

Hybrid LSTM-CNN Deep Learning Model for Enhanced Day-Ahead Photovoltaic Power Forecasting

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ABSTRACT

The photovoltaic (PV) power plants offer considerable environmental and economic advantages; its large penetration poses challenges to power system operation and planning owing to the unpredictable and variable nature of solar generation. Therefore, accurate forecasting of PV power is essential to guarantee provision of high-quality electricity to consumers and to enhance the reliability of the power grid. This research develops a hybrid deep learning model for PV power forecasting that synergistically combines LSTM and CNN architecture. The model is designed to leverage the complementary strengths of each network: the LSTM is employed to learn extended temporal correlations within the historical time-series data, whereas the CNN is utilized to identify complex spatial patterns and local features from the sequence. A case study utilizing a real-world dataset for one year demonstrates the superior performance of the proposed hybrid LSTM-CNN model. The evaluation is based on the annual performance of day-ahead PV output power forecasting. Comparative analysis against standalone LSTM and CNN models demonstrates that the proposed hybrid architecture achieves greater forecasting accuracy and stability, as evidenced by lower values of key performance indicators: RMSE, MAE, and MAPE.

Keywords - Forecasting of PV power, Deep learning, LSTM, CNN, hybrid LSTM-CNN

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I. INTRODUCTION

Over the past century, fossil fuels such as natural gas, coal, and oil were the main sources for producing electrical energy through large capacity generation stations. While they still contribute significantly today, their use has led to major environmental impacts, including global warming, emissions of harmful gases, and widespread pollution. Consequently, the modern world seeks to integrate renewable energy sources (RESs) with high penetration while reducing dependence on fossil fuels in the energy sector [1]. Among RESs, wind and solar energy appear as particularly viable and promising energy sources due to their widespread availability, low costs, and substantial generation possible. These factors are enabling their accelerated penetration into the energy market. Furthermore, growing environmental awareness and supportive government policies worldwide are accelerating their adoption as clean alternatives for energy [2].

Solar energy from Photovoltaic (PV) has achieved widespread global acceptance, establishing itself as a foundational element in the transition to clean and resilient electrical grids. However, this rapid integration introduces significant challenges to electrical grid stability. The fundamental issue lies in

the intermittency and variability of PV power generation [3] which is directly dependent on fluctuating weather conditions like cloud cover, humidity, air pressure and solar irradiance [4]. Consequently, accurate forecasting of generating PV power has become an essential energy management tool for grid operators and utilities. As it contributes to improve the balance between load demand and supply energy, schedule power plants, ensure grid reliability, reduce operational costs mitigate the solar power's unpredictability impacts.

The challenge of predicting solar power generation has stimulated considerable academic and industrial research over the last decade, resulting in a large number of studies proposing forecasting methods. These methods can be broadly categorized by their approach as; statistical, physical, machine Learning (ML), and hybrid models [5].

Physical Models utilize Numerical Weather Prediction (NWP) data and satellite imagery as primary inputs. It depends on some mathematical equations to calculate the physical performance of the PV system. The work in [6] presented a correction method for errors in NWP-based irradiance forecasts. This approach utilized an

extensive set of standard meteorological variables from NWP output in conjunction with a clear sky model. Ref. [7] developed a research forecasting model based on direct-cloud-assimilating NWP uniquely assimilated satellite cloud imagery directly into its initial states. The model was specially configured, with tailored resolution and physics parameterizations, to replicate the life cycle of the region's characteristic low-altitude stratiform clouds. The modeling process for physical models is complicated because it requires detailed meteorological data for PV power stations and geographic information. Additionally, the performance of these models cannot be assured if there are significant variations in weather [8], [9], [10]. In contrast, statistical models forecast PV power output by establishing mathematical relationships between historical generation data and weather parameters through time-series analysis [11][12]. The accuracy of these models is highly sensitive to both input data quality and the forecast horizon. Commonly used statistical models include the autoregressive moving average (ARMA) model [13] and its variants such as ARIMA, SARIMA, and ARMAX [14]—as well as exponential smoothing [15], and regression models (RM) [16][17]. While these techniques are effective for stable time series, they often exhibit significant errors when applied to real-life PV data, which typically exhibits high variability [18].

Machine Learning (ML) models utilize algorithms ranging from regression trees to sophisticated deep neural networks. They establish mappings by training on datasets that include input and output samples [19]. These models have found applications across various engineering and scientific fields, including predicting PV power output. Typically, the modeling process involves four key stages: data preprocessing, model training, model validation, and fine-tuning the final predictions. Commonly employed ML models for PV power generation forecasting include extreme learning machines [20], support vector machines (SVM) [21], recurrent neural networks (RNN) [22] and artificial neural networks (ANN) [23][24][25]. Additionally, Long Short-Term Memory (LSTM) [26], convolutional neural networks (CNN) [27] and Gated Recurrent Units (GRU) [28] are also utilized. Deep learning (DL) models have been extensively validated across a diverse range of solar forecasting

applications. For instance, a study in Turkey utilized a DL model to estimate daily solar radiation for 30 locations [29]. Similarly, an LSTM model applied to meteorological data from Santiago, Cape Verde, for Global Horizontal Irradiance (GHI) forecasting demonstrated a significant improvement over benchmark methods like persistence, backpropagation, and least squares regression [30]. The application of LSTMs extends beyond purely meteorological data; for example, a window-based multi-input/output LSTM model was used to forecast electric load demand [31], while another achieved GHI prediction by applying LSTM to satellite imagery from 21 locations [32]. The nonlinear processing capability of ANNs is particularly advantageous for capturing the high variability of solar power, contributing to their impressive results and widespread adoption in the field.

Hybrid models, which combine two or more techniques, are an effective solution for enhancing forecasting accuracy by leveraging the complementary strengths of different topologies. This approach is demonstrated in several studies: for instance, the particle swarm optimization (PSO), wavelet transform, and SVM was integrated to develop short-term photovoltaic power forecasting, where PSO optimized the SVM's key parameters [33]. Similarly, the colliding bodies optimization algorithm was employed to determine the best neuron count in a DL model [34]. Further showcasing the versatility of this approach, another study utilized both genetic algorithm (GA) and PSO to improve a backpropagation ANN model for estimating daily diffuse solar radiation based on seven meteorological parameters [24]. In a related effort, a hybrid technique using wavelet multiresolution analysis with a discrete wavelet transformation (DWT) algorithm was proposed to decompose complex meteorological signals. This decomposition was then applied to four different ANN architectures to improve modeling performance [25]. A hybrid methodology for day-ahead photovoltaic power forecasting (PPF) coupled with uncertainty analysis was presented in [35]. The model integrated whale optimization algorithm, least squares SVM, non-parametric kernel density estimation, and fuzzy c-means [35]. This work was driven by recent advances in DL and its successful application in the electrical power sector. Several

hybrid DL architectures demonstrate this potential. For instance, one study merged LSTM and CNN models to improve solar power system operations [36], while another implemented the LSTM-CNN to model the joint spatiotemporal characteristics of the input sequences for PV prediction [37]. Other methods included a hybrid prediction approach that uses genetic algorithms and long-term memory for optimization [38], a combination of CNN with the Salp Swarm Algorithm for power output prediction [39], and a Convolutional Self-Attention-based LSTM (CA-LSTM) framework designed to capture local data context and improve accuracy [40]. These models are typically validated using actual power generation and consumption data.

The above-mentioned review of the existing research reveals several persistent challenges and opportunities for advancement in PV forecasting. For example, conventional artificial intelligence methods have inherent limitations, the rapid evolution of DL presents an effective alternative. Moreover, although the PV power fluctuation due to weather instability is widely acknowledged, the strong periodicity and regularity of solar energy are often underutilized. Thus, there is a need for a sophisticated hybrid deep learning framework that moves beyond treating PV data as a simple time series. Additionally, models the dual nature of solar power generation, its deterministic patterns (diurnal, seasonal) and its stochastic disturbances (weather-induced fluctuations) by dynamically integrating high-resolution meteorological.

The remainder of this paper is structured as lists. Section 2 details the methodology of the proposed hybrid DL model for day-ahead PV forecasting. Section 3 describes the evaluation metrics used for assessment. Section 4 presents and discusses the simulation results, evaluating the performance of the proposed model. Finally, Section 5 presents the concluding remarks.

II. PV POWER GENERATION FORECASTING MODELS

This section presents the architecture details for the PV output power forecasting model. The overall methodology consists of sequential steps:

1. Data Preprocessing: Input variables are normalized to standardize the data scale.
2. Data Splitting: The preprocessed dataset was split into training and testing sets.
3. Model Training: The proposed CNN-LSTM model is trained by using the training data patterns.
4. Model Evaluation: The efficiency of all trained models is evaluated using the testing set.

The selection of deep learning architectures is guided by the multivariate time series structure of the data. Two models are employed for their complementary strengths:

1. CNN: This architecture (comprising CL, PL, and FC layers) is applied for its proficiency in extracting spatial features and local patterns from sequential data [41].
2. LSTM: As a specialized RNN, it is utilized for its proficiency in modeling long-range temporal dynamics via its unique gated structure [30].

Due to their different operational mechanisms, the proposed model's performance is compared separately against each of these benchmarks.

2.1 Convolution Neural network

One of the key benefits of the CNN is their relatively low parameter requirements compared to traditional ANNs. This characteristic helps decrease computational complexity and memory usage, leading to enhanced performance. CNNs are structured with three main types of layers: fully connected, max-pooling and convolutional layers [41]. Figure 1 provides an illustration of CNN architecture. Additionally, the subsequent sections will illustrate the functions and descriptions of each layer utilized in the design of the proposed CNN presented in this research.

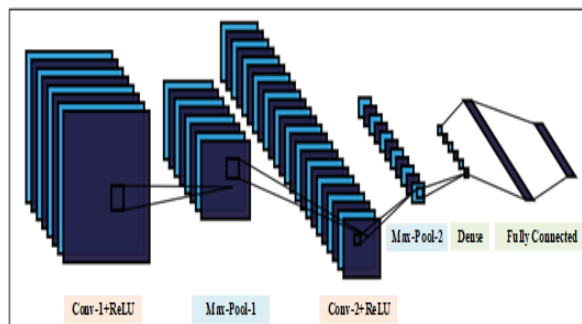


Fig. 1. Proposed CNN construction

2.1.1 Convolutional layers

Convolution layers utilize 2D filters (convolution kernels) to convolve input images, producing two-dimensional feature maps. The number of filters used depends on the neurons' number in the corresponding the subspaces of the input. The size of these filters (width and height) is determined by the dimensions of the sliding window applied across the input array [42] [43]. Crucially, the neurons' number in the output feature map must match the number in the convolutional layer itself. The total layers are configurable based on the network architecture. Mathematically, it can be modelled as:

$$R(c, d) = \sum_{l=1}^L \sum_{k=1}^K M(l, k) * A(c + 1, d + k) \quad (1)$$

where l (mask row) and k (mask column) are indices for the mask M , and c (feature row) and d (feature column) are indices for the feature matrix A . The filter dimensions are L (height/rows) and K (width/columns).

2.1.2 Non-Linearity Layer

The feature maps from the convolutional layer are passed through a Rectified Linear Unit (ReLU), which acts as a non-linear filter that discards negative values as shown in (2). ReLU is widely adopted in CNNs because it significantly accelerates network training [43].

$$F(y) = \begin{cases} y, & y \geq 0 \\ 0, & y < 0 \end{cases} \quad (2)$$

2.1.3 Max-pooling layer

Maximum pooling layers reduce feature map dimensions, decrease computational complexity and redundant information to mitigate overfitting while enhancing robustness [41]. Positioned after convolution and ReLU operations, pooling enables an increased number of filters in convolutional layers without proportionally increasing computational load. This operation is mathematically represented in [43].

$$y_{lk}^L = \max(x_{l'k'}^L : l \leq l' < (l + h), k \leq k' < (k + q)) \quad (3)$$

where, h and q are length and width of the pooling window, respectively. y_{lk}^L and $x_{l'k'}^L$ denote the

elements of the output and input feature maps for layers L and L' , respectively.

2.1.4 Fully connected layer (FC)

The FC layer follows the convolutional layers, integrating all locally learned features for final classification by connecting each of its neurons to every neuron in the previous layer. The neurons' number in the output layer corresponds directly to the number of target variable.

2.2 Long Short-Term Memory (LSTM)

As an advanced variant of RNNs, LSTM networks were developed to model long-term dependencies in sequential data, a task at which conventional RNNs fail due to vanishing and exploding gradients. While RNNs inherently process sequences via internal feedback loops, their inability to learn long-range context is a fundamental drawback. LSTM architecture, pioneered by Hochreiter & Schmidhuber [44], surmounts this limitation by employing memory cells and a multiplicative gating system. The input, forget, and output gates collaboratively manage the cell state, enabling precise control over which information is retained, updated, or discarded over time. This mechanism empowers LSTM networks to capture long-term temporal relationships reliably. The underlying algorithm is depicted in Fig. 2 and formalized mathematically as follows [32]:

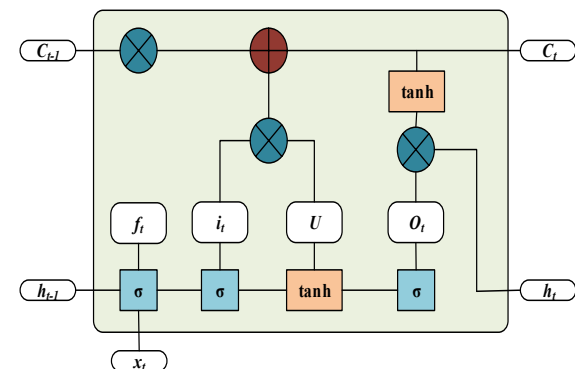


Fig. 2 Architecture of the LSTM network

The forget gate f_t maintains the flow of information by deciding what to remove from the cell state. It computes this using the previous hidden state, h_{t-1} , and current input, x_t .

$$f_t = \sigma(\omega_f [x_t, h_{t-1}] + b_f) \quad (4)$$

A candidate cell state, C'_t , containing potential new information is first computed. The input gate, i_t , then determines the proportion of this candidate state that is added to the network's long-term memory. It learns to select relevant new data from the x_t and h_{t-1} :

$$C'_t = \tanh(\omega_c[x_t, h_{t-1}] + b_c) \quad (5)$$

$$i_t = \sigma(\omega_i[x_t, h_{t-1}] + b_i) \quad (6)$$

The new cell state, C_t , is computed from the previous state, C_{t-1} , and the new candidate cell state C'_t , as follows:

$$C_t = i_t * C'_t + f_t * C_{t-1} \quad (7)$$

The final step involves the output gate, O_t , which filters the updated cell state, C_t , to generate the hidden state, h_t . This output is calculated by multiplying the output gate with a $\tanh$ of the current cell state, C_t , as follows:

$$O_t = \sigma(\omega_o[x_t, h_{t-1}] + b_o) \quad (8)$$

$$h_t = O_t * \tanh(C_t) \quad (9)$$

where, h_{t-1} represents the hidden state from the previous time step, x_t is the current input, σ is logistic sigmoid function, $\tanh$ is the hyperbolic tangent function, $\omega_f, \omega_i, \omega_c$ and ω_o are the weight matrices and b_f, b_i, b_c and b_o are the bias vectors.

2.3 Proposed LSTM-CNN Network

This paper proposes a hybrid DL model for PV power forecasting that synergistically combines CNN and LSTM architectures. The model is designed to leverage the complementary strengths of each network: the LSTM is employed to model long-range temporal dynamics via its unique gated structure, while the CNN is utilized to identify complex spatial patterns and local features from the sequence.

The operational flowchart of the developed model, illustrated in Fig. 3, begins with the input of historical PV data into the LSTM layer. This stage processes sequential information, effectively learning the temporal dynamics critical for forecasting. The output from the LSTM, which represents the extracted temporal features, is then fed as input to the subsequent CNN layer. Then CNN performs convolutional operations to extract higher-level spatial hierarchies from the temporally

enriched data. The final forecast output is generated from this stage. To enhance the model's generalization capability and mitigate overfitting, a dropout layer is incorporated into the architecture.

III. EVALUATION INDICES

To evaluate the proposed hybrid LSTM-CNN model, three error indices are considered. These indices are mean absolute percentage error (MAPE), Mean absolute error (MAE), and root mean square error (RMSE). They are implemented to evaluate the model performance according to forecast results. The definitions of the three indices are described as follow:

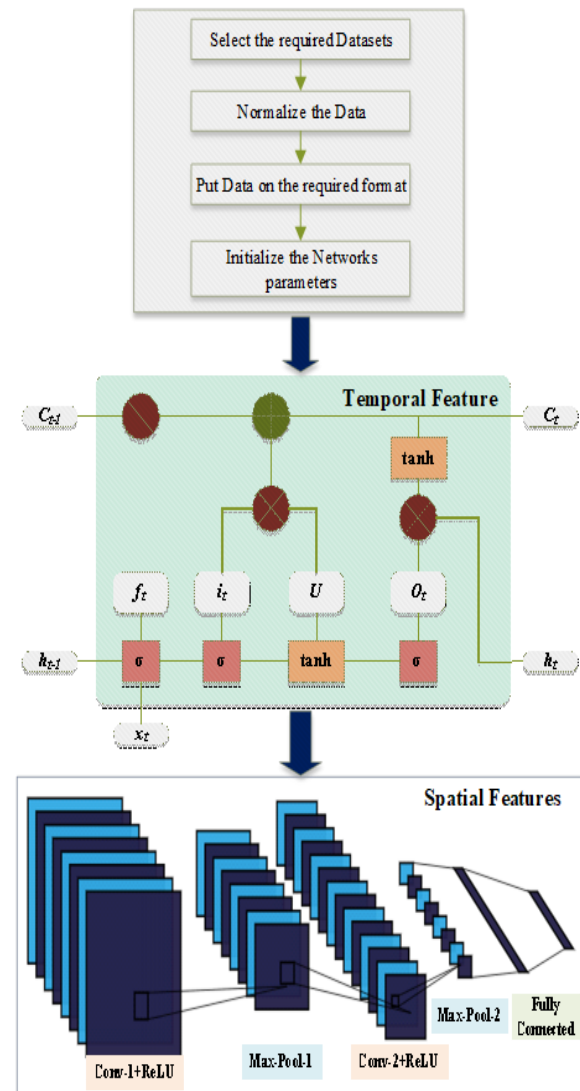


Fig. 3 flowchart of the developed hybrid model

- RMSE is the square root of the average squared differences between actual values and predicted values:

$$RMSE = \sqrt{\frac{\sum_{j=1}^M (A_j - P_j)^2}{M}} \quad (10)$$

- MAE quantifies the average magnitude of the absolute errors between the observed values and the predicted values:

$$MAE = \frac{\sum_{j=1}^M |A_j - P_j|}{N} \quad (11)$$

- MAPE represents the average of the absolute percentage errors, where each error is the absolute difference between the actual value and forecasted value, divided by the actual value.

$$MAE = \frac{1}{M} \sum_{j=1}^M \left| \frac{A_j - P_j}{A_j} \right| \times 100 \quad (12)$$

where P_j is the predicted PV output power, and A_j the corresponding measured output over M datasets. MAE provides a direct measure of the average absolute difference between predictions and observations. RMSE, however, is often more sensitive to large errors because its calculation involves squaring the deviations before averaging, thereby emphasizing outliers. This makes RMSE a valuable metric when large errors are particularly undesirable.

IV. SIMULATION AND DISCUSSION

4.1. Dataset overview

The proposed forecasting models are trained and tested for day-ahead PV power output prediction using the following daily averaged parameters: solar radiation (W/m^2), wind speed (m/s), ambient temperature ($^{\circ}C$), relative humidity (%), and PV power output (W). The original dataset, comprising high-resolution (5-minute interval) measurements from 2017 to 2018, was processed into daily averages to align with the forecasting horizon. The temporal patterns of these data are visualized in Figures 3 through 6. A temporal split was applied to the one-year dataset, allocating the initial 270 days for model training and the remaining 95 days for performance evaluation.

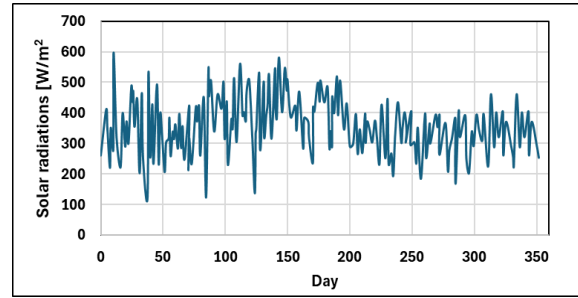


Fig. 3 Daily average solar radiation (W/m^2)

4.2 Proposed LSTM-CNN construction

The optimal performance of the CNN is achieved with a specific architecture comprising one FC, two max-pooling, and two convolutional layers.

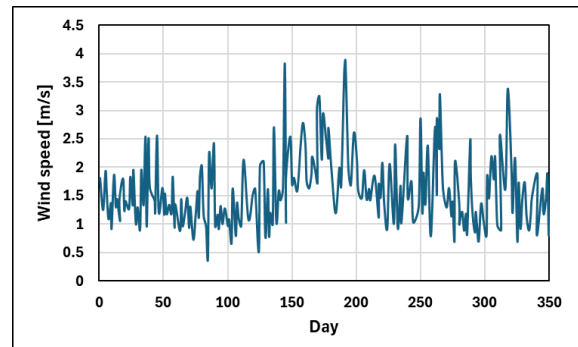


Fig. 4 Daily average wind speed (m/s)

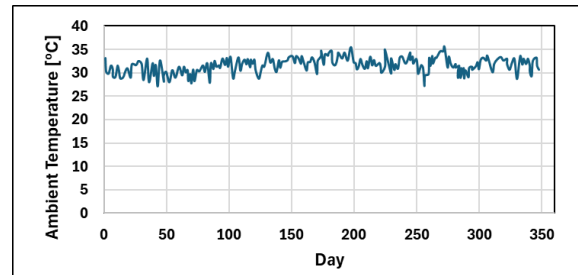


Fig. 5 Daily average ambient temperature ($^{\circ}C$)

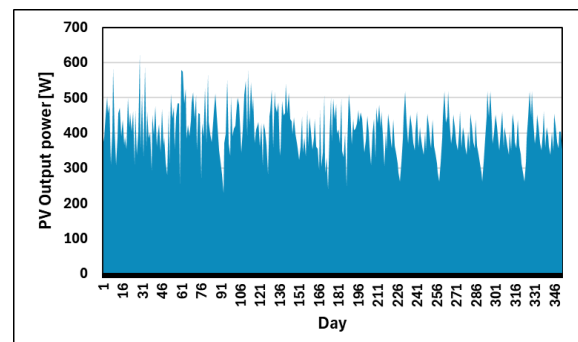


Fig. 6 Daily average PV power output power (W)

A dropout rate of 0.1 was applied as a regularization technique to mitigate overfitting and

improve model generalization. This method randomly excludes 10% of neurons from training during each iteration. The model was trained over 100 epochs with a batch size of 512 and a learning rate of 0.001, using the Adam (Adaptive Moment Estimation) optimizer due to its effectiveness for deep learning tasks. The first convolutional layer employs 386 filters with a 64x64 kernel size, while the second uses 98 filters of size 32x32. The subsequent max-pooling layers have sizes of 32x32 and 16x16, respectively, with the first employing a stride of [2, 2] and zero padding. The FC segment consists of 652 neurons with ReLU activation, followed by a layer of 384 neurons using a TRelu activation function. The final output layer consists of single neuron with a SoftMax activation function to predict the PV output power. The proposed model utilizes a two-layer LSTM architecture. The first layer contains 64 neurons, designed to learn primary, lower-level temporal patterns from the input sequence. The second, deeper layer with 128 neurons builds upon these initial features to capture more complex, long-term dependencies. Both layers employ the TRelu activation function to introduce non-linearity while mitigating the vanishing gradient problem, facilitating more effective learning of the time-series data.

4.3. Performance evaluation

This section provides a detailed performance evaluation of the proposed hybrid LSTM-CNN model. To demonstrate its superiority, the model is compared against several benchmarks: a standalone CNN, a standalone LSTM, and a CNN-LSTM model. The evaluation is based on the annual performance of day-ahead PV output power forecasting. The analysis of model performance clearly demonstrates the advantage of hybrid deep learning architectures over single-model approaches for PV power forecasting. Among all evaluated models, the LSTM-CNN hybrid emerged as the most accurate, registering the lowest error scores across all key metrics: MAE, RMSE, and MAPE. This superior performance is evident when comparing the two hybrid models directly. The LSTM-CNN model showed a notable improvement over the CNN-LSTM model, with its error rates being significantly lower. Furthermore, both hybrid models (CNN-LSTM and LSTM-CNN) provided a more robust and reliable forecasting capability than the single

CNN or LSTM models, which exhibited considerably higher errors. A visual comparison of the forecasting trends over a 92-day period across different seasons confirms these quantitative findings. While all models generally followed the actual pattern of PV power output, the hybrid models, particularly the LSTM-CNN, demonstrated a much higher degree of similarity to the actual values, with its forecasted line being the closest to the observed data.

The forecasting performance of the evaluated models is summarized in Table 1. The results indicate that hybrid models consistently outperform their single-model counterparts. Specifically, the LSTM-CNN architecture demonstrates superior accuracy, achieving the lowest error rates across all metrics: an MAE of 0.231, RMSE of 0.624, and MAPE of 0.041. This represents a significant improvement over the CNN-LSTM model, with reductions of 0.056 in MAE, 0.068 in RMSE, and 0.002 in MAPE. Moreover, the integration of architectures in hybrid models (CNN-LSTM and LSTM-CNN) results in a more robust forecasting performance than using standalone LSTM or CNN models. The low MAE (0.231) for LSTM-CNN indicates that its forecasts are, on average, very close to the actual values. While the low RMSE (0.624), which is more sensitive to large errors, confirms that the model rarely produces drastic forecasting mistakes. Finally, the very low MAPE (0.041 or 4.1%) signifies a high degree of forecasting accuracy in percentage terms, which is highly valuable for practical energy management and grid integration.

Table 1 performance results of the models

Results	Models			
	CNN	LSTM	CNN-LSTM	LSTM-CNN
MAE	0.298	0.301	0.287	0.231
MAPE	0.044	0.512	0.043	0.041
RMSE	0.795	0.796	0.692	0.624

Figure 7 presents the PV power forecasting results of the proposed model compared to other models across different seasons (a 92-day period). The core finding is that combining architectural strengths leads to better performance. Single models like CNN (good at extracting spatial features) or LSTM (good at learning temporal dependencies)

have limitations. Hybrid models like CNN-LSTM and LSTM-CNN likely combine these strengths, allowing them to capture both the spatial patterns in weather data and the temporal sequences in power generation more effectively.

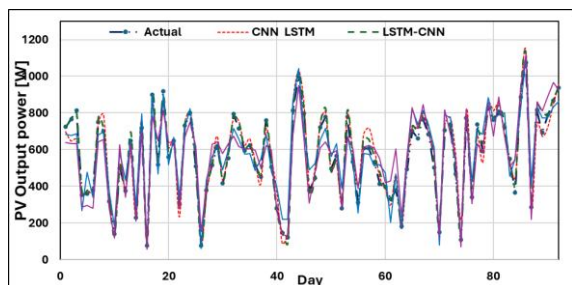


Fig. 7. Comparison of day ahead forecast PV output power based on the LSTM and other models.

V. CONCLUSION

This research successfully demonstrates that hybrid deep learning models significantly enhance the accuracy of photovoltaic power forecasting. The core finding is that combining architectural strengths leads to better performance. Single models like CNN (good at extracting spatial features) or LSTM (good at learning temporal dependencies) have limitations. Hybrid models like CNN-LSTM and LSTM-CNN likely combine these strengths, allowing them to capture both the spatial patterns in weather data and the temporal sequences in power generation more effectively. Moreover, the sequence of integration is critical; the LSTM-CNN model achieves the highest accuracy, with error metrics (MAE=0.231, RMSE=0.624, MAPE=0.041) that are notably lower than those of the CNN-LSTM model (MAE=0.287, RMSE=0.692, MAPE=0.043). This suggests that initially capturing temporal dependencies with LSTM before extracting spatial features with CNN is a more effective strategy for this task. This model's robust performance, validated both numerically and visually, positions it as a superior tool for improving the reliability and efficiency of solar power integration into the energy grid.

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