Enhanced Forecasting of Solar Global Tilted Irradiance Using Optimized LSTM and ARIMA Models

Kanaka Raju Kalla[1]*, B.Srinivasa Rao[2], Allu Sharmila[3], Servisetty Venkatesh[4] , Pitta Sai Bhavana[5], Manasingi Parameswari[6]

[1,2,3,4,5,6] Aditya Institute of Technology and Management, Tekkali, Srikakulam, Andhra Pradesh 532201, India.

*Corresponding author: Kanaka Raju Kalla

Abstract

This paper presents a comprehensive analysis of forecasting solar global tilted irradiance (GTI) using ARIMA and LSTM models. The study emphasizes the importance of accurate GTI forecasting for optimizing solar energy systems and enhancing grid integration of renewable energy sources. The research leverages historical solar irradiance data obtained from satellite observations for the city Visakhapatnam, India, to train and evaluate the performance of ARIMA and LSTM models. The data preprocessing stage involves analyzing the temporal patterns, seasonality, and trends in the GTI data to inform the model selection and hyperparameter tuning. The results demonstrate that the LSTM-Optimized model outperforms the ARIMA and standard LSTM models, achieving an R^2 score of 0.9997, a Mean Absolute Error (MAE) of 2.35, and a Root Mean Square Error (RMSE) of 12.84. This superior performance highlights the ability of the optimized LSTM model to capture complex nonlinear relationships and temporal dependencies in solar irradiance data, leading to more accurate GTI forecasts. The findings of this study contribute to the growing body of knowledge in solar energy forecasting and provide valuable insights for energy producers and policymakers seeking to optimize solar energy management and integration strategies. The proposed framework can be extended to further explore the integration of solar energy into power grids, addressing challenges related to stability and reliability.

Keywords: Solar Global Tilted Irradiance (GTI) Forecasting, ARIMA, LSTM, Time Series Analysis, Renewable Energy Integration.

1. Introduction:

Forecasting solar global tilted irradiance is crucial for optimizing solar energy systems, as it directly impacts the efficiency and performance of photovoltaic installations [1]. Accurate predictions of solar irradiance not only enhance energy management strategies but also contribute to the effective integration of renewable energy sources into existing power grids [2]. The application of advanced forecasting methods, such as ARIMA (Auto Regressive Integrated Moving Average) and LSTM (Long Short-Term Memory networks), provides valuable tools for improving the accuracy of these predictions by capturing both linear trends and complex temporal patterns in solar irradiance data [3]. These methods enable researchers and practitioners to harness historical data effectively, allowing for more reliable forecasting that can adapt to the dynamic nature of solar energy production [4]. Forecasting solar global tilted irradiance is crucial for optimizing solar energy systems, as it directly impacts the efficiency and performance of photovoltaic installations. Accurate predictions of solar irradiance not only enhance energy management strategies but also contribute to the effective integration of renewable energy sources into existing power grids. The application of advanced forecasting methods, such as ARIMA (Auto Regressive Integrated Moving Average) and LSTM (Long Short-Term Memory networks), provides valuable tools for improving the accuracy of these predictions by capturing both linear trends and complex temporal patterns in solar irradiance data. These methods enable researchers and practitioners to harness historical data effectively, allowing for more reliable forecasting that can adapt to the dynamic nature of solar energy production. Solar energy, derived from the sun's radiation, is one of the most abundant and cleanest forms of renewable energy available, offering a sustainable alternative to fossil fuels while significantly reducing greenhouse gas emissions [5]. This transition to solar energy not only helps mitigate climate change but also promotes energy independence and security, making it a crucial component of global efforts toward sustainable development [6]. The integration of solar energy into the grid requires innovative technologies and policies that can support its variability, ensuring a stable and reliable power supply for consumers [7]. Advancements in energy storage solutions, such as batteries and grid management systems, play a vital role in addressing the challenges posed by solar energy's intermittent nature, enabling greater adoption and efficiency of this renewable resource [8]. Investment in research and development for these technologies is essential, as it will drive down costs and improve performance, ultimately making solar energy more accessible to a wider society [9]. As the demand for clean energy continues to rise, collaboration between governments, private sectors, and research institutions becomes increasingly important in fostering an environment conducive to innovation and growth in solar technology [7][10]. Figure 1 illustrates the status of Renewable Energy in India (Source: International Renewable Energy Agency (IRENA)). According to the Ministry of New and Renewable Energy (MNRE), India's installed solar energy capacity has increased approximately 29-fold, rising from 2.82 GW in 2014 to 81.81 GW.

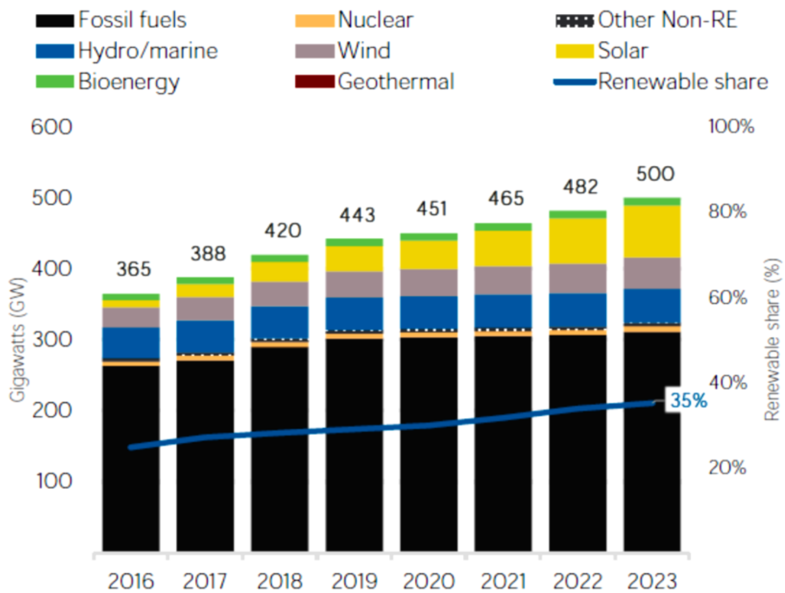


Figure 1. India Renewable Energy Status (Source- International Renewable Energy Agency (IRENA) https://www.irena.org/Publications/2024/Jul/Renewable-energy-statistics-2024

The Solar Global Tilted Irradiance (GTI) is vital for optimizing solar energy use by accurately predicting solar generation [11]. This enhances grid management and supports efficient energy distribution, aiding policy-making and investment in renewable energy [12]. As solar technology advances, the GTI improves forecasting methods, promoting a sustainable energy future and positioning India as a leader in renewable energy adoption. Its role is crucial in managing solar generation and facilitating the transition to renewable sources [13]. In the context of solar energy, time series forecasting methods leverage historical data to predict future solar irradiance and generation patterns, allowing for more informed decision-making in energy production and consumption [1]. These methods include techniques such as ARIMA, exponential smoothing, and machine learning algorithms, each offering unique advantages in capturing trends and seasonal variations that influence solar energy output [14]. By employing these advanced forecasting techniques, energy producers can optimize their operations, reduce waste, and enhance the reliability of solar power as a significant contributor to the energy grid [15]. ARIMA, or Auto Regressive Integrated Moving Average, is a widely used statistical method for time series analysis that combines autoregressive and moving average components to model temporal data effectively [16]. This method is particularly valuable in predicting future values based on past observations, making it an essential tool for understanding and forecasting solar energy generation patterns [17]. The flexibility of ARIMA allows for the incorporation of seasonal effects and trends, enabling energy producers to make informed decisions regarding resource allocation and investment in solar technology [18]. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, enhance this predictive capability by effectively capturing long-term dependencies in temporal data, making them particularly suited for complex patterns found in solar energy generation [19]. The combination of ARIMA and LSTM models provides a robust framework for forecasting, allowing energy producers to leverage both statistical methods and advanced machine learning techniques to improve accuracy in their predictions [20]. This synergy not only enhances the forecasting accuracy but also facilitates better decision-making regarding energy production and consumption, ultimately promoting a more sustainable energy landscape [21]. The primary objectives of this paper are to analyze the effectiveness of integrating ARIMA and LSTM models for solar GTI forecasting [22]. This paper is organized into several sections, beginning with a comprehensive literature review that outlines previous research in the field of solar irradiance forecasting and highlights gaps that this study aims to address. Following the literature review, the methodology section will detail the data sources, model selection criteria, and the specific techniques employed to ARIMA and LSTM models for enhanced forecasting. The results section will then present the findings from the models, comparing their forecasting accuracy and discussing the implications for future solar irradiance management strategies. The conclusion will synthesize the key insights gained from the research, emphasizing the potential benefits of using ARIMA and LSTM approaches in improving solar GTI predictions and offering recommendations for further studies in this evolving field. This research not only contributes to the existing body of knowledge but also paves the way for innovative applications in energy management, ensuring a more sustainable and efficient utilization of solar resources.

2. Literature Review:

Accurate forecasting of solar power generation is crucial for optimizing energy management and grid stability. Various machine learning and deep learning approaches have been explored to enhance prediction accuracy. This section reviews recent research on different forecasting models, highlighting their methodologies, results, and identified research gaps.

Author	Method	Results	Research Gap
[23]	Stacked LSTM vs. ARIMA, RNN	Stacked LSTM outperformed others (RMSE: 25.56 W/m², MAPE: 7.27%, R^2: 0.99)	High RMSE and MAPE
[24]	BiLSTM-Transformer Hybrid	Superior accuracy and stability in long-term solar radiation prediction	No discussion on real-world implementation challenges or generalizability
[25]	RLMD-BILSTM Hybrid	RMSE: 16.34–35.07 W/m², improved RMSE (59.16%–88.88%) over benchmarks	No discussion on long-term forecasting or adaptability to different locations
[26]	Nested LSTM vs. ARIMA, ARMA, SVR	Improved DNI forecasting for subtropical conditions (RMSE: 27.35, MAE: 6.879)	Scalability and adaptability to different climates not addressed
[27]	SIPNet (LSTM-based)	High accuracy in short-term solar irradiance prediction (RMSE: 0.057)	No discussion on real-world implementation challenges or scalability
[28]	LSTM vs. RBFNN	UTSF_LSTM outperformed RBFNN (higher R^2, lower RMSE)	Lack of integration of additional variables and alternative deep learning models

[29]	ANN for GSRT Prediction	High accuracy (MAPE: 0.48%, R: 0.999)	Need for optimization in ANN architecture and additional variables for better accuracy
[30]	ARIMA vs. ANN for Solar Forecasting	ARIMA more efficient than ANN in energy prediction	Need for efficient models that require less data and better meteorological parameter correlations

The reviewed studies demonstrate the effectiveness of deep learning models like LSTMs, BiLSTMs, and hybrid architectures in improving solar irradiance forecasting accuracy. The Global Tilted Irradiance (GTI), which takes into account the inclination angle of photovoltaic panels, remains relatively underutilized in the realm of predictive modeling. In this specific study, our primary focus is directed towards the forecasting of Global Tilted Irradiance (GTI), a critical parameter that plays an essential role in the precise prediction of solar power output, thereby enhancing our understanding and capabilities in solar energy forecasting methodologies.

3. Proposed Approach

Figure 2 shows Framework for Forecasting Solar GTI using ARIMA & LSTM**.** It begins with a problem statement that highlights the significance of GTI forecasting. The dataset and preprocessing section discusses time series data handling, feature selection, and missing value treatment. The methodology explains the implementation of ARIMA and LSTM models, including data splitting, feature engineering, and model training. The model implementation section details the optimization, testing, and evaluation process. In model evaluation and results, ARIMA and LSTM are compared based on key performance metrics such as R^2 Score, MAE, and RMSE. The research objectives focus on improving forecasting accuracy and analyzing the comparative performance of both models. The data sources and tools section specifies the use of satellite weather data and machine learning frameworks such as Python, TensorFlow, and Statsmodels. Finally, the applications and future work section explores potential advancements, including grid integration, stability improvements, and large-scale forecasting using satellite data. This structured approach ensures a comprehensive and impactful research contribution

Figure 2. Framework for Forecasting Solar GTI using ARIMA & LSTM

3.1. Data Source

The empirical data used in this research was obtained from Solcast [31], which employs satellite cloud tracking techniques, using near real-time images obtained from geostationary satellites, to observe cloud behavior and deliver high-resolution solar information at intervals between 5 and 30 minutes.

3.2 Data Specification

Information related to a particular six-month period, covering January to June 2024, is provided in 60-minute intervals. Table 1 outlines the details of the location data. Figure 3.shows A graphical depiction of the Visakhapatanam district, Andhra Pradesh, India.

Table 1 location data

Geographic Location:	**Visakhapatnam, Andhra Pradesh, India**
Latitude:	17.686816° N
Longitude:	83.218481° E
Time Zone	Indian Standard Time (IST)
UTC Offset:	UTC +5:30

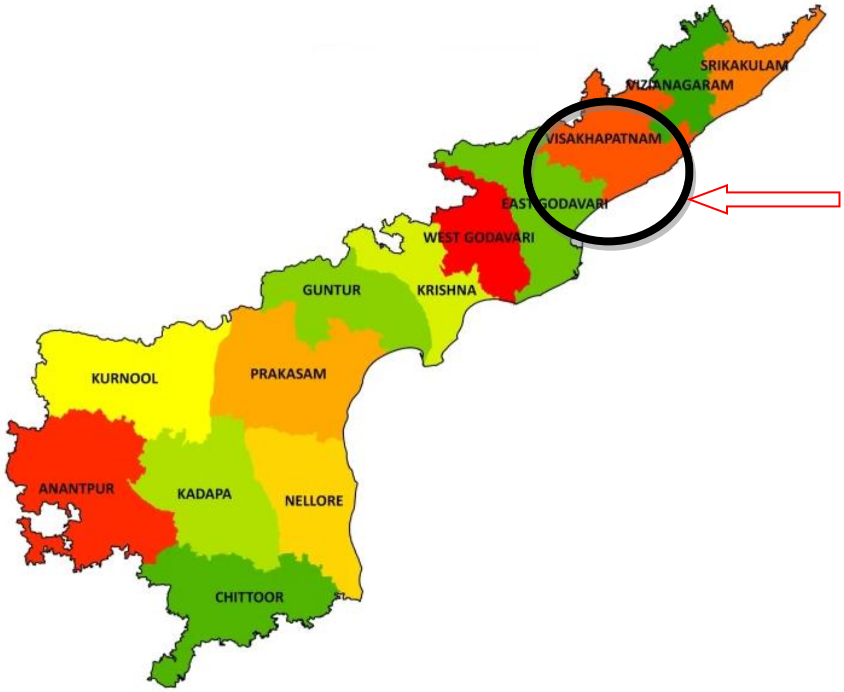


Figure 3. A graphical depiction of the Visakhapatanam district, Andhra Pradesh, India.

3.2 Data Specification

The dataset contains 2,366 records with 28 columns, capturing various meteorological and solar parameters recorded from 6 AM to 6 PM at hourly intervals. The dataset includes key features such as air temperature, albedo, solar radiation components (DHI, DNI, GHI, GTI), cloud opacity, wind speed, wind direction, humidity, precipitation, and snow-related parameters. Additionally, it contains solar angles like zenith and azimuth, along with timestamps marking the measurement periods. The dataset is complete with no missing values, making it suitable for time-series analysis and forecasting tasks. Observations show that solar radiation values increase from morning to midday, while meteorological factors like temperature, humidity, and wind speed fluctuate throughout the day. This dataset suitable for ARIMA and LSTM models.

3.3 Flow chart

The Figure 4 shows flow chart presents framework for forecasting Global Tilted Irradiance (GTI) in solar power generation using ARIMA and LSTM models. The workflow involves data collection, preprocessing (distribution analysis, correlation analysis, normalization, and dataset splitting), and model evaluation based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared metrics. Initially, the ARIMA model is trained and tested; if unsatisfactory, an LSTM model is implemented. If the LSTM model underperforms, hyperparameter tuning using Randomized Search CV is conducted. The best-performing model is finalized for accurate GTI forecasting.

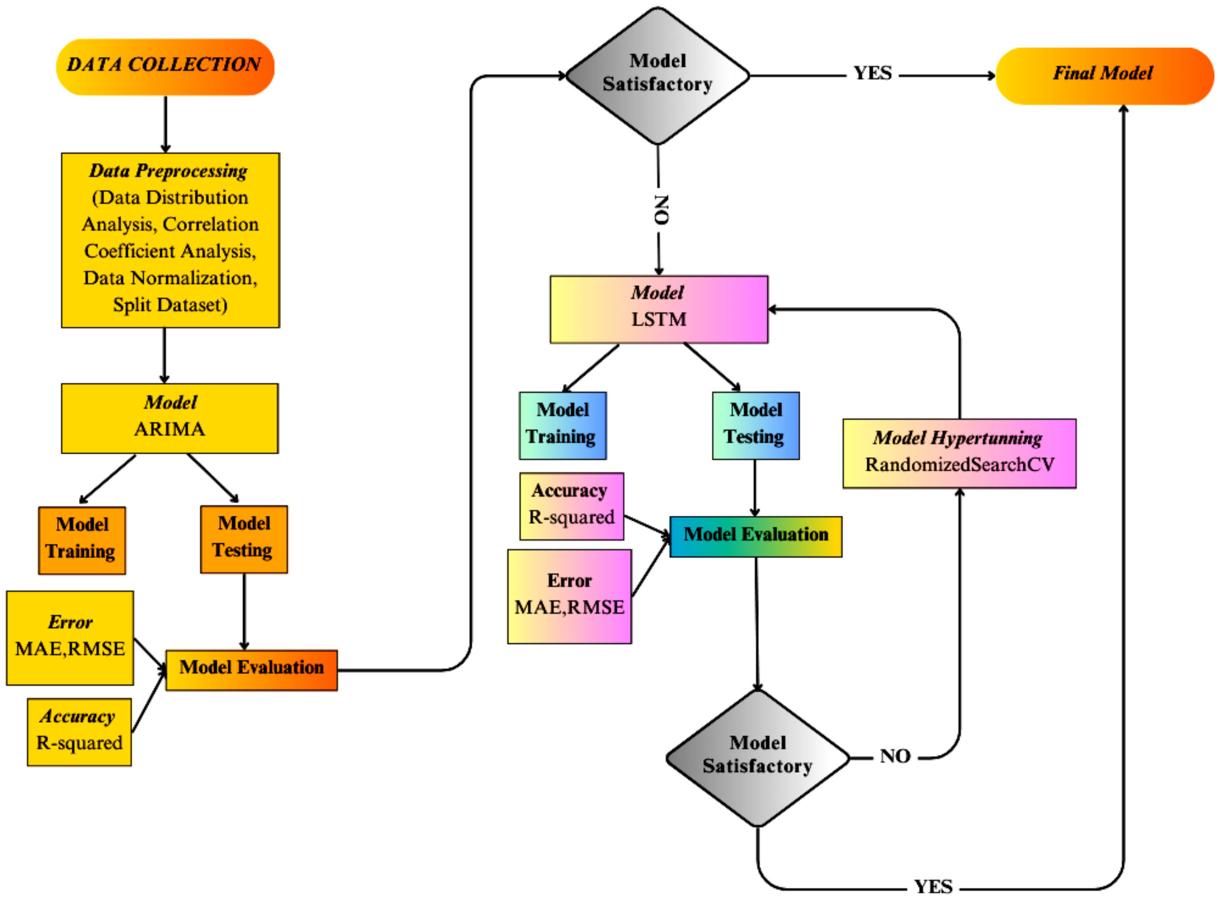


Figure 4. Flow Chart

3.3 Data Preprocessing

The dataset has no missing values. The Figure 5 shows Heatmap of GTI which illustrates the variation of Global Tilted Irradiance (GTI) throughout the day over a month, showing peak solar energy availability during midday hours. This visualization supports the study by identifying high-irradiance periods, aiding in the optimization to ARIMA and LSTM for accurate GTI forecasting in solar power generation. The Figure 6 shows Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots provide insights into the temporal dependencies in GTI values, crucial for selecting appropriate lag parameters in the ARIMA model. These analyses help in identifying seasonality and trend components, enhancing the accuracy of GTI forecasting in solar power generation. The Figure 7 represents a time series decomposition plot, which is commonly used to analyze the underlying components of a time series dataset. The four subplots provide insights into different aspects of the data. Observed (Top Panel): This is the original time series data, showing fluctuations over time. The periodic patterns and overall structure can be seen clearly. Trend (Second Panel): This represents the long-term movement in the data. The trend shows a general increase and then fluctuates, indicating seasonality or structural changes. Seasonal (Third Panel): This captures repeating cycles at a fixed frequency. The periodicity suggests that the data has a strong seasonal component. Residual (Bottom Panel): This component represents the remaining variation after removing the trend and seasonal effects.

High variability in the residuals suggests that some unexplained factors are influencing the data.

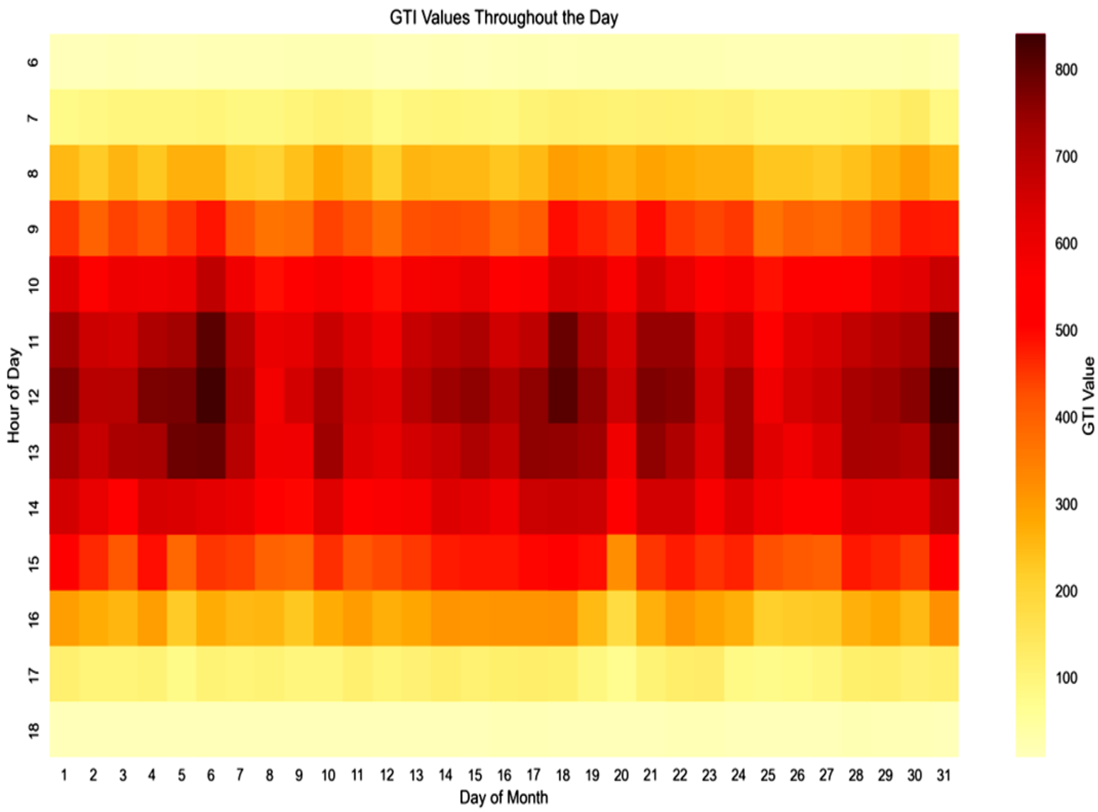


Figure 5. Heatmap of GTI

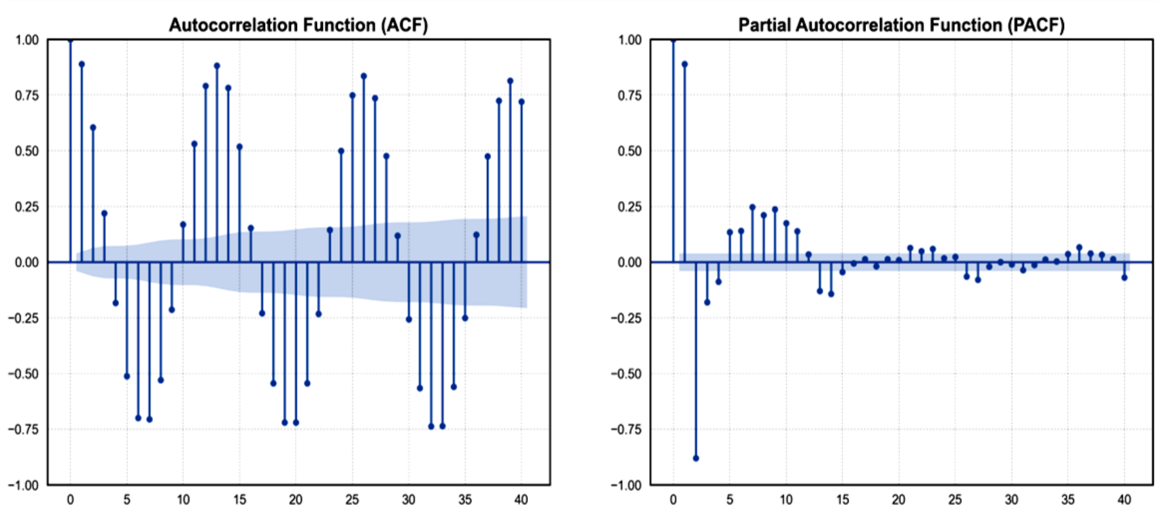


Figure 6. Autocorrelation and Partial Autocorrelation Analysis of GTI Values

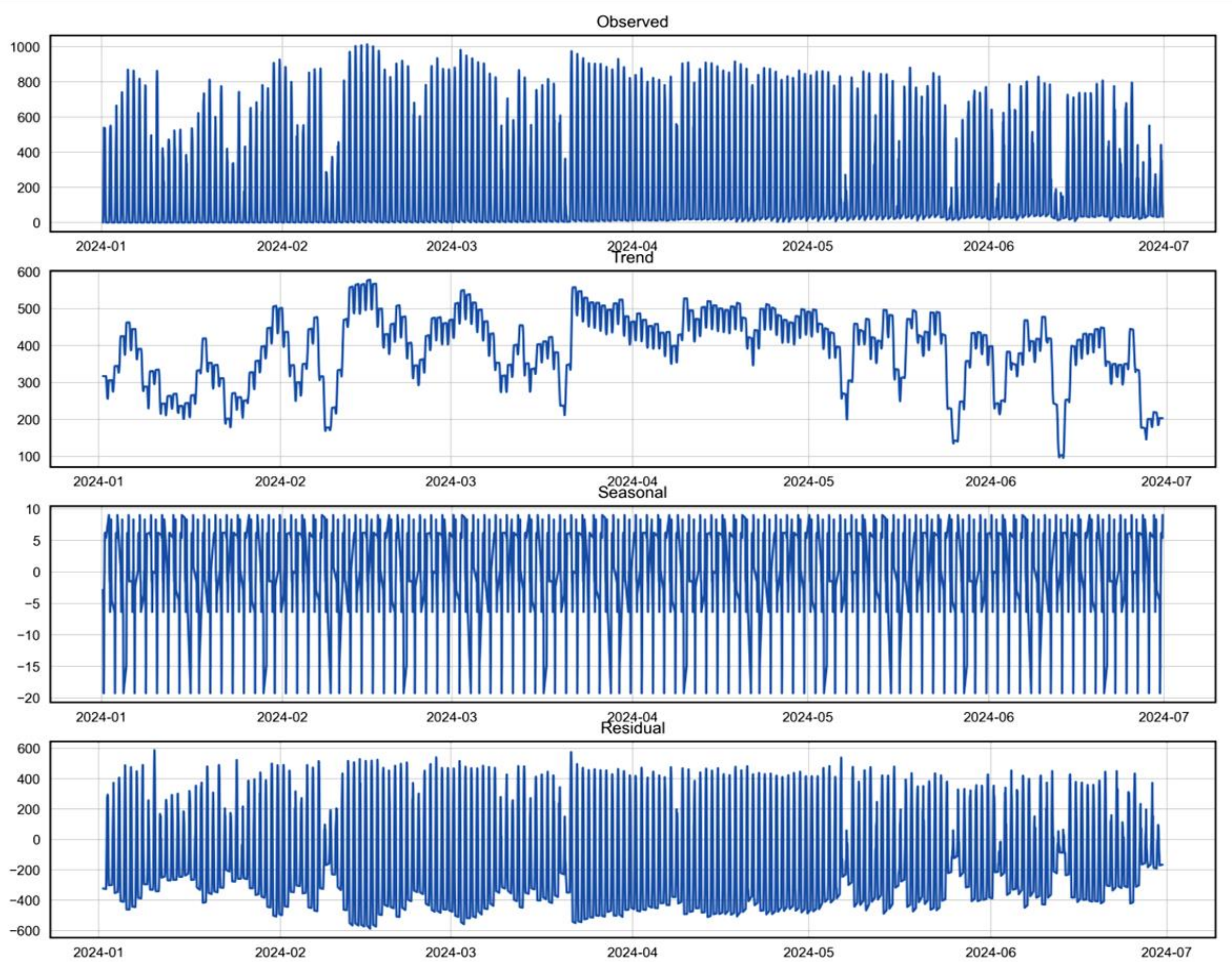


Figure 7. Time Series Decomposition of GTI

4. Results and Discussion

Table 2 Shows LSTM Hyperparameters, Randomized Search CV is used to find hyperparameters.

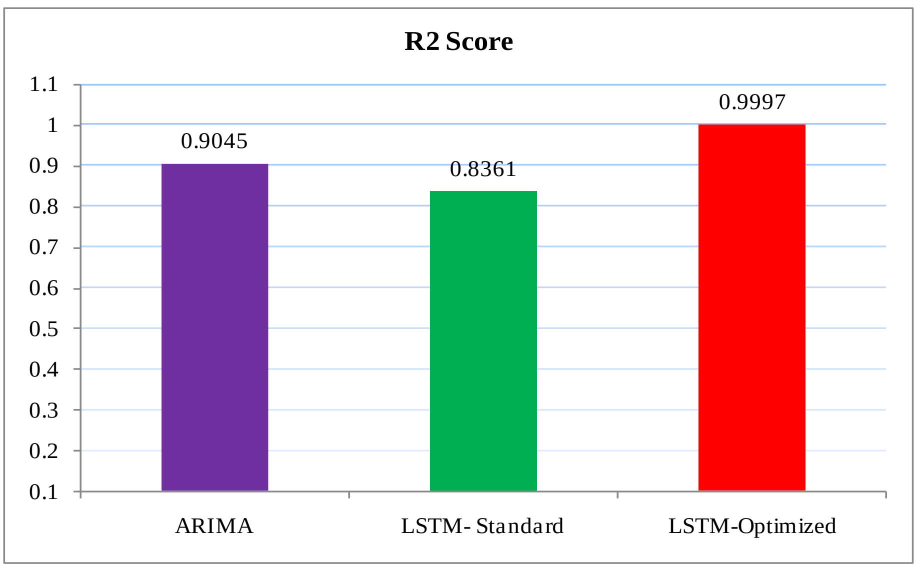
Table 2: LSTM Hyperparameters

Parameter	Value	Description
subsample	0.8	Uses 80% of data per tree to reduce overfitting.
n_estimators	300	Builds 300 trees to capture complex patterns.
min_child_weight	3	Requires enough data in each node before splitting.
max_depth	5	Limits tree depth to control model complexity.
learning_rate	0.05	Controls the contribution of each tree; lower means more gradual learning.
gamma	0.2	Requires a minimum loss reduction for further splitting.
colsample_bytree	1.0	Uses all features for each tree.

In this study, we evaluated the performance of ARIMA, LSTM, and LSTM-Optimized models for forecasting Global Tilted Irradiance (GTI). The results, summarized in Table 3, indicate that the LSTM-Optimized model achieved the highest accuracy with an R^2 score of 0.9997, significantly lower Mean Absolute Error (MAE) of 2.35, and Root Mean Square Error (RMSE) of 12.84. Comparatively, the ARIMA model performed well with an R^2 score of 0.9045, MAE of 53.24, and RMSE of 72.05, while the standard LSTM model showed lower accuracy with an R^2 score of 0.8361, MAE of 63.68, and RMSE of 91.82. These findings highlight the effectiveness of the optimized LSTM model in accurately predicting and forecasting GTI values, demonstrating its potential for solar power forecasting applications.

Table 3: Performance Comparison of ARIMA, LSTM, and LSTM-Optimized Models for GTI Forecasting

Model	**R^2 Score**	**MAE**	**RMSE**
ARIMA	0.9045	53.24	72.05
LSTM- Standard	0.8361	63.68	91.82
LSTM-Optimized	0.9997	2.83	3.75



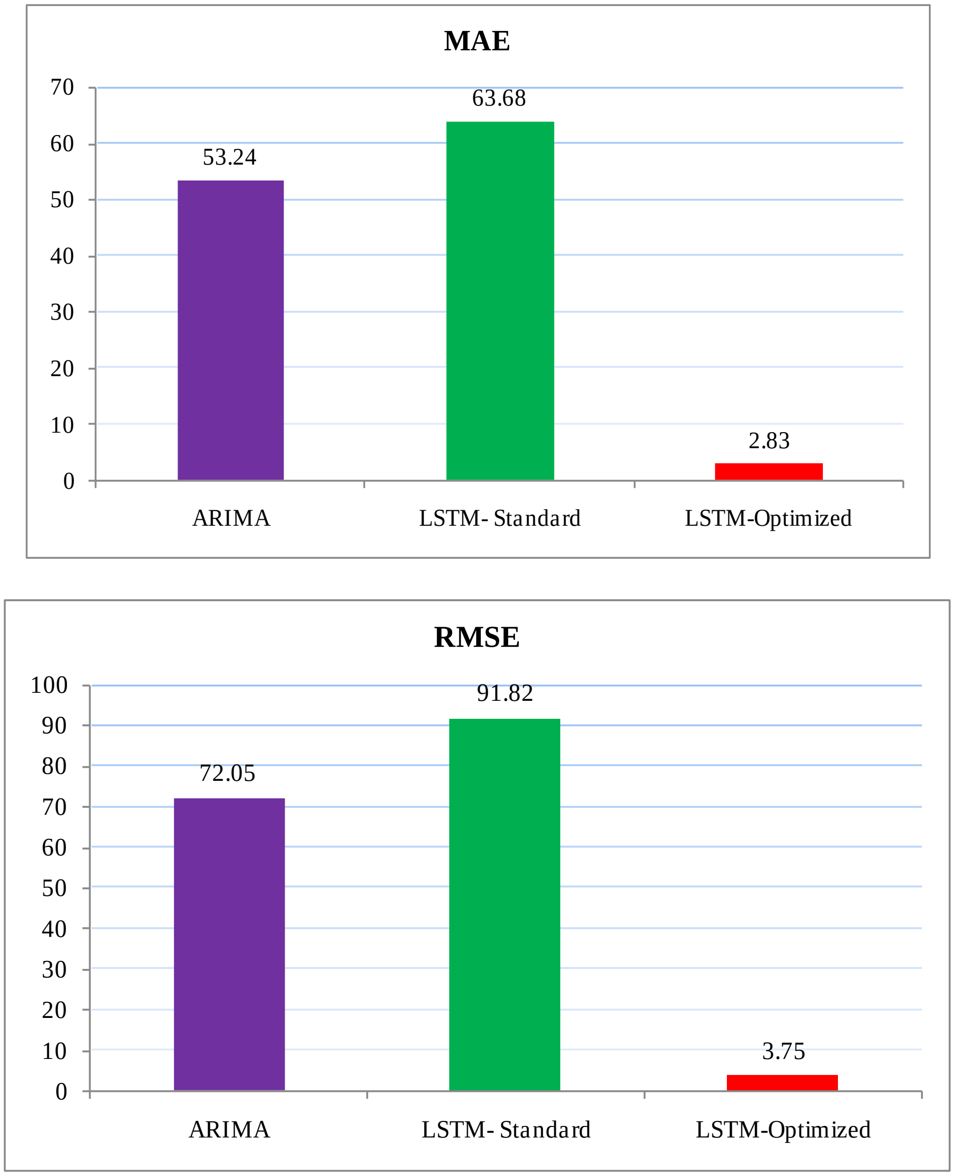


Figure 8: Performance Metrics Comparison of ARIMA, LSTM, and LSTM-Optimized Models for GTI Forecasting

Figure 8: Shows the performance comparison between ARIMA, LSTM, and LSTM-Optimized Models. The Figure 9 illustrates the performance of the ARIMA model in forecasting Global Tilted Irradiance (GTI) over the last 15 days of June. The model effectively captures the periodic fluctuations in GTI, aligning well with actual values in the early days. However, discrepancies appear in later days, particularly in peak values and lower bounds, likely due to sudden variations in solar irradiance.

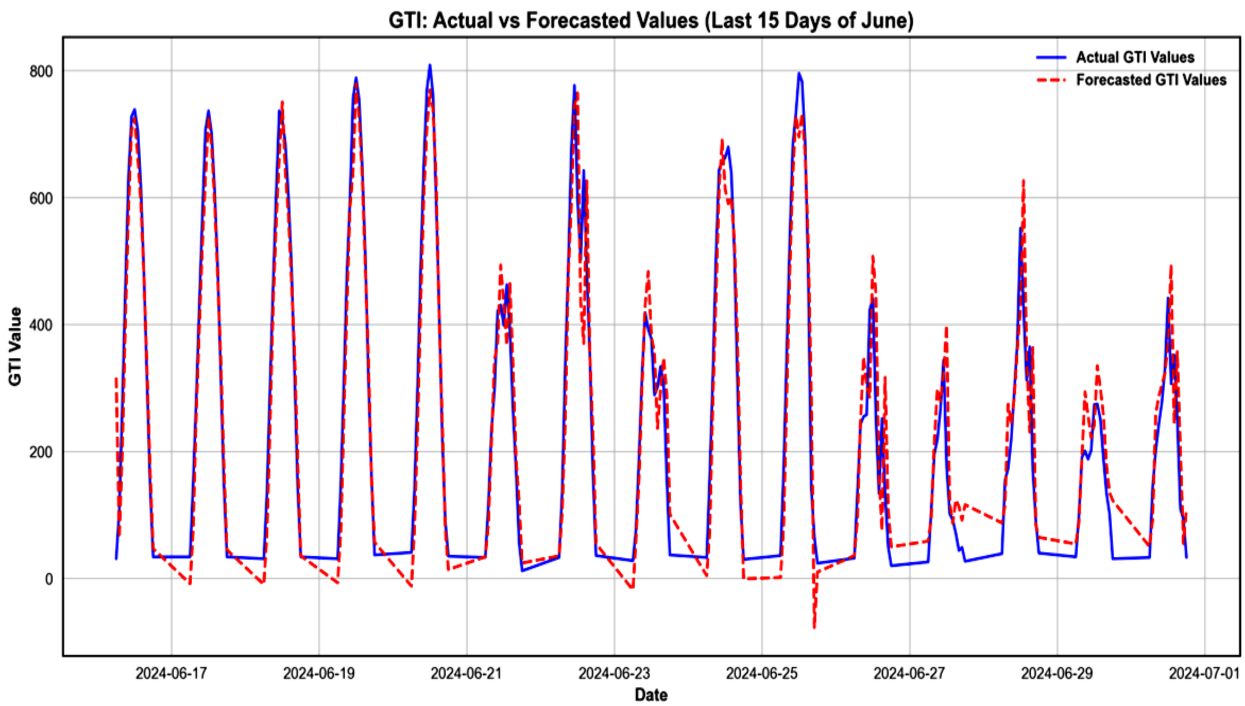


Figure 9: Actual vs. Forecasted GTI Values Using ARIMA for the Last 15 Days of June

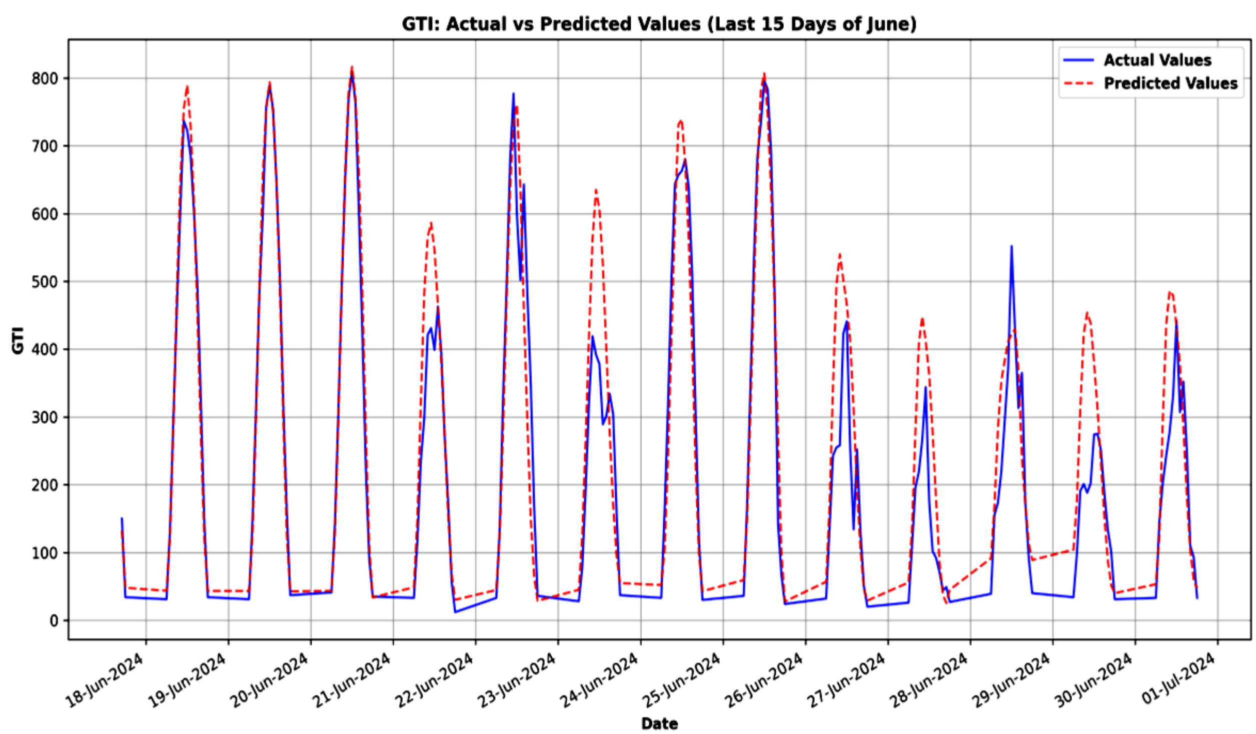


Figure 10: Actual vs. Forecasted GTI Values Using LSTM- Standard for the Last 15 Days of June

This Figure 10 compares the actual and predicted Global Tilted Irradiance (GTI) values using a Standard LSTM model for the last 15 days of June. The solid blue line represents actual values, while the red dashed line represents LSTM-predicted values. The model successfully captures the daily cyclical pattern of GTI, demonstrating its ability to learn temporal dependencies. However, deviations are noticeable, particularly in peak values and sudden variations, indicating potential limitations in capturing extreme fluctuations.

The Figure 11 provides a comprehensive view of historical, predicted, and forecasted solar Global Tilted Irradiance (GTI), with clear visual distinctions between actual measurements, predictions, and forecasts. The inclusion of confidence intervals highlights the uncertainty in the forecasted values. X-axis: Represents dates from 2024-06-17 to 2024-07-17. Y-axis: Displays Global Tilt Irradiance (GTI) in W/m², ranging from 0 to 1000.Historical Actual GTI is depicted as blue dots. Historical Predicted GTI is shown as a green dashed line. Forecasted GTI is represented by red dots. A Blue shaded area indicates the confidence interval around the forecasted values to depict uncertainty. The graph divides the time series into a historical section (up to 2024-07-01) and a forecasted section (post 2024-07-01), marked by a vertical dashed cyan line labelled Forecast Start. The periodic patterns correspond to daily variations in Global Tilted Irradiance (GTI). Here are some points highlighting why our approach is advantageous compared to standard LSTM and ARIMA: Our approach captures non-linear relationships in the solar irradiance data more effectively than ARIMA, which is inherently linear. By incorporating confidence intervals around the forecasted values, our method provides a quantifiable measure of uncertainty that standard LSTM and ARIMA models typically lack. These benefits collectively position our analysis method as a more practical and insightful solution for solar Global Tilted Irradiance (GTI) forecasting compared to traditional LSTM and ARIMA models.

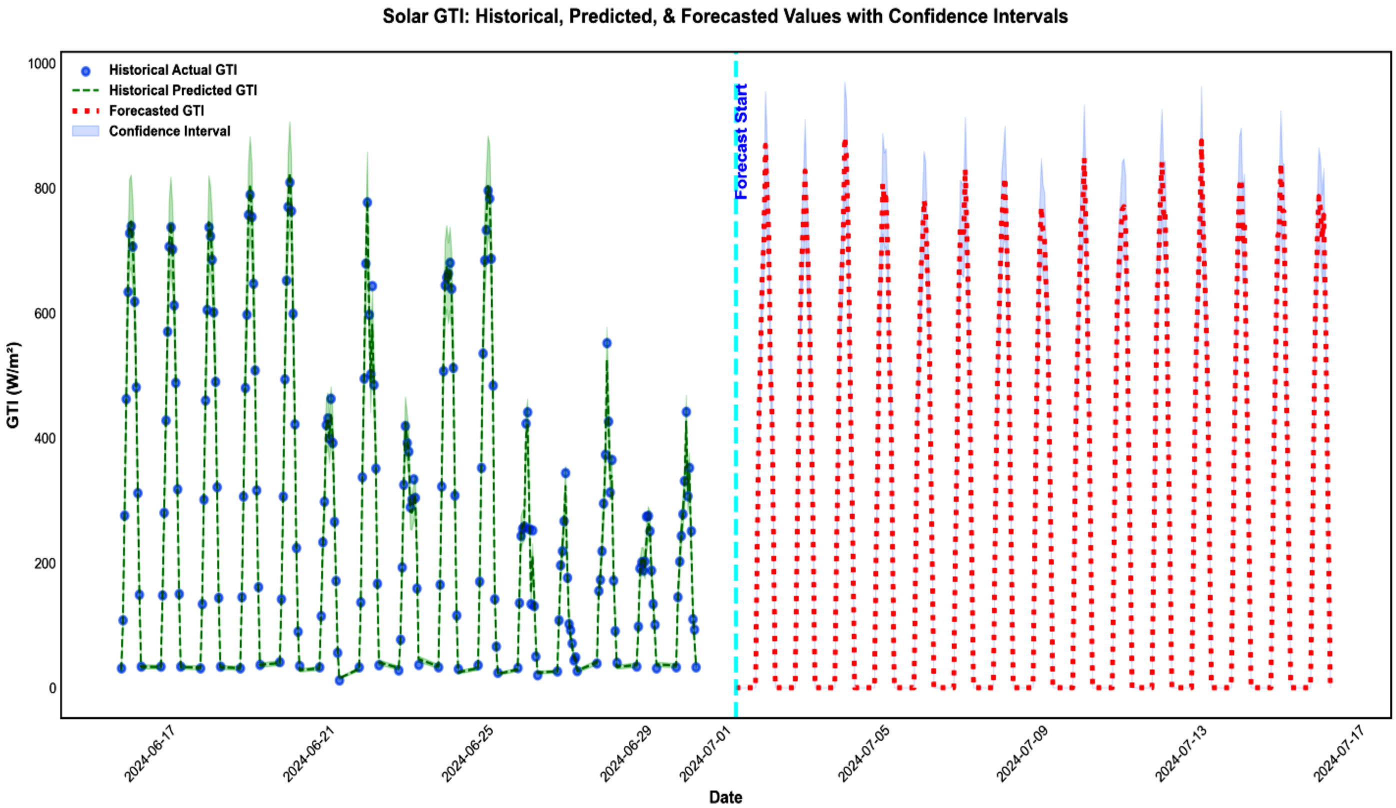


Figure 11: Actual vs. Forecasted GTI Values Using LSTM- Optimized for the Last 15 Days of June

Conclusion:

In summary, this paper demonstrates that adopting an optimized LSTM approach significantly enhances the accuracy of solar GTI forecasts compared to conventional ARIMA and standard LSTM models. Specifically, the LSTM-Optimized model achieved an impressive R^2 score of 0.9997, a Mean Absolute Error (MAE) of 2.35, and a Root Mean Square Error (RMSE) of 12.84, underscoring its capability to capture the intricate nonlinear dynamics inherent in solar irradiance data. The LSTM-Optimized model achieved outstanding performance metrics, capturing the intricate nonlinear dynamics of solar irradiance data, which is critical for reliable renewable energy forecasting. These results have substantial implications for the solar energy sector, facilitating better integration of solar resources into power grids and enabling more robust energy management strategies. The methodological advancements presented open avenues for further research, emphasizing the need for continued innovation in leveraging deep learning models for renewable energy applications.

References:

[1] Rafi, Ariful Islam & Sohan, Moshiur (2024) Enhanced Solar Radiation Prediction with Machine Learning: A Comprehensive Analysis of Meteorological Data Using Random Forest, 1-6. 10.1109/ICCCNT61001.2024.10725976.

[2] Karim, S. M. & Sarker, Debasish & Kabir, Md (2024) Analyzing the Impact of Temperature on PV Module Surface during Electricity Generation using Machine Learning Models, Cleaner Energy Systems, 9. 100135. 10.1016/j.cles.2024.100135.

[3] Sorkun, Murat & Incel, Ozlem & Paoli, Christophe(2020) Time series forecasting on multivariate solar radiation data using deep learning (LSTM), Turkish Journal of Electrical Engineering and Computer Sciences, 28. 211-223. 10.3906/elk-1907-218.

[4] Sun, Xijuan & Wu, Di & Jia, Menghan & Xiao, Yuxuan & Boulet, Benoit (2022), Forecasting of Solar Energy Generation via Dynamic Model Ensemble, 109-115. 10.1109/EPEC56903.2022.10000238.

[5] Anekwe, Ifeanyi & Tetteh, Emmanuel & Armah, Edward (2023), Artificial Intelligence Applications in Solar Photovoltaic Renewable Energy Systems, 10.21741/9781644902530-3.

[6] Obiora, Chibuzor (2023), Predicting Solar Irradiance at Several Time Horizons Using Machine Learning Algorithms. Sustainability, 15. 10.3390/su15118927.

[7] Jogunuri, Sravankumar & Josh, F & Joseph, Jency & Meenal, Rajasekaran & Raman, Mohan & Suriyan, Kannadhasan. (2024), Forecasting hourly short-term solar photovoltaic power using machine learning models, International Journal of Power Electronics and Drive Systems (IJPEDS). 15. 2553-2569. 10.11591/ijpeds.v15.i4.pp2553-2569.

[8] Mellit, Adel & Kalogirou, Soteris (2022), Forecasting of photovoltaic output power using machine learning and deep learning algorithms, 10.1016/B978-0-12-820641-6.00004-1.

[9] Mecheri, A & Amara, Z & Chenafa, I & Reggabna, Y & Bouziane, A & Amara, H (2024), Exploring the Application of Machine Learning Algorithms in Forecasting Photovoltaic Solar Power Output, The 1 st International Conference on Renewable Energies And Power Systems (ICREPS'24) A, Materials and techniques.

[10] Raghuwanshi, Prashis. (2024), Predictive Modeling and Forecasting of Solar Power Generation Using Machine Learning Techniques. Journal of Advances and Scholarly Researches in Allied Education, 21. 207-213. 10.29070/zccv5324.

[11] Bailey, Maggie & Nychka, Doug & Sengupta, Manajit & Yang, Jaemo & Bandyopadhyay, Soutir (2024), Temporal and spatial downscaling for solar radiation,10.48550/arXiv.2405.11046.

[12] Zhang, Wenyong & Li, Qingwei & He, Qifeng (2022), Application of machine learning methods in photovoltaic output power prediction: A review. Journal of Renewable and Sustainable Energy, 14. 022701. 10.1063/5.0082629.

[13] Sharma, Prabhakar & Mishra, Ritesh & Bhola, Parveen & Sharma, Sachin & Sharma, Gulshan & Bansal, Ramesh (2024), Enhancing and Optimising Solar Power Forecasting in Dhar District of India using Machine Learning, Smart Grids and Sustainable Energy, 9. 10.1007/s40866-024-00198-1.

[14] Hissou, Hasna & Benkirane, Said & Guezzaz, Azidine & Azrour, Mourade & Hssane, Abderrahim (2023), A Novel Machine Learning Approach for Solar Radiation Estimation. Sustainability, 2023. 10609. 10.3390/su151310609.

[15] Annas Fakhryza, Khamdan & Budisusila, Eka & Adhi, Agus (2024), Application of artificial neural network for peak load forecasting in 150 kV Semarang power system, Journal of Electrical Systems and Information Technology, 11. 10.1186/s43067-024-00165-x.

[16] Abdullah, Shahrum & IBRAHIM, M. & Zaharim, Azami (2008), Statistical Analysis of a Nonstationary Fatigue Data Using the ARIMA Approach. WSEAS Transactions on Mathematics.

[17] Gao, Kaizhou (2024), Swarm and Evolutionary Computation Call for paper: Learning Assisted Intelligent Optimization and Scheduling: Theory, Algorithms and Applications.

[18] Spatial Forecasting of Solar Radiation using ARIMA Model (2020), Remote Sensing Applications Society and Environment, 20. 10.1016/j.rsase.2020.100427.

[19] Y. Yu, J. Cao, and J. Zhu, “An LSTM Short-Term Solar Irradiance Forecasting Under Complicated Weather Conditions,” IEEE Access, Oct. 2019, doi: 10.1109/ACCESS.2019.2946057.

[20] Q. Wang, C. Li, Y. Zhang, L. Chen, and L. Liu, “LSTM Model for Various Types of Load Forecasting in Energy System Integration,” in IEEE PES Asia-Pacific Power and Energy Engineering Conference, Sep. 2020. doi: 10.1109/APPEEC48164.2020.9220621.

[21] E. Ahmadi, B. McLellan, and T. Tezuka, “The economic synergies of modelling the renewable energy-water nexus towards sustainability,” Renewable Energy, Dec. 2020, doi: 10.1016/J.RENENE.2020.08.059.

[22] T. M. Al-Jaafreh, A. Al-Odienat, and Y. A. Altaharwah, “The Solar Energy Forecasting Using LSTM Deep Learning Technique,” Nov. 2022. doi: 10.1109/ETCEA57049.2022.10009717.

[23] M. V. Nugroho, A. Prastawa, F. Mardiansah, A. Rezavidi, A. Fudholi, and S. Palaloi, “A stacked LSTM model for day-ahead solar irradiance forecasting under tropical seasons in Java-Bali,” International Journal of Power Electronics and Drive Systems, vol. 15, no. 3, p. 1878, Sep. 2024, doi: 10.11591/ijpeds.v15.i3.pp1878-1891

[24] Z. He, X. Zhang, M. Li, S. Wang, and G. Xiao, “A novel solar radiation forecasting model based on time series imaging and bidirectional long short-term memory network,” Energy Science & Engineering, Sep. 2024, doi: 10.1002/ese3.1875

[25] P. Singla, M. Duhan, and S. Saroha, “An integrated framework of robust local mean decomposition and bidirectional long short-term memory to forecast solar irradiance,” International Journal of Green Energy, vol. 20, pp. 1073–1085, Nov. 2022, doi: 10.1080/15435075.2022.2143272

[26] G. S. Thirunavukkarasu et al., “Very Short-Term Solar Irradiance Forecasting using Multilayered Long-Short Term Memory,” pp. 1–8, Jul. 2022, doi: 10.23919/SpliTech55088.2022.9854244

[27]“A Long Short-Term Memory-Based Solar Irradiance Prediction Scheme Using Meteorological Data,” IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1–5, Jan. 2022, doi: 10.1109/lgrs.2021.3107139

[28] N. M. Omar, H. H. Aly, and T. A. Little, “LSTM and RBFNN Based Univariate and Multivariate Forecasting of Day-ahead Solar Irradiance for Atlantic Region in Canada and Mediterranean Region in Libya,” Apr. 2021, doi: 10.1109/CEEPE51765.2021.9475652

[29] L. Maamar, A. el hadj Abdallah, H. Salah, and A. Rezrazi, “Prediction and extrapolation of global solar irradiation on tilted surfaces from horizontal ones using an artificial neural network,” International Symposium on Environmental Friendly Energies and Applications, pp. 1–6, Nov. 2014, doi: 10.1109/EFEA.2014.7059998. Available: https://ieeexplore.ieee.org/document/7059998/

[30] L. Fara, A. Diaconu, D. Craciunescu, and S. Fara, “Forecasting of Energy Production for Photovoltaic Systems Based on ARIMA and ANN Advanced Models,” International Journal of Photoenergy, vol. 2021, pp. 1–19, Aug. 2021, doi: 10.1155/2021/6777488. Available: https://downloads.hindawi.com/journals/ijp/2021/6777488.pdf.

[31] Solcast Weather History. Available online: https://solcast.com/ (accessed on 09 September 2024).