Enriched global horizontal irradiance prediction using novel ensemble improved backpropagation neural network

M. Madhiarasan*

Department of Computer Science and Engineering, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, India–247667, Orcid ID: 0000-0003-2552-0400

Abstract. Penetration of solar energy into the power grid and smart grid is becoming an urge because of the continuous progress in industrialization and advancement. Requires a high accurate Global Horizontal Irradiance (GHI) prediction to achieve effective penetration of solar energy. This paper proposes a novel Ensemble Improved Backpropagation Neural Network (EIBPNN) with enhanced generalization ability because it is developed based on the various inputs' individual improved backpropagation neural networks. Hence, the variance of individual IBPNN and input parameters based uncertainty are overcome and has the generic performance capability. The comparative analysis imparts the proposed prediction model results improved GHI prediction than the existing models. The proposed model has enriched GHI prediction with better generalization.

Keywords: Ensemble, Improved backpropagation neural network, Global horizontal irradiance, and prediction.

1 Introduction

Mitigating global warming, environmental impact, and climatic transmute leads to an increased usage of solar energy systems **Madhiarasan M**[1]. The accurate prediction of Global Horizontal Irradiance (GHI) is primary. It is required for effective grid integration, planning, and control of the grid-connected system to ensure the uninterruptible power provision to the customer **Madhiarasan M & Deepa SN**[2]. The accurate prediction of solar irradiance depends on selecting significant variables as the inputs and optimal parameters **Madhiarasan M, Tipaldi M, and Siano** [3].

Fickle nature, atmospheric parameters influence makes the solar irradiance prediction a very complex and challenging task **Madhiarasan M & Deepa SN**[4 & 5]. The major problem with the neural network is a generalization issue that the proposed novel ensemble improved backpropagation neural network can resolve this problem. This research carried out a prediction of GHI using EIBPNN, which is built based on the various inputs associated with individual IBPNN prediction models.

* Corresponding author email: mmadhiarasan.cse@sric.iitr.ac.in

Contributions:

This paper contribution as mentioned below:

The proposed novel EIBPNN based prediction model overcomes the variance in inputs.

To perform hidden neuron-based stability analysis.

Observed real-time data were used to prove the effectiveness.

The proposed EIBPNN is robust, generic, and achieves reduced performance metrics than other prediction models.

2 Literature studies

A lot of research work exists, which is implied by the many prediction models in the literature. Time series-based solar radiation prediction was performed by **Reikard G**[6]. **Rehman S & Mohandes M**[7] conducted two inputs-based backpropagation neural network-based solar radiation predictions. **Badosa J, Haeffelin M, Kalecinski N, Bonnardot F, & Jumaux G**[8] presented Empirical Statistical Downsampling associated NWP (Numerical Weather Prediction) used to forecast the day-ahead solar irradiance. **Olatomiwa L, Mekhilef S, Shamshirband S, & Petković D**[9] carried out three inputs associated with ANFIS (adaptive neuro-fuzzy inference system) based on solar radiation prediction. **Zeng J & Qiao W**[10] suggested SVM (support vector machine) based on solar power prediction. Hybrid model-based solar irradiance forecasting was pointed out by **Madhiarasan M & Deepa SN**[11 & 12]. The previous works reported in the literature **Madhiarasan M & Deepa SN**[13] and **Madhiarasan M**[14] revealed that individual neural networks lack generalization and stability in other circumstances. Hence, a generic GHI prediction model is necessary for the solar power system.

3 Proposed method concept

The proposed model addresses the uncertainty of the meteorological parameters by considering them as inputs. It helps the predictor manage the uncertainties and improves performance with outstanding, accurate GHI prediction.

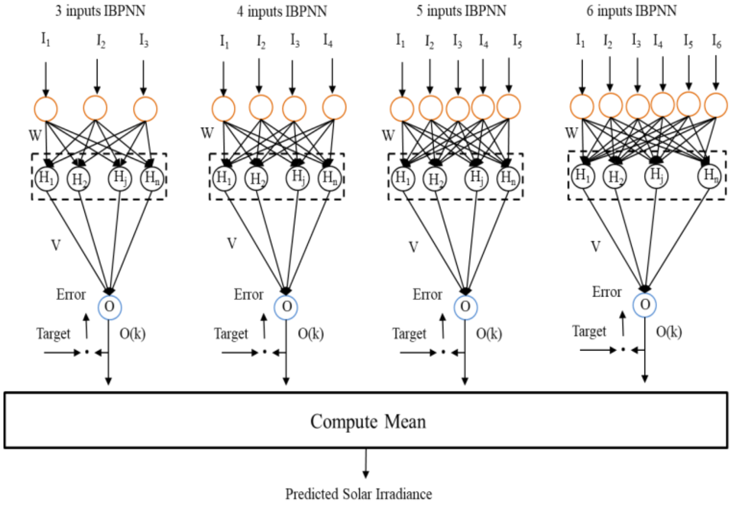

Fig. 1. Proposed EIBPNN architecture.

The proposed Ensemble Improved Backpropagation Neural Network (EIBPNN) was built by accumulating four various input feedforward networks with a backpropagation learning algorithm, incorporation of momentum factor (IBPNN) **Madhiarasan M & Deepa SN**[15]. EIBPNN can balance its memorization and generalization. The computed error propagated backward to the hidden layer and then passed to the input layer. The weights are modified and updated for a given set of training and testing to make the correct GHI prediction with the slightest error. The architecture of the proposed ensemble improved backpropagation neural network model for GHI (solar irradiance) prediction is shown in Figure 1. Design values of the proposed EIBPNN are shown in Table 1.

Table 1. Design Values of the proposed EIBPNN.

Proposed Ensemble IBPNN Design Values	
Input layer neurons	– 3, 4, 5 & 6
Number of hidden layer	– 1
Hidden neurons	– 1-21
Output layer neuron	– 1
Number of epochs	– 1000
Threshold	– 1
Learning Rate	– 0.01
Momentum Factor	– 0.9

Individual IBPNN mathematical model

The output of hidden layer,

$$H_j = f\left(\sum_{i=1}^{n}\sum_{j=1}^{m} I_i W_{ij}\right) \tag{1}$$

Output layer output, $O = f\left(\sum_{j=1}^{m}\left(H_j V_j\right)\right)$, $j = 1,2,.....,m$ (2)

Output layer error, $\delta = \left(T - O\right) f^{'}\left(O_{in}\right)$ (3)

Backpropagated error (δ) to the hidden layer.

Hidden layer error, $\delta_j = \delta_{in\,j}\; f^{'}\left(H_{in\,j}\right)$ (4)

Propagated backward error (δ_j) to the input layer.

Updating of Weight, $V_j\left(t+1\right) = V_j\left(t\right) + \alpha\delta H_j + \eta\left[V_j\left(t\right) - V_j\left(t-1\right)\right]$ (5)

$$W_{ij}\left(t+1\right) = W_{ij}\left(t\right) + \alpha\delta_j\, I_i + \eta\left[W_{ij}\left(t\right) - W_{ij}\left(t-1\right)\right] \tag{6}$$

Where, V - Weight between hidden and output layer, W- Weight between the input to the hidden layer, f - Activation function, n- Number of inputs, m – Number of hidden neurons, $f^{'}\left(O_{in}\right)$- Derivative of the net input of the output layer, $\delta_{in\,j} = \sum_{j=1}^{m} \delta V_j$, $f^{'}\left(H_{in\,j}\right)$- Derivative of the net input of hidden layer, α- Learning rate, η- momentum factor, T- Observed target values.

Designed individual Improved Back Propagation Neural Network (IBPNN) inputs are feedforward with weights W and activation function (hyperbolic tangent sigmoid) for the hidden layer. Output from the hidden layer computed the output feedforward with weight V and activation function (tangent sigmoid). The single hidden layer is used to reduce the complexity. During weights updating, introducing a momentum factor (η) was introduced to speed up convergence.

Ensemble IBPNN mathematical model: The proposed EIBPNN model is developed based on the mathematical formulations mentioned below:

$$\text{EIBPNN output } = \frac{IBPNN_{3input} + IBPNN_{4inputs} + IBPNN_{5inputs} + IBPNN_{6inputs}}{4} \quad (7)$$

Performance metric computation of the EIBPNN:

$$EIBPNN_{MSE} = Mean\left(IBPNN_{3inputs}^{MSE} + IBPNN_{4inputs}^{MSE} + IBPNN_{5inputs}^{MSE} + IBPNN_{6inputs}^{MSE}\right) \quad (8)$$

$$EIBPNN_{MAE} = Mean\left(IBPNN_{3inputs}^{MAE} + IBPNN_{4inputs}^{MAE} + IBPNN_{5inputs}^{MAE} + IBPNN_{6inputs}^{MAE}\right) \quad (9)$$

$$EIBPNN_{MAPE} = Mean\left(IBPNN_{3inputs}^{MAPE} + IBPNN_{4inputs}^{MAPE} + IBPNN_{5inputs}^{MAPE} + IBPNN_{6inputs}^{MAPE}\right) \quad (10)$$

4 Proposed EIBPNN experimentation, results, and discussion

The designed EIBPNN prediction model experimental MATLAB simulation runs on an Acer laptop with a Pentium (R) Dual-Core processor running at 2.30GHZ with 2GB of RAM. The proposed ensemble improved back propagation neural network experimentation incurred steps:

i) Perform the data collection of the considered input parameters, and the variance can be eliminated using the min-max normalization.

ii) Split the data as training and testing.

iii) Design the proposed ensemble improved backpropagation neural network initialize the parameter.

iv) Perform training, testing, and performance metric computation.

v) Carried out different hidden neurons (1-21)-based sensitivity analysis, identifying the optimal hidden neurons using computed performance metrics.

vi) Performance is satisfactory printing output. Otherwise, go to step (iii) until reaching the stopping condition (max epoch).

4.1 Data collection and normalization:

INDIA's one-year hourly observed data at the latitude of 12.9 $^{\circ}N$ longitudes of 79.13 $^{\circ}E$ were collected from NOAA (National Oceanic and Atmospheric Administration), the United States, for a period from January 2020 to December 2020. For each input, 8760 numbers of observed real-time data were collected. Furthermore, the data were split into 70 % and 30 %, respectively, for training and testing. Temperature (T) unit $^{\circ}C$, Precipitable Water (PW) unit cm, Wind Speed (S) unit m/s, Pressure (P) unit mbar, Relative humidity (R) unit %, and Global Horizontal Irradiance (GHI) unit W/m^2 are considered as the input to the proposed prediction model, and network output is predicted Global Horizontal Irradiance (W/m2). Proposed EIBPNN models are developed using four individual IBPNN with various inputs like three inputs (T, PW & S), four inputs (T, PW, S, & P), five inputs (T, PW, S, P, & R) and six inputs (T, PW, S, P, R, and GHI).

The real-time data scaled within the range of 0 to 1 using the following min-max normalization equation,

$$\text{Normalized input, } I_i^{'} = \left(\frac{I_i - I_{\min}}{I_{\max} - I_{\min}}\right)\left(I_{\max}^{'} - I_{\min}^{'}\right) + I_{\min}^{'} \tag{11}$$

Let I_i is the observed input, $I_{\min}$ is the minimum observed input value, $I_{\max}$ is the maximum input data, $I_{\min}^{'}$ is the minimum target value, $I_{\max}^{'}$ is the maximum target value.

4.2 Performance metrics

The Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are used as performance metrics to evaluate the proposed EIBPNN prediction model performance. The mathematical formulas of the considered performance metrics are as follows:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(O_i^{'} - O_i)^2 \tag{12}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|O_i^{'} - O_i\right| \tag{13}$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\left|(O_i^{'} - O_i)/\overline{O_i}\right| \tag{14}$$

Where N is the number of data, $O_i^{'}$ is the observed target GHI, O_i is the predicted GHI, $\overline{O_i}$ is the average observed target output.

The applicability of the proposed GHI prediction model is validated with the observed real-time data. The simulation results of the proposed EIBPNN prediction model with various hidden neuron-based sensitivity analyses are tabulated in Table 2. From the careful study of Table 2 performance metrics, the proposed model containing 16 hidden neurons in the hidden layer shows the superior and outperforming capability of other hidden neurons. Figure 2 shows the input GHI data samples and the obtained results based on the proposed EIBPNN with 16 hidden neurons based prediction models depicted in Figures 3 and 4. It should be noticed that the predicted GHIs are exactly matching with the observed GHIs. Therefore, the errors are minimal, and the variance of the individual neural network can be eliminated, which leads to enriched generalized performance. Furthermore, the proposed prediction model with optimal hidden neurons (16) validity is analyzed with other existing prediction models. The corresponding outputs based on the proposed model and existing methods are reported in Table 3. Table 3 infers that the proposed model outperforms the minor mean square error and achieves the highest generalization capability compared to all considered prediction models.

Table 2. Sensitive analysis of the proposed EIBPNN with various hidden neurons.

Proposed Ensemble IBPNN with various No. of. Hidden Neurons	Performance Metrics		
	MSE	MAE	MAPE
1	914.1571	25.6696	13.2025
2	66.6899	0.4178	3.3008
3	8.7872	2.1362	1.0987
4	1.4735	0.7455	0.3534
5	0.1504	0.7518	0.3866
6	1.4768	0.7454	0.3834
7	0.0864	0.1539	0.0792
8	0.4500	0.3893	0.2002
9	0.0907	0.1589	0.0817
10	0.0286	0.0722	0.0371
11	0.1195	0.1622	0.0834
12	0.4327	0.3783	0.1946
13	0.0932	0.1612	0.0829
14	0.0811	0.1138	0.0585
15	0.0252	0.0650	0.0334
16	**0.0058**	**0.0211**	**0.0108**
17	0.0772	0.1441	0.0741
18	0.0606	0.1082	0.0557
19	0.0770	0.1254	0.0645
20	0.1060	0.1536	0.0790
21	0.0510	0.1085	0.0558

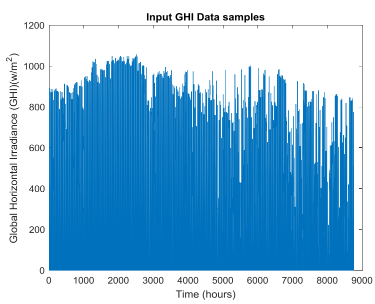

Fig. 2. Input GHI data samples.

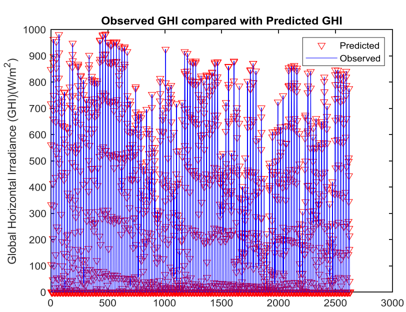

Fig. 3. Observed GHI compared with Predicted GHI.

https://doi.org/10.1051/itmconf/20224501060

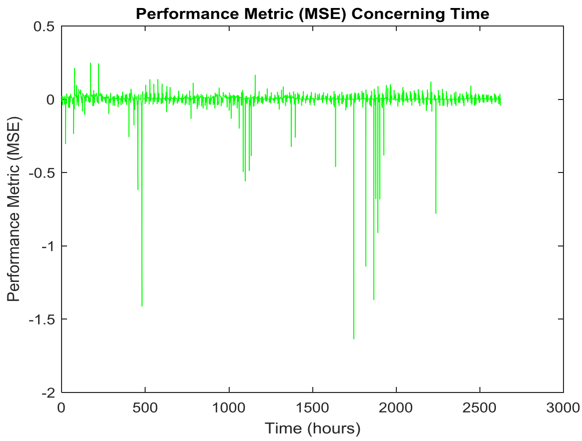

Fig. 4. Performance Metric (MSE) concerning the time.

Table 3. Proposed EIBPNN performance compared with other prediction models.

S. No	Prediction Models	Mean Square Error
1	Persistent	1.3201
2	ARIMA	0.8477
3	BPN	0.6830
4	NWP	0.4691
5	ENN	0.1288
6	ANFIS	0.0394
7	SVM	0.0167
8	IBPNN	0.0082
9	**Proposed EIBPNN**	**0.0058**

5 Conclusion

Power production from the solar energy system highly relies on solar irradiance (GHI). Therefore, a highly accurate and generic prediction is required for the effective operation of the utility system and smart grid. In the literature, extensive research work is trying to develop an outperformed and generic GHI prediction model. Still, the generic GHI prediction is a thrust area in the PV (photovoltaic) system because various atmospheric inputs impact the GHI. This paper considers the various atmospheric inputs as inputs and ensembles four various input-based individual IBPNN. The importance of hidden neurons analyzed with different hidden neurons and 16 number of hidden neurons is selected as optimal. Thus, the proposed ensemble improved backpropagation neural network (EIBPNN) prediction model results demonstrate superior generalization ability and minimal performance metrics (MSE of 0.0058) than the existing prediction models. The advantage of the proposed EIBPNN has enriched the generalization and robustness.

The author expresses his gratitude to the NOAA (National Oceanic and Atmospheric Administration), United States, for providing the dataset to carry out the experimental simulation.

References

1. Madhiarasan M 2018 Certain algebraic criteria for design of hybrid neural network models with applications in renewable energy forecasting Ph D Thesis Anna University Chennai India
2. Madhiarasan M & Deepa SN 2017 Review of Forecasters Application to Solar Irradiance Forecasting International Journal of Scientific Research in Computer Science, Engineering and Information Technology vol 2(2) pp 26-30
3. Madhiarasan M, Tipaldi M, and Siano P 2020 Analysis of Artificial Neural Network Performance Based on Influencing Factors for Temperature Forecasting Applications Journal of High Speed Networks vol 26(3) pp 209-223 DOI: 10.3233/JHS-200639
4. Madhiarasan M and Deepa SN 2016 Precisious Estimation of Solar Irradiance by Innovative Neural Network and Identify Exact Hidden Layer Nodes through Novel Deciding Standard Asian Journal of Research in Social Sciences and Humanities vol 6(12) pp.951-974
5. Madhiarasan M & Deepa SN 2016 Long-Term Wind Speed Forecasting using Spiking Neural Network Optimized by Improved Modified Grey Wolf Optimization Algorithm International Journal of Advanced Research vol 4(7) pp 356-368
6. Reikard G 2009 Predicting solar radiation at high resolutions: A comparison of time series forecasts Solar Energy vol 83(3) pp 342-349
7. Rehman S & Mohandes M 2008 Artificial neural network estimation of global solar radiation using air temperature and relative humidity Energy policy vol 36(2) pp 571-576
8. Badosa J, Haeffelin M., Kalecinski N, Bonnardot F, & Jumaux G 2015 Reliability of day-ahead solar irradiance forecasts on Reunion Island depending on synoptic wind and humidity conditions Solar energy vol 115 pp 306-321
9. Olatomiwa L, Mekhilef S, Shamshirband S & Petković D 2015 Adaptive neuro-fuzzy approach for solar radiation prediction in Nigeria. Renewable and Sustainable Energy Reviews vol 51 pp 1784-1791
10. Zeng J & Qiao, W 2013 Short-term solar power prediction using a support vector machine Renewable Energy vol 52 pp 118-127
11. Madhiarasan M & Deepa SN 2016 Deep Neural Network Using New Training Strategy Based Forecasting Method for Wind Speed and Solar Irradiance Forecast. Middle-East Journal of Scientific Research vol 24(12) pp 3730-3747
12. Madhiarasan M & Deepa SN 2017 A New Hybridized Optimization Algorithm to Optimize Echo State Network for Application in Solar Irradiance and Wind Speed Forecasting World Applied Sciences Journal vol 35(4) pp 596-614
13. Madhiarasan M & Deepa SN 2016 Application of Ensemble Neural Networks for Different Time Scale Wind Speed Prediction International Journal of Innovative Research in Computer and Communication Engineering vol 4 (5) pp 9610-9617
14. Madhiarasan, M 2021 Short-Term Wind Speed Forecasting Using Meta Learning-based Elman Neural Network In Journal of Physics: Conference Series vol 2068 (1) pp 012045
15. Madhiarasan M and Deepa SN 2016 A novel criterion to select hidden neuron numbers in improved back propagation networks for wind speed forecasting Applied intelligence vol 44(4) pp 878-893