Resilient Back propagation Neural Network-Based Hybrid Wind and Photovoltaic Short Term Forecasting System

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Abstract: The rapid growth of renewable energy generation in the power grid, notably from wind and solar energy resources, has made these generators a major source of uncertainty in recent years, with load behavior being the largest driver of unpredictability. Generation and load balancing are critical in the economic scheduling of manufacturing units and energy market activities. Energy forecasting can help to alleviate some of the problems that come with resource unpredictability. Solar and wind energy projections attract the scientific community and numerous research articles are provided. However, the clarity and robustness of existing models may still be improved. For solar and wind power short-term forecasting (STF), this paper proposes a Resilient Back Propagation Neural Network (RBPN) model. Because solar irradiation and wind speed are not linear and unexpected, STF is difficult to complete under changing weather circumstances. However, a Resilient Back Propagation Neural Network (RBPN) is presented and is appropriate for STF modeling. It also improves power quality in various situations, including voltage imbalance correction, active and reactive power control, and voltage regulation. Simulations performed with Matlab Simulink software are used to validate the performance of the proposed forecasting system. The suggested method also includes a sensitivity analysis of numerous input variables for the optimal model selection and model performance comparison with multiple linear regression and persistence models.

Keywords: Resilient Back Propagation Neural Network, Short Term Forecasting, Solar Forecast, Wind Forecast and THD

1. Introduction

The power system is changing due to rising temperatures, climate change, and economic difficulties. This has led to a significant expansion of renewable energy in the power grid during the previous decade. When substantial, fast modifications are made to non-programmable sources, dependability and economy may suffer. Solar and wind power forecasts are used to balance the management load and generated energy. Furthermore, because the changing pattern of wind power cannot be predicted, extra reserves must be used to compensate for the unbalance, raising the total cost of the power system. In order to give accurate and trustworthy information about what may be predicted at a moment, we have to analyze solar and wind energy forecasting systems [1].

In terms of procedure, the regulatory authority has provided precise legislative standards to enhance the forecast of generated energy from solar and wind power in Italy, demanding step-by-step responsibility [2]. The impact of a varied definition of forecast inaccuracy on plant management and power market planning could be significant. As a result, some power providers rely on renewable energy plant monitoring systems to forecast electricity generation [3]. Soft computing approaches became an essential instrument to predict the output of renewable energies 24 hours an hour from NWP, supplied by meteorological services to the network management in recent years.

Reference [4] provides an accurate short-term photovoltaic forecasting model that is done in real-time. So here's an alternative way to look at a similar situation. This study employs the

Resilient Back Propagation Neural Network to build a tool for forecasting solar and wind power for the short term. The remaining part of this work is organized as follows:

i. Section two discuss literature surrey based on existing forecasting methods
ii. Section three discuss working function of proposed forecasting system
iii. Section four discuss the simulation results and performance analysis of proposed forecasting system
iv. Finally section five discuss the conclusion and future work of the research

2. Literature Survey

This section provides a literature review of wind and solar power forecasting or forecasting methods that have been developed during the past several years. In general, models may be categorized as those that involve the system's Numerical Weather Forecasting (NWP).In terms of methodologies that include NWP data, there are two basic approaches: physical and statistical [14]. To arrive at the best feasible wind speed estimate at the wind farm's location, the physical approaches combine NWP and physical aspects. The wind forecast is then translated to a power forecasting by use of a power curve. Many explanatory factors, such as NWP forecasts and past power generation data or meteorological variables, are associated using statistical models [15].

The statistical approaches can be thought of as regression models that estimate a function's parameters that connect future wind power to explanatory variables. Physical or meteorological data, such as orography, roughness, barriers, pressure, and temperature will be input variables for a physical model. The objective of the statistical method is to determine if the online power statistics are correlated. The wind farm history might be utilized to construct a statistical model. Long-term forecasting benefits from the physical method, while short-term forecasting benefits from the statistical method [16, 17].

Certain innovative methods based on artificial intelligence, such as Artificial Neural Network (ANN) [17], fuzzy logic and neuro-fuzzy [18, 19], evolutionary algorithms [20], and some hybrid methods [21, 22], have piqued the interest of researchers in recent years. Power plants that participate in energy market activities benefit from more accurate forecastings by decreasing the need for power curtailments and imbalance fines, resulting in greater income [23]. In the simplest forecasting approach, persistence implies that the solar irradiance or wind speed is the same as the previous step.

In recent years, academics have concentrated their efforts on developing forecasting algorithms that can be utilized for short-term forecastings extending from minutes to a few days. Because this data is important to the operation of power system networks, several tasks require day-ahead forecasts, including scheduling and unit commitment. Day-ahead projections are also crucial for congestion management and reserve allocation. Solar irradiance is adversely affected by cloud movement and wind speed changes, resulting in daily ramps that must be managed at the operational level.

Researchers exhibit several applications of forecasts in terms of spatial resolution and temporal horizon in [26]. The Coupled Autoregressive and Dynamical System (CARDS) model is another statistical method [27]. Since solar radiation includes a seasonal component, Fourier series and power spectrum analysis were used to season the data [28].

3. Proposed Solar and Wind Forecasting System

Figure 2 illustrates the block diagram of the forecasting model produced using the suggested system for Resilient Back Development 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 [29]. RBPN 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 RBPNs can be trained to complete. We need to create a neural network to solve a regression problem to forecast weather variables.

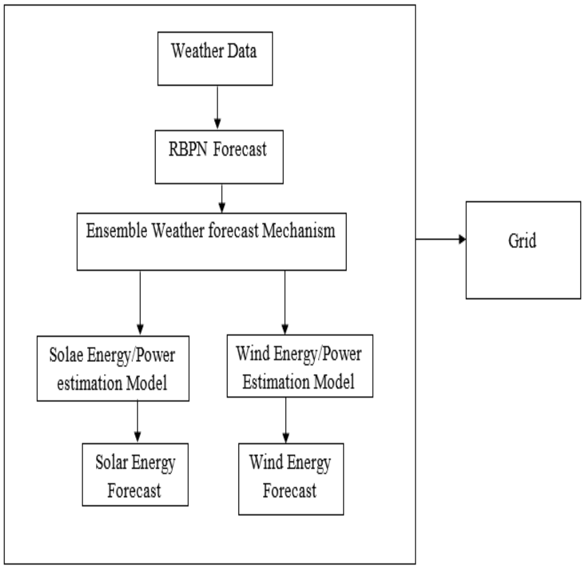

Figure.2 Block Diagram of Proposed system

Resilient Back Propagation Neural Network trained with the Backpropagation (BP) algorithm can approximate a wide range of nonlinear functions. It can be used to predict the weather. Only high-quality historical data is required for accurate projections. Weather forecasting could benefit from the use of the Multi-Layer Perceptron (MLP) model. MLP with BP is a superior option to traditional numerical approaches for predicting dynamic and nonlinear weather processes. Using MLP and Radial Basis Function Network, meteorological factors such as rainfall, wind speed, irradiance, and temperature can be properly projected. The Proposed system consists of three parts such as

i. Solar Forecasting
ii. Wind Forecasting

3.1 Resilient Backpropagation Neural Network Solar Forecasting

Bio neural networks were used to develop the RBPN solar forecasting model based on their structure and information processing. The RBPN solar forecast model is calculated using a network of interconnected neurons and a joining processing algorithm. When the learning phase modifies the weight of the link based on external or internal network information, any system may be imitated. RBPN's ability to learn from existing sample data in a way that resembles natural intelligence is highly useful. RBPN learns from sample data by creating an input-output map that eliminates the need to analyze the model equation. It develops into a crucial nonlinear statistical data modeling tool for describing complicated input-output relationships. Many difficulties like as pattern recognition or classification, function approximation, optimization, forecasting and prediction are tackled with RBPN.

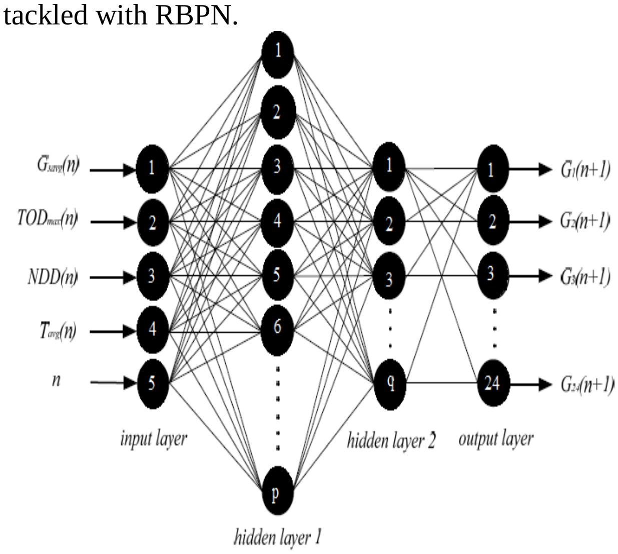

Figure.3 RBPN Model of Solar Forecasting

Any nonlinear mapping can be approximated very accurately by a properly trained RPBN. In the supervised learning mode, a backpropagation error approach computing the connection weights of multilayer feed-forward RBPN is generally used to update the hard learning task.The BP network can generalize well enough to produce the correct output for the training data set inputs. This research uses RBPN to simulate solar irradiance forecastings using statistical feature parameters as an input vector. Conditions dictate how long each series of input and output solar irradiance will last. The short-term forecasting is for the next 24–72 hours. Reconstruction of an input vector in Figure 3 leads to developing an RBPNSFP (RBPN-SFP) short-term forecasting model. Four layers make up this RBPN model: input layer, hidden layers 1, 2, and output. Figure 3 depicts the model in its entirety.

$I_{RBPN} = [G_{savg}, TOD_{max}, NDD, T_{avg}, n] \ldots (1)$

Equation (1) determines the input vector, which includes the data sequence number n, three irradiance statistical feature parameters $G_{savg}(n)$, $TOD_{max}(n)$, and NDD(n), one ambient temperature statistical feature parameter $T_{avg}(n)$, and three irradiance statistical feature parameters $G_{savg}(n)$, $TOD_{max}(n)$, and NDD(n), and one ambient temperature statistical feature parameter $T_{avg}(n)$. The surface irradiance for the next day is represented by 24 components in the output vector (the data sequence number is n + 1). The time resolution for the output vector components is 1 hour. The values p and q denote the number of neurons in each of the two hidden layers in the RBPN model. The RBPN solar forecasting technique is described in full below.

3.1.1 RBPN solar forecasting procedure

Step 1: Create random weights in the range w_{min}, w_{max} and distribute them to hidden and outer layer neurons. Give the input layer's neurons all the same weight.

Step 2: To contribute to the system, give the training data set D and determine the RBP error.

$$e = V_r - V_{out} \ldots (2)$$

Where V_r and V_{out} are the objective function and the network outputs, respectively.

Step 3: The constituents of $V_{out}= (V_h)$ can be derived from each network output neuron as follows:

$$V_h = \sum_{n=1}^{N_{Hid}} w_{nh} y_n \ldots (3)$$

Where

$$y_n = \sum_{j=1}^{N_l} \frac{w_{jn}}{1+e^{-ikl}}$$

N_{Hid} = Quantity of hidden neurons

w_{nh} = Assigned weight of the *n-h* link of the network

V_h = h^{th} output neuron's output

y_n = n^{th} hidden neuron's output.

Step 4: Control the weight adjustment as follows based on the RBP error.

$$\Delta w = \gamma . Vout. e \ldots (4)$$

Where, the knowledge function γ, usually varies from 0.1 to 0.45.

Step 5: Original weights should be regulated as follows:

$$w = w + \Delta w \quad \ldots (5)$$

Step 6: Repeat step (2) until the RBP error reaches the lowest value of 0.1. The network is well prepared to analyze any supplied unknown data after the instruction procedure is completed. The training method will be repeated multiple times to produce an averaged network used to create the Controlled final pulses. The wind zones will be further determined during the validation phase by applying controlled pulses to switches in the topology.

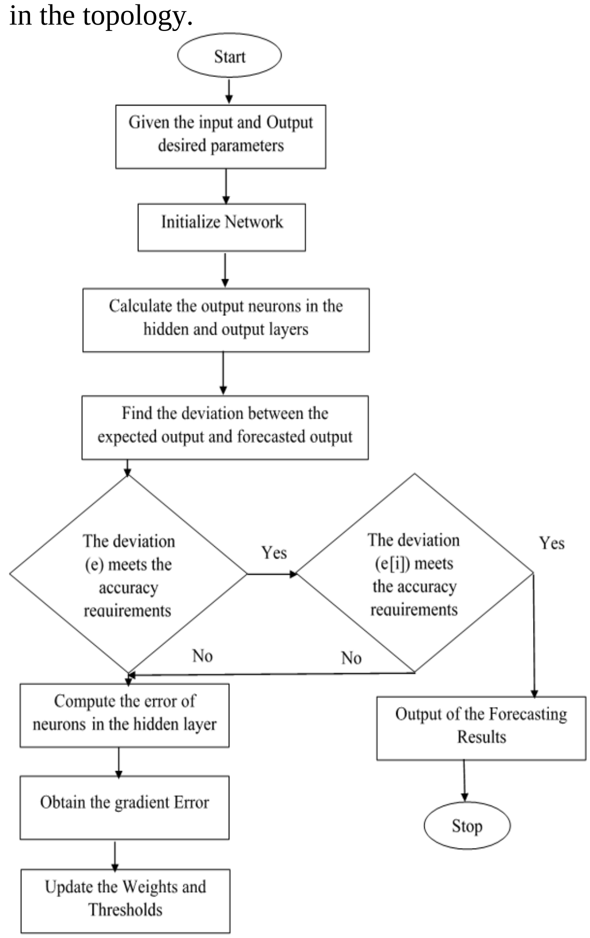

Figure Σφάλμα! Δεν υπάρχει κείμενο καθορισμένου στυλ στο έγγραφο.. **Flow Chart of RBPN solar Forecasting**

Resilient Back Propagation Neural Network's operation and parameters are depicted in Figure 4. They are almost identical, except for weight updating, which is a key difference between Resilient Propagation and Back Propagation. It's important to note that the partial derivative (error gradient) is ignored in resilient propagation, and just the error gradient direction is used to determine the weight update direction.

3.2 Resilient Backpropagation Neural Network-based Wind Power Forecasting

For wind power forecasting, temperature and wind speed are very important parameters. Currently, temporary wind speed forecasts have become more important for power system management or energy trade owing to the wind energy technology and the growth of the wind energy market. In this new era, instant wind speed forecasting is required for producers and consumers to become stable electricity market as in electric grid at any moment, and the balance is maintained between consumption and generation. The wind power forecasts for a series of samples of wind power data using multi-layer RBPN are provided in this section.

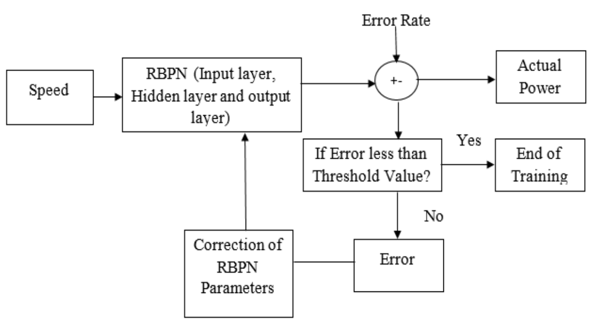

Figure 5. Block Diagram of Wind Power Forecasting System

Figure 5 depicts the proposed wind power forecasting system's block diagram and design elements. Reduced costs and penalties, competitive information advantage and efficient project construction, operations and maintenance contribute to prediction processes in the context of energy trading in real-time and day-to-day markets.

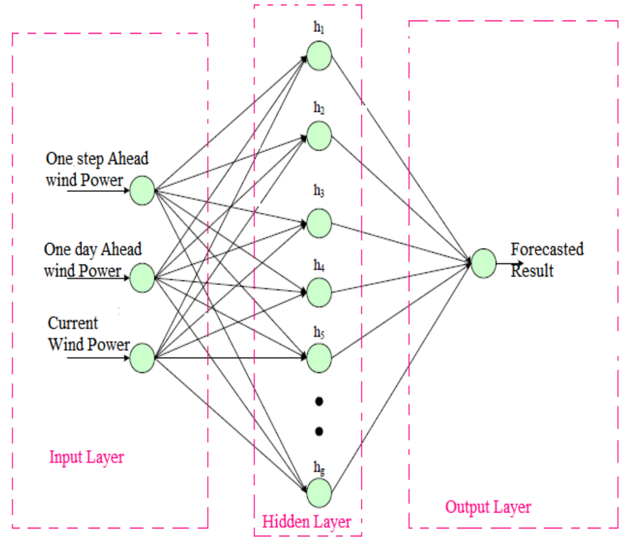

Figure 6. Network Architecture Of RBPN Based Wind Power Forecasting

Figure 6 shows the network architecture of the RBPN-based wind power forecasting. Accurate wind power projections are important to reduce the frequency and duration of power outages, increase worker safety, and limit the physical consequences of bad weather on wind turbines.

3.2.1 Resilient Backpropagation Neural Network Wind Forecasting Procedure

An RBPN has three layers, as shown in Figure 6. An input set must be provided as a starting point for training the node. To gather sets of activation values of a node, the hidden layer multiplies the inputs of each by weight vectors in the next step. For each node, then, a function that transforms all of the inputs to the ideal value may be used as a way to determine their activation value. This will be done before applying the output as input to another layer. The Root Mean Squared Error (MSE) becomes reasonable. In other words, RBPN is trained in three steps such as

i. Forward the input data
ii. Compute and propagate error backward
iii. Update the weights

Two of RBPN's main characteristics are its ability to self-learn and self-organize. For the hidden and output layers, the most well-known functions are linear and sigmoid, respectively. As a result, equations (6) and (7) show the hidden layer's input and output values. Furthermore, equations (8) and (9) contain all of the output layer's input and output values.

$$x_j = \sum_{i=t-1}^{t-n} \sum_{j=1}^{h} w_{ij} \times y_j \times y_j + b_j \ldots (6)$$

$$y_j = \frac{1}{1+exp(-x_j)} \; j = 1, \ldots, h \ldots (7)$$

$$x_t = \sum_{t=1}^{T} w_{it} \times y_j + a_t \ldots (8)$$

$$y_t = x_t \; t = 1, \ldots, T \ldots (9)$$

Where,

x_j ,y_j : input and output jth node in the hidden layer.

w_{ij} : weight between input and hidden layer

b_j, a_j: Range of bias in input and hidden layer[-1, 1].

n, h, t: layer nodes.

x_t, y_t: input and output value concerning time horizon t

w_{ij}: Weights of the j^{th} hidden and output layers' connections

Following the idea stated above, the backpropagation technique for changing the network's weight vectors can be simplified using the gradient descent approach, which uses the squared error sum (The magnitude is the first priority in this work). When weights are adjusted to skip from the hidden to the input layer the output error, the MSE between network forecastings resulting in yt and predicted output $\hat{y}t$ is reduced, as shown in equation (10). T is the number of iterations created based on the weight and bias groups.

$$MSE = \frac{1}{2} \sum_{t=1}^{T} (\hat{y}_t - y_2)^2 \ldots (10)$$

The propagation process is described as (10), (11), (12), and (13) by adjusting the weights of hidden and input neurons (13). Because of the dependence of an error on other network parts, the procedure will be run as equation (7).

$$\Delta_{\omega jt} \alpha - \frac{\sigma MSE}{\sigma_{\omega jt}} \ldots (11)$$

$$\Delta\omega_{ji} = -\eta (\frac{\sigma MSE}{\sigma_{yt}})(\frac{\sigma_{yt}}{\sigma_{xt}})(\frac{\sigma_{xt}}{\sigma_{\omega jt}}) y_j \ldots (12)$$

$$= -\eta(\hat{y}_t - y_t) \left(\frac{\sigma(1+\exp(-x_t)))^{-1}}{\sigma_{xt}}\right) \ldots (13)$$

$$= \eta(\hat{y}_t - y_t) y_t (1 - y_t) y_j \quad \ldots (14)$$

For j =1… h for t=1,… T

Where

∂wjt: Hidden neuronal weights.

η: The rate of learning

$\frac{\sigma MSE}{\sigma_{yt}}$: After activation, a derivative of the error

$\frac{\sigma_{yt}}{\sigma_{xt}}$: The activation values after the total input vectors are derivative.

$\frac{\sigma_{xt}}{\sigma_{\omega jt}}$: Following the weights, the derivative of the total input vectors

When the above equations are implemented, the following weight vectors for the hidden layers are chosen:

$$\Delta\omega_{ij} = -\sum_{t=1}^{T} [\frac{\sigma MSE}{\sigma_{yt}})(\frac{\sigma_{yt}}{\sigma_{xt}})(\frac{\sigma_{xt}}{\sigma_{\omega jt}})] \times (\frac{\sigma_{yj}}{\sigma_{xj}})(\frac{\sigma_{xj}}{\sigma_{\omega ij}}) y_j$$

$$= \eta \sum_{t=1}^{T} [[(\hat{y}_t - y_t) y_t (1 - y_t) \omega_{it}] \, y_j (1 - y_j) y_j \; \ldots.. (15)$$

For i = t − n, ..., t − 1 for j = 1, ..., h

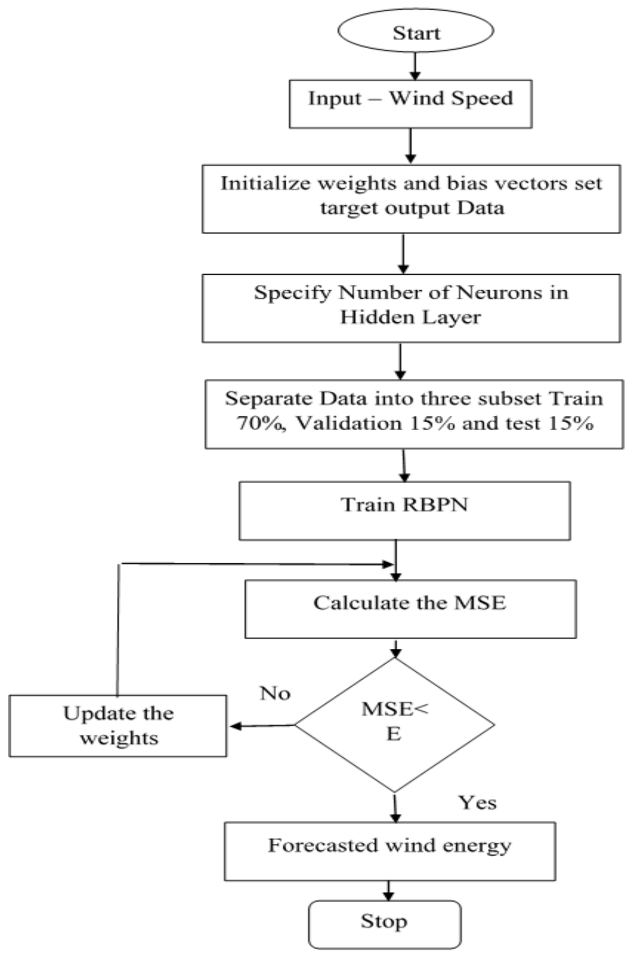

Figure. 7. Flowchart of the proposed wind Power forecasting method

Figure 7 shows the flowchart of the proposed RBPN-based wind speed forecasting method.

This forecast separates the data into training, testing and validation.

3.3 Impact of Solar and Wind Power Grid Integration

In two areas, the implications on the system reliability, reliability, stability, power quality and safety of wind energy penetration are frequently studied. There are a number of consequences on power grids, including the ability to reverse electrical flows.

3.3.1 Power Quality

The voltage volatility and harmonic network distortion are impacted by the power quality. Wind power integration into the system affects the end-voltage user's quality. Many wind turbines are now employing power electronic variable speed wind turbines to save money. Power electronics improve power quality by reducing harmonic distortion.

3.3.2 Transient Stability

Traditional generators are intended to minimize voltage and frequency variations in order to satisfy fluctuating demand for load. Generators accelerate to bridge the gap between mechanical and electrical powers during a malfunction that generates voltage dips. They absorb reactive power when the fault is cleared, lowering the network voltage. There will be a voltage drop if there is not enough reactive power being delivered. Under low voltages, synchronized generator exciters enhance reactive power generation, aiding in voltage restoration. Induction generators, on the other hand, strive to prevent voltage recovery. Wind generating can cause a substantial generation deficit if high penetration is disconnected during low voltage depressions. To avoid this, wind farms are required to supply adequate demand power compensation.

3.3.3 Voltage Control

The nodal voltage of the power system is allowed to fluctuate between 5% and 7%. By delivering or absorbing reactive power, synchronous generators and other devices are utilized as compensators to modulate the nodal voltage. Induction generators nevertheless absorb reactive power and do not regulate reactive power flows. Because the wind farm network is largely capacitive, even variable-speed wind turbines cannot keep the voltage under the limit at the time of connection. The issue with voltage variation is caused by wind velocity and generator torque. The changes in actual and reactive power are directly connected to voltage variations. Under voltage is a frequent classification for voltage fluctuation:

i. Voltage Sag/Voltage Dips
ii. Voltage Surge
iii. Short Interruptions
iv. Long duration voltage variation

The voltage flicker problem suggests that wind turbines or shifting loads caused dynamic network modifications. As a result of continuous operation, power fluctuation from wind turbines arises. The amplitude of voltage fluctuations is determined by the wind turbines' grid strength, network impedance, phase angle, and power factor.

4. Simulation Results and Discussion

The suggested system is simulated using the MATLAB2017a program. Table 1, table 2, and table 3 list the simulation parameters. The data for the suggested system was collected from a technical university campus in Rajasthan, India's northwest state [29].

Table 1. Monthly average meteorological data

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

Solar irradiance and wind speed are summarized in Table 1. While the solar radiation ranges from 4.140 to 7.440 kWh/m2/day daily, the annual average is 5.69kWh/m2/day. From 2.410 to 4.68m/s, the monthly average wind speed in the study area is 3.29 m/s, with an annual average of 3.29 m/s. To make short-term forecastings, we use the PV module's technical data in Table.2.

Table 2. Technical Data of PV module

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)

Table 3. Technical Data of Wind Turbine

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

As shown in Table 3, the turbine's production specifications and economic issues are listed. Based on wind speed and power curves, wind energy is created in real time [29].

4.1 Forecasting Metrics Evolution - RBPN

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 a 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 Root Mean Square Error (RMSE). Lower MAE numbers indicate better forecasts. The MAE has the drawback that a big number of very small errors can rapidly overpower a small number of significant errors. In systems where extreme events are a worry, this scenario can be troublesome. The following formulae were used to determine the MAE and RMSE.

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

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

Where

Pi = Actual Power Generation at ith time

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

N = Number of Data evaluated

Table 4: 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 [29]	1.88	8.72	10.19	8.35	60.1
PSO [29]	4.28	6.67	7.5	9.8	56.4
SPES [29]	5.30	5.12	6.52	10.98	40.12
RBPN	4.6	4.30	5.69	9.86	30.1

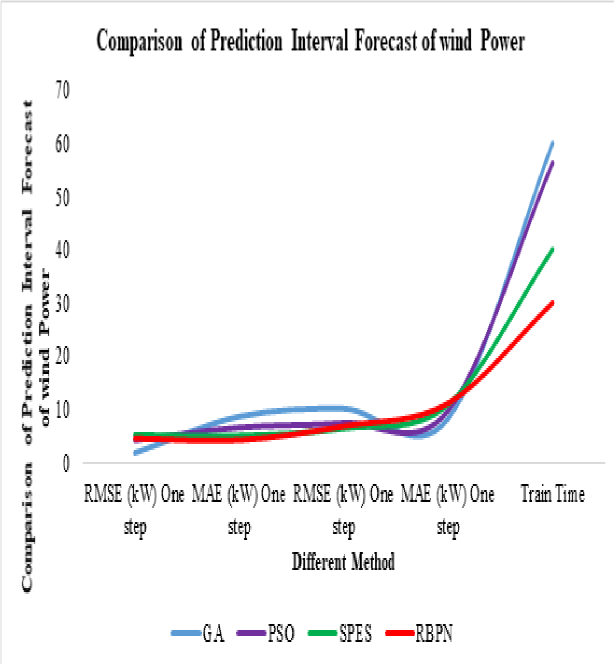

Figure.8 Comparison of Forecasting Interval Forecast of wind Power

Table 4 and figure 8 illustrate the results of using alternative ways to check the forecast error for one step (10 minutes) and one day ahead, respectively. Apart from RBPN, Table 4 shows train time, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) for three different approaches: Genetic Algorithm (GA) [30], Particle Swarm Optimization (PSO) [31], and RBPN. Compared to the GA, PSO, and RBPN approaches, the proposed RBPN method produces the best results for all parameters.

Table 5: 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 [29]	5.53	5.50	12.32	7.65	23.43
PSO [29]	4.05	4.03	11.47	7.04	20.95
SPES [29]	3.76	3.71	10.21	7.798	17.21
RBPN [29]	3.02	3.10	9.30	7.21	10.30

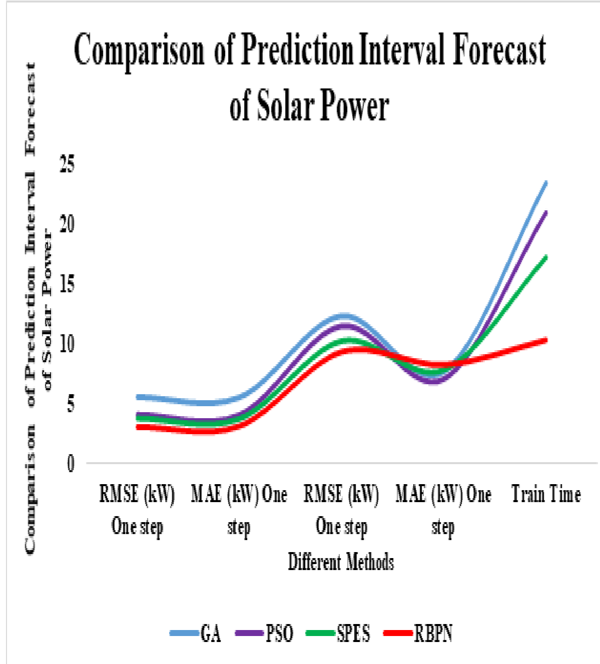

Figure.9 Comparison of Forecasting Interval Forecast of Solar Power

The RBPN model and other models' RMSE and MAE values for solar power forecast are compared in Tables 5 and 9. 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 [29].

5. Conclusion

The quality of the energy management system is crucial in the dispatch of renewable energy. The forecasting of wind and solar electricity is also an important factor. This research provides a Resilient Back Propagation Control algorithm for the forecasting system to tackle wind and solar power forecasting and increase forecasting capacity. When measuring simulation performance and comparing it to other machine learning approaches, RMSE and MAE indicators were employed to assess the control algorithm's efficacy presented in this work. Two existing algorithms were compared in this study: a Genetic Algorithm and Particle Swarm Algorithm. Training and testing data were separated from the projected simulation outcome in this investigation. The performance of MAE and RMSE calculations is evaluated using training and testing data. The proposed wind forecasting has RMSE and MAE values of 4.60 (one step ahead) and 4.30 (one step ahead), respectively. The proposed solar forecasting has RMSE and MAE values of 3.02 (one step ahead) and 3.10 (one step ahead), respectively. As a result, when compared to other approaches, the proposed RBPN produces the best outcomes under all operating conditions. The accuracy of hybrid solar and wind power plant operation, control, maintenance planning, and power estimation could all be improved in the future.

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