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Research Article

Statistical Analysis of Novel Ensemble Recursive Radial Basis Function Neural Network Performance on Global Solar Irradiance Forecasting

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Reliable operation of energy management systems, grid stability, and managing energy demand responses are becoming challenging because of the flickering nature of solar irradiance. Accurate forecasting of global solar irradiance, i.e., global horizontal irradiance (GHI), plays a significant role in energy policy-making and the energy market. This paper proposes a novel global solar irradiance forecasting model based on the ensemble recursive radial basis function neural networks (ERRBFNNs). The various atmospheric inputs based on the built ensemble recursive radial basis function neural networks make the network more stable and robust to climatic uncertainty. This paper statistically investigates the performance of novel feed-forward neural networks based on forecasting models with various hidden nodes for global solar irradiance forecasting applications. We validated the proposed ERRBFNN global solar irradiance forecasting model using real-time data sets. The simulation results confirm that the proposed ensemble recursive radial basis function neural network based on global solar irradiance forecasting improves the accuracy, generalization, and network stability. Furthermore, the proposed ERRBFNN lowers the forecasting error to the least compared to other state-of-the-art forecasting models.

1. Introduction

Solar energy is a sustainable and significant resource in renewable energy. Because of the intermittent and non-dispatchable nature, a considerable penetration of solar energy may cause power quality and grid stability issues. In recent years, great interest has been gained in PV systems; global horizontal irradiance (GHI) is a crucial parameter for PV systems. It was encountered that the most significant improvements are noted to demonstrate the possibility of forecasting future solar irradiance. A forecasting study on solar irradiance is necessary to overcome the possibility of relevant issues that concern the penetration of solar energy systems into the grid. Many academics are involved in forecasting solar irradiance since environmental factors play a significant role in the functioning of any photovoltaic module. Neural networks have exceptional capabilities in simulating and mapping complex systems instantaneously. The forecasts are added together. As a result, an accurate estimate of solar irradiance might be obtained in this manner. The proposed ensemble recursive radial basis function neural network (ERRBFNN) is the framework for forecasting solar irradiance using various inputs incurring recursive radial basis function neural networks (RRBFNNs). The key benefits of the forecasting model are backup resource minimization, balancing energy marketing, optimization of the power system, and effective utilization of solar energy. The supply and energy demand management is carried out with the help of the short-term prediction model [1].

The needs for solar energy system and GHI forecasting are as follows:

(i) Continuous progress in technology and industrialization yields an increase in energy demand. With the collaboration of solar energy systems, we can fulfill the energy crisis.

(ii) The energy produced by the photovoltaic system fluctuates in nature; thus, matching the power to consumer demand becomes crucial.

(iii) The quality of service of solar energy systems improved with the help of the forecasting of global horizontal irradiance (GHI).

The contributions of the proposed ERRBFNN method are as follows:

(i) A novel ensemble recursive radial basis function neural network (ERRBFNN) is designed and validated for one week ahead of global horizontal irradiance

(ii) The proposed framework to mitigate the variance in the input

(iii) Statistical analysis was performed with various hidden nodes

(iv) The proposed forecasting method outperforms the one-week-ahead global horizontal irradiance

(v) The proposed novel feed-forward neural network (ERRBFNN) result is the best compared to the other methods.

2. Literature Study

Solar irradiance forecasting is essential to ensure the grid's stability and security. Therefore, in the literature, many forecasting techniques are devised by various researchers to better understand the literature review presented in the tabular form in Table 1. Traditional models in reality, have difficulty forecasting the trajectory of solar irradiance because they necessitate the exact characterization of issue domains and the determination of mathematical equations. The next step in boosting forecast fidelity would be to look into ensemble techniques to reduce the gamut of probable inaccuracies. It was discovered that an average prediction per period was insufficient since it did not account for intraperiod fluctuations in renewable energy. GHI influencing the atmospheric variables considered as the inputs leads to better forecasting. The proposed provided model takes to cater both to computing effort and forecast accuracy. We provide a unique framework for deterministic solar irradiance forecasting; we depict the graphical overview shown in Figure 1. The proposed model can meet the lowest evaluation metric for the solar irradiance (GHI) forecasting application.

Highlights of this paper are as follows:

(i) Develop a unique framework based on the recursive radial basis function neural networks

(ii) Overcome the uncertainty regarding input variance

(iii) We carried out hidden nodes based on stability analysis

(iv) We performed one-week-ahead forecasting global horizontal irradiance

(v) The proposed novel forecasting model (ERRBFNN) yields better results than traditional forecasting models.

3. Proposed Ensemble Recursive Radial Basis Function Neural Network (ERRBFNN) Framework and Workflow

3.1. Dataset Details. The real-time data such as pressure, temperature, relative humidity, wind speed, cloud cover, and global horizontal irradiance are collected from the NOAA (National Oceanic and Atmospheric Administration) and are utilized to validate the proposed forecasting model. Input and output node descriptions of the proposed approach are presented in Table 2.

3.1.1. Motivation for the Selected Inputs and Correlation Analysis. The proposed model was developed with various atmospheric inputs. These inputs, such as pressure, temperature, relative humidity, wind speed, and cloud cover, impact the cause of climatic uncertainty, which affects solar irradiance. A correlation analysis aids in determining the existence or lack of an association between two variables. A positive correlation indicates that a rise in one variable leads to a boost in the other and vice versa. A negative correlation signifies that a rise in one variable causes a drop in the other and vice versa. For the considered dataset, we performed a correlation analysis to investigate the importance of the considered inputs' influence on the global horizontal irradiance. The pressure and global horizontal irradiance have a positive correlation, and the correlation coefficient is 0.15, while temperature and global horizontal irradiance have a negative correlation corresponding to a correlation coefficient of −0.35. Relative humidity and global horizontal irradiance have a positive correlation, and the correlation coefficient is 0.32. The wind speed and global horizontal irradiance have a negative correlation, and the correlation coefficient is 0.22. The cloud cover and global horizontal irradiance have a positive correlation, and the correlation coefficient is 0.25. Hence, from the correlation analysis, we noticed that the considered inputs are positively and negatively correlated with global horizontal irradiance and are valid for forecasting.

3.2. Normalization. Normalization enhances the prediction performance by increasing the training efficiency. The real inputs are normalized using the min-max method. The min-max formulation is as follows:

$$\text{normalized input, } I'_j = \left(\frac{I_j - I_{\min}}{I_{\max} - I_{\min}}\right), \tag{1}$$

Table 1: Literature comparative study.

Years	Authors	Proposed models
2014	Ekici [2]	Least squares support vector machine (LS-SVM) model
2016	Madhiarasan and Deepa [3]	Six ANN models (EN-elman network, RBFN, BPN-backpropation network, IBPN, MLPN, and RRBFN)
2014	Mellit and Pavan [4]	MLP (multilayer perceptron) model
2018	Kumar et al. [5]	NARX (nonlinear autoregressive for exogenous inputs)-ANN
2012	Huang et al. [6]	ARMA (autoregressive-moving average) model
2013	Zeng et al. [7]	Support vector machine (SVM) model
2019	Yu et al. [8]	Long short-term memory (LSTM) model
2020	Madhiarasan [9]	RRBFNN (recursive radial basis function neural network) model
2022	Hoyos-Gómez et al. [10]	Data-driven machine learning based on a short-term forecasting model
2022	Madhiarasan and Louzazni [11]	Combined long short-term memory network model

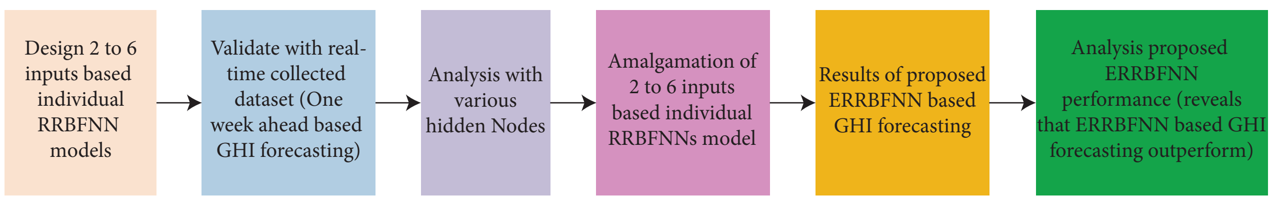

Figure 1: Graphical overview.

where I_j is the actual input value, $I_{\min}$ is the minimum input value, and $I_{\max}$ is the maximum input value.

3.3. Ensemble Recursive Radial Basis Function Neural Networks (ERRBFNNs). Motivation for choosing a multilayered feed-forward neural network: A multilayer feed-forward neural network with proper weights has been proven to be capable of approximating any input-output function, making it an appealing technique for forecasting and modeling purposes [12]. With this motivation, this paper endeavors to ensemble recursive radial basis function neural network amalgamation of various inputs associated with the multilayer feed-forward network RRBFNN. An individual recursive radial basis function neural network has three layers: input, hidden, and output. Each individual recursive radial basis function iteratively alters the network weights to decrease the output error. The distance between the centers of the input and hidden layer inputs generates the input layer outputs. The output of the input layer was sent nonlinearly to the hidden layer. The Gaussian activation function is employed [13]. The hidden layer's outputs are linear weighted approximations of the input layer's, which are subsequently transferred to the output layer. The weights are recursively updated to produce the least output error. In the weight update operation, the gradient descent rule is applied.

$$\begin{aligned}&\text{Weight vectors of hidden to output vector}, SV = [SV_1, SV_2, \ldots, SV_m],\\&\text{Gaussian activation function}, f(Z_{in}) = e^{(-Z_{in}^2)},\end{aligned} \tag{2}$$

where Z_{in} is the net input.

The output of recursive radial basis function neural networks is as follows:

$$Z_{in} = \sum_{i=1}^{n} f\left(\left\|I - C_i\right\|\right) * SV_{ik}, k = 1, 2, \ldots, m, \tag{3}$$

where n is the number of hidden neurons, I is the input vector, C_i is the i^{th} center node in the hidden layer, $\|I - C_i\|$ is the Euclidean distance between C_i and I, f is the activation function (Gaussian function), and SV_{ik} is the weight between hidden and output layer.

Modeling of the proposed ensemble recursive radial basis function neural network was performed using the following mathematical equation:

$$\text{ERRBFNN} = \frac{\left(\text{RRBFNN}^{2\text{inputs}} + \text{RRBFNN}^{3\text{inputs}} + \text{RRBFNN}^{4\text{inputs}} + \text{RRBFNN}^{5\text{inputs}} + \text{RRBFNN}^{6\text{inputs}}\right)}{5}. \tag{4}$$

Table 2: Input and output nodes description.

Input nodes	Description	Unit	Output nodes	Description	Unit
I_1	Pressure	Millibar (mb)	O	Forecast global horizontal irradiance (GHI)	Watts per square meter (W/m^2)
I_2	Temperature	Celsius (°C)			
I_3	Relative humidity	Percentage (%)			
I_4	Wind speed				
I_5	Cloud cover	Oktas			
I_6	Global horizontal irradiance	Watts per square meter (W/m^2)			

The independent RRBFNN model is designed using Table 3 set parameters. The input nodes vary from two to six, and the number of the hidden layer is chosen as one because adding more hidden layers makes the network more complex. The hidden nodes vary between one and fifteen, and the output node is one (i.e., forecasted global horizontal irradiance and modeling). The number of epochs is chosen as one thousand, and the spread value is chosen as 2.1. The abovementioned set parameters are chosen based on reference [9] mathematical model and the author's own expertise with experimentation.

The framework of the proposed ERRBFNN and workflow are shown in Figures 2 and 3, respectively. The atmospheric weather variables like temperature, pressure, cloud cover, relative humidity, and wind speed highly affect the photovoltaic system performance. We fed these variables as inputs to the proposed ERRBFNN model, along with the global horizontal irradiance. The pressure and temperature are engaged as two inputs for the two inputs based on the developed RRBFNN. The pressure, temperature, and relative humidity are involved as the three inputs for the three inputs based on the developed RRBFNN. Pressure, temperature, relative humidity, and wind speed are the four inputs for the four inputs based on the RRBFNN. Pressure, temperature, relative humidity, wind speed, and cloud cover are engaged as the five inputs for the five inputs based on the developed RRBFNN. Pressure, temperature, relative humidity, wind speed, cloud cover, and global horizontal irradiance are engaged as the six inputs for the six inputs based on the developed RRBFNN. The independently designed recursive radial basis function network salient feature weights are recursively updated using a recursive learning algorithm, which is leveraged to minimize the forecasting error.

The overall working of the proposed ERRBFNN: the collected input data are passed to the min-max normalization process; then, the normalized inputs are divided into training and testing datasets. With the use of the training dataset, the proposed ERRBFNN model was trained. Each developed individual input incurred RRBFNNs are trained using the training dataset. The trained ERRBFNN performance was validated on the unseen testing dataset with various hidden nodes, as illustrated in Figure 3. At last, by taking the mean of all individual RRBFNNs, the generalized ensemble RRBFNN model forecasted GHI computed and stored.

Table 3: Set parameters of the proposed ERRBFNN.

ERRBFNN set parameters
Input nodes = 2–6
Hidden layer = 1
Hidden nodes = 1–15
Output nodes = 1
Epochs = 1000
Spread = 2.1

3.4. Effect of Hidden Nodes. It is crucial that exactly the hidden nodes are determined. The high number of hidden nodes results in network unstable and overfitting issues. The underfitting and stability issue arises because of the low number of hidden nodes. There is no rule of thumb for hidden node estimation. Using the trial-and-error technique, the number of neurons was found in the hidden layer [14]. Thus, we performed the statistical analysis with respect to the hidden node from one to fifteen and identified the proposed model's optimal framework concerning the hidden nodes.

3.5. Training and Testing Datasets. One-hour averaged data for a year consists of 8760 data points of considered input fed as the training data and tested on the one-hour averaged data consisting of unseen 168 points of considered input for one week.

3.6. Evaluation Metric. Generally, in regression analysis, the performance of the forecasting model has evaluated through the use of the evaluation metrics such as root mean squared error (RMSE), normalized root mean squared error (NRMSE), mean squared error (MSE), and mean relative error (MRE). MSE measures residual variance, whereas RMSE measures the residual standard deviation. NRMSE is a useful metric for comparing models with various dependent variables, whereas MRE measures the variance of relative error. The lower the value of the above-said metric leverage, the higher the forecasting accuracy of the forecasting model. The following evaluation metrics formulations are used to gauge the effectiveness of the proposed ERRBFNN.

$$\begin{aligned}
\text{Normalized root mean squared error NRMSE} &= \frac{RMSE}{\overline{A}},\\
\text{RMSE} &= \sqrt{\left(\frac{1}{T}\sum_{n=1}^{T}\left(A_n - F_n\right)^2\right)},\\
\text{MSE} &= \frac{1}{T}\sum_{n=1}^{T}\left(A_n - F_n\right)^2,\\
\text{MRE} &= \frac{1}{T}\sum_{n=1}^{T}\left|\frac{\left(A_n - F_n\right)}{\overline{A}_n}\right|,
\end{aligned} \tag{5}$$

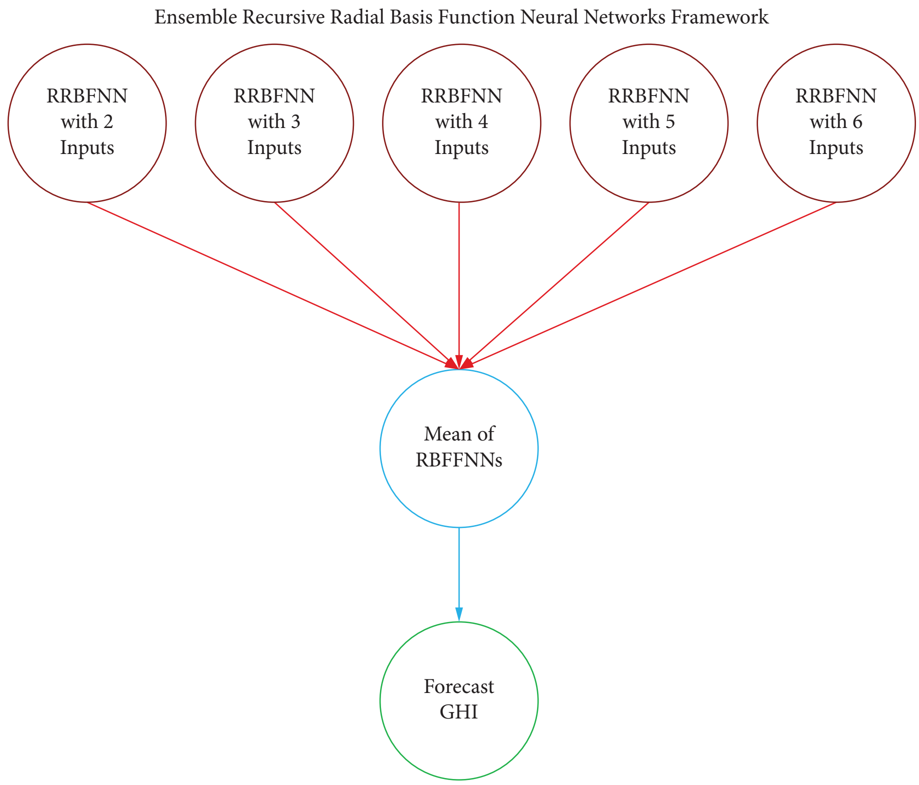

Figure 2: Proposed ERRBFNN framework.

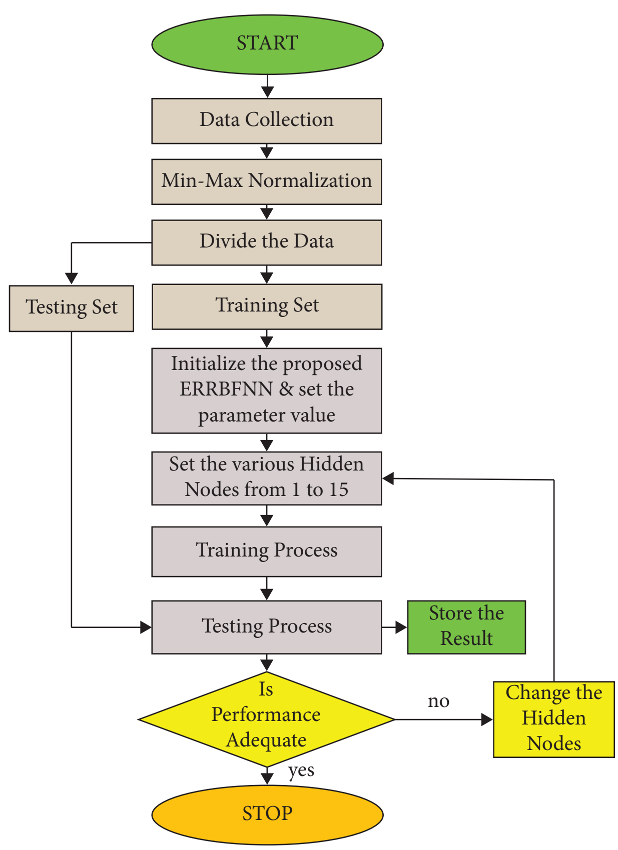

Figure 3: Proposed ERRBFNN workflow.

Table 4: Evaluation metrics of the proposed ERRBFNN model with various hidden nodes.

Forecasting models	Hidden nodes	Evaluation metrics NRMSE	RMSE	MSE	MRE
ERRBFNN	1	5.3375×10^{-05}	0.0113	1.2841×10^{-04}	3.3336×10^{-05}
	2	1.4556×10^{-04}	0.0309	9.5493×10^{-04}	5.5225×10^{-05}
	3	4.7728×10^{-05}	0.0101	1.0267×10^{-04}	2.6272×10^{-05}
	4	$1.4819e \times 10^{-04}$	0.0315	9.8980×10^{-04}	8.4643×10^{-05}
	5	7.5862×10^{-04}	0.1611	0.0259	6.4762×10^{-04}
	6	0.0465	9.8647	97.3129	5.8933
	7	7.5830×10^{-05}	0.0161	2.5917×10^{-04}	3.1891×10^{-05}
	8	0.0305	6.4783	41.9680	0.0230
	9	0.0011	0.2372	0.0562	6.7809×10^{-04}
	10	$\mathbf{2.2533 \times 10^{-05}}$	**0.0048**	$\mathbf{2.2884 \times 10^{-05}}$	$\mathbf{1.2009 \times 10^{-05}}$
	11	2.5358×10^{-04}	0.0538	0.0029	1.7072×10^{-04}
	12	3.5166×10^{-04}	0.0747	0.0056	1.6618×10^{-04}
	13	0.0039	0.8305	0.6898	0.0017
	14	0.0011	0.2401	0.0576	6.1433×10^{-04}
	15	0.0019	0.3953	0.1562	0.0011

The bold values imply the best result.

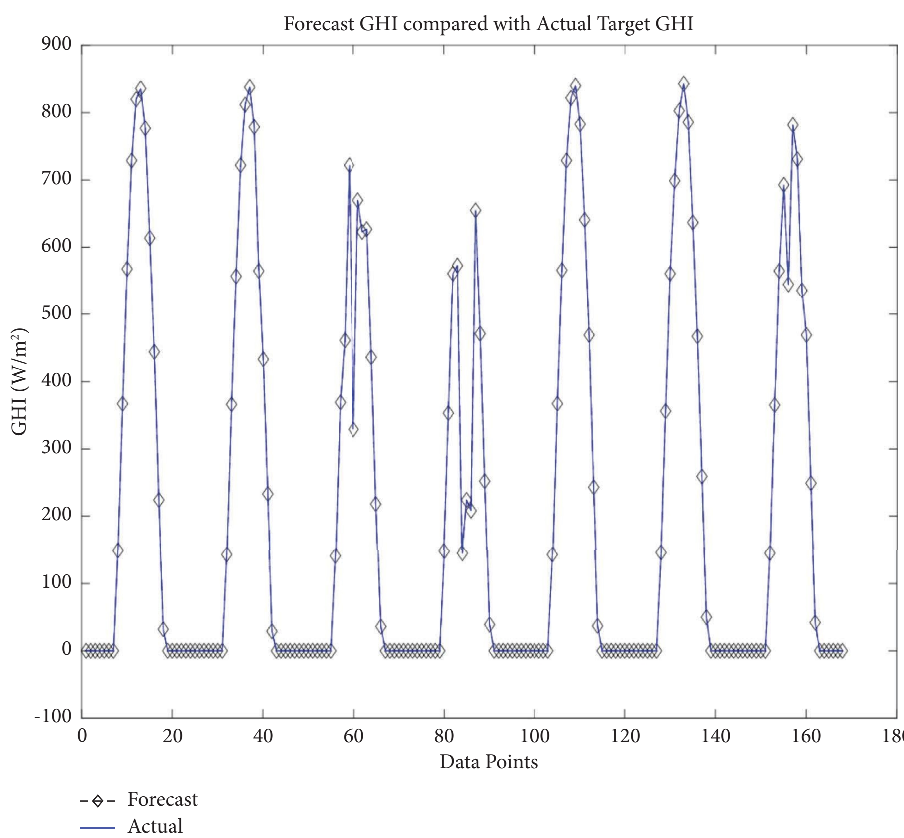

Figure 4: Forecast GHI compared with the actual target GHI.

where $\overline{A}$ is the average of the actual target GHI value, A_n is the actual target GHI value, and F_n is the forecast GHI value.

4. Experimental Simulation of the Proposed ERRBFNN, Results, and Discussion

The MATLAB 2021b software is used to design the proposed ERRBFNN and runs on a HP laptop with the specification AMD Ryzen 5 3550H processor, 4 GB NVIDIA GeForce GTX 1650, 8 GB RAM, and 2.1 GHz.

4.1. Proposed ERRBFNN Performance Statistical Analysis with Various Hidden Nodes. The proposed ERRBFNN-based GHI forecasting model stability based on various hidden nodes is analyzed with various hidden nodes from one to fifteen. The obtained results are tabulated in Table 4. From

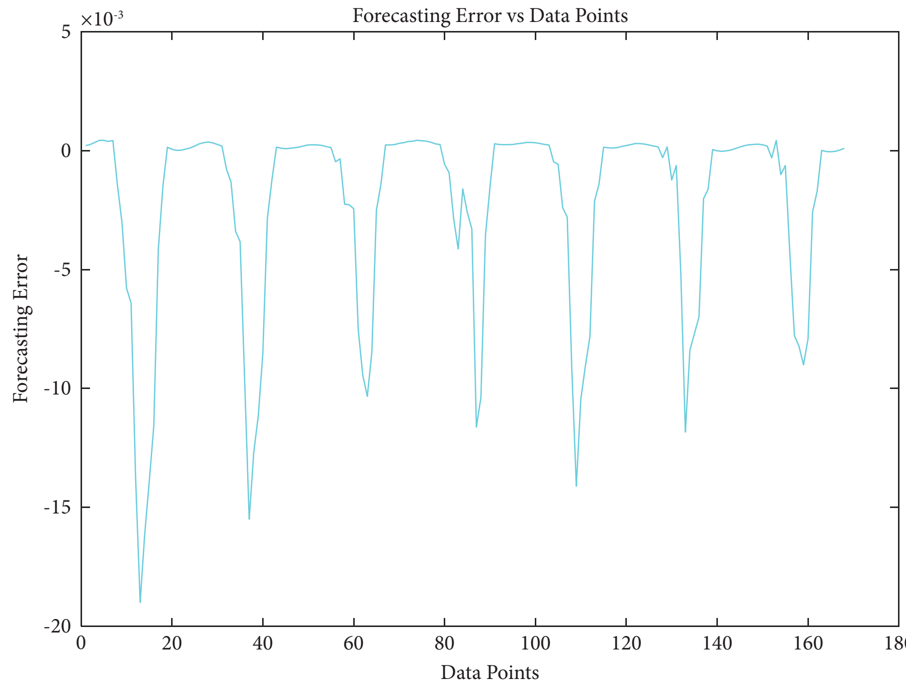

Figure 5: Forecasting error vs. data points.

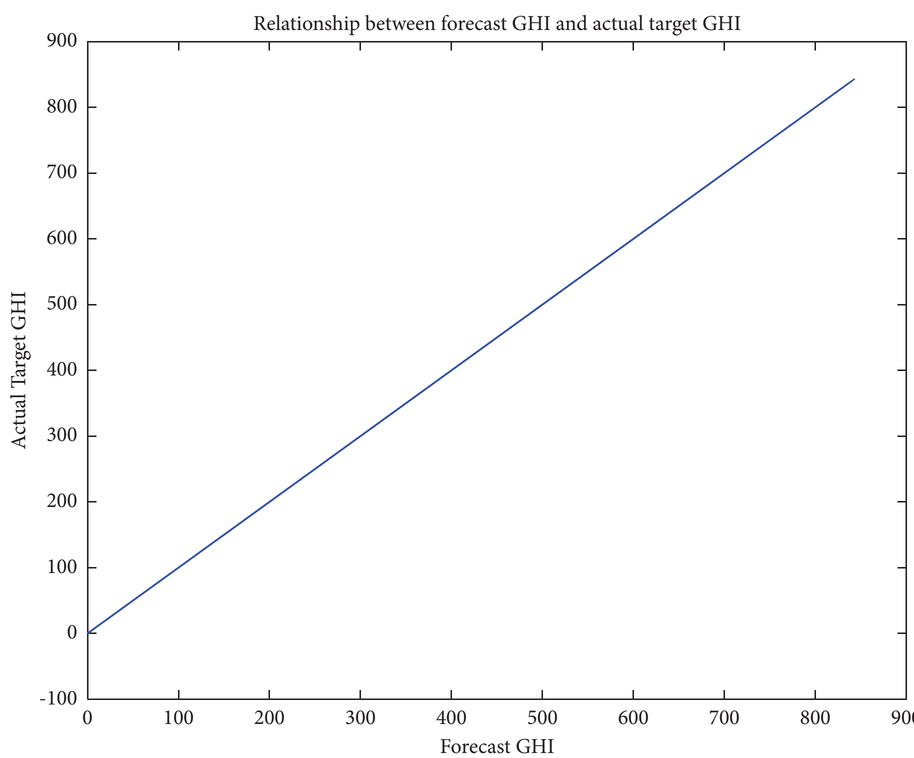

Figure 6: Relationship plot between forecast GHI and actual target GHI.

the different hidden nodes based on statistical analysis, we encountered that ten hidden nodes incurred in the proposed ERRBFNN-based GHI forecasting achieve minimal forecasting error. Figures 4–6 reveal the forecasting ability of the proposed ERRBFNN with optimal hidden nodes (ten hidden nodes). The forecast curve corresponds to the empirical actual GHI curve noted in Figure 4. Highly accurately, the forecasting GHI agrees with the actual GHI. Thus, the

Table 5: Comparative analysis of the proposed ERRBFNN with other forecasting models.

Forecasting models	Evaluation metrics			
	NRMSE	RMSE	MSE	MRE
Persistent [7]	0.0458	9.7140	94.3618	0.0170
ARMA [7]	0.2834	60.1653	$3.6199 \times 10^{+03}$	0.1920
NARX-ANN [5]	0.0015	0.3228	0.1042	8.0877×10^{-04}
ENN [3]	0.0059	1.2509	1.5647	0.0021
MLP [4]	0.0016	0.3386	0.1147	0.0010
BPN [3]	0.0120	2.5563	6.5345	0.0088
SVM [7]	0.0018	0.3829	0.1466	0.0010
LS-SVM [2]	3.7316×10^{-04}	0.0792	0.0063	2.2953×10^{-04}
RNN [15]	0.0031	0.6688	0.4472	0.0024
RBFN [3]	7.9803×10^{-04}	0.1694	0.0287	5.3412×10^{-04}
LSTM [8]	3.5166×10^{-04}	0.0747	0.0056	1.6618×10^{-04}
RRBFNN [9]	2.5744×10^{-04}	0.0547	0.0030	1.1605×10^{-04}
Proposed ERRBFNN	$\mathbf{2.2533 \times 10^{-05}}$	**0.0048**	$\mathbf{2.2884 \times 10^{-05}}$	$\mathbf{1.2009 \times 10^{-05}}$

The bold values imply the best result.

forecasting error is minimal and has a linear relationship with GHI forecasting for one week. It is clearly perceived in Figures 5 and 6, respectively.

4.2. Comparative Analysis of the Proposed ERRBFNN with Other Forecasting Models. The measure of the proposed model effectiveness and the evaluation metrics are computed and tabulated in Table 5. These values were then compared with those of the traditional forecasting models to assess the success of the proposed ERRBFNN. The majority of traditional technologies such as Persistent [7], ARMA [7], NARX-ANN [5], ENN [3], MLP [4], BPN [3], SVM [7], LS-SVM [2], RNN [15], RBFN [3], LSTM [8], and RRBFNN [9] have quite large errors and are occasionally may challenging to apply broadly. Conversely, when using the ensemble ERRBFNN approach, NRMSE, RMSE, MSE, and MRE eventually settle errors that seem to be minuscule, making them excellent, accessible, and consistent solar forecasting models.

We developed the proposed model with various atmospheric inputs; these inputs impact the cause of climatic uncertainty affecting solar irradiance. By considering all these variables as the input, we achieve robustness and the ensemble of various RRBFNN lead generics and perform better. We notice from Table 5 that compared with the various forecasting models, the proposed ERRBFNN-based GHI forecasting is better than the other models.

5. Conclusion

The proposed model is robust to weather uncertainty conditions because we used high-impact solar energy weather variables to develop an independent recursive radial basis function neural network. Furthermore, the proposed various inputs incurred five independently designed recursive radial basis function neural network averaged ERRBFNN stability is statistically analyzed with one hidden node to fifteen nodes on the collected real-time data. For the one-week-ahead forecasting horizon, the proposed ERRBFNN with ten hidden nodes based design global horizontal irradiance forecasting model provides excellent forecasting with the least evaluation metrics. Moreover, the comparative investigation verified the effectiveness. From the comparative result analyses, we noted that the proposed framework-based GHI forecasting model rigorously proved the effectiveness with NRMSE of 2.2533×10^{-05}, RMSE of 0.0048, MSE of 2.2884×10^{-05}, and MRE of 1.2009×10^{-05}. The proposed ERRBFNN is generic and robust regarding the model and climate uncertainty.

5.1. Limitations of the Proposed ERRBFNN. The limitation of the proposed ERRBFNN is that the computation burden may increase when we increase the number of hidden neurons, which needs a powerful computing machine.

5.2. Extension of Future Work

(i) We will perform the statistical analysis with more hidden nodes in future work

(ii) We will carry out an arbitrary input combination-based analysis

(iii) The proposed ERRBFNN model generic capability will be proven through various month-based GHI forecasting.

Data Availability

We derived these datasets from the following domain resources https://www.noaa.gov/ upon request links to access their ordered data from an FTP site and so such as third-party right authors who are not provided the data openly.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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