Improving Short-Term Solar Power Prediction through a Hybrid Deep Learning Model

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ABSTRACT

Reliable solar energy is fundamental to sustaining clean energy systems; however, its inherent variability poses significant challenges to the stability and operational reliability of modern power grids. Accurate short-term Photovoltaic (PV) power forecasting is therefore essential for effective energy management and the smooth operation of smart grid infrastructures. In this work, we introduce an adapted hybrid Long Short-Term Memory–Temporal Convolutional Network (LSTM-TCN) architecture that represents the core methodological contribution of the study. This hybrid design leverages the ability of LSTM networks to capture long-term temporal dependencies while exploiting the expanded receptive field and efficient parallelization offered by TCNs. This architecture is applied for the first time to PV power forecasting under Moroccan climatic conditions. The proposed model is trained and validated using a decade-long real-world dataset (2013–2023) collected in Dakhla, Morocco, a region characterized by distinctive meteorological patterns that enhance the robustness and relevance of the evaluation. Comparative analyses against standalone LSTM and TCN architectures show that the hybrid model achieves the highest predictive accuracy, yielding the lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)values and a coefficient of determination (R^2) of 0.9975. These results demonstrate the effectiveness

of the proposed hybrid framework in delivering reliable PV power forecasts and supporting improved integration of solar energy into smart grid systems.

Keywords-solar energy; PV power forecasting; deep learning; LSTM; TCN; hybrid LSTM-TCN model

I. INTRODUCTION

The global shift toward sustainable and renewable energy, driven by escalating concerns over pollution and environmental degradation, is reshaping the modern energy landscape. Within this transition, solar Photovoltaic (PV) systems have emerged as essential contributors to clean power generation, supporting both carbon-emission reduction and energy independence by mitigating reliance on finite fossil-fuel resources [1].

Despite its promise, the large-scale deployment of solar energy faces significant operational challenges. PV power output is inherently intermittent and strongly influenced by meteorological variability, including cloud cover, temperature fluctuations, and atmospheric humidity. These rapidly changing conditions introduce uncertainty in electricity production [2], which complicates grid management. Accurate short-term forecasting is therefore critical to ensure stable power system operation, enabling operators to anticipate fluctuations, optimize dispatch strategies, and maintain the balance between supply and demand [3].

Various forecasting methods address PV variability. Physical models need detailed meteorological data and high computational resources [4], whereas statistical models are simple but limited in capturing nonlinear patterns [5]. Artificial Intelligence (AI) and deep learning have enhanced forecasting, with architectures like Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCNs), and hybrids capturing complex temporal and nonlinear behaviors [6]. LSTM networks outperform traditional methods for short-term variability [7], and combining LSTM with Convolutional Neural Networks (CNNs) improves accuracy by modeling temporal and spatial features [8].

Hybrid approaches advance performance further. TCN–ECANet–GRU and RNN–LSTM models improve short-term forecasts and robustness across datasets [9, 10], whereas TCN-based hybrids capture long-range dependencies [11]. CNN-LSTM, ConvLSTM, and LSTM–XGBoost frameworks enhance predictive precision by integrating spatial-temporal learning and optimization [12, 13].

Broader Machine Learning (ML) methods also contribute: data-driven heuristics support very short-term forecasting [14], ML algorithms adapt across environments [15], and ANN vs. LSTM comparisons reveal strengths across horizons [16]. Reviews highlight the dominance of hybrid and data-driven approaches in short-term PV prediction [17].

Recent studies refine these strategies further, using optimization, hybrid architectures, and convolution/autoencoder models for improved accuracy, reliability, and applicability in data-scarce or satellite-driven settings [18-23].

Although recent studies have considerably advanced PV power forecasting, several limitations continue to affect the reliability and operational usefulness of existing approaches:

- Limited regional validation: Very few studies evaluate forecasting models using real operational data from southern Morocco, despite its distinctive climatic characteristics and significant solar potential.
- Underexplored hybrid architectures in North Africa: Hybrid LSTM-TCN models, although promising, have not been systematically assessed under North African environmental conditions, which pose unique forecasting challenges.
- Dependence on extensive feature engineering: Many existing works rely heavily on satellite-derived variables or complex preprocessing, leaving limited exploration of the forecasting value of simple meteorological inputs for short-term PV prediction.

To address these gaps, this study develops and evaluates deep learning models for one-hour-ahead PV power forecasting using ten years of real operational data (2013–2023) from a PV installation in Dakhla, Morocco. The main contributions are:

- A practical forecasting framework based exclusively on standard meteorological variables, making it suitable for environments with limited computational or data resources.
- A hybrid LSTM-TCN model designed to combine LSTM with the fast temporal pattern extraction of TCNs, enabling more robust handling of PV variability.
- A comprehensive comparative analysis between the proposed hybrid model and its standalone LSTM and TCN counterparts, evaluating improvements in accuracy, stability, and generalization.

By demonstrating that a compact hybrid deep learning model can outperform conventional architectures, this study provides a reliable tool for enhancing PV power forecasting in data-constrained regions. The results contribute directly to improving grid stability in Morocco, supporting large-scale renewable integration, and advancing future smart grid planning.

II. PHOTOVOLTAIC DATASET ACQUISITION AND PREPROCESSING

A. Data Acquisition and Feature Selection

The dataset used in this study was obtained from the Photovoltaic Geographical Information System (PVGIS), developed by the European Commission's Joint Research Centre. PVGIS provides high-resolution solar and meteorological data for global locations. Hourly measurements from 2013 to 2023 were collected for Dakhla, Morocco (23.694° N, –15.943° W), yielding 96,419 data points per variable and ensuring a robust long-term characterization of local solar conditions.

The input features include global irradiance on the inclined plane G(i), solar zenith angle H sun, air temperature at 2 m (T2m), and wind speed at 10 m (WS10m), all of which are known to significantly affect PV output. The target variable is the PV system power output (W). These parameters were selected due to their direct physical relevance and consistent availability within the PVGIS dataset.

B. Data Preprocessing

Data preprocessing is a critical step in PV power forecasting, as it ensures data quality, reduces noise, preserves meaningful temporal patterns, and improves model accuracy and stability:

- Removal of invalid and physically inconsistent values: Records with negative irradiance, unrealistic temperatures, or zero daytime irradiance were removed to avoid learning non-physical patterns. This step ensures data quality and stabilizes model training.
- Handling missing values (linear interpolation) and outliers (Interquartile Range (IQR)): Linear interpolation was applied to missing values because hourly meteorological variables change smoothly over time. Extreme outliers were filtered using the IQR method to eliminate sensor spikes without removing genuine rapid weather variations, improving model robustness.
- Feature normalization using Min–Max scaling: All features were scaled to [0, 1] to ensure stable gradients and faster convergence in LSTM and TCN models, which are sensitive to feature magnitude differences.
- 24-hour sliding window for sequence generation: A 24-hour window was chosen as it captures the full diurnal cycle of solar irradiance and provides adequate temporal context for both long-term dependency learning (LSTM) and short-term pattern extraction (TCN).

C. Training and Testing Dataset

To preserve the temporal integrity of PV generation data, the dataset was split chronologically into training, validation, and testing sets:

- Training set: 80% of the earliest samples, used to fit model parameters.
- Validation set: 10% of subsequent samples, used for hyperparameter tuning and early stopping.
- Testing set: 10% of the latest samples, used to evaluate the model's generalization on unseen data.

This chronological split prevents information leakage, maintains real-world forecasting conditions, and ensures that the model learns realistic temporal patterns for short-term PV power prediction.

D. Hyperparameter Optimization

A random search strategy implemented in Keras was employed to systematically explore the hyperparameter space and determine the optimal configurations for all three models. This approach enhances predictive performance, whereas the dilated causal convolutions capture short-term fluctuations, residual connections improve gradient stability, and the dense output layer generates the predicted PV power values.

III. DEEP LEARNING-BASED PHOTOVOLTAIC POWER FORECASTING

A. Temporal Convolutional Network

The TCN is a deep learning model for sequential or time-series data that extends CNNs with dilated causal convolutions and residual connections [24]. Dilated convolutions allow the network to capture long-term temporal dependencies by expanding the receptive field without increasing depth or breaking temporal order. Residual connections improve training stability by routing inputs through 1 × 1 convolution shortcuts, combined with the dilated output. Features are further refined with weight normalization, ReLU activation, and dropout for robust learning and regularization [25].

Formally, a 1D dilated causal convolution is defined as:

$$F(s) = \sum_{i=0}^{K-1} f(i).x_{s-d.i} \tag{1}$$

where x represents the input sequence, f is the convolutional filter, K denotes the kernel size, and d is the dilation factor that ensures the convolution incorporates past time steps. The base hyperparameters are set as follows:

- nb_filters = 128
- kernel_size = 2
- Dropout rate = 0.3
- Learning rate = 0.0001
- Batch_size = 64
- Epochs = 100
- Optimizer = Adam
- Activation function = ReLu

B. Long Short-Term Memory Network

The LSTM network is a specialized RNN designed to overcome the vanishing and exploding gradient problems of conventional RNNs, enabling effective learning of long-term dependencies [26]. Its core unit is the memory cell, containing a Constant Error Carousel (CEC) that maintains stable error propagation over time. LSTM uses three gates, input, forget, and output [27], to regulate information flow: the input gate controls new information incorporation, the forget gate determines how much past memory is retained, and the output gate governs the hidden state contribution. Formally, these operations are expressed as [28]:

$$f(t) = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{2}$$

$$i(t) = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$o(t) = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{4}$$

where σ denotes the sigmoid activation function, W and U are weight matrices, and b are bias vectors associated with each gate.

The candidate state is computed as:

$$\tilde{s_t} = \tanh(W_s x_t + U_s h_{t-1} + b_s) \quad (5)$$

The cell state s_t, which represents the internal memory of the unit, is then updated as:

$$s_t = f_t \odot s_{t-1} + i_t \odot \tilde{s_t} \quad (6)$$

Finally, the hidden state h_t, which serves as the output of the LSTM unit at time step t, is derived by modulating the cell state through the output gate:

$$h_t = o_t \odot \tanh(s_t) \quad (7)$$

Here, ⊙ denotes the Hadamard (element-wise) product.

The base hyperparameters are set as follows:

- LSTM units = 128
- Dropout rate = 0.1
- Learning rate = 0.0005
- Batch_size = 32
- Epochs = 100
- Optimizer = Adam
- Activation function = tanh

C. *Hybrid LSTM-TCN Model*

The hybrid LSTM-TCN model integrates the advantages of both models for forecasting sequential data. Although LSTMs are very good at long-term dependency modeling with their gated memory cells, TCNs can capture local and multi-scale temporal patterns by employing dilated causal convolutions. By combining these two methods, the hybrid model can capture not only the hierarchical temporal correlation but also the long-range sequential dependence in a parallel manner, which can be useful in complex time series prediction problems, including PV power production prediction [29]. The proposed hybrid LSTM-TCN model integrates recurrent and convolutional mechanisms to simultaneously capture long-term dependencies and short-term temporal patterns in PV power data.

As illustrated in Figure 1, the model first processes the input sequences through m stacked LSTM layers. The final LSTM layer contains 32 units, producing a sequence of hidden representations that encode long-range nonlinear temporal dynamics. These LSTM-generated features are then fed into n stacked TCN layers. Each TCN layer applies causal dilated convolutions with nb_filters = 64 and kernel_size = 5, ensuring that temporal causality is preserved while enabling multi-scale feature extraction through dilation. ReLU activation functions are used throughout the TCN block, and a dropout rate of 0.1 is applied to prevent overfitting and improve generalization. The output of the last TCN stack, consisting of o filters, is passed to a point-wise output neuron that generates the final PV power prediction for each sample in the batch.

Model training is conducted with the Adam optimizer using a learning rate of 0.0001, a batch size of 16, and 100 epochs, ensuring stable convergence and efficient learning. The combined architecture leverages LSTM's ability to model long-range dependencies and TCN's strength in capturing local short-term fluctuations, resulting in a robust hybrid forecasting framework.

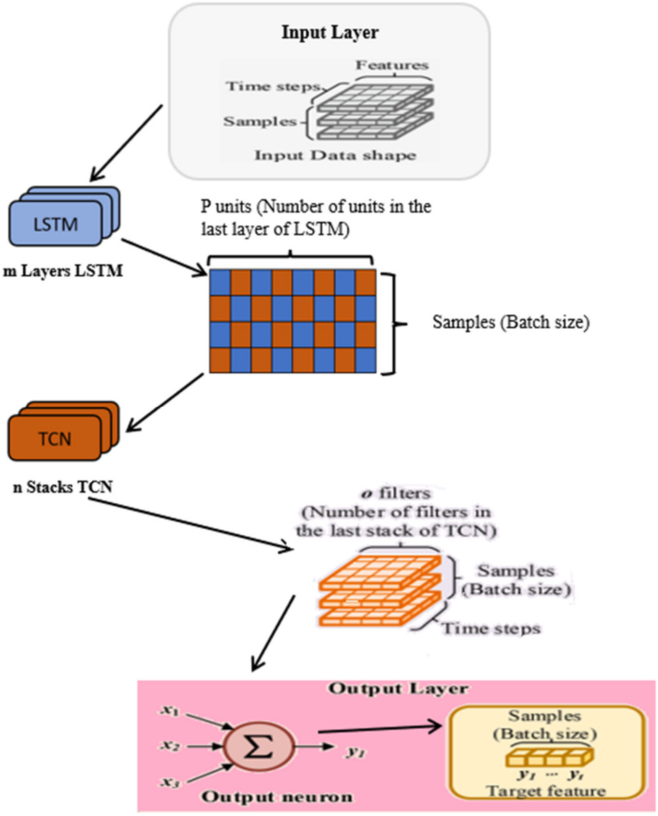

Fig. 1. Flowchart of the proposed LSTM-TCN model.

D. *Model Evaluation*

The dataset was separated chronologically into training (80%), validation (10%), and testing (10%) splits to maintain temporal order. Model performance was assessed using three commonly used statistics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R²). These metrics offer different perspectives on the accuracy and reliability of the predictions. Lastly, comparative experiments were performed with standalone models (e.g., LSTM, TCN) to see which forecasting architecture is the best. The evaluation metrics are defined as follows [30]:

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2\right]^{\frac{1}{2}} \quad (8)$$

$$\mathrm{MAE} = \frac{1}{N}\sum|\hat{y}_i - y_i| \quad (9)$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y_i})^2} \quad (10)$$

IV. RESULTS AND DISCUSSION

This paper focuses on exploring the best LSTM, TCN, and hybrid LSTM-TCN network designs for PV energy generation prediction in Dakhla city, using 10 years of data measured at a 10 kWp solar plant.

A. Photovoltaic Power Production Forecasting

Figure 2 compares the forecasting performance of the LSTM, TCN, and hybrid LSTM-TCN models. The LSTM reproduces the general diurnal profile of PV production but shows notable deviations during sunrise, sunset, and peak generation periods. This behavior reflects its tendency to over-smooth the signal and its limited capacity to capture rapid fluctuations caused by transient meteorological changes. The TCN model demonstrates improved tracking of short-term variability, with sharper responses to abrupt transitions, owing to its dilated causal convolutions. However, residual underestimation at peak hours indicates that its purely convolutional structure is less effective in modeling long-range temporal dependencies. The hybrid LSTM-TCN model achieves the closest match to the actual PV production curve across the entire horizon. By combining TCN's ability to model high-frequency dynamics with LSTM's strength in learning extended temporal relationships, the hybrid architecture significantly reduces forecasting errors. Its consistent performance across low-, mid-, and high-production intervals highlights superior generalization and robustness under varying solar conditions.

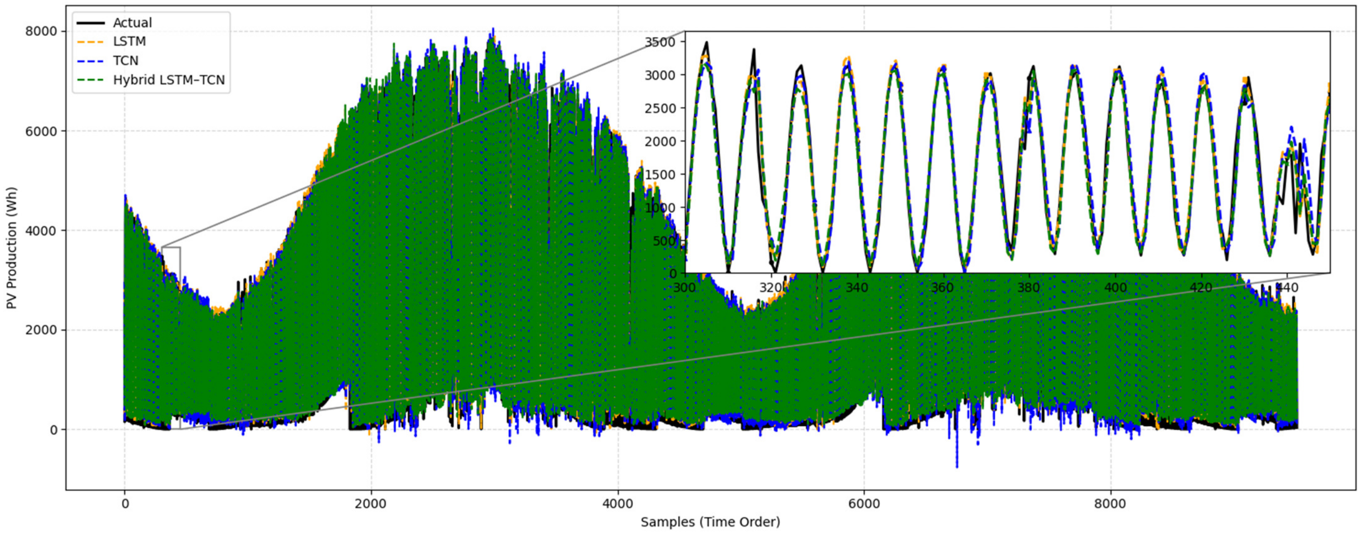

Fig. 2. Time-series comparison of actual and predicted PV production using LSTM, TCN, and hybrid LSTM-TCN models.

B. Regression Performance

Figures 3, 4, and 5 present regression plots comparing actual versus predicted PV power for the LSTM, TCN, and hybrid LSTM-TCN models, with the diagonal line indicating perfect prediction. The LSTM model maintains strong overall correlation but exhibits systematic deviations at higher power levels (>6,000 Wh). These deviations are primarily due to nonlinear saturation effects and abrupt irradiance drops caused by transient clouds—phenomena that purely recurrent architectures often struggle to capture, as errors tend to accumulate over long sequences.

The TCN model displays a broader dispersion in the mid-to-high range (2,000–6,000 Wh), reflecting its sensitivity to rapid short-term fluctuations such as sudden cloud movements or temperature-driven efficiency changes. While TCN captures localized variability well, its limited long-range memory contributes to residual biases during sustained high-irradiance periods.

The hybrid LSTM-TCN model achieves the closest alignment with the ideal regression line across the full output range. Its integrated design enables simultaneous learning of slow diurnal trends (solar elevation, temperature evolution) and fast nonlinear perturbations (cloud transients, wind-induced cooling), resulting in reduced error variance. Although the regression plots alone appear nearly linear, the underlying residual patterns—particularly the reduction of heteroscedasticity and bias in the hybrid model—confirm that the models, and especially the hybrid architecture, learn complex temporal dependencies rather than merely fitting linear trends. This deeper analysis reinforces the hybrid model's superior capacity to represent the nonlinear and meteorologically driven dynamics of PV power generation.

Figure 6 illustrates the evolution of the training and validation loss for the proposed hybrid LSTM-TCN model over 40 epochs. Initially, both losses are high, reflecting the model's unfamiliarity with the underlying PV generation patterns. Rapid loss reduction during the first few epochs indicates that the model quickly learns dominant temporal and meteorological features. As training continues, the training loss steadily decreases, whereas the validation loss stabilizes around a low value after 10–12 epochs, demonstrating early convergence and effective generalization. The narrow gap between training and validation loss throughout training confirms that the model does not overfit, even when exposed to unseen sequences.

To further verify that the model captures complex temporal dependencies, we analyzed the residual errors (predicted minus actual PV power) across different ranges of solar irradiance and power outputs. Residuals are randomly scattered around zero, without systematic trends, indicating that the model effectively learns both short-term fluctuations (e.g., cloud transients) and long-term diurnal and seasonal patterns. Notably, the hybrid model reduces large deviations observed in the standalone LSTM and TCN models at extreme PV outputs, reflecting its ability to combine long-range memory with local temporal feature extraction.

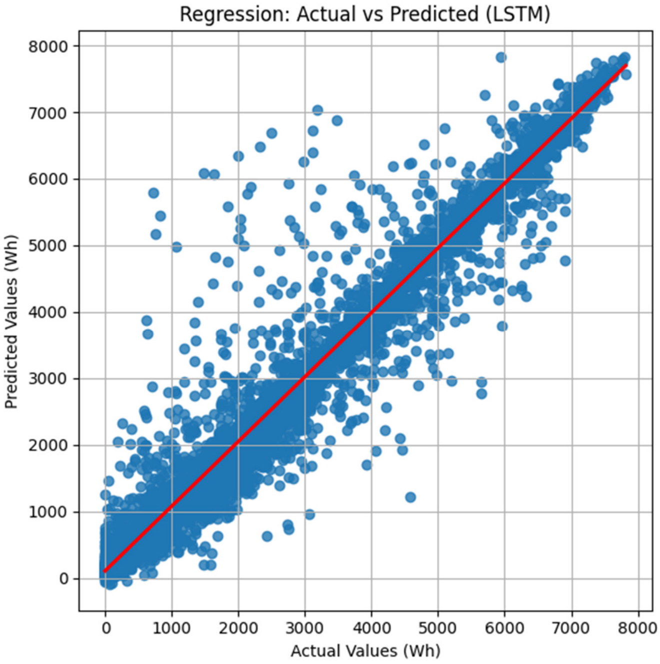

Fig. 3. Regression analysis of actual versus LSTM-predicted PV values.

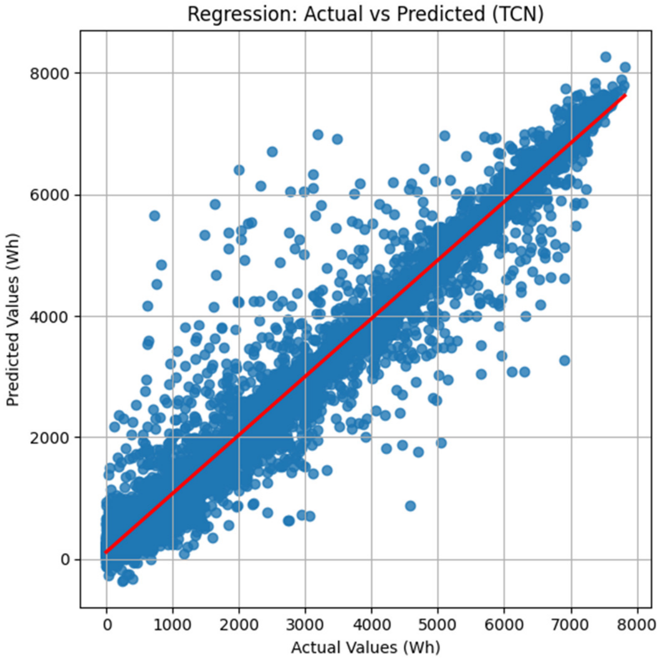

Fig. 4. Regression analysis of actual versus TCN-predicted PV values.

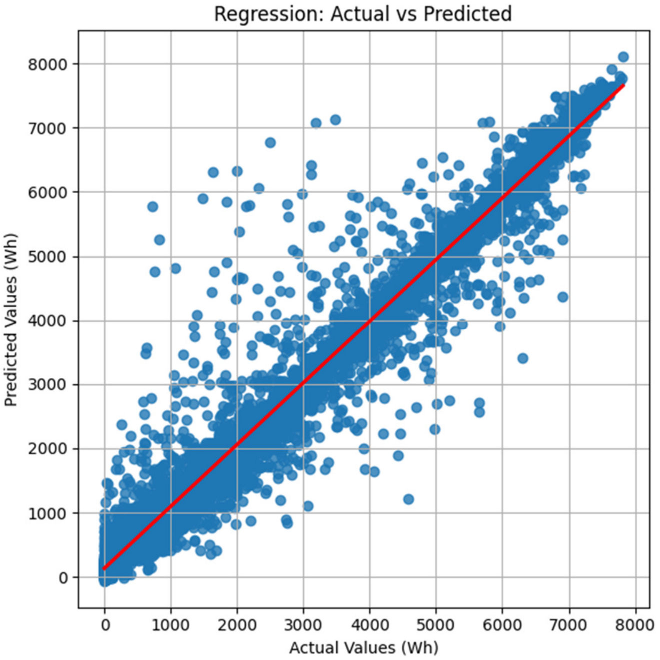

Fig. 5. Regression analysis of actual versus hybrid LSTM-TCN predicted PV values.

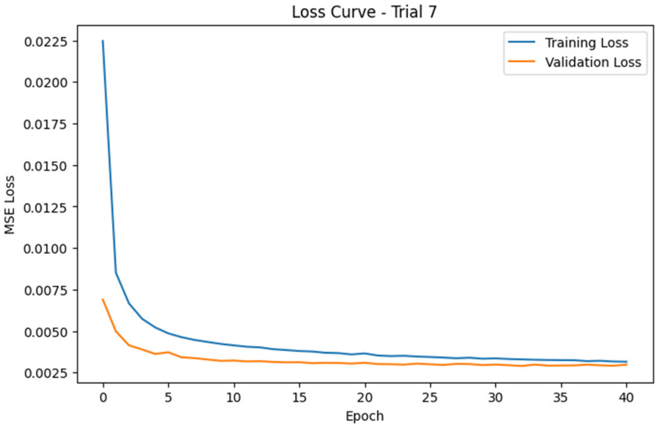

Fig. 6. Training and validation loss evolution across epochs for the hybrid LSTM-TCN model.

C. Forecasting Accuracy Evaluation Using Error Metrics

Table I presents statistical metrics of the three forecasting models, implemented on a 10 kWp PV system. LSTM achieves an RMSE of 385.10 Wh, an MAE of 192.81 Wh, and an R^2 of 0.9822. Therefore, this model is highly efficient in capturing the general production trends, despite excessively smoothing short-term fluctuations, resulting in reduced responsiveness to faster irradiance changes. The TCN model achieves an RMSE of 421.82 Wh, an MAE of 229.80 Wh, and an R^2 of 0.9891. This model provides improved local modeling of temporal variations, but its RMSE and MAE are 9.5% and 19.2% higher, respectively, than those of the LSTM model, indicating a slight challenge in modeling the long-term dependencies. In contrast, the hybrid LSTM-TCN model achieves the best forecasting performance, with an RMSE of 303.04 Wh, an MAE of 103.94 Wh, and an exceptional R^2 of 0.9975. This represents a 21.3%

reduction in RMSE and a 46.1% decrease in MAE compared to the LSTM model, as well as a 28.1% and 54.8% reduction, respectively, relative to the TCN model. These improvements demonstrate the hybrid architecture's enhanced learning capability, effectively combining the LSTM's strength in capturing long-term dependencies with the TCN's ability to model short-term dynamics. Overall, the hybrid model substantially reduces forecasting errors and unexplained variance compared to the standalone models, confirming its superior accuracy, stability, and robustness.

TABLE I. COMPARISON OF FORECASTING ACCURACY METRICS FOR LSTM, TCN, AND HYBRID LSTM-TCN MODELS

Error metrics	LSTM	TCN	LSTM-TCN
RMSE	385.10	421.823	303.037
MAE	192.81	229.803	103.937
R^2	0.9822	0.9891	0.9975

V. COMPARATIVE ANALYSIS OF RESULTS

A comparative assessment was conducted to position the performance of the proposed hybrid TCN-LSTM model relative to recent work (Table II). Studies employing Multilayer Perceptron (MLP) architectures in Morocco and India reported strong but variable accuracy, with R^2 values between 0.9245 and 0.9999, and 0.9377–0.962, respectively, reflecting the sensitivity of feedforward networks to local weather conditions and input selection. Classical ML approaches applied in Morocco, including XGBoost, Gradient Boosting Machine (GBM), RNN, and ANN models, showed considerably lower performance (R^2 = 0.06–0.62), underscoring their limitations in modeling the nonlinear temporal dependencies inherent in PV generation. More advanced deep learning models demonstrated improved results. In the Galapagos Islands, optimized LSTM and Gated Recurrent Unit (GRU) architectures achieved R^2 values of 0.9962 and 0.9961, outperforming their baseline versions (0.9514 and 0.9528). These findings confirm the benefits of recurrent models equipped with optimized hyperparameters for short-term PV forecasting.

TABLE II. COMPARISON OF FORECASTING ACCURACY OF THE PROPOSED METHOD WITH EXISTING LITERATURE

Ref.	Year	Study area	Model	R^2
[31]	2025	Morocco	MLP-Min MLP-Max	0.9245 0.9999
[32]	2024	India	MLP-1 MLP-2	0.9377 0.962
[33]	2024	Morocco	XGBOOST GBM RNN ANN	0.4 0.31 0.06 0.62
[34]	2023	Galapagos Islands	LSTM GRU LSTM optimized GRU optimized	0.9514 0.9528 0.9962 0.9961
This article	2025	Morocco	Hybrid LSTM-TCN	0.9975

Against this backdrop, the proposed hybrid TCN-LSTM model reached an R^2 of 0.9975 on Moroccan PV data, exceeding most previously reported results and performing on par with the best optimized architectures. This improvement stems from the complementary strengths of TCN in capturing multi-scale temporal patterns and LSTM in modeling sequential dependencies, enabling the model to better accommodate Morocco's highly variable climatic conditions. These results highlight the effectiveness of hybrid temporal architectures in achieving state-of-the-art forecasting accuracy.

VI. CONCLUSION

This study evaluated three deep learning models for short-term Photovoltaic (PV) production forecasting: Long Short-Term Memory (LSTM), Temporal Convolutional Network (TCN), and the hybrid LSTM-TCN. The findings can be summarized as follows:

- LSTM effectively captures long-term temporal dependencies but struggles with abrupt fluctuations, leading to occasional forecasting errors.
- TCN excels at modeling local temporal patterns and short-term variability but exhibits reduced accuracy in long-range dependency modeling.
- The hybrid LSTM-TCN model consistently outperforms both standalone models, achieving the highest accuracy, robustness, and generalization. Its near-perfect coefficient of determination (R^2 = 0.9975) highlights its ability to reproduce actual PV production dynamics across diverse operating conditions.

Overall, the results demonstrate that hybrid deep learning architectures provide a powerful framework for solar energy forecasting, combining the complementary strengths of recurrent and convolutional neural networks. The superior performance of the proposed hybrid model underscores its potential for practical deployment in energy management systems, smart grids, and renewable integration strategies, where accurate and reliable forecasts are essential for enhancing grid stability, reducing operational costs, and supporting sustainable energy transitions.

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