IKSAD INSTITUTE
Institute of Economic Development and Social Research

VI. INTERNATIONAL EURASIAN SCIENTIFIC RESEARCH AND INNOVATION CONGRESS

January 6-10, 2026 / DUBAI

PROCEEDINGS BOOK

Editor
Prof. Dr. Osman Kubilay GÜL

ISBN: ISBN: 979-8-89695-312-8

PROCEEDINGS BOOK

VI. INTERNATIONAL EURASIAN SCIENTIFIC RESEARCH AND INNOVATION CONGRESS

January 6-10, 2026 / DUBAI

Editor

Prof. Dr. Osman Kubilay GÜL

20.01.2026

by Liberty Academic Publishers, New York, USA

adopted by Mariam Rasulan
ISBN: ISBN: 979-8-89695-312-8

PROCEEDINGS BOOK

CONGRESS ID

TITLE OF CONGRESS
VI. INTERNATIONAL EURASIAN SCIENTIFIC RESEARCH AND INNOVATION CONGRESS

PARTICIPATION
Keynote & Invited

DATE - PLACE
January 6-10, 2026 / DUBAI

ORGANIZATION
İKSAD-Institute of Economic Development and Social Researches

HEAD OF CONGRESS
Prof. Dr. Osman Kubilay GÜL - Sivas Cumhuriyet University

ORGANIZING COMMITTEE MEMBERS
Prof. Dr. Osman Kubilay GÜL - Sivas Cumhuriyet University
Prof. Dr. Florian MOBO - Philippines Merchant Marine Academy
Assoc. Prof. Dr. Ethem İlhan ŞAHİN - Adana Alparslan Türkeş Science and Technology University
Dr. Nurlan AKHMETOV - Khoja Ahmed Yessevi University
Dr. Muhammad Faisal - Director Ministry of Human Rights, Pakistan
Research Assistant Merve KÜÇÜK - IKSAD Institute

SCIENCE & ADVISORY COMMITTEE

Prof. Dr. Cavansir Zeynalov - Nakhchivan State University
Prof. Dr. Osman Kubilay GÜL - Sivas Cumhuriyet University
Prof. Dr. Sedaqet Hesenova - Nakhchivan State University
Prof. Dr. Florian MOBO - Philippines Merchant Marine Academy
Prof. Dr. Emin Sixeliyev - Nakhchivan State University
Assoc. Prof. Dr. Cem Özkurt - Trabzon University
Assoc. Prof. Dr. Meftun İsmayilov - Nakhchivan State University
Assoc. Prof. Dr. Arif Agalarov - Nakhchivan State University

PARTICIPATING COUNTRIES (14)

Saudi Arabia, Türkiye, Nigeria, Romania, Bangladesh, Ukraine, Albania, Morocco, Iran, India, Vietnam, Algeria, Pakistan, Hungary

TOTAL PAPERS: 78

The number of papers from foreign countries: **42**

The number of papers from Türkiye: **36**

LANGUAGES

Turkish, English

MULTI-SCALE FORECASTING OF PHOTOVOLTAIC POWER GENERATION USING LSTM NETWORKS

İbrahim ÇOMA

Bilecik Seyh Edebali University, Institute of Graduate, Department of Energy Systems Engineering, Bilecik, Türkiye.

ORCID ID: https://orcid.org/0009-0005-5703-0192

Assoc. Prof. Emre DANDIL

Bilecik Seyh Edebali University, Faculty of Engineering, Department of Computer Engineering, Bilecik, Türkiye.

ORCID ID: https://orcid.org/0000-0001-6559-1399

ABSTRACT

Accurate forecasting of photovoltaic (PV) power generation is essential for maintaining power grid stability and improving the operational efficiency of solar power plants. However, most existing forecasting approaches rely heavily on external meteorological data such as solar irradiance, temperature, and wind speed, which may not always be available due to sensor limitations, high installation costs, or data transmission failures. This dependency significantly restricts the practical applicability of such models in real-world scenarios. In this study, Long Short-Term Memory (LSTM) deep learning-based forecasting framework is proposed to predict PV power generation using historical production data. Hourly power generation data collected from a grid-connected photovoltaic power plant located in Sakarya, Türkiye, covering a period of 26 months, are utilized. LSTM networks are employed due to their ability to model long-term temporal dependencies in time series data. The proposed approach incorporates cyclical time features representing hour-of-day and month-of-year into the model using transformations. This enables the network to learn daily and seasonal periodic patterns. The proposed approach is evaluated across daily, weekly, monthly, seasonal and yearly forecasting horizons. Model performance is rigorously assessed using an out-of-time validation strategy where the model is trained using historical data and tested using completely unseen data. The experimental results show high forecasting accuracy at all time scales. The model achieved an R^2 score of 0.997 for short-term daily forecasts. Seasonal and yearly analyses further confirm the model's robust performance, particularly during the summer months. These findings indicate that the proposed method is a cost-effective and scalable solution for reliable PV power forecasting in real-world photovoltaic energy management applications.

Keywords: Photovoltaic Panel, Power Forecasting, Time Series Prediction, Deep Learning, Long Short-Term Memory (LSTM).

INTRODUCTION

Renewable energy, defined as energy obtained from continuously available natural resources, is a sustainable, environmentally friendly alternative to traditional fossil fuels (Sirmaçek et al., 2023). These sources play a critical role in combating global warming and climate change, both of which have intensified in recent years (Marouani, 2024). Solar energy, derived from sunlight, is a renewable, environmentally friendly energy source. The main advantages of solar energy are that it is available as long as the sun is shining, has low operating costs, provides energy independence, and is environmentally friendly.

The increasing demand for energy and the environmental impact of fossil fuels have heightened global interest in renewable energy sources. Photovoltaic (PV) solar energy is one of the fastest-growing methods due to its clean, sustainable nature and low operating costs. PV panels, batteries, and concentrated solar power technologies are widely used to generate electricity and heat (Ayvaz & Bayrak, 2024). PV energy production has become a fundamental component of sustainable energy systems due to its low environmental impact and rapidly decreasing installation costs (Peters, 2025; Tawalbeh et al., 2021). However, the intermittent nature of solar energy poses significant challenges regarding grid stability, energy planning, and real-time operation. PV power output, or the amount of energy produced, is strongly influenced by meteorological factors such as solar radiation, humidity, temperature, and cloud cover. This leads to highly variable production profiles that are difficult to predict accurately (Ndiaye et al., 2025). Therefore, accurately forecasting photovoltaic energy production is critical for grid stability and plant efficiency.

The increased use of renewable energy sources, combined with growing demands for sustainability and efficiency, is causing significant changes in the global energy market. Highly accurate forecasts are necessary for effectively managing supply and demand in this market. Anticipating deficiencies and inefficiencies in energy production and developing appropriate plans allows for a more effective evaluation of resource use, investments, and opportunities (Carnevale et al., 2024). The trend toward renewable energy sources is increasing due to environmental issues, the limited nature of fossil fuel resources, the impact of geopolitical instability, and difficulties in accessing resources. Consequently, the proportion of energy needs met by renewable energy sources increases yearly.

Traditional approaches to forecasting PV power output primarily rely on physical models or statistical methods based on meteorological data. However, these studies depend heavily on external meteorological data, such as radiation, temperature, and wind speed, to improve prediction accuracy (Ye et al., 2022). The limited availability of sensors that provide this data at each power plant, the high cost of these sensors, and interruptions in data transmission limit the applicability of these models in real-world settings.

In recent years, deep learning-based models have emerged as a prominent approach in PV power forecasting due to their ability to model complex nonlinear relationships and temporal dependencies (Xiang et al., 2024). Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, are widely used in PV forecasting studies because they can learn long-term dependencies in time series data (Agga et al., 2022; Sharma et al., 2022). Studies have shown that, when sufficient historical data and meteorological information are available, LSTM-based models provide higher accuracy than traditional machine learning and statistical methods (Li et al., 2021; Mohamad Radzi et al., 2025; Srivastava & Lessmann, 2018).

Despite advances in deep learning, most PV forecasting studies still rely on external meteorological inputs, such as solar radiation and temperature (Xu et al., 2025). Many approaches have been proposed that combine LSTM networks with convolutional neural networks or different optimization techniques. However, most of these models still require meteorological data (Agga et al., 2022; Mohamad Radzi et al., 2025; Xu et al., 2025). Consequently, recent studies have confirmed that LSTM-based models trained solely on historical PV production data can achieve acceptable levels of accuracy.

This study proposes a multi-scale LSTM-based forecasting framework that uses only historical PV production data. To compensate for the lack of meteorological data, the model incorporates cyclical time features that represent hourly and monthly information. This allows the model to learn daily and seasonal periodicities, which play a dominant role in PV production. We evaluated the proposed approach at daily, monthly, seasonal, and annual prediction timescales. We analyzed the model's performance using an out-of-time validation strategy, which involves training the model on one year's data and testing it on an entirely different second year's data. This study tested the method on real field data obtained from a grid-connected photovoltaic power plant in Sakarya, Turkey. The results demonstrate that the method provides a scalable, reliable, and cost-effective photovoltaic power forecasting solution when meteorological data is unavailable or incomplete.

METHOD

Dataset

This study uses energy production data from a 5 MW PV solar power plant (SPP) that began operating in September 2023 in the Karaman region of Sakarya Province, Turkey. The dataset covers a 26-month period from September 2023 to November 2025. The study used a dataset based on approximately

19,000 hours of electricity production data obtained from the plant's SCADA program. Figure 1 shows the hourly energy production of the photovoltaic power plant and long-term production trends. The gray line represents the raw production values measured on an hourly basis, and the black line shows the 30-day moving average, which reveals the seasonal and annual trends in production more clearly. The graph illustrates that PV production significantly increases in the summer and decreases in the winter due to reduced sunshine duration. These results indicate a strong seasonal cyclicality in production, suggesting that periodic patterns are critical for time series–based forecasting models.

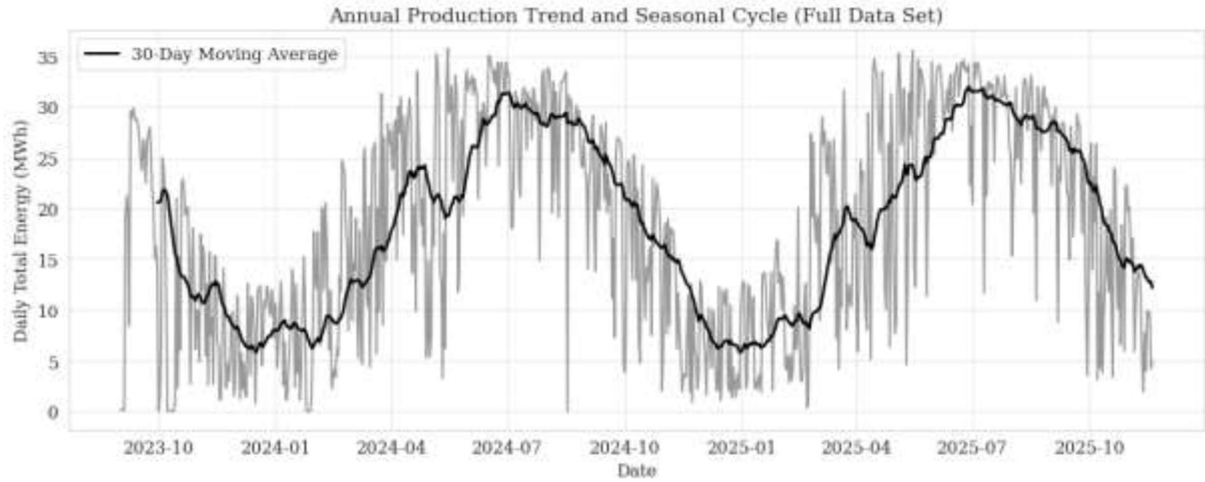

Figure 1. Annual photovoltaic power production trend and seasonal cycle with 30-day moving average

Data pre-processing

The primary variable in the dataset is the active power (kW) supplied by the power plant to the grid. In line with the main hypothesis of the study, the model did not include external meteorological data such as radiation, temperature, or cloud cover. The goal was for the model to predict based solely on historical production patterns. During the data preprocessing stage, production values below 5 kW were set to 0 because they were likely caused by sensor error during nighttime hours. The data preparation stages used in the study are shown in the block diagram in Figure 2.

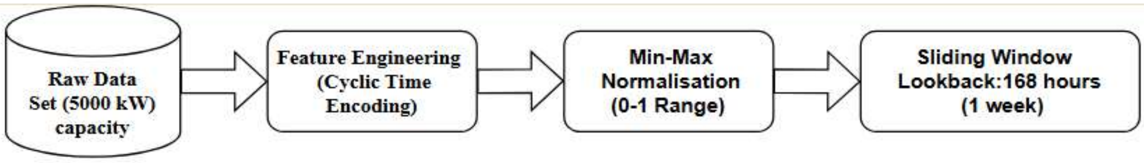

Figure 2. Preprocessing stages of PV power output data

The raw dataset was preprocessed with feature engineering steps before being fed into the model. In this case, feature extraction was performed using hourly raw energy production data obtained from a 5 MW (5000 kW) photovoltaic power plant. The structured data preparation process, as shown in the diagram, enabled the model to learn temporal and periodic patterns more effectively. Specifically, time-related variables (hour, month, etc.) were expressed using sine and cosine transformations via the Cyclical Time Encoding approach. This approach incorporates dominant periodic behaviors in photovoltaic production into the model. This transformation preserves the nonlinear and cyclical nature of the time variables to enable the model to learn daily and seasonal periodicity. Another stage of the preprocessing involved applying Min-Max normalization to eliminate the negative effects of variables with different scales on model training. This process scaled all features to the [0, 1] range. This normalization process contributes to faster, more stable, and more efficient convergence of gradient-based deep learning algorithms, such as LSTM. Finally, the time series data were converted into a supervised learning format using the sliding window method. In this case, the look-back window length was set to 168 hours (one week), and the model used production information from the previous 168 hours as input to predict the next hourly production value. This approach enables the model to learn daily and weekly production patterns.

Proposed LSTM model

One of the deep learning methods used in renewable energy systems is the recurrent neural network (RNN), a specialized model for tasks involving sequential inputs. RNN architecture maintains the previous input state using a structure called a state vector, combining it with the new input value to establish a relationship between the two (Sherstinsky, 2020). However, RNNs have the disadvantage of being unable to store information for long periods. To address this issue, the long short-term memory (LSTM) model was developed. In the LSTM model, memory cells store hidden states. These cells determine which data to delete and which to retain. LSTMs learn quickly and have proven successful in complex, long-delay tasks (Hochreiter & Schmidhuber, 1997).

LSTM networks, widely used in many fields such as text, handwriting, and music generation, machine translation, and time series forecasting, stand out due to their ability to model long-term dependencies in sequential data (Breuel, 2017; Eck & Schmidhuber, 2002; Messina & Louradour, 2015; Wen & Li, 2023). Studies in the energy sector have reported that LSTM-based models provide higher prediction accuracy compared to other deep learning approaches (Akhter et al., 2022; Dhaked et al., 2023; Konstantinou et al., 2021). In this context, LSTM networks are effectively used in many critical applications, such as solar radiation prediction, feature extraction and forecasting in wind speed and power time series, total load estimation in energy grids, and short-, medium-, and long-term forecasting of PV power production.

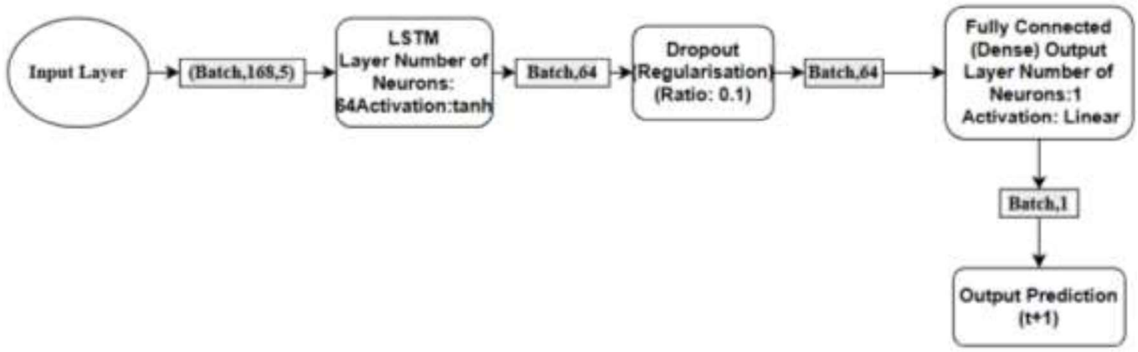

Figure 3. Block diagram of the proposed LSTM architecture for PV panel power output prediction

Figure 3 shows the block diagram of the proposed LSTM architecture for PV panel power output estimation. In the input layer, the data is presented to the model as a tensor of size (batch, 168, 5). In this structure, 168 represents the number of time steps (lookback window) and 5 represents the number of features provided to the model (day sine and cosine components of past power production with cyclic time coding). The LSTM layer is the basic processing unit that learns long-term dependencies in time series. In this layer, the model's learning capacity is limited to 64 neurons. The tanh function is the standard activation function used in LSTM cells. This choice ensures that the outputs remain within the range of −1 to 1, which contributes to stable training progress by preserving gradient flow. The output of the LSTM layer is a feature vector of size (Batch, 64). To prevent overfitting and improve the model's generalization performance, a dropout layer was added after the LSTM layer. During the training process, 10% of the neurons were randomly disabled. In the fully connected output layer, the summary representations obtained from previous layers are reduced to a single neuron. Since a regression-based prediction problem is addressed, a linear activation function is used in the output layer, thus enabling the model to predict any real value. Finally, during the t+1 prediction step, the model outputs the photovoltaic power generation value for the subsequent time step.

EXPERIMENTAL RESULTS

In this study, a single-variable LSTM-based power forecasting model that does not require meteorological sensor data was developed using 26 months of actual production data from the Sakarya-Karaman GES site. The study's novel approach involved enriching the raw time series data using the cyclical feature engineering method, thereby enhancing the model's ability to recognize seasonal and daily patterns. All experiments were conducted on an x64-based computer with a Windows 11 Pro 64-bit operating system. The computer was equipped with a 13th Generation Intel Core i5-13420H processor (2.10 GHz), a 500 GB hard disk drive (HDD), 16 GB of random-access memory (RAM), and a 6 GB graphics processing unit (GPU). This hardware infrastructure enabled stable, efficient execution of the deep learning model training and testing processes. Experimental studies were conducted using Python 3 and the TensorFlow-based Keras library for deep learning modeling and prediction.

In this study, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R2 error metrics were used to evaluate the performance of the proposed LSTM architecture for predicting PV solar energy production in the dataset. These metrics are based on the difference between actual and predicted solar energy production values. RMSE measures the average error between predicted and actual values. RMSE is useful because it intuitively measures how well a model's predictions match the actual data. MAE evaluates how close the predicted values are to the actual values by averaging the absolute differences between them. R^2 is commonly used to assess the goodness of fit of a model. It indicates how well the model's predictions match the actual data. RMSE is often used alongside other metrics, such as MAE and R^2. While RMSE highlights large errors, MAE provides a more balanced view by treating all errors equally. Therefore, both metrics are typically reported together. Equations (1), (2), and (3) show RMSE, MAE, and R^2, respectively.

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

Here, n denotes the total number of data points (observations), y_i denotes the actual measurement value at the i-th time step, $\widehat{y_i}$ denotes the value predicted by the model, and $\bar{y}$ denotes the average of the actual values.

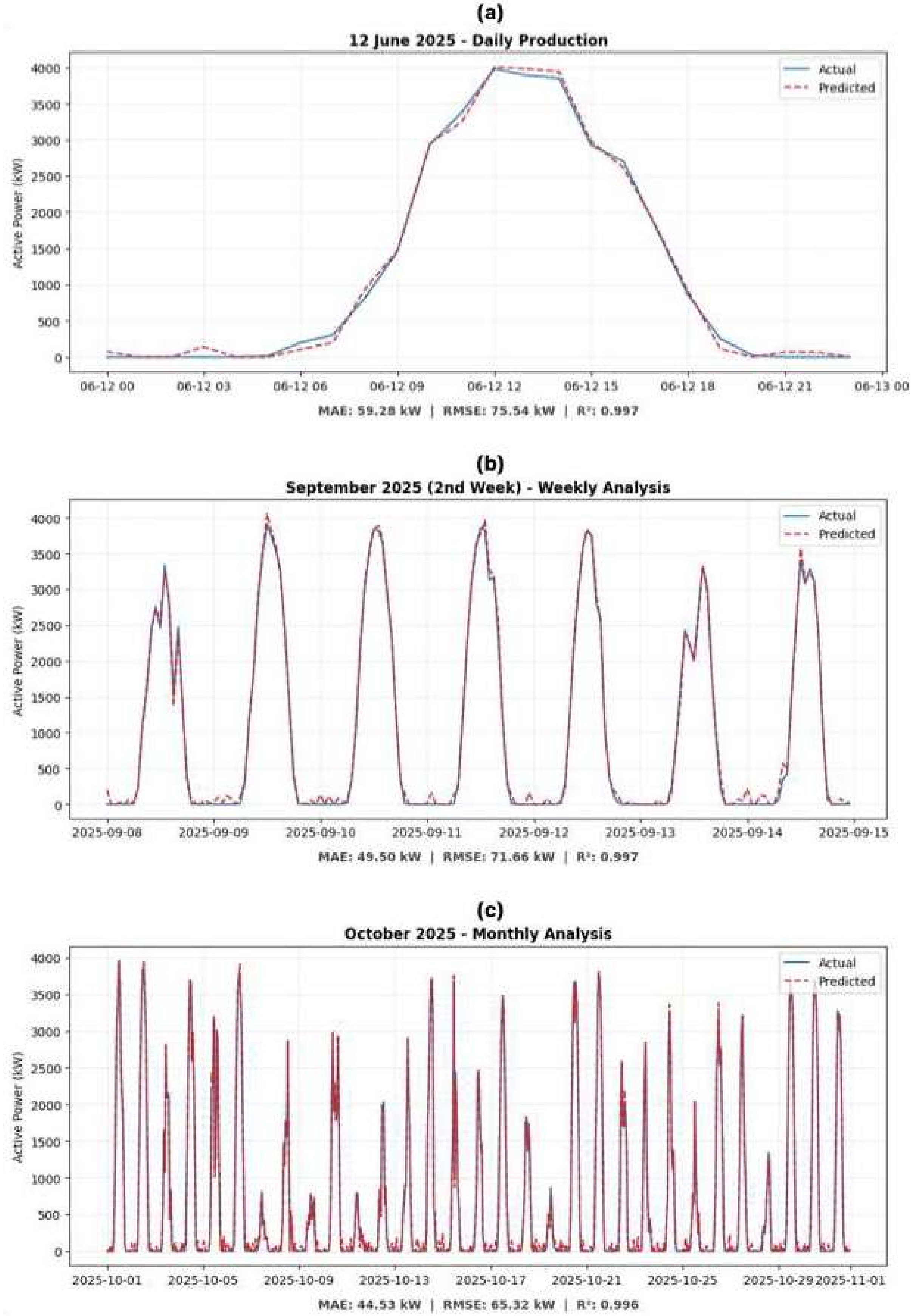

Figure 4. Multi-scale photovoltaic power generation forecasting performance of the proposed LSTM model: (a) daily, (b) weekly, and (c) monthly analysis

Figure 4 shows the photovoltaic (PV) power generation prediction performance of the proposed LSTM-based model at different time scales (daily, weekly, and monthly). Figure (a) presents daily hourly production forecasts for June 12, 2025. The model is seen to successfully track the rapid power increases and decreases occurring during sunrise and sunset. The high level of agreement between the predicted values during peak production hours and the actual measurements indicates that the model has correctly learned the short-term dynamics. The low MAE (59.28 kW) and RMSE (75.54 kW) values obtained, along with the high R^2 score (0.997), reveal that the daily prediction accuracy is quite high. Figure (b) shows the weekly prediction results for the second week of September 2025. The model has consistently captured the recurring daily production cycles on a weekly basis and successfully modeled the inter-day variation. In particular, the minimal deviations during nighttime hours when production is close to zero confirm the effectiveness of the model's time-based cyclical feature engineering. The MAE (49.50 kW), RMSE (71.66 kW), and R^2 (0.997) values obtained from the weekly analysis show that the model has high generalization capability for medium-term forecasts. Figure (c) shows the monthly prediction performance for October 2025. Despite the short-term production fluctuations observed on a monthly scale, the model accurately tracks the general production trend and daily peaks. Occasional sudden drops and rises notwithstanding, low error metrics (MAE: 44.53 kW; RMSE: 65.32 kW) and a high R^2 score (0.996) suggest that the model yields stable and reliable results, even in long-term forecasts. Overall, these results demonstrate that the LSTM model achieves high prediction success across different time scales when developed using only historical production data and cyclical time characteristics, without the need for external meteorological data.

Figure 5 clearly shows that the proposed LSTM-based model achieves high forecasting accuracy for seasonal PV power generation, as demonstrated by the R^2 performance metric. The figure illustrates a comparison of historical production data from the first year with actual and predicted total seasonal generation values from the second year. The predicted values show strong agreement with the actual production profiles across all seasons. During the winter season, the model achieves an R^2 score of 0.9009. Despite the reduced solar availability and increased variability characteristic of winter, this result suggests that the model can capture underlying seasonal production patterns using only historical generation data. The forecasting performance improves in the spring season, reaching an R^2 value of 0.9302. This suggests that the proposed approach effectively learns the transitional dynamics associated with increasing solar activity and seasonal changes. The model attains its highest forecasting performance during the summer season, with an R^2 score of 0.974. This period's high coefficient of determination reflects the model's strong ability to learn stable, highly periodic production behavior under consistent solar conditions. Despite transitional effects and increased variability in the autumn season, the model maintains high forecasting accuracy, achieving an R^2 value of 0.9375. This result confirms the robustness of the LSTM framework in generalizing across different seasonal regimes.

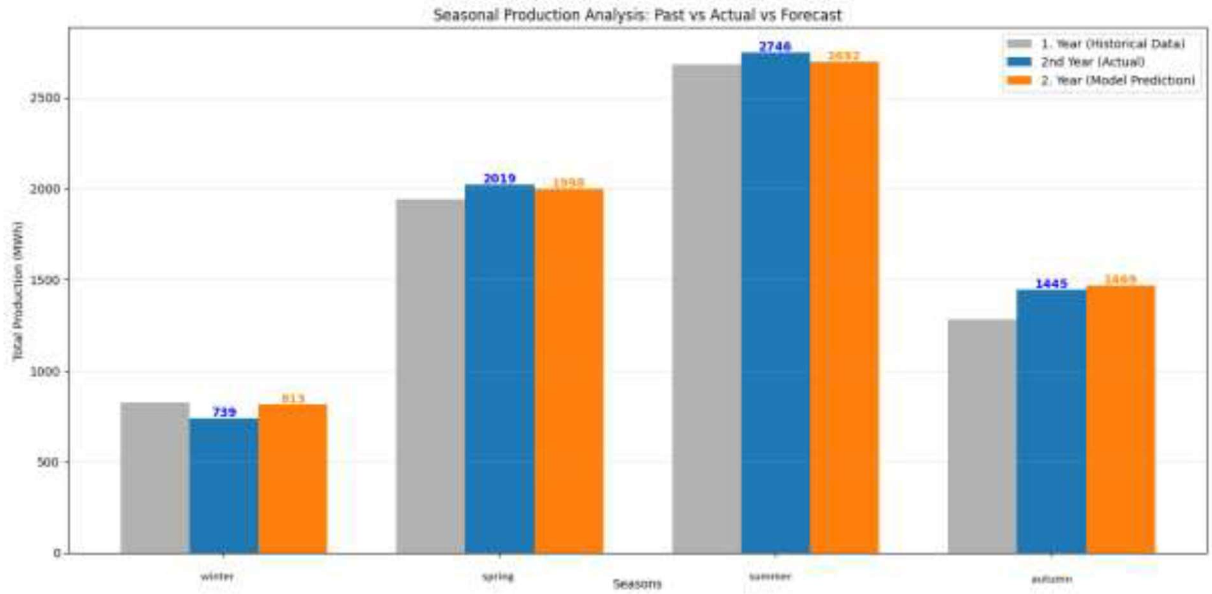

Figure 5. Comparison of actual and predicted seasonal photovoltaic power generation

In this study, model performance was evaluated using the out-of-time validation approach, which is commonly used for time series forecasting problems. In this case, the first 12 months (September 2023–September 2024) of production data from the Sakarya Karaman GES were used as the training set, and the model parameters were updated based solely on this period's data. The subsequent 12-month period (September 2024–September 2025) was designated as the test set. The model's prediction performance was then evaluated using this previously unseen data. Figure 6 shows the annual photovoltaic power production prediction results obtained using this validation strategy. The figure presents a comparative view of the historical production profiles from the training period and the actual and model-predicted production values from the test period. The visual results demonstrate that, despite being trained only on the first year's data, the model successfully captured the production trends and seasonal variations of the second year. These results show that the proposed LSTM-based approach can effectively learn long-term temporal dependencies and produce reliable predictions over an unseen annual production period without requiring external meteorological data.

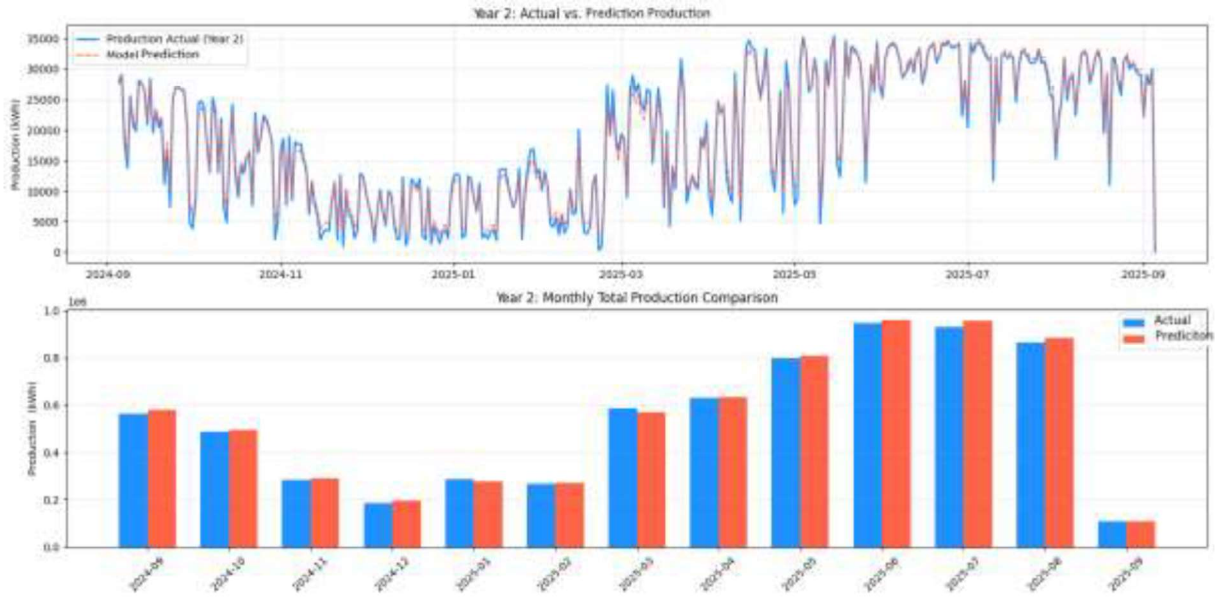

Figure 6. Annual photovoltaic power generation forecasting results using out-of-time validation

CONCLUSION

In this study, hourly production data obtained from the Sakarya Karaman Solar Power Plant was used to perform a multi-scale PV power production forecast based solely on historical power production information. The study's main objective is to develop a prediction model applicable to real-world conditions that is highly accurate without requiring meteorological sensor data. In this regard, LSTM networks, which have the ability to learn long-term temporal dependencies, were preferred. The proposed approach integrates hourly and monthly information into the model using cyclic time encoding to enable learning daily and seasonal periodic patterns. The model's performance was evaluated under daily, weekly, monthly, seasonal, and annual forecasting scenarios. Notably, out-of-time validation analysis, which involved training the model on the first year's data and testing it on unseen second-year data, demonstrated the approach's generalization capability. The experimental results demonstrate that the proposed LSTM-based model has high predictive capabilities across all time scales. The model's ability to effectively learn hourly production dynamics is revealed by the high accuracy levels achieved in short-term daily forecasts, while the results obtained in seasonal and annual forecasts show that long-term production trends can be reliably predicted. The high R^2 values obtained, particularly in the summer, confirm the model's stability during periods of strong periodic behavior. In conclusion, this study demonstrates that an LSTM-based prediction model developed using only historical production data and time-based features offers an effective, scalable, and low-cost solution for photovoltaic power production forecasting. This approach has significant potential to support energy management, grid planning, and operational strategies in power plants where access to meteorological data is limited or sensor infrastructure is unavailable. Future studies may aim to increase the model's generalizability by using data from different geographical regions and by further improving performance through hybrid deep learning architectures.

ACKNOWLEDGMENTS

We would like to thank Sakarya Metropolitan Municipality for providing the PV power output dataset used in this study and for allowing its use.

REFERENCES

Agga, A., Abbou, A., Labbadi, M., El Houm, Y., & Ali, I. H. O. (2022). CNN-LSTM: An efficient hybrid deep learning architecture for predicting short-term photovoltaic power production. *Electric Power Systems Research*, *208*, 107908.

Akhter, M. N., Mekhilef, S., Mokhlis, H., Almohaimeed, Z. M., Muhammad, M. A., Khairuddin, A. S. M., Akram, R., & Hussain, M. M. (2022). An hour-ahead PV power forecasting method based on an RNN-LSTM model for three different PV plants. *Energies*, *15*(6), 2243.

Ayvaz, B. Ş., & Bayrak, A. (2024). Electricity generation methods from solar energy. *Mühendis ve Makina*(716), 521-557.

Breuel, T. M. (2017). High performance text recognition using a hybrid convolutional-lstm implementation. 2017 14th IAPR international conference on document analysis and recognition (ICDAR),

Carnevale, D., Cavaiola, M., & Mazzino, A. (2024). A novel AI-assisted forecasting strategy reveals the energy imbalance sign for the day-ahead electricity market. *Energy Reports*, *11*, 4115-4126.

Dhaked, D. K., Dadhich, S., & Birla, D. (2023). Power output forecasting of solar photovoltaic plant using LSTM. *Green Energy and Intelligent Transportation*, *2*(5), 100113.

Eck, D., & Schmidhuber, J. (2002). A first look at music composition using lstm recurrent neural networks. *Istituto Dalle Molle Di Studi Sull Intelligenza Artificiale*, *103*(4), 48-56.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.

Konstantinou, M., Peratikou, S., & Charalambides, A. G. (2021). Solar photovoltaic forecasting of power output using LSTM networks. *Atmosphere*, *12*(1), 124.

Li, Y., Ye, F., Liu, Z., Wang, Z., & Mao, Y. (2021). A short-term photovoltaic power generation forecast method based on LSTM. *Mathematical Problems in Engineering*, *2021*(1), 6613123.

Marouani, I. (2024). Contribution of renewable energy technologies in combating phenomenon of global warming and minimizing GHG emissions. *Clean Energy Science and Technology*, *2*(2), 164.

Messina, R., & Louradour, J. (2015). Segmentation-free handwritten Chinese text recognition with LSTM-RNN. 2015 13th International conference on document analysis and recognition (icdar),

Mohamad Radzi, P. N. L., Mekhilef, S., Mohamed Shah, N., Akhter, M. N., Seyedmahmoudian, M., & Stojcevski, A. (2025). Optimizing solar power forecasting with metaheuristic algorithms and deep learning models for photovoltaic grid connected systems. *Scientific reports*, *15*(1), 40045.

Ndiaye, A., Faye, M., Gueye, D., Ba, A., & Traore, M. (2025). Analysis of the impact of irradiance and temperature on photovoltaic production: A statistical and machine learning approach. *MethodsX*, 103716.

Peters, I. M. (2025). From fossil fuels to photovoltaics: energy's role in human development and sustainability. *EES Solar*, *1*(5), 712-723.

Sharma, J., Soni, S., Paliwal, P., Saboor, S., Chaurasiya, P. K., Sharifpur, M., Khalilpoor, N., & Afzal, A. (2022). A novel long term solar photovoltaic power forecasting approach using LSTM with Nadam optimizer: A case study of India. *Energy Science & Engineering*, *10*(8), 2909-2929.

Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D: Nonlinear Phenomena*, *404*, 132306.

Sirmaçek, B., Gupta, S., Mallor, F. n., Azizpour, H., Ban, Y., Eivazi, H., Fang, H., Golzar, F., Leite, I., & Melsión, G. I. (2023). The potential of artificial intelligence for achieving healthy and sustainable societies. In *The ethics of artificial intelligence for the sustainable development goals* (pp. 65-96). Springer.

Srivastava, S., & Lessmann, S. (2018). A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data. *Solar Energy*, *162*, 232-247.

Tawalbeh, M., Al-Othman, A., Kafiah, F., Abdelsalam, E., Almomani, F., & Alkasrawi, M. (2021). Environmental impacts of solar photovoltaic systems: A critical review of recent progress and future outlook. *Science of the total environment*, *759*, 143528.

Wen, X., & Li, W. (2023). Time series prediction based on LSTM-attention-LSTM model. *IEEE access*, *11*, 48322-48331.

Xiang, X., Li, X., Zhang, Y., & Hu, J. (2024). A short-term forecasting method for photovoltaic power generation based on the TCN-ECANet-GRU hybrid model. *Scientific reports*, *14*(1), 6744.

Xu, Y., Ji, X., & Zhu, Z. (2025). A photovoltaic power forecasting method based on the LSTM-XGBoost-EEDA-SO model. *Scientific reports*, *15*(1), 30177.

Ye, H., Yang, B., Han, Y., & Chen, N. (2022). State-of-the-art solar energy forecasting approaches: Critical potentials and challenges. *Frontiers in Energy Research*, *10*, 875790.