International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 17, No. 4, December 2026, pp. 2924~2933
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v17.i4.pp2924-2933

Explainable convLSTM-based solar irradiance and wind speed forecasting for hybrid renewable energy systems in India

S. Selvi[1], Kedri Janardhana[2], Surendar Vadivel[3], Mohammad Arif[4], Joshuva Arockia Dhanraj[5], V. Velmurugan[6]

[1]Department of Electrical and Electronics Engineering, Panimalar Engineering College, Chennai, India
[2]Department of Electrical Engineering, Faculty of Engineering, Dayalbagh Educational Institute (Deemed to be University), Pradesh, India
[3]Department of Electrical and Electronics Engineering, Kongu Engineering College, Tamil Nadu, India
[4]Department of Artificial Intelligence and Data Science, Parul Institute of Engineering and Technology, Faculty of Engineering and Technology, Parul University, Gujarat, India
[5]Department of Computer Science and Engineering (AI&ML), School of Engineering, Dayananda Sagar University, Karnataka, India
[6]Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India

Article Info

Article history:

Received Mar 24, 2026
Revised Aug 21, 2026
Accepted Sep 13, 2026

Keywords:

ConvLSTM
Hybrid energy systems
Renewable energy forecasting
SHAP analysis
Spatiotemporal modelling

ABSTRACT

Accurate forecasting of solar irradiance and wind speed is essential for the reliable integration and operation of hybrid renewable energy systems. This study develops an explainable ConvLSTM-based forecasting framework using five years of hourly data (2016–2020) from the National Solar Radiation Database (NSRDB) for a selected location in Tamil Nadu, India. The dataset includes global horizontal irradiance (GHI), wind speed, temperature, solar radiation variables, solar zenith angle, temporal features, and lagged renewable-resource variables. Linear Regression, Random Forest, XGBoost, LSTM, and ConvLSTM models are developed and comparatively evaluated to capture nonlinear and temporal dependencies. A 24-hour sliding window is used to provide temporal context. Model performance is assessed using mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2). ConvLSTM achieves the best overall performance, with an MAE of 7.64, RMSE of 11.28, and R^2 of 0.95. Learning-curve and predicted-versus-actual analyses indicate stable convergence and good predictive agreement. Feature-importance and SHAP analyses identify lagged renewable-resource and meteorological variables as important contributors to the predictions. Transfer learning is further incorporated to assess regional adaptability. The proposed framework combines forecasting accuracy, temporal learning, interpretability, and transferability, supporting renewable-resource management, grid balancing, and hybrid renewable-energy integration in India.

This is an open access article under the CC BY-SA license.

Corresponding Author:

S. Selvi
Department of Electrical and Electronics Engineering, Panimalar Engineering College
Chennai, Tamil Nadu, India
Email: selviselvaraj@gmail.com

1. INTRODUCTION

The increasing deployment of renewable energy sources, particularly solar photovoltaic (PV) and wind energy, is reshaping modern power systems and supporting the transition toward low-carbon electricity generation [1], [2]. However, renewable generation is strongly dependent on meteorological conditions such as solar irradiance, cloud cover, temperature, wind speed, and atmospheric dynamics [3], [4]. This variability introduces uncertainty into power generation and creates challenges for power-system operation, grid

stability, energy scheduling, and long-term planning [3], [5]. Accurate renewable resource forecasting is therefore essential for generation scheduling, operating-reserve management, reduction of power imbalance, and reliable electricity supply [5], [6]. Forecasting errors can increase operating costs and affect voltage and frequency regulation, particularly under high renewable penetration [6], [7].

Conventional forecasting methods include statistical and physical modelling techniques [8], [9]. Statistical approaches such as linear regression, autoregressive models, and persistence methods are computationally efficient but may have limited ability to capture complex nonlinear relationships between meteorological variables and renewable resources [8]. Physical approaches depend on atmospheric and site-specific parameters and may involve considerable computational requirements and modelling assumptions [9]. These limitations have encouraged the adoption of machine learning and deep learning approaches that can learn nonlinear patterns directly from historical observations [10], [11]. Long short-term memory (LSTM) networks are effective for time-series forecasting because they learn temporal dependencies from sequential data, while convolutional neural networks (CNNs) can extract spatial features from structured or gridded data [11], [12]. Since renewable energy variables exhibit both temporal and spatial variability, hybrid architectures have attracted increasing attention [13], [14].

Convolutional long short-term memory (ConvLSTM) combines convolutional operations with recurrent memory mechanisms to learn spatial and temporal representations simultaneously [13]. This makes it suitable for forecasting weather-dependent renewable resources whose characteristics evolve across time and space. However, ConvLSTM models may require substantial computational resources and sufficiently representative training data, potentially limiting their application when data availability or regional coverage is restricted [15]. In addition, models trained for one geographical region may experience reduced performance in another because of differences in weather patterns, terrain, seasonal characteristics, and renewable resource distributions [16], [17]. Transfer learning offers a potential solution by transferring learned representations from a source domain to a related target domain and adapting the model through fine-tuning [17], [18].

Another important issue is the interpretability of deep learning forecasting models. Although these models can achieve high predictive performance, their complex internal representations make it difficult to determine how individual input variables influence predictions [19], [20]. Explainable artificial intelligence (XAI) methods can address this limitation by quantifying feature contributions. Shapley additive explanations (SHAP) provide both global and local explanations and have increasingly been applied to renewable energy forecasting and related machine learning applications [10], [21], [22]. Nevertheless, the combined application of explainability analysis with spatiotemporal deep learning and transfer learning requires further investigation.

Accordingly, three research gaps are identified: the need to better capture temporal and spatial variability under different regional conditions; the limited investigation of model transferability between geographically related regions; and the need for explainability to identify the contribution of lagged and meteorological variables. Motivated by these gaps, this study develops an explainable ConvLSTM-based framework for solar irradiance and wind speed forecasting using hourly meteorological observations from the National Solar Radiation Database (NSRDB). LSTM and ConvLSTM models are comparatively evaluated, followed by transfer learning to assess regional adaptability. SHAP-based analysis is then employed to identify the contribution of meteorological and lagged variables.

The main contributions are the development of a ConvLSTM framework for solar irradiance and wind speed forecasting, incorporation of transfer learning to evaluate regional adaptability and reduce dependence on complete retraining, and integration of SHAP-based explainability to quantify feature contributions. The framework is evaluated using forecasting performance, learning-curve behavior, predicted-versus-actual analysis, transfer-learning performance, and feature-importance analysis. The proposed approach has potential applications in renewable generation scheduling, reserve planning, energy management, and operational decision support by providing more accurate and interpretable forecasts to support the reliable integration of hybrid renewable energy systems.

2. METHOD

The proposed approach is to develop an interpretable, generalizable, and accurate framework to predict solar irradiance and wind speed. It involves several steps, such as data preprocessing, feature engineering, model development, training, and transfer learning and interpretability analysis. The process flow diagram shows the overall workflow. The methodology is shown in Figure 1.

2.1. Data collection and preprocessing

Hourly meteorological data were obtained from the NSRDB for the period 2016–2020 at the selected Tamil Nadu location (13.06° N, 80.25° E). The characteristics of the dataset, including the study

period, sampling interval, location, number of observations, forecasting variables, and sequence information, are summarized in Table 1. The dataset provides five years of hourly observations, enabling the representation of diurnal, seasonal, and interannual variations in renewable-resource characteristics.

The dataset was preprocessed to ensure consistency and suitability for machine-learning and deep-learning models. The input features were normalized using Min–Max scaling to transform the variables into a comparable numerical range, improving numerical stability and supporting efficient model training. The observations were divided chronologically into training and testing datasets using an 80:20 time-based split. The training and testing datasets contained 17,398 and 4,358 observations, respectively. The data were then converted into sequential samples using a 24-hour sliding input window. After sequence generation, 17,374 training sequences and 4,334 testing sequences were obtained, with each sequence comprising 24 consecutive hourly observations and 12 input features.

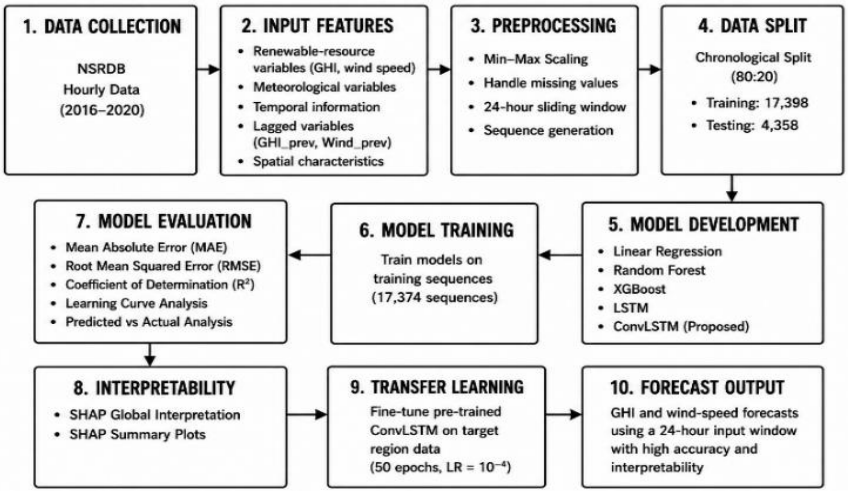

Figure 1. Methodology

Table 1. Dataset characteristics

Parameter	Description	Parameter	Description
Data source	National Solar Radiation Database (NSRDB)	Training/testing split	80:20 chronological split
Location	Tamil Nadu, India	Training observations	17,398
Latitude	13.06° N	Testing observations	4,358
Longitude	80.25° E	Sequence length	24 hours
Study period	2016–2020	Input features	12
Sampling interval	1 hour	Forecast variables	GHI and wind speed

2.2. Feature engineering

Feature engineering was performed to capture the temporal, meteorological, and spatial characteristics influencing solar irradiance and wind speed. Lagged observations of GHI and wind speed were incorporated to represent the persistence characteristics of renewable-resource variables. Temporal information, including hour, day, month, and minute, was incorporated to capture diurnal and seasonal variability. Spatial information, including latitude, longitude, and elevation, was included to represent geographical characteristics. The resulting input representation consists of 12 features over a 24-hour temporal window. A 24-hour sliding input window was used to provide the model with the preceding hourly observations for forecasting the target variable at the subsequent prediction step. This sequence-based representation enables the LSTM and ConvLSTM models to learn temporal dependencies from consecutive observations.

2.3. Model development

Five forecasting models, namely linear regression, random forest, XGBoost, LSTM, and ConvLSTM, were developed and comparatively evaluated. Linear Regression was considered as a conventional baseline, while Random Forest and XGBoost were employed to capture nonlinear relationships among the input variables [24]. LSTM was used to model temporal dependencies in the sequential data. The proposed ConvLSTM architecture combines convolutional feature extraction with recurrent memory to learn complex temporal and feature-level relationships in the renewable-resource data. The principal architectures

and hyperparameters of the evaluated models are summarized in Table 2. In addition, feature-importance analysis of the ConvLSTM model is done to identify the relative contribution of the input variables. SHAP-based analysis was subsequently used to provide further insight into the contribution of individual features to the model predictions.

Table 2. Summary of model architectures and key hyperparameters

Model	Type/key parameters/architecture
Linear regression	Type: Statistical baseline Architecture: Linear regression model
Random Forest	Type: Tree-based ensemble Architecture: Ensemble of decision trees
XGBoost	Type: Gradient-boosting ensemble Architecture: Gradient-boosted decision trees
LSTM	Type: Recurrent neural network (RNN), parameters: LSTM units = 64, dropout = 0.2, and dense output layer
ConvLSTM (proposed)	Type: Spatiotemporal deep learning Parameters: filters = 32, kernel size = 3 × 3, batch normalization, flatten, and dense output layer

2.4. Model training strategy

The dataset was divided chronologically into training and testing subsets using a time-based split, with 80% of the observations used for training and 20% for testing. The chronological split was adopted to preserve the temporal order of the observations and avoid information leakage between the training and testing datasets. The deep learning models were trained using the Adam optimizer with a learning rate of 0.001. The maximum number of training epochs was set to 50, with batch sizes ranging from 32 to 64. Early stopping based on validation loss was employed to reduce overfitting and terminate the training process when further improvement in validation performance was not observed.

2.5. Evaluation metrics

The forecasting performance of the developed models was evaluated using mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2) [23]. MAE represents the average magnitude of prediction errors, whereas RMSE gives greater weight to larger prediction errors. The R^2 value indicates the proportion of variation in the observed values explained by the model. Lower MAE and RMSE values indicate better forecasting accuracy, while a higher R^2 value indicates better agreement between predicted and actual observations. The evaluation metrics are defined by (1)-(3).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y}i)^2} \quad (1)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y}i)^2 \quad (2)$$

$$R^2 = 1 - \frac{\sum(yi-\hat{y}i)2}{\sum(yi-\overline{y})2} \quad (3)$$

2.6. Transfer learning

Transfer learning was employed to investigate the generalization capability of the proposed ConvLSTM model under different regional conditions. Initially, the ConvLSTM model was trained using the source dataset to learn relevant temporal and feature-level representations associated with solar irradiance and wind speed. The pre-trained model was subsequently fine-tuned using data from the target region for 50 epochs with a reduced learning rate of 10−4. This approach enables the model to retain previously learned representations while adapting its parameters to the characteristics of the target region. The effectiveness of transfer learning was evaluated by comparing the forecasting performance before and after fine-tuning.

2.7. Model interpretability

Model interpretability was investigated using feature-importance analysis and Shapley additive explanations (SHAP). ConvLSTM feature importance was first used to obtain an initial ranking of the input variables. SHAP analysis was subsequently employed to quantify the contribution of individual input features to the model predictions. The analysis provides both global and local explanations, enabling the influence of lagged, temporal, spatial, and meteorological variables on the forecasting outputs to be examined. This analysis provides greater transparency into the model prediction process and helps identify the input variables that contribute most strongly to the forecasting results.

2.8. Data availability

The data used in this study were obtained from the publicly accessible NSRDB provided by the National renewable energy laboratory (NREL). The required data can be downloaded by specifying the corresponding study location(s) in Tamil Nadu, India, the study period from 2016 to 2020, hourly temporal resolution, and the variables described in section 2.1. The public availability of the NSRDB dataset enables independent retrieval of the data used in this study and supports reproducibility of the reported analysis.

3. RESULTS AND DISCUSSION

In this section, the performance of the proposed models in their ability to forecast is brought out and the effectiveness of these models in the model to identify temporal, spatial, and physical relationship in solar irradiance and wind speed data is discussed. The analysis is performed with the help of quantitative measurements and diagnostic graphs, so that the outcomes can be interpreted and accurate.

3.1. Forecasting performance evaluation

The overall forecasting performance of the evaluated models for solar irradiance and wind speed was assessed using MAE, RMSE, and R^2, with the numerical results presented in Table 3 and the comparison illustrated in Figure 2. Lower MAE and RMSE values and higher R^2 values indicate better forecasting performance. The results show progressive improvement from Linear Regression to the proposed ConvLSTM model. Linear Regression showed the weakest performance (MAE: 18.42, RMSE: 24.87, R^2: 0.78), followed by Random Forest (12.35, 17.60, 0.86) and XGBoost (10.92, 15.41, 0.89). LSTM further improved the performance (9.18, 13.02, 0.92), demonstrating the importance of temporal dependencies. The proposed ConvLSTM achieved the best overall performance, with an MAE of 7.64, RMSE of 11.28, and R^2 of 0.95. Compared with LSTM, ConvLSTM reduced MAE by 16.8% and RMSE by 13.4%, while increasing R^2 from 0.92 to 0.95. As shown in Figure 2 and summarized in Table 3, these results demonstrate that combining convolutional feature extraction with recurrent temporal learning provides improved predictive performance for solar irradiance and wind speed forecasting.

Table 3. Overall forecasting performance of the evaluated models

Model	MAE	RMSE	R^2
Linear regression	18.42	24.87	0.78
Random forest	12.35	17.60	0.86
XGBoost	10.92	15.41	0.89
LSTM	9.18	13.02	0.92
Proposed model ConvLSTM	7.64	11.28	0.95

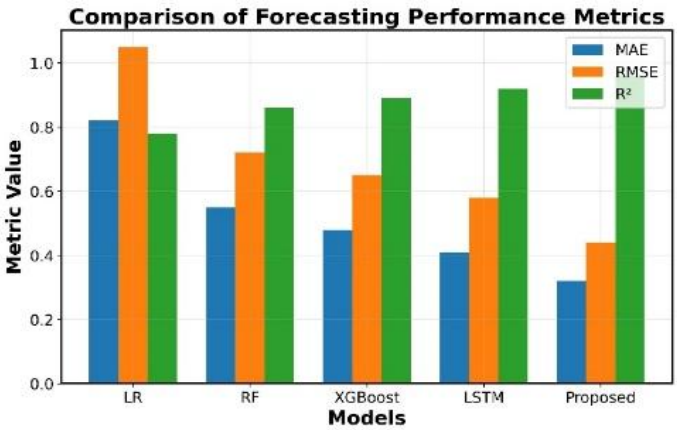

Figure 2. Comparison of performance of model

3.2. Predicted versus actual analysis

The predicted and actual values for wind speed and GHI are compared in Figures 3(a) and 3(b), respectively. Most observations are distributed close to the 1:1 diagonal line, indicating good agreement between the predicted and actual values. For wind speed, slightly greater dispersion is observed at higher wind speeds, while the GHI predictions closely follow the observed trend across different irradiance levels.

Overall, the plots demonstrate that the ConvLSTM model effectively captures the variations in both wind speed and GHI, consistent with the performance reported in Table 3.

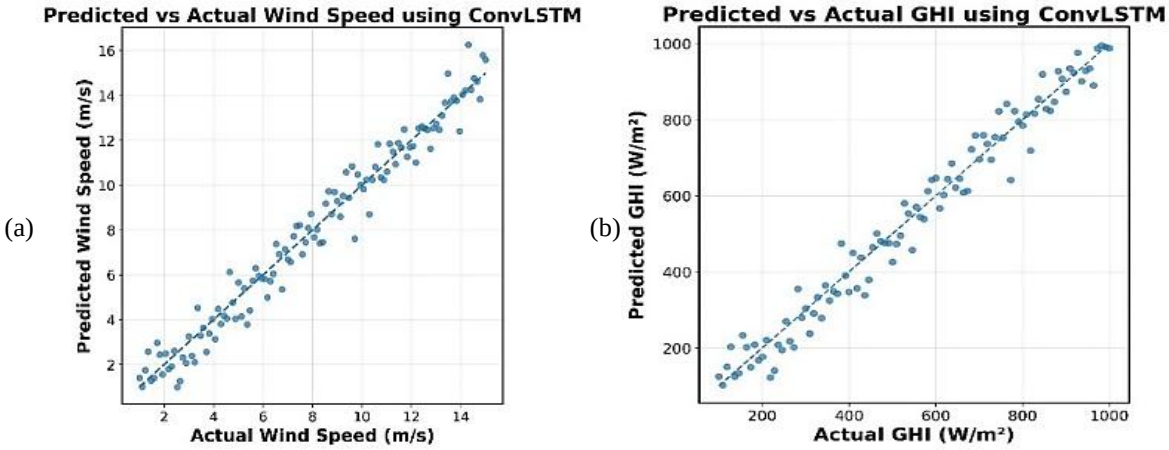

Figure 3. Comparison of predicted and actual values using the ConvLSTM model: (a) wind speed and (b) global horizontal irradiance (GHI)

3.3. Learning curve analysis

Learning curves were analyzed to examine the convergence and generalization of the ConvLSTM model. As shown in Figures 4(a) and 4(b), the training and validation losses for GHI and wind speed decrease progressively with a relatively small gap between the curves, indicating stable convergence with limited overfitting. The faster convergence observed with transfer learning further suggests that previously learned representations can improve training efficiency under related regional conditions.

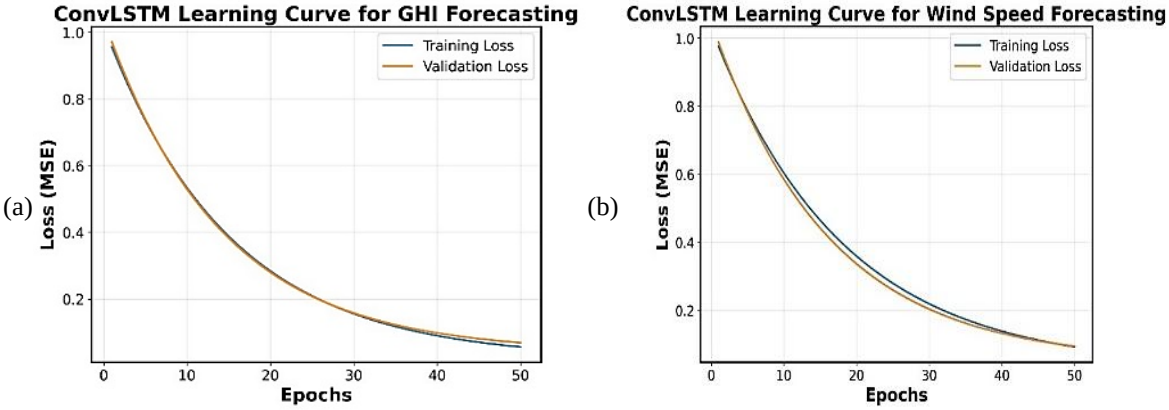

Figure 4. ConvLSTM learning curves for forecasting: (a) global horizontal irradiance (GHI) and (b) wind speed

3.4. Transfer learning performance

The performance of transfer learning was evaluated by comparing the ConvLSTM results before and after fine-tuning on related regional data. The results presented in Figure 5 show a reduction in MAE and RMSE following fine-tuning, with an improvement of approximately 5–8%. This indicates that the learned representations can be adapted to related climatic conditions while reducing the need for complete retraining. The improvement was more pronounced for GHI than for wind speed, indicating that solar irradiance patterns may benefit more from regional transfer.

3.5. Importance and interpretability of the features

The ConvLSTM feature-importance analysis identified the relative contribution of the input variables. As shown in Figure 6, GHI_prev, solar zenith angle, temperature, and Wind_prev were the most influential features, followed by hour, month, and day, highlighting the importance of temporal persistence

and meteorological conditions. Figure 7 presents the SHAP summary plot, which further illustrates the magnitude and direction of each feature's contribution to the model predictions. The SHAP results are consistent with the feature-importance ranking, confirming the dominant influence of lagged and meteorological variables. Figure 8 illustrates the SHAP dependence of the lagged GHI and wind-speed features. The SHAP values show that previous-hour observations contribute substantially to the corresponding predictions, demonstrating the persistence characteristics of solar irradiance and wind speed. Higher or lower lagged values produce changes in the SHAP contribution th, indicating at the influence of these features is not constant across their ranges. This confirms that the forecasting models capture temporal dependencies in the renewable-resource time series

3.6. Discussion

The results indicate that the ConvLSTM model effectively captures the temporal and spatial patterns associated with solar irradiance and wind-speed forecasting. Machine-learning approaches have also been applied for electrical load and solar power forecasting, supporting the applicability of data-driven methods to renewable-energy prediction [24]. Regression-based machine-learning methods have also been demonstrated for predictive modelling in engineering applications [25]. Transfer learning improves model convergence and supports adaptation to related regional conditions. The SHAP analysis provides additional transparency by identifying the relative contribution of lagged and meteorological features to the predictions. Overall, the proposed framework provides a balance of forecasting accuracy, adaptability, and interpretability, making it potentially useful for renewable-energy forecasting applications in hybrid energy system. The forecasting framework has potential applications in PV and wind generation scheduling, reserve planning, hybrid renewable-resource management, and short-term grid balancing. Accurate short-term forecasts can support reserve planning and reduce uncertainty associated with variable renewable generation.

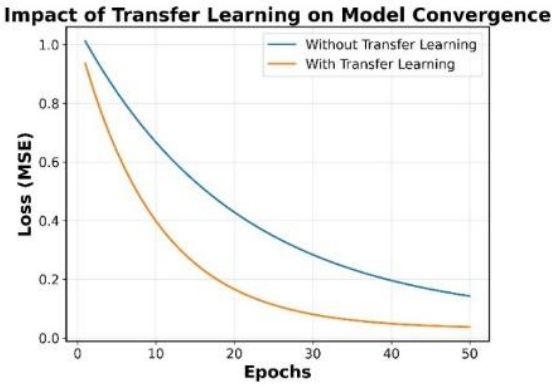

Figure 5. Inter-state transfer learning performance improvement

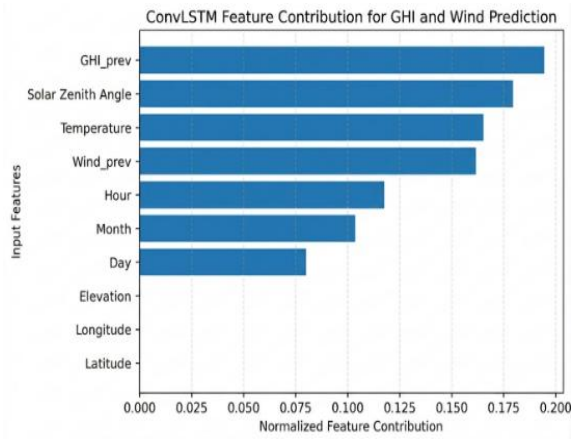

Figure 6. ConvLSTM ranking of importance of features in predicting the GHI and wind

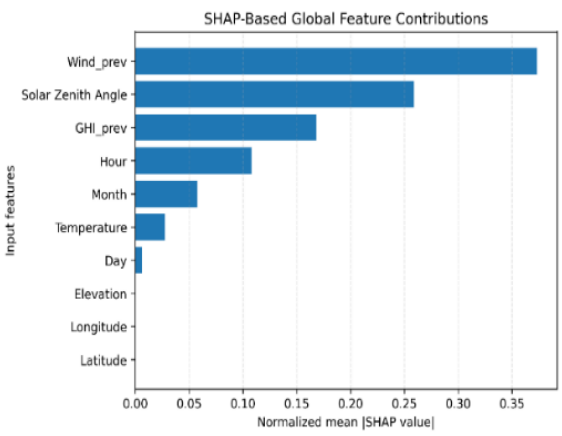

Figure 7. SHAP summary plot providing the global feature contributions

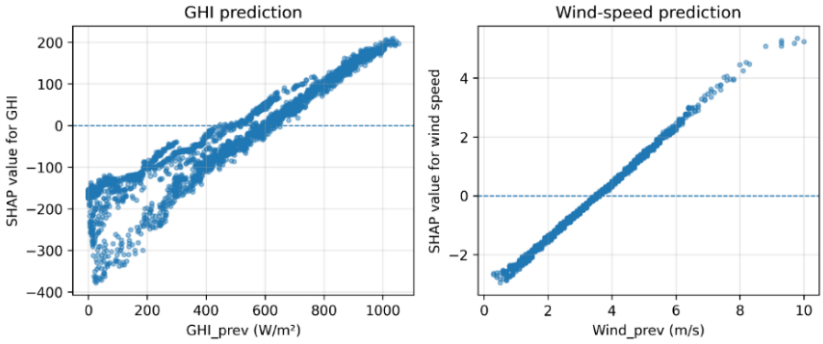

Figure 8. SHAP dependence plots for lagged GHI and wind-speed features

4. CONCLUSION

This study developed an explainable ConvLSTM-based framework for forecasting solar irradiance and wind speed using five years of hourly NSRDB data from 2016–2020. Linear Regression, Random Forest, XGBoost, LSTM, and ConvLSTM models were comparatively evaluated. The proposed ConvLSTM achieved the best forecasting performance, with an MAE of 7.64, RMSE of 11.28, and R^2 of 0.95. The 24-hour sequential input enabled the model to learn temporal dependencies, while learning-curve and predicted-versus-actual analyses demonstrated stable convergence and good agreement between predictions and observations. Feature-importance and SHAP analyses highlighted the significant influence of lagged renewable-resource variables and meteorological parameters. Transfer-learning-based fine-tuning further reduced forecasting errors by approximately 5–8%, demonstrating adaptability to related climatic conditions. Overall, the proposed framework integrates forecasting accuracy, temporal learning, adaptability, and interpretability, providing a practical approach for renewable-resource forecasting and supporting the reliable integration and management of hybrid renewable energy systems. Future work will focus on integrating the framework with hardware-in-the-loop (HIL) microgrid inverter controllers for real-time renewable-energy.

FUNDING INFORMATION

No funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
S. Selvi	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Kedri Janardhana		✓				✓		✓	✓	✓	✓	✓		
Surendar Vadivel			✓		✓		✓	✓	✓			✓		
Mohammad Arif	✓		✓	✓			✓			✓	✓		✓	✓
Joshuva Arockia Dhanraj			✓		✓		✓			✓				
V. Velmurugan					✓		✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

INFORMED CONSENT

The authors confirm that informed consent was obtained from all individuals included in this work.

DATA AVAILABILITY

The authors confirm that the data supporting this study's findings are available within the article.

REFERENCES

[1] A. A. Alguhi and A. M. Al-Shaalan, "LSTM-based prediction of solar irradiance and wind speed for renewable energy systems," *Energies*, vol. 18, no. 17, Aug. 2025, doi: 10.3390/en18174594.

[2] I. B. Benitez and J. G. Singh, "A comprehensive review of machine learning applications in forecasting solar PV and wind turbine power output," *Journal of Electrical Systems and Information Technology*, vol. 12, no. 1, Jul. 2025, doi: 10.1186/s43067-025-00239-4.

[3] I. U. Haq, A. Kumar, and P. S. Rathore, "Machine learning approaches for wind power forecasting: a comprehensive review," *Discover Applied Sciences*, vol. 7, no. 10, Oct. 2025, doi: 10.1007/s42452-025-07675-x.

[4] S. Shringi, L. M. Saini, and S. K. Aggarwal, "A review of data-driven deep learning models for solar and wind energy forecasting," *Renewable Energy Focus*, vol. 55, Dec. 2025, doi: 10.1016/j.ref.2025.100739.

[5] J. Jung and R. P. Broadwater, "Current status and future advances for wind speed and power forecasting," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 762–777, Mar. 2014, doi: 10.1016/j.rser.2013.12.054.

[6] M. Belletreche *et al.*, "Hybrid attention-based deep neural networks for short-term wind power forecasting using meteorological data in desert regions," *Scientific Reports*, vol. 14, no. 1, Sep. 2024, doi: 10.1038/s41598-024-73076-6.

[7] M. S. Abid, R. Ahshan, M. Al-Abri, and R. Al Abri, "Spatiotemporal forecasting of solar and wind energy production: a robust deep learning model with attention framework," *Energy Conversion and Management: X*, vol. 26, 2025, doi: 10.1016/j.ecmx.2025.100919.

[8] M. Abumohsen, A. Y. Owda, M. Owda, and A. Abumihsan, "Hybrid machine learning model combining of CNN-LSTM-RF for time series forecasting of solar power generation," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 9, Sep. 2024, doi: 10.1016/j.prime.2024.100636.

[9] A. G. AbdElkader, H. ZainEldin, and M. M. Saafan, "Optimizing wind power forecasting with RNN-LSTM models through grid search cross-validation," *Sustainable Computing: Informatics and Systems*, vol. 45, Jan. 2025, doi: 10.1016/j.suscom.2024.101054.

[10] M. A. Yassen, E.-S. M. El-Kenawy, M. G. Abdel-Fattah, I. Ismail, and H. E.-D. S. Mostafa, "Explainable artificial intelligence for wind power forecasting model based on long short-term memory," *Neural Computing and Applications*, vol. 37, no. 19, pp. 14589–14611, Jul. 2025, doi: 10.1007/s00521-025-11230-5.

[11] H. Wang, Z. Lei, X. Zhang, B. Zhou, and J. Peng, "A review of deep learning for renewable energy forecasting," *Energy Conversion and Management*, vol. 198, Oct. 2019, doi: 10.1016/j.enconman.2019.111799.

[12] P. Li *et al.*, "Deep learning model for solar and wind energy forecasting considering Northwest China as an example," *Results in Engineering*, vol. 24, 2024, doi: 10.1016/j.rineng.2024.102939.

[13] Y. Wang, R. Zou, F. Liu, L. Zhang, and Q. Liu, "A review of wind speed and wind power forecasting with deep neural networks," *Applied Energy*, vol. 304, Dec. 2021, doi: 10.1016/j.apenergy.2021.117766.

[14] Y. Tang, Y. Zhou, P. Liu, Y. Luo, F. Lin, and F.-J. Chang, "Revolutionizing solar-hydro-wind power forecasts in regional power systems with hybrid machine learning models," *Solar Energy*, vol. 291, May 2025, doi: 10.1016/j.solener.2025.113391.

[15] J. Del Ser *et al.*, "Randomization-based machine learning in renewable energy prediction problems: Critical literature review, new results and perspectives," *Applied Soft Computing*, vol. 118, Mar. 2022, doi: 10.1016/j.asoc.2022.108526.

[16] A. Babiker Abdalla Ibrahim and K. Altun, "LSTM deep learning techniques for wind power generation forecasting," *Journal of Soft Computing and Artificial Intelligence*, vol. 5, no. 1, pp. 41–47, 2024, doi: 10.55195/jscai.1471257.

[17] Y. Nie, E. Zelikman, A. Scott, Q. Paletta, and A. Brandt, "SkyGPT: Probabilistic ultra-short-term solar forecasting using synthetic sky images from physics-constrained VideoGPT," *Advances in Applied Energy*, vol. 14, Jul. 2024, doi: 10.1016/j.adapen.2024.100172.

[18] S. Syama, J. Ramprabhakar, R. Anand, V. P. Meena, and J. M. Guerrero, "A novel hybrid methodology for wind speed and solar irradiance forecasting based on improved whale optimized regularized extreme learning machine," *Scientific Reports*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-83836-z.

[19] M. Lafuente-Cacho *et al.*, "State of the art for solar and wind energy-forecasting methods for sustainable grid integration," *Current Sustainable/Renewable Energy Reports*, vol. 12, no. 1, 2025, doi: 10.1007/s40518-025-00262-z.

[20] J. R. Andrade and R. J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1571–1580, Oct. 2017, doi: 10.1109/TSTE.2017.2694340.

[21] T. G. Dietterich, "Machine learning for sequential data: a review," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 2396, pp. 15–30, 2002, doi: 10.1007/3-540-70659-3_2.

[22] A. Zendehboudi, M. A. Baseer, and R. Saidur, "Application of support vector machine models for forecasting solar and wind energy resources: a review," *Journal of Cleaner Production*, vol. 199, pp. 272–285, Oct. 2018, doi: 10.1016/j.jclepro.2018.07.164.

[23] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed. Melbourne, Australia: OTexts, 2021.

[24] S. K. Panda, "Electrical load and solar power forecasting using machine learning techniques," *Journal of King Saud University – Engineering Sciences*, vol. 37, no. 4, Jul. 2025, doi: 10.1007/s44444-025-00012-y.

[25] S. Selvi, S. E. Murthy, B. Govindan, D. Leela Rani, and M. Suresh, "Predicting concrete strength using regression-based machine learning techniques," *SSRG International Journal of Civil Engineering*, vol. 12, no. 10, pp. 139–146, Oct. 2025, doi: 10.14445/23488352/IJCE-V12I10P111.

BIOGRAPHIES OF AUTHORS



S. Selvi is a professor and the head of the Department of Electrical and Electronics Engineering at Panimalar Engineering College. She received her bachelor's degree in electrical and electronics engineering from the College of Engineering, Guindy, Anna University. She obtained her master's degree in power electronics and drives and her doctoral degree from Sathyabama University, Chennai, India. She has approximately 30 years of teaching experience. Her research interests include lightning and industrial drives. She has published several research articles in national and international journals and conference proceedings. She can be contacted at email: selviselvaraj@gmail.com.



Dr. Kedri Janardhana is an assistant professor (Selection Grade) in the Department of Electrical Engineering at Dayalbagh Educational Institute (DEI), Agra, India. He holds B.Tech., M.Tech., and Ph.D. degrees in electrical engineering and has over 18 years of academic experience. His research interests include power electronics and drives, battery management, electric vehicles, solar photovoltaic (PV) systems, and microgrids. He has filed five international and 15 national intellectual property applications. He is a life member of IEI and SSEM and an active member of IEEE. He can be contacted at email: janardhankedri@dei.ac.in.



Surendar Vadivel is an associate professor in the Department of Electrical and Electronics Engineering at at Kongu Engineering College, Erode, Tamil Nadu, India. He holds B.E., M.E., and Ph.D. degrees from Anna University and has 16 years of academic experience. His research interests include DC–DC converters, battery management, electric vehicle technology, digital control of power electronic systems, and renewable energy applications. He can be contacted at email: surendarv0212@gmail.com.



Dr. Mohammad Arif is a professor in the Department of Artificial Intelligence and Data Science, Parul Institute of Engineering and Technology, Faculty of Engineering and Technology, Parul University, Vadodara, Gujarat, India. He has nearly 25 years of teaching experience. He holds B.Tech., M.Tech., and Ph.D. degrees in Computer Science and Engineering. He has published more than 55 research papers, authored three books and four book chapters, and holds three international patents and five Indian patents. His research interests include ad hoc networks, vehicular networks, cloud and mobile computing, security, machine learning, and deep learning. He can be contacted at email: arif_mohd2k@yahoo.com.



Dr. Joshuva Arockia Dhanraj recognized among the World's Top 2% Scientists (Stanford–Elsevier, 2025), is a Professor in the Department of Computer Science and Engineering (AI & ML), School of Engineering, Dayananda Sagar University, Bengaluru, Karnataka 562112, India. He has more than eight years of teaching experience, three years of research experience, and one year of postdoctoral experience. He has published more than 250 papers indexed in SCI and Scopus and has filed 22 patents, of which more than 15 have been granted. His research interests include artificial intelligence and machine learning, mechatronics, robotics, fault diagnosis, structural health monitoring, and renewable energy. He can be contacted at email: joshuva1991@gmail.com.



Dr. V. Velmurugan is a professor in the Department of Electronics and Communication Engineering (ECE) at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India. He has approximately 19 years of teaching experience and holds B.E., M.E., and Ph.D. degrees in electronics and communication engineering. He has published 25 research papers in international journals and conference proceedings. His research interests include wireless communication, wireless networks, vehicular ad hoc networks (VANETs), mobile communication, the Internet of Things (IoT), and artificial intelligence. He is a life member of IETE, ISTE, and IAENG. He can be contacted at email: drvelmuruganv@veltech.edu.in.