

## Research Article

# Novel Cooperative Multi-Input Multilayer Perceptron Neural Network Performance Analysis with Application of Solar Irradiance Forecasting

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To forecast solar irradiance with higher accuracy and generalization capability is challenging in the photovoltaic (PV) energy system. Meteorological parameters are highly influential in solar irradiance, leading to intermittent and randomicity. Forecasting using a single neural network model does not have sufficient generalization ability to achieve the optimal forecasting of solar irradiance. This paper proposes a novel cooperative multi-input multilayer perceptron neural network (CMMLPNN) to mitigate the issues related to generalization and meteorological effects. Authors develop a proposed forecasting neural network model based on the amalgamation of two inputs, three inputs, four inputs, five inputs, and six inputs associated multilayer perceptron neural network. In the proposed forecasting model (CMMLPNN), the authors overcome the variance based on the meteorological parameters. The amalgamation of five multi-input multilayer perceptron neural networks leads to better generalization ability. Some individual multilayer perceptron neural network-based forecasting models outperform in some situations, but cannot assure generalization ability and suffer from the meteorological weather condition. The proposed CMMLPNN (cooperative multi-input multilayer perceptron neural network) achieves better forecasting accuracy with the generalization ability. Therefore, the proposed forecasting model is superior to other neural network-based forecasting models and existing models.

#### 1. Introduction

In recent trends, solar energy is an inevitable renewable energy source to avoid environmental hazards, climatic changes, etc. Solar energy is receiving a center of attraction because of the pollution-free renewable resources, and the vast potential is available to supply power to the entire world. Although solar energy has many advantages and special features, one major issue for the solar energy system is irregular in nature and volatile. Thus, it creates pressure on the power system engineers. It requires accurate forecasting of future solar irradiance to eliminate the problem of solar energy system irregularity, because solar power production from the solar PV system highly depends on solar irradiance. Effect of shift measurement and shift noise and solution: Measurement shift and noise cause the variability of the solar irradiance forecasting. Onsite measurement datasets with continuous maintenance, commissioning, sensor calibration, quality check, and data evaluation can prevent the uncertainty related to the measurement shift and noise.

The forecasting accuracy can be improved by applying feature selection and parameter optimization. Some of the researchers performed the forecasting accuracy improvement by applying the feature selection methods [1–3]. For machine learning and deep learning based on solar irradiance forecasting, one of the preprocessing is feature selection/extraction, used to remove redundant and irrelevant input information and extract significant input features.

Statistical methods like time series (regression, ARMA, LASSO, etc.), machine learning, deep learning, and hybrid models are widely used for data-driven-based forecasting [5–7]. Underlying mapping of solar irradiance data is effectively captured by a data-driven model. Data-driven method limitations are requiring high computation and cost. Uncertainty quantification helps to prove the validity of the model [8–10].

Once the future solar irradiance is forecasted, the power system scheduling planning of reserve requirement can be performed effectively, which reduces the pressure of power system engineers and improves the economy. This paper is aimed at proposing a forecasting model capable of generalized well and results in better forecasting output with high accuracy to avoid the impact of meteorological parameters.

Highlights of the proposed model compared to the existing models are as follows:

- (i) Averaging and combining the various input-based individual multilayer perceptron neural network benefits than the existing methods
- (ii) Escape from the overfitting and underfitting problem
- (iii) In most cases, a single individual model could not reach the generalized solution, but the proposed model tradeoff between variance and bias leads to a better generalized solution.
- (iv) Uncertainty regards the interannual variability addressed by the proposed model because we use 38 year periods of datasets to build the proposed model
- (v) The proposed cooperative model is an averaging a multi-input-based individual model that can overcome the limitation of a single individual model and uncertainties
- (vi) The proposed model is practical and simple and achieves improved forecasting than the existing model

This paper, organized as Section 1, describes the introduction, followed by the problem statement that is stated in Section 2, the literature review is carried out in Section 3, the proposed methodology is explained, detailed in Section 4, followed by Section 4 results and discussion reported in Section 5, the informative conclusion is stated in Section 6, and proposed model limitation and future work are discussed in Section 7.

#### 2. Problem Statement

Throughout a period (day), the power requirement varies regarding all nations' periods, and there is an irregularity, such as the daytime power required is more than the night

time. Forecasting is needed to maintain the power requirement and power production in a balanced manner, because it is complicated to manage due to nonrenewable energy resources that are exhaustible and not a pollution-free resource that endangers human life and the environment. Nature always provides a tremendous amount of resources to the human, and amongst one of the significant resources is the sun (solar energy). Hence, lots of countries implemented solar energy systems to fulfill the energy demand. Still, the problem is it did not guarantee stability, and power productions have fluctuated because of uncertainty and meteorological effects. This intermittent nature of the power production resource interconnected with a grid system creates security issues and a grid outage problem. The variability of solar energy production can be overcome by accurate future prediction so that the power system operator manages the problem associated with solar energy integrated with the power grid.

There is a possibility of various local minima and local maxima in an artificial neural network because of the nonconvex function. Therefore, it has an unstable performance and fails to generalize in some other circumstances. The amalgamation can effectively resolve these issues and average various input-based individual forecasting models. The paper proposes a new cooperative multi-input multilayer perceptron neural network, and the validity is confirmed by a solar irradiance forecasting application.

#### 3. Literature Review

In the literature, numerous research is done in the field of solar energy system for solar irradiation forecasting, which is discussed as follows:

Solmaz et al. 2010 [11] presented an artificial neural network-based solar radiation prediction. Remark: performance was not guaranteed for other datasets. Benghamm and Mellit 2010 [12] performed solar radiation prediction using a radial basis function network: remark: problem of optimal hidden neuron identification. Takenaka et al. 2011 [13] pointed out a neural network-based solar radiation prediction: remark: radioactive transfer aid for performance improvement in training and testing states.

Yadav and Chandel 2012 [14] presented a solar radiation estimation model using an artificial neural network. Remark: the generalization issue was not addressed; comparative performance investigation with other existing methods was not done. Chua et al. 2012 [15] suggested a backpropagation algorithm, adopting a multilayer perceptron neural networkbased forecasting model for medium-term solar insolation forecasting. Remark: the issue of apt hidden neuron estimation and performance was not ascertained.

Plangklang and Nantaphunkul 2015 [16] performed a multilayer feed-forward network with a backpropagation algorithm (Levenberg-Marquardt algorithm)- based model for solar irradiance forecasting. Remark: it is noticed from the result that the ANN-based forecasting results 4.60 percentages of MAPE in the Omar platform. De Leone et al. 2015 [17] performed support vector regression-based short-term photovoltaic energy production forecasting: remark: not generalize well.

Madhiarasan and Deepa 2016 [18] developed an innovative neural network-based solar irradiance forecasting, and they identified apt hidden neurons using a new deciding standard: remark: overcome the generalization problem, but sometimes, convergence takes much time because of the average of various neural network models. Madhiarasan and Deepa 2016 [19] performed solar irradiance forecasting based on a new training strategy associated with a deep neural network. Remark: compared with classical deep neural networks and other existing methods, the self-regulated particle swarm optimization-based fine-tuned deep neural network results in better performance for wind speed and solar irradiance forecasting.

Kumar et al. 2017 [20] suggested an artificial neural network with four logical variables based on solar irradiance forecasting in the long-term horizon: remark: lack a comparative analysis to prove the validity of the suggested system. Madhiarasan and Deepa 2017 [21] reviewed various recent papers existing in solar irradiance forecasting. Jensona and Praynlin 2017 [22] performed backpropagation neural network and radial basis function network-based solar irradiance forecasting. Remark: validation on NCEP and SODO datasets, the RBFN-based forecasting leads to better results than BPN for NCEP dataset, and BPN achieves better results than RBFN for SODO data sets. Ehsan et al. 2017 [23] suggested multilayer perceptron-based solar photovoltaic output power forecasting concerns for 24 hours ahead range. Remark: performance is not generic, and convergence is poor.

Kartini and Chen 2017 [24] presented a combinational solar irradiance forecasting model based on a multilayer backpropagation neural network and *K*-nearest neighbor algorithm: remark: lacking in comparative analysis. Madhiarasan and Deepa 2017 [25] carried out wind speed and solar irradiance forecasting using echo state network with GSANPSO (gravitational search algorithm new particle swarm optimization) based on optimized parameters and weights. Remark: according to the receiver operating characteristics (ROC), they observe that ESN-GSANPSO leads better forecasting with respect to wind speed and solar irradiance than other methods.

Leu et al. 2018 [26] suggested a neural network with an association of electromagnetism like an algorithm-based forecasting model for short-term solar irradiance forecasting. Remark: compared to BPNN, EMNN achieved better forecasting regarding the solar irradiance forecasting application. Lima et al. 2018 [27] pointed out one-hour advanced solar irradiance forecasting using a multilayer perception neural network to incorporate a backpropagation algorithm: remark: discrepancy of performance analysis and occurrence of generalization issues.

Luyao et al. 2018 [28] presented solar PV power output forecasting in a short-term horizon using the weight varying ensemble (WVE) method. Remark: generalization is not assured, and convergence problems occurred. Wanady 2018 [29] pointed out ARMA (auto regression moving average) based on solar irradiance forecasting with meteorological data sets. Laopaiboon et al. 2018 [30] suggested a backpropagation algorithm associated with neural networkbased solar forecasting in the hour-ahead range. Remark: the BPNN model performs better compared to ARMA with respect to solar irradiance forecasting. Bruneau et al. 2018 [31] presented solar irradiance forecasting using MLP and  $X_{gboost}$  (gradient boosting) with Arima vector association. Remark: Arima vector-associated MLP and  $X_{gboost}$  forecasting models lead to better solar irradiance forecasting with minimal RMSE and MAE.

Shihabudheen and Pillai 2018 [32] proposed RELAN-FIS- (regularized extreme learning adaptive neurofuzzy system-) based forecasting model for solar irradiance and wind speed prediction. Remark: generalization and robustness were not guaranteed. Tiwari et al. 2018 [33] performed gradient boost regression associated with numerical weather prediction methods for solar irradiance forecasting in the short-term time horizon. Vanderstas et al. 2018 [34] suggested artificial neural network-based solar irradiance forecasting for two hours ahead of the time horizon. Remark: remote monitoring stations are optimally spaced by GA. Mohanty 2018 [35] performed solar radiation prediction using artificial neural network models, and PV inverter active and reactive current were controlled. Remark: the ANFIS model results in better performance than the artificial neural network and support vector machine- (SVM-) based models. Awad and Qasrawi 2018 [36] pointed out a solar cell output power forecasting model using a radial basis function neural network with the association of the singular value decomposition, K-nearest neighbor, and K -means clustering algorithm. Remark: generalization was not guaranteed.

Rogies and Mohamudally, 2019 [37] suggested (NARX) nonlinear autoregressive neural network-based PV power production forecasting using the Lora IoT network. Remark: comparative analysis with existing models was not addressed. Ozoegwu 2019 [38] carried out global solar irradiance forecasting using artificial neural networks and nonlinear autoregression. Remark: the limitations with respect to nonlinear autoregression and artificial neural networks are overcome. Hence, the author got better results than ANN and NARX. Paulescu and Paulescu, 2019 [39] presented solar irradiance nowcasting using upgraded twostate models in the short-term horizon range. Elshaikh et al. 2019 [40] studied artificial neural network-based solar energy system modeling.

Sempe Leholo et al. 2019 [41] performed hourly average solar irradiance forecasting by an artificial neural network with various training functions. Remark: the results revealed that the Levenberg Marquardt (LM) training function associated with ANN achieves good results compared with other training functions. Kamadinate et al. 2019 [42] carried out an artificial neural network-based 1-5 minute advance solar irradiance forecasting using sky images: remark: appropriate for very short-term horizons, a limitation with respect to time horizon forecasting.

Nowadays, developing countries and well-developed countries are developing lots of projects to promote power generation from the solar energy system (PV system) to meet the renewable energy portfolio standard and positive energy price policy. Various forecasting models exist in the field of solar energy systems, which is noticed from the existing literature review, but a generic forecasting model is needed. This paper addresses the issue with the current methods.

3.1. Necessity of the Proposed Model. Accurate forecasting is crucial because of the uncertainty about meteorological influences, interannual data, and design issues regarding the improper selection of model parameters. Despite the accuracy, the generalization also needs to be addressed. In solar irradiance forecasting, many challenges still exist due to uncertain natures. Thus, a generalized and high accurate model is obligate.

Solar irradiance poses uncertainty due to influence by the influence of climatic conditions and meteorological parameters. This research manages the solar irradiance uncertainty by considering the influence parameters as the inputs and averaging the multi-input multilayer perceptron neural network. Due to the lack of a generic model in solar irradiance forecasting, in this paper, we design a cooperation multi-input MLPNN model, and the performance is quantified using performance indicators. The proposed model intends to improve the accuracy with minor forecasting errors.

3.2. Benefits of the Proposed Model. Solar irradiance possesses uncertainty regarding various aspects. Meteorological/atmospheric inputs are highly influenced and cause irregularities in solar irradiance. This paper intends to enhance the generalization ability. The proposed model can diminish the variance concern to the inputs, interannual data, individual models, and hidden neurons. Combining the multi-input multilayer perceptron neural network leads to reduced performance indicators, enhanced accuracy, and superior generalizing ability than individual models.

#### 4. Proposed Methodology

This paper proposes novel cooperative multi-inputs and multilayer perceptron neural networks, and the applicability is validated for solar irradiance forecasting.

4.1. Proposed Cooperative Multi-Input Multilayer Perceptron Neural Network Framework and Concept. The imperfection of each individual model can be overcome by combining several individual models to achieve the generalization ability because the individual model's generalization ability could not reach the desired level. The majority of the cooperative model's average cooperation of different model results may have minor variation compared to the individual model, and the cooperative model achieves better generalization. Still, the individual models may be diverse in generalization. Hence, the cooperative neural network model is termed as an expert model superior to individual models. This paper proposed a model developed based on the joined together and averaged (ensemble) of two inputs, three inputs, four inputs, five inputs, and six inputs associated 

 TABLE 1: Proposed cooperative multi-input multilayer perceptron neural network designed parameters.

	CMMLPNN
Input neurons	= multi-inputs (2, 3, 4, 5, and 6 inputs)
Number of hidden layers	=1
Number of hidden neurons	=1-20
Output neuron	=1
Number of epochs	=1000
Threshold	=1
Learning rate	=0.9

with multilayer perceptron neural networks, which can be applied to the solar irradiance application.

Table 1 represented the designed parameters of the proposed CMMPLNN. In CMMPLNN, each developed neural network (MLPNN) has the same parameters except the number of input parameters. According to Table 1, mentioned parameter-based design of a cooperative multi-input multilayer perceptron neural network framework is shown in the Figure 1 for better understanding. Solar irradiance and temperature are considered as the inputs for the developed two input-based multilayer perceptron neural networks. It has one hidden layer in which the hidden neurons vary from 1 to 20; based on the minimal error, the optimal hidden neurons are chosen for the hidden layer and have one output layer to forecast the solar irradiance as the output neuron.

For the designed three input-based multilayer perceptron neural networks, solar irradiance, temperature, and relative humidity are considered as the inputs. It has one hidden layer in which hidden neurons vary from 1 to 20 based on the minimal error optimal hidden neurons that are chosen for the hidden layer and has one output layer to forecast solar irradiance as the output neuron.

For the developed four input-based multilayer perceptron neural networks, solar irradiance, temperature, relative humidity, and wind speed are considered as the inputs. It has one hidden layer in which hidden neurons vary from 1 to 20 based on the minimal error optimal hidden neurons are chosen for the hidden layer and has one output layer to forecast solar irradiance as the output neuron.

The inputs are considered for the designed five inputbased multilayer perceptron neural networks, solar irradiance, temperature, relative humidity, wind speed, and pressure. It has one hidden layer in which hidden neurons vary from 1 to 20. Based on the minimal error, the optimal hidden neurons are chosen for the hidden layer and have one output layer to forecast solar irradiance as the output neuron.

For the developed six input-based multilayer perceptron neural networks, solar irradiance, temperature, relative humidity, wind speed, pressure, and cloud cover are considered as the inputs. It has one hidden layer in which hidden neurons vary from 1 to 20 based on the minimal error optimal hidden neurons that are chosen for the hidden layer and has one output layer to forecast solar irradiance as the output neuron.



FIGURE 1: The framework of the proposed cooperative multi-input multilayer perceptron neural network.

According to the amalgamation and averaging of the developmental individual multi-input-based multilayer perceptron neural network, the proposed cooperative multiinput multilayer perceptron neural network outputs are achieved.

4.2. Mathematical Modeling of Proposed Cooperative Multi-Input Multilayer Perceptron Neural Network. In neural network modeling, one of the thrust fields is the development of generic models. For a multilayer perceptron neural network, the output neurons are defined as neurons without the source of any link, and hidden neurons are defined as neurons with the linkage of input and output neurons. Input neurons are defined as neurons with no target of linkage. Each neuron in the neural network has an activation function, and the net input exists only in the hidden and output neurons. The mathematical modeling of the proposed CMMLPNN is as follows:

CMMLPNN output = 
$$\frac{1}{T} \sum_{n=1}^{T} C_{n\text{MLPNN}}$$
 for  $n = 1, 2.3 \cdots, T$ . (1)

Let *T* be the number of multi-input multilayer neural networks:

Forecasted solar irradiance

$$=\frac{C_{2MLPNN} + C_{3MLPNN} + C_{4MLPNN} + C_{5MLPNN} + C_{6MLPNN}}{5}.$$
(2)

The output of the individual MLPNN:

$$C_{\text{nMLPNN}} = f\left(\sum_{b=1}^{m} (G_b S_b)\right).$$
(3)

Hidden layer output of the individual MLPNN:

$$G_b = f\left(\sum_{a=1}^{o} \sum_{b=1}^{m} r_a L_{ab}\right) \tag{4}$$

Let S be the hidden to output layer linkage weight, L is the input to hidden layer linkage weights, m is the number of hidden neurons, r is the inputs, o is the number of input neurons, and G is the output of the hidden layer.

Perform the training and testing process, compute the performance indicator (error value), and based on the least error value, hidden neurons are chosen in the hidden layer, and the performance is quantified. The following formulations are used in the computation of the proposed CMMLPNN performance indicator.

$$MSE_{CMMLPNN} = \frac{1}{T} \sum_{n=1}^{T} MSE_{nMLPNN},$$
(5)

$$RMSE_{CMMLPNN} = \frac{1}{T} \sum_{n=1}^{T} RMSE_{nMLPNN}, \qquad (6)$$

$$MAE_{CMMLPNN} = \frac{1}{T} \sum_{n=1}^{T} MAE_{nMLPNN},$$
 (7)



FIGURE 2: The process flow of the proposed cooperative multi-input multilayer perceptron neural network. Note: The MSE, RMSE, MAE, MRE, MAPE, *R*, and convergence time are chosen as the performance indicator.

Solar irradiance (W/m <sup>2</sup> )	Temperature (°C)	Relative humidity (%)	Wind speed (m/s)	Pressure (mbar)	Cloud cover (Oktas)
38	26	88	4.1	992	3
162	29	85	5.2	993	2
297	30	75	6.2	992	1
392	31	72	7	991	1
436	36	70	7.2	993	0
419	33	67	6	993	1
273	30	67	6.3	992	2
120	25	72	4	991	2
59	22	75	5	992	3
5	19	75	8	993	5

 TABLE 2: Acquired real-time input data samples.

$$MRE_{CMMLPNN} = \frac{1}{T} \sum_{n=1}^{T} MRE_{nMLPNN},$$
 (8)

$$MAPE_{CMMLPNN} = \frac{1}{T} \sum_{n=1}^{T} MAPE_{nMLPNN}.$$
 (9)

Based on the abovementioned mathematical formulations, the proposed model is developed.

4.3. Experimental Design Flow. Furthermore, providing a better understanding of the proposed model process flow illustrated in Figure 2, which infers the clear working mechanism of the proposed model.

4.3.1. Algorithm of the Proposed CMMLPNN-Based Forecasting Model. The proposed cooperative multi-input multilayer perceptron neural network algorithm is as follows:

- (i) Start process of cooperative multi-input multilayer perceptron neural network-based forecasting
- (ii) Solar irradiance forecasting is chosen to validate the proposed model; so, real-time measured data related to the solar irradiance and the influencing parameters are also acquired
- (iii) The acquired real-time measured data sets possess various parameters; each parameter has various values and various units. The process of normalization is required to resolve the variance present in the real-time data. In this work, the proposed model min-max normalization method is adopted for normalization
- (iv) The acquired data are classified into two sets; one set is used for the training purpose, and another set is used for the testing purpose. Note: both training and testing data sets are not the same; the unseen data during training are only considered for testing purposes
- (v) The proposed cooperative multi-input multilayer perceptron neural networks possess a compound





FIGURE 3: Acquired dataset solar irradiance vs. data samples.

of five individual multi-input multilayer perceptron neural networks (i.e., 2 inputs MLPNN, 3 inputs MLPNN, 4 inputs MLPNN, 5 inputs MLPNN, and 6 inputs MLPNN) each individually developed MLPNN posses one input layer, one hidden layer, and one output layer. The hidden neurons in the hidden layer vary from 1 to 20; similarly, the input neurons in the input layer vary from 2 to 6

- (vi) After choosing the individual neural network parameters, each developed individual multilayer perceptron neural network models (i.e., 2 inputs MLPNN, 3 inputs MLPNN, 4 inputs MLPNN, 5 inputs MLPNN, and 6 inputs MLPNN) are undergoing the training process. Authors verify the trained individual neural network performance with the help of the testing data set. If it results in acceptable performance in the testing process, the further moves to the next phase; else, it changes the neural network parameters again
- (vii) The individually developed various input-based multilayer perceptron neural networks achieve good, acceptable performance in the testing



FIGURE 4: (a) Training dataset solar irradiance vs. data samples. (b) Testing dataset solar irradiance vs. data samples.

Number of hidden neurons	MSE	RMSE	MAE	MRE	MAPE	R	Time
1	5.9621 <i>E</i> -04	2.4400E-02	1.8400 <i>E</i> -02	7.8434E-05	7.8000E-03	1	58
2	2.5732E-05	5.1000E-03	3.5000E-03	1.4916E-05	1.5000E-03	1	65
3	2.0864E-05	4.6000E-03	3.1000E-03	1.3117 <i>E</i> -05	1.3000E-03	1	72
4	3.2662E-05	5.7000E-03	3.7000E-03	1.5963E-05	1.6000E-03	1	63
5	9.9427 <i>E</i> -05	1.0000 <i>E</i> -02	5.8000E-03	2.4773E-05	2.5000E-03	1	84
6	3.2997E-05	5.7000E-03	4.0000E-03	1.7155E-05	1.7000E-03	1	95
7	1.0345 <i>E</i> -05	3.2000E-03	2.1000E-03	9.0101 <i>E</i> -06	9.0101 <i>E</i> -04	1	94
8	3.9008E-05	6.2000E-03	4.3000E-03	1.8411 <i>E</i> -05	1.8000E-03	1	115
9	1.0326E-05	3.2000E-03	1.9000E-03	8.2489E-06	8.2489E-04	1	123
10	2.3071 <i>E</i> -05	4.8000 <i>E</i> -03	2.5000E-03	1.0649 <i>E</i> -05	1.1000 <i>E</i> -03	1	130
11	4.6940 <i>E</i> -05	6.9000 <i>E</i> -03	4.3000E-03	1.8278E-05	1.8000E-03	1	138
12	1.7479 <i>E</i> -05	4.2000E-03	2.6000E-03	1.1246E-05	1.1000 <i>E</i> -03	1	143
13	1.4382E-04	1.2000 <i>E</i> -02	6.4000 <i>E</i> -03	2.7454 <i>E</i> -05	2.7000E-03	1	149
14	7.3628E-05	8.6000E-03	4.7000E-03	2.0134E-05	2.0000E-03	1	158
15	8.8216E-05	9.4000E-03	4.9000E-03	2.0812E-05	2.1000E-03	1	167
16	1.5738E-05	4.0000E-03	2.2000E-03	9.3960E-06	9.3960E-04	1	174
17	7.2175E-06	2.7000E-03	1.6000E-03	7.0335E-06	7.0335E-04	1	181
18	4.3428E-05	6.6000E-03	1.6000E-03	6.9534E-06	6.9534E-04	1	186
19	5.9552 <i>E</i> -04	2.4400 <i>E</i> -02	1.3500 <i>E</i> -02	5.7478 <i>E</i> -05	5.7000 <i>E</i> -03	1	195
20	3.2674 <i>E</i> -05	5.7000 <i>E</i> -03	2.7000 <i>E</i> -03	1.1551 <i>E</i> -05	1.2000 <i>E</i> -03	1	175

TABLE 3: Two input multilayer perceptron neural network performance analyses with different numbers of hidden neurons.

Bold implies the optimal result.

process. All obtained results from the individual multilayer perceptron neural networks are accumulated and averaged, facilitating the cooperative multi-input multilayer perceptron neural network output

(viii) Check the performance of the cooperative multilayer perceptron neural network if its acceptable or not. If the performance is acceptable, record the result; else, change the number of hidden neurons and again do the design, initialization, training, testing, accumulation, and averaging process until the optimal output is achieved with minimal errors 4.3.2. Data Description. The required real-time data are collected from the NOAA (National Oceanic and Atmospheric Administration, United States) to validate the proposed forecasting model. The real-time data were collected for the period from January 1981 to December 2019. A total of 3, 32, 880 numbers of data samples of each considered input parameter are acquired. The solar irradiance (W/m<sup>2</sup>), temperature (°C), relative humidity (%), wind speed (m/s), pressure (mbar), and cloud cover (Oktas) are inputs to the developed neural network, and the neural network output is the forecast solar irradiance (W/m<sup>2</sup>). Authors consider these atmospheric parameters as the most influencing parameters of the solar irradiance forecasting process.



FIGURE 5: (a) Two input MLPNN-based forecasting model original targets compared to forecast solar irradiance. (b) Two input MLPNNbased forecasting model forecasting errors vs. the number of data samples.

Table 2 shows the acquired real-time data sample inputs. Concerning the acquired real-time dataset, a cooperative multi-input multilayer perceptron neural network was proposed for the forecasting of solar irradiance. Some portions of the acquired data samples with respect to the solar irradiance are shown in Figure 3: acquired dataset solar irradiance vs. data samples.

4.3.3. Normalization. To deal with the real-time data set, the process of normalization is much needed; the real-time data possess the variance with respect to different ranges and different units. Therefore, the acquired real-time data scaled within the range of 0 to1 with the help of the min-max normalization process. The normalization process aids in accurate numeric computation and output accuracy improvement. The real-time data are normalized based on the following transformation equation.

Normalized input is as follows:

$$R_i' = \left(\frac{R_i - R_{\min}}{R_{\max} - R_{\min}}\right) \left(R_{\max} - R_{\min}\right) + R_{\min}.$$
 (10)

Let  $R_i$  be the actual input data,  $R_{\min}$  is the minimum input data,  $R_{\max}$  is the maximum input data,  $'R_{\min}$  is the minimum target value, and  $'R_{\max}$  is the maximum target value.

4.3.4. Training and Testing. Solar irradiance prevails with arbitrary nature. Several years (past decades) of hourly solar irradiance and meteorological data are acquired from the National Oceanic and Atmospheric Administration (NOAA), which are processed for the training and testing process of the proposed model. To evaluate the proposed model's effectiveness, real-time acquired data sets are used for the training and testing process.

For the experimental simulation, 70 percentages of realtime data sets were used in the neural network for the training process as the training data set. The remaining 30 percent of the data samples of the real-time measured data set are used in the neural network testing process as the testing data set. We show some of the training data set portions with respect to the solar irradiance in Figure 4(a): training dataset solar irradiance vs. data samples; similarly, we show some portions of the testing data set regarding solar irradiance in Figure 4(b): testing dataset solar irradiance vs. data samples.

4.3.5. Performance Indicators. Authors quantify the performance and effectiveness based on the performance indicators (i.e., MSE, RMSE, MAE, MRE, MAPE, *R*, and time). Following performance indicators such as MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error), MRE (mean relative error), MAPE (mean absolute percentage error), and *R* (correlation coefficient) are quantifying the efficacy of proposed CMMLPNN.

$$MSE = \frac{1}{K} \sum_{d=1}^{K} \left( R'_{d} - R_{d} \right)^{2},$$
 (11)

$$\text{RMSE} = \sqrt{\left(\frac{1}{K}\sum_{d=1}^{K} \left(R'_d - R_d\right)^2\right)},$$
 (12)

MAE = 
$$\frac{1}{K} \sum_{d=1}^{K} \left( R'_d - R_d \right),$$
 (13)

$$MRE = \frac{1}{K} \sum_{d=1}^{K} \left| \left( R'_d - R_d \right) / \bar{R}_d \right|, \qquad (14)$$

MAPE = 
$$\frac{100}{K} \sum_{d=1}^{K} \left| \left( R'_d - R_d \right) / \bar{R}_d \right|,$$
 (15)



FIGURE 6: (a) Two input MLPNN-based forecasting model regression graphs. (b) Two input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons.

$$R = 1 - \left(\frac{\sum_{d=1}^{K} \left(R'_{d} - R_{d}\right)}{\sum_{d=1}^{K} R_{d}}\right)^{2}.$$
 (16)

Let K be the total number of data samples,  $R'_d$  is the original target output,  $\overline{R}_d$  is the average original target output, and  $R_d$  is the forecast output.

4.3.6. Fixation of Hidden Neurons. For neural network modeling, the fixation of hidden neurons is a significant problem. The hidden neurons are increased, which increases the complexity and computation time and overfitting issue; else, the hidden neurons are decreased, which causes the underfitting issue [43–45]. Therefore, it is crucial to fix the number of hidden neurons in a neural network. The proposed and developed neural network model, optimal hidden neurons, is chosen with respect to the trial-and-error method. The developed neural network hidden layer hidden neurons vary from one to twenty among the optimal number of hidden neurons that is chosen based on the computed performance indicator.

#### 5. Results and Discussion

Solar energy vendor companies require a forecasting tool for planning effectively to achieve optimal production and dispatch. The power grid's efficient operation requires accurate forecasting of resources and power production to avoid power outages and reduce the spare (standby) power capacity. This research paper worked on cooperative multi-input MLPNN to prevent the generalization problem and the meteorological impact of solar irradiance forecasting.

The accumulation and average of various finite numbers of individual artificial neural networks are known as cooperative neural networks, in which considered all individual artificial neural networks are trained and tested for the con-



FIGURE 7: Two input MLPNN-based forecasting model simulation times vs. the number of hidden neurons.

sidered application. Even though the training and testing set are the same, the developed individual neural network results in various outputs for various hidden neurons in the hidden layer. For multiple inputs, data sets indeed result in variance in output. The major problem with respect to the forecasting model results in a better result for the considered input parameters. Still, it cannot generalize better for the other number of input parameters. The input parameters and hidden neurons play vital roles in neural network performance. Hence, this paper proposes the cooperative multi-input multilayer perceptron neural network. Even though the input parameters are different, the training and testing data sets are different, and the proposed model outperforms especially generalizations well.

Suppose the atmospheric pressure changes lead to changes in the wind velocity, which affects the solar irradiance and temperature, similarly, cloud cover varies; it affects

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TABLE 4: Three input multi	ayer perceptron net	iral network performance	ce analyses with a differe	nt number of hidden neurons.
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Number of hidden neurons	MSE	RMSE	MAE	MRE	MAPE	R	Time
1	7.5132E-04	2.7400 <i>E</i> -02	2.1500E-02	9.1951 <i>E</i> -05	9.2000E-03	1	62
2	2.2009E-05	4.7000E-03	3.1000E-03	1.3413E-05	1.3000E-03	1	84
3	3.7842E-06	1.9000E-03	1.3000E-03	5.4536E-06	5.4536E-04	1	71
4	3.2406E-05	5.7000E-03	3.8000E-03	1.6203E-05	1.6000E-03	1	117
5	1.9311 <i>E</i> -04	1.3900 <i>E</i> -02	7.1000 <i>E</i> -03	3.0474 <i>E</i> -05	3.0000 <i>E</i> -03	1	125
6	1.3315E-05	3.6000E-03	2.3000E-03	9.7935E-06	9.7935 <i>E</i> -04	1	120
7	5.7396E-06	2.4000E-03	1.5000 <i>E</i> -03	6.3661 <i>E</i> -06	6.3661 <i>E</i> -04	1	99
8	7.6763E-05	8.8000 <i>E</i> -03	5.0000 <i>E</i> -03	2.1517E-05	2.2000E-03	1	116
9	2.9000E-03	5.4300 <i>E</i> -02	9.9000E-03	4.2146E-05	4.2000E-03	1	124
10	9.9727E-05	1.0000E-02	6.5000E-03	2.7714E-05	2.8000E-03	1	111
11	5.9904E-06	2.4000E-03	1.7000E-03	7.0656E-06	7.0656E-04	1	101
12	2.9376E-05	5.4000E-03	3.3000E-03	1.4139E-05	1.4000 <i>E</i> -03	1	150
13	3.9100E-02	1.9780E-01	2.8700E-02	1.2250E-04	1.2300E-02	1	161
14	3.6238E-06	1.9000E-03	1.2000E-03	5.0432E-06	5.0432E-04	1	101
15	2.4000E-03	4.8700E-02	1.1700E-02	4.9846E-05	5.0000E-03	1	167
16	8.8000E-03	9.3600E-02	1.3500 <i>E</i> -02	5.7755 <i>E</i> -05	5.8000E-03	1	206
17	4.6900 <i>E</i> -04	2.1700E-02	7.8000 <i>E</i> -03	3.3439 <i>E</i> -05	3.3000E-03	1	204
18	9.4980E-08	3.0819E-04	1.2680E-04	5.4138E-07	5.4138E-05	1	156
19	1.2000 <i>E</i> -03	3.5200 <i>E</i> -02	9.6000E-03	4.0829E-05	4.1000E-03	1	159
20	9.3967E-04	3.0700 <i>E</i> -02	9.5000 <i>E</i> -03	4.0628 <i>E</i> -05	4.1000 <i>E</i> -03	1	195

Bold implies the optimal result.



FIGURE 8: (a) Three input MLPNN-based forecasting model original targets compared to forecast solar irradiance. (b) Three input MLPNN-based forecasting model forecasting errors vs. the number of data samples.

solar irradiance. The meteorological impact on solar irradiance forecasting is overcome by considering the most influencing atmospheric parameters as the inputs to the developed neural network.

This paper carried out a statistical performance analysis of the designed and proposed neural network models with

respect to the various hidden neurons in the solar irradiance forecasting application.

5.1. Statistical Performance Analysis of Two Input MLPNN-Based Forecastings of Solar Irradiance. The developed two input-based multilayer perceptron neural network (MLPNN)



FIGURE 9: (a) Three input MLPNN-based forecasting model regression graphs. (b) Three input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons.

forecasting model performances are statistically analyzed based on various hidden neurons from one to twenty hidden neurons. We tabulate the results in Table 3.

From the careful analysis of Table 3, it was noticed that the 17 numbers of hidden neurons in the hidden layer of two input-based MLPNNs achieve the minimal errors (i.e., MSE as 7.2175E-06, RMSE as 2.7000E-03, MAE as 1.6000E-03, MRE as 7.0335E-06, MAPE as 7.0335E-04, and *R* as 1) among the other considered number of hidden neurons. We show the obtained portion of the results based on two input MLPNNs with 17 hidden neurons in the hidden layer in Figure 5 due to page limitation.

Figure 5(a) shows the two input-MLPNN-based forecasting model original target comparison to forecast solar irradiance. It implies that the developed model-based forecasted solar irradiance highly matched with the original target taken into consideration. Therefore, it results in very minimal errors, which can be seen from Figure 5(b): two input MLPNN-based forecasting model forecasting errors vs. a number of data samples and Figure 6(a): two input MLPNN-based forecasting model regression graphs. The developmental model-based regression graph is linear in nature, which states the developed model's good forecasting performance. Furthermore, the statistical analysis considering the number of hidden neurons is graphically represented in Figure 6(b): two input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons. The hidden neurons vary, and the neural network's stability is also varied, which causes the irregular nature of the forecasting errors. The computational time-based impact on the hidden neurons is shown in Figure 7. Two input MLPNN-based forecasting model simulation times vs. the number of hidden neurons is irregular in nature because hidden neurons impact errors and impact the computational time, which



FIGURE 10: Three input MLPNN-based forecasting model simulation times vs. the number of hidden neurons.

can be understood from Figure 7. The validation results indicate that the proposed model is capable of forecasting accurate solar irradiance.

5.2. Statistical Performance Analysis of Three Input MLPNN-Based Forecastings of Solar Irradiance. The designed three input-based multilayer perceptron neural network (MLPNN) forecasting model performances are statistically analyzed based on various hidden neurons from one to twenty hidden neurons. The obtained results are tabulated in Table 4. From the careful analysis of Table 4, it was noticed that the 18 numbers of hidden neurons in the hidden layer of three input-based MLPNNs achieve the minimal errors (i.e., MSE as 9.4980E-08, RMSE as 3.0819E-04,

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Number of hidden neurons	MSE	RMSE	MAE	MRE	MAPE	R	Time
1	7.4471 <i>E</i> -04	2.7300E-02	2.1600E-02	9.2146 <i>E</i> -05	9.2000E-03	1	66
2	3.0940E-05	5.6000E-03	3.8000E-03	1.6033 <i>E</i> -05	1.6000 <i>E</i> -03	1	91
3	2.6547E-05	5.2000E-03	3.7000E-03	1.5660 <i>E</i> -05	1.6000E-03	1	96
4	2.1062E-05	4.6000E-03	3.1000E-03	1.3174 <i>E</i> -05	1.3000E-03	1	105
5	1.3344E-05	3.7000E-03	2.5000E-03	1.0689 <i>E</i> -05	1.1000E-03	1	84
6	2.3965E-05	4.9000E-03	3.4000E-03	1.4307 <i>E</i> -05	1.4000E-03	1	42
7	6.8545E-06	2.6000E-03	1.7000 <i>E</i> -03	7.2897 <i>E</i> -06	7.2897 <i>E</i> -04	1	50
8	3.9139E-05	6.3000 <i>E</i> -03	4.0000 <i>E</i> -03	1.7231 <i>E</i> -05	1.7000 <i>E</i> -03	1	69
9	5.2354E-06	2.3000E-03	1.5000 <i>E</i> -03	6.3354 <i>E</i> -06	6.3354 <i>E</i> -04	1	135
10	7.5525E-06	2.7000E-03	1.8000E-03	7.6150E-06	7.6150E-04	1	137
11	8.4789E-05	9.2000E-03	5.4000E-03	2.3004 <i>E</i> -05	2.3000E-03	1	151
12	1.4577E-04	1.2100 <i>E</i> -02	7.3000E-03	3.0965 <i>E</i> -05	3.1000E-03	1	196
13	4.1533E-04	2.0400E-02	6.9000E-03	2.9265E-05	2.9000E-03	1	178
14	1.6703 <i>E</i> -04	1.2900E-02	5.4000E-03	2.3216E-05	2.3000E-03	1	253
15	6.2997E-08	2.5099E-04	1.4464E-04	6.1756E-07	6.1756E-05	1	70
16	2.0957E-05	4.6000E-03	1.6000E-03	7.0276 <i>E</i> -06	7.0276 <i>E</i> -04	1	139
17	2.4974 <i>E</i> -06	1.6000E-03	6.9899 <i>E</i> -04	2.9845 <i>E</i> -06	2.9845 <i>E</i> -04	1	174
18	7.1545E-05	8.5000E-03	4.7000E-03	2.0092E-05	2.0000E-03	1	247
19	5.2397E-04	2.2900E-02	5.5000E-03	2.3429 <i>E</i> -05	2.3000E-03	1	218
20	1.1324 <i>E</i> -05	3.4000E-03	1.9000E-03	8.1852 <i>E</i> -06	8.1852E-04	1	212

Bold implies the optimal result.



FIGURE 11: (a) Four input MLPNN-based forecasting model original targets compared to forecast solar irradiance. (b) Four input MLPNNbased forecasting model forecasting errors vs. the number of data samples.

MAE as 1.2680E-04, MRE as 5.4138E-07, MAPE as 5.4138E -05, and *R* as 1) among the other considered number of hidden neurons. We show the obtained portion of the results based on three input MLPNNs with 18 hidden neurons in the hidden layer in Figure 8 due to page limitation.

Figure 8(a) shows that the three input MLPNN-based forecasting model original target comparisons to forecast

solar irradiance implies that the developed model-based forecasted solar irradiance highly matched with the original target taken into consideration. Therefore, it results in very minimal errors, which can be seen from Figure 8(b): three input MLPNN-based forecasting model forecasting errors vs. number of data samples and Figure 9(a): three input MLPNN-based forecasting model regression graphs. The



FIGURE 12: (a) Four input MLPNN-based forecasting model regression graphs. (b) Four input MLPNN-based forecasting model forecasting error vs. the number of hidden neurons.

designed model-based regression graph is linear in nature, which states the developed model's good forecasting performance.

Furthermore, the statistical analysis considering a number of hidden neurons is graphically represented in Figure 9(b): three input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons. The hidden neurons vary, and the neural network's stability is also varied, which causes the irregular nature of the forecasting errors. The computational time-based impact on the hidden neurons is shown in Figure 10. Three input MLPNNbased forecasting model simulation times vs. the number of hidden neurons are irregular in nature because hidden neurons impact errors and the computational time, which can be understood from Figure 10. The validation results indicate that the proposed model is capable of forecasting accurate solar irradiance.

5.3. Statistical Performance Analysis of Four Input MLPNN-Based Forecastings of Solar Irradiance. The developed four input-based multilayer perceptron neural network (MLPNN) forecasting model performances are statistically analyzed based on various hidden neurons from one to twenty hidden neurons, and the obtained results are tabulated in Table 5. From the careful analysis of Table 5, it was noticed that the 15 numbers of hidden neurons in the hidden layer of four input-based MLPNNs achieve the minimal errors (i.e., MSE as 6.2997E-08, RMSE as 2.5099E-04, MAE as 1.4464E-04, MRE as 6.1756E-07, MAPE as 6.1756*E*-05, and *R* as 1) among the other considered number of hidden neurons. We show the obtained portion of the results based on four input MLPNNs with 15 hidden neurons in the hidden layer in Figure 11 due to page limitation. Figure 11(a) shows that the four input MLPNN-based forecasting model original target comparisons to forecast solar



FIGURE 13: Four input MLPNN-based forecasting model simulation times vs. number of hidden neurons.

irradiance implies that the developed model-based forecasted solar irradiance highly matched with the original target taken into consideration. Therefore, it results in very minimal errors, which can be seen from Figure 11(b): four input MLPNN-based forecasting model forecasting errors vs. the number of data samples and Figure 12(a): four input MLPNN-based forecasting model regression graphs.

The developmental model-based regression graph is linear in nature, which states the developed model's good forecasting performance. Furthermore, the statistical analysis considering the number of hidden neurons is graphically represented in Figure 12(b). The hidden neurons vary, and the neural network's stability is also varied, which causes the irregular nature of the forecasting errors. The computational time-based impact on the hidden neurons is shown in

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Number of hidden neurons	MSE	RMSE	MAE	MRE	MAPE	R	Time
1	8.8866E-04	2.9800E-02	2.1400 <i>E</i> -02	9.1578E-05	9.2000E-03	1	63
2	2.1000E-03	4.5800 <i>E</i> -02	2.8200 <i>E</i> -02	1.2054 <i>E</i> -04	1.2100 <i>E</i> -02	1	77
3	2.1164 <i>E</i> +01	4.6005	2.5291	1.0800 <i>E</i> -02	1.0798	9.9997E-01	85
4	1.4053E-04	1.1900E-02	6.8000E-03	2.8928E-05	2.9000E-03	1	86
5	1.8456E-04	1.3600 <i>E</i> -02	7.3000E-03	3.1340E-05	3.1000 <i>E</i> -03	1	76
6	1.4665	1.2110	1.0607	4.5000 <i>E</i> -03	4.5290E-01	1	114
7	2.4758E-04	1.5700 <i>E</i> -02	1.1800 <i>E</i> -02	5.0208E-05	5.0000E-03	1	78
8	4.3498E+02	2.0856E+01	1.3909 <i>E</i> +01	5.9400 <i>E</i> -02	5.9386	9.9945 <i>E</i> -01	136
9	7.9277E+01	8.9037	6.7448	2.8800E-02	2.8798	9.9989E-01	144
10	1.1000 <i>E</i> -03	3.2500E-02	2.3300E-02	9.9492 <i>E</i> -05	9.9492E-05	1	146
11	1.5882E+02	1.2602E+01	1.1004E+01	4.7000 <i>E</i> -02	4.6982	9.9984 <i>E</i> -01	167
12	2.2279E+03	4.7200E+01	3.5290E+01	1.5070E-01	1.5068E+01	9.9655E-01	176
13	5.3100E-02	2.3050E-01	8.9600E-02	3.8240 <i>E</i> -04	3.8200E-02	1	183
14	1.4020E-01	3.7450E-01	2.2400E-01	9.5640 <i>E</i> -04	9.5600E-02	1	192
15	9.0506 <i>E</i> +01	9.5135	3.7441	1.6000 <i>E</i> -02	1.5986	9.9960E-01	200
16	2.1349E+01	4.6205	2.0997	9.0000E-03	8.9650E-01	9.9994 <i>E</i> -01	162
17	1.3000E-03	3.6500 <i>E</i> -02	2.8500E-02	1.2188 <i>E</i> -04	1.2200E-02	1	124
18	3.0136 <i>E</i> +02	1.7360E+01	5.8302	2.4900 <i>E</i> -02	2.4893	9.9907E-01	100
19	2.1978E+03	4.6881 <i>E</i> +01	3.8933 <i>E</i> +01	1.6620 <i>E</i> -01	1.6623 <i>E</i> +01	9.9662E-01	247
20	1.1940 <i>E</i> +02	1.0927E+01	7.6431	3.2600 <i>E</i> -02	3.2633	9.9984 <i>E</i> -01	240

Bold implies the optimal result.



FIGURE 14: (a) Five input MLPNN-based forecasting model original targets compared to forecast solar irradiance. (b) Five input MLPNN-based forecasting model forecasting errors vs. the number of data samples.

Figure 13. Four input MLPNN-based forecasting model simulation times vs. the number of hidden neurons is irregular in nature because hidden neurons impact errors and the computational time, which can be understood from Figure 13. The validation results indicate the proposed model that is capable of forecasting accurate solar irradiance. 5.4. Statistical Performance Analysis of Five Input MLPNN-Based Forecastings of Solar Irradiance. The designed five input-based multilayer perceptron neural network (MLPNN) forecasting model performances are statistically analyzed based on the various hidden neurons, from one to twenty hidden neurons, and the obtained results are



FIGURE 15: (a) Five input MLPNN-based forecasting model regression graphs. (b) Five input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons.

tabulated in Table 6. From the careful analysis of Table 6, it was noticed that the 4 numbers of hidden neurons in the hidden layer of five input-based MLPNNs achieve the minimal errors (i.e., MSE as 1.4053E-04, RMSE as 1.1900E-02, MAE as 6.8000E-03, MRE as 2.8928E-05, MAPE as 2.9000E-03, and *R* as 1) among the other considered number of hidden neurons. We show the obtained portion of the results based on five input MLPNNs with four hidden neurons in the hidden layer in Figure 14 due to page limitation.

Figure 14(a) shows that the five input MLPNN-based forecasting model original target comparisons to forecast solar irradiance implies that the developed model-based forecasted solar irradiance highly matched with the original target taken into consideration. Therefore, it results in very minimal errors, which can be seen from Figure 14(b): five input MLPNN-based forecasting model forecasting errors vs. the number of data samples and Figure 15(a): five input MLPNN-based forecasting model regression graphs. The designed model-based regression graph is linear in nature, which states the developed model's good forecasting performance. Furthermore, the statistical analysis considering the number of hidden neurons is graphically represented in Figure 15(b): five input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons.

The hidden neurons vary, and the neural network's stability is also varied, which causes the irregular nature of the forecasting errors. The computational time-based impact on the hidden neurons is shown in Figure 16. Five input MLPNN-based forecasting model simulation times vs. the number of hidden neurons is irregular because hidden neurons impact errors and computational time, which can be understood from Figure 16.

The validation results indicate that the proposed model is capable of forecasting accurate solar irradiance.



FIGURE 16: Five input MLPNN-based forecasting model simulation times vs. the number of hidden neurons.

5.5. Statistical Performance Analysis of Six Input MLPNN-Based Forecastings of Solar Irradiance. The developed six input-based multilayer perceptron neural network (MLPNN) forecasting model performances are statistically analyzed based on various hidden neurons, from one to twenty hidden neurons, and the obtained results are tabulated in Table 7. From the careful analysis of Table 7, it was noticed that the 2 numbers of hidden neurons in the hidden layer of six input-based MLPNNs achieve the minimal errors (i.e., MSE as 4.3744E-05, RMSE as 6.6000E-03, MAE as 4.0000E-03, MRE as 1.7068E-05, MAPE as

TABLE 7: Six inputs multilayer perceptron neural network performance analyses with different numbers of hidden neurons.

Number of hidden neurons	MSE	RMSE	MAE	MRE	MAPE	R	Time
1	1.0000 <i>E</i> -03	3.1900 <i>E</i> -02	2.3100E-02	9.8823 <i>E</i> -05	9.9000E-03	1	63
2	4.3744E-05	6.6000E-03	4.0000E-03	1.7068E-05	1.7000E-03	1	76
3	1.8655 <i>E</i> -04	1.3700 <i>E</i> -02	8.4000E-03	3.5887 <i>E</i> -05	3.6000E-03	1	81
4	1.7000E-03	4.1300E-02	2.6300E-02	1.1221 <i>E</i> -04	1.1200 <i>E</i> -02	1	95
5	2.0640E-01	4.5430E-01	3.9950E-01	1.7000 <i>E</i> -03	1.7060E-01	1	103
6	3.5592+03	5.9659 <i>E</i> +01	4.6116 <i>E</i> +01	1.9690E-01	1.9690E+01	9.9217E-01	111
7	2.0000E-03	4.5100E-02	2.2700E-02	9.6818E-05	9.7000E-03	1	122
8	7.9925 <i>E</i> +02	2.8271E+01	$2.0471E{+}01$	8.7400 <i>E</i> -02	8.7402 <i>E</i> +00	9.9905 <i>E</i> -01	138
9	2.4900E-02	1.5790E-01	9.9800E-02	4.2595 <i>E</i> -04	4.2600 <i>E</i> -02	1	145
10	7.0902 <i>E</i> -04	2.6600E-02	1.1300 <i>E</i> -02	4.8255 <i>E</i> -05	4.8000E-03	1	107
11	2.3000E-03	4.7900 <i>E</i> -02	3.9800E-02	1.6988 <i>E</i> -04	1.7000E-02	1	104
12	3.5173 +03	5.9307E+01	4.7161 <i>E</i> +01	2.0140E-01	2.0136E+01	9.9170E-01	176
13	8.0220E-01	8.9560E-01	4.4290E-01	1.9000E-03	1.8910E-01	1	177
14	5.9200E-01	7.6940 <i>E</i> -01	5.2990E-01	2.3000E-03	2.2620E-01	1	195
15	4.5008 <i>E</i> +03	6.7088 <i>E</i> +01	5.3522E+01	2.2850E-01	2.2852E+01	9.9208E-01	119
16	2.5650E-01	5.0650E-01	3.7800E-01	1.6000E-03	1.6140 <i>E</i> -01	1	139
17	8.4281	2.9031	1.0193	4.4000 <i>E</i> -03	4.3520E-01	9.9998E-01	232
18	1.0000E+02	1.0000E+01	7.1652	3.0600 <i>E</i> -02	3.0593	9.9985 <i>E</i> -01	172
19	1.0600 <i>E</i> -02	1.0280E-01	4.6700 <i>E</i> -02	1.9945 <i>E</i> -04	1.9900 <i>E</i> -02	1	174
20	1.3955E+01	3.7357	2.9459	1.2600 <i>E</i> -02	1.2578	9.9997 <i>E</i> -01	231

Bold implies the optimal result.



FIGURE 17: (a) Six input MLPNN-based forecasting model original targets compared to forecast solar irradiance. (b) Six input MLPNNbased forecasting model forecasting errors vs. the number of data samples.

1.7000*E*-03, and *R* as 1) among the other considered number of hidden neurons. Due to page limitation, the obtained portion of the results based on six input MLPNNs with two hidden neurons in the hidden layer is shown in Figures 17.

Figure 17(a) shows the six input MLPNN-based forecasting model original target comparisons with forecast solar irradiance, and it implies that the developed model-based forecasted solar irradiance highly matched with the original target taken into consideration. Therefore, it results in very minimal errors, which can be seen from Figure 17(b): six input MLPNN-based forecasting model forecasting errors vs. the number of data samples and Figure 18(a): six input MLPNN-based forecasting model regression graphs. The designed model-based regression graph is linear in nature,



FIGURE 18: (a) Six input MLPNN-based forecasting model regression graphs. (b) Six input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons.

which states the developed model's good forecasting performance. Furthermore, the statistical analysis considering the number of hidden neurons is graphically represented in the Figure 18(b): six input MLPNN-based forecasting model forecasting errors vs. the number of hidden neurons. The hidden neurons vary, and the neural network's stability is also varied, which causes the irregular nature of the forecasting errors. The computational time-based impact on the hidden neurons is shown in Figure 19. Six input MLPNN-based forecasting model simulation times vs. the number of hidden neurons is irregular because hidden neurons impact errors and computational time, which can be understood from Figure 19. The validation results show that the proposed model is capable of forecasting accurate solar irradiance.

5.6. Statistical Performance Analysis of Proposed Cooperative Multi-Input MLPNN-Based Forecasting of Solar Irradiance. The proposed cooperative multi-input multilayer perceptron neural network (CMMLPNN) forecasting model performance is statistically analyzed based on various hidden neurons, from one to twenty hidden neurons, and the obtained results are tabulated in Table 8. From the careful analysis of Table 8, it was noticed that the 4 numbers of hidden neurons in the hidden layer of CMMLPNN achieve the minimal errors (i.e., MSE as 0.000385, RMSE as 0.01384, MAE as 0.00874, MRE as 3.73E-05, MAPE as 0.00372, and R as 1) among the other considered number of hidden neurons. We show the obtained portion of the results based on CMMLPNN with 4 hidden neurons in the hidden layer in Figure 20 due to page limitation.

Figure 20(a) shows that the CMMLPNN-based forecasting model's original target compared to the forecast solar



FIGURE 19: Six input MLPNN-based forecasting model simulation times vs. the number of hidden neurons.

irradiance implies that the developed model-based forecasted solar irradiance is highly matched with the original target taken into consideration. Hence, it results in very minimal errors, which can be seen from Figure 20(b): CMMLPNN-based forecasting model forecasting error vs. the number of data samples and Figure 21(a): CMMLPNN-based forecasting model regression graph. The proposed model-based regression graph is linear, stating the developed model's good forecasting performance. Furthermore, the statistical analysis considering the number of

<b>TABLE 8: Cooperative multi-input</b>	ıt multilayer percep	tron neural network	performance analy	ysis with o	different numbers	of hidden neurons.
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Number of hidden neurons	MSE	RMSE	MAE	MRE	MAPE	R	Time
1	0.000796	0.02816	0.0212	9.06 <i>E</i> -05	0.00906	1	62
2	0.000444	0.01356	0.00852	3.64 <i>E</i> -05	0.00364	1	79
3	4.232908	0.92518	0.50912	0.002174	0.217369	0.999994	81
4	0.000385	0.01384	0.00874	3.73E-05	0.00372	1	93
5	0.041378	0.0991	0.08444	0.000359	0.03606	1	94
6	0.366643	12.17678	9.43732	0.040288	4.029396	0.998434	96
7	0.000454	0.0138	0.00796	3.39 <i>E</i> -05	0.003393	1	89
8	246.8467	9.82972	6.87858	0.029371	2.9369	0.9997	115
9	15.86092	1.82428	1.37158	0.005857	0.585612	0.999978	134
10	0.000388	0.01532	0.00908	3.87 <i>E</i> -05	0.001912	1	126
11	31.76393	2.53374	2.21096	0.009444	0.944001	0.999968	132
12	556.975	21.30572	16.49282	0.070431	7.04184	0.99765	168
13	0.178992	0.27126	0.1149	0.000492	0.04904	1	170
14	0.146489	0.23346	0.15304	0.000661	0.065321	1	180
15	918.2618	15.33193	11.45663	0.048914	4.891572	0.998336	145
16	4.322847	1.04584	0.499	0.002135	0.213068	0.999988	164
17	1.685976	0.59312	0.21158	0.000913	0.09034	0.999996	183
18	80.27228	5.475042	2.600365	0.011131	1.11027	0.999784	172
19	439.5626	9.41328	7.80156	0.033304	3.33094	0.999324	199
20	26.67178	2.94052	2.12062	0.009052	0.905444	0.999962	211

Bold implies the optimal result.



FIGURE 20: (a) CMMLPNN-based forecasting model original target compared to forecast solar irradiance. (b) CMMLPNN-based forecasting model forecasting error vs. the number of data samples.

hidden neurons is graphically represented in Figure 21(b): CMMLPNN-based forecasting model forecasting error vs. a number of hidden neurons. The hidden neurons vary, and the neural network's stability is also varied, which causes the irregular nature of the forecasting errors. The computational time-based impact on the hidden neurons is shown in Figure 22. CMMLPNN-based forecasting model simulation time vs. a number of hidden neurons is irregular because hidden neurons impact errors and computational time, which can be understood from Figure 22. The proposed model's effectiveness is demonstrated with the experimental simulation results, which implies that the proposed model achieves improved generalization with more stable and accurate outputs.



FIGURE 21: (a) CMMLPNN-based forecasting model regression graph. (b) CMMLPNN-based forecasting model forecasting error vs. the number of hidden neurons.

The atmospheric parameters (i.e., temperature, relative humidity, wind speed, pressure, and cloud cover) influence solar irradiance. Because of these influencing factors, solar irradiance possesses an irregular nature, affecting the energy production from the solar energy system. The varying and uncertain amount of power production from solar energy systems leads to grid security, imbalance, and outage problems. It significantly reduces the output forecasting error based on the proposed model to the minimum values. Although the individual neural network achieves impressive forecasting outputs under certain considered conditions, it cannot generalize well under various circumstances or data sets. The reason for proposing a cooperative multi-input multilayer perceptron neural network is to overcome the irregularity of meteorological parameters and the assurance of generalization.

From the obtained results based on the proposed model, we have confirmed that cooperative multi-input multilayer perceptron neural networks generalize well amongst other developed MLPNNs. It is noteworthy to mention that hidden neurons influence highly in neural network stability. The proposed forecasting model improves the forecasting accuracy with much minimal error and is generalized with respect to solar irradiance forecasting. Henceforth, it consequently aids in better power system performance with intermittent solar energy integration.

5.7. Comparative Analysis of the Proposed Method with *Existing Methodologies*. The proposed model's effectiveness is verified by real-time data-based experimental simulation and compared the proposed model performance with other existing traditional methods.



FIGURE 22: CMMLPNN-based forecasting model simulation time vs. the number of hidden neurons.

The inference of Table 9 based on comparative analysis is the proposed CMMLPNN not only generalized well but also a proposed competitive model that provides a better result than other models for the comparative analysis. We graphically illustrate the comparative analysis of existing and proposed methods in Figure 23 for better clarity of understanding. The comparative analysis in Table 9 infer the proposed model validity on solar irradiance forecasting.

TABLE 9: Comparative ana	lysis of different approach	performances of the existing	g and proposed methods.
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S. no	Year	Methods	Authors	Performance indicator (MSE)
1	2010	BPN	Özgür Solmaz et al. [11]	0.8472
2	2010	RBFN	Mohammed Benghamm and Adel Mellit [12]	0.0189
3	2012	ANN	Amit Kumar Yadav and S S Chandel [14]	2.8460
4	2012	BP-MLPN	H G CHUA et al. [15]	1.1744
5	2016	IBPN	Madhiarasan, M. and Deepa, SN [46]	0.0507
6	2016	INN	Madhiarasan, M. & Deepa, SN [18]	0.0036
7	2017	K-NN-BPLNN	Unit Three Kartini and Chao Rong Chen [24]	5.4827
8	2017	MLPN	Madhiarasan, M. and Deepa, SN [47]	0.0012
9	2018	NWP	Sowmya Tiwari et al. [33]	8.2628
10	2018	Elman neural network	Madhiarasan, M. and Deepa, SN [48]	0.1422
11	2018	ARMA	Irene Wanady [29]	1.6140
12	2018	BPN	Tanawat Laopaiboon et al. [30]	0.7336
13	2018	MLP	Marcello Anderson F. B. Lima et al. [27]	0.0283
14	2018	RELANFIS	Shihabudheen K V and G V Pillai [32]	0.6384
15	2018	WVE	Luyao et al. [28]	0.0781
16	2019	NARX	John Kevin Rogies and Nawaz Mohamudally [37]	0.9568
17	2019	LM based ANN	Sempe Leholo et al. [41]	0.2591
18	2019	ANN-NARX	Chigbogu Godwin Ozoegwu [38]	0.1918
19	2021	Proposed CMMLPNN	Madhiarasan, M et al.	0.000385

Bold implies an optimal result.



FIGURE 23: Comparative analysis of existing and proposed methods.

#### 6. Conclusion

In the future, renewable energy resources fulfill the power supply for industry and domestic, such as solar and wind, which say goodbye to the environment polluting power production scheme. Inevitably, solar energy plays a significant role in the forthcoming future. The solar energy system's forecasting model that ensures safe grid integration can resolve the variability problem. The power system engineer and research scientists give equal importance to accurate prediction and generalization. The variance present in the individual forecasting model can reduce by proposing a cooperative multi-input multilayer perceptron neural network, which improves the forecasting performance in terms of generalization and accuracy with the least forecasting error.

The neural network-based forecasting model performance is not only decided by the training and testing dataset. The selection of parameters like hidden neurons also has a potent influence on the predicted results. Therefore, this paper carried out a statistical analysis of each proposed MLPNN model with various numbers of hidden neurons from one to twenty. The performance analysis noticed that the neural network stability highly depends on the optimal hidden neurons. For one neural network model, the association of some hidden neurons gets a better result, and the model cannot address the generalization of other neural networks. To address this generalization problem, this paper endeavors a novel cooperative multi-input multilayer perceptron neural network to overcome the meteorological, hidden neuron, and generalization issues.

To prove the validity and effectiveness of the proposed neural network, a comparative analysis is carried out with other existing networks (i.e., BPN, ANN, BP-MLPN, ARMA, K-NN-BPLNN, NARX, NWP, Elman neural network, MLPN, INN, IBPN, LM based ANN, RBFN, WVE, ANN-NARX, and RELANFIS). The comparative analysis revealed that the CMMLPNN achieves the best performance among the other methods in the comparison table. CMMLPNN is a robust and superior one to other existing models.

The achieved results infer the proposed model's superiority in terms of generalization and accurate solar irradiance forecasting with the least minimal error indicator. The proposed model successfully applied for solar irradiance forecasting application in photovoltaic (PV) energy systems and achieved the aim fruitfully. The proposed model works well for various applications.

#### 7. Proposed Model Limitation and Future Work

Although the suggested forecasting model overcomes the uncertainty concerned with the interannual data, meteorological inputs, hidden neurons, and individual models, the limitation of the proposed model is the computational cost is more than the individual model. In future research, the authors plan to implement the proposed model in realtime scenarios, develop a hybrid deep learning-based ensemble model, and improve the optimal hyperparameter selection and fine tuning by novel optimization algorithms.

#### **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 that are not provided the data openly.

#### **Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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