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Short term renewable energy forecasting based on feed Forward Back Propagation Neural Network strategy

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Abstract: The fundamental inputs used as a renewable energy source are wind speed and solar radiation. Both parameters are very nonlinear and depending on their surroundings. As a result, reliable prediction of these characteristics is required for usage in a variety of agricultural, industrial, transportation, and environmental applications since they reduce greenhouse gas emissions and are environmentally benign. In this study, we used a Feed Forward Back Propagation Neural Network (FFBPN) technique to predict proper data such as temperature, relative moisture, sun radiations, rain, and wind speed. The FFBPN will be trained in such a way that it can conduct hybrid forecasting with little changes to the programming codes, ranging from hourly (short term forecasting) to daily forecasting (medium term forecasting). This feature is one of the significant improvements, showing the suggested hybrid renewable energy forecasting system's high robustness. Because the hybrid forecasting system is a unique approach, the system's accuracy will be determined by comparing the findings to the corresponding values of the persistent model, a stand-alone forecasting model. Finally, the completely created system package could be sold and/or used in future research initiatives to help researcher's analyses, validate, and illustrate their models across a variety of areas.

Keywords: Solar irradiance, wind speed, back propagation, forecasting

I. INTRODUCTION

Renewable energy sources such as wind and solar energy have been severely criticized as the energy problem worsens. According to statistics, global wind power generation reached 733 GW in 2020, an increase of 17.8% over 2019. Solar power generation worldwide reached 714 GW in 2020, up 21.6 percent from the previous year [1]. Wind and photovoltaic (PV) electricity generation are, in reality, both variable and intermittent. High levels of renewable energy penetration in power networks pose serious threats to the grid's security and economy [2]. As a result, under the concept of guaranteeing the power grid's economic and stable operation, we should strengthen the power grid's ability to penetrate more renewable energy.

On the one hand, energy storage devices such as concentrated solar power (CSP) with heat storage can be deployed on the grid to meet this requirement [3,4]. On the other hand, because to the complementarity and smoothness of wind and solar energy [5,6], combining different sources of renewable energy in the same region [7] is an effective way to increase renewable energy penetration. Nonetheless, CSP and bundled grid connection technologies cannot ensure renewable energy generation reliability.

More machine learning and artificial intelligence technologies have been applied in forecasting as computer processing speeds have improved. Machine learning methodologies, as compared to statistical and physical forecasting approaches, typically produce better outcomes [8–10]. As a result, in this paper, we employ a machine learning approach based on Feed Forward Back Propagation Neural Networks to forecast solar and wind power. The following objectives are motivated for this research work.

I. To reduce the issues and impact concerning distributed energy resources (wind energy and solar energy) and endorsing the optimal working of an energy system. This is achieved by the proposed novel and hybrid based forecasting models.

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II. To improve accuracy and reduce the error to minimal by proposing hybrid forecasting techniques.
III. By proposing novel optimization algorithms to avoid local minima issue and improve the convergence.
IV. To examine the contribution of wind energy by including solar energy in the study area.

The remaining part of this work is organized as follows: Section two discuss literature surrey based on existing forecasting methods. Section three discuss working function of proposed forecasting system. Section four discuss the simulation results and performance analysis of proposed forecasting system. Finally section five discuss the conclusion and future work of the research.

II. LITERATURE SURVEY

Artificial neural networks that use feed-forward back propagation are the most basic and fastest. Data flows solely in one way in feed-forward networks, from input nodes to output nodes via hidden nodes. In feed forward networks, there are no recurrent loops [11]. Forecasting is vital in decision-making, and developments in feed-forward neural networks have seen fast growth [12–14]. The goal of forecasting is to develop a mathematical model that can predict future events based on previously collected data [15].

Different types of forecasting algorithms, such as the time series approach, Support Vector Machine (SVM), and Artificial Neural Networks, are explored in the literature to anticipate future observations (ANN). In [16] described a time series method for analysing data's temporal dynamics and forecasting future values. A overview of support vector machines and its applications in time series data forecasting was published in [17,18]. Traditional methods such as artificial neural network models [19], ARIMA [20], and machine learning techniques [21] were provided by a number of researchers.

Layer recurrent neural network models are similar to feed-forward networks, but they have recurrent connections between each layer. In [22], addressed layer recurrent models for wind speed and power forecasting. In [23], a comparison of feed-forward back propagation and layer recurrent neural network models for ground-level ozone forecasting was presented. In another paper, the researchers combined the attributes of two traditional approaches to enhance the forecast error [24].The Following Research gaps are identified form literature survey

i. There is an essential requirement for estimation of solar radiation and wind speed before erecting the solar-wind plant. There has been a shortage of substantial evidence in the literature for the applicability of these models for evaluating daily global solar radiations and wind speeds.
ii. Most studies have been for hourly resolutions as recommended for wind and solar power, but higher resolution may be required if penetration levels grow. Methods used in one area should be extended to other areas and synchronized data collection and modeling.
iii. Additionally, more research into the smoothing impact and overall variability for combinations of diverse renewable resources is required.
iv. For forecasting, there is a need for better collaboration and common metrics. As can be seen in the evaluation of estimation approaches, the estimation accuracy measures used for the numerous sources examined in this study differ for several reasons, making it impossible to compare estimation competence.
v. The relative error, in terms of the installed power-dependent and represented root mean squared error (RMSE), and the systematic and unsystematic error separated, appears to be the most appropriate statistic. However, all analysis-related data estimation methods should be included in the study (e.g., installed power). The reported RMSE is probably the most important metric for power system performance, it can be converted due to power inaccuracy.

III. PROPOSED SOLAR AND WIND FORECASTING SYSTEM

Figure 1 illustrates the block diagram of the forecasting model produced using the suggested system for Feed Forward Back Propagation Neural Network. This research employs a sort of short-term forecasting. Historical weather data is available at the Technical University campus in Rajasthan, India's northern state [25]. FFBPN is a recent approach that is based on biological neural networks. They operate based on interconnected neurons that form a network between inputs and outputs; the neurons are made up of a mathematical function, biases, and weights. This network of neurons is built during the training phase to learn the data using proper learning algorithms. Clustering, Classification, and Regression are some of the jobs that FFBPN can be trained to complete.

We need to create a neural network to solve a regression problem to forecast weather variables.

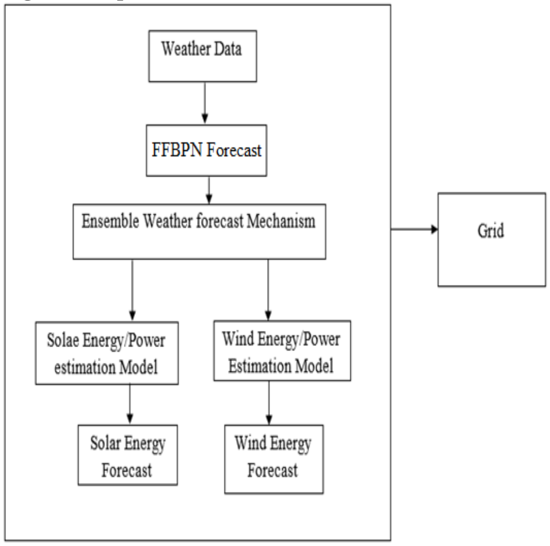

Figure1. Block Diagram of Proposed system

A. Feed Forward Back Propagation Neural Network Solar Forecasting

Schematic diagram of a multilayer feed-forward neural network architecture is shown in Fig.2. The outputs of neurons in each layer are fed forward to their next level, until the entire output of network is obtained. It usually consists of an input layer, multiple hidden layers and an output layer. Through adaptable synaptic weights, each single neuron is connected to other neurons of a previous layer. Knowledge is usually stored as a set of connection weights

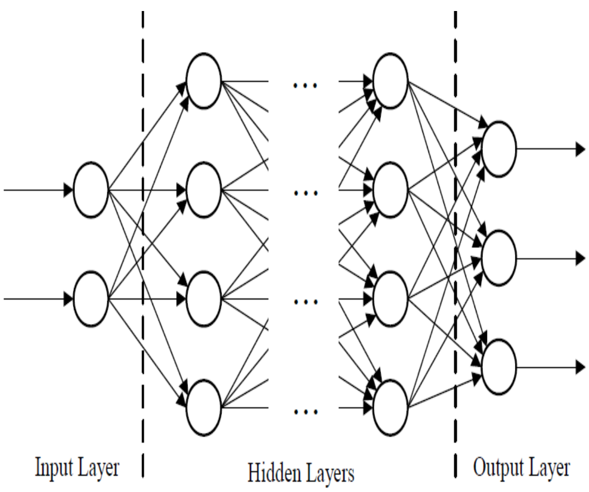

Figure 2. Structure of Feed Forward Back Propagation Neural Network

The hit-and-trial strategy was employed in the previous analysis. Feed Forward Back Propagation (FFBP) is a method of propagating information from one Traditional approaches offer the ability to make better, faster, and more practical forecasts than neural networks. They are more accurate than standard simulation models and regression techniques for predicting energy usage. With ten hidden neurons, the neural network model was employed. If the network does not perform well after training, go back to the previous stage and modify the number of hidden neurons. With 10 neurons, it produced the best results. Figure 3 shows the architecture of the neural network that was used.

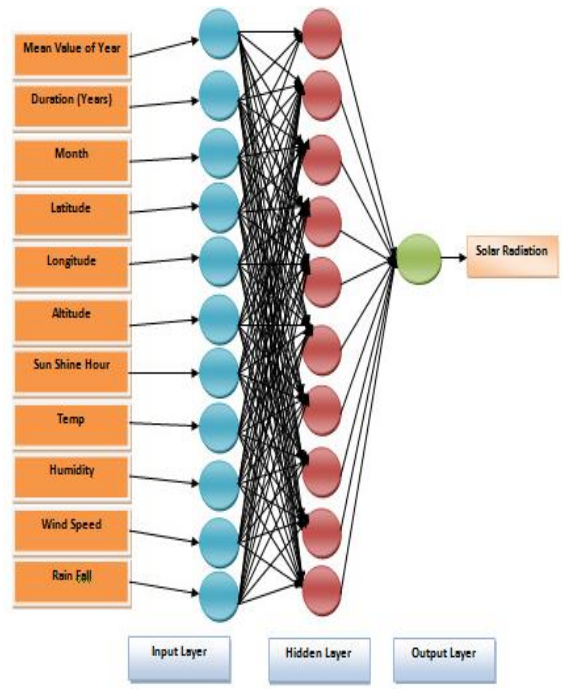

Figure 3. Architecture of proposed Solar Forecasting

In order to train the developed Feed Forward Back Propagation Neural Network model for the estimation of global solar radiation 70% of the measured data has been used while 15 % data has been used for the purpose of validation and the remaining 15 % data has been used for the testing purpose.

A.1. Algorithm Steps of FFBPN – Solar Forecasting

Presented improved Feed Forward back propagation networks achieve speed up convergence by incorporation of the momentum factor (μ). Improved back propagation network outperform than back propagation network in terms of reduced

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statistical error and faster convergence. The architecture of the proposed back propagation networks model for the wind speed forecasting shown in Figure 3. Input to the hidden weight vectors,

$$V = [V_{11}, V_{12}, \ldots . V_{1n}, V_{21}, V_{22}, \ldots . V_{2n}, V_{31}, V_{32}, \ldots . V_{3n}, V_{41}, V_{42}, \ldots . V_{4n} \quad V_{51}, V_{52}, \ldots . V_{5n}, V_{61}, V_{62}, \ldots . V_{6n}] \ \ldots (1)$$

Hidden layer net Input, $z_{in,j} = f(\sum_{i=1}^{6} \sum_{i=1}^{6} U_i V_{ij})$ … (2)

Where

U = input.

V = weights between input and hidden layer

n= number of hidden neurons

Weight vectors of hidden to output vector, $W = [W_1, W_2, \ldots W_n]$ … (3)

Output layer net input, $Y_{in} = \sum_{j=1}^{n} (Z_j W_j)$ … (4)

Where,

W - Weight between hidden and an output layer.

f - Activation function

Output Layer error, $\delta = (T - Y) f'(Y_{in})$ …. (5)

Where, f ' (Yin) - derivative of the output layer net input. Evolved error (δ) back propagated to the hidden layer. Each hidden neuron (Z_j , j =1,2,....,n) sums its delta inputs from output layer neurons.

$$\delta_{in,j} = \sum_{j=1}^{n} \delta W_j \ \ldots (6)$$

Hidden layer error, $\delta_j = \delta_{in,j} f'(Z_{in,j})$ … (7)

Where, f ' (Z_{inj}) - derivative of the net input of hidden layer. Evolved error (δj) propagated backward to the input layer.

$$Ouptut\ Layer, E = [\delta] \ \ldots (8)$$

$$Input\ Layer, E_j = [\delta_j] \ \ldots (9)$$

Weight modifying expression, $W_j[t+1) = WE_j(t) + \eta \delta Z_j + \mu\, [W_j(t) - W_j(t-1)$

$V_{ij}[t+1) = V_j(t) + \eta \delta U_j + \mu\, [V_{ij}(t) - V_{ij}(t-1)$ …. (10)

Where, η - Learning rate, μ - momentum factor.

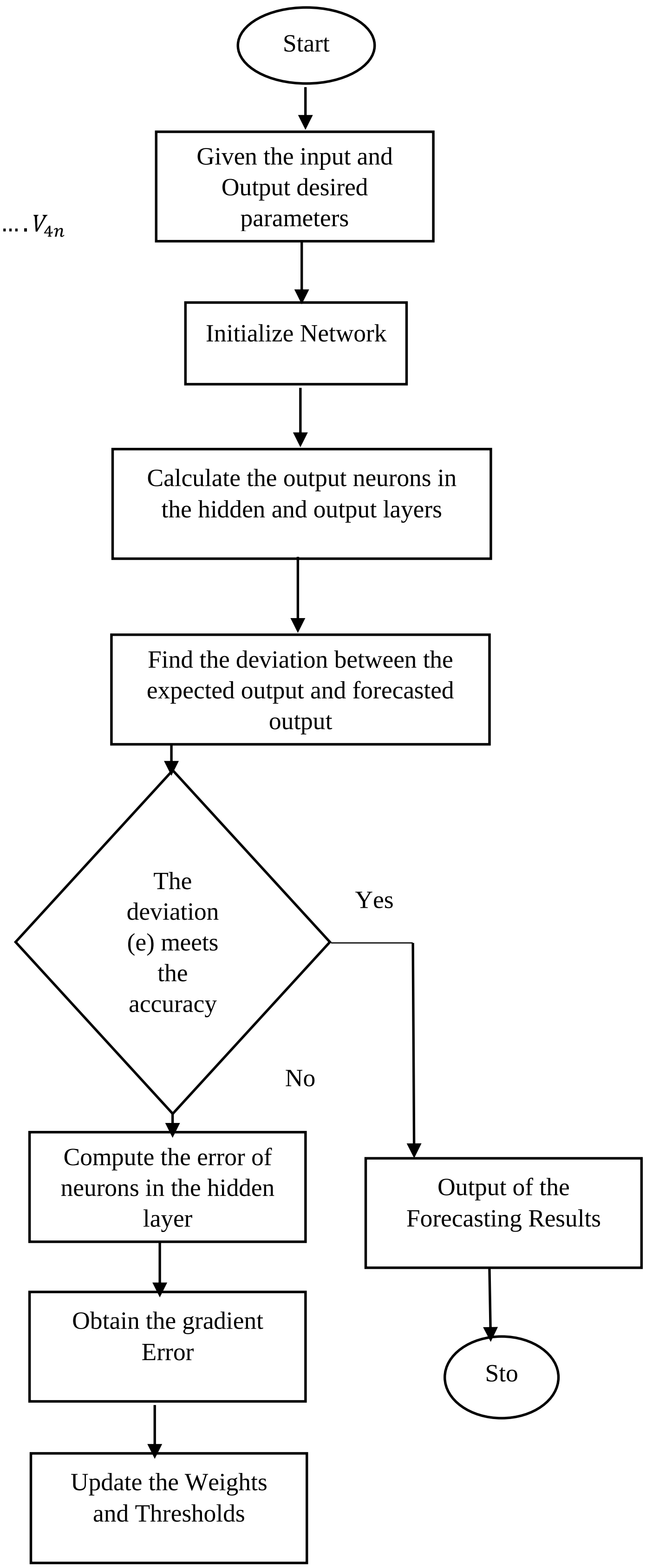

Figure 4. Flow Chart of FFBPN Solar Forecasting

The FFBPN algorithm's operation and parameters are shown in Figure 4. The FFBPN are very much similar except for the weight update routine. Resilient propagation does not consider the value of the partial derivative (error gradient) but rather considers only the sign of the error gradient to indicate the direction of the weight update.

B. Feed Forward Backpropagation Neural Network-based Wind Power Forecasting

Accurate short-term wind speed forecasting is essential for integrating wind power into current grid systems. As a result, the suggested short-term wind speed forecasting approach is a significant scientific contribution to the dependable forecasting of large-scale wind power. In this work use Feed Forward Back Propagation method to forecast the wind power.

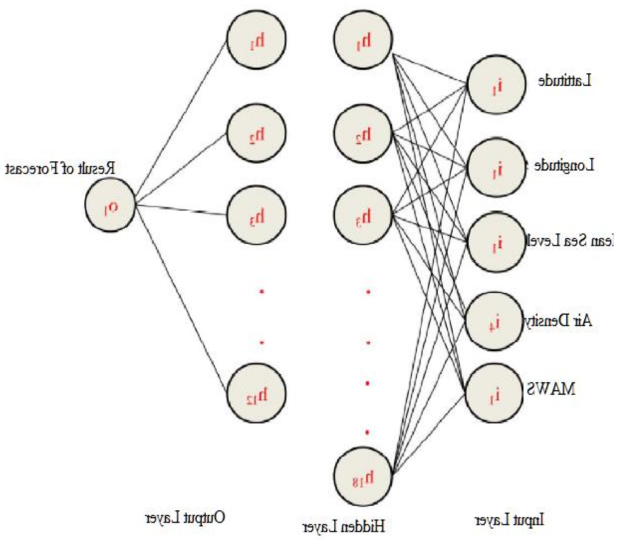

Figure 5. Wind Power Forecasting - FFBPN

The architecture of Feed Forward Back Propagation method (shown in Figure 5) to constructed in order to estimate wind power density a new place which is a function of above inputs. FFBPN is designed after the examination of each of the input output pairs. Solar radiation at a particular location influences ambient temperature at instrument height. Temperature influences air density at that particular site. Air density here is published. Topographical distribution is represented by longitude, latitude and mean sea level. Mean wind speed measured at the locations majorly contributes to wind power density.

B.1 Algorithm of FFBPN –Wind Forecasting

Parameters of wind energy resource assessment are - mean annual wind power density, mean annual wind speed, longitude, latitude, mean sea level, mast height and air density. Mean Annual Wind Power Density (MAWPD) is an authentic indication of wind energy potential at a given topographical site. It gives the measure of combined effect of wind speed distribution and air density at different wind speeds. WPD is defined as the wind power available per unit area swept by the wind turbine blades and is given by the following equation

$$WPD = \frac{1}{2n}\sum_{1}^{n} \rho v_i^3 \frac{w}{m^2} \dots (11)$$

Where 'ρ' is air density in kg/m3 is, *vi* is wind speed in m/sec and n is the number of records in the average interval taken.Air density given by

$$\boldsymbol{\rho = \left(\frac{P_0}{RT}\right) exp^{\left(\frac{-g.z}{RT}\right)} \ (kg/m^3) \dots (12)}$$

Po = the standard sea level atmospheric pressure (101,325 Pa), or the actual sea level-adjusted pressure reading; g = the gravitational constant (9.8 m/s²); and z = the site elevation above sea level in m. The flowchart of the proposed FFBPN based wind speed forecasting algorithm is depicted in Figure 5.

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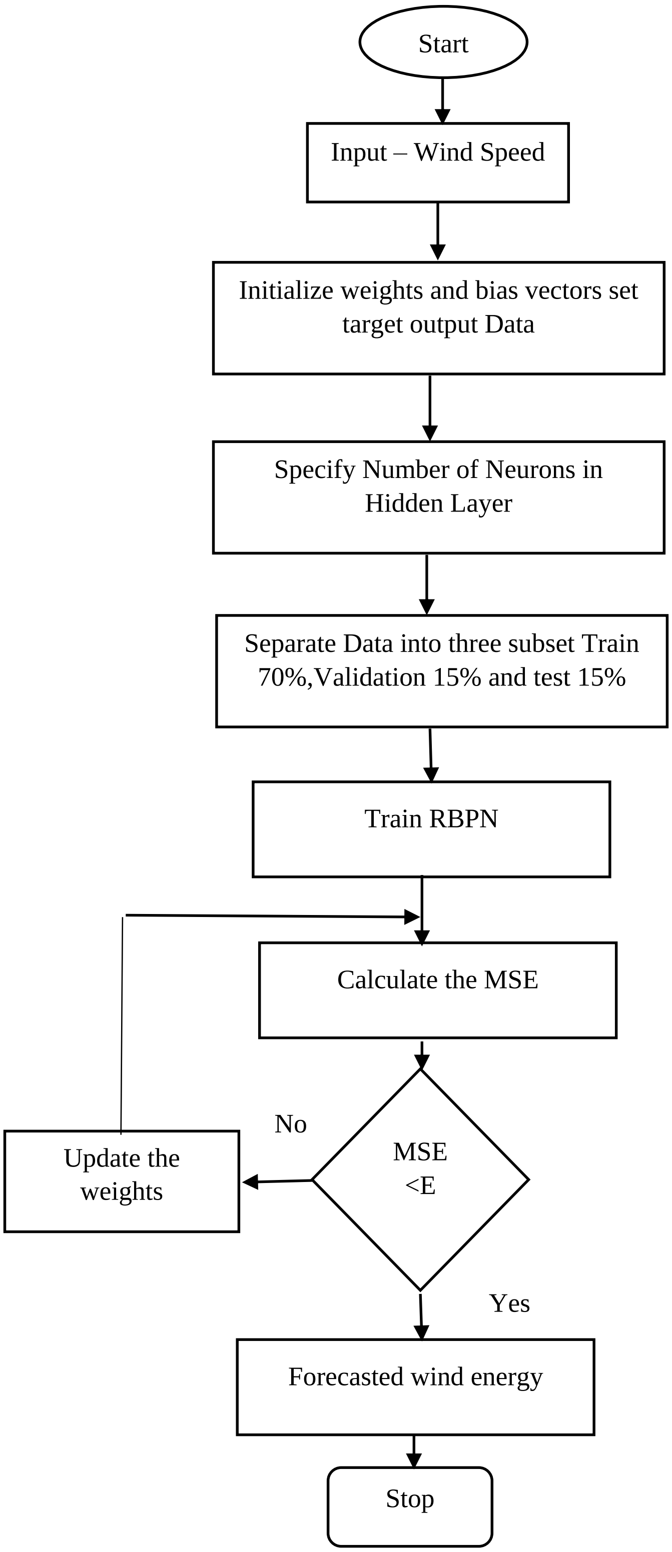

Figure 6. Flowchart of the proposed wind Power forecasting method

IV. SIMULATION RESULTS AND DISCUSSION

The suggested system is simulated using the MATLAB2017a program. Figure 7, figure 8 and Figure 9 list the simulation parameters. The data for the suggested system was collected from a technical university campus in Rajasthan, India's northwest state [25].

Month	Clearness Index	Average Radiation ($kW/h/m^2$)	Average wind speed (m/s)
January	0.661	4.43	2.640
February	0.691	5.42	3.150
March	0.692	6.41	2.769
April	0.676	7.05	3.790
May	0.673	7.44	4.500
June	0.585	6.58	4.680
July	0.478	5.31	4.060
August	0.477	5.04	3.330
September	0.619	5.91	3.21
October	0.706	5.76	2.460
November	0.686	4.75	2.410
December	0.654	4.14	2.520
Annual Average	0.634	5.69	3.29

Figure 7. Solar irradiance and wind speed

Figure 7 depicts the solar irradiation and wind speed. The yearly average is 5.69kWh/m2/day, with daily solar radiation ranging from 4.140 to 7.440 kWh/m2/day. The monthly average wind speed in the research area ranges from 2.410 to 4.68 m/s, with an annual average of 3.29 m/s. We use the technical data from the PV module in Figure 8 to construct short-term forecasts.

Technical Data	Value	Unit
Manufacture	TATA Power Plant	
Model	TS250	
Nominal Power Output	250	(W)
Power tolerance	±2.5	(%)
Module Efficiency	15.00	(%)
Voltage at PMAX VMPP	30.7	(V)
Current at PMAX IMPP	8.16	(A)
Open Circuit Voltage VOC	38.1	(V)
Short Circuit Current ISC	8.58	(A)

Figure 8. Technical Data of PV module

Technical Data	*Value*	*Unit*
Rated Electrical Power	100,3,400,50	kW, phase, volt, Hz
Rated Wind Speed	15	m/s
Minimum Wind Speed	2	m/s
Maximum Wind Speed	25	m/s
Extreme Wind Speed	59.5	m/s
Weight of Rotor and nacelle	6500	Kg
Rotor Diameter	20.7	M
Height from the Ground	37	M
Power Factor	0.9 lagging to 0.9 leading	
Temperature	-20 to +50	°C

Figure 9. Technical Data of Wind Turbine

The turbine's production specs and economic difficulties are listed in Figure 9. Wind energy is generated in real time based on wind speed and power curves [29].

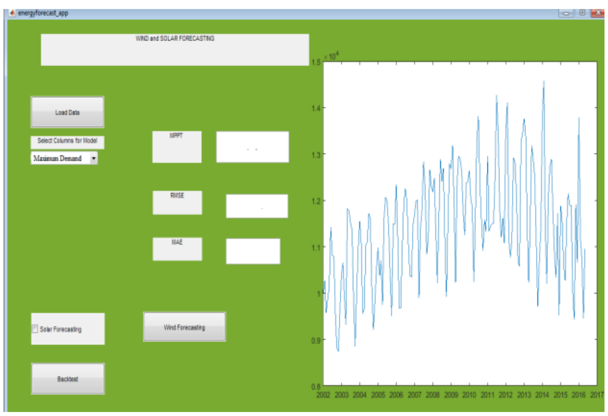

Figure 10. Maximum Power Demand

The maximum power demand of the solar forecasting in the grid-connected system is shown in Figure 10. The SPES strategy can perform hybrid forecasting within a range of hours (short term).

Table 1. Performance of Wind Turbine Generation

Wind speed (km/h)	Wind speed (m/s)	Power density (Watts/m^2)
1	0.278	0.013
10	2.778	12.860
25	6.944	200.939
50	13.889	1607.510
75	20.833	5425.347
100	27.778	12860.082
125	34.722	25117.348

Table 1 shows the wind turbine generation and the speed of the turbine. Power density has been also noted in proposed system and the power evaluation of wind turbine generation is shown in Figure 11.

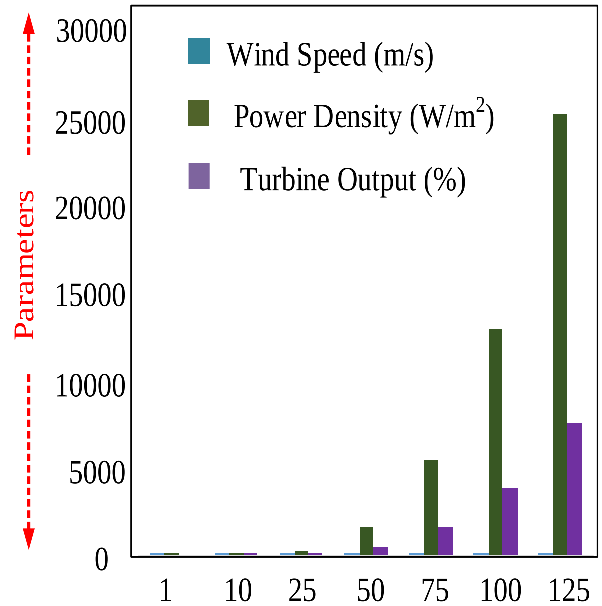

Figure 11 Performance of Wind Turbine Generation

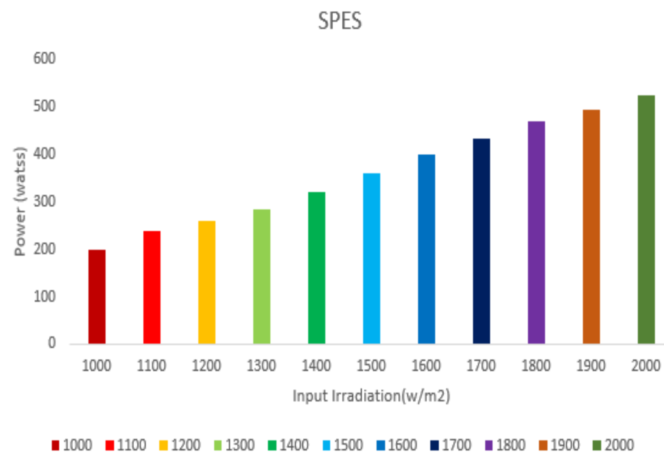

Figure 12 Performance of Solar Power generation

The performance analysis of solar power generation based on various irradiation responses is shown in Figure 12.

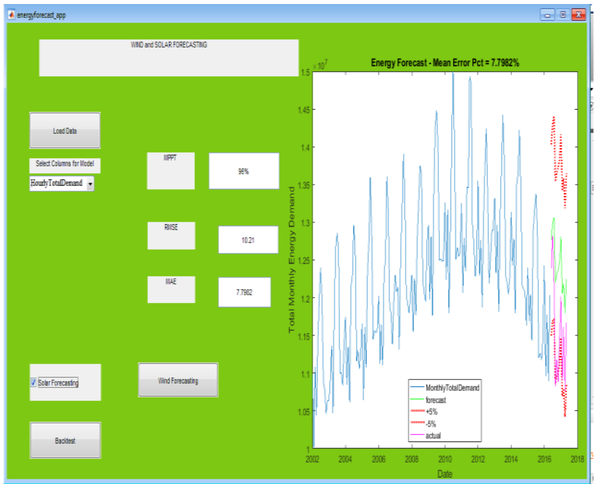

Figure 13. Total demand in solar forecasting

Total power demand of the solar forecasting in the grid-connected system is shown in Figure 13. This forecasting data are taken in the hourly demand of the solar forecasting system. In this figure, actual forecasted maximum tolerance is only 5% and the actual demand and forecasting ratio are highlighted in pink and green colors respectively.

Figure 14 Total demand in wind forecasting

The Total power demand of the wind forecasting in the grid-connected system is shown in Figure 14. This forecasting data are taken in the hourly demand of the wind forecasting system. In this figure, actual forecasted maximum tolerance is only 10% and the actual demand and forecasting ratio are highlighted in pink and green colors respectively.

A. Performance Evaluation

Mean Absolute Error (MAE) has been frequently used to assess forecast performance in regression issues and renewable energy business. Using the MAE measure, you can determine how accurate forecasting is in terms of the overall accuracy of the forecast. A significant difference is that it does not punish larger forecasting errors like the RMSE. Lower MAE numbers indicate better forecasts

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\widehat{P_i} - P_i| \ldots (16)$$

$$RMSE = \frac{1}{N}\sum_{i=1}^{N} (\widehat{P_i} - P_i)^2 \ldots (17)$$

Where

Pi = Actual Power Generation at ith time

$\widehat{P_i}$ = Power Generation Estimated by Forecasting Model

N = Number of Data evaluated

Table 2: Comparison of Forecasting Interval Forecast of wind Power

Methods	One Step Ahead		One Day Ahead		Train Time
	RMSE (kW)	MAE (kW)	RMSE (kW)	MAE (kW)	
GA [25]	1.88	8.72	10.19	8.35	60.1
PSO [25]	4.28	6.67	7.5	9.8	56.4
SPES [25]	5.30	5.12	6.52	10.98	40.12
FFBPN	4.35	4.12	5.26	9.19	25.03

Table 2 illustrate the results of using alternative ways to check the forecast error for one step (10 minutes) and one day ahead, respectively. Apart from FFBPN, Table 1 shows train time, MAE, and RMSE for three different approaches: Genetic Algorithm (GA) [25], Particle Swarm Optimization (PSO) [25], and FFBPN. Compared to the GA, PSO, and RBPN approaches, the proposed RBPN method produces the best results for all parameters. The RMSE value of one step Ahead of wind forecasting of GA, PSO, SPES and RBPN are 1.88, 4.28, 5.30 and 4.6. The MAE value of one step Ahead of wind forecasting of GA, PSO, SPES and FFBPN are 8.72, 6.67, 5.12 and 4.12. The RMSE value of one day Ahead of wind forecasting of GA, PSO, SPES and FFBPN are 10.19, 7.5, 6.52 and 4.35. The MAE value of one day Ahead of wind forecasting of GA, PSO, SPES and RBPN are 8.35, 9.8, 10.98 and 9.19.

Table 3: Comparison of Forecasting Interval Forecast of Solar Power

Methods	One Step Ahead		One Day Ahead		Train Time
	RMSE (kW)	MAE (kW)	RMSE (kW)	MAE (kW)	
GA [25]	5.53	5.50	12.32	7.65	23.43
PSO [25]	4.05	4.03	11.47	7.04	20.95
SPES [25]	3.76	3.71	10.21	7.798	17.21
FFBPN	2.92	2.96	8.92	6.92	9.13

The RBPN model and other models' RMSE and MAE values for solar power forecast are compared in Table 3. The findings show one-day and 10-minute forecasts, with RBPN achieving the lowest RMSE for one-day and one-step-ahead forecasts, outperforming other techniques again [25]. The RMSE value of one step Ahead of solar forecasting of GA, PSO, SPES and RBPN are 5.53, 4.05, 3.76 and 2.92. The MAE value of one step Ahead of solar forecasting of GA, PSO, SPES and RBPN are 5.50, 4.03, 3.71 and 2.96. The RMSE value of one day Ahead of solar forecasting of GA, PSO, SPES and RBPN are 12.32, 11.47, 10.21 and 8.92. The MAE value of one day Ahead of solar forecasting of GA, PSO, SPES and RBPN are 7.65, 7.04, 7.798 and 6.92.

V. CONCLUSION

The most common renewable energy generation methods are wind and solar energy; the most important explanatory variables for wind and solar power generation are wind speed and solar irradiance, respectively. In this work used a Feed Forward Back Propagation Neural Network (FFBPN) technique to predict proper data such as temperature, relative moisture, sun radiations, rain, and wind speed. The FFBPN will be trained in such a way that it can conduct hybrid forecasting with little changes to the programming codes, ranging from hourly (short term forecasting) to daily forecasting (medium term forecasting). This feature is one of the significant improvements, showing the suggested hybrid renewable energy forecasting system's high robustness. The efficacy of the suggested FFBPN is further investigated by comparing it to previous techniques in the literature. According on the results of the comparative analysis, the proposed neural network model outperforms the existing technique.

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Author Contributions: Please, indicate the role and the contribution of each author:
Example
Dhanalakshmi implemented the Algorithm and takes the simulation results.
Sunil kumar and Anitha gives the idea about forecasting process.