IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 12, 2021, accepted January 21, 2021, date of publication February 2, 2021, date of current version February 25, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3056562

Average Monthly Wind Power Forecasting Using Fuzzy Approach

IRAM AKHTAR[1], SHEERAZ KIRMANI[1,2], MOHMMAD AHMAD[3], AND SULTAN AHMAD[4], (Member, IEEE)

[1]Department of Electrical Engineering, Faculty of Engineering and Technology, Jamia Millia Islamia, Delhi 110025, India
[2]Department of Electrical Engineering, Faculty of Engineering and Technology, Aligarh Muslim University, Aligarh 202002, India
[3]Department of Electrical Engineering, Rajkiya Engineering College at Bijnor, Bijnor 246725, India
[4]Department of Computer Science, College of Computer Engineering and Sciences, Prince Sattam Bin Abdulaziz University, Alkharj 11942, Saudi Arabia

Corresponding authors: Iram Akhtar (iram1208@gmail.com; akhtariram12@gmail.com), Sheeraz Kirmani (sheerazkirmani@gmail.com), Mohmmad Ahmad (ahmadbtech@gmail.com), and Sultan Ahmad (s.alisher@psau.edu.sa)

ABSTRACT The growth in sustainable generation technology such as fuel cell, wind energy conversion system, photovoltaic system, increase in fuel cost, energy necessity and the reduction in the fossil fuel reserve, for better power quality and reliability, is obliging the power sector to use the renewable based energy sources. In India, wind energy is gradually becoming an important and significant energy resource. Keeping in opinion the aforementioned wind energy prediction is becoming an essential study for harnessing the wind energy prospective. This paper proposes an effective technique based on intelligent approach for predicting wind power in different areas. This technique is based on using an intelligent model concerning the predicted gap to its similar one and two year old data. There are many intelligent and conventional models existed in literature for the wind power prediction like support vector machines (SVM), back propagation (BP) prediction etc. In this paper an effective fuzzy logic and model predictive control based models have been developed and offered for the wind power prediction for microgrid application by using air density and wind speed as the input parameters for fuzzy system. The outcomes are compared with the computed data and existing models and it can be observed that the different errors are found within the permissible limits. The outcomes obtained from fuzzy based technique are very close to calculated values if compared with model predictive based technique. Hence, the proposed models can be employed for the prediction of wind speed and wind power generation in the selected stations. The existing models results are compared with Kolkata city outcomes. The Error RMSE with Support vector machine, Back propagation, Model of forecast error correction +SVM and Model of forecast errors correction +BP, Neural Network method, model predictive based system, and proposed fuzzy logic based system are 30.48%, 32.83%, 26.81%, 28.58%, 1.1431%, 1.38% and 1.12% respectively. Therefore, the proposed techniques provide the best results and even these are observed within the suitable limits. Additionally, the achieved outcomes can be used for Microgrid/SmartGrid applications.

INDEX TERMS Wind energy, model predictive control, fuzzy logic, microgrid.

NOMENCLATURE

SVM	Support vector machines
BP	Back propagation
AI	Artificial intelligence
W_{wind}	Energy taken from wind turbine
V_1	Upstream turbine speed
V_2	Wind speed at turbine
V_3	Downstream turbine speed
V	Wind velocity
A_r	Rotor shaft area
P_a	Wind Power
P_{max}	Maximum wind power
A	Swept area
ρ	Densityofair
$\mathrm{V}_{\mathrm{k}}^{*}$	Reference wind speed data
V_{k}	Output wind speed data
$V(k+1)$	Future value of the wind speed in next sampling period

The associate editor coordinating the review of this manuscript and approving it for publication was Amedeo Andreotti.

$g(k)$	Quality function
$RMSE$	Root Mean Square Error
MAD	Mean Absolute Deviation
MSE	Mean Square Error
P_e	Estimated wind power
P_p	Predicted wind power

I. INTRODUCTION

The growth in sustainable generation technology such as photovoltaic system, wind energy conversion system, fuel cell, increase in fuel cost, power necessity and the reduction in the fossil fuel reserves, improved reliability and power quality is agreeable the power sector to employ the renewable energy resources. Additionally, wind energy has developed considerably in the recent years. Until 2015, the total notice capacity was 432GW as there are more than two hundred wind turbines working worldwide.

The European Union alone permitted 100 GW notice capacity in 2012, whereas the United States exceeded 75 GW in 2015. The wind uncertainty is the main barrier against more wind power perception and the uncertainty raises the regulation level and reserves required to keep stability. The foundation of large scale wind energy use is the precise prediction of wind speed forecasting. There are many methods available for wind power prediction like data-driven modeling and numerical weather prediction methods. Numerical weather prediction is based on a meteorological formula set and can generally get trustworthy weather prediction. Still, the costly computational rate bounds the use of numerical weather forecast. The data-driven modeling technique is still employed in short-term wind speed prediction [1], [2]. There are many problems associated with power system which comprises of renewable energy system and hence the precise wind prediction is good solution to overcome many issues. To initiate with, suitable inducements for pleasant market value are specified on power imbalance duties which are mostly based on the normal shared market cost. Hence, a true prediction assists in evolving good working hour ahead or day ahead markets [3], [4]. To advance the precision in wind speed and wind power prediction, the techniques in the literature are gathered into physical models [5], artificial intelligence (AI) models [6]–[8] and arithmetical models [9]–[11]. There are numerous intelligent and conventional models presented in the literature to forecast the wind power [12]- [15]. The wind power generation is a difficult method and it is inclined by many strange factors. There are many techniques available for finding wind direction and speed. The linear time series dependent model concerning the forecasting interval to its consequent previous year data is used for wind speed prediction and direction [16]. Whereas, when connecting wind sources to microgrid, the precise prediction of wind speed is the main concern to allow reliable and effective operation of microgrid. The wind speed prediction technique in the present literature is prone to errors due to the unplanned characteristics of wind speed and the restricted simplification of prediction algorithms. The wind speed model which based on a system of prediction, error rectification, support vector machines and back propagation prediction algorithms are used to overcome the error difficulties [17]. There is problem of uncertainty quantification, therefore data driven forecasting approach has been provided with ramp event [18].

Further, to calculate the indecision fluctuation risk of speed of wind and decrease the doubt in the route of changing wind power, a Lorenz disturbance distribution has been presented [19]. A wind speed prediction technique based on PSO-SVR and Grey grouping systems is presented [20], which is used to improve the optimization value. Further, a grid voltage based partitioning technique that includes the wind energy stability in a complete approach is also presented in [21]. The source relevance based wind power forecasting method has discussed in literature [22].

The short term type wind speed prediction can also be determined by intelligent approach. The possibility measurement can be used so that the intelligent model captures the indecisions and assurance an improved forecasting in stochastic situation [23]. The incorporation of wind sources into the main grid executes many tests since the control strategy and energy dispatch is limited due to their irregular features. The wind power prediction in time series is more significant and interesting task, where forecasting interval are desirable outcomes of the prediction, relatively point approximations, since them give information on the self-assurance in the forecasting [24]. In this area, the short term type wind speed prediction is more important in significant wind power diffusion. Though, there is a more gap between the necessity of forecasting act and the current methods. One of the accurate methods is pattern-based approach to know the short term wind speed. As, the wind changes in different pattern in various climate circumstances, therefore, we must use different models to define the patterns, while most present works use single model for wind speed prediction [25]. The indeterminate input data expressed in intermissions is also used with neural network for predicting the wind power [26]. Whereas the radial basis type function system of the artificial neural network based method may be employed to determine the one-step forward wind speed. To advance this technique, the profiteering method of S-Transform is used for extracting the features of variables [27]. Besides the fuzzy based prediction model with genetic algorithm based learning arrangement is also suggested by many researchers. It is confirmed that the intelligent based prediction attains an satisfactory understanding of the problem [29]–[31]. The difference in successive value in time series is used for building the fuzzy rules to avoid the shortcomings of non-stationary model. Hence, fuzzy model is being suggested for knowing the wind speed [28] and also enhance the effectiveness of forecasting. Whereas different systems are added to get the profits increasing system [32] and online optimization can be achieved with time coupling constraints [33].

A novel technique which includes the particle swarm and ant colony optimization is also presented in the literature to know the energy output of wind energy system.

This technique comes under the group of swarm intelligence. Moreover, ant colony optimization is influenced from the contact of ants in the colony while particle swarm optimization is influenced from the nature of bird block. Both techniques are able to deal with the non-convex harms [34]. Whereas the long term prediction of wind power has become a novel hot spot in many areas. The neural network based technique has been given to overcome the problem of long term forecasting of wind power. In this method, outcomes are compared with the actual values and found to be more accurate because of the criterion [35]. Although these methods are good enough to predict the wind power in the particular location however these include the complex analysis and took more time to design the models. Moreover, these difficulties are escaped by the proposed method in the paper.

Whereas, cyber attack can bring anytime in the system, and gives harmful outcomes hence this must be carefully taken for safety of the overall system [36]. Cyber attack becomes emerging fear to every power management system. The hacker can disturb the system security due to coupling between the physical and cyber facilities [37]. For system stability, many techniques such as deeply hidden moving target defense technique have been proposed to avoid the cyber attacks and save the system from any of the threats [38].

In India, the state-wise dispersion levels are achieved in different ways. Tamil Nadu is having 37 %, Rajasthan is 26%, Karnataka is 25%, Gujarat is 22% and the Maharashtra is 12 % approx. As the distributed networks in the microgrid has smaller inertia and take severe stability tasks in comparison with the old power networks [39], [40], therefore, precise wind speed prediction becomes serious issue for microgrids when connected to wind sources. It is very difficult to estimate the hybrid energy based system due to their inconsistency. Keeping in view of aforementioned aspects, fuzzy logic based model for the prediction of wind power is presented considering air density, wind speed, temperature and relative humidity for the particular location. Similarly, the model predictive wind power estimation is rarely available in literature; therefore the model predictive control model has designed for microgrid application. As, wind power varies along with the changes in wind speed and the weather conditions hence it is relatively hard to evaluate the accurate wind power by using regression techniques and mathematical formulas at a specific time. However, these difficulties are escaped by fuzzy based method. The main limitation of the study is that they are dependent on human expertise and knowledge which needs to regularly update the rules of the system.

Whereas reinforcement learning is helpful for simplification as it allows the design of model-free techniques [41]. It is used for energy management as mentioned in the literature and can minimize the energy loss. Error correction model with machine learning is employed to know the wind power [42]. Frequency control can also be done by using reinforcement learning [43], however fuzzy based wind power prediction minimizes the calculation and complexity.

Based on the computed data, fuzzy logic and model predictive system are used to predict the wind power at five different Indian stations that has different geographical and climate conditions. Analysis shows that fuzzy based system is easy to implement.

Hence, the main contribution of the present work is to develop fuzzy model and model predictive control for prediction of wind power for the particularly selected location in India. Consequently, the wind power prediction for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata are presented in the paper using smart technique in microgrid applications. Achieved results are then simulated for microgrid applications using intelligent approaches. Therefore, an effective fuzzy logic and model predictive control based models have been developed and presented for the wind power prediction for microgrid application. The results obtained from the fuzzy based model and model predictive control based model are compared with the computed data as well as with available models and then, it can be observed that the different errors are found within the permissible limits.

However, the proposed models can be employed for the estimation of wind speed and wind power generation of any location in the world with having the complete information. The model can also be used to estimate the wind power at those locations which have similar parameters.

In this paper, an eco-friendly wind energy grid connected system is described in Section II. In Section III, fuzzy logic approach for wind speed assessment is discussed. Fuzzy model for wind system output prediction for microgrid application is described in section IV. Model predictive system for assessment of wind system output is discussed in Section V. Results and discussion are given in Section VI. Finally, concluding reports are presented in Section VII.

II. AN ECO-FRIENDLY WIND ENERGY GRID CONNECTED SYSTEM

Fig. 1 shows the grid-connected wind energy based system. It consists of a wind power system, DC/DC converter, inverter, different loads and grid-connected thermal power station. The reason to connect to the grid is that, the thermal power plant produces less power which results in the reduction of carbon emission. The worldwide electricity sector and its consumers are handled with a number of trials that are unequalled since the start of global electrification. Trials comprising of climate change, rising energy rates, energy safety and energy efficiency are congregating to drive necessary change in the method of power generated, transmitted and utilized. Keeping in view of above-mentioned aspects, the electricity system must generate and transmit electricity which should be clean, reliable and inexpensive. To get the same, both microgrid and the present managing system must be smarter. Therefore there is a strong need of intelligent control for the microgrid/grid. Further, world is attempting into the non-conventional energy resources like wind and solar. With such changeable energy sources, power supplying

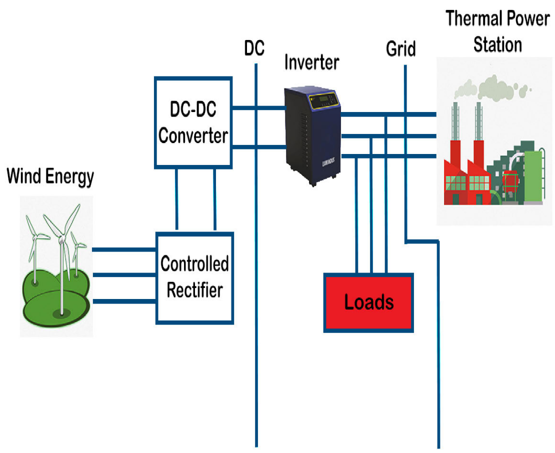


FIGURE 1. Grid-connected wind energy system.

the grid must be adaptive in terms of energy supply and demand.

Microgrid is used to smartly respond to the actions of all the associated consumers with intelligent control. It is also used to efficiently supply the sustainable electricity services to the users. The major advantage of smart microgrid uses in terms of benefits and outages: lower maintenance, lower operational cost, lower global warming, and efficient power management.

In the wind power assessment, there are certain geographical features like air density, wind speed, temperature and relative humidity. Output power changes with cubic value of the wind speed i.e. wind Power $P_a = \frac{1}{2}\rho AV^2$ where V is wind velocity in m/s, A is the swept area in m^2 and ρ is density of air in Kg/m^3.

Apart from this, relative humidity also influences the wind energy. Keeping in mind the different climate circumstances are presented in Table-1 for selected five stations such as Trivandrum, Bangalore, Hyderabad, Vishakhapatnam and Kolkata.

TABLE 1. Geographical features of the selected Indian places.

Place	Latitude (°N)	Longitude (°E)	Height above the mean sea level (m)	Weather Zone
Trivandrum	8.61	76.52	64	Warm and humid
Bangalore	12.51	77.61	92	Moderate
Hyderabad	17.28	78.21	545	Moderate
Vishakhapatnam	17.41	83.10	3	Moderate
Kolkata	22.45	88.32	6	Humid and warm

III. FUZZY LOGIC APPROACH FOR WIND SPEED ASSESSMENT

The fuzzy based model has been designed to predict the wind power using MATLAB fuzzy tool box. The first step is to choose the variables. Wind speed and air density are chosen as input signals and wind power is selected as an output signal.

Since the wind power depends on the air density as well as wind speed therefore these parameters are considered as the input.

The monthly averaged (1986-2000) hourly meteorological data is taken from Ministry of New and Renewable Energy and Indian Meteorological Department [44], [45]. The fuzzy system has rules which are established from qualitative explanations. The inputs to the rules are relative humidity and vapour pressure, and the output resultant is the wind speed. The rules are brief in fuzzy decision matrix presented in Table 7. The fuzzy variables, relative humidity, vapour pressure and wind speed are defined by the fuzzy terms low, low-med/extra, low-nor, nor, high-nor, high-med/extra, high. These variables, defined by linguistic terms, are stated by the membership functions.

The inputs for all the selected stations are fuzzified into seven fuzzy subsets. All the data taken in the proposed work is defined in normalized form to escape merging difficulty during the learning procedure. Membership function corrector is used to describe all the membership functions shapes. The estimated wind speed is obtained using these parameters. Data of meteorological parameters for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata are presented in Table 2, 3, 4, 5 and 6 respectively.

TABLE 2. Monthly average data for Trivandrum.

Month	Vapour Pressure hPa	Lowest Temp. °C	Highest Temp °C	Relative Humidity %	Wind Speed (Km.p.h)
Jan	23.9	17.8	35.5	75	20
Feb	24.8	18.1	35.0	76	19
Mar	27.6	20.6	36.2	78	20
Apr	30.3	20.3	36.0	81	21
May	30.6	21.1	35.2	84	25
Jun	29.4	20.0	34.4	89	25
Jul	28.5	20.2	32.4	89	26
Aug	28.5	18.2	32.8	88	28
Sep	28.4	20.8	33.4	86	25
Oct	28.8	20.6	33.4	87	21
Nov	28.3	18.9	34.3	85	17
Dec	25.6	18.2	34.4	78	17

The impact of relative humidity and vapour pressure is most significant as reported in literature. Consequently, it is essential to pick these as the input parameters so as to obtain more accurate wind speed. Therefore, relative humidity and vapour pressure are chosen as input meteorological parameters for assessment of wind speed. Besides, we have taken also the impact into the concerns, for the consequence of geographical parameters like longitude, altitude and latitude as inputs, although these parameters stay constant for chosen location.

The rules listed in the Table 7 have been applied by fuzzy toolbox in MATLAB for making the model to calculate approximately the wind speed as presented in Fig 2.

TABLE 3. Monthly average data for Bangalore.

Month	Vapour Pressure hPa	Lowest Temp. °C	Highest Temp °C	Relative Humidity %	Wind Speed (Km.p.h)
Jan	15.8	7.8	32.2	78	29
Feb	15.5	9.4	34.5	68	26
Mar	17.2	11.1	37.2	63	28
Apr	21.7	14.4	38.3	71	26
May	22.6	16.7	38.9	77	29
Jun	22.0	16.7	37.8	84	28
Jul	21.7	16.1	33.3	86	29
Aug	21.9	14.4	33.3	89	29
Sep	21.6	15.0	33.3	87	28
Oct	21.4	13.2	32.2	84	27
Nov	18.8	9.6	31.1	79	28
Dec	16.8	8.9	31.1	80	30

TABLE 4. Monthly average data for Hyderabad.

Month	Vapour Pressure hPa	Lowest Temp. °C	Highest Temp °C	Relative Humidity %	Wind Speed (Km.p.h)
Jan	15.9	6.1	35.0	75	30
Feb	15.4	6.9	37.2	62	25
Mar	16.1	13.2	42.2	51	27
Apr	19.5	16.1	43.3	51	25
May	19.8	17.6	44.4	49	25
Jun	23.5	17.8	45.5	70	16
Jul	24.6	18.6	37.2	81	16
Aug	24.4	19.2	36.1	82	19
Sep	24.6	17.8	36.1	81	24
Oct	22.8	11.7	36.7	75	28
Nov	18.3	7.4	33.9	71	29
Dec	15.6	7.1	33.3	72	30

TABLE 5. Monthly average data for Vishakhapatnam.

Month	Vapour Pressure hPa	Lowest Temp. °C	Highest Temp °C	Relative Humidity %	Wind Speed (Km.p.h)
Jan	20.5	10.5	33.4	74	27
Feb	22.6	13.3	38.0	72	24
Mar	25.7	14.4	39.2	70	23
Apr	29.8	18.3	40.5	69	19
May	32.2	20.0	44.9	73	22
Jun	31.7	21.1	45.3	79	20
Jul	30.8	21.3	39.4	79	19
Aug	30.7	21.1	38.3	79	21
Sep	30.9	21.5	37.6	79	23
Oct	28.3	17.6	37.2	76	24
Nov	23.0	12.9	33.9	68	26
Dec	19.6	11.3	32.8	67	27

IV. FUZZY MODEL FOR WIND SYSTEM OUTPUT PREDICTION FOR MICROGRID APPLICATION

The integration of the renewable energy sources to the Micro-grid/Grid is a tough job for the researcher because of variable and random nature of the different sources especially for wind system. This difficulty can be skipped by predicting

TABLE 6. Monthly average data for Kolkata.

Month	Vapour Pressure hPa	Lowest Temp. °C	Highest Temp °C	Relative Humidity %	Wind Speed (Km.p.h)
Jan	14.6	5.0	32.5	72	23
Feb	17.2	6.1	35.7	69	23
Mar	23.1	12.1	40.6	69	27
Apr	29.4	16.6	42.8	72	27
May	32.7	17.9	43.0	74	27
Jun	33.7	19.2	43.7	81	27
Jul	33.2	20.9	37.2	83	28
Aug	33.1	22.1	37.2	84	28
Sep	32.7	21.7	35.8	82	26
Oct	28.8	16.7	35.9	77	27
Nov	20.8	11.7	34.2	71	25
Dec	15.5	6.1	31.4	72	26

TABLE 7. Decision matrix for estimation of wind speed.

AND		Vapour Pressure						
		Low	Low-Med	Low-Nor	Nor	High-Nor	High-Med	High
Relative Humidity	Low	Low	Low-Extra	Nor	High-Nor	High-Med	High-Med	High-Extra
	Low-Extra	Low	Low-Extra	Nor	Nor	High-Nor	High-Extra	High
	Low-Nor	Low	Low-Extra	Nor	High-Med	High-Med	High-Extra	High
	Nor	Low	Nor	Nor	High-Med	High-Med	High-Extra	High
	High-Nor	Low	Low-Extra	High-Nor	Low-Nor	Nor	High-Extra	High
	High-Extra	Nor	Low-Extra	High-Med	Low-Nor	High-Med	High	High
	High	Low-Extra	Low-Med	Nor	Low-Nor	High-Med	High	High

the output of wind system intelligently. Depending on output power of the wind system, the consumers are permitting to cut their need. Keeping in view of above-mentioned, an effort is applied to predict the wind energy using fuzzy based system for Microgrid application. In fuzzy based system, rules can be fired with certain degree using interfacing: while, in earlier expert schemes, rules are either fired or not fired. For the wind power assessment difficulty, rules are well-defined for defining the assessment of wind speed at selected stations. Keeping above mentioned parameters as constant, fuzzy rules set is being defined. By using wind speed and air density, wind energy is calculated. The inputs to the rules are air

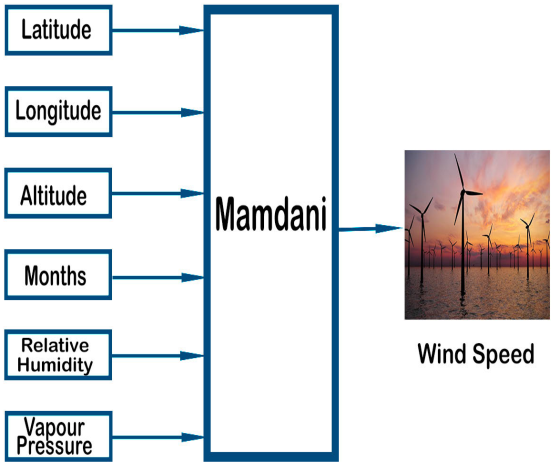


FIGURE 2. Fuzzy logic approach for prediction of wind power output.

density and wind speed, and the output consequent is the wind power. The fuzzy variables like air density, wind speed and wind power are defined by the fuzzy terms such as low, low-med, low-nor, nor, high-nor, high-med, high. These variables defined by linguistic terms and presented by the membership functions. The membership functions for air density, speed of wind and power of wind are shown in Fig 4(a-c) respectively.

In this paper, prediction of wind power is done on the basis of data attained from fuzzy based system, by estimating the wind system output for the given air density and calculated wind speed. The speed of wind in time series such as V(i), V(i-1), V(i-2),…., V(i-m+1) to fuzzy or model predictor is given. Some statistic properties of time series inputs are used as inputs to fuzzy or model predictor. The 200 kW, 3 blades, horizontal axis wind system is chosen and the wind energy is given by the following equations.

The energy taken from turbine of wind could be calculated as:

$$W_{wind} = V_a \frac{1}{2} \rho \left(V_1^2 - V_3^2\right) \tag{1}$$

Wind power available is given as:

$$P_a = \frac{d(V_a \frac{1}{2} \rho \left(V_1^2 - V_3^2\right))}{dt} \tag{2}$$

$$P_a = \frac{1}{2} \rho A_r \left(V_1^2 - V_3^2\right) V_2 \tag{3}$$

According to Betz, maximum power output of wind when $V_2 = 2/3V_1$ and $V_3 = 1/3V_1$

$$P_{max} = \frac{16}{54} A_r \rho V_1^3$$
$$A_r = A \tag{4}$$

Wind power

$$P_a = \frac{1}{2} \rho A V^3 \tag{5}$$

where,

V_1 : Upstream turbine speed $[m/s]$
V_2 : Wind speed at turbine $[m/s]$
V_3 : Downstream turbine speed $[m/s]$
V: Wind velocity $[m/s]$
A_r : Rotor shaft area $\left[m^2\right]$
P_a : Power ofwind $[W]$
A: Swept area $\left[m^2\right]$
ρ : Density ofair $\left[kg/m^3\right]$

This presents that the maximum power is obtained from wind turbine variation giving to the cubic of wind speed. Average wind power for Microgrid application can be efficiently estimated using fuzzy based system shown in Fig. 3.

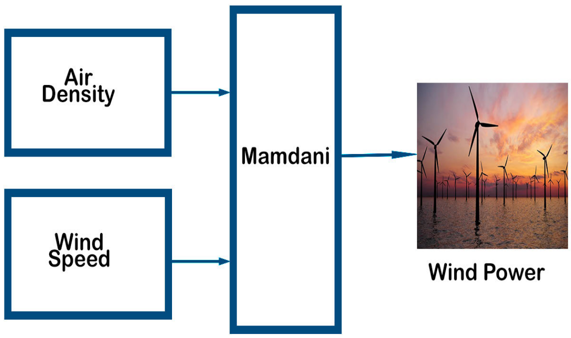


FIGURE 3. Fuzzy logic approach for prediction of wind power output.

Table 8 presents the fuzzy rules for forecasting the wind power. In the suggested model, wind velocity and air density are chosen as input parameters and power is the output parameter. This predicted data can be used for many purposes like supply reliability, grid safety, power management and stability of grid.

V. MODEL PREDICTIVE SYSTEM FOR ASSESSMENT OF WIND SYSTEM OUTPUT

For the estimation of wind power at Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata, a model predictive system has been developed. It is based on the reality that only a finite number of appropriate wind speed time series data can be generated. The possible number of wind speed data could be provided which can be applied to predict the behavior of selected variable. A quality function is defined for getting the predicted values of selected variable to be controlled. For each appropriate data series, the future value prediction of the selected site is evaluated. The data series which decreases the quality function has to be selected. The reference wind speed data series V_k^* is provided and output wind speed data V_k is calculated. Predictive model is employed to predict the future value of the wind speed in next sampling period $V(k + 1)$. The quality function calculates the error between reference wind speeds V_k^* and predicted wind speed $V(k + 1)$ in succeeding sampling period. The value of reference wind speed data is defined from the hermite

TABLE 8. Decision matrix for estimation of wind power.

AND		Air Density						
		Low	Low-Med	Low-Nor	Nor	High-Nor	High-Med	High
Wind Speed	Low	Low	Low-Med	Low-Nor	Nor	High-Nor	High	High
	Low-Med	Low	Low-Med	Low-Nor	Nor	High-Nor	High-Med	High
	Low-Nor	Low	Low-Med	Low-Nor	High-Nor	High-Med	High-Med	High
	Nor	Low	Low-Med	Nor	High-Med	High-Med	High-Med	High
	High-Nor	Low	Low-Med	High-Nor	High-Med	High-Med	High-Med	High
	High-Med	Nor	Nor	High-Nor	High-Med	High-Med	High	High
	High	Low-Med	Low-Nor	High-Nor	High-Med	High-Med	High	High-Med

polynomial and it is applied when the values of V (k) and its derivative V′(k) are known.

$$V_k^* = 5V^*[k] - 3V^*[k-1] + 5V^*[k-2] \tag{6}$$

The above mention equation is used for a wide data range. The quality function can be defined as follow:

$$g(k) = \left(V^*[k] - V^*[k+1]\right)^2 + \left(V^*[k] - V^*[k+1]\right)^2 + \left(V^*[k] - V^*[k+1]\right)^2 \tag{7}$$

The performance of system using model predictor with 2 step prediction is shown in Fig.7. The quality functions for this case as follows:

$$\begin{aligned} g(k) = {} & \left(V^*[k] - V^*[k+1]\right)^2 + \left(V^*[k] - V^*[k+1]\right)^2 \\ & + \left(V^*[k] - V^*[k+1]\right)^2 + \left(V^*[k] - V^*[k+2]\right)^2 \\ & + \left(V^*[k] - V^*[k+2]\right)^2 + \left(V^*[k] - V^*[k+2]\right)^2 \end{aligned} \tag{8}$$

The two steps prediction gives better result in comparison with single step prediction that's why we choose two steps prediction. To avoid the higher calculation, two steps prediction taking the same data have applied during the two sampling intervals. The quality function for 3 steps prediction case is as follows:

$$\begin{aligned} g(k) = {} & \left(V^*[k] - V^*[k+1]\right)^2 + \left(V^*[k] - V^*[k+1]\right)^2 \\ & + \left(V^*[k] - V^*[k+1]\right)^2 + \left(V^*[k] - V^*[k+2]\right)^2 \\ & + \left(V^*[k] - V^*[k+2]\right)^2 + \left(V^*[k] - V^*[k+2]\right)^2 \\ & + \left(V^*[k] - V^*[k+3]\right)^2 + \left(V^*[k] - V^*[k+3]\right)^2 \\ & + \left(V^*[k] - V^*[k+3]\right)^2 \end{aligned} \tag{9}$$

The long horizon gives better performance. Although 2 steps and 3 steps prediction give almost same results. Hence, wind speed is used to compute the wind power for particular site. Therefore, average wind power for Microgrid application can be efficiently estimated using model predictive system as presented in Fig. 4.

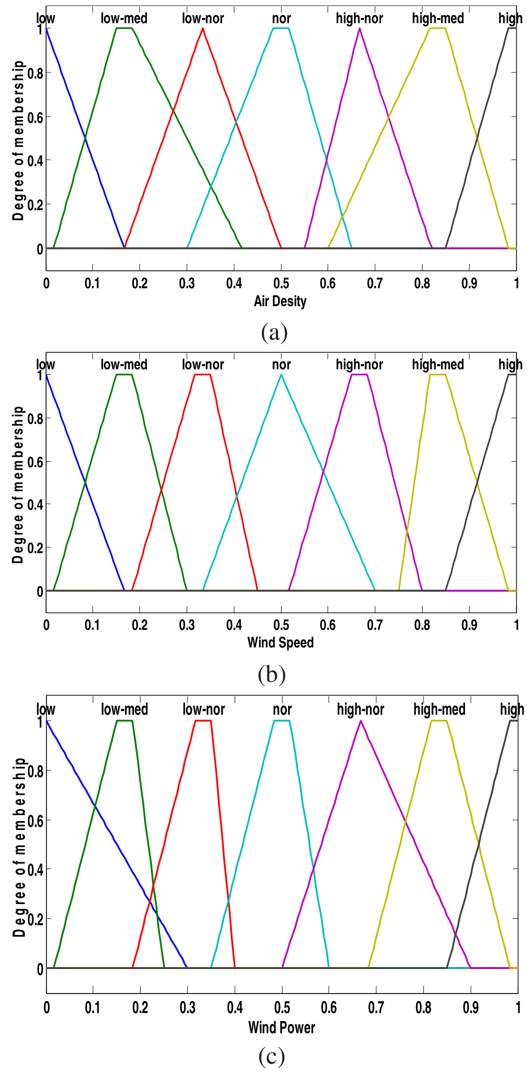


FIGURE 4. (a, b, c). Fuzzy subsets membership functions for air density, fuzzy subsets membership functions for the wind speed and fuzzy subsets membership functions for wind power respectively.

VI. RESULTS AND DISCUSSIONS

The fuzzy based model is developed for the prediction of wind power using the above defined data for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata stations. Consequences of fuzzy logic based system are compared with that of defined system for validation purpose. To compute the power in different months at selected stations, a MATLAB program has been written. The computational time for calculating the wind power is 1 second. It is difficult to estimate the wind power during the summer period when wind speed is very low. Besides, the predictive model control based system taking the same input parameters is also defined in the Appendix. The rules given in Table 8 have been executed using the fuzzy logic toolbox of MATLAB for implementing the system to calculate the wind power of the selected station in India.

The computed output power for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata are presented in Table 9, 10, 11, 12 and 13 respectively. The predicted wind power using fuzzy logic and model predictive based model is compared with the computed data for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata stations and also presented in Table 14, 15, 16, 17, 18 and 19 respectively. Both models are developed using MATLAB and performance is calculated on the basis of Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD) and Mean Square Error (MSE) which are expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(P_e - P_p\right)^2}{n}} \tag{10}$$

$$MAD = \frac{\sum_{t=1}^{n}\left|P_e - P_p\right|}{n} \tag{11}$$

$$MSE = \frac{\sum_{t=1}^{n}\left(P_e - P_p\right)^2}{n} \tag{12}$$

TABLE 9. Calculated wind speed, air density and power for Trivandrum.

Month	Wind Speed (m/s)	Air Density (kg/m^3)	Dew point Air Temperature C(degree)	Computed Power (KW)
Jan	5.55	1.105	20.3	65.83
Feb	5.12	1.105	20.5	51.68
Mar	5.55	1.104	20.9	65.77
Apr	5.71	1.104	21.5	71.62
May	7.10	1.104	22.1	137.70
Jun	7.11	1.103	23.1	138.16
Jul	7.32	1.103	23.1	150.76
Aug	7.81	1.103	22.9	183.11
Sep	7.12	1.103	22.5	138.74
Oct	5.92	1.103	22.7	79.75
Nov	4.82	1.104	22.3	43.08
Dec	5.12	1.104	20.9	51.63

The results obtained from computed system are respectively. The performance of above mentioned model is improved as compared to the models existing in literature. Further, the results obtained from model predictive system are somewhat better however it can be conceded with other merits of fuzzy based system like mixed with conventional control methods, easily developed, less complex, more flexible, tolerant of inexact data apart from easy to employ and better accepting.

In addition, the predicted values obtained from fuzzy based system and model predictive based system as compared to computed data are presented graphically in Fig. 6 (a-e) for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam and Kolkata respectively. Fig. 6 (a) shows the measured wind power and estimated power of wind from fuzzy logic as well as from model predictive systems for Trivandrum. Fig 6 (b) shows the measured power of wind and estimated power of wind from fuzzy logic and model predictive systems for Bangalore. Fig 6 (c) shows the measured power of wind and estimated power of wind from fuzzy logic and model predictive systems

TABLE 10. Calculated wind speed, air density and power for Bangalore.

Month	Wind Speed (m/s)	Air Density (kg/m^3)	Dew point Air Temperature C(degree)	Computed Power (KW)
Jan	8.52	1.104	20.9	237.95
Feb	7.51	1.106	18.7	163.25
Mar	7.92	1.107	17.5	191.65
Apr	7.45	1.105	19.4	159.23
May	8.56	1.105	20.7	241.53
Jun	8.10	1.104	22.1	204.46
Jul	9.10	1.103	22.9	289.66
Aug	9.23	1.103	23.1	302.26
Sep	8.90	1.103	22.7	270.98
Oct	8.56	1.104	22.1	241.31
Nov	9.12	1.104	22.1	291.84
Dec	9.54	1.104	21.3	334.05

TABLE 11. Calculated wind speed, air density and power for Hyderabad.

Month	Wind Speed (m/s)	Air Density (kg/m^3)	Dew point Air Temperature C(degree)	Computed Power (KW)
Jan	8.56	1.105	20.3	241.53
Feb	7.12	1.107	17.2	139.24
Mar	7.80	1.108	14.2	183.24
Apr	8.12	1.108	14.2	206.73
May	8.16	1.109	13.5	209.99
Jun	5.45	1.106	19.1	124.78
Jul	5.40	1.104	21.5	60.58
Aug	7.12	1.104	21.7	138.87
Sep	7.43	1.104	21.5	157.81
Oct	8.98	1.105	20.3	278.86
Nov	9.12	1.105	19.4	292.11
Dec	9.15	1.105	19.6	289.00

TABLE 12. Calculated wind speed, air density and power for Vishakhapatnam.

Month	Wind Speed (m/s)	Air Density (kg/m^3)	Dew point Air Temperature C(degree)	Computed Power (KW)
Jan	7.50	1.105	20.0	162.46
Feb	6.82	1.105	19.6	122.15
Mar	6.45	1.106	19.1	103.42
Apr	5.34	1.106	19.1	191.92
May	6.34	1.106	18.9	98.22
Jun	5.65	1.105	19.8	69.45
Jul	5.40	1.104	21.1	60.58
Aug	5.95	1.104	21.1	81.04
Sep	6.45	1.104	21.1	103.24
Oct	6.80	1.105	20.5	120.97
Nov	7.55	1.106	18.7	165.88
Dec	7.54	1.106	18.4	159.37

TABLE 13. Calculated wind speed, air density and power for Kolkata.

Month	Wind Speed (m/s)	Air Density (kg/m^3)	Dew point Air Temperature C(degree)	Computed Power (KW)
Jan	6.41	1.105	19.6	101.42
Feb	6.52	1.106	18.9	106.83
Mar	7.50	1.106	18.9	162.60
Apr	7.83	1.105	19.6	184.86
May	7.98	1.105	20.0	195.69
Jun	7.85	1.104	21.5	186.11
Jul	7.78	1.104	21.9	181.18
Aug	8.12	1.104	22.1	205.98
Sep	7.54	1.104	21.7	164.92
Oct	8.22	1.105	20.7	213.88
Nov	7.12	1.105	19.4	138.99
Dec	7.52	1.105	19.6	163.76

TABLE 14. Estimated monthly wind power in comparison with measured data for Trivandrum.

Month	Measured Power (KW)	Estimated Power (KW)	
		Fuzzy logic System	Model Predictive System
Jan	65.83	**64.52**	64.22
Feb	51.68	**50.12**	49.90
Mar	65.77	**64.56**	64.36
Apr	71.62	**70.12**	69.98
May	137.70	**136.88**	135.65
Jun	138.16	**137.45**	137.22
Jul	150.76	**149.57**	148.22
Aug	183.11	**184.12**	185.45
Sep	138.74	**137.42**	137.20
Oct	79.75	**78.16**	78.12
Nov	43.08	**42.86**	42.45
Dec	51.63	**50.34**	50.48

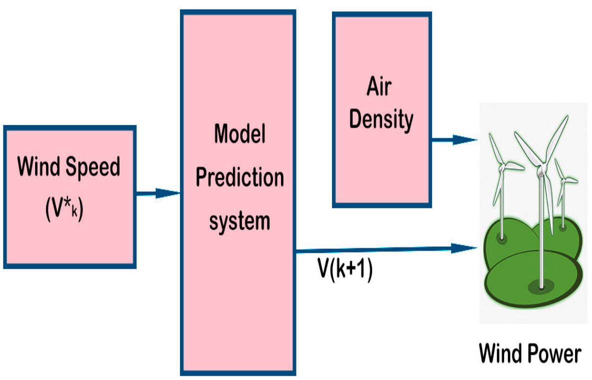


FIGURE 5. Model prediction approach for prediction of wind power output.

for Hyderabad. Fig 6 (d) shows the measured power of wind and estimated power of wind from fuzzy logic and model predictive systems for Vishakhapatnam. Fig 6 (e) shows the measured power of wind and estimated wind power from fuzzy logic and model predictive systems for Kolkata.

TABLE 15. Estimated monthly wind power in comparison with measured data for Bangalore.

Month	Measured Power (KW)	Estimated Power (KW)	
		Fuzzy logic System	Model Predictive System
Jan	237.95	**235.98**	235.45
Feb	163.25	**162.78**	162.12
Mar	191.65	**190.57**	190.12
Apr	159.23	**158.78**	158.92
May	241.53	**240.42**	240.34
Jun	204.46	**203.68**	203.46
Jul	289.66	**290.43**	290.65
Aug	302.26	**302.89**	302.90
Sep	270.98	**269.93**	269.68
Oct	241.31	**240.72**	240.14
Nov	291.84	**290.18**	289.96
Dec	334.05	**333.68**	333.76

TABLE 16. Estimated monthly wind power in comparison with measured data for Hyderabad.

Month	Measured Power (KW)	Estimated Power (KW)	
		Fuzzy logic System	Model Predictive System
Jan	241.53	**240.37**	240.14
Feb	139.24	**138.63**	138.54
Mar	183.24	**182.96**	182.54
Apr	206.73	**205.98**	205.65
May	209.99	**208.15**	208.19
Jun	124.78	**123.87**	123.55
Jul	60.58	**61.19**	61.72
Aug	138.87	**139.63**	139.74
Sep	157.81	**156.15**	156.10
Oct	278.86	**277.56**	277.48
Nov	292.11	**291.68**	291.69
Dec	289.00	**288.36**	288.12

This can be concluded that the computed and predicted values are very close to each other. It is presented that the model performance using intelligent control techniques is acceptable. Obtained outcomes of wind speed are simulated along with air density to estimate the output power of wind system. The estimated power of wind system as compared with computed power is fairly precise.

The forecasting performance for different months can be calculated by using different parameters. The computed power and power estimated by using intelligent techniques are slightly different. It can be seen that the errors are minimized using advanced control techniques. When loads follow the production of wind energy prediction at the location, then this becomes the driving parameter for output power computations in the system. If the system can predict the wind energy at a selected site then economic scheduling, use time and valuing can be done smartly to supply all the loads when satisfactory power is obtained. When the output power of

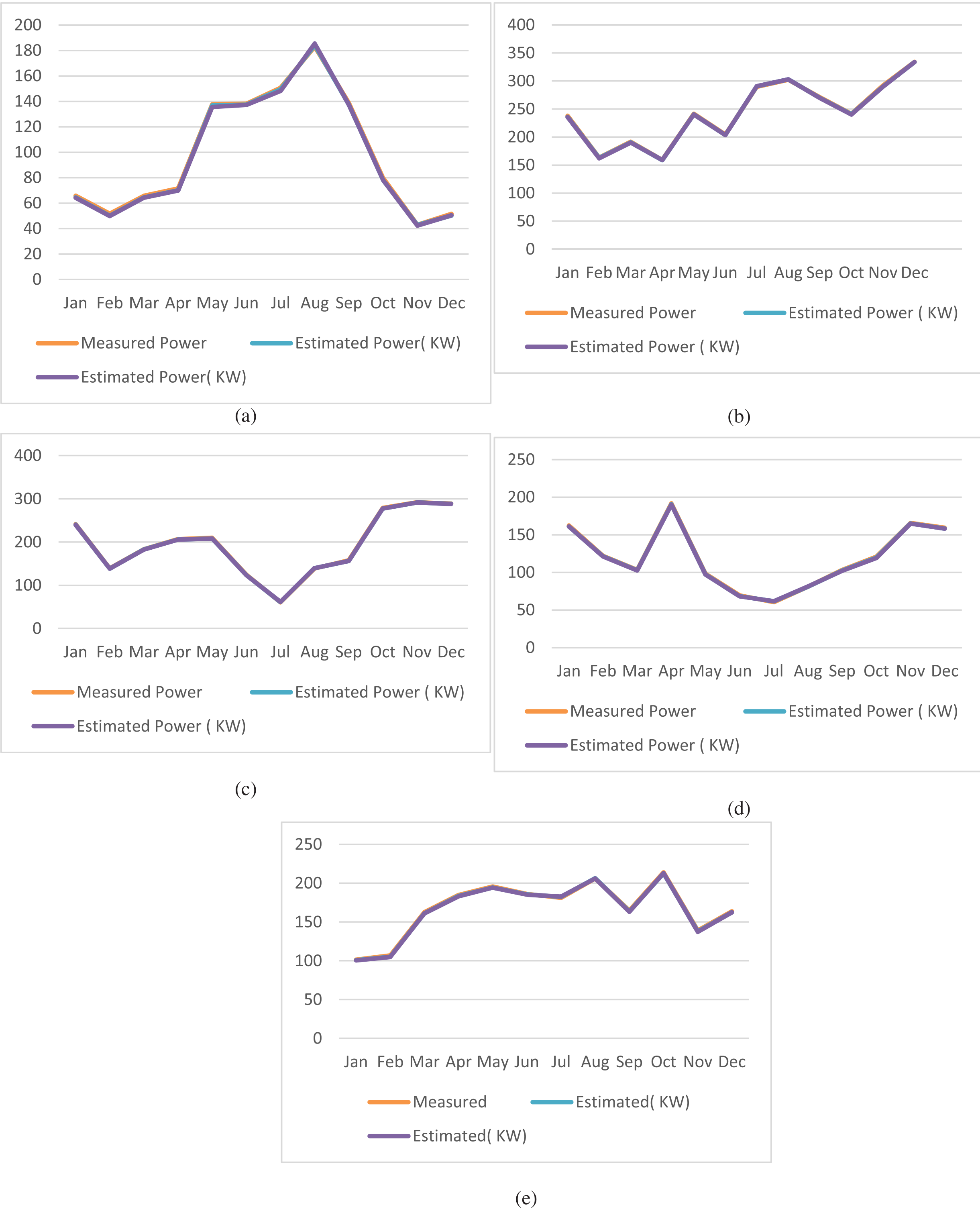


FIGURE 6. (a, b, c, d, e). Graphical representation of wind power estimation for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam and Kolkata.

wind system is achieved in lesser amount, then only important load is to be supplied.

With the accurate data, wind energy system can be fairly installed and begin the supplying power to the grid. Graphical presentations show that the fuzzy based wind power prediction method is good choice in India. Wind energy generation is important part for developing country like India. Furthermore, the global warming is enhanced by using coal based

TABLE 17. **Estimated monthly wind power in comparison with measured data for Vishakhapatnam.**

Month	Measured Power (KW)	Estimated Power (KW)	
		Fuzzy logic System	Model Predictive System
Jan	162.46	**161.18**	161.14
Feb	122.15	**121.65**	121.24
Mar	103.42	**102.98**	102.65
Apr	191.92	**190.75**	190.31
May	98.22	**97.42**	97.12
Jun	69.45	**68.45**	68.28
Jul	60.58	**61.56**	61.78
Aug	81.04	**81.12**	81.45
Sep	103.24	**102.61**	102.18
Oct	120.97	**119.76**	119.18
Nov	165.88	**165.12**	165.03
Dec	159.37	**158.49**	158.24

TABLE 18. **Estimated monthly wind power in comparison with measured data for Kolkata.**

Month	Measured Power (KW)	Estimated Power (KW)	
		Fuzzy logic System	Model Predictive System
Jan	101.42	**100.76**	100.53
Feb	106.83	**105.27**	104.95
Mar	162.60	**161.30**	161.12
Apr	184.86	**183.64**	183.07
May	195.69	**194.38**	194.26
Jun	186.11	**185.64**	185.25
Jul	181.18	**182.31**	182.75
Aug	205.98	**206.43**	206.10
Sep	164.92	**163.68**	163.15
Oct	213.88	**212.61**	212.95
Nov	138.99	**137.87**	137.34
Dec	163.76	**162.55**	162.52

plant which affects the environment and hence renewable energy sources are better option to decrease the carbon emission and save the earth from adverse effects.

The fuzzy based wind power prediction method gives the better results in comparison with other methods and also easy to implement. This can be used in general, for wind speed and wind power prediction, especially in those areas where wind power prediction is difficult, and slightly tough to calculate the wind speed. So fuzzy based prediction techniques based on different parameters are easy to implement.

The forecast errors by fuzzy and model predictive methods are presented graphically in the Fig 7 (a-b), 8 (a-c) for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata respectively. These figures show the graphical representation of the different errors calculated for the selected cities, so as to validate the accuracy of results. The wind speed and air density affects the power output of wind system. Root Mean Square Error (RMSE) using fuzzy based system for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata

TABLE 19. **Comparison of forecast errors by different methods for Trivandrum.**

Error (%)	Fuzzy based system	Model predictive based system
RMSE	**1.20**	1.68
MAD	**1.14**	1.60
MSE	**1.45**	2.84

TABLE 20. **Comparison of forecast errors by different methods for Bangalore.**

Error (%)	Fuzzy based system	Model predictive based system
RMSE	**1.04**	1.30
MAD	**0.91**	1.16
MSE	**1.05**	1.70

are 1.20 %, 1.04 %, 1.01 %, 0.87 %, 1.12 % respectively, while this is observed as 1.68 %, 1.30 %, 1.17 %, 1.16 %, 1.38 % respectively using model predictive method. The results obtained from well-established model are 1.98 %, 1.62 %, 1.45 %, 1.25 %, and 1.42 % respectively. These errors are observed within the limits. The outcomes indicate that by using proposed method, wind power predictions errors can be reduced. Also, mean absolute deviation (MAD) using fuzzy based system for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata are observed as 1.14 %, 0.91 %, 0.91 %, 0.81 %, 1.07 % respectively, whereas it is obtained as 1.60 %, 1.16 %, 1.10 %, 1.11 %, 1.30 % respectively using model predictive method. Besides, Mean Square Error (MSE) using fuzzy based system for Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata are found as 1.45 %, 1.05 %, 1.04 %, 0.77 % and 1.27 % respectively, however it is found as 2.84 %, 1.70 %, 1.38 %, 1.35 % and 1.93 % respectively using model predictive method. The results taken from fuzzy based technique are obtained to very close to calculated values, which prove that the model performance is acceptable. The forecasted output of wind system is quite accurate in comparison with the computed power. Hence, the proposed models can be employed for the estimation of wind speed and wind power generation that comprises the complete information. The model may be also used to estimate the wind power at those locations which have similar parameters. Moreover, in future, the achieved outcomes can be used for smart grid applications in load scheduling, demand side management where it is required to predict power output with load demand variation.

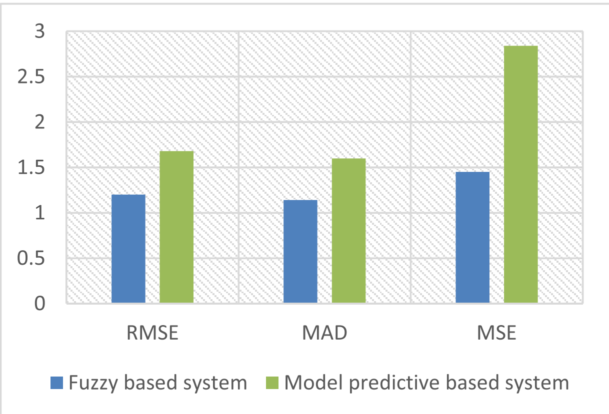
Comparison of consequences with existing models is presented in Table 24. The existing models results are compared with Kolkata city results. The Error RMSE with support vector machine, Back propagation, Model of forecast error correction +SVM and Model of forecast error correction +BP are 30.48%, 32.83%, 26.81% and 28.58% respectively [17]. Similarly with Neural Network method, this

TABLE 21. Comparison of forecast errors by different methods for Hyderabad.

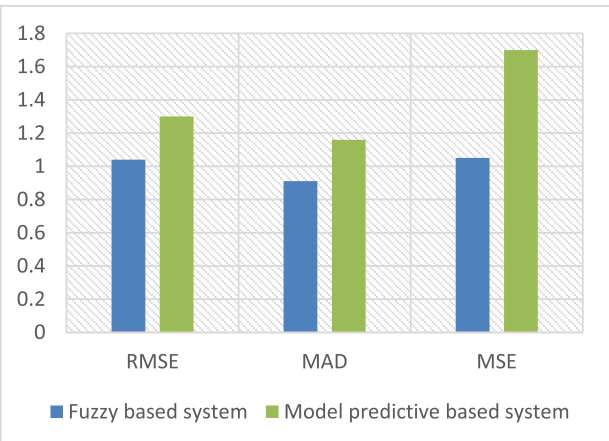
Error (%)	Fuzzy based system	Model predictive based system
RMSE	**1.01**	1.17
MAD	**0.91**	1.10
MSE	**1.04**	1.38

TABLE 22. Comparison of forecast errors by different methods for Vishakhapatnam.

Error (%)	Fuzzy based system	Model predictive based system
RMSE	**0.87**	1.16
MAD	**0.81**	1.11
MSE	**0.77**	1.35



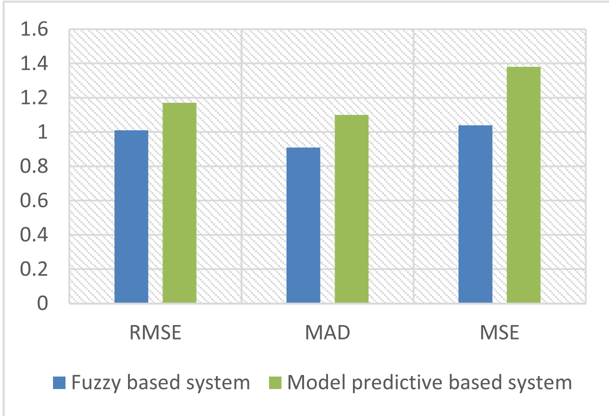
(a)



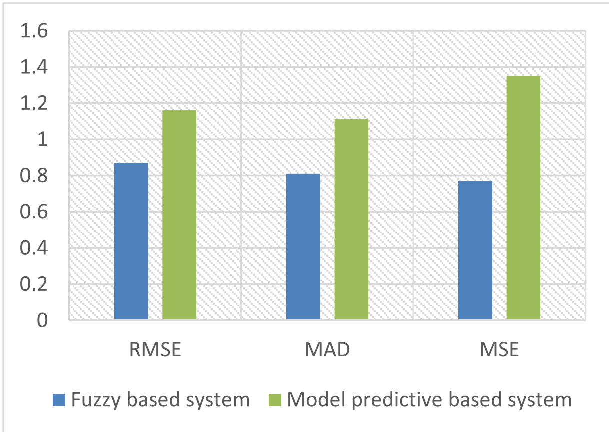
(b)

FIGURE 7. (a, b). Graphical presentation of forecast errors for Trivandrum and Bangalore.

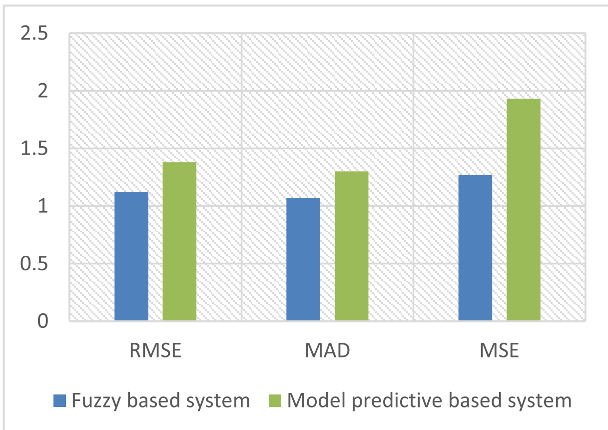
value is 1.14% [18]. The comparison table shows that consequences are well within the appropriate limits. For further, to know the accuracy and significant difference between the obtained results from the proposed model and other models,



(a)



(b)



(c)

FIGURE 8. (a, b, c). Graphical presentation of forecast errors for Hyderabad, Vishakhapatnam and Kolkata.

a T-test is performed. A T-test basically a statistical hypothesis test, which gives testing of an assumption application to the results and provides the probability of getting results by chance. The P-value is compared with a significance level (a) of different models, and P-value (0.021) is found less than significance level (a) in every case, so null hypothesis is rejected. Therefore, the results obtained from proposed model are significant.

TABLE 23. Comparison of forecast errors by different methods for Kolkata.

Error (%)	Fuzzy based system	Model predictive based system
RMSE	**1.12**	1.38
MAD	**1.07**	1.30
MSE	**1.27**	1.93

TABLE 24. Comparison of results with existing models.

Method	Error RMSE (%)
Support vector machine [17] (SVM)	30.48
Back propagation(BP)[17]	32.83
Model of forecast error correction +SVM [17]	26.81
Model of forecast error correction +BP [17]	28.58
Neural Network [23]	1.14
Model predictive based system	1.38
Proposed Fuzzy based system	**1.12**

VII. CONCLUSION

In this paper, a fuzzy based model for predicting the wind power for selected stations is presented. The meteorological parameters like relative humidity as well as vapour pressure and the geographical parameters like longitude, latitude, altitude of the selected location are defined as input parameters. Since, wind power varies along with the wind speed variations and hence it becomes quite difficult to estimate the accurate wind power by using regression methods and mathematical formulas at a specific time that is more important in the plan of wind based power station. However, these difficulties are avoided by the fuzzy based method. Based on the computed data, fuzzy logic and model predictive system are utilized to predict the wind power at five different Indian stations having different geographical and climate conditions. The analysis concludes that fuzzy based system is easy to implement.

The results obtained from the fuzzy based model are judged against the computed data and it can be seen that the different errors are observed within the allowable limits. Further, by using this model other conditions may also be used easily in predicting the wind power in a more precise way for the selected location of wind based power stations. Moreover, proposed wind power prediction technique with integration to the grid would be analyzed in future for smart grid implementation considering load scheduling and demand side management etc. Therefore, the wind speed prediction and wind power estimation would be more useful in wind system integration to the Smartgrid/Microgrid applications.

APPENDIX

For the prediction of monthly wind power at Trivandrum, Bangalore, Hyderabad, Vishakhapatnam, and Kolkata, a model predictive based model has been developed and presented in Figure 9.

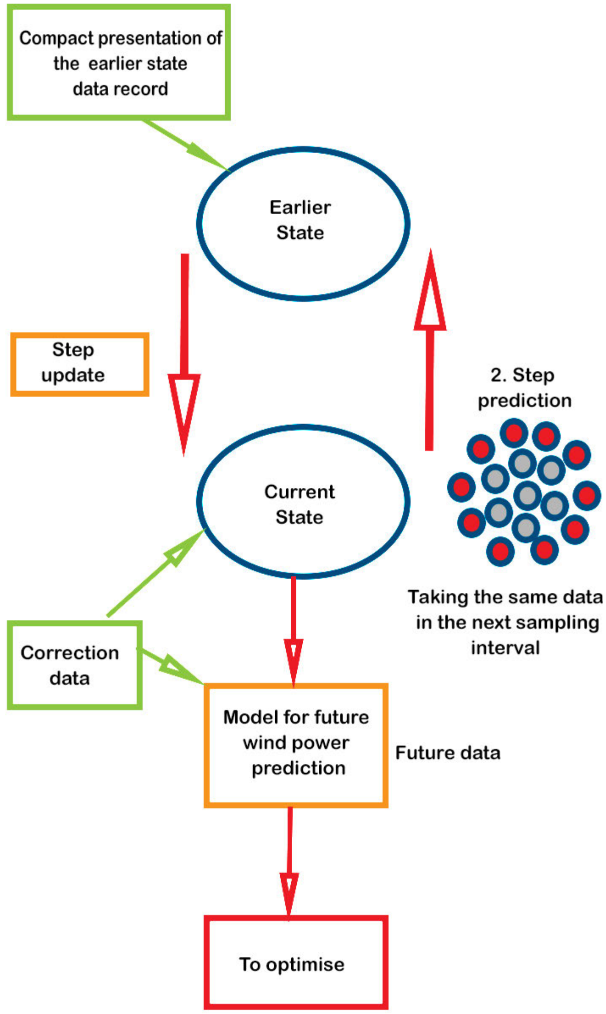


FIGURE 9. Model Predictive Model for the estimation of monthly wind power.

REFERENCES

[1] G. V. Kuik, B. Ummels, and R. Hendriks, *Sustainable Energy Technologies*. Amsterdam, The Netherlands: Springer, 2007.

[2] A. Kusiak, H. Zheng, and Z. Song, "Wind farm power prediction: A data-mining approach," *Wind Energy*, vol. 12, no. 3, pp. 275–293, Apr. 2009.

[3] Y.-K. Wu and J.-S. Hong, "A literature review of wind forecasting technology in the world," in *Proc. IEEE Power Tech*, Jul. 2007, pp. 504–509.

[4] M. Negnevitsky, P. Johnson, and S. Santoso, "Short term wind power forecasting using hybrid intelligent systems," in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, Jun. 2007, pp. 1–4.

[5] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, "A review on the forecasting of wind speed and generated power," *Renew. Sustain. Energy Rev.*, vol. 13, no. 4, pp. 915–920, May 2009.

[6] Z. Guo, W. Zhao, H. Lu, and J. Wang, "Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model," *Renew. Energy*, vol. 37, no. 1, pp. 241–249, Jan. 2012.

[7] T. Pinto, S. Ramos, T. M. Sousa, and Z. Vale, "Short-term wind speed forecasting using support vector machines," in *Proc. IEEE Symp. Comput. Intell. Dyn. Uncertain Environ. (CIDUE)*, Dec. 2014, pp. 40–46.

[8] G. Santamaría-Bonfil, A. Reyes-Ballesteros, and C. Gershenson, "Wind speed forecasting for wind farms: A method based on support vector regression," *Renew. Energy*, vol. 85, pp. 790–809, Jan. 2016.

[9] O. Ait Maatallah, A. Achuthan, K. Janoyan, and P. Marzocca, "Recursive wind speed forecasting based on hammerstein auto-regressive model," *Appl. Energy*, vol. 145, pp. 191–197, May 2015.

[10] D. Chen, P. Li, X. Li, C. Xu, Y. Xiao, and B. Lei, "Short-term wind speed forecasting considering heteroscedasticity," in *Proc. Int. Conf. Adv. Power Syst. Autom. Protection*, vol. 2, Oct. 2011, pp. 884–888.

[11] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-ARIMA models," *Renew. Energy*, vol. 34, no. 5, pp. 1388–1393, May 2009.

[12] A. K. Singhal, M. Rizwan, S. Kirmani and A. Ahmed, "Generalized methodology for the prediction of wind powor: A fuzzy logic based approch," *Int. J. Eng. Sci. Res.*, vol. 2, pp. 57–60, Jul. 2011.

[13] M. C. Mabel and E. Fernandez, "Estimation of energy yield from wind farms using artificial neural networks," *IEEE Trans. Energy Convers.*, vol. 24, no. 2, pp. 459–464, Jun. 2009.

[14] A. Sagbas and T. Karamanlioglu, "The application of artificial neural networks in the estimation of wind speed: A case study," in *Proc. Int. Adv. Technol. Symp.*, Ankara, Turkey, May 2011, pp. 78–81.

[15] M. C. Mabel and E. Fernandez, "Analysis of wind power generation and prediction using ANN: A case study," *Renew. Energy*, vol. 33, no. 5, pp. 986–992, 2008.

[16] T. H. M. El-Fouly, E. F. El-Saadany, and M. M. A. Salama, "One day ahead prediction of wind speed and direction," *IEEE Trans. Energy Convers.*, vol. 23, no. 1, pp. 191–201, Mar. 2008.

[17] M. Mao, J. Ling, L. Chang, N. D. Hatziargyriou, J. Zhang, and Y. Ding, "A novel short-term wind speed prediction based on MFEC," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 4, no. 4, pp. 1206–1216, Dec. 2016.

[18] Y. Cao, W. Wei, C. Wang, S. Mei, S. Huang, and X. Zhang, "Probabilistic estimation of wind power ramp events: A data-driven optimization approach," *IEEE Access*, vol. 7, pp. 23261–23269, 2019.

[19] Y. Zhang, Y. Zhao, G. Pan, and J. Zhang, "Wind speed interval prediction based on lorenz disturbance distribution," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 807–816, Apr. 2020.

[20] Y. Zhang, H. Sun, and Y. Guo, "Wind power prediction based on PSO-SVR and grey combination model," *IEEE Access*, vol. 7, pp. 136254–136267, 2019.

[21] X. Zhang, Y. Chen, Y. Wang, R. Ding, Y. Zheng, Y. Wang, X. Zha, and X. Cheng, "Reactive voltage partitioning method for the power grid with comprehensive consideration of wind power fluctuation and uncertainty," *IEEE Access*, vol. 8, pp. 124514–124525, 2020.

[22] Y. Sun, Z. Li, X. Yu, B. Li, and M. Yang, "Research on ultra-short-term wind power prediction considering source relevance," *IEEE Access*, vol. 8, pp. 147703–147710, 2020.

[23] G. Zhang, H.-X. Li, and M. Gan, "Design a wind speed prediction model using probabilistic fuzzy system," *IEEE Trans. Ind. Informat.*, vol. 8, no. 4, pp. 819–827, Nov. 2012.

[24] R. Ak, O. Fink, and E. Zio, "Two machine learning approaches for short-term wind speed time-series prediction," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 27, no. 8, pp. 1734–1747, Aug. 2016.

[25] Q. Hu, P. Su, D. Yu, and J. Liu, "Pattern-based wind speed prediction based on generalized principal component analysis," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 866–874, Jul. 2014.

[26] R. Ak, V. Vitelli, and E. Zio, "An interval-valued neural network approach for uncertainty quantification in short-term wind speed prediction," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 11, pp. 2787–2800, Nov. 2015.

[27] H. Mori and S. Okura, "An ANN-based method for wind speed forecasting with S-transform," in *Proc. IEEE Region 10 Conf. (TENCON)*, Nov. 2016, pp. 642–645.

[28] I. G. Damousis, M. C. Alexiadis, J. B. Theocharis, and P. S. Dokopoulos, "A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation," *IEEE Trans. Energy Convers.*, vol. 19, no. 2, pp. 352–361, Jun. 2004.

[29] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-15, no. 1, pp. 116–132, Jan./Feb. 1985.

[30] P. A. Mastorocostas, J. B. Theocharis, and A. G. Bakirtzis, "Fuzzy modeling for short term load forecasting using the orthogonal least squares method," *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 29–36, Feb. 1999.

[31] J.-S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Trans. Syst., Man, Cybern.*, vol. 23, no. 3, pp. 665–685, May/Jun. 1993.

[32] C. Opathella, A. Elkasrawy, A. A. Mohamed, and B. Venkatesh, "Optimal scheduling of merchant-owned energy storage systems with multiple ancillary services," *IEEE Open Access J. Power Energy*, vol. 7, pp. 31–40, Mar. 2020.

[33] S. Fan, G. He, X. Zhou, and M. Cui, "Online optimization for networked distributed energy resources with time-coupling constraints," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 251–267, Jan. 2021.

[34] R. Rahmani, R. Yusof, M. Seyedmahmoudian, and S. Mekhilef, "Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting," *J. Wind Eng. Ind. Aerodyn.*, vol. 123, pp. 163–170, Dec. 2013.

[35] H. B. Azad, S. Mekhilef, and V. G. Ganapathy, "Long-term wind speed forecasting and general pattern recognition using neural networks," *IEEE Trans. Sustain. Energy*, vol. 5, no. 2, pp. 546–553, Apr. 2014.

[36] M. G. Angle, S. Madnick, J. L. Kirtley, and S. Khan, "Identifying and anticipating cyberattacks that could cause physical damage to industrial control systems," *IEEE Power Energy Technol. Syst. J.*, vol. 6, no. 4, pp. 172–182, Dec. 2019.

[37] C. Chen, M. Cui, X. Fang, B. Ren, and Y. Chen, "Load altering attack-tolerant defense strategy for load frequency control system," *Appl. Energy*, vol. 280, Dec. 2020, Art. no. 116015.

[38] M. Cui and J. Wang, "Deeply hidden moving-target-defense for cybersecure unbalanced distribution systems considering voltage stability," *IEEE Trans. Power Syst.*, early access, Oct. 15, 2020, doi: 10.1109/TPWRS.2020.3031256.

[39] I. Akhtar, S. Kirmani, and M. Jamil, "Analysis and design of a sustainable microgrid primarily powered by renewable energy sources with dynamic performance improvement," *IET Renew. Power Gener.*, vol. 13, no. 7, pp. 1024–1036, May 2019.

[40] S. Kirmani, M. Jamil, and I. Akhtar, "Economic feasibility of hybrid energy generation with reduced carbon emission," *IET Renew. Power Gener.*, vol. 12, no. 8, pp. 934–942, Jun. 2018.

[41] E. Oh and H. Wang, "Reinforcement-learning-based energy storage system operation strategies to manage wind power forecast uncertainty," *IEEE Access*, vol. 8, pp. 20965–20976, 2020.

[42] Z. Li, L. Ye, Y. Zhao, X. Song, J. Teng, and J. Jin, "Short-term wind power prediction based on extreme learning machine with error correction," *Protection Control Mod. Power Syst.*, vol. 1, no. 1, pp. 4–11, Dec. 2016.

[43] C. Chen, M. Cui, F. Li, S. Yin, and X. Wang, "Model-free emergency frequency control based on reinforcement learning," *IEEE Trans. Ind. Informat.*, vol. 17, no. 4, pp. 2336–2346, Apr. 2021.

[44] *Solar Radiation Handbook*, SEC and IMD, New Delhi, India, 2008.

[45] A. Mani, "Handbook solar radiation data for India," Allied Publishers India, Solar Energy Centre, MNRE Indian Metrological Dept., India, Tech. Rep., 1980.

IRAM AKHTAR received the B.Tech. degree in electrical engineering from BBDNITM, Lucknow, in 2010, the M.Tech. degree in power electronics and drives from the Madan Mohan Malaviya University of Technology (Formerly Madan Mohan Malaviya Engineering College), Gorakhpur, in 2012, and the Ph.D. degree in electrical engineering from Jamia Millia Islamia (A Central University), New Delhi, India, in 2020.

She has published/presented more than 25 articles in various international journals/conferences. Her current research interests include new and renewable energy sources (solar and wind), resource assessment, smart grids, distributed generation, grid integration of renewable energy sources, application of intelligent techniques to electrical power systems, smart grid, and reactive power compensation.

SHEERAZ KIRMANI is working as Associate Professor with the Department of Electrical Engineering, Aligarh Muslim University, Aligarh, India since December 2020. Earlier he had worked with the Department of Electrical Engineering, Jamia Millia Islamia and Department of Energy and Environment, TERI University, New Delhi, India. He completed his B.Tech in Electrical engineering from Aligarh Muslim University, Aligarh (A Central University) in 2005, M.Tech in Energy Studies from Indian Institute of Technology Delhi. In 2007, Ph.D. from Jamia Millia Islamia (A Central University), New Delhi, India in 2014 in the area of Distributed Solar power generation. He has published/presented many papers in various peer reviewed International Journals and conferences. He has also visited Open University, Milton Keynes, United Kingdom under UKIERI grant.

He is also a life member of ICTP. His research interest area includes smart grids, Distributed Generation, Grid Integration of Renewable Energy Sources.

MOHMMAD AHMAD is working as an Assistant Professor at Rajkiya Engineering College Bijnor in the department of Electrical Engineering since December 2017. Earlier he has worked as Assistant Professor in Noida Institute of Engineering and Technology (NIET), Greater Noida from January 2013 to December 2017. He is also pursuing his Ph.D. from Jamia Millia Islamia New Delhi in Electrical Engineering department since November 2016. He has teaching and research experience of about 8 years. He has published/presented 12 papers in International Journals and IEEE conferences. He has completed his B.Tech and M.Tech with first division from Aligarh Muslim University, Aligarh in 2010 and 2012 respectively. His research interest area includes power electronics and drives, power quality improvement, grid integration of solar PV system.

SULTAN AHMAD (Member, IEEE) is currently working as Lecturer in Department of Computer Science, College of Computer Engineering and Sciences, Prince Sattam Bin Abdulaziz University, Alkharj, Saudi Arabia. He has a unique blend of education and experience. He has received his Master of Computer Science and Applications from the prestigious Aligarh Muslim University, India with distinction marks. He graduated in Computer Science and Applications in 2002 from Patna University, India. He has more than 12 years of teaching and research experience. His research and teaching interests include Cloud Computing, Big Data, Machine Learning and Internet of Things. He has presented his research papers in many national and international conferences and published research papers in many peer-reviewed reputed journals. He is a member of IEEE, IACSIT and Computer Society of India.