Automation and Machine Learning (2026)
Clausius Scientific Press, Canada

DOI: 10.23977/autml.2026.070206
ISSN 2516-5003 Vol. 7 Num. 2

High-Precision Photovoltaic Power Forecasting under Complex Weather Conditions

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Keywords: Photovoltaic Power Forecasting; Renewable Energy; Time Series Prediction; Intelligent Forecasting

Abstract: To address the issues of strong fluctuations and significant nonlinear characteristics in photovoltaic (PV) power generation under complex weather conditions, as well as the insufficient accuracy of traditional prediction models, a PV power prediction model integrating Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (BiGRU), and an attention mechanism is proposed. First, CNN is used to extract local fluctuation features and multivariate coupling information from the PV power sequence. Then, BiGRU is used to learn the bidirectional dynamic dependencies in the time series. Finally, an attention mechanism is introduced to dynamically weight features at key time steps, enhancing the model's ability to perceive complex weather changes. Experiments are conducted based on real PV power plant data, and comparative analyses are performed using models such as BP, GA-BP, CNN, LSTM, GRU, and CNN-GRU. Experimental results show that the predicted curve of the proposed model has a high consistency with the actual power change trend. Furthermore, monthly error analysis and attention visualization results further verify the model's stability and effectiveness under complex weather scenarios. The research results indicate that the proposed model can effectively improve the accuracy of PV power prediction, providing technical support for new energy grid-connected operation and grid dispatch.

1. Introduction

With the continuous advancement of the "dual-carbon" strategy and the rapid expansion of new energy power generation, photovoltaic (PV) power generation has gradually become an important component of modern power systems [1-2]. Compared to traditional fossil fuels, PV power generation has advantages such as being clean, low-carbon, and renewable, playing a crucial role in the energy structure transformation process [3-4]. However, PV power output is affected by various factors such as solar irradiance, ambient temperature, air humidity, and sudden weather changes, exhibiting significant randomness, fluctuation, and intermittency [5]. When complex weather conditions occur, PV output can change drastically, increasing the difficulty of grid dispatch, power balance, and energy management. Therefore, achieving high-precision and stable PV power prediction has become an important research direction in the grid-connected operation of new energy sources and the safe dispatch of the power grid [6].

Currently, scholars both domestically and internationally have conducted extensive research on PV power prediction. Traditional prediction methods mainly include multiple linear regression, support vector machines (SVM), random forests (RF), and backpropagation (BP) neural networks [7]. Among these, BP neural networks, due to their nonlinear mapping capabilities, are widely used in the field of new energy power prediction. Simultaneously, some studies have optimized BP network parameters using genetic algorithms to improve model convergence and prediction accuracy [8]. Related research shows that the GA-BP model can, to some extent, reduce the problem of traditional BP networks getting trapped in local optima and improve prediction performance under complex meteorological conditions. However, these traditional shallow network models still have limited ability to express high-dimensional temporal features. When input variables exhibit strong volatility and complex coupling relationships, the model struggles to effectively extract long-term temporal dependencies, leading to significant errors in prediction results during peak fluctuation phases.

In recent years, with the development of deep learning technology, models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) have been increasingly applied to new energy power prediction tasks [9]. Among them, CNNs can extract local fluctuation features in time series through local receptive field mechanisms, exhibiting a strong advantage in processing high-frequency changing data; GRUs can utilize gating structures to learn long-term dependencies in time series, improving training efficiency while reducing model complexity. Compared to traditional unidirectional recurrent networks, Bidirectional Gated Recurrent Units (BiGRUs) can simultaneously learn forward and backward temporal information, thereby enhancing the model's ability to express complex dynamic changes. However, relying solely on CNN or BiGRU still struggles to accurately identify the differences in importance across different time periods, and the model's ability to focus on key time-step features remains insufficient in complex weather scenarios.

To address these issues, this paper proposes a photovoltaic power prediction model that integrates CNN, BiGRU, and Attention. First, CNN is used to extract local fluctuations and multivariate coupling features from the photovoltaic power sequence. Then, BiGRU is used to learn the bidirectional time dependencies in the power sequence to enhance the model's ability to express long-term dynamic features. Finally, an Attention mechanism is introduced to dynamically weight features at different time steps, thereby improving the model's ability to capture features from key meteorological change stages. To verify the effectiveness of the proposed model, experimental studies are conducted based on multi-meteorological variable data, and comparative analyses are performed with models such as BP, GA-BP, LSTM, and GRU. Experimental results show that the proposed model can effectively reduce prediction errors under complex weather conditions and exhibits superior prediction performance on relevant evaluation metrics.

2. Proposed Method

To address the problems of severe fluctuation, nonlinear characteristics, and insufficient feature extraction capability in photovoltaic power sequences under complex weather conditions, this paper proposes a photovoltaic power forecasting model integrating CNN, BiGRU, and Attention Mechanism. Through the multi-layer deep feature learning architecture, the proposed model can jointly capture local fluctuation features, long-term temporal dependency information, and key temporal features, thereby improving forecasting accuracy under complex meteorological environments. The overall framework takes multi-meteorological variables as inputs. First, the

CNN module is employed to extract local fluctuation features from the time-series data. Subsequently, the BiGRU module is utilized to learn bidirectional temporal dependency relationships within photovoltaic power sequences. Finally, the Attention mechanism dynamically assigns weights to different temporal features, and the fully connected layer outputs the final prediction results. The overall structure of the proposed model is illustrated in Figure 1.

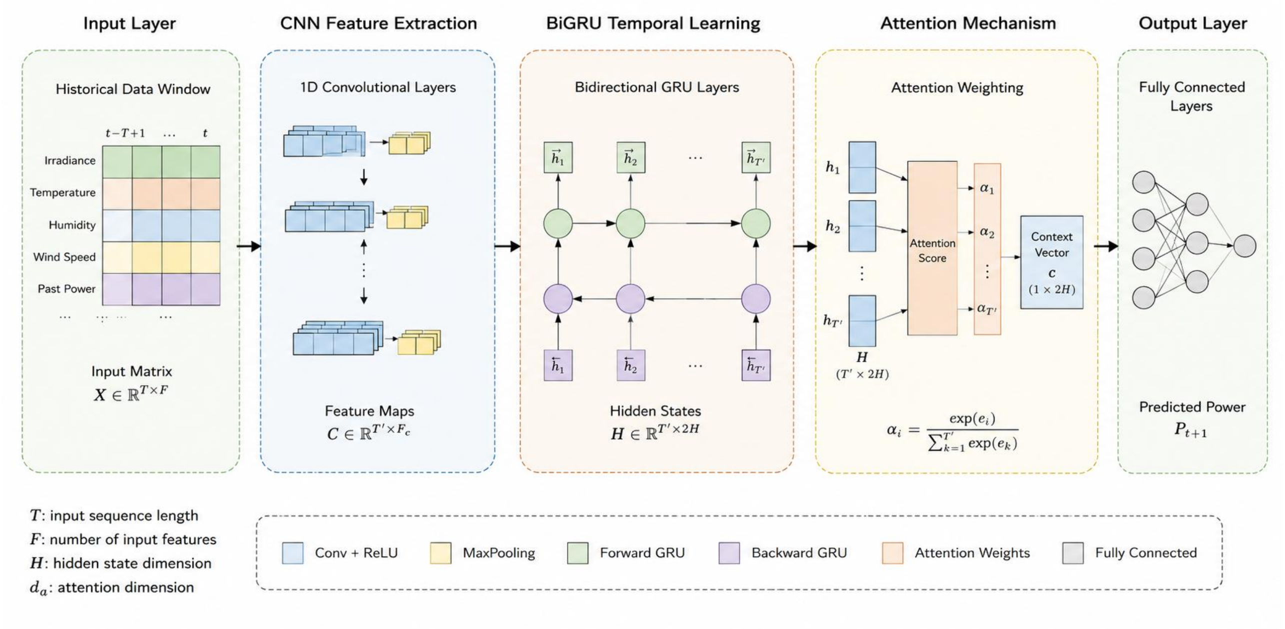

Figure 1: Overall Flowchart.

2.1. Data Preprocessing

Since photovoltaic power generation is influenced by multiple environmental factors such as solar irradiance, ambient temperature, air humidity, and wind speed, this study adopts multivariate meteorological data as model inputs to improve feature representation capability under complex environments. The selected input variables mainly include solar irradiance, temperature, humidity, wind speed, and historical photovoltaic power data.

Considering the large differences in physical scales among different variables, directly feeding the raw data into the model may lead to unstable gradient updates during training. Therefore, data normalization is required before model training. In this study, the Min-Max normalization method is adopted to map all input variables into the interval $[0,1]$ [10], thereby improving training stability. The normalization formula is given as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x denotes the original input data, $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the dataset, respectively, and x' is the normalized result.

In addition, to enhance the model's capability in learning temporal dynamic patterns, a sliding time window strategy is employed to construct training samples [11]. Assuming that the input sequence length is T, the model utilizes the previous T time steps to predict future photovoltaic power output. Through the sliding window mechanism, the model can effectively capture temporal evolution characteristics and improve forecasting accuracy.

2.2. CNN Feature Extraction Module

Photovoltaic power sequences under complex weather conditions exhibit obvious local fluctuation characteristics. Conventional recurrent neural networks often have limited capability in extracting high-frequency local variation features. Therefore, CNN is first introduced to perform local feature extraction on the input sequences, thereby enhancing the representation capability of short-term fluctuation characteristics [12-13].

CNN extracts local temporal features by sliding convolution kernels along the time dimension. The convolution process can be expressed as follows:

$$y_i = f\left(\sum_{j=1}^{k} w_j x_{i+j} + b\right) \tag{2}$$

where x_{i+j} denotes the local input sequence, w_j represents the convolution kernel weight, b is the bias term, $f(cdot)$ denotes the activation function, and y_i is the convolution output.

After the convolution layer, the Rectified Linear Unit (ReLU) activation function is adopted to improve nonlinear representation capability. Its expression is given as follows:

$$f(x)=max(0,x) \tag{3}$$

Through the CNN module, the model can effectively capture local variation features from photovoltaic power sequences and reduce the influence of complex meteorological disturbances on subsequent temporal learning processes.

2.3. BiGRU Temporal Learning Module

Although CNN can effectively extract local fluctuation features, its capability in modeling long-term temporal dependencies remains limited. Therefore, BiGRU module is further introduced to learn long-term dynamic features from the photovoltaic power sequence.

GRU selectively preserves historical information through update gates and reset gates. The update gate is formulated as follows [14-15]:

$$z_t = \sigma(W_z[h_{t-1}, x_t]) \tag{4}$$

The reset gate is defined as:

$$r_t = \sigma(W_r[h_{t-1}, x_t]) \tag{5}$$

The hidden state updating process can be expressed as:

$$h_t = (1 - z_t)h_{t-1} + z_t\tilde{h}_t \tag{6}$$

Compared with conventional unidirectional GRU, BiGRU can simultaneously learn forward and backward temporal dependency information, thereby enhancing the perception capability of complex dynamic variations. Through the bidirectional temporal learning structure, the proposed model can more comprehensively capture long-term evolution patterns in photovoltaic power sequences.

2.4. Attention Mechanism

Under complex weather conditions, different time steps contribute differently to the final prediction results. To improve the model’s capability in focusing on critical temporal features, an

Attention mechanism is introduced after the BiGRU layer to dynamically weight different hidden states.

The attention weight calculation is defined as follows:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T}\exp(e_k)} \tag{7}$$

where e_t represents the importance score of the current time step and a_t denotes the corresponding attention weight.

Subsequently, the context vector is obtained through weighted summation of hidden states:

$$c = \sum_{t=1}^{T}\alpha_t h_t \tag{8}$$

Through the Attention mechanism, the proposed model can automatically strengthen important temporal features, thereby improving forecasting stability and prediction accuracy under complex meteorological conditions.

2.5. Loss Function

To evaluate the deviation between predicted values and actual observations, the Mean Squared Error (MSE) is adopted as the loss function in this study. The MSE is defined as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{9}$$

where y_i represents the actual photovoltaic power value, $\hat{y}_i$ denotes the predicted value, and N is the total number of samples.

The MSE loss function can effectively reflect the overall prediction error level and imposes larger penalties on larger prediction deviations, thereby improving the overall forecasting accuracy of the proposed model.

3. Experiments

3.1. Experimental Dataset

The experimental data for this study was collected from an actual photovoltaic power plant. The dataset contains historical photovoltaic power generation records and corresponding meteorological variables under different weather conditions. To ensure sufficient temporal continuity and environmental diversity, the collected data covers multiple seasons and various weather scenarios, including sunny, cloudy, rainy, and partially shaded days.

The selected input variables mainly include solar irradiance, ambient temperature, air humidity, wind speed, and historical photovoltaic power generation data.

Before model training, outliers and missing data in the dataset were processed using interpolation and data cleaning methods. Detailed information about the experimental dataset is summarized in Table 1.

Table 1: Dataset Description.

Item	**Description**
Data Source	Photovoltaic Power Station
Time Resolution	15 min

Total Samples	35,000
Input Variables	Irradiance, Temperature, Humidity, Wind Speed, Historical Power
Prediction Target	Photovoltaic Power Output
Training Set Ratio	70%
Validation Set Ratio	10%
Testing Set Ratio	20%

3.2. Experimental Setup

To ensure fair comparison and stable training performance, all comparison models were trained under the same experimental environment and parameter settings. The proposed CNN-BiGRU-Attention model is implemented based on the PyTorch deep learning framework. During training, the Adam optimizer was used to accelerate convergence and improve optimization stability.

All experiments were conducted on a workstation equipped with an NVIDIA RTX4060 GPU. The operating environment was based on Python and the PyTorch deep learning library. Detailed experimental parameter settings are listed in Table 2.

Table 2: Experimental Parameter Settings.

Parameter	**Value**
Framework	PyTorch
Optimizer	Adam
Epoch	100
Batch Size	64
Learning Rate	0.001
Loss Function	MSE
GPU	NVIDIA RTX4060
Convolution Kernel Size	3
Hidden Units of BiGRU	128
Dropout Rate	0.2

In addition, to comprehensively evaluate the forecasting performance of the proposed model, several representative forecasting models were selected for comparison, including BP, GA-BP, CNN, LSTM, GRU, and CNN-GRU models. All comparison models were trained under identical dataset partitioning and experimental conditions to ensure fairness and reliability of the experimental results.

3.3. Evaluation Metrics

To comprehensively evaluate the performance of the proposed model in photovoltaic power prediction, this paper selects root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) as model evaluation indicators.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{10}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{11}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{13}$$

where $\bar{y}$ denotes the mean value of actual observations. where y_i denotes the actual value, $\hat{y}_i$ represents the predicted value, and N denotes the total number of samples.

3.4. Comparison Experiments

To verify the effectiveness of the proposed CNN-BiGRU-Attention model in photovoltaic power prediction under complex weather conditions, this paper selects BP, GA-BP, CNN, LSTM, GRU, and CNN-GRU models as comparison methods, and conducts comparative experiments under the same experimental environment and dataset conditions.

Evaluation metrics are used for quantitative analysis. Experimental results are shown in Table 3.

Table 3: Comparison Results.

Model	**RMSE**	**MAE**	**MAPE (%)**	**(R^2)**
BP	8.924	7.115	9.82	0.861
GA-BP	6.347	5.282	7.13	0.903
CNN	5.914	4.763	6.52	0.921
LSTM	5.406	4.321	5.98	0.935
GRU	5.128	4.067	5.63	0.941
CNN-GRU	4.782	3.854	5.11	0.952
Proposed	3.964	3.126	4.27	0.971

Table 3 shows that the traditional BP model has the worst prediction performance among all models, with an RMSE of 8.924, a MAE of 7.115, and a MAPE as high as 9.82%, indicating that the BP network is prone to large prediction biases under complex weather scenarios. This is mainly because the traditional BP neural network lacks the ability to model complex time-dependent relationships and struggles to effectively represent the nonlinear dynamic changes in photovoltaic power sequences. Furthermore, its R^2 is only 0.861, indicating a weak ability to fit the actual power change trend.

Compared to the traditional BP model, the GA-BP model, after optimizing the network weights and thresholds using a genetic algorithm, shows a significant improvement in prediction performance. Specifically, the RMSE decreased from 8.924 to 6.347, a reduction of approximately 28.9%; the MAE decreased from 7.115 to 5.282, a reduction of approximately 25.8%; and the MAPE decreased to 7.13%. At the same time, the R^2 increased from 0.861 to 0.903, indicating that the genetic algorithm can, to some extent, mitigate the problem of the BP network easily getting trapped in local optima, thereby improving the overall prediction stability. However, GA-BP remains a shallow network structure, and its ability to represent complex temporal features at a deeper level is still limited, resulting in overall performance lower than deep learning models.

Among deep learning models, CNN models can effectively extract local fluctuation features from photovoltaic power sequences, thus further reducing its RMSE to 5.914, a decrease of approximately 6.8% compared to GA-BP. Simultaneously, MAE and MAPE decreased to 4.763 and 6.52%, respectively, indicating that convolutional structures have a good advantage in local feature learning. However, due to the lack of long-term temporal dependency modeling capabilities, CNN's overall prediction performance still has certain limitations.

LSTM and GRU models enhance time series learning capabilities through gated recurrent structures, thus further improving overall prediction performance. The RMSE of the LSTM model is 5.406, while GRU further reduces it to 5.128; simultaneously, the MAE of the GRU model decreases to 4.067, and the MAPE decreases to 5.63%. Compared to LSTM, GRU, due to its lighter structure and fewer parameters, performs better in terms of training stability and prediction efficiency. Furthermore, the GRU model achieves an R^2 of 0.941, indicating its strong ability to fit the trend of photovoltaic power changes.

Furthermore, the CNN-GRU model achieves joint modeling of local change information and long-term dynamic features by fusing convolutional local feature extraction with a recurrent time-dependent learning structure. Experimental results show that the RMSE of the CNN-GRU model is further reduced to 4.782, a decrease of approximately 6.7% compared to the GRU alone; MAE is reduced to 3.854; and MAPE is reduced to 5.11%. Simultaneously, the R^2 increases to 0.952, demonstrating that the fusion of convolutional features and time-dependent information effectively improves the overall prediction accuracy of the model.

Compared to all the contrasting models, the proposed CNN-BiGRU-Attention model achieves the best results across all evaluation metrics. The RMSE was only 3.964, a decrease of approximately 55.6% compared to the traditional BP model, approximately 37.5% compared to GA-BP, and a further decrease of approximately 17.1% compared to CNN-GRU; the MAE decreased to 3.126; and the MAPE was only 4.27%, indicating that the overall prediction error of the model has been significantly controlled. Meanwhile, the proposed model achieved an R^2 of 0.971, close to 1, demonstrating a very high consistency between the predicted results and the actual power change trend.

To further illustrate the differences in prediction performance among the various models, this paper presents a comparison of prediction curves between the actual values and the predicted values from different models, as shown in Figure 2. It is evident that the traditional BP model exhibits significant deviation during the peak phase, while GA-BP, although able to reduce the error to some extent, still shows noticeable fluctuations in the overall curve. In contrast, the CNN-BiGRU-Attention model proposed in this paper shows the prediction curve most closely matches the trend of the actual value, maintaining high prediction accuracy in both the peak and fluctuating phases, further validating the effectiveness and stability of the proposed model in complex weather scenarios.

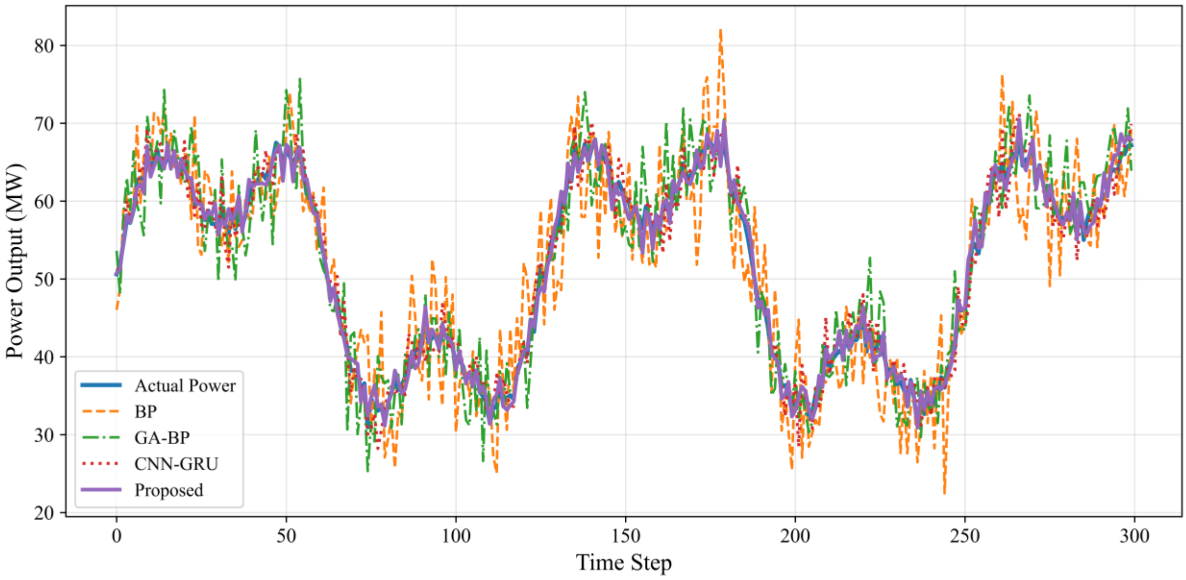

Figure 2: Prediction curve.

3.5. Monthly Error Analysis

To further analyze the predictive stability of the proposed model in different months, this paper, referencing the presentation of experimental results in the original paper, statistically analyzes the actual, predicted, and predicted power outputs for all 12 months of the year. Monthly error analysis can more intuitively reflect the model's predictive performance under different seasons, different light conditions, and different meteorological fluctuations. The experimental results are shown in Table 4.

Table 4: Monthly Prediction Error Analysis.

Month	Actual Power	Predicted Power	Error
1	65.20	66.84	-1.64
2	66.20	67.51	-1.31
3	78.00	77.26	0.74
4	77.00	78.18	-1.18
5	77.50	78.36	-0.86
6	79.50	80.32	-0.82
7	77.20	76.51	0.69
8	75.20	76.44	-1.24
9	71.00	72.08	-1.08
10	79.50	78.93	0.57
11	70.50	69.72	0.78
12	62.40	64.03	-1.63

Table 4 shows that the proposed CNN-BiGRU-Attention model maintained small prediction errors throughout the year. The largest absolute error occurred in January (1.64), and the smallest absolute error occurred in October (0.57). Compared to the traditional GA-BP model, where errors exceeded 5 in some months, the proposed model significantly reduced monthly prediction bias, indicating stronger stability under different seasonal conditions.

From a seasonal perspective, from March to October, sunlight conditions were relatively abundant, and photovoltaic power was generally at a high level. The deviation between the model's predicted and actual values was small, indicating that the CNN-BiGRU-Attention model can effectively learn the power variation patterns during periods of high power generation. January, February, and December are the low-power phases of winter, and prediction is relatively more difficult due to the influence of solar altitude angle, sunshine duration, and weather fluctuations. However, the model still managed to keep the error at a low level, demonstrating that the Attention mechanism effectively enhances the model's ability to focus on key fluctuations.

To more intuitively illustrate the monthly error distribution, this paper further plots a bar chart comparing the actual value, predicted value, and prediction error, as shown in Figure 3. It can be seen that the prediction curve closely follows the trend of the actual value, and the overall amplitude of the error bars is relatively small, further validating the prediction stability of the proposed model on an annual scale.

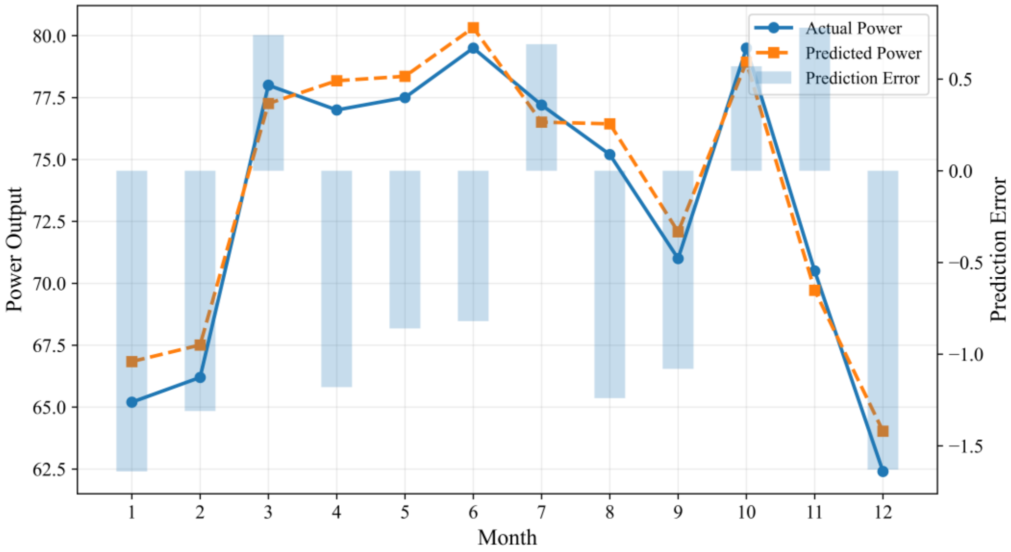

Figure 3: Monthly Error Distribution.

3.6. Attention Visualization

To further explain the feature attention mechanism of the proposed model, this paper visualizes the weight distribution of the Attention layer output. The core function of the Attention mechanism is to dynamically weight the prediction results according to the importance of different time steps, enabling the model to pay more attention to key moments that have a significant impact on future photovoltaic power changes. Therefore, by plotting an Attention Heatmap, the intensity of the model's attention at different time steps and for different input features can be visually observed.

Figure 4 shows the Attention weight distribution of the proposed model in typical prediction samples. The horizontal axis represents the input time step, and the vertical axis represents the main input features, including solar irradiance, temperature, humidity, wind speed, and historical power. The darker the color, the higher the model's attention to that feature or time step.

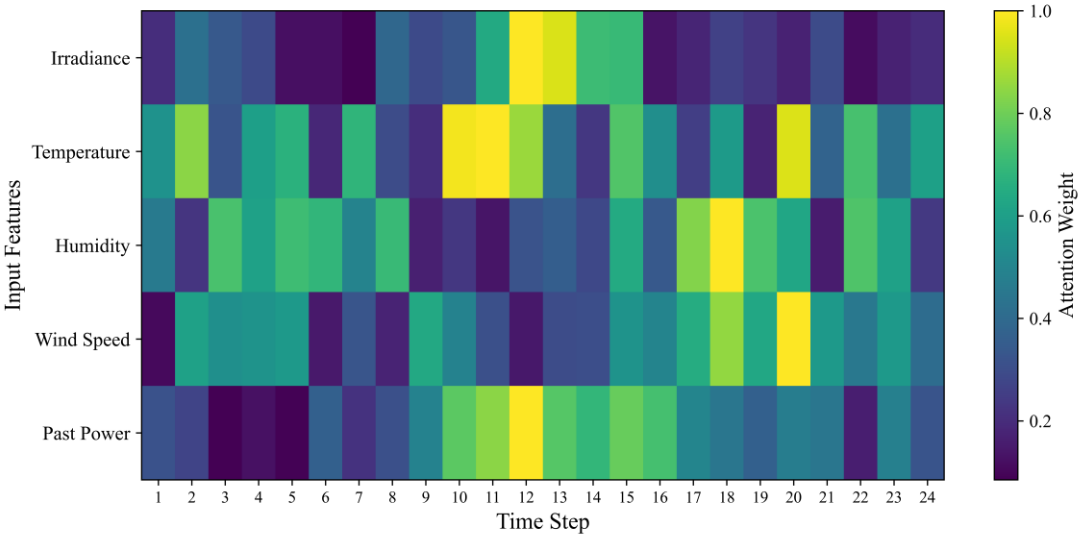

Figure 4: Attention Heatmap.

As can be seen from Figure 4, the model assigns higher attention weights near the midday solar irradiance peak, indicating that solar irradiance and historical power play a crucial role in photovoltaic power prediction. Simultaneously, the Attention weights also show a significant increase during periods of sudden cloudy weather changes or rapid power fluctuations, indicating that the model can automatically capture key fluctuation information caused by complex weather changes. Compared to the ordinary CNN-GRU model, CNN-BiGRU-Attention can not only learn local fluctuations and temporal dependencies, but also further distinguish the importance of different time steps, thereby improving the stability and interpretability of the prediction results.

4. Conclusion

To address the challenges of strong volatility, significant nonlinearity, and insufficient accuracy of traditional PV sequences under complex weather conditions, this paper proposes a CNN-BiGRU-Attention PV power prediction model that integrates convolutional neural networks, bidirectional gated recurrent units, and an attention mechanism.

Monthly error analysis and visualization of attention weights reveal that the proposed model not only fits the annual PV power trend well but also maintains high prediction accuracy during peak power periods and periods of abrupt weather changes. Specifically, the CNN module effectively enhances the model's ability to extract local high-frequency change information; the BiGRU structure further improves the model's learning effect on long-term temporal dependencies; and the attention mechanism dynamically monitors key meteorological changes, thereby reducing the impact of complex weather disturbances on the prediction results. Compared to traditional shallow network models, the proposed model demonstrates significant advantages in prediction error control, generalization ability, and interpretability, validating the effectiveness of deep feature fusion structures in PV power prediction.

Overall, the CNN-BiGRU-Attention model proposed in this paper provides a high-precision and stable solution for photovoltaic power prediction under complex weather conditions, and has certain engineering application value for new energy grid-connected operation, grid dispatch, and energy management. Future research can further optimize the prediction stability under extreme weather conditions by combining multi-site spatial correlation features, probabilistic prediction methods, and long-sequence modeling structures such as Transformer.

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