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Performance enhancement of photovoltaic systems using hybrid LSTM–CNN solar forecasting integrated with P&O MPPT

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ABSTRACT

The increasing penetration of photovoltaic (PV) systems in smart grids highlights the need for reliable solutions to mitigate the inherent intermittency of solar energy. Short-term variability in solar irradiance remains a critical challenge for stable grid operation and efficient PV energy management. This paper proposes an integrated forecasting–control framework that combines short-term global horizontal irradiance (GHI) prediction with a conventional P&O MPPT strategy to enhance PV system performance. A hybrid LSTM–CNN architecture is developed to forecast one-step-ahead GHI under the semi-arid climatic conditions of Dakhla, Morocco, a region characterized by high solar potential and pronounced irradiance fluctuations. The forecasting model is validated using measured irradiance data from the National Renewable Energy Laboratory (NREL) via the National Solar Radiation Database (NSRDB). Predicted irradiance is then used to improve PV power estimation and support predictive maximum power point tracking (MPPT) operation. Simulation results obtained in MATLAB/Simulink demonstrate that the proposed framework achieves accurate GHI forecasting, faster MPPT convergence, reduced steady-state oscillations, and improved PV power stability under rapidly changing irradiance. The proposed approach provides a practical and computationally efficient solution for enhancing the dynamic response and energy extraction efficiency of PV systems in smart grid applications.

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1. INTRODUCTION

The growing demand for clean and sustainable energy has accelerated the global deployment of photovoltaic (PV) systems, positioning solar power as a key component of modern smart grids [1]. Despite its environmental and economic advantages, PV generation remains highly variable due to its strong dependence on meteorological conditions such as solar irradiance, wind speed, humidity, and ambient temperature [2]. In addition, power electronic converters, the nonlinear behavior of PV modules, and grid interactions lead to frequent power fluctuations that may compromise voltage stability, power quality, and overall grid reliability if not properly managed [3].

Accurate short-term PV power forecasting is therefore essential for reliable grid operation, optimal energy scheduling, and efficient energy management [4], [5]. Forecasting also supports demand response strategies and energy storage planning, enabling higher PV penetration in smart grids. PV forecasting methods are generally categorized into direct approaches, which estimate power output directly from historical data, and indirect approaches, which first predict key meteorological variables most notably global horizontal irradiance (GHI) and subsequently derive PV power using analytical models. GHI represents the combined direct, diffuse, and reflected solar radiation incident on a horizontal surface and serves as a fundamental indicator of solar resource availability [6]. However, its accurate estimation remains challenging due to atmospheric variability driven by clouds, aerosols, and humidity.

Traditional physical models rely on detailed atmospheric formulations and are more suitable for long-term forecasting, while statistical and machine learning (ML) techniques, such as ARIMA [7], support vector regression, random forests, and artificial neural networks (ANNs), have demonstrated effectiveness for short-term horizons. Nevertheless, these models often struggle under rapidly changing weather conditions. Recent advances in deep learning (DL), particularly recurrent neural networks, long short-term memory networks, and convolutional neural networks, have significantly improved forecasting accuracy by capturing nonlinear and multivariate temporal patterns [8].

To further enhance predictive performance, several studies have explored hybrid DL architectures. Attention-based LSTM models [9], comparative analyses of recurrent networks using long-term satellite data [10], and CNN–LSTM combinations [11] have demonstrated improved accuracy under various climatic conditions. Additional investigations have assessed univariate and multivariate hybrid models [12], spatiotemporal extensions incorporating neighboring-site data [13], clustered CNN–LSTM architectures [14], and seasonal forecasting strategies [15]. Overall, these studies confirm the effectiveness of hybrid DL models for short-term GHI prediction. However, their robustness across diverse climatic regions, particularly semi-arid environments characterized by abrupt irradiance variations, remains limited [16].

While accurate forecasting enhances grid-level planning, real-time PV energy extraction depends on efficient maximum power point tracking (MPPT). Traditional MPPT techniques such as perturb and observe (P&O), incremental conductance, and Hill climbing are commonly implemented because they are straightforward to design and require minimal computational resources. However, their performance degrades under rapidly varying irradiance, leading to slow convergence and steady-state oscillations. Although advanced intelligent and metaheuristic MPPT techniques improve adaptability, they often introduce increased complexity and tuning requirements. Consequently, P&O remains the most commonly implemented method in commercial PV systems. Despite extensive research on deep learning-based solar forecasting and MPPT algorithms, few studies have integrated hybrid deep learning forecasting with conventional MPPT control, particularly in semi-arid climates. This disconnect limits the practical exploitation of forecasting intelligence for real-time PV control.

To address this gap, this paper proposes an integrated framework that combines hybrid LSTM–CNN-based short-term GHI forecasting with the P&O MPPT algorithm to enhance PV system efficiency and stability. The proposed approach is validated using real irradiance data from Dakhla, Morocco, a semi-arid region with high solar variability. Simulation results obtained in MATLAB/Simulink demonstrate improved forecasting accuracy, faster MPPT convergence, reduced oscillations, and enhanced power stability under rapidly changing conditions.

The main contributions of this article are summarized as follows:

- Development of a hybrid LSTM–CNN approach for accurate short-term GHI forecasting.
- Integration of DL-based irradiance prediction with the conventional P&O MPPT strategy to improve dynamic tracking performance.
- Validation using real-world data from a semi-arid Moroccan climate, highlighting model robustness. Demonstration of improved PV power stability and energy extraction efficiency through integrated forecasting–control design.
- By unifying data-driven forecasting with real-time PV control, the proposed framework supports enhanced operational intelligence, contributing to improved sustainable renewable energy integration and smart grid resilience.

2. METHOD

2.1. Solar forecasting models

2.1.1. Long short-term memory network

LSTM networks were developed to address the vanishing and exploding gradient limitations of conventional RNNs [17]. By employing memory cells controlled by input, forget, and output gates, LSTMs effectively capture long-term temporal dependencies in sequential data, making them well-suited for time-series forecasting. Although computationally intensive and sensitive to hyperparameter selection, enhanced variants such as attention-based and bidirectional LSTMs further improve feature representation and learning capability [18].

The functioning of the different gates in a neural network, such as the input gate it, forget gate ft, intermediate gate gt, and output gate ot, can be mathematically expressed as (1)-(4) [19].

$$i_t = \sigma(W_{ix}X_t + W_{ih}h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\left(W_{fx}X_t + W_{fh}h_{t-1} + b_f\right) \tag{2}$$

$$g_t = \sigma\left(W_{gx}X_t + W_{gh}h_{t-1} + b_g\right) \tag{3}$$

$$o_t = \sigma(W_{ox}X_t + W_{oh}h_{t-1} + b_o) \tag{4}$$

The sigmoid activation function is denoted by σ. The weight matrices corresponding to the input X_t and the prior hidden state h_{t-1} are indicated by W_x and W_h, respectively. The bias term unique to each gate is represented by b.

The forget gate ft determines which information from the previous memory cell m_{t-1} should be retained, while the input gate it calculates the information to be stored in the current memory cell mt. The updated memory cell mt is computed using (5) [19].

$$m_t = g_t i_t + m_{t-1} f_t \tag{5}$$

Here, g_t represents the intermediate gate's contribution, it controls the input's influence, and f_t regulates the retention of past information.

2.1.2. Convolutional neural network

A CNN is a deep learning architecture originally developed for image recognition, but it can also be applied to time-series analysis, as it is effective at capturing local patterns and short-term dependencies within sequential data. CNNs use convolutional filters to extract local patterns and correlations among input features, as opposed to recurrent models, which explicitly describe temporal relationships. CNNs are modified for 1D sequential data in the context of time series forecasting, like GHI. Usually, the model has multiple important layers [15].

Convolutional layer: Applies multiple 1D filters over subsequences of the input time series to extract local features. The operation for the k-th filter is given by (6).

$$h_{k,i} = f\left(\sum_{j=0}^{F-1} W_{k,j} \, . \, x_{i+j} + b_k\right) \tag{6}$$

F is the filter size, Wk,j is the learnable weights, bk is the bias, and f is the activation function, typically rectified linear unit (ReLU).

Pooling layer: Performs a max pooling operation to down sample the feature maps produced by the convolutional layer, thereby reducing dimensionality and computational complexity while retaining salient features:

$$Z_k = \max_{i=1} h_{k,i} \tag{7}$$

fully connected layer: uses a dense layer to flatten the pooled maps and add features to the output:

$$y = g(W_z + b) \tag{8}$$

g is the final activation function used for prediction, W and b are the weights and biases of the dense layer.

2.1.3. Hybrid LSTM-CNN model

To predict short-term variations in GHI, a hybrid LSTM–CNN model was developed. The motivation behind this architecture stems from the complementary strengths of the two deep learning components: CNN layers are effective at extracting local spatial patterns from temporal data, while LSTM layers capture long-term temporal dependencies and dynamic relationships within sequential inputs. In the implemented model, the input layer receives a sequence of past irradiance values corresponding to a fixed look-back window (e.g., 48 hours). In order to extract typical patterns and smooth short-term variations, the CNN component first applies one-dimensional convolutional filters. The network may simultaneously learn spatial and temporal correlations thanks to the LSTM layers, which are fed the extracted feature maps and simulate the patterns' temporal evolution over time. The output layer represents the expected GHI value for the following hour and is made up of a single neuron with a linear activation function. Through iterative backpropagation, the model learns to reduce the prediction error between the actual and forecasted GHI during training. The MSE was utilized as the loss function, and the Adam optimizer was utilized for effective gradient descent with adaptive learning rates.

2.2. Forecasting performance metrics

The models were developed in Python using the TensorFlow and Keras frameworks, while data visualization was carried out with Matplotlib. To ensure a fair comparison, the three forecasting approaches, LSTM, CNN, and the hybrid LSTM–CNN, were trained and evaluated on the same dataset using identical experimental settings. Model performance was quantitatively assessed based on three standard statistical metrics [20]:

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2\right]^{\frac{1}{2}} \tag{9}$$

$$MAE = \frac{1}{N}\sum|\hat{y}_i - y_i| \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y_i})^2} \tag{11}$$

2.3. Dataset description and preprocessing procedures

The dataset used in this study was sourced from the National Renewable Energy Laboratory (NREL) through the National Solar Radiation Database (NSRDB). It provides high-resolution, ground-based solar irradiance measurements for Dakhla, Morocco a region characterized by a semi-arid climate and exceptional solar potential. It comprises hourly measurements of GHI, ambient temperature, and other relevant meteorological parameters for the entire year of 2022, yielding 8,760 data points that capture both seasonal and daily variations in solar radiation. Data preprocessing, sequence preparation, model training, and evaluation followed the workflow summarized in Algorithm 1, with dataset details and hyperparameter settings provided in Table 1.

Algorithm 1. Pseudocode for the optimized deep learning framework for GHI prediction
1. Start
2. Load GHI dataset (2022)
3. Preprocess data
   - Clean and standardize column names
   - Interpolate missing values (for all meteorological features)
   - Construct Datetime column
   - Normalize all input features (min–max scaling)
4. Prepare sequences
   - Create input sequences X and target y based on sequence_length = 30
5. Split dataset
   - Training (64%), Validation (16%), Testing (20%)
6. Define base models
   - LSTM → Dense
   - CNN → MaxPooling → Flatten → Dense → Dense
   - Hybrid CNN–LSTM → Dense
7. Optimize hyperparameters
   - Define search space (LSTM units, CNN filters, kernel size, activation, batch size, learning rate)
   - Apply random search to minimize validation MSE
8. Train and Select Best Models
   - Train on training set
   - Validate and select configuration with lowest validation loss
9. Final Training
   - Train optimized models on combined training + validation data (100 epochs)
10. Prediction and Evaluation
    - Predict GHI on test set
    - Compute RMSE, MAE, R^2
11. Results analysis
    - Store predictions and metrics
    - Build results table (Datetime, Actual GHI, Predicted GHI)
    - Plot regression and time-series graphs
12. Export Outputs
- Export results to CSV and Excel
13. End

Table 1. Summary of dataset characteristics and deep learning hyperparameters for GHI prediction

Parameter/setting	Value/range	Notes
Sequence length	30	Time steps per input sequence
Train/validation/test split	64% / 16% / 20%	Chronological split
Hyperparameter tuning strategy	Random search (Keras Tuner)	Used for all models
LSTM units	32, 64, 128, 256	128 selected via random search as the best configuration
CNN filters	32, 64, 128	Optimal filter size found via random search: 64
CNN kernel size	3, 5	Optimal kernel size determined by tuning: 3
Activation functions	ReLU, tanh	ReLU selected for best performing models
Batch size	16, 32, 64	32 selected via random search
Learning rate	1e-4, 1e-3, 1e-2	Optimal learning rate: 1e-3
Epochs (final training)	100	Training on the combined train + validation set
Optimizer	Adam	Used for all tuned models
Hybrid model architecture	Conv1D(64 filters) → LSTM(128 units) → Dense	Best performing hybrid configuration
Features normalized	All inputs	Min–Max scaling
Loss function during tuning	MSE	Used to minimize validation loss

2.4. Mathematical modeling of the PV panel

The photovoltaic (PV) system in this study is designed to simulate the electrical behavior of a solar array under varying irradiance. The PV array is based on the Kyocera Solar KC200GT module, arranged with 10 series-connected modules (N_s = 10) and 2 parallel strings (N_p = 2), providing suitable voltage and current for DC–DC conversion and load operation. Its mathematical model is derived from the single-diode equivalent circuit, comprising a current source, diode, series resistance (R_s), and shunt resistance (R_{sh}). The PV module output current (I_{PV}) is given by (12) [21].

$$I_{pv} = N_p I_{ph} - N_p I_0 \left[\exp\left(\frac{q\left(V_{pv}/_{N_s} + I_{pv}R_s/_{N_p}\right)}{AKT}\right) - 1\right] - \frac{V_{pv}/_{N_s} + I_{pv}R_s/_{N_p}}{R_{sh}} \quad (12)$$

Where A is the diode ideality factor, T is the cell temperature in Kelvin, q is the electron charge, I_0 is the diode reverse saturation current, k is the Boltzmann constant, and I_{ph} is the photocurrent that is influenced by temperature and solar irradiation

The Simulink PV array is fed with predicted irradiance and a constant temperature of 25 °C. The PV voltage (V_PV) and current (I_PV) are continuously measured and provided to the MPPT controller to ensure maximum power extraction under varying conditions. A DC–DC boost converter raises the PV voltage to the desired load level. It consists of an inductor, a MOSFET switch, a diode, and an output capacitor, and operates in continuous conduction mode to ensure a stable output voltage with low ripple. The input–output voltage relationship is given by (13) [22].

$$V_{out} = \frac{V_{in}}{1-D} \quad (13)$$

Where D denotes the duty cycle controlled by the P&O-based MPPT algorithm to maintain the PV array at its maximum power point. The system dynamics are given by (14) and (15).

$$L\frac{di_L}{dt} = V_{in} - (1-D)V_{out} \quad (14)$$

$$C\frac{dV_{out}}{dt} = (1-D)i_L - \frac{V_{out}}{R} \quad (15)$$

Where R denotes the load resistance, this converter enables effective power delivery from the PV array to the load while adapting to changes in irradiance and temperature. The PWM-driven duty cycle controls the MOSFET, and the resulting boosted voltage (V_{boost}) is monitored to assess converter performance and stability.

2.5. P&O MPPT algorithm

The MPPT technique is an essential component in photovoltaic (PV) energy systems to ensure that the PV generator operates at its optimal power point under varying environmental conditions. Among the numerous MPPT algorithms proposed in the literature, the P&O technique is among the most commonly used techniques, appreciated for its straightforward design, simple implementation, and reliable overall performance [23]. The P&O algorithm's basic idea is to observe how the output power changes in response to minor perturbations that are periodically introduced to the PV system's operational voltage or current. The operating point is shifted in the same way in the subsequent iteration when a perturbation causes the power to increase. In contrast, the direction of the disturbance reverses if the power drops. Until the system reaches the MPP, when the rate of change of power with respect to voltage (dP/dV) approaches zero, this iterative process keeps going.

Mathematically, the instantaneous PV power is given by (16):

$$P(k)=V(k)\times I(k) \quad (16)$$

and the change in power between two consecutive samples is expressed as (17).

$$\Delta P=P(k)-P(k-1) \quad (17)$$

Similarly, the change in voltage is (18).

$$\Delta V=V(k)-V(k-1) \quad (18)$$

The operating principle can be outlined as follows:
- If $\Delta P>0$ and $\Delta V>0$, the PV array voltage is increased.
- If $\Delta P>0$ and $\Delta V<0$, the PV array voltage is decreased.
- If $\Delta P<0$ and $\Delta V>0$, the PV array voltage is decreased.
- If $\Delta P<0$ and $\Delta V<0$, the PV array voltage is increased.

This process keeps the PV system operating near the MPP despite variations in temperature and irradiance. However, the P&O method can induce small steady-state oscillations around the MPP, which can be reduced by adaptively adjusting the perturbation step size.

As illustrated in Figure 1 [24]. The algorithm measures the instantaneous PV voltage and current, computes the output power, and evaluates its variation from the previous sample. Based on the signs of ΔP and ΔV, the reference voltage is increased or decreased to move toward the MPP, and the procedure is repeated for continuous real-time tracking [25].

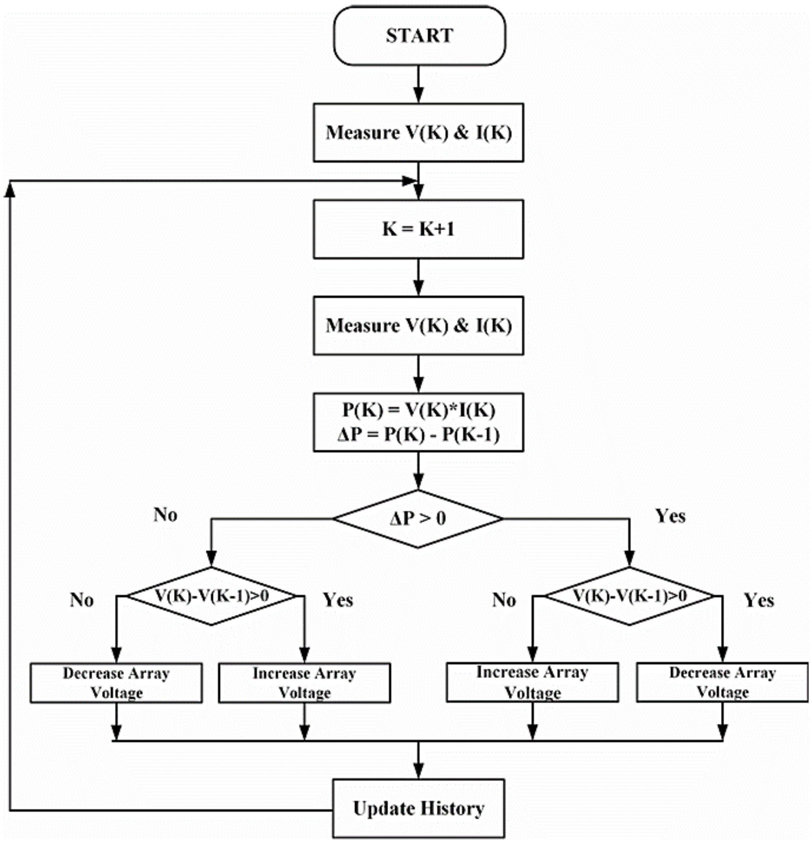

Figure 1. Flowchart of the P&O MPPT algorithm

2.6. Integration of GHI Forecasting with MPPT control

The proposed framework (Figure 2) integrates short-term GHI forecasting directly into the MPPT control loop to improve PV system responsiveness under rapidly varying irradiance. A hybrid LSTM–CNN model generates one-step-ahead GHI predictions, Ĝ(t+1), from recent meteorological data. These forecasts are translated into a reference PV power and the corresponding optimal operating voltage, $\widehat{V_{MPP}}(t+1)$, using temperature-dependent PV characteristics. Unlike the conventional P&O algorithm, which relies solely on instantaneous power perturbations and is prone to oscillations and delayed convergence, the proposed scheme employs $\widehat{V_{MPP}}(t+1)$ as a feedforward reference to pre-adjust the DC–DC converter duty cycle. The P&O algorithm then acts only as a local refinement mechanism around this predicted operating point. This predictive feedforward–feedback structure enables proactive adaptation to irradiance changes, reducing transient power losses, limiting steady-state oscillations, and accelerating convergence to the true MPP. Overall, embedding data-driven irradiance forecasting transforms MPPT from a reactive strategy into a predictive control-enhanced approach, yielding improved power stability and energy capture under highly variable atmospheric conditions.

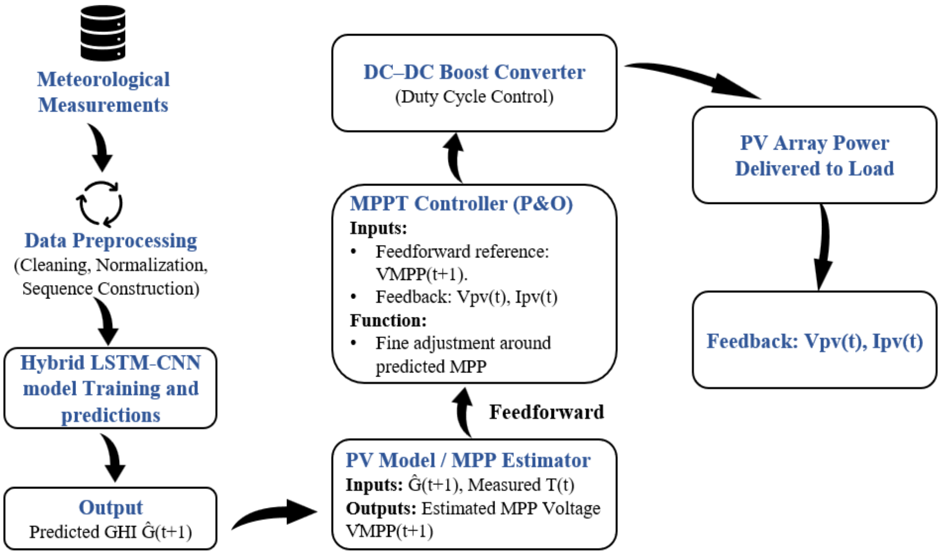

Figure 2. Flowchart of the integration of hybrid LSTM–CNN GHI forecasting with the conventional P&O MPPT controller

3. RESULTS AND DISCUSSION

3.1. Predictive performance of GHI forecasting models

Figure 3 illustrates how the three deep-learning models reproduce the real GHI profile over time. While all models capture the general daily rhythm of solar irradiance, the hybrid LSTM–CNN aligns much more tightly with the measured curve. Its predictions remain closer to the actual fluctuations, especially during rapid changes typically caused by passing clouds or atmospheric disturbances. This behavior reflects the benefit of combining temporal learning from the LSTM with the CNN's ability to extract meaningful patterns from the input features. Overall, the figure highlights the hybrid model's stronger stability and accuracy, confirming its advantage for short-term irradiance forecasting and its potential for more reliable solar-based energy management.

Figures 4(a)-4(c) demonstrate that all three models achieve a strong correlation between predicted and measured GHI values; however, their predictive reliability differs markedly. The LSTM model captures the overall temporal evolution of irradiance but exhibits increased dispersion at low and moderate irradiance levels, indicating reduced robustness during rapidly varying conditions. The CNN model shows improved alignment in the mid-irradiance range, reflecting its effectiveness in learning localized feature patterns, yet its performance deteriorates at irradiance extremes due to limited temporal modeling capability. In contrast, the hybrid LSTM–CNN model delivers the most consistent and unbiased predictions, with data points closely concentrated along the ideal regression line across the full irradiance range. This behavior confirms that combining convolutional feature extraction with recurrent temporal learning effectively mitigates the individual limitations of standalone LSTM and CNN architectures.

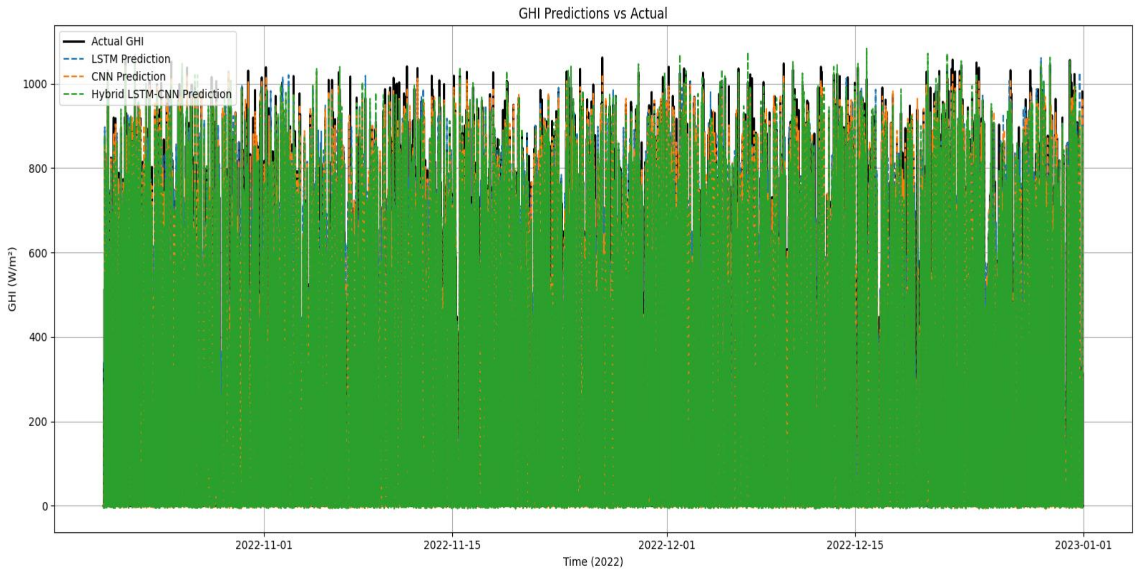

Figure 3. Predicting GHI with the three architectures

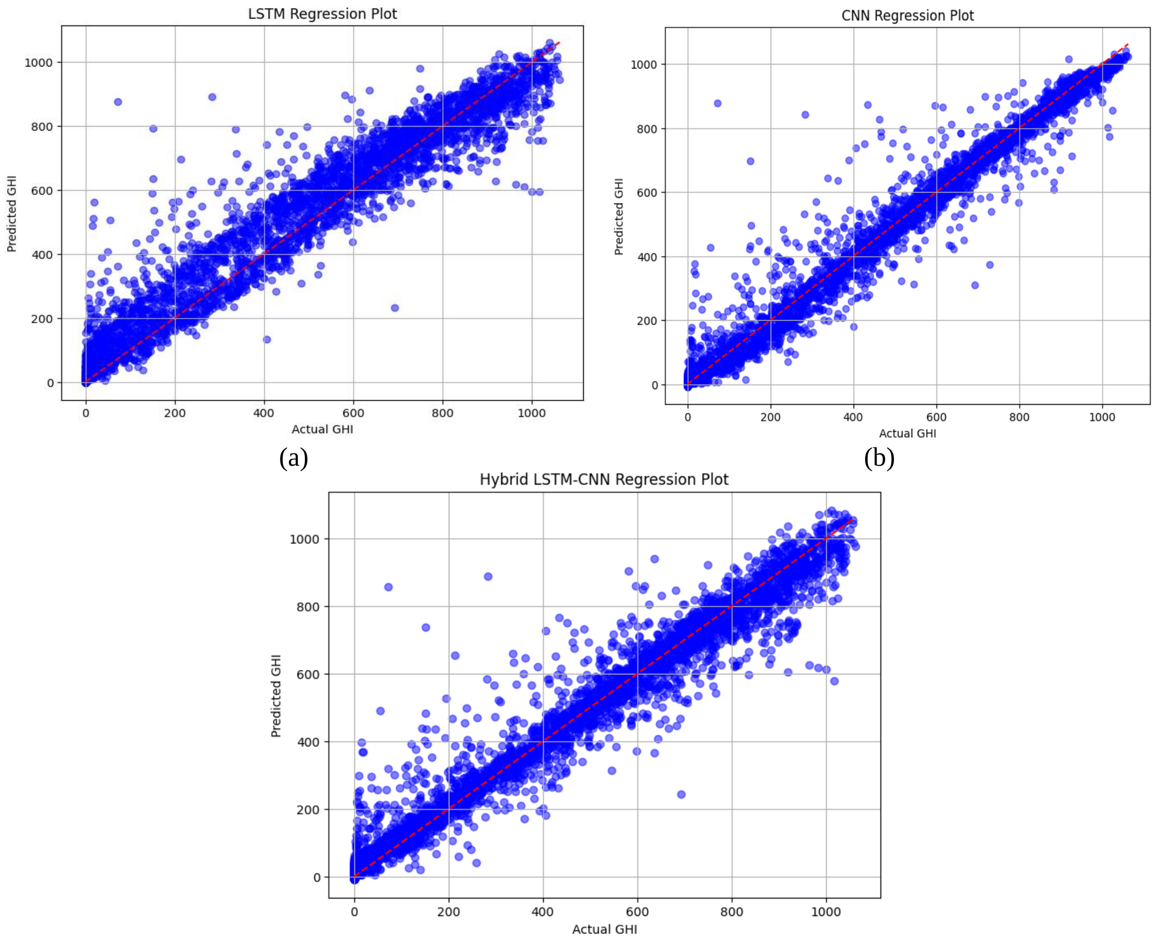

Figure 4. Regression analysis of (a) LSTM, (b) CNN, and (c) hybrid LSTM-CNN models for GHI prediction

3.2. Performance evaluation of deep learning architectures for GHI prediction

Table 2 confirms the superior performance of the hybrid LSTM–CNN model, which achieves the lowest prediction errors and highest goodness of fit among the evaluated approaches. The hybrid architecture records the minimum RMSE (29.99 W/m²) and MAE (23.93 W/m²), together with the highest coefficient of determination ($R^2 = 0.993$), indicating enhanced accuracy and reduced prediction bias. The standalone LSTM model shows competitive but less consistent performance, with increased error levels during periods of rapid irradiance variation, reflecting its limited ability to capture localized feature dynamics. In contrast, the CNN model exhibits the largest errors and lowest R^2 value, highlighting the inadequacy of purely convolutional structures for modeling the temporal variability of solar irradiance.

A comparison with recent studies further emphasizes the effectiveness of the proposed approach. Previous hybrid deep learning models for short-term solar irradiance forecasting typically report RMSE values above 35 W/m² and R^2 values below 0.99 [26]. Deep learning models evaluated over longer forecasting horizons generally exhibit higher error levels when applied to high-resolution temporal data [27]. More recent hybrid and transfer-learning-based forecasting frameworks report RMSE values in the range of 30–40 W/m² and MAE values exceeding 25 W/m², particularly under rapidly changing atmospheric conditions [28], [29]. In contrast, the proposed hybrid LSTM–CNN model consistently achieves lower error metrics and stronger goodness of fit, confirming its robustness and superior predictive capability for short-term GHI forecasting.

Table 2. Comparative performance metrics of the three predictive models for GHI estimation

Evaluation metrics	Deep learning models		
	LSTM	CNN	LSTM-CNN
RMSE	40.009243	60.119850	29.998512
MAE	31.935667	47.954825	23.932267
R^2	0.987509	0.971797	0.992978

3.3. Assessment of MPPT performance using the P&O controller

The proposed model for this work, designed and tested in MATLAB/Simulink, is shown in Figure 5. Using the predicted GHI from the hybrid LSTM–CNN model as input, Figure 6 illustrates the dynamic response of the photovoltaic (PV) system under the P&O MPPT control strategy. This approach allows the PV system to adjust proactively to irradiance conditions forecasted by the deep learning model. Throughout the simulation, solar irradiance follows a smooth, bell-shaped diurnal profile, resulting in proportional variations in PV voltage (<V_PV>), current (<I_PV>), and power output. The measurements confirm that the system consistently tracks the MPP, while the duty cycle (<duty>) stabilizes after a brief initial transient, demonstrating that the P&O algorithm effectively converges despite the non-linear behavior of the PV system.

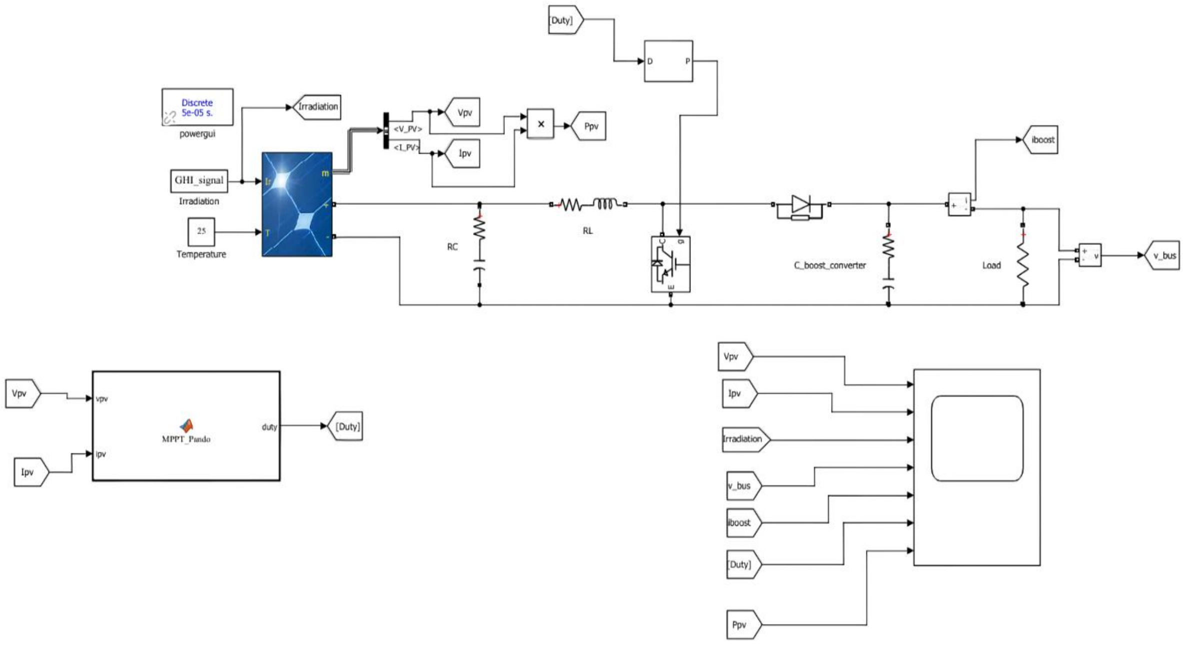

Figure 5. Simulink model of PV system with P&O MPPT and boost converter

These observations highlight the strong synergy between accurate data-driven irradiance forecasting and MPPT control. By integrating hybrid LSTM–CNN predictions with the P&O algorithm, the PV system can anticipate changes in solar conditions and adjust its operating point in real time. This integration improves power stability, ensures efficient energy extraction, and enhances the system's resilience to rapid irradiance fluctuations. Moreover, reliable short-term forecasting facilitates better energy scheduling and smooth power injection into the grid, contributing to overall grid stability.

The instantaneous PV power output during the MPPT simulation driven by hybrid LSTM–CNN predictions follow the expected bell-shaped daily trajectory, reaching a peak of approximately 850 W around midday. Minor oscillations are observed, reflecting the normal perturbation behavior of the P&O method. These small deviations indicate a suitable trade-off between fast tracking and stable regulation, ensuring consistent system performance throughout the day.

By combining accurate short-term forecasting with real-time MPPT control, this framework not only maximizes PV efficiency but also strengthens grid integration. Predictable PV generation allows operators to schedule energy more effectively, reduces variability in power injection, and enhances the resilience of PV systems under dynamic weather conditions. The results underscore the potential of coupling intelligent forecasting with classical control strategies to optimize PV performance, support reliable energy supply, and facilitate smarter management of distributed solar resources in semi-arid regions like Morocco and in broader smart-grid applications.

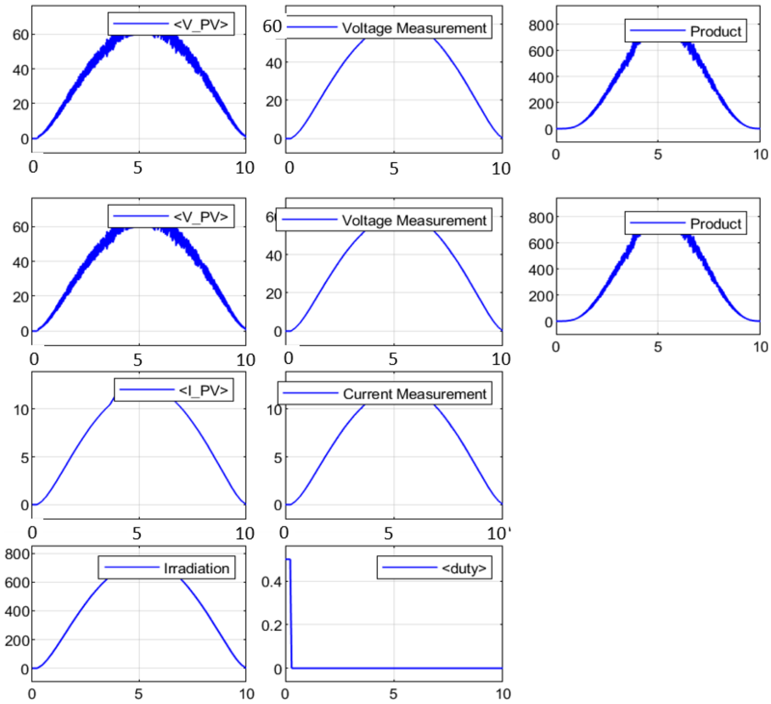

Figure 6. Simulation results of P&O MPPT algorithm

4. CONCLUSION

This study developed and validated a hybrid LSTM–CNN forecasting model integrated with a P&O MPPT controller for photovoltaic systems. The model achieved the highest predictive accuracy among the tested architectures, with an RMSE of 29.99 W/m², an MAE of 23.93 W/m², and an R^2 of 0.993, representing a significant improvement over standalone LSTM and CNN networks. When applied to the MPPT simulation, forecasted GHI enabled faster duty-cycle convergence and reduced oscillations around the MMP, resulting in smoother voltage, current, and power profiles and more stable PV energy output.

These results have direct implications for renewable energy integration strategies. In Morocco, where solar resources are abundant but subject to high irradiance variability, accurate short-term forecasting combined with adaptive MPPT enhances grid stability, improves energy scheduling, and maximizes PV contribution to the national energy mix. Globally, the approach demonstrates a scalable pathway for integrating distributed PV systems into smart grids, supporting efficient energy management, and mitigating intermittency challenges in variable climates.

The study is limited by its reliance on a single regional dataset and one year of measurements, as well as the computational cost of hybrid model training. Future work will extend validation across multiple climates, explore hybrid AI-based MPPT strategies, and implement real-time embedded solutions to enable practical deployment in both Moroccan and international smart-grid applications.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data used in this study can be accessed publicly at https://nsrdb.nrel.gov/.

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