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Enhancing power quality in solar-wind grid-connected systems through soft computing techniques

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ABSTRACT

This work intends to improve estimates of solar and wind energy generation through the application of resilient backpropagation control and substantial power evolution strategy (SPES) algorithms. In comparison to particle swarm optimization and genetic algorithms, the main goal is to minimize predicting mistakes. These methods increase grid reliability by lowering total harmonic distortion (THD) and improving power quality when integrated with the IEEE-9 bus standard. In order to evaluate the hybrid system's transient and steady-state reactions, the study also highlights the importance of bolstering operation and control. A revolutionary deep learning-based approach is also suggested for predicting wind and solar hybrid energy. The power grid's efficiency and dependability in handling renewable energy sources have significantly improved, according to the results.

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1. INTRODUCTION

Greenhouse gas emissions from one of the energy sources that is non-renewable is modern difficulties; these emissions have an adverse effect on the environment and raise health concerns in the vicinity of power plants. Furthermore, there limited are conventional power sources. To integrate wind power into the grid and handle output voltage changes, large wind turbines need mechanical systems and inverters. Since solar cells and wind turbines produce rectified AC output, which charges batteries for load supply, combining solar and wind energy improves power system reliability [1]-[3]. By 2050, IRENA envisions an 86% renewable energy share. India targets 175 GW by 2022, including 5 GW small hydro, 60 GW wind, and 100 GW solar. The IEA forecasts a 50% rise in renewables by 2024, led by solar. Soft computing aids accuracy amid resource uncertainties [4].

Academics investigate methods of producing solar and wind energy while taking local differences into account. Reducing reliance on fossil fuels and emissions is the goal of renewable energy, whereas hybrid systems improve sustainability [5], [6]. The techno-economic-environmental (TEE) performance is enhanced by the "Integrated Load-Side Management of Hybrid Renewable Energy Systems for Rural Electrification" [7]. Remote villages can always have electricity thanks to a standalone microgrid made of solar and wind power. We look at energy storage technologies such as seawater-pumped storage systems. Stochastic optimization is one method used to tackle problems in renewable energy storage; models such as the neuro-

fuzzy adaptive inference System are used to improve the accuracy of solar spectrum forecasts [8]-[10]. Numerous studies explore optimization techniques like loss of load probability for sizing PV systems in remote locations, considering load profiles and meteorological variables. Reddy and Ranjan employ artificial neural network (ANN) models for precise hourly and monthly solar radiation estimations [11].
Kalogirou develops a method using regression relationships to compute monthly low solar radiation for various climatic conditions [12]. Karimi et al propose a load-sharing scheme for a PV-based hybrid microgrid [13]. Rebollal *et al.* emphasize the inverter's significance in solar installations [14]. Butt *et al.* discuss smart grid impacts on power distribution [15]. The literature calls for improved coordination and synchronization in wind and solar power studies, focusing on hourly resolutions for accurate forecasting and addressing energy system inefficiencies [16]-[18]. Researchers prioritize wind and solar energy to meet renewable portfolio standards and emission reduction targets, developing comprehensive forecasting models considering influencing elements and temporal fluctuations for increased accuracy [19], [20]. Special algorithms are employed to optimize energy system forecasts, particularly in the context of novel hybrid forecasting models [21], [22].

2. PROPOSED DYNAMIC APPROACH

Despite wind energy forecasting progress surpassing solar methods, the integration of solar electricity from distributed energy resources (DERs) is pivotal for grid operations. Accurate load predictions are essential for economic production and grid-dependent load balancing. The grid-tied wind and solar system, illustrated in Figure 1 emphasizes the contribution of distributed PV systems to the net load curve [23]. Addressing challenges like load variability and uncertainty in solar irradiance forecasting is crucial for optimizing economic production and reducing operational costs stemming from PV over generation [24], [25].

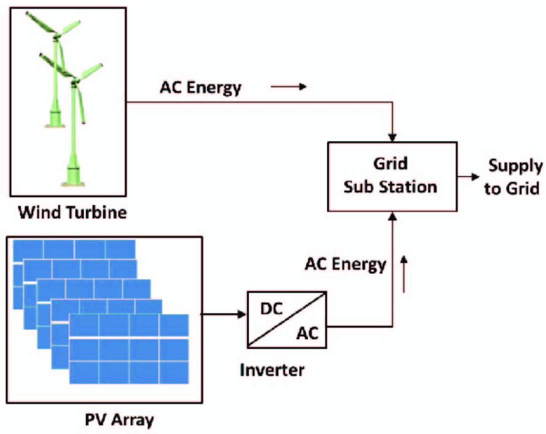

Figure 1. Grid-connected solar and wind system's block diagram

Accurate forecasts shown in Figure 2 enhance utility by improving reliability, grid parameters, frequency stability, and load tracking for economical dispatch. Figure 3 illustrates the block diagram of a short-term forecasting system using historical meteorological data from the Technical University Campus in Rajasthan, India, using a resilient back propagation neural network. integrated with the IEEE–9 bus network, this model mitigates power quality issues, employing the resilient back propagation neural network (RBPN) inspired by biological neural networks, capable of tasks like clustering, classification, and regression for weather variable forecasting. Multi-layer perceptron (MLP) with back-propagation (BP)outperforms traditional methods in predicting dynamic and non-linear weather processes, accurately forecasting variables elements including temperature, irradiance, wind speed, and rainfall. The proposed system comprises three components: solar forecasting, wind forecasting, and the impact of solar and wind power integration.

2.1. Resilient back propagation neural network for solar forecasting

Figure 4 depicts the operation and parameters of the algorithm for robust backpropagation neural networks. Resilient propagation and backpropagation share similarities, differing primarily within the routine weight update. Unlike backpropagation, in resilient propagation, the weight update's direction is established.

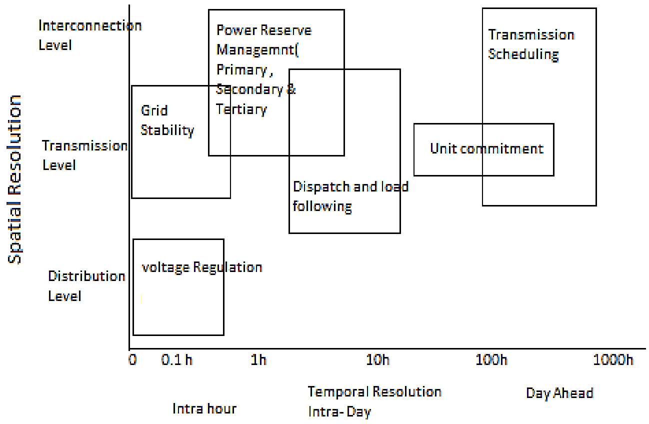

Figure 2. Depicts forecast applications

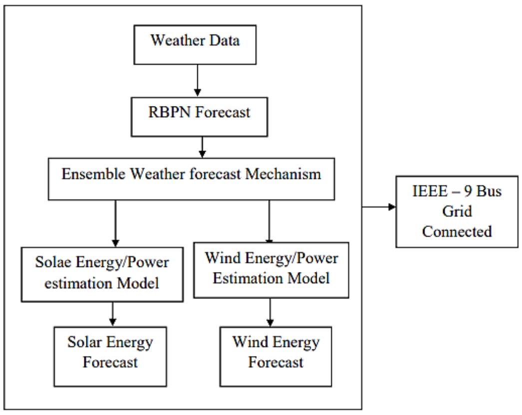

Figure 3. Block diagram of proposed system

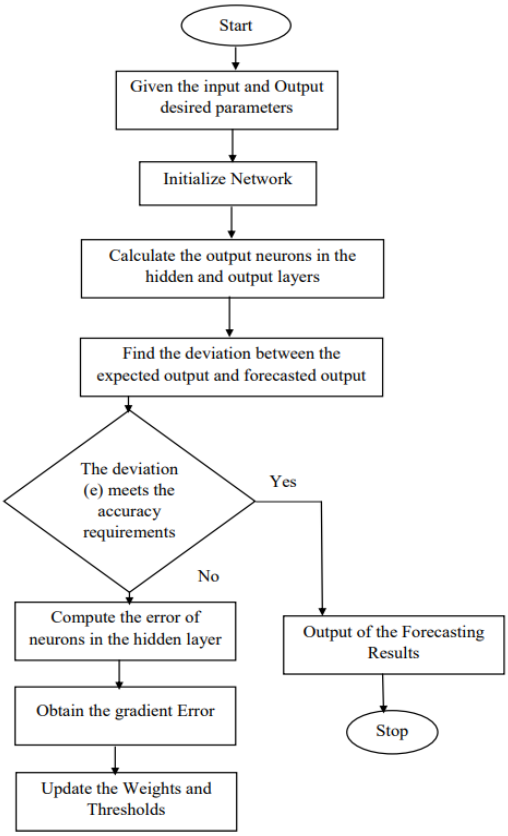

Figure 4. Resilient back propagation neural network flowchart

2.2. Neural network-based resilient backpropagation wind power forecasting

This section, multilayer RBPN is used to forecast wind power, with particular attention paid to temperature and wind speed as key variables to ensure that maintain stability in the electricity market and enable effective power system management and energy trading in the dynamic wind energy market, instant wind speed forecasts are now a must. A system for wind power forecasting is presented, as shown in Figure 5, which minimizes imbalance charges and enhances energy market trading and project efficiency. Wind power integration affects voltage management, transient stability, and power quality. Power electronics in turbines reduce harmonic distortion and voltage fluctuations. Exciters and conventional generators stabilize voltage and frequency, ensuring transient stability. Voltage control issues in induction generators cause problems like voltage sag, surge, and flicker, influenced by network impedance, grid strength, and power factor.

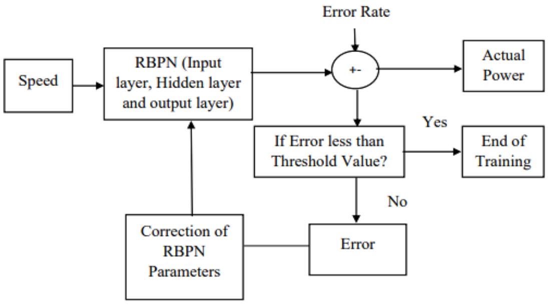

Figure 5. Block diagram of the forecasting system for wind power

3. RESULTS AND DISCUSSION

The average annual solar irradiation is 5.69 kWh/m^2, with daily variations between 4.140 and 7.440 kWh/m^2. In the research area brief shown in Table 1, the monthly wind speed varies from 2.410 to 4.68 m/s, with a stable yearly average of 3.29 m/s. The suggested system is simulated using MATLAB 2017a, with simulation parameters detailed in Tables 2-4. Data is sourced from a technical university campus in north-western India.

Table 1. Solar irradiance and wind speed

Month	Clearness index	Average radiation (kW/h/m^2)	Average wind speed (m/s)
January	0.651	4.43	2.63
February	0.691	5.42	3.150
March	0.692	6.41	2.769
April	0.676	7.05	3.79
May	0.673	7.44	4.54
June	0.585	6.58	4.68
July	0.478	5.31	4.06
August	0.477	5.04	3.33
September	0.619	5.91	3.21
October	0.706	5.76	2.46
November	0.686	4.75	2.41
December	0.654	4.14	2.52
Annual average	0.634	5.69	3.29

Table 2. Comparison between SPES and RBPN for wind power prediction interval forecasts

Forecast horizon		GA	PSO	SPES	RBPN
One step ahead	MAE (KW)	8.63	6.7	5.22	4.31
	RMSE (KW)	1.72	4.21	5.2	4.61
One day ahead	MAE (KW)	8.26	9.80	10.9	9.87
	RMSE (KW)	10.1	7.49	6.51	5.7
Train time		60.1	56.3	40.1	30.1

Table 3. Comparing solar power prediction interval forecasts with SPES and RBPN

Forecast horizon		GA	PSO	SPES	RBPN
One step ahead	MAE (KW)	5.50	4.07	3.61	3.15
	RMSE (KW)	5.41	4.07	3.86	3.12
One day ahead	MAE (KW)	7.54	7.06	7.81	7.24
	RMSE (KW)	12.22	11.5	10.23	9.2
Train time		23.33	21.1	17.15	10.4

Table 4. Reactive power analysis of RBPN with existing methods

Methods	Reactive power 3rd bus	Reactive power 5th Bus
GA	20.62	21.50
PSO	16.13	17.46
SPES	7.52	8.13
RBPN	5.12	6.3

There is more unpredictability in the power system as a result of the increase in variable energy generation, particularly from solar and wind power. A model for short-term forecasting (STF) of solar and wind power is developed using the resilient back propagation neural network (RBPN) in order to overcome this difficulty. RBPN integrates with the IEEE-9 bus system to minimize total harmonics distortion (THD) and address power quality concerns in MATLAB Simulink simulations. The suggested technique for predicting solar and wind power in grid-connected situations is shown in Figure 6. Comparative results in Table 2 and Figure 7 reveal RBPN's superior performance over genetic algorithm (GA), particle swarm optimization (PSO), and substantial power evolution strategy (SPES) in one-step and one-day ahead wind forecasting.

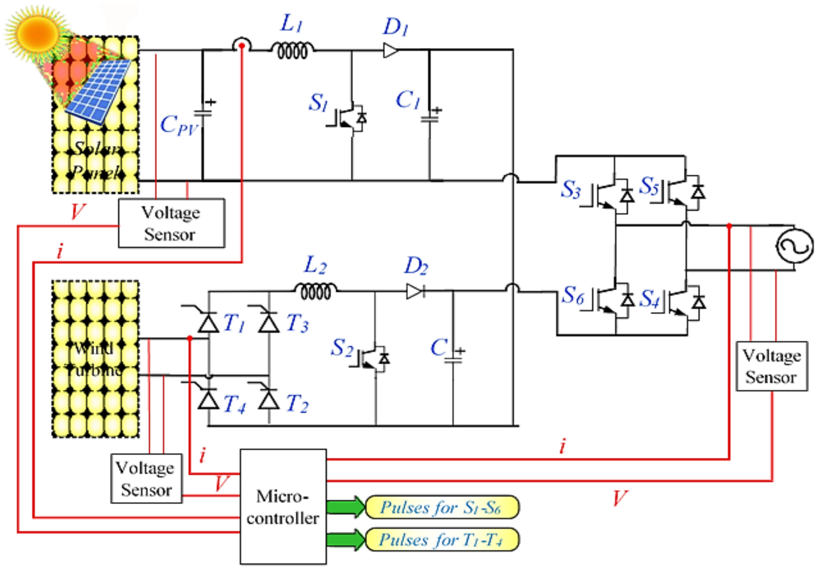

Figure 6. A forecasting method for grid-connected solar and wind power is proposed

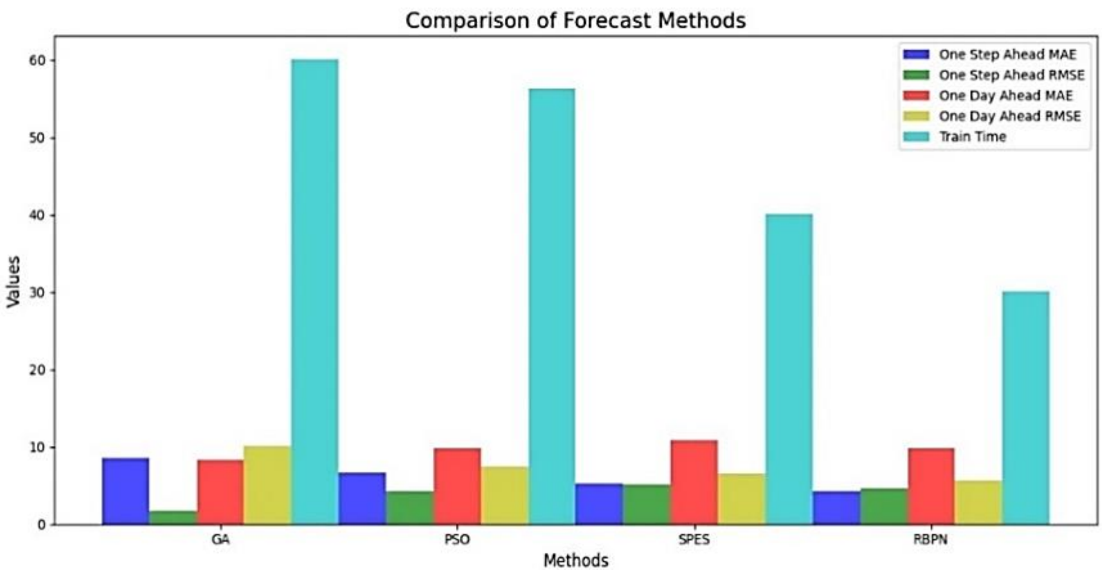

Figure 7. Evaluation of wind power prediction interval forecasts using SPES and RBPN in comparison

Table 3 and Figure 8 illustrate the root mean squared error (RMSE) and mean absolute error (MAE) value comparison of the SPES model with alternative models for solar power forecasting, showcasing superior performance for both one-day and 10-minute ahead predictions. SPES achieves the lowest RMSE values (3.76 and 10.21) and MAE values (3.71 and 7.798) compared to GA, PSO, and RBPN across forecast horizons. Figure 9 shows the direct application of the RBPN forecasting method on the IEEE-9 bus reveals improved power quality, with THD values of 2.21% and 0.45% for the 3rd and 5th buses, surpassing GA and PSO methods. Table 4 showcases the superior performance of SPES and RBPN algorithms in reactive power analysis, surpassing existing methods, with SPES revealing values of 7.52 and 8.13 in the 3rd and 5th buses, and RBPN exhibiting values of 5.12 and 6.30.

Table 5 demonstrates the superior performance of SPES and RBPN algorithms in voltage magnitude analysis, surpassing existing methods, with SPES exhibiting values of 0.968 (pu) and 0.961 (pu) in the 3rd and 5th buses, and RBPN showing 0.986 (pu) and 0.985 (pu). In Table 6, SPES and RBPN methods exhibit significantly reduced line loss, with SPES recording 1.6 (pu) and 1.52 (pu), and RBPN showing 0.62 (pu) and 0.81 (pu) in the 3rd and 5th buses.

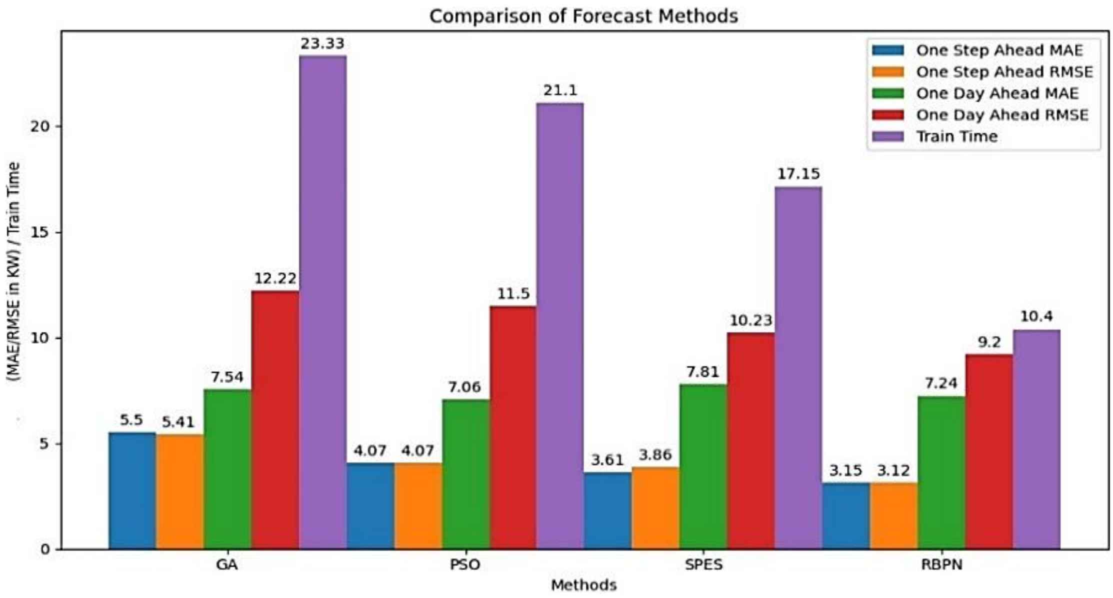

Figure 8. Comparison of prediction interval forecast of solar power using SPES and RBPN

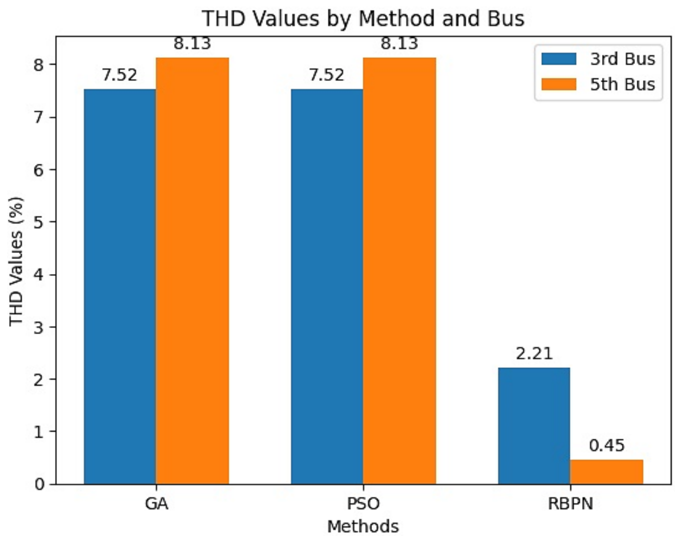

Figure 9. Power quality analysis of IEEE-9 bus with PV and wind using SPES and RBPN

Table 5. Analysis of voltage magnitude of RBPN with existing methods

Methods	Voltage magnitude (pu) 3rd bus	Voltage magnitude (pu) 5th bus
GA	0.861	0.876
PSO	0.853	0.846
SPES	0.968	0.961
RBPN	0.986	0.985

Table 6. Analysis of line loss with RBPN vs existing methods

Methods	Voltage magnitude (pu) 3rd bus	Voltage magnitude (pu) 5th bus
GA	2.06	2.13
PSO	2.42	2.25
SPES	1.6	1.52
RBPN	0.62	0.81

4. CONCLUSION

In comparing PSO and GA to SPES and RBPN for solar and wind energy forecasting, the study demonstrated higher accuracy in minimizing mistakes. Reactive power was optimized for increased grid stability and decreased THD by integration into the IEEE-9 bus system, which also increased voltage (RBPN: 0.986 pu and 0.985 pu) and decreased line losses (0.62 pu and 0.81 pu). Deep learning integration will be the focus of future research to enable more accurate projections of renewable energy and sophisticated control techniques. By lowering dependency on conventional energy and increasing the efficiency of solar and wind resources, SPES and RBPN promote sustainability. Economic viability analyses, which take investment returns and lifespan costs into account, are essential for the wider deployment of RBPN and SPES. Hybrid renewable energy systems benefit greatly from the combined efforts of SPES and RBPN, which calls for further development and widespread implementation to advance energy infrastructures.

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