Research Article

Combined Long Short-Term Memory Network-Based Short-Term Prediction of Solar Irradiance

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1. Introduction

Nowadays, much attention pays to solar energy systems because of increased energy crises and CO₂ emissions. Unfortunately, we do not have consistent sunshine for 24 hours. Sometimes we have sunny and cloudy days despite the seasons. The most frequently changing tendency of solar irradiance creates a challenging task to integrate the PV system into the power system. Short-term solar irradiance prediction is aimed at predicting the solar irradiance for 30 minutes to 6 hours. The short-term prediction of solar irradiance requires making effective operational decisions, automatic generation control, energy commercialization, maintenance, scheduling, economic dispatch, and unit commitment [1, 2]. The multivariate problem and dependence of inputs can learn more effectively by the artificial neural network than by statistical and NWP-based prediction models. The recurrent neural network belongs to the feedback artificial neural network. LSTM is a variant of recurrent neural networks. A tremendous amount of interest has been received in the long short-term memory (LSTM) of time series and sequence database applications. Recently, LSTM was used for a wide range of applications [3–6]. The prediction model’s performance depends not only on the selection of the input but also on the model
framework playing an essential role in prediction accuracy. Through the use of data-driven models, it is possible to capture the underlying mapping of solar irradiance. BRT (boosted regression trees) and other data-driven method-based solar irradiance were analyzed in [7] but suggested model error increases with the horizon. However, the computations and costs are high for the data-driven method. Prediction model validation using uncertainty quantification was carried out in [8]. By optimizing the parameters and selecting features, the predictive model accuracy improves. Using feature selection and interpretable methods tried to increase the forecasting accuracy in [9, 10], but it is a complex and high computation burden task.

Sometimes, the individual model performance is not satisfactory, which pays attraction towards an ensemble predictive model. The best way to conquer the limitation of the individual prediction model is to combine the various

![Figure 1: The framework of the proposed CLSTMN.](image)

![Figure 2: Sunny day dataset training and testing samples.](image)

![Figure 3: Cloudy day dataset training and testing samples.](image)

| Hour ahead prediction | RMSE in W/m² | MAPE in % | MSE in W/m² |
|-----------------------|-------------|-----------|-------------|
| 1 hour ahead          | 7.7729 × 10^{-04} | 8.2479 × 10^{-05} | 6.0419 × 10^{-07} |
| 2 hours ahead         | 0.0031      | 2.5029 × 10^{-04} | 9.5190 × 10^{-06} |
| 3 hours ahead         | 0.0087      | 6.7010 × 10^{-04} | 7.5604 × 10^{-05} |
| 4 hours ahead         | 0.0130      | 0.0010     | 1.6916 × 10^{-04} |
| 5 hours ahead         | 0.0162      | 0.0015     | 2.6139 × 10^{-04} |
| 6 hours ahead         | 0.0157      | 0.0017     | 2.4627 × 10^{-04} |

Table 1: Proposed CLSTMN-based results on sunny datasets for different hours ahead prediction of solar irradiance.
models into averaged models to achieve high accuracy [11]. This paper presents a novel combined long short-term memory network to predict solar irradiance in short-term horizons. The proposed model comprises six individual LSTMs with various input and framework structures. The primary aim of the proposed CLSTMN model is to improve the generalization and prediction ability.

The significant contributions of the proposed prediction CLSTMN models are described as follows:

1. A novel short-term solar irradiance prediction model is proposed using six individual input LSTMs
2. A unique combinational framework is proposed
3. Real-time actual sunny and cloudy day datasets are applied to verify the proposed CLSTMN model performance
4. The proposed framework improves the generalization and accuracy
5. The problem of input data based uncertain can overcome the use of the proposed CLSTMN
6. The proposed prediction model versatile capability proved on sunny and cloudy weather dataset based on prediction of solar irradiance for one-hour- to six-hour-ahead prediction
7. Carry out the performance comparison with other baseline prediction models

Section 1 describes the introduction and the prior works related to solar irradiance prediction discussed in Section 2. Section 3 presents the proposed combined long short-term memory network framework and mathematical modeling. Section 4 covers the experimental details, and Section 5 presents the results and discussion on sunny and cloudy days. Finally, Section 6 summarizes the conclusion, and Section 7 discusses the proposed predictive model limitations and future research.

2. Related Work

Several short-term prediction models were developed in the field of solar irradiance prediction applications. Xiang et al. [12] carried out the persistence extreme learning machine-based solar power forecasting for the short-term horizon. Ferrari et al. [13] presented solar radiation prediction using the statistical approach and stated that ARIMA has minimum parameters compared to the AR and ARMA. de Araujo [14] investigated the WRF (Weather Research Forecasting) and LSTM performance to forecast solar radiation. A-Sbou and Alawasa [15] performed prediction of solar radiation in Mutah city with NARX (Nonlinear Autoregressive RNN with exogenous). El Alani et al. studied multilayer perceptron neural network based on global horizontal irradiance for short-term horizon [16]. Madhiarasan and Deepa [17] developed a solar irradiance forecasting model with an innovative neural network, and apt hidden neurons are identified with the use of the deciding standard. Gutierrez-Corea et al. [18] pointed out various inputs associated with artificial neural networks based on global solar irradiance forecasting for short-term horizons. Halpern-Wight et al. [19] analyzed LSTM with one and five hidden layers for the solar forecasting application. The investigation stated that for over five hidden layers, LSTM single LSTM-based forecasting model provides the lowest errors.

Kartini and Chen [20] presented a combinational forecasting model that used k-NN (k-nearest neighbour) and BPLNN (multilayer backpropagation learning neural network) for one-hour-ahead GSI (global solar irradiance) forecasting. Mishra and Palanisamy [21] suggested RNN (recurrent neural network) based on solar irradiance forecasting for multitime horizons. Bae et al. [22] suggested K-mean clustering associated support vector machine based on one-hour-ahead prediction of solar irradiance. Complex structured hybrid prediction model requires more
computation, which leads to increase the training time. We still need a reliable and robust prediction model to address the solar irradiance prediction. Although more research exists on solar irradiance prediction, a generalization issue still needs to be addressed. This paper overcomes the deficiencies of the individual LSTM models and meteorological parameters’ impact on solar irradiance. This research work used combinations of various inputs and frameworks based on the LSTM model to enhance the generalization ability for the short-term solar irradiance prediction.

Using the combination of individual long short-term memory networks with various inputs, we accomplish the following benefits than the prior predictive models:

![Figure 5: Prediction error vs. time for sunny day one-hour-ahead prediction.](image)

![Figure 6: Relationship between actual vs. predicted solar irradiance for sunny day one-hour-ahead prediction.](image)

![Figure 7: Comparison of predicted solar irradiance and actual solar irradiance for sunny day two-hour-ahead prediction.](image)
(i) By compromising variance and bias, the proposed model can reach a better generalized solution in most cases

(ii) Ability to resolve underfitting and overfitting issues

(iii) Network stability issue gets rid of the proposed combination approach based on CLSTMN

(iv) In contrast to a single LSTM model approach, the proposed CLSTMN is an average of numerous input-associated LSTM models that can overcome the limitations and uncertainties associated with a single LSTM model

(v) Occurrence of local minima is avoided

(vi) Able to manage seasonal and cyclical changes

(vii) The suggested model is more useful, easier to use, and more accurate in the prediction of short-term solar irradiance than the current model

3. Proposed Combined Long Short-Term Network

This paper presents a novel combined LSTM network-based prediction for the short-term solar irradiance prediction.
The concept, framework, and mathematical modeling of the proposed CLSTMN are detailed in this section.

3.1 Long Short-Term Memory Network. In 1997, Hochreiter and Schmidhuber [23] devised a long short-term memory network that can overcome the vanishing gradient issue and handle the long-term dependence. Therefore, LSTM is suitable for time series prediction applications. It is a particular variant of the recurrent neural network. The CEC (constant error carousel) is used to store the long-term dependence. It is a linear unit self-connected recurrently. The LSTM network comprises a cell state and three gates: input, forget, and output. The steps incurred in the LSTM network are as follows:

![Graph showing the relationship between actual and predicted solar irradiance for sunny days three hours ahead prediction.](image1)

**Figure 12:** Relationship between actual vs. predicted solar irradiance for sunny day three-hour-ahead prediction.

![Graph comparing predicted and actual solar irradiance for sunny days four hours ahead prediction.](image2)

**Figure 13:** Comparison of predicted solar irradiance and actual solar irradiance for sunny day four-hour-ahead prediction.
Step 1. Forget gate identifies the irrelevant information from the pastime step and passes it to the cell state.

Step 2. With the help of the input gate, it updates the cell state with the new input information.

Step 3. The critical information passed to the next hidden state is determined using the output gates.

Step 4. Cell state is used to have the knowledge of the past relevant over a long time.

3.1.1. Mathematical Model of LSTM.

Forget gate, \( F_t = \sigma_{\text{sig}}(W_F[u_t, H_{t-1}] + b_F) \) \hspace{1cm} (1)

Input gate, \( I_t = \sigma_{\text{sig}}(W_I[u_t, H_{t-1}] + b_I) \) \hspace{1cm} (2)

Cell agent \( C_t = \sigma_{\text{tanh}}(W_C[u_t, H_{t-1}] + b_C) \) \hspace{1cm} (3)

Output gate, \( O_t = \sigma_{\text{sig}}(W_O[u_t, H_{t-1}] + b_O) \) \hspace{1cm} (4)

Hidden state \( H_t = O_t \circ \sigma_{\text{tanh}}(S_t) \) \hspace{1cm} (5)

Cell state, \( S_t = F_t \circ S_{t-1} + I_t \circ C_t \) \hspace{1cm} (6)

where \( \circ \) is the Hadamard Product, \( W \) is weights of the respective gates, \( H_{t-1} \) is the time stamp \( t-1 \) past LSTM block.
output, $u_t$ is the current timestamp input, and $b$ is the bias of the respective gates.

3.2. Combined-Long Short-Term Memory Network. Under different inputs, model architecture, and uncertainties, maintaining stable performance is the aim of generalization. The six LSTM models with various inputs and hidden neurons (framework) are used to develop the proposed model. We can overcome the uncertain irregularity present in solar irradiance with the help of atmospheric input features. Using the combinations of the LSTM model can reduce the error values and improve the network stability. We fix hidden neurons by a trial-and-error approach [24, 25] and the identified optimal hidden neurons for each individual LSTM are used for the development of the proposed CLSTMN structure. Figure 1 shows the proposed CLSTMN framework.
The proposed CLSTMN mathematical model is as follows:

\[
\text{CLSTMN output} = \frac{1}{N} \sum_{j=1}^{N} \text{LSTM}_j \quad \text{for} \quad j = 1, 2, \ldots, N. \quad (7)
\]

Let, \( N \) the number of LSTMs.

\[
\text{Predicted solar irradiance} = \frac{(\text{LSTM}_2\text{inputs} + \text{LSTM}_3\text{inputs} + \text{LSTM}_4\text{inputs} + \text{LSTM}_5\text{inputs} + \text{LSTM}_6\text{inputs} + \text{LSTM}_7\text{inputs})}{6}. \quad (8)
\]
Steps of the proposed CLSTMN algorithm are as follows:

Step 1. Collect the solar irradiance and meteorological parameters for sunny and cloudy days.
Step 2. Normalize the data.
Step 3. Divide the data into training and testing.
Step 4. Design the individual LSTM models with various inputs.
Step 5. Train the designed LSTM model and predict the solar irradiance on test data.
Step 6. Average all LSTM models predict the final solar irradiance.
Step 7. Compute the evaluation metric and compare it again with the other baseline prediction models.

The proposed CLSTMN model parameters and values are as follows:
- Input neurons = 2, 3, 4, 5, 6, and 7.
- Hidden neurons = 2, 4, 5, 7, 9, and 11.
- Output neuron = 1.
- Optimizer = Adam.
- Loss function = RMSE.
- Epochs = 200.

Moreover, the individual model generalization inability can be improved by averaging the various framework-based LSTM prediction models. We improved the accuracy in terms of a reduction in prediction error. The proposed model could manage the model stability and convergence.

4. Experimental Details

The proposed solar irradiance prediction approach runs on the MATLAB platform using a hp laptop with AMD Ryzen 3550 H processor, 8 GB RAM, 2100 Mhz, and 4 GB NVIDIA GeForce GTX 1650. Achieving the desired prediction accuracy is crucial because of solar irradiance’s randomness characteristics. This paper attempts to predict solar irradiance over a period of a few minutes to 6 hours. Various inputs and different frameworks incurred in LSTM models were used to develop the proposed model. Averaging the six individual LSTM models improved accuracy and reduced error.

4.1. Dataset and Input Parameter Details. We got the sunny day and cloud day dataset from the NOAA. The dataset was collected from the latitude 40.05° N and longitude 88.37° W during the period of 2021. The following parameters are used as inputs to the proposed CLSTMN model.
Solar irradiance in W/m²
Temperature in °C
Wind speed in m/s
Wind direction in degrees
Pressure in mb
Relative humidity in %
Cloud cover in Oktas

4.2 Normalization. Normalization improves the prediction performance based on the training efficiency improvement. The actual inputs are normalized based on the Min–Max normalization. The Min–Max formulation is as follows:

\[
\text{Normalized input, } u_j' = \left( \frac{u_j - u_{\text{min}}}{u_{\text{max}} - u_{\text{min}}} \right),
\]

where \( u_j \) is the actual input value, \( u_{\text{min}} \) is the minimum input value, and \( u_{\text{max}} \) is the maximum input value.
4.3. Training and Testing Datasets. We carried out the proposed model training using a two-day data sample of 2800 and testing with 6 hours of data samples of 360. Figures 2 and 3 depict the sunny day dataset training and testing samples and cloudy day dataset training and testing samples, respectively. We validate the proposed prediction model on the sunny and cloudy day datasets.

4.4. Evaluation Metric. We used the RMSE, MAPE, and MSE as an evaluation metric to evaluate the proposed CLSTMN model performance. Stated evaluation metric formulations are as follows:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (u_j' - u_j)^2},
\]

\[
MAPE = \frac{100}{N} \sum_{j=1}^{N} \left| \frac{u_j' - u_j}{\bar{u}_j} \right|,
\]

\[
MSE = \frac{1}{N} \sum_{j=1}^{N} (u_j' - u_j)^2,
\]

where \( N \) is the total number of data samples, \( u_j' \) is the actual output, \( \bar{u}_j \) is the average actual output, and \( u_j \) is predicted output.

5. Results and Discussion

We report the proposed CLSTMN model-based simulation results for short-term solar irradiance prediction on sunny and cloudy days. We tested the proposed CLSTMN model on a testing dataset (360 data samples of each cloudy day and sunny day), tabulating the achieved results reported in Tables 1 and 2.

5.1. Short-Term Prediction of Solar Irradiance on Sunny Days. The performance of the proposed CLSTMN model was evaluated on sunny day datasets.

The achieved results for short-term solar irradiance prediction such as one hour ahead, 2 hours ahead, 3 hours ahead, 4 hours ahead, 5 hours in Table 1 and Figures 4–21. Consequently, the predicted solar irradiance for sunny days is accurately matched with the actual solar irradiance, it is noted in Figures 4, 7, 10, 13, 16, and 19. Figures 5, 8, 11,
14, 17, and 20 show that the prediction on sunny days exactly matches the actual solar irradiance; thus, the prediction errors are near to zero. The predicted solar irradiance is linearly matched with the actual solar irradiance, and it is clearly perceived from Figures 6, 9, 12, 15, 18, and 21.

The prediction errors for one-hour-ahead prediction are the lowest RMSE $7.7729 \times 10^{-04}$, MAPE $8.2479 \times 10^{-05}$, and MSE $6.0419 \times 10^{-07}$, and the predictions are better than other hour-ahead-based predictions. The sunny day-based results from the proposed 6-hour-ahead CLSTMN prediction model have the evaluation metrics as RMSE 0.0157, MAPE 0.0017, and MSE $2.4627 \times 10^{-04}$. The performance of the proposed CLSTMN model on the sunny day dataset based on short-term solar irradiance prediction results in better prediction accuracy on one-hour, two-hour, three-hour, four-hour, five-hour, and six-hour-ahead prediction of solar irradiance.

5.2. Short-Term Prediction of Solar Irradiance on Cloudy Days. The proposed CLSTMN model performance is further evaluated on the cloudy day dataset, and the achieved results for short-term solar irradiance prediction such as one hour ahead, 2 hours ahead, 3 hours ahead, 4 hours ahead, 5 hours ahead, and 6 hours ahead are tabulated in Table 2 and Figures 22–39. From Figures 22, 25, 28, 31, 34, 37, for cloudy
days, the predicted solar irradiance is matched accurately with the actual solar irradiance perceived clearly. Therefore, the prediction errors are the lowest. It was noticed in Figures 23, 26, 29, 32, 35, and 38. The prediction on the cloudy day dataset exactly matches the actual solar irradiance with the predicted solar irradiance. Thus, the linear relationship between actual vs. predicted solar irradiance for the cloudy day dataset depicts in Figures 24, 27, 30, 33, 36, and 39.

For the cloudy day dataset, the proposed CLSTMN model is based on 6-hour-ahead prediction result RMSE 0.0176, MAPE 0.0043, and MSE $3.0863 \times 10^{-4}$. One-hour-ahead prediction of solar irradiance results is more precise than the other hour-ahead-based predictions with RMSE $1.2969 \times 10^{-4}$, MAPE $1.6882 \times 10^{-4}$, and MSE $1.6819 \times 10^{-8}$. The proposed CLSTMN model evaluation on cloudy day datasets results in better accuracy for short-term solar irradiance prediction (one to 6 hours ahead).
Sunny days have a higher solar irradiance than cloudy days. The sunny day-based prediction using the CLSTMN is competing with the cloudy day-based prediction. The proposed CLSTMN model can generalize well to the model and input uncertainty and accurately predict the actual solar irradiance with the minor evaluation metrics. Based on the analysis of the obtained result, we identify the proposed CLSTMN prediction model achieved improved prediction accuracy and generalization ability on both sunny and cloudy day datasets. Through the precise prediction of the solar irradiance using the proposed CLSTMN makes benefits and effective planning and scheduling of solar energy systems.

5.3. Comparative Analysis with the Baseline Model. In addition, the comparative analysis was carried out to prove the predictive model’s ability with the baseline models. The persistence
model and other well-known predictive models (ARIMA, WRF, RNN, k-NN-BPLNN, SVM, MLP, NARX, and LSTM) were used as a baseline model to verify and compare the performance of the proposed CLSTMN prediction model. We kept the considered baseline model set parameters the same as mentioned in the respective research papers but validated on our collected datasets. For sunny and cloudy day datasets, the proposed CLSTMN model provides a consistent result for one hour, two hours, three hours, four hours, five hours, and six hours ahead the prediction of solar irradiance. Thus, the proposed CLSTMN model can accurately predict the solar irradiance that matches the actual solar irradiance on the short-term horizon.

The compared baseline predictive model was less accurately predicting the solar irradiance in short-term horizons on the considered datasets. This is clearly observed in Table 3, for a better understanding of the 3D column chart depicted in Figure 40. The baseline model-based predicted solar irradiance is not almost the same as the actual values in both datasets; hence, the performance evaluation metrics are increasing, and the accuracy decreased.

In summary, the highly accurate short-term prediction model is proposed using the combined long short-term memory network, and it makes it easy to adapt to climatic conditions and model framework variations. The proposed model-based predicted solar irradiance values are a good fit for the actual values. The proposed model can handle the changes in inputs and model framework; thus, it is well generalized to both datasets and results in the best progress than the other compared predictive models.
6. Conclusion

The amalgamation of various input and framework-based individual LSTM models may help increase the prediction accuracy and learning ability and make it suitable for general application. The relationship among various inputs is handled effectively with the proposed CLSTMN model. Six different input and framework-based LSTM model ensembles enable the proposed model to extract the solar irradiance and meteorological parameter dependencies accurately.
Thus, the uncertainties about the model framework and inputs are managed effectively, which makes the better prediction results of the proposed model concerned with short-term solar irradiance prediction. The learning ability of the proposed model is highly improved, and this makes the proposed model can predict 1 hour, 2 hours, 3 hours, 4 hours, 5 hours, and 6 hours ahead of solar irradiance precisely.

In addition, sunny day and cloudy day datasets based on performance validation were performed to verify the prediction ability of the proposed CLSTMN model for 1-hour to 6-hour ahead prediction. The evaluation of sunny day- and cloudy day-based datasets shows that the proposed model can cause better performance in a greatly uncertain situation. Thus, we attain the best prediction results on sunny and cloudy days for 1-hour- to 6-hour-ahead predictions regarding the proposed CLSTMN model. The proposed CLSTMN model, compared with the baseline predictive models and result analysis, has proved the prediction effectiveness of the proposed CLSTMN model for sunny and cloudy days based on short-term solar irradiance with the lowest evaluation metrics. Risk of solar energy integration to the electric grid is eliminated through the simple and workable proposed CLSTMN short-term prediction model.

7. Proposed Predictive Model Limitations and Future Research

This model has limitations of higher computational cost than the individual model, despite its improved prediction accuracy.

The future works are as follows:

(i) This paper extends the applicability of the proposed CLSTMN and further investigates by performing the multihorizon-based solar irradiance prediction

(ii) The authors intend to use an optimization algorithm to identify the optimal hyperparameters of the LSTM network

(iii) Develop the FPGA model, and apply the model to real-world scenarios

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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References

[1] M. Madhiarasan, Certain Algebraic Criteria for Design of Hybrid Neural Network Models with Applications in Renewable Energy Forecasting, [Ph.D. thesis], Anna University, Chennai, India, 2018.

[2] M. Madhiarasan and S. N. Deepa, “Review of forecasters application to solar irradiance forecasting,” International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 2, no. 2, pp. 26–30, 2017.

[3] K. Liu, Q. Peng, H. Sun, M. Fei, H. Ma, and T. Hu, “A transferred recurrent neural network for battery calendar health prognostics of energy-transportation systems,” IEEE Transactions on Industrial Informatics, 2002.

[4] A. M. Alonso, F. J. Nogales, and C. Ruiz, “A single scalable LSTM model for short-term forecasting of massive electricity time series,” Energies, vol. 13, no. 20, p. 5328, 2020.

[5] M. Chai, F. Xia, S. Hao, D. Peng, C. Cui, and W. Liu, “PV power prediction based on LSTM with adaptive hyperparameter adjustment,” IEEE Access, vol. 7, pp. 115473–115486, 2019.

[6] Y. Yu, J. Cao, and J. Zhu, “An LSTM short-term solar irradiance forecasting under complicated weather conditions,” IEEE Access, vol. 7, pp. 145651–145666, 2019.

[7] C. Huang, L. Wang, and L. L. Lai, “Data-driven short-term solar irradiance forecasting based on information of neighboring sites,” IEEE Transactions on Industrial Electronics, vol. 66, no. 12, pp. 9918–9927, 2019.

[8] K. Liu, Y. Shang, Q. Ouyang, and W. D. Widanage, “A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion battery,” IEEE Transactions on Industrial Electronics, vol. 68, no. 4, pp. 3170–3180, 2020.

[9] K. Liu, Q. Peng, K. Li, and T. Chen, “Data-based interpretable modeling for property forecasting and sensitivity analysis of Li-ion battery electrode,” Automot. Innov., vol. 5, no. 2, pp. 121–133, 2022.

[10] K. Liu, M. F. Niri, G. Apachitei et al., “Interpretable machine learning for battery capacities prediction and coating parameters analysis,” Control Engineering Practice, vol. 124, article 105202, 2022.

[11] M. Madhiarasan, M. Louazzani, and P. P. Roy, “Novel cooperative multi-input multilayer perceptron neural network performance analysis with application of solar irradiance forecasting,” International Journal of Photoenergy, vol. 2021, Article ID 7238293, 24 pages, 2021.

[12] X. Xiang, Y. Sun, and X. Deng, “Short time solar power forecasting using persistence extreme learning machine approach,” in E3S Web of Conferences, vol. 294, Strasbourg, France, 2021.

[13] S. Ferrari, M. Lazzaroni, V. Piuri, L. Cristaldi, and M. Faifer, “Statistical models approach for solar radiation prediction,” in In 2013 IEEE international instrumentation and measurement technology conference (I2MTC), pp. 1734–1739, IEEE, Minneapolis, MN, USA, 2013.

[14] J. de Araujo and M. Soares, “Performance comparison of solar radiation forecasting between WRF and LSTM in Gifu, Japan,” Environmental Research Communications, vol. 2, no. 4, article 45002, 2020.

[15] Y. A. Al-Shou and K. M. Alawasa, “Nonlinear autoregressive recurrent neural network model for solar radiation
prediction,” *International Journal of Applied Engineering Research*, vol. 12, no. 14, pp. 4518–4527, 2017.

[16] E. Alani, H. G. Omaima, and A. Ghennioui, “Short term solar irradiance forecasting using artificial neural network for a semi-arid climate in Morocco,” in *In 2019 International Conference on Wireless Networks and Mobile Communications (WINCOM)*, pp. 1–7, IEEE, Fez, Morocco, 2019.

[17] M. Madhiarasan and S. N. Deepa, “Precise 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, no. 12, pp. 951–974, 2016.

[18] F.-V. Gutierrez-Corea, M.-A. Manso-Callejo, M.-P. Moreno-Regidor, and M.-T. Manrique-Sancho, “Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations,” *Solar Energy*, vol. 134, pp. 119–131, 2016.

[19] N. Halpern-Wight, M. Konstantinou, A. G. Charalambides, and A. Reinders, “Training and testing of a single-layer LSTM network for near-future solar forecasting,” *Applied Sciences*, vol. 10, no. 17, p. 5873, 2020.

[20] U. T. Kartini and C. R. Chen, “Short term forecasting of global solar irradiance by k-nearest neighbor multilayer backpropagation learning neural network algorithm,” in *Proceedings of the International Conference on Graphics and Signal Processing*, pp. 96–100, Singapore Singapore, 2017.

[21] S. Mishra and P. Palanisamy, “Multi-time-horizon solar forecasting using recurrent neural network,” in *In 2018 IEEE Energy Conversion Congress and Exposition (ECCE)*, pp. 18–24, IEEE, Portland, OR, USA, 2018.

[22] K. Y. Bae, H. S. Jang, and D. K. Sung, “Hourly solar irradiance prediction based on support vector machine and its error analysis,” *IEEE Transactions on Power Systems*, vol. 32, no. 2, pp. 935–945, 2017.

[23] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[24] M. Madhiarasan, M. Tipaldi, and P. Siano, “Analysis of artificial neural network performance based on influencing factors for temperature forecasting applications,” *Journal of High Speed Networks*, vol. 26, no. 3, pp. 209–223, 2020.

[25] M. Madhiarasan and M. Louzazni, “Analysis of artificial neural network: architecture, types, and forecasting applications,” *Journal of Electrical and Computer Engineering*, vol. 2022, 23 pages, 2022.