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An LSTM-Based Approach for Short-Term Solar Power Forecasting with Diurnal and Intra-Day Variability

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Abstract. The increasing penetration of solar photovoltaic (PV) systems into modern power grids demands accurate, reliable short-term power forecasting to ensure operational stability and efficient energy management. However, solar power generation exhibits strong nonlinearity, non-stationarity, and pronounced temporal dependencies, driven by diurnal cycles and rapid environmental variations, which pose significant challenges for conventional forecasting approaches. This study aims to develop an efficient Long Short-Term Memory (LSTM)-based framework for short-term DC power prediction that effectively captures the temporal dynamics of solar power generation while maintaining low computational complexity. The proposed approach utilizes historical power and operational data collected from two utility-scale solar PV plants in India. A comprehensive time-series preprocessing pipeline is applied, including temporal feature extraction, categorical transformation, and Min–Max normalization. Multiple LSTM architectures with varying numbers of hidden units are systematically evaluated to identify an optimal balance between model complexity and predictive performance. Model training is conducted using the Adam optimizer with exponential learning rate decay and early stopping to prevent overfitting. Experimental results demonstrate that the proposed LSTM model with a 25–50 unit configuration achieves the best performance, yielding a test Mean Squared Error of 51.92 and a prediction error of only 0.36%. Visual and quantitative analyses confirm that the model accurately reconstructs diurnal patterns and intra-day fluctuations, with strong generalization capability on unseen data. The findings indicate that a carefully configured LSTM can deliver high forecasting accuracy without relying on complex hybrid architectures or additional weather data, making it suitable for practical solar energy management applications.

Keywords: Solar power forecasting; Long short-term memory; Time-series prediction; Photovoltaic systems; Deep learning

1. INTRODUCTION

The increased penetration of solar power generation in modern energy systems requires accurate and reliable power prediction methods [1]. The characteristics of solar power generation, which are highly dependent on environmental conditions, cause significant temporal fluctuations at both daily and intra-daily scales [2], [3]. This uncertainty is a major problem in power grid management, as power prediction errors can directly impact system stability, energy scheduling efficiency, and power supply reliability [4], [5].

The main challenge in solar power generation prediction lies in the nonlinearity and non-stationarity of the data, as well as their strong temporal dependence [6], [7]. The dominant diurnal pattern is often accompanied by short-term fluctuations due to changes in weather conditions and the operational dynamics of photovoltaic systems [8], [9], [10]. Conventional modeling approaches based on linear regression or classical statistical methods generally struggle to capture these complex temporal relationships, resulting in limited accuracy, especially during transition periods and peak generation [11], [12], [13].

To address these issues, this study aims to develop a solar power prediction model based on Long Short-Term Memory (LSTM) to effectively capture nonlinear temporal dynamics. The model is designed to utilize historical power and operational variable information to generate accurate short-term DC power predictions. In addition, this study

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The main contributions of this study can be summarized as follows. First, this study presents an LSTM-based solar power prediction framework that reconstructs diurnal patterns and intra-daily fluctuations with very low error rates, as shown by quantitative and visual evaluation results. Second, a comparative analysis of several LSTM architecture configurations was conducted to identify the optimal balance between model complexity and prediction performance. Third, this study provides an in-depth visual analysis by comparing actual and predicted values, including zoom-in visualizations, demonstrating the model's ability to capture local temporal dynamics with precision. Thus, the results of this study make a significant contribution to the development of reliable solar power generation prediction systems to support energy management and power grid operation planning.

2. RELATED WORK

Studies on deep learning-based solar power generation prediction over the last five years have seen a significant shift from conventional statistical approaches to recurrent neural network-based time-series models, particularly Long Short-Term Memory (LSTM). Malakar et al. [14] emphasize that LSTM has advantages for modeling short- and long-term temporal dependencies in nonlinear, nonstationary renewable energy data. Their study shows that an optimized LSTM architecture can significantly improve prediction accuracy compared to classical methods such as ARIMA and linear regression.

Further development of the LSTM architecture was carried out by Garip et al. [15], who examined photovoltaic power prediction based on weather data using LSTM in a day-ahead forecasting scenario. The results of this study show that LSTM can represent diurnal patterns well, but its performance is sensitive to parameter selection and the quality of meteorological data. Similar findings were also reported by Nguyen et al., who applied LSTM to large-scale solar power plants and emphasized the importance of temporal feature engineering to improve prediction stability [16].

As data complexity and accuracy requirements increase, several studies have begun to propose multi-layer and hybrid LSTM architectures. Gaur et al. showed that stacked LSTMs outperform single LSTMs in modeling solar power fluctuations, especially over short time horizons [17]. Meanwhile, Sadeghi et al. compared various hybrid deep learning approaches and reported that integrating LSTMs with optimization and feature-extraction techniques consistently reduces prediction error [18].

Attention-based approaches are also increasingly used to improve LSTMs' ability to capture complex temporal dynamics. Yang et al. proposed an LSTM model with a dual-stage attention mechanism and demonstrated a significant improvement in accuracy, especially under changing weather conditions [19]. A recent study by Zhou et al. combined CNNs, LSTMs, and attention mechanisms with Bayesian optimization, achieving superior performance but at the cost of increased computational complexity [20].

Although various hybrid approaches show high performance, most previous studies have focused on improving architecture and integrating additional features, at the cost of relatively high computational expenses and challenges in model interpretability. Furthermore, visual evaluation of the suitability of predictions and actual values at a local temporal scale remains relatively limited. Based on these gaps, this study focuses on developing and evaluating an efficient yet accurate LSTM architecture, with in-depth quantitative and visual analyses to assess the model's ability to represent the diurnal and intra-daily dynamics of solar power generation.

3. METHODS

This study proposes a deep learning-based methodological framework for modeling time series of solar power generation, with the main objective of accurately and stably predicting short-term photovoltaic system output power. The developed methodology is systematically designed to capture the nonlinear temporal characteristics of energy generation data while minimizing the risk of overfitting and data leakage, which are common in time-series modeling. All stages of the study, from data acquisition and pre-processing to model training and evaluation, are organized in an integrated pipeline that reflects the actual operational conditions of solar power generation systems. The Long Short-Term Memory (LSTM) architecture was chosen as the core of the predictive model due to its ability to model long-term dependencies in sequential data, which is highly relevant to the dynamics of solar radiation-based energy production, as shown in Figure 1.

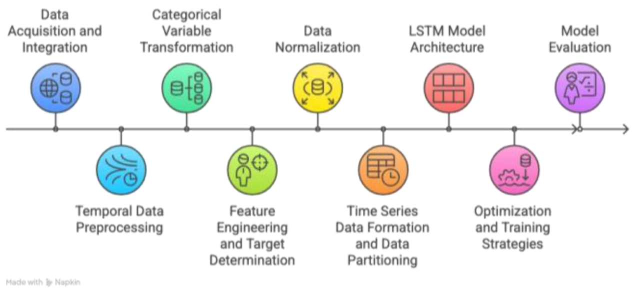

Fig. 1. Overview of the proposed LSTM-based methodological pipeline for short-term solar power forecasting, including data acquisition and integration, temporal preprocessing, categorical transformation, feature engineering and target determination, data normalization, time-series formation and partitioning, LSTM model architecture design, optimization and training strategies, and model evaluation.

3.1. Data Acquisition and Integration

This study uses a publicly available solar power generation dataset obtained from Kaggle, comprising operational data from two utility-scale photovoltaic plants (Plant 1 and Plant 2) located in India. The dataset was collected over a continuous 34-day observation period

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and consists of high-resolution time-series measurements recorded at the inverter level. In total, the integrated dataset contains approximately 67,000 records, capturing detailed variations in power generation across multiple inverters. Data from both plants were loaded separately and concatenated into a unified dataset to develop a more general, location-independent prediction model. This integration process was performed after ensuring consistency in attribute structures, temporal resolution, and timestamp formatting across the two datasets.

3.2. Temporal Data Preprocessing

The time attribute (DATE_TIME) was converted into a datetime format to enable richer temporal information extraction. Several time features were derived from this attribute, namely year, month, day, hour, minute, and second. This approach aimed to capture periodic and seasonal patterns that inherently affect solar power production, particularly the daily pattern (diurnal cycle), which is particularly dominant in photovoltaic systems.

3.3. Categorical Variable Transformation

The SOURCE_KEY attribute, which represents the inverter's identity, is a categorical variable that neural network-based models cannot directly use. Therefore, a Label Encoding transformation is applied to convert each inverter identity into a discrete numerical representation. This approach allows the model to distinguish between inverter characteristics without losing structural information.

3.4. Feature Engineering and Target Determination

In this study, the target variable predicted is DC_POWER, which represents the direct current power generated by solar panels before the inversion process. Meanwhile, the input features consist of a combination of operational and temporal variables, namely AC_POWER, PLANT_ID, SOURCE_KEY, DAILY_YIELD, TOTAL_YIELD, and all time-derived features. The selection of these features is based on the functional correlation between DC power, AC power, energy accumulation, and the time dynamics of the photovoltaic system's operation.

3.5. Data Normalization

To ensure the stability of the training process and accelerate model convergence, all input features are normalized using Min–Max scaling. This process maps each feature to the range [0, 1] using Equation (1).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x is the original value of the feature, while x_{min} and x_{max} are the minimum and maximum values of the feature, respectively. This normalization is very important in LSTM models because differences in feature scales can cause certain gradients to dominate, reducing learning performance.

3.6. Time Series Data Formation and Data Partitioning

The normalized dataset is sorted by time to maintain temporal consistency and prevent data leakage. Next, the data is split into training and test sets at an 80:20 ratio, without shuffling (shuffle=False). This approach reflects a real-world prediction scenario in which the model is trained on historical data and tested on future data. The data is then reshaped into the three-dimensional format (samples, timesteps, features) required by the LSTM architecture, with timesteps set to 1.

3.7. LSTM Model Architecture

Long Short-Term Memory (LSTM) is an extension of recurrent neural networks designed to model long-term temporal dependencies in nonlinear time series data. This capability is achieved through an internal memory mechanism controlled by three main gates, namely the forget gate, input gate, and output gate, which adaptively regulate the flow of information throughout the time sequence.
At each time step t, the forget gate f_t in Equation (2), the proportion of historical information from the previous cell state C_{t-1} that is retained, while the input gate i_t in Equation (3), controls the integration of new information represented by the candidate cell state $\widetilde{C}_t$ in Equation (4). The cell state update C_t in Equation (5) is performed through a selective combination of past information and relevant new information, allowing the model to maintain long-term memory without accumulating temporal noise. Furthermore, the output gate o_t in Equation (6), the portion of the cell state exposed as the hidden state h_t in Equation (7), which is used as a latent representation at time t and as input at the next time step, through this mechanism, LSTM can stably capture complex temporal dynamics, making it suitable for modeling solar power generation that is affected by time variations and operational conditions.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$
$$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t \tag{5}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$
$$h_t = o_t \odot \tanh(C_t) \tag{7}$$

The model was tested on several configurations of the number of neuron units in two LSTM layers (25 and 50 units) to evaluate the effect of model complexity on prediction performance.

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3.8. Optimization and Training Strategies

The model training process used the Adam optimizer combined with an Exponential Learning Rate Decay scheme. The initial learning rate was set relatively high to accelerate the exploration of the solution space, then decreased exponentially to improve convergence stability. This strategy was formulated as Equation (8).

$$\alpha_t = \alpha_0 \cdot \gamma^t \quad (8)$$

where α_0 is the initial learning rate and γ is the decay rate. In addition, an Early Stopping mechanism based on validation loss is applied to prevent overfitting and ensure that the model stops training when there is no significant improvement in performance.

3.9. Model Evaluation

Model performance is evaluated using Mean Squared Error (MSE) as the main loss function, which is formulated as Equation (9)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (9)$$

In addition to numerical evaluation, a visual analysis was performed by comparing the actual value curve with the DC_POWER prediction in the test data. This approach provides an intuitive understanding of the model's ability to follow the temporal dynamics of solar power generation.

4. RESULTS AND DISCUSSIONS

4.1. Results

The visualization results show the time series patterns of DC Power and AC Power generation at Plant 2 during the observation period. In general, both signals display consistent diurnal patterns, with power near zero at night, a sharp increase after sunrise, and a peak in generation around midday. This pattern confirms that the data realistically represent the physical characteristics of the photovoltaic system and is valid for further analysis, as shown in Figure 2.

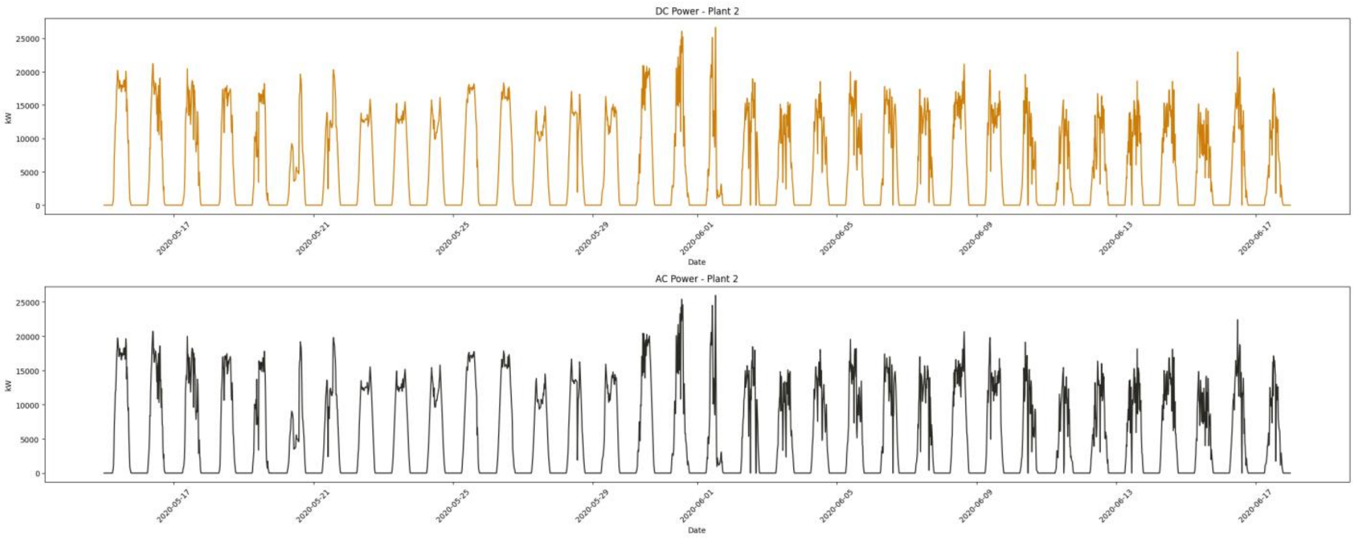

Fig. 2. Time-series visualization of DC power and AC power generation at Plant 2, illustrating consistent diurnal patterns with near-zero output during nighttime and peak generation around midday.

In the DC Power signal, there are significant variations in daily peak amplitude between days. Some days show relatively stable, high-power peaks, while other days experience sharp fluctuations and temporary drops during the daytime. This phenomenon indicates the presence of external influences such as changes in solar radiation intensity due to weather conditions, partial shading, or potential panel performance degradation. In addition, the presence of spikes and sudden drops during active production hours indicates nonlinear dynamics that challenge conventional linear prediction models.

The AC Power signal shows a temporal pattern that generally follows DC Power, but with slightly lower values due to the energy conversion process in the inverter. However, at some time intervals, the curve shape appears rougher and more fluctuating than the DC signal. This indicates variations in inverter efficiency or in the system's response to rapid changes in input power. These differences in characteristics reinforce the importance of time-series-based modeling that can capture the nonlinear relationship and temporal delay between DC and AC power.

A comparison of the two signals also shows that, although the global trends are similar, there are certain intervals in which the decline in DC power is not fully matched by a decline in AC power in the same proportion, and vice versa. This condition suggests potential inconsistencies in inverter performance or a smoothing effect on the power conversion system. From a modeling perspective, these characteristics confirm that the relationship between the input and target variables is not static but is influenced by the system's temporal context and operational conditions.

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Overall, these visualization results confirm that solar power generation data exhibits strong temporal patterns, nonlinear fluctuations, and short- and medium-term dependencies, making it highly suitable for modeling with a Long Short-Term Memory (LSTM)-based architecture. These characteristics also explain why a deep learning approach is necessary to achieve stable, accurate predictions in solar energy generation systems.

In this study, four Long Short-Term Memory (LSTM) architectures were evaluated to examine the effect of the number of neurons per layer on solar power prediction performance. Models A to D represent variations in the number of units in two LSTM layers, with all other components—including the data pre-processing scheme, optimizer, initial learning rate, and evaluation strategy—kept the same. Model A uses 25 units in both LSTM layers (25–25), Model B uses 25 units in the first layer and 50 units in the second layer (25–50), Model C uses 50 units in the first layer and 25 units in the second layer (50–25), while Model D uses 50 units in both LSTM layers (50–50).

TABLE 1. Performance comparison of LSTM architectures for solar power prediction.

LSTM Configuration	Layer 1 Units	Layer 2 Unit	Epoch Optimal	Lowest Validation Loss	Test Loss	Error (%)
Model A	25	25	7	63.98	63.98	0.44
Model B	**25**	**50**	**9**	**51.92**	**51.92**	**0.36**
Model C	50	25	3	73.67	73.67	0.51
Model D	50	50	4	65.59	65.59	0.46

Based on the results summarized in Table 1, each configuration produces a different level of accuracy, even though all models achieve stable convergence. Model B (25–50) showed the best performance, with the lowest validation and test losses and the smallest prediction error percentage. This finding indicates that increasing the representation capacity in the second layer of the LSTM, which plays a role in capturing advanced temporal dependencies, significantly improves the model's generalization ability.

In contrast, Model A (25–25) and Model C (50–25) show relatively lower performance. In Model A, the smaller number of units in both layers limits the model's capacity to represent the complexity of solar power generation dynamics. Meanwhile, in Model C, the dominance of capacity in the first layer, without being balanced by the second layer, reduces the effectiveness of modeling medium-term temporal dependencies.

Model D (50–50), which has the highest complexity, does not yield a significant performance improvement over Model B. This shows that excessive addition of units tends to increase the risk of training instability and is not always followed by improved accuracy. Thus, these results confirm that choosing a balanced LSTM architecture is more important than simply increasing model complexity.

Overall, this analysis shows that Model B is the optimal configuration for solar power prediction on the dataset used, achieving the best balance between prediction accuracy and generalization. Therefore, this model was selected as the final model for further analysis and discussion.

The graph in Figure 3 shows the dynamics of the training and validation losses during LSTM model training. In the early epochs, the training loss declined sharply, indicating that the model quickly learned the basic temporal patterns in the solar power generation data. This decline reflects the effectiveness of parameter initialization and the LSTM architecture's ability to capture the data's nonlinear structure.

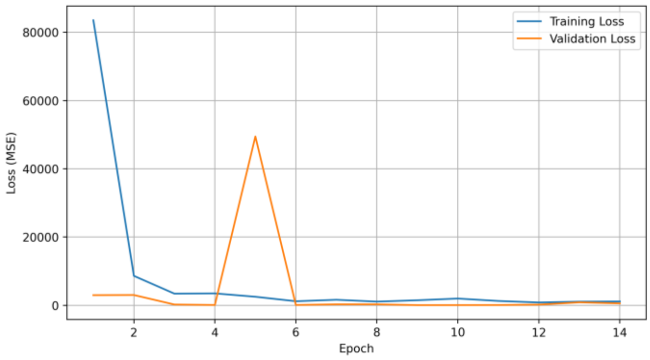

Fig. 3. Training and validation loss curves of the LSTM model (25–50 units) during the learning process.

As the number of epochs increases, the training loss gradually decreases, indicating good convergence. The validation loss shows fluctuations in the early epochs, including a significant spike, indicating the model's sensitivity to variations in the validation data. However, after this initial phase, the validation loss decreases and reaches a minimum at epoch 9, which is then used as the optimal training point via the early stopping mechanism.

The consistency between the training and validation loss trends in the final epochs indicates that the model does not exhibit significant overfitting. The distance between the two curves is relatively small at the optimal point, indicating the model has good generalization ability to data not used during training. Thus, this graph confirms that the proposed LSTM configuration achieves an effective balance between accuracy and learning stability.

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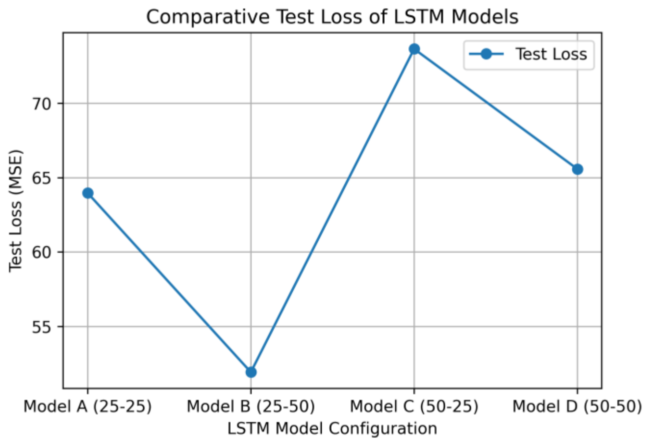

Fig. 4. Comparative test loss (MSE) of different LSTM model configurations. The results indicate that Model B (25–50) achieves the lowest test loss, demonstrating superior generalization performance compared to other architectures.

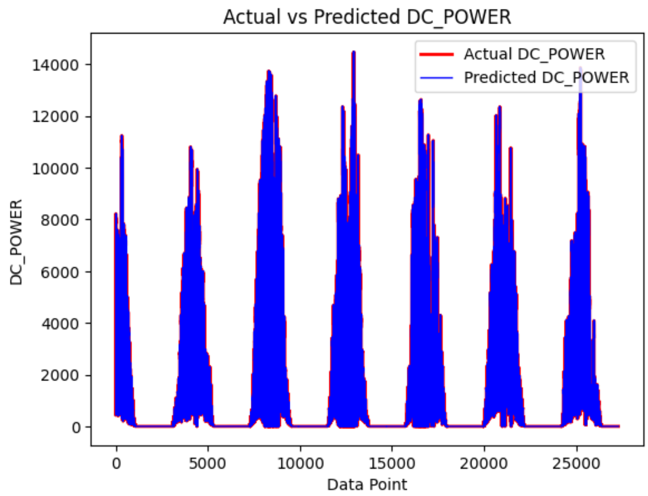

Fig. 5. Comparison between actual and predicted DC power output using the proposed LSTM model.

The graph in Figure 4 compares test loss (MSE) values for the four LSTM architectures tested: Model A (25–25), Model B (25–50), Model C (50–25), and Model D (50–50). Model B (25–50) achieved the lowest test loss of 51.92, confirming it as the optimal configuration for modeling the temporal dynamics of solar power generation. The significant decrease in test loss in Model B indicates that increasing the number of units in the second layer—which plays an important role in capturing advanced temporal dependencies—improves the model's generalization.

Conversely, Model C (50–25) shows the highest test loss, indicating that increasing the capacity of the first layer without adequate support from subsequent layers is ineffective at capturing the complexity of time-series patterns. Model A (25–25) and Model D (50–50) produce intermediate performance, with Model D showing no commensurate improvement despite having the highest architectural complexity. This confirms that excessive increases in model complexity do not always correlate with increases in prediction accuracy. Overall, this graph reinforces the quantitative findings in Table 1: a balanced LSTM configuration (Model B) provides the best and most stable performance.

The graph in Figure 5 compares the actual DC_POWER value with the predicted DC_POWER value, indicating a very high level of agreement across the test data range. Visually, the prediction curve closely follows the main pattern of the actual curve, from the power increase after sunrise through the peak generation around midday to the power decrease to zero in the afternoon to evening. This conformity indicates that the LSTM model successfully captures the dominant temporal dynamics that govern the solar power generation process.

During the daytime, when the DC_POWER value reaches its peak, the model reconstructs the power amplitude with high accuracy. Although there are small deviations at some extreme peaks, the short-term fluctuation pattern is well maintained. This shows that the model not only learns global trends but is also sensitive to local variations arising from changes in environmental conditions and photovoltaic system operations.

During the transition interval between inactive and active conditions, particularly in the early phase of power increase and decrease, the prediction curve continues to align consistently with the actual data. This capability reflects the LSTM memory mechanism's effectiveness in modeling sharp, nonlinear temporal changes, which are generally difficult to capture with static model-based prediction approaches.

The difference between the predicted and actual values is relatively small and does not exhibit a systematic pattern of deviation. The discrepancies that arise are sporadic and localized, indicating that prediction errors are more influenced by data natural variability than by the model's structural limitations. This aligns with the low test loss and error rate, confirming the model's ability to generalize to previously unseen data.

Overall, this graph confirms that the proposed LSTM approach can produce accurate and stable DC power predictions. The level of agreement between predictions and actual values indicates that the model has strong potential for application in short-term solar power generation prediction scenarios within energy management systems and power grid operation planning.

4.2. Discussions

Previous studies, such as those conducted by Malakar et al., Garip et al., and Nguyen et al., have shown that LSTM outperforms conventional statistical methods in modeling temporal dependencies in solar power generation data [14], [15], [16]. However, most of these studies focused on

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improving accuracy by adding weather variables or enriching external features, so model performance was highly dependent on the quality and availability of meteorological data.

In contrast to these approaches, this study focuses on exploring LSTM architectures trained on historical power data, aiming to achieve a balance between model accuracy and efficiency. Experimental results show that a balanced LSTM configuration (Model B: 25–50) can achieve high accuracy without requiring complex hybrid architectures or additional mechanisms such as attention.

Studies by Gaur et al. [17] and Sadeghi et al. [18] report improved performance with stacked LSTMs and hybrid models, but at the cost of increased computational complexity. Meanwhile, this study shows that increased complexity does not always result in significant improvements in accuracy, as demonstrated by Model D (50–50), which does not exceed Model B's performance.

The attention-based approaches proposed by Yang et al. and Zhou et al. have proven effective in highly dynamic weather conditions. However, local visual evaluation and training stability analysis are often not discussed in depth [19], [20]. This study fills this gap by presenting a comprehensive visual analysis, including prediction-versus-actual graphs and zoom-ins, to evaluate the model's ability to capture local temporal dynamics.

TABLE 1. Comparison of previous studies on solar power generation forecasting and the proposed LSTM-based approach.

Study	Method	Additional Data	Forecast Horizon	Evaluation Metrics	Key Findings
[14]	LSTM	Weather	Short-term	RMSE, MAE	LSTM outperforms ARIMA
[15]	LSTM	Weather	Day-ahead	RMSE, MAPE	Sensitive to weather data quality
[16]	LSTM	Operational	Short-term	MAE, RMSE	Temporal features have a significant effect
[17]	Stacked LSTM	–	Short-term	RMSE	Improved accuracy, high complexity
[18]	Hybrid DL	Weather + optimization	Multi-horizon	RMSE, MAPE	High accuracy, high computational cost
[19]	LSTM + Attention	Weather	Short-term	RMSE	Stable under dynamic weather conditions
[20]	CNN–LSTM–Attention	Weather	Short-term	RMSE, MAE	High accuracy, complex architecture
Our Study	**LSTM (25–50)**	**Historical power**	**Short-term**	**MSE, Error (%)**	**High accuracy, efficient, stable**

Most previous studies used RMSE and MAE as the primary performance metrics. This study used Mean Squared Error (MSE) and percentage error, which directly reflect the quadratic deviation between actual and predicted values. The results showed an error rate of 0.36%, which is competitive with previous studies, even without the use of weather features or complex hybrid architectures.

Analysis of the training–validation loss curve shows stable convergence and no indication of significant overfitting, in line with the study objective of producing a robust model with good generalization capabilities.

Overall, compared to previous studies, the main contribution of this study lies in presenting a simple yet effective LSTM model, with comprehensive quantitative and visual evaluations. These findings show that improving solar power prediction performance does not always require increasingly complex architectures, but can be achieved by selecting appropriate LSTM configurations and by in-depth analysis of the temporal behavior of the data.

5. CONCLUSIONS

This study aims to develop an accurate and stable short-term solar power generation prediction model by leveraging Long Short-Term Memory (LSTM) for modeling nonlinear temporal dynamics. This objective is based on the need for a reliable prediction method to support energy management and power grid operation planning in renewable energy-based systems. Based on the results obtained, the objectives of this study have been successfully achieved.

The experimental results show that the LSTM model accurately represents diurnal patterns and intra-daily fluctuations in solar power generation. Evaluation of several LSTM architecture configurations indicates that the balance of the number of neurons between layers plays an important role in determining model performance. The best configuration, namely a model with 25 units in the first layer and 50 units in the second layer, yielded low prediction errors and demonstrated consistent generalization on the test data.

The main contribution of this study is the presentation of an efficient yet effective LSTM approach that does not rely on complex hybrid architectures or additional weather-based features. Furthermore, this study enriches solar power prediction analysis through comprehensive visual evaluation, including comparisons of actual and predicted values and zoom-in analysis to assess model performance on a local temporal scale. This approach provides a deeper understanding of the model's behavior in representing solar power generation dynamics.

Overall, this study's findings confirm that selecting an appropriate LSTM configuration can yield accurate, stable short-term solar power predictions with relatively low complexity. Thus, the proposed model has the potential to be integrated into energy management systems and into

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the planning of solar power plant operations. Future studies could focus on testing the model across more diverse datasets, integrating environmental variables, and developing interpretability approaches to increase confidence in its application in real-world operational environments.

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