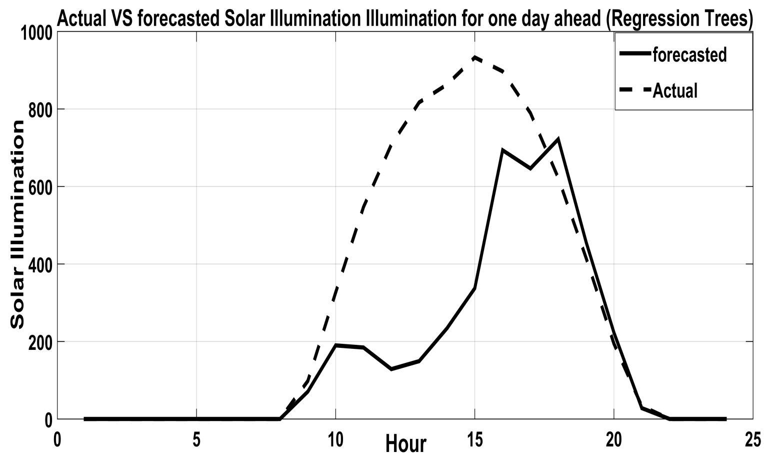

FIGURE 6.7: A day ahead solar Illumination Prediction

6.3.3 MLR model based prediction Results

Figure 6.8 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. Figure 6.9 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.

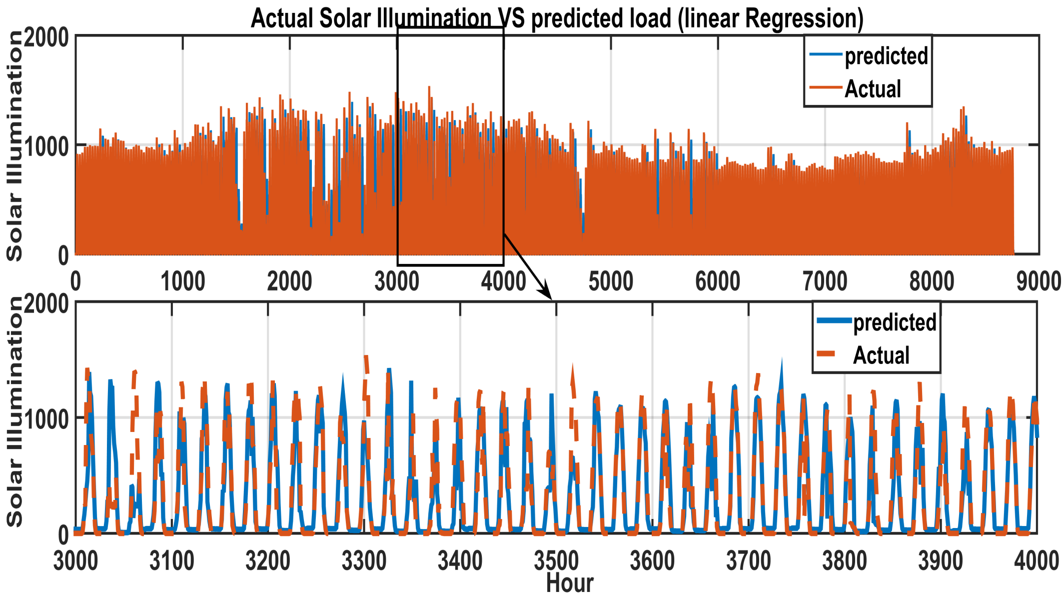

FIGURE 6.8: Long-term Prediction of Solar Illumination

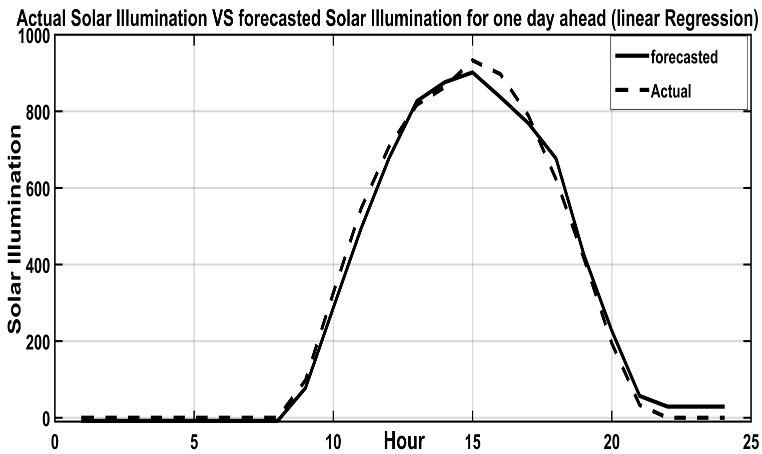

FIGURE 6.9: A day ahead solar Illumination Prediction

6.4 Prediction wind speed

6.4.1 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 Figure 6.10, Figure 6.11.

From Figure 6.11 it can be comprehended that the NN-based prediction model has fore-casted the day ahead wind speed accurately with a minimum deviation between predicted and actual values.

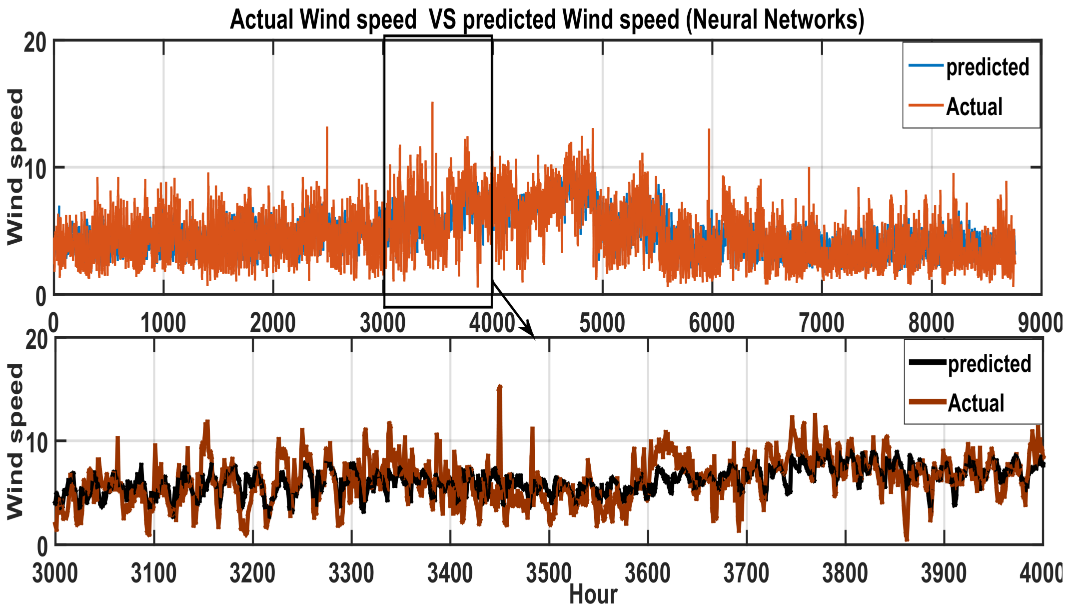

FIGURE 6.10: Long-term wind speed prediction

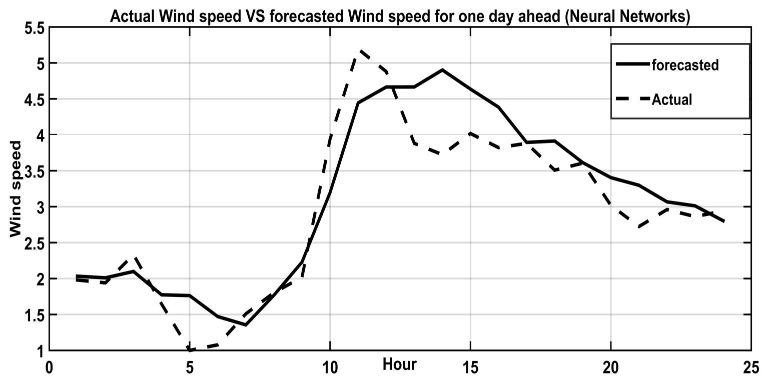

FIGURE 6.11: A day ahead wind speed forecast

6.4.2 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 Figure 6.12, Figure 6.13. From Figure 6.12 it can be comprehended that the RTM based prediction technique has accurately predicted long-term historical data of wind speed.

From Figure 6.13 it can be observed that the fore-casted of the day ahead wind speed resembles the actual wind speed with large deviation from actual value. The RTM has fore-casted accurate long term wind speed but has deviation in short term prediction.

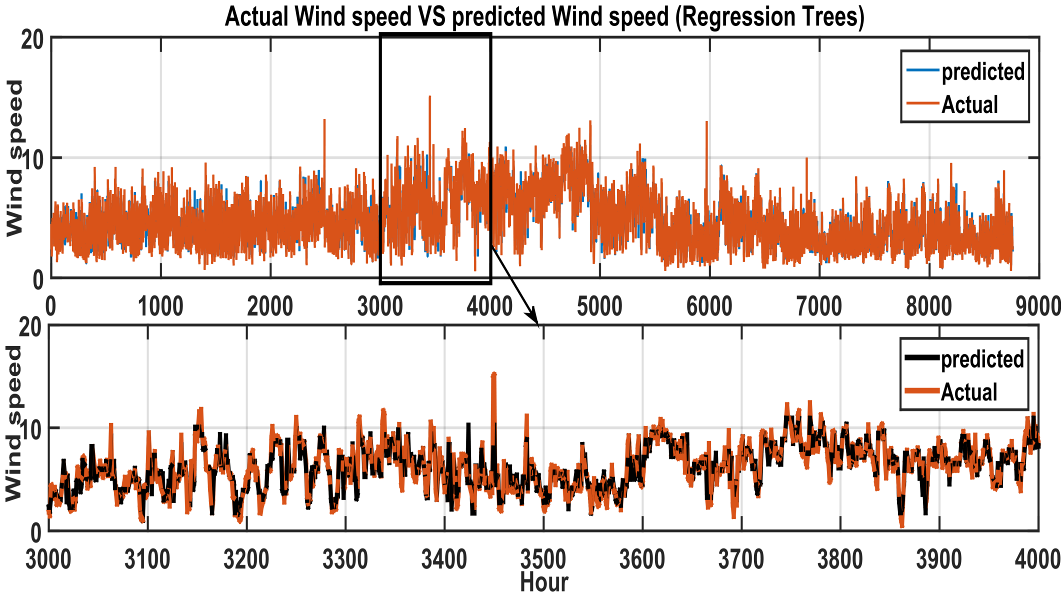

FIGURE 6.12: Long-term wind speed prediction

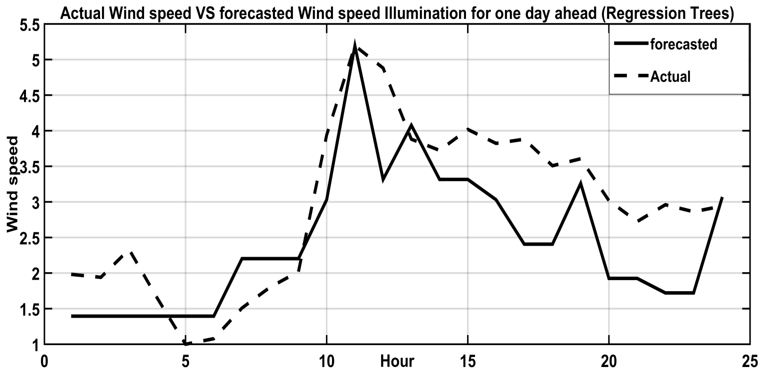

FIGURE 6.13: A day ahead wind speed forecast

6.4.3 MLR model based Prediction Results

An MLR based long-term wind speed prediction of historical data and a day ahead wind speed forecast is graphically shown in Figure 6.14, Figure 6.15. From Figure 6.14 it can be comprehended that the MLR based prediction technique has accurately predicted long-term historical data of wind speed. From Figure 6.15 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

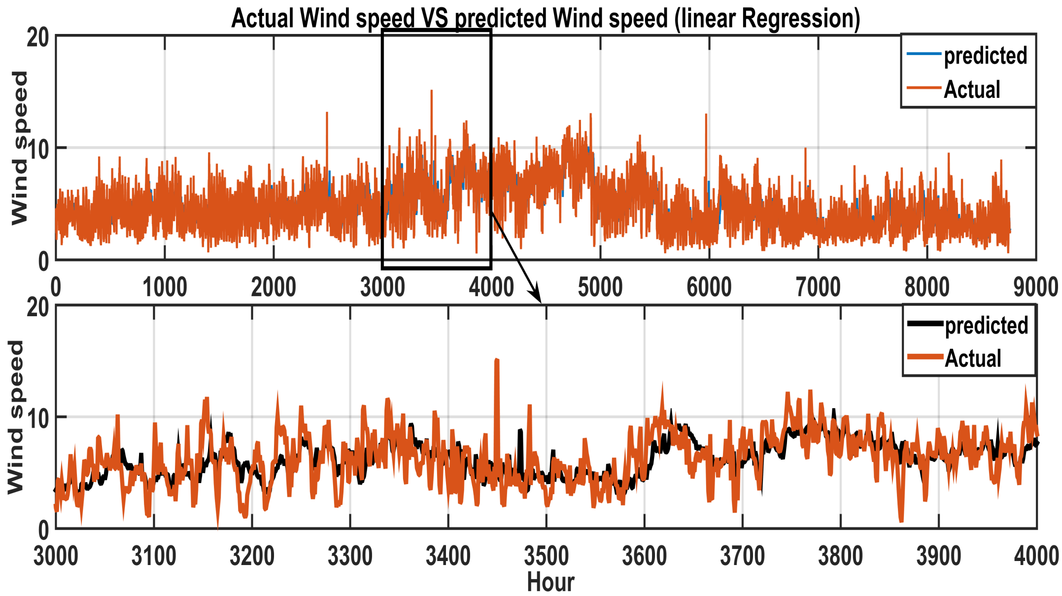

FIGURE 6.14: Long-term wind speed prediction

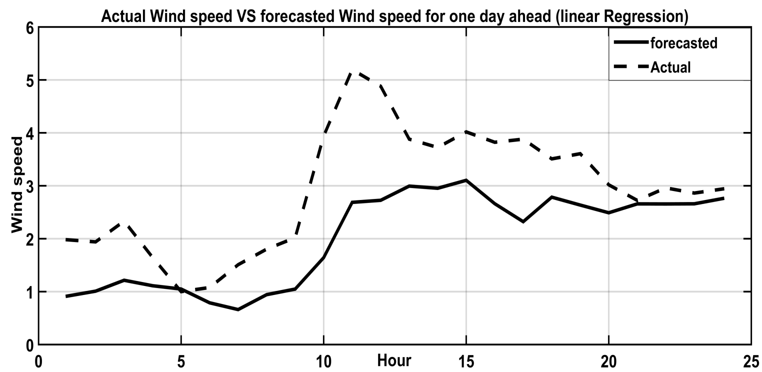

FIGURE 6.15: A day ahead wind speed forecast

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.

6.5 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. The fore-casted PV and wind power are graphically represented in Figure 6.16 and Figure 6.17. It can be comprehended that the NN-based prediction technique forecasts

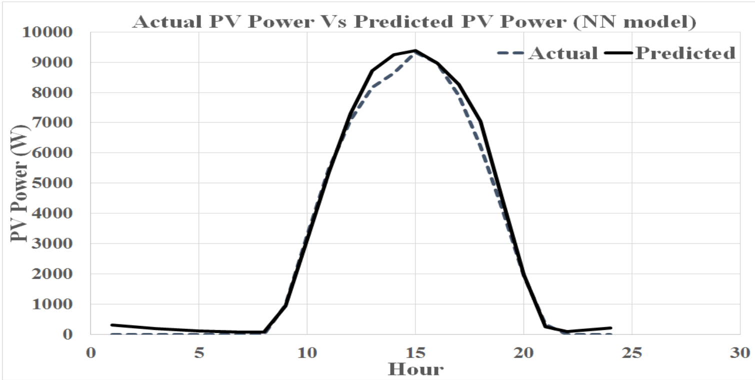

FIGURE 6.16: A day ahead PV power fore-cast by NN model

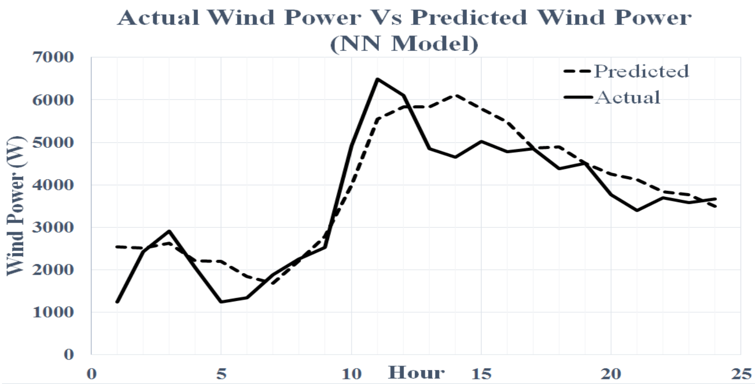

FIGURE 6.17: A day ahead wind power forecast by NN model

the power generated from PV and the Wind accurately with a minimum deviation of predicted value from the actual value. A comparative analysis of MAPE is tabulated in Table 6.1 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.

TABLE 6.1: 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 Long Term Prediction	5.76	14.099	40.992	24.933	12.399	31.017

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 fore-casted accurate results for the long term and a day ahead prediction for both Solar and the Wind. Whereas, RTM and MLR prediction technique has fore-casted 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 fore-casted 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.

6.6 Forecasting the Solar irradiation and wind speed profile for Years 2016 and 2017:

Utilizing the historical data recorded at BITS-Pilani, Hyderabad campus for years 2012 to 2014 all the above-mentioned techniques are utilized to predict the wind speed and solar irradiation for the year 2015. The NN model for prediction has fore-casted accurate results for both solar irradiation and wind speed. Further, the NN-based model is utilized to forecast the solar irradiation and wind speed profile for upcoming years 2016 and 2017.

6.6.1 Forecast of Solar illumination and Wind speed profile for year 2016:

The long term prediction of solar illumination for the year 2016 is shown in Figure 6.18 and the predicted solar illumination is validated by comparing the actual data measured at the location as shown in Figure 6.18.

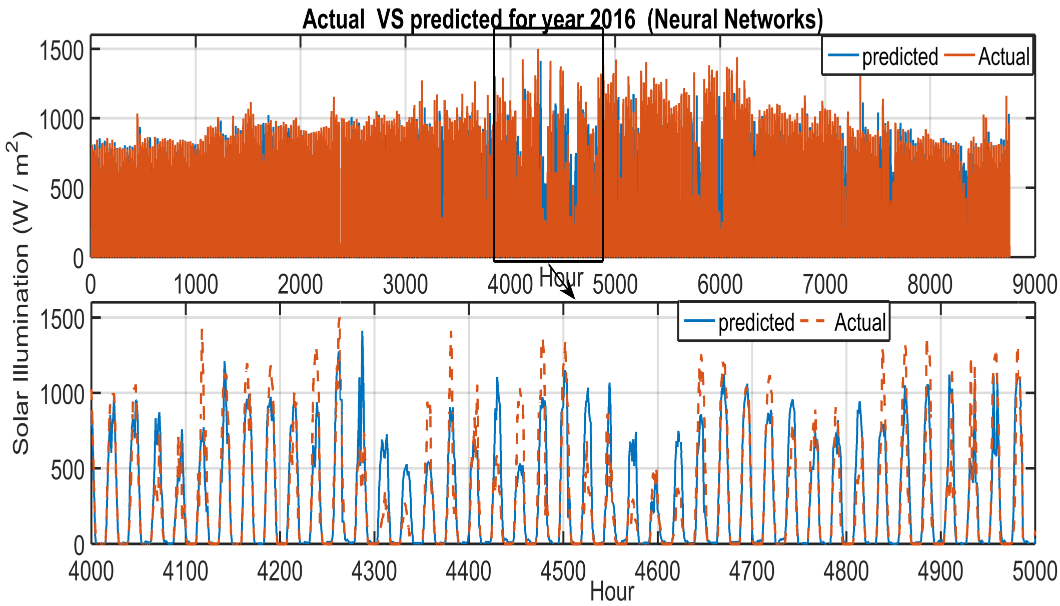

FIGURE 6.18: Long-term solar illumination prediction for year 2016 by NN model

A day ahead prediction of the solar illumination is graphically represented in Figure 6.19.

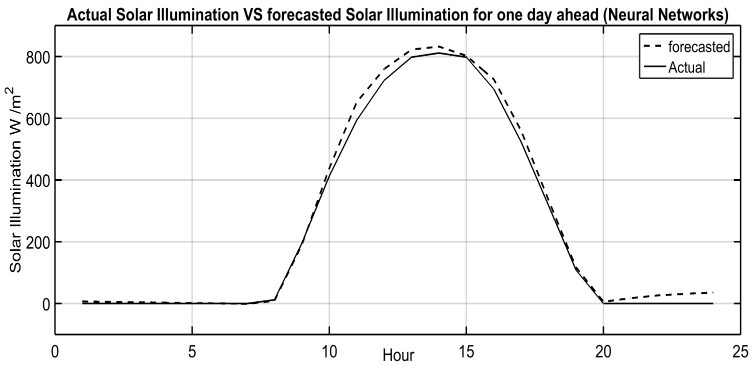

FIGURE 6.19: A day ahead solar illumination forecast by NN model

It can be comprehended from the Figure 6.18 , Figure 6.19 the predicted solar illumination for year 2016 replicates the actual solar illumination measured at the location.

The long term prediction of wind speed profile for year 2016 is shown in Figure 6.20 and a day ahead forecast of wind speed is graphically represented in Figure 6.21. The predicted wind speed data is compared with the actual data of wind speed measured at BITS-Pilani Hyderabad campus for validation. It can be comprehended from the Figure 6.20 , Figure 6.21 the predicted wind speed for year 2016

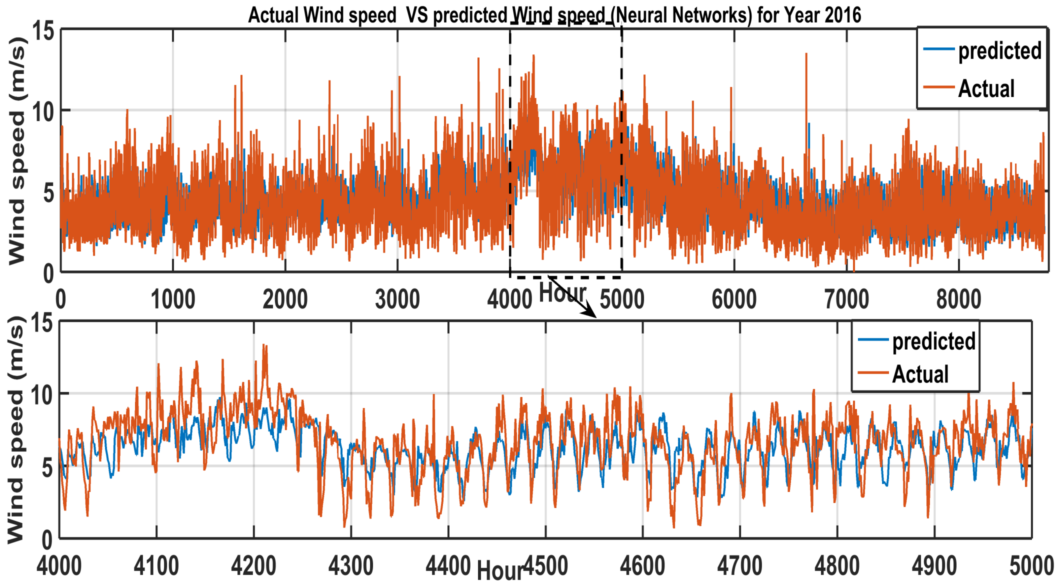

FIGURE 6.20: Long-term wind speed prediction for year 2016 by NN model

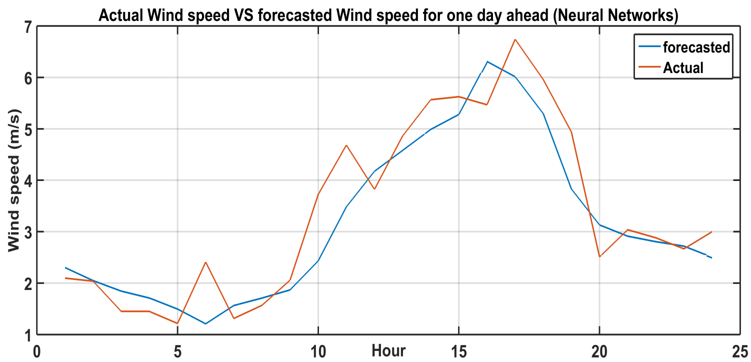

FIGURE 6.21: A day ahead wind speed forecast by NN model

replicates the actual wind speed measured at the location.

6.6.2 Forecast of Solar illumination and Wind speed profile for year 2017:

The long term prediction of solar illumination for the year 2017 is shown in Figure 6.22. The long

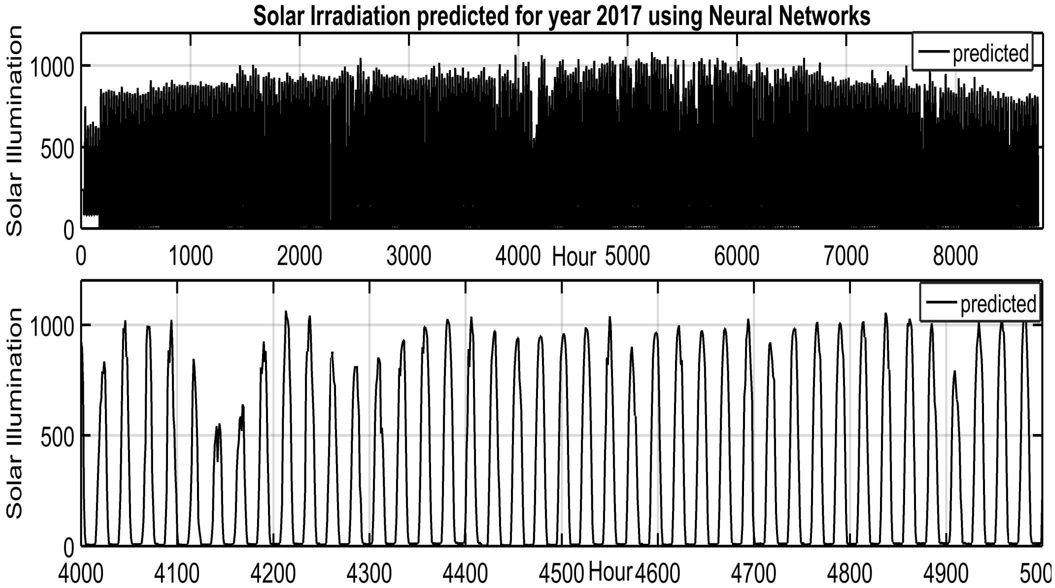

FIGURE 6.22: Long-term solar illumination prediction for year 2017 by NN model

term prediction of Wind speed profile for the location BITS-Pilani, Hyderabad campus for year 2017 is graphically represented in Figure 6.23.

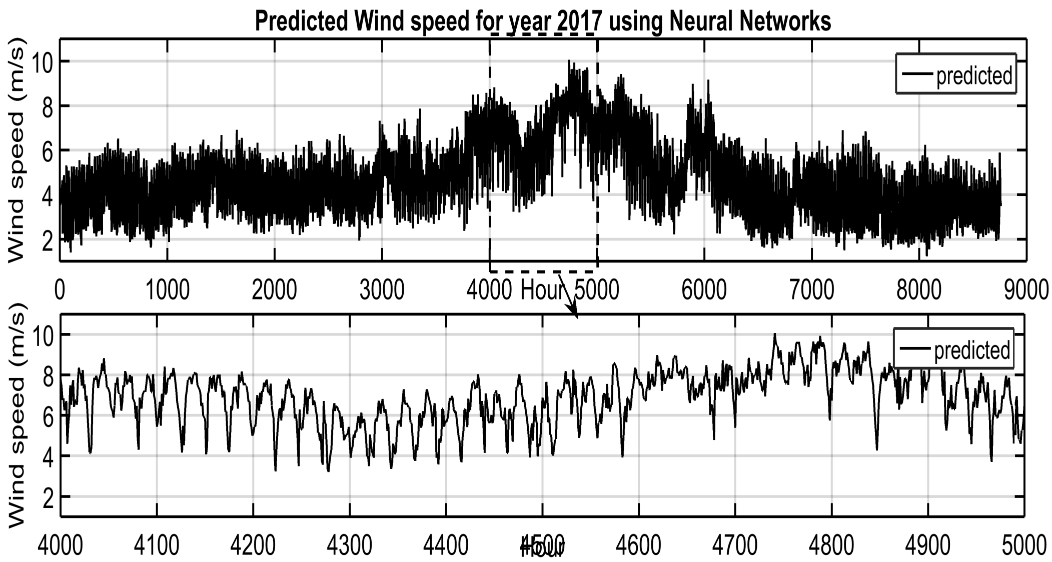

FIGURE 6.23: Long-term wind speed prediction for year 2017 by NN model

Utilizing the predicted solar illumination and wind speed profile the amount of power that can be generated from the hybrid power system can be forecasted accordingly.

6.7 Summary:

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 forecast accurate results for the long term and a day ahead prediction for both Solar and the Wind. Whereas, RTM and MLR prediction technique has forecast 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 predicting solar illumination and wind speed profile for years 2016 and 2017. For year 2016 long term and a day ahead forecast of real time data of solar illumination and wind speed are analyzed. The forecasted profile demonstrates accurate results as compared to the actual value and for year 2017 the wind speed and solar illumination are predicted.