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Photovoltaic Power Generation Forecasting Based on CNN-LSTM-PINNs Hybrid Model

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Abstract

Accurate photovoltaic (PV) power forecasting is essential for reliable microgrid operation, efficient energy dispatch, and improved utilization of renewable energy resources. Existing forecasting methods often have limited capacity to represent the nonlinear relationships between meteorological conditions and PV power output. They also tend to underrepresent the temporal dynamics of PV generation and the physical principles governing photovoltaic energy conversion. To address these limitations, this study proposes a hybrid forecasting framework, CNN-LSTM-PINNs, that integrates Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Physics-Informed Neural Networks (PINNs). In the proposed framework, CNNs extract spatial dependencies among multivariate meteorological variables, LSTM networks capture temporal dependencies in PV generation, and PINNs incorporate soft physical constraints derived from photovoltaic energy conversion mechanisms. The proposed model is evaluated using publicly available datasets from three large-scale PV power stations in China, with observations recorded at 15-min intervals. The empirical results show that CNN-LSTM-PINNs outperform the conventional CNN-LSTM benchmark across the primary station-level datasets. Relative to the benchmark model, the proposed framework reduces Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and improves the coefficient of determination (R^2). These results indicate that embedding physical constraints into data-driven forecasting models can improve PV power prediction accuracy. The model also shows stronger robustness and generalization performance under heterogeneous operating conditions, although its effectiveness is contingent on relatively stable data distributions. Feature-importance analysis further indicates that global horizontal irradiance (GHI) and irradiance-derived variables are the most informative predictors of PV power output. Overall, this study provides a physics-informed hybrid modeling approach for high-resolution PV power forecasting in microgrid applications.



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1. Introduction

Global installed photovoltaic (PV) capacity reached approximately 2800 GW by 2025, establishing solar PV as the world's largest source of electricity generation [1]. However, PV power output is inherently stochastic, driven by meteorological factors such as global

horizontal irradiance (GHI), ambient temperature, relative humidity, and wind speed, and exhibits pronounced intermittency and volatility [2]. These characteristics pose significant challenges to the safe and reliable operation of modern power grids, particularly in microgrids with high penetration of distributed PV systems [3].

Accurate PV power forecasting is therefore critical for microgrid operation, energy dispatch optimization, and economic scheduling [4]. At the planning stage, precise forecasts enable optimal sizing of energy storage and reserve capacities. During operation, robust forecasts support day-ahead scheduling, intra-day dispatch, and real-time power balancing. From an economic perspective, accurate forecasting reduces PV curtailment and grid procurement costs, thereby improving the overall economic benefits of microgrid systems [5].

Existing PV forecasting methodologies can be broadly categorized into five paradigms: physical models, statistical models, machine learning models, deep learning models, and hybrid models [6]. Di Leo et al. [6] provide a comprehensive review of these approaches, emphasizing that methodology selection should be tailored to the specific forecasting horizon, geographic context and application requirements. Physical models simulate solar irradiance transfer and photoelectric conversion with clear interpretability [7], but require precise component parameters and high-quality meteorological inputs, limiting their applicability in data-scarce scenarios [8]. Statistical models, such as ARIMA and seasonal decomposition, treat PV output as a time series process [9,10]. While computationally efficient, they struggle to capture the complex nonlinear dynamics inherent in meteorological-to-power mappings [11]. Machine learning and deep learning methods leverage data-driven feature engineering to learn abstract representations among high-dimensional variables, thereby uncovering subtle coupling relationships between meteorological factors and power generation [12,13]. Convolutional Neural Networks (CNN) excel at extracting spatial hierarchical features from multi-dimensional meteorological data [14], whereas Recurrent Neural Networks (RNN) and their variants, particularly Long Short-Term Memory (LSTM) networks, are proficient at modeling temporal dependencies in sequential power data [15]. To enhance the model's ability to focus on critical time steps, attention mechanisms have been integrated into forecasting architectures [16,17].

Hybrid models, which combine complementary prediction methods to leverage the respective strengths of each component, have become the dominant paradigm for improving PV power forecasting accuracy [18,19]. Contemporary hybrid strategies can be classified into decomposition-based prediction [20,21], clustering-based prediction [22,23], feature extraction-based prediction [24,25] and multi-model ensemble approaches [26,27]. Among the principal hybrid strategies, feature extraction-based CNN-LSTM architectures have attracted particular research attention due to their inherent compatibility with the spatial-temporal characteristics of PV generation data. Lim et al. [25] proposed a CNN-LSTM model that classifies weather conditions via CNN and learns power generation patterns via LSTM, achieving a mean absolute percentage error of 4.58% on sunny days and 7.06% on cloudy days. Wang et al. [28] conducted a systematic comparative study, demonstrating that the CNN-LSTM hybrid architecture consistently outperforms standalone CNN and LSTM models across multiple evaluation metrics. Furthermore, signal decomposition techniques [29], optimization algorithms [30], Graph Neural Networks [31,32] and probabilistic methods [33,34] have also been widely adopted in hybrid models.

Physics-Informed Neural Networks (PINNs) have emerged as a promising approach to embedding physical constraints into data-driven models. In the domain of PV power forecasting, Cong et al. [35] developed a physics-informed day-ahead forecasting method with seasonal trend mitigation and clear-sky template integration, achieving an average mean squared error reduction of 14.78% across over one hundred large-scale power plants

in China. Wang et al. [36] proposed a PINN-based temperature prediction model that integrates temperature features with a long-short term cross-attention mechanism, attaining R-squared values exceeding 0.98 across different seasons. Wang et al. [37] introduced a Dynamic-Parameter Physics-Informed Neural Network (DP-PINN) framework that dynamically adjusts physical equations based on weather types, demonstrating substantially lower RMSE under extreme conditions compared to both static-parameter PINNs and pure data-driven models.

Despite these advances, existing hybrid models predominantly focus on two-dimensional fusion paradigms: either spatial-temporal fusion (CNN-LSTM) or data-physical fusion (PINNs), lacking a unified three-dimensional framework that simultaneously integrates spatial feature extraction, temporal dependency modeling, and physical constraint guidance. PV power forecasting is fundamentally a spatio-temporal evolution process governed by physical laws; single two-dimensional fusion is insufficient to fully characterize its intrinsic mechanisms. CNN excels at extracting spatial hierarchical features from multi-dimensional meteorological data but exhibits limited capability for modeling long-term temporal dependencies. LSTM effectively captures temporal dynamics but lacks explicit spatial structure modeling and ignores the physical constraints of photovoltaic generation, potentially yielding physically implausible predictions. PINNs provide physical consistency guarantees by embedding governing equations; moreover, physical constraints can guide CNN feature learning toward representations more aligned with photovoltaic physics.

Motivated by the above analysis, this paper proposes a CNN-LSTM-PINNs hybrid prediction model that simultaneously leverages CNN's spatial feature extraction capability, LSTM's temporal modeling strength, and PINNs' physical constraint mechanism. While two-component hybrid models such as CNN-LSTM and LSTM-PINN have been extensively investigated in recent years, research on the organic integration of all three components remains surprisingly scarce in the existing literature. To the best of the authors' knowledge, no prior study has deeply integrated these three complementary paradigms within a unified end-to-end framework for PV power prediction. The proposed CNN-LSTM-PINNs hybrid framework consists of three tightly coupled modules: (1) CNN module: High-dimensional multivariate meteorological data are structured into three-dimensional tensors, and multiple stacked convolutional and pooling layers extract hierarchical spatial distribution features and mutual correlations among meteorological parameters. (2) LSTM module: The high-level meteorological features extracted by the CNN module are concatenated with historical PV power time series and fed into a stacked LSTM network for temporal sequence modeling, which learns complex dynamic evolution patterns and both short-term and long-term temporal dependencies. (3) PINN module: The preliminary data-driven predictions from the LSTM module are integrated with fundamental photovoltaic generation physical equations to construct a comprehensive physics-informed loss function, enabling end-to-end physics-informed training of the entire hybrid framework.

The main contributions of this paper are threefold: (1) Theoretical contribution: A novel physics-informed hybrid deep learning architecture is proposed, which organically integrates the powerful data-driven feature learning capabilities of deep neural networks with domain-specific physical mechanism prior knowledge. (2) Methodological innovation: A customized physics-constrained loss function based on fundamental photovoltaic cell physics is designed, which embeds the solar cell output power equation and temperature correction model as soft constraints into the end-to-end model training process, effectively improving prediction robustness under extreme weather conditions. (3) Practical application value: Comprehensive systematic experiments are conducted using real-world measured data from three geographically distinct PV power stations in China, covering

diverse climatic and operational conditions. An in-depth analysis of the influence mechanisms of different station characteristics and data distributions on prediction performance is provided.

The remainder of this paper is structured as follows. Section 2 presents the fundamental theoretical principles of CNNs, LSTM networks, and PINNs, along with the detailed overall architecture of the proposed CNN-LSTM-PINN hybrid forecasting framework. Section 3 details the dataset sources, comprehensive data preprocessing pipeline, and feature engineering strategies. Section 4 outlines the model hyperparameter configurations, experimental design methodology, and provides an in-depth analysis and discussion of the experimental results. Section 5 concludes the paper by summarizing the key research findings and proposing promising future research directions.

2. Models and Methods

2.1. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of feedforward neural networks distinguished by their inherent local connectivity and weight-sharing properties, originally developed for processing Euclidean grid-structured data such as digital images and later extended to univariate and multivariate time series. CNNs dramatically reduce the total number of trainable network parameters via their local connectivity and weight-sharing mechanisms while simultaneously enabling efficient extraction of hierarchical local features from high-dimensional input data.

The fundamental building blocks of a typical CNN architecture include convolutional layers, pooling layers, and fully connected layers. A convolutional layer performs local feature extraction by sliding a set of learnable convolutional kernels across the input data, whose operation can be mathematically formulated as:

$$y_i^{(l)} = f\left(\sum_{j=1}^M x_j^{(l-1)} \otimes k_{ij}^{(l)} + b_i^{(l)}\right) \quad (1)$$

where $x_j^{(l-1)}$ is the j -th input feature map of layer $(l-1)$; $k_{ij}^{(l)}$ is the convolutional kernel connecting the j -th input to the i -th output; $b_i^{(l)}$ is the bias term; $f(\cdot)$ is the activation function (ReLU); and $\otimes$ denotes the convolution operation. Figure 1 shows the standard architecture of CNN.

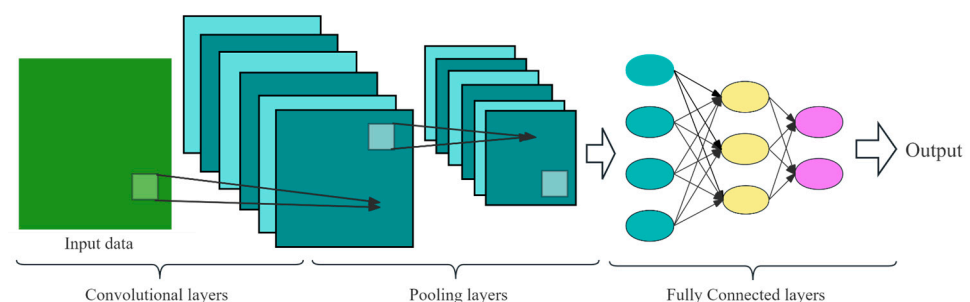


Figure 1. The standard architecture of CNN.

In the context of PV power generation forecasting, CNNs are specifically utilized to extract intricate spatial correlation features from high-dimensional multivariate meteorological parameter matrices. Through successive stacked convolutional and pooling operations, the CNN architecture is capable of automatically learning the underlying hierarchical coupling relationships among various meteorological variables (including global horizon-

tal irradiance (GHI), ambient temperature, and relative humidity) and their nonlinear influence mechanisms on PV power generation output.

2.2. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized variant of Recurrent Neural Network (RNN) architecture. LSTM networks effectively mitigate the vanishing and exploding gradient problems commonly encountered by conventional RNNs when processing long sequential data by incorporating adaptive gating mechanisms, enabling the network to capture long-range temporal dependencies inherent in time series. The fundamental building block of an LSTM network is the LSTM cell, whose core architecture comprises two key components: a persistent cell state and a set of gating mechanisms. The cell state acts as a dedicated “memory channel” for information propagation through the network, while three specialized gating units—the input gate, forget gate, and output gate—regulate the selective modification, retention, and retrieval of information stored in the cell state. The detailed mathematical formulations governing the operation of each gating unit are provided below:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

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

where f_t , i_t , $\tilde{C}_t$, C_t , o_t , h_t denote forget gate, input gate, candidate memory, cell state update, output gate and hidden state; σ denotes the sigmoid function: $\sigma(x) = \frac{1}{1+e^{-x}}$; $\odot$ denotes element-wise multiplication; W_f , W_i , W_C , W_o are weight matrices; and b_f , b_i , b_C , b_o are bias vectors. Figure 2 shows the standard architecture of LSTM.

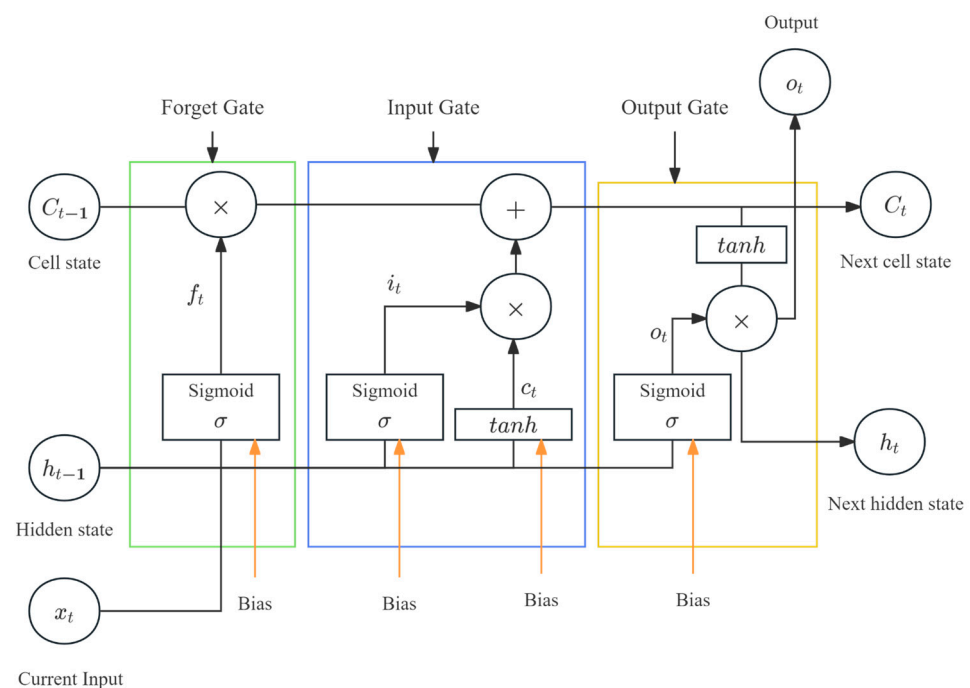


Figure 2. The standard architecture of LSTM.

In the domain of PV power generation forecasting, LSTM networks are specifically employed to model the temporal dynamic evolution characteristics of PV power output. PV power generation time series exhibit strong inherent temporal autocorrelations, meaning that the power output at a given time step is significantly influenced by the power values at preceding time steps. Benefiting from their distinctive adaptive gating architecture, LSTM networks are capable of simultaneously capturing both short-term stochastic fluctuations and long-term periodic trends inherent in PV power sequences, thereby extracting robust temporal features that serve as critical inputs for accurate power forecasting.

2.3. Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) represent a transformative deep learning framework that synergistically integrates data-driven machine learning approaches with first-principles physical mechanisms. The core principle underlying PINNs is to explicitly embed soft physics constraint terms formulated from fundamental governing equations, including partial differential equations and ordinary differential equations, into the neural network's loss function. This dual-objective optimization framework constrains the network to adhere to known physical laws simultaneously with fitting empirical observed data, thereby generating predictions that are not only data-consistent but also physically plausible and interpretable. The total composite loss function of PINNs, which consists of a data fidelity term and a physics consistency term, is mathematically formulated as:

$$L_{total} = L_{data} + \lambda_{physics} L_{physics} \quad (8)$$

$$L_{data} = \frac{1}{N} \sum_{i=1}^N \left(y_{pred,i} - y_{true,i} \right)^2 \quad (9)$$

$$L_{physics} = \frac{1}{N} \sum_{i=1}^N \left| \mathcal{F}[y_{pred}, x; \theta] \right|^2 \quad (10)$$

where L_{total} is the total loss function; L_{data} is the data-driven loss function; $L_{physics}$ is the physics constraint loss function; $\mathcal{F}[\cdot]$ is the residual of the physical equation (governing equation); $\lambda_{physics}$ is the physics loss weight coefficient; and θ represents the network parameters.

In the present work, the physics-informed constraint term is rigorously derived from the fundamental physical equations governing the photovoltaic power conversion process. The output power of a PV module is fundamentally determined by two dominant factors: the incident solar irradiance received by the module surface and the operating temperature of the PV cells, as described by the following well-established physical relationship:

$$P = P_{STC} \cdot \frac{G}{G_{STC}} \cdot [1 + \alpha_P (T_c - T_{STC})] \quad (11)$$

where P is the actual power output; P_{STC} is the power under standard test conditions; G is the actual irradiance; G_{STC} is the standard test condition irradiance (1000 W/m^2); α_P is the power temperature coefficient; T_c is the cell temperature; and T_{STC} is the standard test condition temperature (25°C). This physical relationship, originally formulated in the Sandia PV Array Performance Model and widely adopted in PV system analysis [38], describes the fundamental dependency of PV module output power on incident irradiance and cell operating temperature. It is selected as the embedded physical constraint because it captures the two dominant physical factors governing PV power conversion—incident solar irradiance and cell temperature—while maintaining a computationally tractable form suitable for gradient-based optimization in PINNs. Alternative models, such as the

single-diode or double-diode equivalent circuit models, offer higher fidelity but require additional parameters (e.g., series resistance, shunt resistance, diode ideality factor) that are not consistently available in standard meteorological datasets. The trade-off between model fidelity and data availability renders Equation (11) a pragmatic choice for macroscopic, data-driven forecasting frameworks such as the one proposed in this study. This physical equation is embedded into the PINN loss function as a soft constraint, ensuring that the model predictions conform to the fundamental physical laws of photovoltaic generation.

2.4. CNN-LSTM-PINNs Hybrid Model

The proposed CNN-LSTM-PINN hybrid forecasting framework synergistically integrates the hierarchical local feature extraction capability of Convolutional Neural Networks (CNNs), the long-range temporal dependency modeling capability of Long Short-Term Memory (LSTM) networks, and the first-principles physical constraint enforcement capability of Physics-Informed Neural Networks (PINNs).

Accurate PV power generation forecasting faces three inherent technical challenges: strong temporal sequence dependencies, complex multi-source feature coupling, and strict physical constraint conditions. First, multivariate meteorological variables (including global horizontal irradiance (GHI), ambient temperature, relative humidity, and wind speed) exhibit intricate nonlinear coupling relationships. CNNs are uniquely suited to extract these local spatial correlation patterns from high-dimensional feature spaces, and their stacked convolutional and pooling layers inherently provide effective feature dimensionality reduction while preserving critical information. Second, PV power output exhibits pronounced temporal dynamics driven by solar irradiance and temperature variations, including strong diurnal periodicity (24-h cycle) and seasonal fluctuation patterns. LSTMs, with their adaptive gating architecture, are specifically designed to capture both short-term stochastic fluctuations and long-range temporal dependencies in such sequential data. Finally, PV power output is fundamentally bounded by the theoretical maximum photoelectric conversion efficiency and exhibits a well-documented negative correlation with PV cell operating temperature. Purely data-driven models often generate physically implausible predictions under extreme or unseen conditions, which PINNs address by embedding these physical laws as soft constraints into the loss function.

The overall architecture of the proposed framework is schematically illustrated in Figure 3.

The proposed CNN-LSTM-PINN hybrid framework consists of three tightly coupled, functionally complementary modules that collectively address the aforementioned challenges:

- (1) **CNN module:** Performs hierarchical local feature extraction by sliding learnable convolutional kernels across the input tensor to capture correlation patterns among adjacent time-step features. The weight-sharing mechanism inherent in CNNs significantly reduces the number of trainable parameters, mitigating overfitting risk and enhancing generalization capability. Multi-layer stacked convolutional and pooling layers progressively abstract feature representations from low-level local patterns to high-level global correlations.
- (2) **LSTM module:** Models temporal dynamics by selectively retaining or forgetting historical information through its persistent cell state and adaptive gating mechanisms. This architecture effectively mitigates the vanishing gradient problem encountered in traditional Recurrent Neural Networks (RNNs), enabling robust capture of long-sequence temporal correlations. Stacked LSTM layers further enhance the model's ability to abstract complex hierarchical temporal features from the input sequences.
- (3) **PINNs module:** Enforces physical consistency by integrating fundamental photovoltaic conversion principles into the model training process. By incorporating physi-

cal priors, the module reduces the model's dependence on large volumes of labeled training data and provides inherent physical interpretability for the prediction results. Specifically, the physics-informed loss term penalizes predictions that violate established physical laws such as energy conservation and the temperature-dependent efficiency relationship.

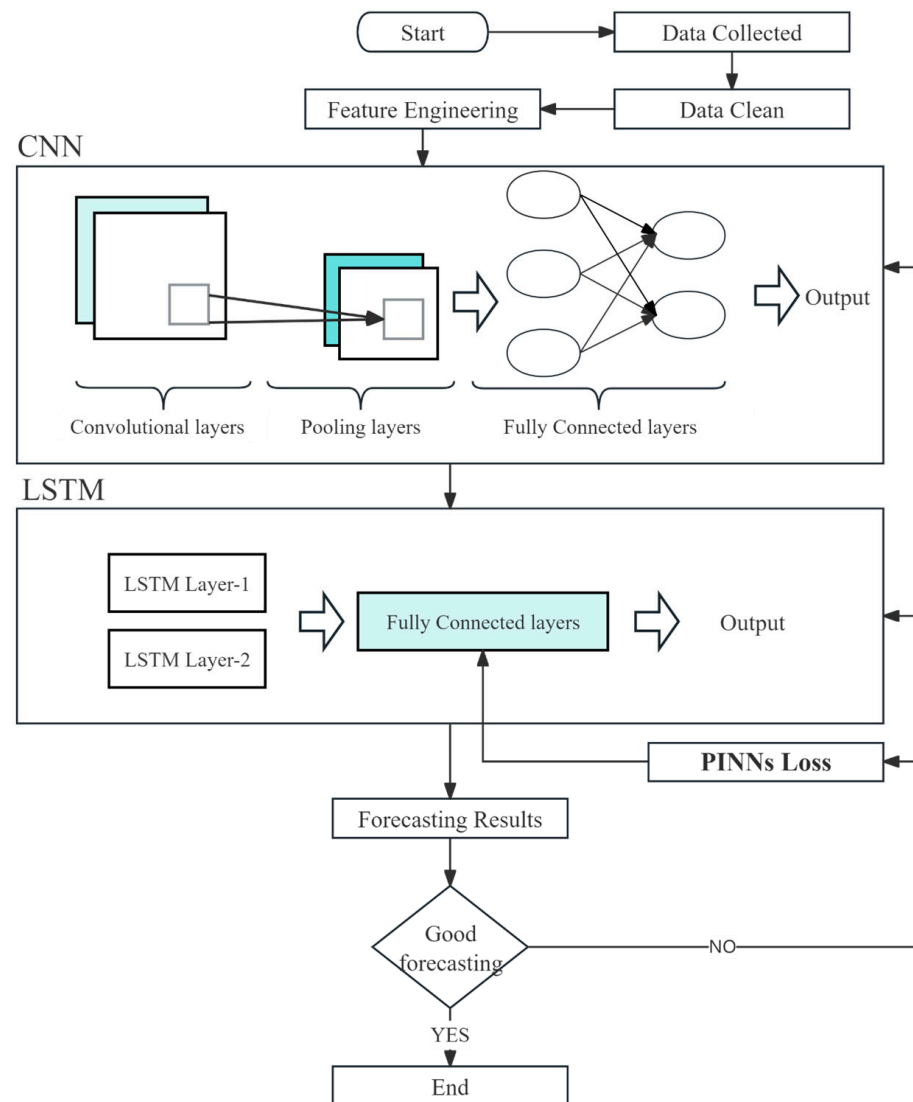


Figure 3. CNN-LSTM-PINNs hybrid model architecture.

To ensure stable convergence and optimal performance, the training process of the proposed hybrid framework is divided into three progressive stages: (1) Pre-training: The CNN and LSTM modules are first pre-trained exclusively using the data fidelity loss L_{data} to establish robust basic feature extraction and temporal sequence modeling capabilities. This stage allows the model to learn general patterns from the available training data without being constrained by physical laws. (2) Physics-informed fine-tuning: Subsequently, the physics consistency loss term $L_{physics}$ is introduced into the loss function, and the composite total loss L_{total} is optimized to align model predictions with fundamental physical constraints. This stage gradually injects physical knowledge into the pre-trained data-driven model. (3) End-to-end joint optimization: Finally, the entire network architecture, including the CNN feature extraction module, LSTM temporal modeling module, and physics constraint layer, is jointly optimized through end-to-end

backpropagation. This final stage enables the model to simultaneously achieve excellent data fitting performance and strict physical consistency.

3. Data Preparation and Preprocessing

3.1. Data Source and Description

The experimental datasets utilized in this study are obtained from publicly accessible PV power station monitoring databases. The datasets comprise de-identified ambient meteorological measurements, ground-measured solar irradiance data, and synchronized PV power generation records from three utility-scale PV power stations located in a representative region of China. The three PV power stations exhibit distinctly different climatic characteristics and operational profiles. Station 1 serves as a stable benchmark facility located in a temperate climate zone, featuring high solar irradiance, moderate installed capacity, and high-power output stability. Station 2 is classified as a high-noise and curtailment-affected site. Also situated in a temperate climate zone, it has a moderate installed scale and medium power stability, with a relatively high proportion of zero-power output during daytime hours. Station 3 is characterized by pronounced seasonal power fluctuations. Located in a plateau climate zone with high ambient temperature and strong wind speeds, it has a large installed capacity and demonstrates the most significant seasonal generation variability among the three plants. Collectively, this group of three stations covers three representative challenging scenarios in PV power forecasting: stable baseline operation, curtailment-disturbed operation, and seasonally fluctuating operation.

All data are recorded at a 15-min sampling interval, spanning three consecutive years from April 2016 to July 2018. Detailed specifications of the experimental datasets are summarized in Table 1.

Table 1. Overview of PV power station datasets.

Dataset	Start Date	End Date	Records	Key Variables ¹
Station 1	1 April 2016	30 April 2018	66,859	Time, GHI, wind speed, wind direction, ambient temperature, atmospheric pressure, relative humidity, POA irradiance, AC power output
Station 2	2 January 2017	30 April 2018	43,755	Same as above
Station 3	1 August 2017	31 July 2018	29,792	Same as above

Note: ¹ Global Horizontal Irradiance (GHI, W/m²): Total horizontal solar radiation received at the Earth’s surface; Wind speed (m/s) and wind direction (°): Meteorological measurements recorded at the nearest ground meteorological station; Ambient temperature (°C): Air temperature measured at 2 m above ground level; Atmospheric pressure (hPa): Barometric pressure at the measurement site; Relative humidity (%): Ratio of actual water vapor pressure to saturation water vapor pressure at ambient temperature; Plane-of-Array (POA) irradiance (W/m²): Effective solar irradiance incident on the tilted surface of PV modules; AC power output (kW): Measured alternating current power generated by the PV power station inverters.

Scatter plots illustrating the correlation between GHI and AC power output, as well as between POA irradiance and AC power output, for all three datasets are presented in Figures 4 and 5, respectively. These plots clearly demonstrate the strong linear and nonlinear relationships between solar irradiance and PV power generation, validating the rationality and feasibility of employing meteorological features as primary inputs for data-driven PV power forecasting models.

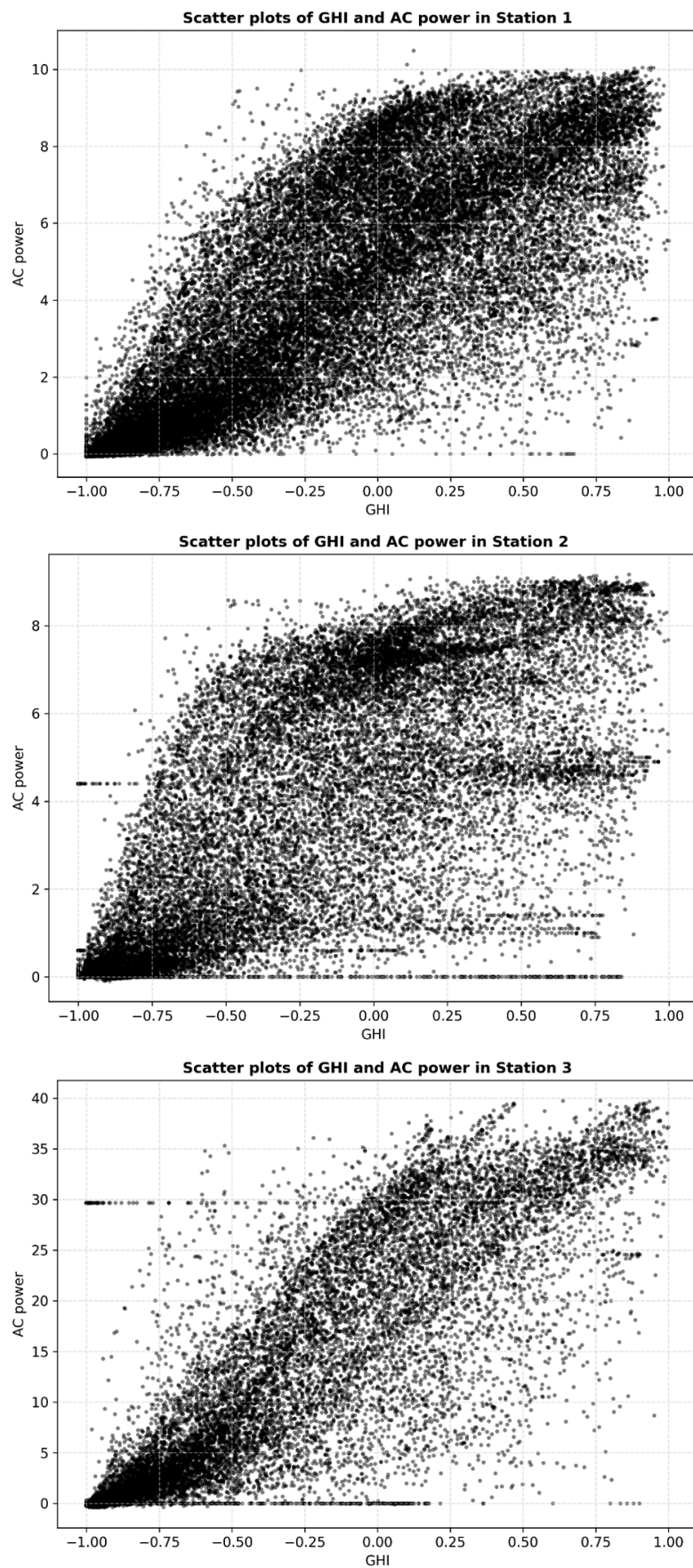


Figure 4. Scatter plots of GHI and AC power.

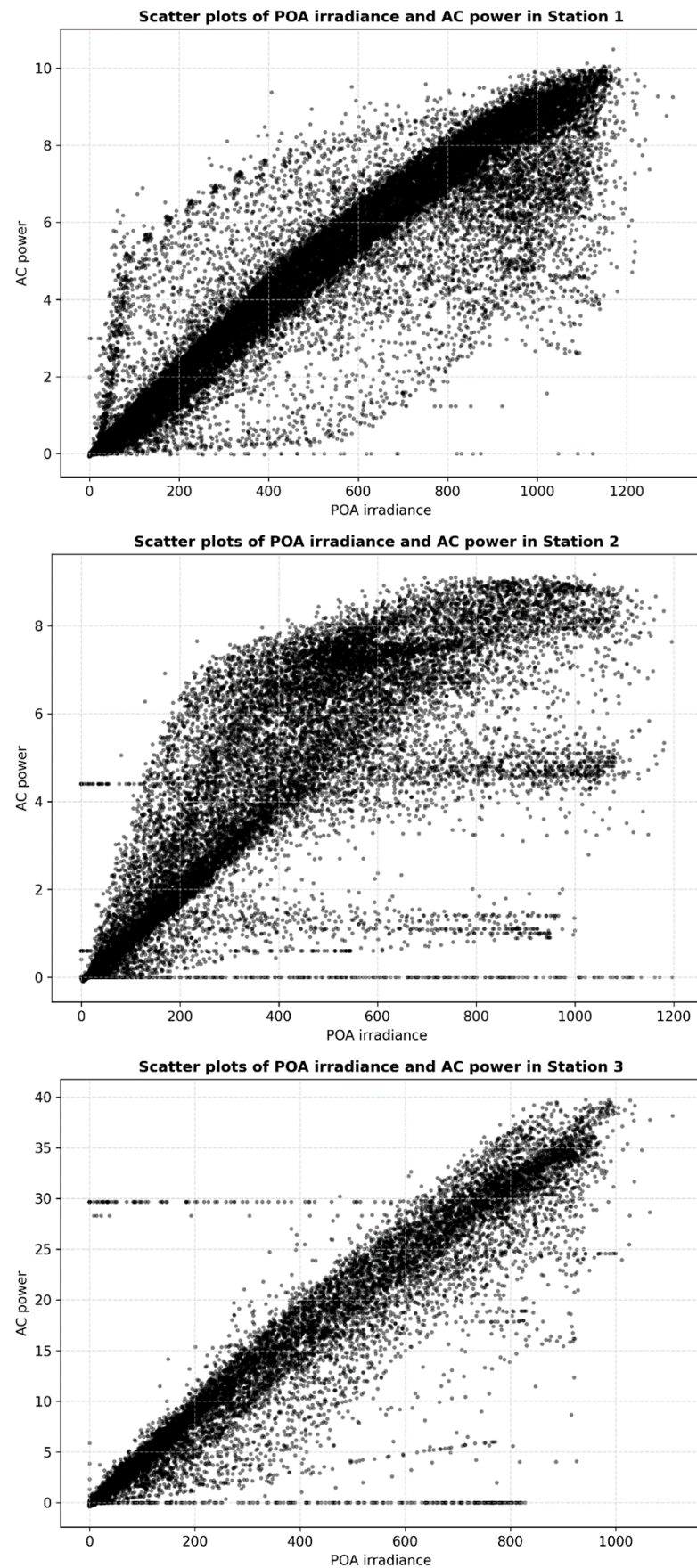


Figure 5. Scatter plots of POA irradiance and AC power.

3.2. Data Preprocessing

Raw experimental data typically contain missing values, outliers, and stochastic noise interference introduced during sensor measurement, data transmission, and storage processes, which necessitates a rigorous and systematic data preprocessing pipeline to ensure data quality and model reliability. The comprehensive data preprocessing workflow implemented in this study consists of two core steps:

- (1) **Missing value handling:** Zero irradiance values recorded during daytime hours (defined as periods when solar elevation angle $> 0^\circ$) are treated as invalid missing values and imputed using the forward fill method. Data segments with severe quality degradation on specific dates are completely removed from the dataset. Specifically, data recorded on 1 April 2018 for Station 1, 10–12 April 2017 for Station 2, and 4–6 August 2017 for Station 3 are excluded due to significant data corruption. Remaining missing values for all numerical meteorological and power features are imputed using column-wise mean imputation.
- (2) **Outlier detection and correction:** The widely adopted 3σ statistical criterion is utilized to detect potential outliers, defined as data points falling outside the range of $[\text{mean} - 3\sigma, \text{mean} + 3\sigma]$ for each individual feature. For identified outliers, those corresponding to physically impossible measurements (e.g., non-zero PV power output during nighttime when $\text{GHI} = 0 \text{ W/m}^2$) are directly discarded. Outliers resulting from transient sensor noise or abnormal fluctuations are corrected using a 5-point sliding-window median filter, which effectively suppresses impulse noise while preserving the underlying temporal trends of the original signals.

3.3. Feature Engineering

To fully exploit the complex nonlinear correlation information between multivariate meteorological variables and PV power generation, this study employs a systematic two-stage feature engineering strategy to progressively construct a comprehensive and discriminative feature set. The first stage focuses on two core tasks: extracting temporal features to capture the inherent diurnal and seasonal periodic patterns of PV power generation, and conducting standardized preprocessing of raw meteorological and power features to eliminate the adverse effects of inconsistent feature scales on model convergence and prediction performance. The detailed definitions of the constructed basic features are summarized in Table 2.

Table 2. Basic feature information.

Feature Type	Feature Name	Description
Temporal	month, day, time	Year/month/day/time (minutes)
Original	GHI, wind speed, wind direction, temperature, pressure, humidity	Original features after Z-score standardization
Peak distance	dis2peak_irradiance	Distance to daily irradiance peak
Interaction	GHI + wind speed, GHI + temperature, GHI + pressure, etc.	Additive interactions
Daily statistics	max_GHI, daytime GHI difference, daytime GHI mean	Daily aggregated statistics

The second stage primarily generates extended features, as listed in Table 3.

Table 3. Extended feature information.

Feature Type	Feature Name	Description
POA irradiance statistics	max_POA irradiance, daytime POA mean/std/difference	Daily statistics of POA irradiance
POA irradiance peak	dis2peak_POA irradiance	Distance to daily POA irradiance peak
Polynomial features	Temperature ² , humidity ² , wind speed ²	Squared terms
Cross features	GHI * temperature, etc.	Multiplicative interactions
Daily average	Average GHI, etc.	Daily average GHI

Note: The superscript (2) denotes the square symbol, and the superscript * denotes the multiplication symbol.

3.4. Dataset Split

Each individual PV power station dataset is strictly chronologically partitioned into three non-overlapping subsets: a training set (60%), a validation set (20%), and a held-out test set (20%). The training set is exclusively used for optimizing the trainable parameters of the deep learning model; the validation set is employed for hyperparameter tuning, model selection, and implementation of the early stopping criterion; the held-out test set is reserved solely for unbiased final performance evaluation. This time-based splitting strategy ensures complete temporal continuity among training, validation, and test samples without any future information leakage, which strictly adheres to the causal principle of time series forecasting and accurately reflects real-world operational forecasting scenarios.

4. Experimental Design and Results

This study employs the proposed CNN-LSTM-PINNs hybrid forecasting framework to perform 15-min interval AC power output prediction for the three aforementioned utility-scale PV power stations. To quantitatively demonstrate the superiority and effectiveness of the proposed physics-informed framework, a state-of-the-art data-driven hybrid deep learning baseline model—CNN-LSTM, which lacks explicit physical constraint enforcement—is selected for comprehensive comparative analysis. The CNN-LSTM model is chosen as the primary baseline because it represents the most widely adopted benchmark for spatio-temporal PV power forecasting and shares an identical data-driven backbone architecture with the proposed model, enabling a fair and controlled comparison of the unique contribution of physical constraints. Three universally recognized quantitative evaluation metrics are adopted to comprehensively assess the prediction performance of all models: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2).

4.1. Model Hyperparameter Configurations

Following rigorous systematic hyperparameter optimization, the optimal hyperparameter configurations for both the proposed CNN-LSTM-PINNs hybrid framework and the CNN-LSTM baseline model are summarized in Table 4.

Table 4. Parameter configuration.

Parameter Name	CNN-LSTM-PINNs Optimal Value	CNN-LSTM Optimal Value
Number of convolutional layers	2	2
Filter sizes	[32, 64]	[64, 128]
Conv1 filters	32	64
Conv2 filters	64	128
LSTM hidden units	32	128

Table 4. *Cont.*

Parameter Name	CNN-LSTM-PINNs Optimal Value	CNN-LSTM Optimal Value
Fully connected layer size	16	64
Dropout rate	0.3	0.3
Learning rate	0.002	0.002
Batch size	256	128
Physics-informed loss weight ¹	0.1	/
Weight decay	0.01	0.01
Optimizer	Adam	Adam

Note: ¹ The physics-informed loss weight λ was determined through a systematic grid search over the candidate set {0.00, 0.01, 0.10, 0.20, 0.30, 0.50, 1.00} on the dataset of Station 1. The selection criteria were MAE, RMSE and R^2 . The grid search results are 0.065, 0.076 and 0.631 for $\lambda = 0.00$; 0.053, 0.064 and 0.737 for $\lambda = 0.10$; 0.064, 0.073 and 0.658 for $\lambda = 0.20$; 0.066, 0.083 and 0.560 for $\lambda = 1.00$. The results indicate that $\lambda = 0.10$ achieves the optimal balance between data fitting accuracy and physical constraint satisfaction. The sensitivity analysis confirms that $\lambda = 0.1$ provides a robust trade-off, yielding the best validation performance.

4.2. Prediction Performance

To comprehensively evaluate the forecasting performance of the proposed CNN-LSTM-PINNs hybrid framework, systematic comparative experiments were conducted on all three PV power station datasets, with its performance benchmarked against the CNN-LSTM baseline model. The quantitative evaluation results for both models on the training, validation, and held-out test sets are summarized in Tables 5, 6 and 7, respectively.

The experimental results show that for both models, the prediction performance on the held-out test set is consistently lower than that on the training and validation sets, which is consistent with the general behavior of deep learning models, as test sets contain completely unseen data that the model has not been exposed to during training.

On the training and validation sets, the proposed CNN-LSTM-PINNs model outperforms the CNN-LSTM baseline across all three evaluation metrics, achieving modest improvements of approximately 1% in R^2 . More significantly, on the independent test sets, the proposed physics-informed framework demonstrates substantial performance gains. For Station 1, the CNN-LSTM-PINNs model achieves a 58.17% reduction in MAE, a 49.80% reduction in RMSE, and a remarkable 351.00% improvement in R^2 compared to the baseline. For Station 2, the proposed model achieves a 3.69% reduction in MAE, a 14.65% reduction in RMSE, and an 87.43% improvement in R^2 . These empirical results clearly demonstrate the superior generalization capability of the proposed CNN-LSTM-PINNs framework over the purely data-driven CNN-LSTM baseline. The significant performance improvements on the test sets confirm that embedding physical constraints effectively mitigates overfitting and enhances the model's robustness to unseen operating conditions.

However, notably different results were observed for Station 3 on the held-out test set. The CNN-LSTM baseline model achieves an R^2 of -86.16% , while the proposed CNN-LSTM-PINNs model achieves an R^2 of -106.03% . Both models exhibit severely degraded prediction performance on this dataset, indicating severe generalization failure rather than conventional overfitting. Subsequent in-depth analysis of the original Station 3 dataset revealed a significant covariate shift (data distribution shift) problem in the PV power generation data, which cannot be resolved through hyperparameter tuning alone. A detailed comparison of the data distribution characteristics between the training and test sets for Station 3 is presented in Table 8.

Table 5. Forecasting performance in training sets.

Dataset	Model	MAE	RMSE	R ² (%)
Station 1 training sets	CNN-LSTM	0.1020	0.1345	98.19
	CNN-LSTM-PINNs	0.0623	0.0997	99.01
	Improvement	−38.89%	−25.87%	+0.83%
Station 2 training sets	CNN-LSTM	0.0937	0.1502	97.74
	CNN-LSTM-PINNs	0.0694	0.1075	98.84
	Improvement	−25.96%	−28.41%	+1.13%
Station 3 training sets	CNN-LSTM	0.0934	0.1469	97.84
	CNN-LSTM-PINNs	0.0786	0.1266	98.40
	Improvement	−15.88%	−13.81%	+0.57%

Table 6. Forecasting performance in validation sets.

Dataset	Model	MAE	RMSE	R ² (%)
Station 1 validation sets	CNN-LSTM	0.1278	0.1629	97.58
	CNN-LSTM-PINNs	0.0905	0.1236	98.60
	Improvement	−29.18%	−24.08%	+1.05%
Station 2 validation sets	CNN-LSTM	0.1573	0.2175	96.41
	CNN-LSTM-PINNs	0.1351	0.1804	97.53
	Improvement	−14.12%	−17.09%	+1.16%
Station 3 validation sets	CNN-LSTM	0.1299	0.1836	96.79
	CNN-LSTM-PINNs	0.1142	0.1631	97.46
	Improvement	−12.07%	−11.14%	+0.70%

Table 7. Forecasting performance in test sets.

Dataset	Model	MAE	RMSE	R ² (%)
Station 1 test sets	CNN-LSTM	0.1015	0.1137	17.57
	CNN-LSTM-PINNs	0.0425	0.0571	79.23
	Improvement	−58.17%	−49.80%	+351.00%
Station 2 test sets	CNN-LSTM	0.0441	0.0637	23.70
	CNN-LSTM-PINNs	0.0425	0.0544	44.41
	Improvement	−3.69%	−14.65%	+87.43%
Station 3 test sets	CNN-LSTM	0.0542	0.0700	−86.16 ¹
	CNN-LSTM-PINNs	0.0599	0.0737	−106.03
	Improvement	+10.33%	+5.20%	−23.06%

Note: ¹ A negative R-squared (R²) indicates that the model is overfitted and the results are unreliable.

Table 8 shows that the normalized power data for Station 3 exhibits three distinct distribution anomalies: (1) severe mean shift (normalized test set mean ≈ -0.65 versus normalized training set mean ≈ 0.1 , representing a difference of 0.75 normalized units); (2) extreme variance compression (the standard deviation of the normalized test set is

approximately 19.5 times smaller than that of the training set); and (3) significant range narrowing (test set power values are almost entirely concentrated within the narrow range $[-0.7, -0.1]$). These dramatic changes in data distribution characteristics fundamentally alter the power generation patterns learned by the models during training, leading to the observed generalization failure for both the CNN-LSTM-PINNs and CNN-LSTM models. Such significant data distribution shifts in PV power generation systems are typically caused by factors such as equipment aging, inverter calibration changes, partial shading due to vegetation growth, or prolonged maintenance periods. These findings highlight the critical importance of conducting comprehensive data characteristic analysis prior to deploying deep learning forecasting models in real-world PV power generation systems.

Table 8. Data distribution comparison for Station 3.

Metric	Training Set	Test Set	Difference
Mean	0.099	−0.651	0.75
Standard deviation	1.045	0.054	19.5×
Range	[−0.67, 3.28]	[−0.67, −0.12]	Extremely narrow

The severe degradation observed on Station 3 is fundamentally a data distribution shift problem rather than a model architecture limitation. To address this challenge in practical deployments, the following feasible strategies are recommended: (1) Domain Adaptation (DA): Techniques such as adversarial domain adaptation or moment matching can be employed to align the feature distributions between the training and test domains, reducing the impact of covariate shift. (2) Online/Incremental Learning: Incremental learning frameworks enable the model to continuously adapt to evolving environmental conditions and equipment states without catastrophic forgetting, which is particularly suitable for long-term operational PV systems. (3) Data Augmentation and Re-calibration: Pre-deployment data quality assessment, including outlier detection, sensor re-calibration, and systematic data validation, can identify and mitigate distribution shifts before they degrade model performance. These strategies are practical and implementable in real-world microgrid systems.

4.3. Feature Importance Analysis

To quantitatively investigate the contribution of different meteorological variables and derived features to PV power generation forecasting performance, this study employs the SHAP (SHapley Additive exPlanations) framework—a widely adopted game theory-based interpretable machine learning approach that provides consistent and unbiased feature importance estimates. Feature importance analysis is conducted based on the held-out test set data from Station 1 and Station 2, where both models achieved satisfactory generalization performance. The top 10 most influential features identified for Station 1 and Station 2 are summarized in Tables 9 and 10, respectively.

To evaluate the cross-station stability of feature importance rankings, the coefficient of variation (CV) of importance scores for features that appear in the top 10 lists of both stations is calculated and presented in Table 11.

The SHAP analysis results reveal four key findings: (1) Plane-of-Array (POA) irradiance is the most dominant predictive feature, consistently ranking first in both datasets; (2) Irradiance-related features (including Global Horizontal Irradiance (GHI), POA irradiance, and their derived combination features) occupy the majority of top positions in the feature importance rankings; (3) Cross-feature interaction terms (such as $GHI \times$ relative humidity and $GHI \times$ ambient temperature) demonstrate stronger predictive power than individual meteorological features; (4) Nonlinear transformed features (such as GHI squared) and

temporal features (such as the distance-to-peak feature, which measures the time difference from the current time to the daily solar noon peak) also exhibit high predictive importance.

Table 9. Top 10 most influential features for the Station 1 test set.

Rank	Feature	SHAP Importance
1	POA irradiance	0.008141
2	dis2peak_POA irradiance	0.003813
3	GHI	0.003764
4	GHI + humidity	0.003657
5	GHI + pressure	0.003360
6	dis2peak_GHI	0.003264
7	GHI + wind direction	0.003213
8	GHI + temperature	0.002810
9	Daytime POA irradiance mean	0.002656
10	GHI + wind speed	0.002450

Table 10. Top 10 most influential features for the Station 2 test set.

Rank	Feature	SHAP Importance
1	POA irradiance	0.010163
2	GHI	0.006483
3	GHI + humidity	0.006396
4	GHI + wind direction	0.005072
5	GHI + pressure	0.005065
6	dis2peak_POA irradiance	0.005009
7	GHI + wind speed	0.004911
8	GHI ²	0.004342
9	dis2peak_GHI	0.004177
10	GHI * humidity	0.003443

Note: The superscript (2) denotes the square symbol, and the superscript * denotes the multiplication symbol.

Table 11. Cross-station stability analysis of common influential features.

Feature	Station 1	Station 2	CV
POA irradiance	0.0081	0.0102	0.1105
GHI + temperature	0.0028	0.0034	0.0978
dis2peak_POA irradiance	0.0038	0.0050	0.1356
dis2peak_GHI	0.0033	0.0042	0.1228
GHI	0.0038	0.0065	0.2654
GHI + humidity	0.0037	0.0064	0.2724
GHI + wind direction	0.0032	0.0049	0.2090
GHI + pressure	0.0034	0.0051	0.2023

The SHAP analysis results demonstrate that the current set of input variables—particularly irradiance-related features (GHI, POA irradiance) and their interaction terms—captures the dominant factors influencing PV power generation across Station 1 and Station 2. The top 10 features consistently explain the majority of predictive variance, validating that the selected variables are sufficient for the forecasting task under typical operating conditions. However, we acknowledge that additional variables could potentially further improve model performance. Variables such as soiling ratio, spectral irradiance, module degradation index, and local shading conditions are known to influence PV power output but were not available in the publicly accessible datasets used in this study. The current feature set thus represents the best available compromise given the dataset constraints,

while the framework itself is flexible enough to accommodate additional inputs if they become available.

5. Conclusions

This paper addresses two critical limitations of existing PV power generation forecasting methods: their inability to fully capture the complex nonlinear spatio-temporal relationships between multivariate meteorological features and PV power output, and their neglect of the intrinsic physical mechanisms governing photovoltaic energy conversion. To overcome these challenges, a novel hybrid forecasting framework (CNN-LSTM-PINNs) that synergistically integrates CNNs, LSTMs, and PINNs is proposed. Through systematic experimental validation on three utility-scale PV power station datasets, the following key conclusions are drawn:

- (1) The proposed CNN-LSTM-PINN hybrid framework achieves significantly superior prediction performance compared to the CNN-LSTM baseline model on the held-out test sets of Stations 1 and 2, with substantial reductions in MAE and RMSE and remarkable improvements in R^2 . These results clearly verify that embedding first-principles physical constraints into data-driven deep learning models effectively enhances prediction accuracy. Furthermore, the proposed framework exhibits stronger prediction robustness under diverse operating conditions, provided that the training and test data distributions remain relatively stable. The improvements observed on Stations 1 and 2 demonstrate that physical constraints can effectively regularize the model and mitigate overfitting when data distributions are consistent.
- (2) When datasets exhibit severe covariate shift (data distribution shift) problems, as observed in Station 3, both the CNN-LSTM-PINNs and CNN-LSTM models exhibit severe generalization failure, even with the incorporation of physical constraints. This finding indicates that extreme data distribution shifts cannot be resolved through model architecture improvements alone. Therefore, comprehensive data characteristic analysis and quality assessment are critically important prior to deploying any deep learning forecasting model in practical PV power generation systems. The generalization capability of the proposed framework is conditional on the stability of the data distribution between training and test periods.
- (3) Feature importance analysis using the SHAP framework reveals that Plane-of-Array (POA) irradiance is consistently the most dominant predictive feature across multiple stations. Irradiance-related features occupy the majority of top positions in the feature importance rankings, and cross-feature interaction terms demonstrate stronger predictive power than individual meteorological features.

This study has several notable limitations that warrant further investigation in future work. First, the physical constraints employed in this paper are based on a simplified irradiance- and temperature-dependent PV power equation; more sophisticated physical models that account for factors such as spectral effects and module degradation could be considered to further improve physical consistency. Second, the experimental data are limited to a three-year time span, and the long-term influences of seasonal variations and equipment aging trends have not been fully explored. Finally, the model hyperparameters, particularly the physics loss weight λ , was determined through systematic grid search; adaptive parameter adjustment strategies that dynamically optimize the trade-off between data fitting and physical consistency could be developed. Additionally, the framework's generalization capability under severe data distribution shifts, as observed in Station 3, could be enhanced through domain adaptation or incremental learning techniques, which represent practical and implementable directions for future research.

Potential future research directions include: (1) incorporating more comprehensive physical models, such as detailed photovoltaic cell equivalent circuit models and atmospheric radiative transfer models, to enhance the physical fidelity of the forecasting framework; (2) extending the proposed deterministic forecasting framework to probabilistic forecasting to provide prediction intervals and rigorous uncertainty quantification, which is essential for supporting risk-aware decision-making in power system operation; (3) developing online learning or incremental learning mechanisms to enable the model to continuously adapt to evolving environmental conditions and gradual equipment aging; and (4) validating the proposed framework on larger and more diverse datasets from different geographic regions and climate zones to further assess its cross-regional generalization capability.

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Abbreviations

The following abbreviations are used in this manuscript:

PV	Photovoltaic
CNNs	Convolutional Neural Networks
LSTM	Long Short-Term Memory (LSTM) networks
PINNs	Physics-Informed Neural Networks
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
R ²	Coefficient of Determination
GHI	Global Horizontal Irradiance
IEA	International Energy Agency
RNN	Recurrent Neural Networks
GNN	Graph Neural Networks
TiDE	Time-series Dense Encoder
WPD	Wavelet Packet Decomposition
SSA	Sparrow Search Algorithm
ST-GNN	Spatio-Temporal Graph Neural Networks
DP-PINN	Dynamic-Parameter Physics-Informed Neural Network

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