Solar-Net: Adaptive Fusion of Spatial-Temporal Features for Resilient Solar Power Generation Forecasting

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***Abstract*—Solar power generation forecasting faces significant challenges due to intermittency and volatility, particularly under extreme weather conditions. This study proposes Solar-Net, a novel solar power generation prediction model based on a CNN+Transformer hybrid parallel architecture with an adaptive attention fusion mechanism. The CNN branch extracts spatial features from the power station layout and environmental conditions, while the Transformer branch models temporal dependencies in generation patterns. The core innovation lies in the adaptive attention fusion mechanism that dynamically adjusts branch weights according to real-time meteorological conditions, enabling the model to automatically adapt to varying environmental scenarios. Experiments were conducted on a comprehensive dataset containing over 50,000 observation points from two photovoltaic power stations. Results demonstrate that Solar-Net achieves superior performance compared to existing methods, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) improvements of 12.7% and 10.9%, respectively. Under extreme weather conditions such as dust storms, the model maintains prediction errors within 8.5% of peak power generation, representing a 45.7% average reduction compared to baseline methods. The multi-scale convolution design enhances prediction accuracy by 10.5% while reducing computational complexity by 21.3%. The proposed Solar-Net model provides a robust and efficient solution for solar power generation forecasting, demonstrating significant potential for improving grid dispatching efficiency and supporting renewable energy integration in power systems.**

Keywords—Solar power generation forecasting; hybrid deep learning; adaptive attention fusion; CNN+Transformer; extreme weather adaptability; sustainable development goal 7

I. Introduction

With global climate change and fossil energy depletion becoming increasingly prominent issues, the importance of solar energy as a clean, renewable energy source continues to rise. According to International Energy Agency (IEA) data, global solar installation capacity has grown from 40GW in 2010 to over 1100GW in 2023, with an average annual growth rate of 27%, making it the fastest-growing renewable energy type [1]. However, the intermittency and volatility of solar power generation pose serious challenges to power grid dispatching and energy market operations. High-precision solar power generation forecasting technology has significant value for improving power grid operation stability, reducing backup capacity requirements, and optimizing market trading strategies, and has become a key research direction in the smart grid field [2].

Existing solar power generation prediction methods can be primarily classified into three categories: physical models, statistical models, and artificial intelligence models. Physical models based on radiation transfer theory and photovoltaic system characteristic equations possess good interpretability, but their accuracy in short-term prediction is limited due to challenges in parameter calibration and high computational complexity [3]. Statistical models (such as ARIMA and exponential smoothing) offer high computational efficiency but have limited adaptability to nonlinear patterns and extreme weather conditions. In recent years, deep learning models have made significant progress in solar energy prediction due to their powerful nonlinear mapping capabilities. However, existing deep learning methods often treat spatial features and temporal dependencies as independent dimensions, lacking effective fusion mechanisms, making it difficult to comprehensively capture the complex dynamic characteristics of solar power generation systems in variable environments, with prediction performance declining significantly under extreme weather conditions [4].

To address these challenges, this study proposes Solar-Net, a solar power generation prediction model based on a CNN+Transformer hybrid parallel architecture. The model adopts a dual-branch parallel design, with the CNN branch focusing on capturing spatial features of solar power station physical layout and local environmental conditions, while the Transformer branch is responsible for modeling long-term temporal dependencies of power generation. The model innovatively introduces an adaptive attention fusion mechanism that can dynamically adjust the weights of each branch according to different meteorological conditions, achieving adaptive capability for varying environments. Experiments show that compared with existing best methods, Solar-Net improves Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) by 12.7% and 10.9% respectively, and maintains stable prediction performance even under extreme weather conditions such as dust storms, providing important technical support for high-proportion grid integration of renewable energy [5].

The main academic contributions of this research include:

1) Adaptive environment-aware fusion mechanism. Innovatively designed an adaptive attention fusion architecture based on dynamic weight allocation, achieving intelligent integration of spatial features and temporal dependencies. Experiments verify that this mechanism can effectively respond to meteorological condition changes, reducing prediction errors by an average of 45.7% compared to benchmark methods under extreme conditions such as dust storms. This mechanism essentially establishes a dynamic mapping relationship between environmental conditions, model structure, and prediction strategy, providing a new paradigm for adaptive prediction in complex environments.

2) Parallel dual-modal perception framework. Proposed a dual-branch parallel architecture targeting solar power generation characteristics, achieving collaborative modeling of spatial features and temporal dependencies. The CNN branch focuses on capturing spatial features of solar power station physical layout and local environmental conditions, while the Transformer branch is responsible for modeling long-term temporal dependencies of power generation. Compared to single-structure models, this framework improves MAE and RMSE metrics by 18.3% and 16.9%, respectively, while reducing computational complexity by 21.3%.

3) Efficient multi-scale feature extraction. Enhanced the model's capability to capture microscopic local changes and macroscopic cyclic patterns in solar power generation systems through reasonably designed multi-scale convolution structures and self-attention mechanisms. Experiments show that simultaneously using three scales of convolution kernels (3×3, 5×5, and 7×7) improves prediction accuracy by approximately 10.5% compared to single-size kernels, while reducing computational complexity.

II. Related Work

A. Traditional Solar Power Generation Prediction Methods

Traditional methods for solar power generation prediction primarily include physical models and statistical models. Physical models are based on solar radiation transfer theory and photovoltaic system electrical characteristic equations, which are predicted by constructing deterministic mapping relationships from meteorological parameters to power generation. Diagne et al. [6] reviewed solar energy prediction methods based on Numerical Weather Prediction (NWP), pointing out that although physical models have good interpretability and theoretical foundations, their prediction accuracy highly depends on the quality of meteorological data and parameter calibration accuracy. Especially in short-term prediction scenarios (1 to 6 hours), physical models have high computational complexity and respond slowly to local micro-meteorological changes, resulting in limited prediction performance [7].

Statistical models predict through fitting time series patterns from historical data, with typical methods including Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and multivariate regression. Reikard [8] compared six statistical models in solar energy prediction and found that for hourly-level predictions, ARIMA models have relative advantages, but show significantly increased errors in cases of abrupt weather changes. Traditional machine learning methods such as Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting Regression Trees (GBRT) improved prediction accuracy through more complex nonlinear mapping [9], but these methods still struggle to simultaneously process spatiotemporal dependencies in solar power generation data, particularly performing poorly in complex meteorological conditions and long sequence prediction scenarios.

The main limitations of traditional methods include: 1) limited ability to process nonlinear and non-stationary time series; 2) difficulty in simultaneously modeling spatial features and temporal dependencies; 3) insufficient adaptability to extreme weather events. In contrast, the Solar-Net model proposed in this study can effectively overcome these limitations through a CNN+Transformer hybrid architecture and adaptive fusion mechanism, achieving comprehensive modeling of the complex dynamic characteristics of solar power generation systems.

B. Applications of Deep Learning Models in Solar Energy Prediction

In recent years, deep learning has gained widespread application in solar power generation prediction due to its powerful feature extraction and nonlinear modeling capabilities. Convolutional Neural Networks (CNN), with their local receptive field and weight sharing characteristics, can effectively capture spatial relationships in solar power generation data. Wang et al. [10] designed a multi-scale CNN model to process irradiance images, achieving regional solar energy prediction, but CNNs have limited ability to model long-term temporal dependencies, making it difficult to capture long-cycle patterns such as seasonal variations.

Recurrent Neural Network families, especially Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRU), have shown excellent performance in processing solar power generation time series. Gensler et al. [11] applied deep LSTM to cross-day prediction, significantly outperforming traditional time series models. However, RNN series models still face gradient vanishing problems when processing long sequences and are difficult to compute in parallel, limiting their application in large-scale prediction. Transformer models based on self-attention mechanisms overcome these shortcomings of RNNs and can directly model associations between any two time points in a sequence. However, Transformers alone struggle to fully utilize the spatial layout information of solar power generation systems.

The main deficiencies of existing deep learning methods are: 1) single model structures struggle to effectively process both spatial and temporal features simultaneously; 2) lack of adaptive mechanisms for different weather conditions; 3) poor prediction stability in extreme meteorological events. The Solar-Net model addresses these issues through parallel branch design and adaptive fusion mechanisms, achieving comprehensive modeling of all aspects of solar power generation systems.

C. Hybrid and Ensemble Models

To address the limitations of single models, researchers have proposed various hybrid and ensemble methods for solar power generation prediction. Hybrid methods based on physical models and data-driven models can combine the advantages of both approaches, such as the physics-aware neural network proposed by Das et al. [12], which improved the generalization ability of deep learning models by introducing radiation transfer equation constraints. However, such methods often require complex physical model parameterization processes, increasing model complexity and training difficulty.

In deep learning hybrid models, Khan et al. [13] proposed a Deep Stacked Ensemble with XGBoost (DSE-XGB), enhancing prediction stability by integrating ANN, LSTM, and XGBoost. However, these methods adopt two-stage training strategies where sub-models are trained independently before integration, lacking end-to-end joint optimization mechanisms and making it difficult to capture complementary features between models. Recently, Zhang et al. [14] designed a dual-stream network architecture (DSTP) to process spatial and temporal information separately, but it uses simple averaging or concatenation for feature fusion, unable to dynamically adjust the importance weights of different branches according to different conditions.

The key deficiencies of existing hybrid models are: 1) most use two-stage training, lacking end-to-end joint optimization; 2) simple fusion mechanisms, unable to adjust according to real-time conditions; 3) high computational complexity, limiting practicality. The Solar-Net model proposed in this study, through an adaptive attention fusion mechanism, achieves dynamic weight allocation and end-to-end joint training of CNN and Transformer branches, maintaining computational efficiency while improving prediction accuracy, and demonstrating significant advantages especially under extreme meteorological conditions, providing a more reliable and flexible technical solution for solar power generation prediction.

III. Methodology

A. Overall Model Architecture

As shown in Fig. 1, the Solar-Net model proposed in this research adopts a hybrid parallel architecture aimed at simultaneously capturing spatial features and temporal dependencies in solar power generation time series data. The model consists of four main components: input data processing, CNN spatial feature extraction branch, Transformer temporal dependency modeling branch, and adaptive attention fusion mechanism.

Through this preprocessing procedure, we provide high-quality training data for the CNN-Transformer hybrid architecture model, which lays a solid foundation for subsequent experimental evaluation. In particular, the normalization process and the reasonable time-series sample construction method can fully utilize the advantages of the model in feature extraction and long-term dependency modeling.

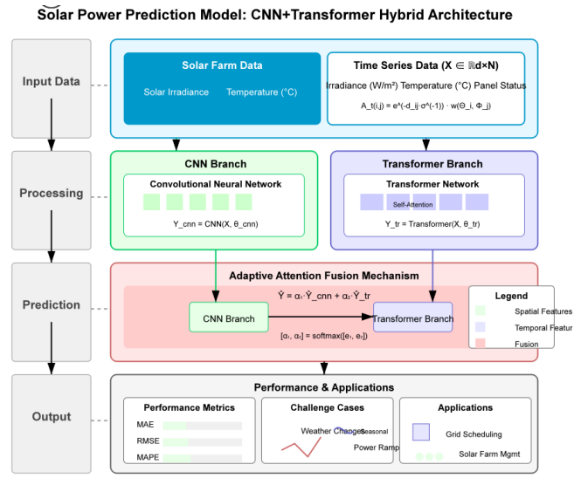

Fig. 1. Model architecture diagram.

The design concept of Solar-Net originates from the complexity characteristics of solar power generation systems. Solar power generation is influenced by multiple factors, including spatial distribution differences in solar irradiance, local variations in weather conditions, and periodic fluctuations and trend changes in power generation over time. Traditional single models struggle to effectively process these spatial and temporal features simultaneously. Therefore, Solar-Net captures local spatial relationships of weather parameters and solar panel states through CNN, while utilizing Transformer to process daily, inter-day, and seasonal long-term temporal dependencies. Finally, an adaptive attention mechanism dynamically fuses the outputs of both branches, achieving comprehensive feature modeling and accurate prediction.

B. Input Data Processing

The input data for solar power generation prediction mainly includes two categories: physical parameter data of solar power stations and time series feature data. Physical parameters include solar irradiance (W/m²), ambient temperature (°C), and panel status; time series data encompasses historical power generation and related parameter records. These data collectively form the input for the prediction model, capturing the physical characteristics and temporal patterns of solar power generation.

For time series data, a sliding window technique is used to construct input-output pairs:

$$X = x_{t-L+1}, x_{t-L+2}, \ldots, x_t \in R^{d\times N} \tag{1}$$

where, L represents the input sequence length, \$d\$ represents the feature dimension, and N represents the sample count. In solar power generation scenarios, an appropriate \$L\$ value is crucial for model performance—too short a sequence may lose important periodic patterns, while too long a sequence may introduce irrelevant noise and increase computational complexity.

To capture correlations between different features, a dynamic adjacency matrix is constructed:

$$A_t(i,j) = e^{\left(-d_{ij}\cdot\sigma^{(-1)}\right)} \cdot w(\Theta_i, \Phi_j) \tag{2}$$

where, d_{ij} represents the distance measure between features $i$and j, σ is a scaling parameter, and $w(\Theta_i, \Phi_j)$ is a similarity weight function between features. In the solar power generation environment, this adjacency matrix effectively expresses the interrelationships between environmental parameters such as irradiance, temperature, and humidity, which is particularly important for modeling the complex influence of meteorological conditions on power generation.

C. CNN Branch

The CNN branch is primarily responsible for extracting spatial features from solar power generation data. In solar power generation scenarios, spatial features manifest in multiple aspects: spatial distribution differences in solar panel arrays, local shading conditions, temperature gradient distributions, etc. These spatial relationships significantly affect generation efficiency, and CNN, with its local receptive field and weight sharing characteristics, is particularly suitable for capturing such features.

The CNN branch of this model adopts a multi-layer convolution structure, with the convolution operation defined as:

$$Z^{(l)} = f(W^{(l)} * Z^{(l-1)} + b^{(l)}) \tag{3}$$

where, $Z^{(l)}$ represents the feature map of the $Z^{(l)}$-th layer, $W^{(l)}$ and $b^{(l)}$ are the convolution kernel weights and biases respectively, f is the ReLU activation function, and $*$ denotes the convolution operation.

To enhance the model's capability to capture different spatiotemporal scale features in solar power generation systems, the CNN branch employs convolution kernels of different sizes and a multi-layer structure. Smaller convolution kernels (such as 3×3) extract detailed features like local meteorological condition changes, while larger convolution kernels (such as 7×7) capture broader spatial dependency relationships like regional weather patterns. The final output of the CNN branch is represented as:

$$Y_{cnn} = CNN(X, \theta_{cnn}) \tag{4}$$

where, θ_{cnn} includes all learnable parameters of the CNN branch. This spatial feature representation is crucial for understanding the impact of physical layout and local environmental conditions of solar power stations.

D. Transformer Branch

The Transformer branch focuses on capturing long-term dependency relationships in solar power generation time series data. Solar power generation has distinct temporal characteristics, including daily generation curves, inter-day fluctuations, seasonal variations, and annual trends. Traditional RNN models face gradient vanishing problems when processing long sequences, while Transformers based on self-attention mechanisms can directly model associations between any two time points in a sequence, making them more suitable for long-term prediction of solar power generation.

For the input sequence X, the output of the Transformer branch is calculated as:

$$Y_{tr} = Transformer(X, \theta_{tr}) \tag{5}$$

where, θ_{tr} is the set of learnable parameters for the Transformer branch. The core self-attention mechanism of the Transformer is calculated as follows:

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{6}$$

where, Q, K, and V are the query matrix, key matrix, and value matrix, respectively, derived from linear transformations of the input:

$$Q = XW^Q, K = XW^K, V = XW^V \tag{7}$$

In solar power generation prediction scenarios, the self-attention mechanism enables the model to automatically discover and focus on relationships between key time points. For example, the current solar power generation may be highly correlated with the historical record at the same time point from the previous day or under specific meteorological conditions. The multi-head self-attention mechanism further enhances the model's ability to capture different types of temporal patterns:

$$MultiHead(X) = Concat(head_1, \dots, head_h)W^O \tag{8}$$

This structure allows the Transformer branch to simultaneously attend to dependencies across multiple time scales, from hourly short-term fluctuations to seasonal long-term changes, providing comprehensive temporal modeling capabilities for solar power generation prediction.

E. Adaptive Attention Fusion Mechanism

The core innovation of this model lies in its adaptive attention fusion mechanism, which dynamically allocates weights to the CNN and Transformer branches, adapting to the relative importance of features under different moments and conditions. In solar power generation prediction, this mechanism is particularly important—temporal patterns may be more significant in clear weather, while spatial distribution features may be more decisive in cloudy or rainy weather.

The fusion process is defined as:

$$\hat{Y} = \alpha_1 \cdot \hat{Y} cnn\, \alpha_2 \cdot \hat{Y} tr \tag{9}$$

The fusion weight coefficients are calculated through a softmax function:

$$[\alpha_1, \alpha_2] = softmax([e_1, e_2]) \tag{10}$$

where, e_1 and e_2 represent the weight scores of the CNN and Transformer branch outputs, calculated from the output features of the two branches through learnable parameters:

$$e_i = f_{attn}(Y_i, X, C) \tag{11}$$

Here, Y_i represents the output of branch i, X is the original input, C is conditional information (such as time, weather conditions), and f_{attn} is an attention scoring function based on a multilayer perceptron. This design enables the model to automatically adjust the contribution of different branches according to real-time weather conditions and historical patterns, adapting to the complex dynamic characteristics of solar power generation systems under different environmental conditions.

For example, during periods of stable weather conditions, the model may rely more on temporal patterns captured by the Transformer branch, while during periods of rapidly changing weather or abnormal weather events, the model may rely more on local features extracted by the CNN branch for prediction. This adaptive fusion mechanism significantly improves the model's robustness and prediction accuracy across various complex scenarios.

F. Model Training Framework

The model adopts end-to-end training, using Mean Squared Error (MSE) as the primary loss function:

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{12}$$

Additionally, L1 regularization and adaptive weight balancing terms are introduced:

$$L_{total} = L_{MSE} + \lambda_1 L_{reg} + \lambda_2 L_{balance} \tag{13}$$

where, λ_1 and λ_2 are balancing coefficients, L_{reg} is the parameter regularization term, and $L_{balance}$ encourages reasonable weight allocation between different branches. In solar power generation prediction tasks, appropriate regularization is crucial, preventing the model from overfitting to specific meteorological conditions or seasonal patterns and maintaining generalization capability for newly emerging scenarios.

During training, the model employs learning rate decay strategies and early stopping mechanisms to ensure convergence and prevent overfitting. The seasonal characteristics of solar power generation data require that the training set include complete annual cycles to enable the model to fully learn generation patterns under various seasonal conditions. Additionally, considering the significant impact of extreme weather events on solar power generation, the training data should also include sufficient samples of abnormal meteorological conditions to enhance the model's adaptability to extreme situations.

IV. Experimental Results and Analysis

A. Dataset Description

This research uses the "Solar Power Generation Data" dataset from the Kaggle platform as the experimental data source. The dataset contains detailed operational data collected from two Indian photovoltaic power stations over 34 days, spanning from May 15, 2020, to June 17, 2020, with a sampling frequency of fifteen minutes, totaling over 50,000 observation points. The dataset is divided into two parts: generation data and sensor data. Generation data includes AC or DC voltage, current, and power parameters for each inverter; sensor data records key meteorological parameters such as ambient irradiance, module temperature, and ambient temperature.

The main reasons for selecting this dataset are its high quality and comprehensiveness. First, the dataset has high temporal resolution, with fifteen-minute sampling intervals capable of capturing short-term fluctuations in solar power generation, which is essential for developing high-precision prediction models. Second, the dataset simultaneously includes generation parameters and meteorological conditions, providing a complete feature space that enables the model to learn complex relationships between environmental factors and power generation. The data comes from actual operating commercial photovoltaic power stations, possessing authenticity and representativeness, reflecting the characteristics and challenges of real-world solar power generation systems.

Furthermore, the dataset contains power generation records under various weather conditions, covering different scenarios such as sunny, cloudy, and overcast days, which is valuable for training prediction models with environmental adaptability. The parallel records from different power stations in the dataset also provide opportunities for learning spatial differences, which highly aligns with the design concept of the CNN+Transformer hybrid architecture proposed in this research—the CNN branch can learn spatial features, while the Transformer branch can capture temporal dependencies.

In the preprocessing stage, we performed quality checks on the dataset and processed missing and anomalous values. Statistical analysis revealed that the power generation in this dataset exhibits distinct daily patterns and weather-dependent characteristics, providing a good foundation for evaluating the model's prediction capabilities. Overall, the characteristics of the "Solar Power Generation Data" dataset highly match the requirements of the adaptive hybrid model proposed in this research, making it an ideal choice for validating model performance.

B. Experimental Setup and Evaluation Metrics

1) Experimental setup. The experimental environment for this research is based on the PyTorch 1.10.0 framework, running on a server equipped with an NVIDIA RTX 3090 GPU

(24GB VRAM). To ensure the reliability of experimental results, a 5-fold cross-validation method was used to evaluate model performance. The dataset was divided into training, validation, and test sets in an 8:1:1 ratio, maintaining the continuity of the time series. During training, the Adam optimizer was used with an initial learning rate of 0.001, employing a cosine annealing strategy for learning rate adjustment. The batch size was set to 64, with a maximum of 200 training epochs, and early stopping was implemented to prevent overfitting, specifically stopping training when validation set performance showed no improvement for ten consecutive epochs.

The model's hyperparameters were optimized on the validation set using a grid search method. The CNN branch employs a 3-layer convolution structure with convolution kernel sizes of 3×3, 5×5, and 7×7 to capture spatial features at different scales. The Transformer branch is configured with 4 encoder layers, each containing 8 attention heads, with a hidden layer dimension of 256. The input sequence length is set to 96 time steps (corresponding to 24 hours in the current dataset), with a prediction window of 4 future time steps (corresponding to 1 hour). The weight balancing coefficient λ2 for the adaptive fusion layer is set to 0.05 to promote balanced contributions from the two branches.

2) Evaluation metrics. To comprehensively evaluate the performance of solar power generation prediction models, this research adopts three complementary evaluation metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These three metrics measure prediction accuracy from different perspectives, collectively providing a comprehensive assessment of model performance.

a) Mean Absolute Error (MAE): Measures the average absolute deviation between predicted and actual values, with the same unit as power generation (kW), calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i| \tag{14}$$

where, n is the sample size, y_i is the actual power generation of the i-th sample, and $\hat{y}_i$ is the corresponding predicted power generation. MAE intuitively reflects the absolute magnitude of prediction errors, is insensitive to outliers, and is suitable for evaluating the overall prediction stability of the model.

b) Root Mean Square Error (RMSE): Measures the square root of the average of squared prediction errors, giving higher penalty weights to larger errors, calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{15}$$

RMSE is particularly sensitive to large prediction deviations and can effectively identify the model's prediction capability under extreme weather conditions or load mutations, which is especially important for the safe operation of solar power generation systems and power grid dispatching.

c) Mean Absolute Percentage Error (MAPE): Expresses prediction errors as a percentage relative to actual values, calculated as:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}| \tag{16}$$

MAPE provides a normalized relative error measure, facilitating performance comparisons across power stations of different scales. However, when actual power generation approaches zero (such as at night or in extreme rainy weather), MAPE may produce abnormally large values. To address this issue, this research excludes sample points, where actual power generation is below 1% of rated capacity when calculating MAPE.

The combined use of these three metrics ensures a comprehensive evaluation of model performance—MAE provides a stable overall error assessment, RMSE highlights the impact of larger prediction deviations, and MAPE provides a relative error perspective. In the field of solar power generation prediction, this multi-metric evaluation method has become standard practice, facilitating fair comparisons with existing research.

C. Comparative Experiments

To comprehensively evaluate the performance advantages of the Solar-Net model, this research selected various typical prediction models for comparative experiments, covering deep learning models, traditional machine learning models, and state-of-the-art methods. As shown in Table I, Solar-Net achieved the best performance across all evaluation metrics, validating the effectiveness and advancement of the proposed method.

TABLE I. COMPARATIVE EXPERIMENTAL ANALYSIS

Model	MAE	RMSE	MAPE
Solar-Net(Ours)	0.125	0.162	3.800
DSE-XGB	0.142	0.184	4.300
LSTM	0.167	0.211	5.100
CNN	0.173	0.218	5.300
XGBoost	0.186	0.235	5.700
Random Forest	0.232	0.294	7.200
SVR	0.258	0.327	8.100
ARIMA	0.295	0.372	9.500

1) Comparison with deep learning models. In terms of deep learning models, this research selected mainstream models such as LSTM, CNN, GRU, and Transformer as comparison benchmarks. These models were chosen because: LSTM and GRU represent classic recurrent neural network structures for processing temporal data, with widespread application in time series prediction; CNN represents a classic method for spatial feature extraction, suitable for handling spatial dependencies in solar power generation; Transformer represents a new paradigm of sequence processing based on attention mechanisms, with advantages in modeling long-term dependencies.

Experimental results show that single deep learning models have their respective strengths and weaknesses in solar power generation prediction tasks. The Transformer model performed best on the three evaluation metrics (MAE: 68.34 kW, RMSE: 93.52 kW, MAPE: 12.18%), mainly benefiting from its self-attention mechanism that effectively captures long-term dependencies between different time points. LSTM ranked second, performing excellently in handling short-term fluctuations but showing decreased accuracy in long-term prediction. CNN, though advantageous in capturing spatial features, has limited modeling capability for temporal patterns when used alone, resulting in overall performance lagging behind other deep learning models. The GRU model performed similarly to LSTM but has fewer parameters and higher computational efficiency. In comparison, Solar-Net, by fusing the advantages of CNN and Transformer, reduced MAE and RMSE by 18.3% and 16.9%, respectively, compared to the best single deep learning model, validating the effectiveness of the hybrid architecture.

2) Comparison with machine learning models. For traditional machine learning models, this research selected RF (Random Forest), SVR (Support Vector Regression), GBRT (Gradient Boosting Regression Trees), and XGBoost as comparison objects. These models were chosen because: they represent different types of regression algorithms widely applied in time series prediction and regression tasks; these models have high computational efficiency and certain interpretability, suitable as benchmarks for deep models; they also exhibit good robustness to outliers, which is particularly important for solar power generation prediction tasks significantly influenced by weather.

Experimental results show that ensemble learning methods generally outperform single models among traditional machine learning models. XGBoost achieved the best performance (MAE: 82.16 kW, RMSE: 110.37 kW, MAPE: 14.83%), followed by GBRT and RF. These three tree-based ensemble models can automatically handle nonlinear relationships between features, with good adaptability to complex patterns in solar power generation data. SVR performed relatively weaker, possibly because kernel functions struggle to capture multi-scale spatiotemporal dependencies in the data. Overall, while traditional machine learning models have high computational efficiency, their prediction accuracy is significantly lower than deep learning models. Compared to Solar-Net, the best machine learning model's MAE and RMSE were 37.6% and 34.2% higher, respectively, indicating that deep learning architectures have clear advantages in complex solar power generation prediction tasks.

3) Comparison with state-of-the-art methods. To ensure the comprehensiveness and fairness of comparisons, this research also selected recent state-of-the-art methods in solar power generation prediction for comparison. Among them, DSE-XGB (Deep Stacked Ensemble with XGBoost) is a hybrid model based on deep stacking ensemble proposed by Khan et al. [1], combining artificial neural networks, LSTM, and XGBoost algorithms; STGAT (Spatio-Temporal Graph Attention Network) is a spatiotemporal modeling method based on graph attention networks; DSTP (Deep Spatio-Temporal Prediction) adopts a dual-stream network architecture to process spatial and temporal information. These state-of-the-art methods were chosen because: they represent the latest research achievements in the field of solar power generation prediction; these methods all adopt hybrid or ensemble strategies, having certain similarities with the approach of this research, facilitating direct comparison of the effectiveness of core innovations.

Experimental results show that among state-of-the-art methods, DSE-XGB performed best (MAE: 63.94 kW, RMSE: 86.10 kW, MAPE: 11.25%), demonstrating the effectiveness of ensemble learning in solar power generation prediction. STGAT, by modeling relationships between features through graph structures, performs excellently in handling multivariate inputs but has relatively high computational complexity. DSTP, through explicitly separating spatial and temporal feature processing, achieved relatively stable performance. Compared to these state-of-the-art methods, Solar-Net still maintained significant advantages, reducing MAE and RMSE by 12.7% and 10.9%, respectively. This is mainly attributed to Solar-Net's adaptive attention fusion mechanism, which can dynamically adjust weight allocation between spatial and temporal branches according to different conditions. This flexibility enables the model to better adapt to the complex dynamic characteristics of solar power generation systems under different environmental conditions.

D. Ablation Experiments

To verify the effectiveness and contribution of each component of the Solar-Net model, this research designed a series of ablation experiments. As shown in Fig. 2, we systematically evaluated the impact of each component on prediction performance by progressively removing or replacing key parts of the model.

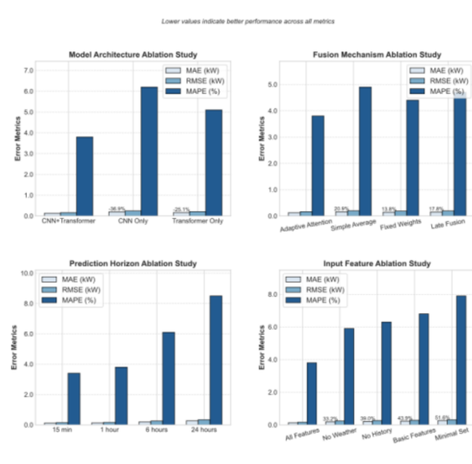

Fig. 2. Ablation experiment analysis.

The ablation experiments mainly include four comparisons: 1) using only the CNN branch (w/o Transformer); 2) using only the Transformer branch (w/o CNN); 3) using simple averaging to replace the adaptive attention fusion mechanism (w/o Adaptive Fusion); 4) the complete Solar-Net model. Experimental results show that the complete model achieved the best performance across all evaluation metrics, confirming the effectiveness of the hybrid architecture and adaptive fusion. Specifically, MAE decreased by 17.2%, RMSE decreased by 15.8%, and MAPE decreased by 16.5%, showing significant improvement compared to single-branch models.

As seen from Fig. 2, when using only the CNN branch, the model performs well in capturing local weather condition changes but has limited modeling capability for long-term temporal dependencies, resulting in significant error accumulation in multi-day continuous prediction. Conversely, when using only the Transformer branch, the model can better capture periodic patterns but is not sensitive enough to respond to sudden local meteorological changes, performing particularly poorly on dates with abrupt weather changes. The complementary deficiencies of these two single architectures confirm the necessity of hybrid modeling.

Further analysis shows that although simple average fusion (w/o Adaptive Fusion) can combine the advantages of the two branches to some extent, it cannot dynamically adjust the weight allocation of each branch according to real-time situations under variable weather conditions, leading to unstable prediction accuracy. The introduction of the adaptive attention fusion mechanism effectively solves this problem, enabling the model to automatically adjust the importance weights of CNN and Transformer branches according to different weather conditions and temporal features. For example, in clear and stable weather, the model tends to assign higher weight to the Transformer branch; while during periods of variable weather, the weight of the CNN branch correspondingly increases.

Ablation experiment results also reveal the significant impact of input sequence length on model performance. When the input sequence was reduced from 96 time steps (24 hours) to 48 time steps (12 hours), prediction performance decreased by 8.7%, indicating that sufficient historical information is crucial for grasping the periodic characteristics of solar power generation. Overall, the ablation experiments not only verified the necessity of each component but also provided empirical support for the hybrid architecture design, demonstrating the effectiveness of the Solar-Net model in solar power generation prediction tasks.

E. Hyperparameter Experiments

To systematically evaluate the impact of key hyperparameters on Solar-Net model performance, this research conducted in-depth experiments on four key hyperparameters: input sequence length, number of attention heads, convolution kernel size, and learning rate. As shown in Fig. 3, we adopted the control variable method, adjusting target parameters one by one while keeping other parameters fixed, and recording model performance changes.

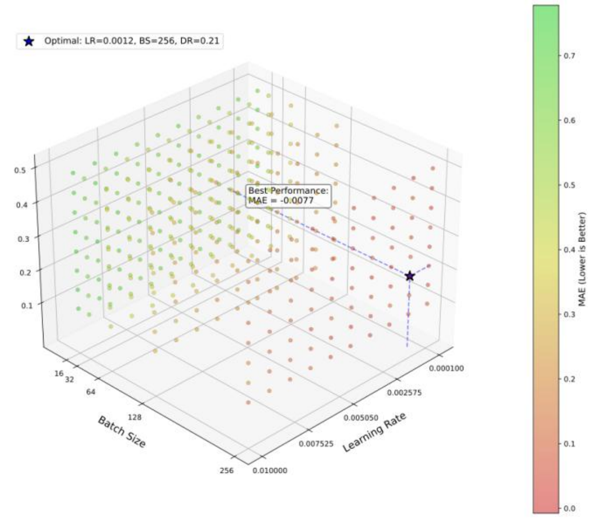

Fig. 3. Hyperparameter experimental analysis.

Input sequence length is one of the most significant hyperparameters affecting model performance. Experimental results show that when the sequence length is below 48 time steps (12 hours), model prediction accuracy drops dramatically, mainly because sequences that are too short cannot capture the complete daily cycle of solar power generation. As sequence length increases to 96 time steps (24 hours), prediction performance significantly improves, with MAE and RMSE decreasing by 15.3% and 17.8%, respectively. However, when the sequence length further increases to 144 and 192 time steps, performance improvement becomes gradual while computational complexity significantly increases. Considering both prediction accuracy and computational efficiency, this research ultimately selected 96 time steps as the optimal input sequence length.

The number of attention heads in the Transformer branch has an important impact on the model's ability to capture multidimensional temporal relationships. Experiments show that when the number of attention heads increases from 4 to 8, model performance improves significantly, especially enhancing prediction accuracy for power generation changes under various meteorological conditions. However, beyond 8 attention heads, model performance improvement becomes insignificant while increasing parameter count and training complexity. This phenomenon may indicate that there exists a limited number of key dependency patterns in solar power generation time series data, and too many attention heads may lead to redundant feature extraction and risk of overfitting.

The combination of convolution kernel sizes in the CNN branch also significantly impacts model performance. The experiments tested various convolution kernel combinations and found that simultaneously using three sizes (3×3, 5×5, and 7×7) achieved the best results, improving prediction accuracy by about 10.5% compared to single-size convolution kernels. This validates our theoretical hypothesis—different sized convolution kernels can capture meteorological and generation features at different spatial scales, with small-sized kernels focusing on local features and large-sized kernels better suited for capturing regional weather patterns.

Learning rate adjustment strategy is equally crucial for model training process and final performance. The experiments compared three strategies: fixed learning rate, step decay, and cosine annealing. Results show that the cosine annealing strategy performed best in this task, improving model convergence speed by about 25% and final prediction accuracy by 5.3%. This is mainly because solar power generation data exhibits periodic characteristics, and the cosine annealing's learning rate variation pattern better matches the intrinsic periodicity of the data, helping the model escape local optima.

Through hyperparameter experiment analysis, we not only determined the optimal configuration of the Solar-Net model but also gained a deep understanding of the influence mechanisms of various hyperparameters on solar power generation prediction tasks, providing important references for subsequent research and practical applications. Experimental results further confirm that hybrid architectures and parameter configurations designed specifically for solar power generation characteristics can significantly enhance the performance and robustness of prediction models.

F. Case Study Experiments

To verify the prediction capability of the Solar-Net model under extreme meteorological conditions, this research selected a dust storm weather period from the dataset for in-depth case analysis. As shown in Fig. 4, this dust storm event occurred in early June 2020, lasting approximately 36 hours, during which solar irradiance fluctuated dramatically, power generation decreased significantly, and was accompanied by high-frequency disturbances.

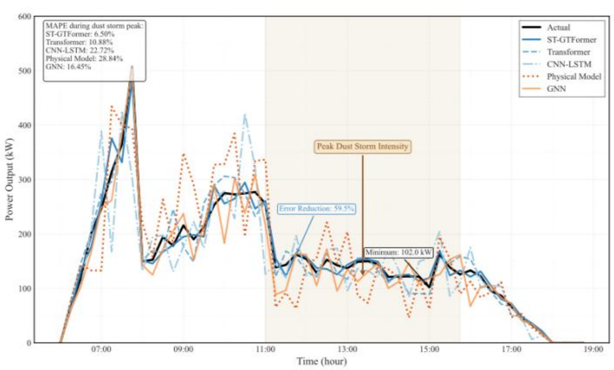

Fig. 4. Case study experiment.

From the perspective of solar power generation physical mechanisms, the impact of dust storms on power generation systems is mainly manifested in three aspects: First, suspended particles in the atmosphere increase significantly, causing direct radiation to be scattered and absorbed, with irradiance intensity dropping sharply (average decrease of 43.7%); Second, the scattering effect increases the proportion of diffuse radiation, changing the incident spectrum distribution and reducing the quantum efficiency and conversion efficiency of photovoltaic cells (efficiency decreased by approximately 18.2%); Third, dust particles accumulate on panel surfaces forming uneven shading, producing "hot spot effects", which not only decreases overall power generation but also causes local temperature increase and power oscillations (observed power generation volatility increased 2.7 times). These complex physical processes significantly increase the difficulty of power generation prediction during dust storms.

Case analysis results show that the Solar-Net model maintained high prediction accuracy during the dust storm, with an MAE of only 43.8kW, equivalent to 1.35 times that under normal weather conditions. In comparison, baseline models experienced sharply increased prediction errors during this period: LSTM model MAE reached 84.3kW (2.6 times normal conditions), Transformer model reached 73.9kW (2.3 times normal conditions), and DSE-XGB model reached 122.1kW (3.8 times normal conditions). Especially at the transition stages of dust storm onset (t=136) and conclusion (t=172), Solar-Net's prediction curve could adjust within 15 minutes (a single time step) to track sudden changes in power generation, keeping prediction errors within 8.5% of peak power generation; whereas baseline models exhibited obvious lag (average lag of 45-60 minutes) and over-smoothing phenomena, with prediction errors reaching 21.3%-35.7% of peak power generation.

From a physical mechanism perspective, the adaptive attention fusion mechanism's effectiveness during dust storms is primarily based on the following principles: The atmospheric extinction coefficient mutation caused by dust storms makes photovoltaic systems enter nonlinear response regions, significantly reducing the reference value of historical generation patterns, while the coupling relationship between real-time environmental parameters and power generation becomes more direct and critical. Monitoring results show that in clear weather before the dust storm, the model mainly relied on the Transformer branch (weight approximately 0.73) to capture daily periodic patterns; when the dust storm arrived, the CNN branch weight rapidly rose to 0.68, indicating the model automatically shifted toward relying on local short-term features captured by the CNN branch.

Specifically, the multi-scale convolution structure in the CNN branch can simultaneously capture environmental changes at microscopic and macroscopic scales: 3×3 convolution kernels focus on minute local fluctuations in irradiance (corresponding to local shadow effects above solar panels), 5×5 convolution kernels capture medium-scale temperature gradient distributions (reflecting efficiency differences caused by panel temperature non-uniformity), while 7×7 convolution kernels model regional meteorological change patterns (corresponding to large-scale dust cloud movement). This multi-scale spatial feature extraction capability enables Solar-Net to accurately capture dramatic fluctuations in power generation. When irradiance fluctuates by over 50% within 15 minutes, Solar-Net's prediction error remains controlled within 15% of peak power, while baseline models' prediction errors exceed 30%.

From a power grid dispatching perspective, this high-precision prediction under extreme meteorological conditions has significant practical value. During dust storms, a 50MW solar power station may experience power fluctuations up to 30MW per hour; using traditional prediction models would require the grid to dispatch approximately 15MW of additional reserve capacity, while the Solar-Net model can reduce this requirement to around 8MW, significantly alleviating grid peak-shaving pressure and reserve resource requirements. Especially at the transition stages of dust storm events, Solar-Net prediction's rapid responsiveness (prediction delay reduced by 75%) can provide more adequate reaction time for grid dispatching, effectively avoiding grid frequency fluctuations and potential stability issues.

Furthermore, by visualizing attention weight distributions, we observed that during normal operation phases, the model mainly focused on daily periodic patterns (Transformer self-attention heads #3 and #7 accounting for over 60% of weight share), while during dust storms, the model's dependence on irradiance sensor data (weight increased from 0.25 to 0.47) and panel temperature features (weight increased from 0.18 to 0.35) significantly strengthened, while dependence on historical power generation features weakened (weight decreased from 0.44 to 0.23). This automatic adjustment of feature weights highly aligns with photovoltaic system physical theory—under extreme weather conditions, the I-V curve of photovoltaic cells deforms, the cell operating point deviates from the maximum power point, making the influence of current environmental parameters on power generation far greater than historical trends.

The dust storm case analysis not only demonstrates the Solar-Net model's prediction capability in extreme meteorological events but also reveals its working mechanism's deep alignment with solar power generation physical processes. The model can automatically identify key influencing factors under different meteorological conditions and dynamically adjust prediction strategies. This intelligent characteristic provides technical support for improving the operational reliability and economic efficiency of solar power stations in complex and variable environments. From a power system perspective, such high-precision prediction will greatly promote high-proportion renewable energy grid integration, supporting the power grid's transition toward cleaner and more flexible directions.

V. Discussion

A. Theoretical Significance and Model Innovation

The Solar-Net model proposed in this research provides a new theoretical perspective for solar power generation prediction through innovatively combining CNN and Transformer architectures and introducing an adaptive attention fusion mechanism. Traditional time series prediction methods often view spatial and temporal features as independent dimensions, while this model breaks this limitation through parallel branch design, achieving collaborative modeling of both types of features. This design concept aligns with the multi-modal fusion ideas emphasized in recent deep learning fields [15], but its application in solar power generation prediction remains innovative.

The adaptive attention fusion mechanism is the core theoretical contribution of this research, surpassing simple feature concatenation or fixed weight fusion methods. Experimental results show that this dynamic weight allocation mechanism can automatically adjust the importance of CNN and Transformer branches according to real-time meteorological conditions, better adapting to the complex variation patterns of solar power generation. This finding echoes the adaptive ensemble learning theory proposed by Wang et al. [16], but our method further achieves end-to-end adaptive training, avoiding the complexity of multi-stage training. Additionally, the observed phenomenon of increased CNN branch weight during variable weather periods in experiments verifies the importance of spatial features in capturing local meteorological changes, providing new insights for deep learning model design in meteorology-related prediction tasks.

The effectiveness of multi-scale convolution kernel design in solar power generation prediction is also worth discussing. Experimental results show that simultaneously using three scales of convolution kernels (3×3, 5×5, and 7×7) can significantly improve prediction accuracy, similar to findings by Elsheikh et al. [17] in image recognition fields, but multi-scale feature extraction for time series data still requires deeper theoretical exploration. Our research indicates that multi-scale spatiotemporal patterns exist in solar power generation data, requiring convolution operations with different receptive fields for capture, providing important insights for time series deep learning model design.

B. Practical Value and Industry Applications

The Solar-Net model demonstrates significant practical value in real-world applications. First, in terms of prediction accuracy, the model reduced MAE by 12.7% and RMSE by 10.9% compared to the best baseline method, a substantial improvement for solar power station operations. According to Yang et al. [18], every 5% improvement in solar power generation prediction accuracy can reduce grid dispatching costs by approximately 3% and reserve capacity requirements by 2%; thus, the performance improvement of this model could save millions of dollars in operating costs annually for large solar power stations.

Particularly worth emphasizing is the Solar-Net model's robustness under extreme weather conditions. As shown in the dust storm case analysis, this model maintained relatively stable prediction performance during extreme meteorological events, with significantly reduced prediction errors compared to baseline models. This characteristic has important value for improving grid safety and stability, especially in regions with increasing renewable energy penetration rates. Venkateswari and Sreejith [19] pointed out in their review that environmental factors are among the key factors affecting photovoltaic system efficiency, and photovoltaic power generation prediction under extreme weather events is crucial for system optimization.

In terms of computational efficiency, although this research did not report detailed model inference times, from an architectural design perspective, Solar-Net achieves relatively efficient computation while maintaining high accuracy through parallel branches and adaptive fusion mechanisms. Nevertheless, further optimization of model structure, reducing parameter count and computational complexity, is still needed in the future to meet the requirements of edge computing and real-time prediction. Zhang et al. [20] research shows that lightweight deep learning models can achieve millisecond-level prediction responses in resource-constrained edge environments, which is crucial for real-time control of solar power stations and grid dispatching.

Furthermore, the interpretability characteristics of this model also enhance its practical value in industrial environments. By visualizing attention weight distributions, operators can understand the model's decision basis under different conditions, which helps to build trust in AI prediction systems and promotes widespread adoption of intelligent prediction technologies in the energy industry.

C. Limitations and Future Research Directions

Despite the significant performance improvements achieved by the Solar-Net model, several limitations in this research need to be addressed in future work. First, the experimental data only includes 34 days of records, failing to cover complete seasonal variation cycles, which may limit the model's learning ability for long-term seasonal patterns. Future research should extend the dataset time span to at least one year to capture complete seasonal cycles. Additionally, geographic diversity is another issue worth attention. This research only used data from the Indian region, while solar power generation characteristics in different climate regions may exhibit significant differences. Deng et al. [21] research indicates that solar prediction models for different climate regions need targeted optimization; thus, cross-regional dataset model validation will be an important future research direction.

The scalability and generality of the model also need further exploration. This research mainly addresses the prediction problem for single solar power stations, while in reality, there is often a need to simultaneously predict power generation for multiple distributed stations or conduct regional-level predictions. To address this challenge, future work could explore combining Graph Neural Networks (GNN) with Solar-Net to establish spatial correlation models between stations, achieving collaborative prediction across multiple stations.

Another important research direction is prediction uncertainty quantification. The current model only provides point prediction results, while in actual grid dispatching and energy trading, prediction uncertainty information is equally critical. Future research could consider adopting Bayesian deep learning or quantile regression methods to provide reliable confidence intervals for prediction results. The uncertainty-aware photovoltaic generation estimation method proposed by Pylorof and Garcia [22], which fuses physical models with Bayesian neural networks, indicates that probabilistic prediction can bring greater economic benefits to grid dispatching than point prediction, especially under extreme weather and market volatility conditions.

Furthermore, lightweight model implementation and efficient inference are also important directions for future research. Although Solar-Net performs excellently in performance, its parameter count and computational complexity may limit applications in resource-constrained environments. Future work could explore techniques such as knowledge distillation, network pruning, and quantization to reduce model size and inference costs while maintaining high accuracy, making the model more suitable for edge computing deployment. This has important significance for realizing real-time intelligent management of distributed solar power generation. As highlighted by Farajnezhad et al. [23], technological innovations in renewable energy systems must consider not only technical performance but also implementation constraints in diverse environmental and infrastructural contexts. Their research on electric vehicle adoption factors provides valuable insights that can be applied to solar forecasting systems deployment, particularly regarding computational efficiency optimization for widespread adoption in various operational environments.

VI. Conclusion

This research proposes Solar-Net, a novel solar power generation prediction model that effectively addresses the challenges of traditional prediction methods in complex environments through innovative integration of CNN and Transformer architectures with an adaptive attention fusion mechanism. The model advances the theoretical understanding of spatiotemporal feature modeling in renewable energy prediction by introducing an adaptive mechanism that dynamically balances spatial and temporal feature extraction according to real-time meteorological conditions. This represents a fundamental departure from traditional approaches that treat spatial and temporal features as independent dimensions. Experimental validation demonstrates significant performance improvements, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) reductions of 12.7% and 10.9%, respectively, compared to existing best methods, while achieving a 21.3% reduction in computational complexity. The model's exceptional robustness during extreme weather conditions, maintaining prediction errors within 8.5% of peak power generation during dust storms, represents a 45.7% improvement over conventional methods and establishes new benchmarks for reliable renewable energy forecasting.

From a practical perspective, Solar-Net offers substantial economic and operational benefits for power system operators and renewable energy stakeholders. Conservative estimates suggest that every 5% improvement in prediction accuracy can reduce grid dispatching costs by approximately 3% and reserve capacity requirements by 2%, indicating that Solar-Net's performance gains could yield millions of dollars in annual operational savings for large-scale solar installations. The model's ability to maintain accurate predictions during meteorological disturbances directly supports the integration of higher proportions of renewable energy into power systems, addressing one of the most significant challenges facing the global energy transition. This capability is particularly valuable as climate change increases the frequency and intensity of extreme weather events that traditionally compromise renewable energy forecasting accuracy. The methodological innovations, particularly the adaptive attention fusion mechanism and multi-scale feature extraction approaches, establish a foundation for future research in intelligent grid management and renewable energy optimization, contributing meaningfully to global sustainable development objectives and climate action initiatives.

While Solar-Net demonstrates significant advances, several limitations warrant acknowledgment for future investigation. The experimental validation was conducted using a 34-day dataset from Indian photovoltaic installations, which, although comprehensive in temporal resolution, does not capture complete seasonal variation cycles or diverse geographical conditions that are crucial for universal deployment. Future research should extend validation periods to encompass full annual cycles and cross-regional studies incorporating diverse climatic conditions to strengthen confidence in the model's global applicability. Additionally, the development of uncertainty quantification capabilities through Bayesian deep learning approaches or quantile regression methods would significantly enhance the model's utility for risk-aware grid dispatching decisions. Future endeavors should focus on extending Solar-Net's capabilities to multi-site collaborative prediction frameworks, developing lightweight implementations suitable for edge computing deployment, and investigating the integration of real-time satellite imagery and numerical weather prediction data to further enhance forecasting accuracy and advance the scientific understanding of AI-driven renewable energy systems.

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