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A Rolling Error Correction Framework for Short-Term Photovoltaic Power Forecasting under Complex Weather Conditions

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Abstract: To address the issues of photovoltaic (PV) power generation being significantly affected by meteorological factors, exhibiting strong output sequence volatility, and having short-term prediction accuracy susceptible to error accumulation, this paper proposes a short-term PV power prediction method based on Stacking-Convolutional Neural Network (CNN)-Temporal Convolutional Network-Attention (TCN). This method first employs a Stacking ensemble learning model to integrate the prediction advantages of multiple base learners to obtain initial power prediction results. Then, CNN-TCN error correction network is constructed to perform deep feature learning on the initial prediction error. The CNN captures local fluctuation features, the Temporal Convolutional Network extracts temporal dependency information, and the Attention mechanism enhances the weight representation of key error segments. Finally, a rolling iteration strategy is combined to achieve continuous multi-step prediction. Experimental results show that this method exhibits high prediction accuracy and stability in typical daily predictions, comparisons with different models, and monthly error analysis, effectively improving the short-term PV power prediction performance under complex weather conditions.

1. Introduction

As the global energy structure continues its transformation towards low-carbon and clean energy, solar power generation, with its abundant resources, wide distribution, and green, pollution-free characteristics [1-2], has gradually become an important component of the new energy power generation system. In recent years, the construction and grid connection of large-scale photovoltaic (PV) power plants have been continuously expanding [3-4], significantly increasing the proportion of PV power generation in modern power systems. However, the output power of PV power generation is easily affected by various factors such as solar irradiance, temperature, cloud cover, and weather changes, exhibiting significant randomness, volatility, and intermittency. This instability poses significant challenges to grid dispatch, power balance, and the absorption of new energy sources. Therefore, improving the accuracy of short-term PV power prediction has become one of the key research directions in the optimized operation of new energy power systems.

Currently, PV power prediction methods mainly fall into two categories: traditional machine learning methods and deep learning methods [5-6]. Traditional machine learning methods, such as Support Vector Machines (SVM) and Random Forests (RF), have good prediction efficiency when processing small to medium-sized datasets, but their ability to express complex nonlinear time-series features is limited, and they are prone to increased prediction errors under complex weather conditions. With the development of deep learning, models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer have been widely applied to photovoltaic power prediction tasks. Among them, LSTM and GRU have certain advantages in time series modeling, but they may still suffer from gradient decay and error accumulation problems during long-term dependent learning [7-8]. While Transformer can effectively capture global temporal features, its large model parameter scale leads to high training costs, and it is prone to error propagation during multi-step rolling prediction, resulting in decreased stability of subsequent prediction results.

To further improve the accuracy of photovoltaic power prediction, some studies have begun to adopt ensemble learning, error correction [9], and hybrid deep networks to construct combined prediction models [10]. Although existing methods have improved prediction performance to some extent, they still have the following shortcomings: First, some models mainly focus on the initial prediction results, lacking in-depth modeling of the dynamic changes in prediction errors; second, the error distribution varies significantly across different seasons and weather conditions, making it difficult for traditional unified modeling methods to effectively adapt to complex scenarios; furthermore, most methods still lack the ability to jointly extract local fluctuation features and long-term dependent features, resulting in limited model stability during complex nonlinear error learning processes. Therefore, constructing a photovoltaic short-term power prediction model that simultaneously considers local feature extraction, long-term temporal dependency modeling, and dynamic error learning capabilities is of significant research importance.

To address the aforementioned issues, this paper proposes a photovoltaic short-term power prediction method based on ST-CNN-TCN-Attention. First, a Stacking ensemble learning model is used for initial photovoltaic power prediction to improve the overall generalization ability of the model. Then, the error between the initial prediction and the true value is analyzed, and a CNN-TCN-Attention error correction network is constructed. Here, a convolutional neural network is used to extract local fluctuation features, a temporal convolutional network is used to learn long-term temporal dependencies, and an attention mechanism is used to dynamically focus on key error features. Finally, a rolling iterative prediction mechanism is introduced to achieve multi-step continuous short-term power prediction. Experimental results show that the proposed method achieves high prediction accuracy under different seasons and prediction step sizes, and outperforms various comparative models in terms of RMSE and MAE, demonstrating good stability and application prospects.

2. Overall Framework of ST-CNN-TCN-Attention

2.1. Overall Prediction Framework

To improve the stability and multi-step forecasting accuracy of short-term photovoltaic power prediction, this paper proposes a hybrid forecasting framework based on ST-CNN-TCN-Attention. The proposed framework mainly consists of a data preprocessing module, a Stacking-based initial forecasting module, an error learning module, and a rolling iterative forecasting module. By combining ensemble learning with a deep temporal error correction mechanism, the proposed method can effectively reduce the prediction bias of traditional single models under complex weather conditions and enhance the learning capability for nonlinear fluctuation features.

In terms of input features, the model takes historical photovoltaic output power as the core variable and further integrates meteorological variables such as temperature, solar irradiance, wind speed, and humidity to construct a multivariate time-series input. Since photovoltaic power generation is highly correlated with environmental conditions, the incorporation of multi-source meteorological features can improve the model's ability to perceive environmental variations and further enhance the robustness of forecasting results.

The overall prediction process is as follows. First, the raw data are subjected to outlier removal, missing value completion, and normalization preprocessing. Subsequently, the processed data are fed into the Stacking ensemble forecasting model to obtain the initial photovoltaic power forecasting results. Then, the prediction error sequence between the predicted values and the actual values is calculated and input into the CNN-TCN-Attention network for dynamic error learning. Finally, a rolling iterative strategy is employed to accomplish continuous multi-step forecasting and generate the final short-term photovoltaic power prediction results. The overall forecasting framework is illustrated in Figure 1.

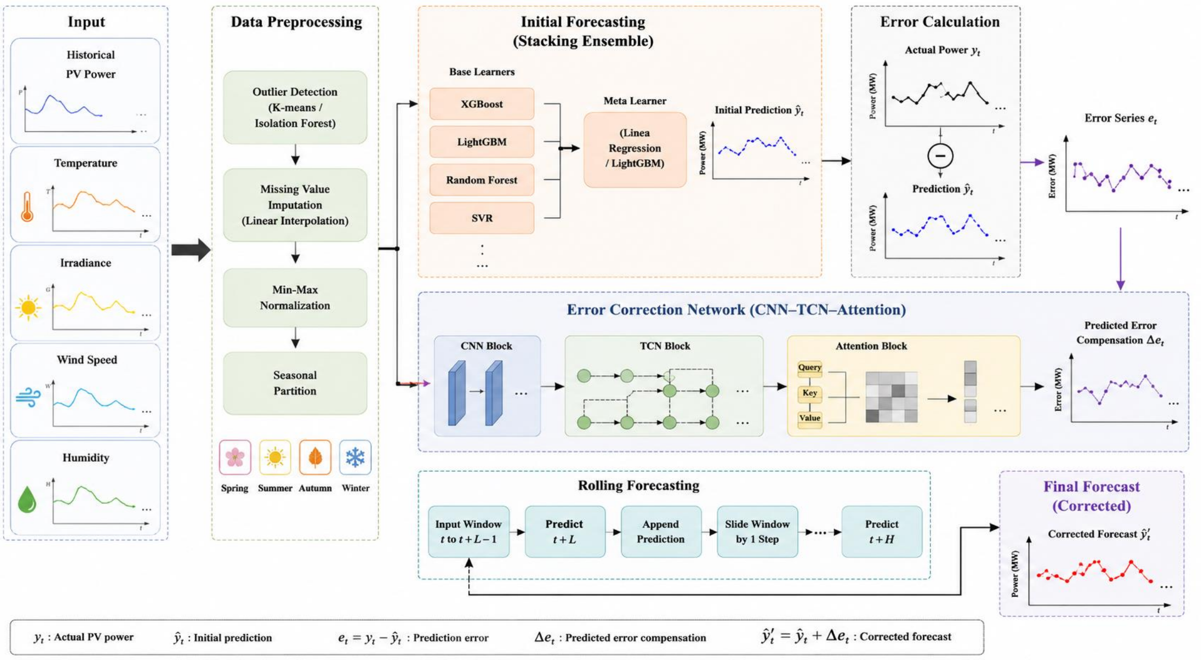

Figure 1: Structure of induction system.

To facilitate the subsequent error learning process, the prediction error is defined as follows:

$$e_t = y_t - \hat{y}_t \tag{1}$$

where y_t denotes the actual photovoltaic output power at time, $\hat{y}_t$ represents the initial predicted value, and e_t is the prediction error. The final corrected forecasting result can be expressed as:

$$\hat{y}_t' = \hat{y}_t + \Delta e_t \tag{2}$$

where Δe_t denotes the error compensation term generated by the error correction network, and $\hat{y}_t'$ represents the final corrected prediction result.

2.2. Data Preprocessing

Since photovoltaic power generation systems are easily affected by equipment fluctuations, environmental disturbances, and measurement errors during operation, the raw dataset usually contains outliers, missing values, and feature scale inconsistencies. Directly feeding the raw data into the forecasting model may lead to unstable training behavior and reduced prediction accuracy. Therefore, systematic data preprocessing is required before model training to improve data quality and enhance the generalization ability of the forecasting model.

First, outliers in the dataset are detected and removed. Considering that photovoltaic power data exhibit obvious clustering characteristics, the K-means clustering algorithm is adopted to identify abnormal samples. When a sample deviates significantly from the cluster center, it is regarded as an outlier and removed from the dataset, thereby reducing the influence of abnormal fluctuations on model training.

Second, linear interpolation is employed to fill missing values in the dataset. This method reconstructs missing samples according to the variation trend between adjacent time points, thereby preserving the continuity of the time-series sequence.

After outlier removal and missing value completion, Min-Max normalization is further applied to standardize the input data and eliminate the influence caused by inconsistent feature scales [11-12]. The normalized data can effectively accelerate the model training process and improve the stability of parameter updates in deep neural networks. The normalization process can be expressed as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

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

3. ST-CNN-TCN-Attention Error Correction Forecasting Model

3.1. Stacking-Based Initial Forecasting Model

To improve the stability and generalization capability of the initial photovoltaic power forecasting results, a Stacking ensemble learning-based initial forecasting model is first constructed in this paper. Compared with a single forecasting model, ensemble learning can integrate the advantages of multiple models, thereby reducing model bias and improving forecasting accuracy under complex scenarios. Since different machine learning models exhibit varying abilities in learning temporal features, nonlinear relationships, and local fluctuation patterns, the adoption of a multi-model fusion strategy can effectively enhance the representation capability of complex photovoltaic power variation characteristics.

The proposed Stacking model consists of two layers of learners, including a base learner layer and a meta learner layer. In the base learner layer, XGBoost, LightGBM, Random Forest, and Support Vector Regression (SVR) are employed to construct multiple initial predictors. Among them, tree-based models are capable of learning complex nonlinear feature relationships, while SVR exhibits strong stability for nonlinear fitting on small-scale datasets. The diversity among different models enables complementary feature learning during the forecasting process.

For the input time-series sequence:

$$X_t = [x_{t-n+1}, x_{t-n+2}, \ldots, x_t] \tag{4}$$

each base learner generates a corresponding forecasting result:

$$\hat{y}_t^{(i)} = f_i(X_t) \tag{5}$$

where $f_i(.)$ denotes the i-th base learner and $\hat{y}_t^{(i)}$ represents its corresponding prediction output.

Subsequently, the forecasting outputs generated by multiple base learners are further input into the meta learner for fusion to obtain the final initial forecasting result:

$$\hat{y}_t = g(\hat{y}_t^{(1)}, \hat{y}_t^{(2)}, \dots, \hat{y}_t^{(m)}) \tag{6}$$

where $g(.)$ denotes the mapping function of the meta learner. In this study, Linear Regression or LightGBM is adopted as the meta learner to accomplish the final prediction task.

Through the Stacking ensemble forecasting mechanism, the proposed model can fully exploit the feature learning advantages of different models and improve the adaptability of the initial forecasting results to complex weather conditions and non-stationary photovoltaic power sequences.

3.2. CNN Local Feature Extraction Layer

Although the Stacking ensemble model can achieve relatively high initial forecasting accuracy, prediction errors still exist due to the strong randomness and local nonlinear fluctuation characteristics of photovoltaic power sequences. Therefore, it is necessary to further perform dynamic learning and correction on the prediction error sequence. To enhance the extraction capability of local fluctuation features, CNN structure is first introduced into the error correction network [13-14].

CNN possesses excellent local feature perception capability and can extract local variation patterns from the error sequence through convolution kernels, thereby improving the model's ability to learn short-term fluctuations and local mutation features. For the input error sequence:

$$E_t = [e_{t-n+1}, e_{t-n+2}, \dots, e_t] \tag{7}$$

The convolution operation can be expressed as:

$$h_t = \sigma(W * E_t + b) \tag{8}$$

where W denotes the convolution kernel parameter, $*$ represents the convolution operation, b is the bias term, $\sigma(\cdot)$ denotes the activation function, and h_t is the output feature of the convolution layer.

Through multiple convolution operations, the model can progressively extract local trend features from the error sequence and provide richer high-dimensional feature representations for subsequent temporal dependency learning.

3.3. TCN Temporal Dependency Learning Layer

After completing local feature extraction, it is further necessary to learn the long-term temporal dependency relationships within the error sequence. Traditional recurrent neural networks are prone to gradient vanishing and error accumulation during long-sequence learning. Therefore, TCN is employed in this paper to construct the long-term temporal feature learning layer [15].

TCN adopts a Causal Convolution structure to ensure that the output at the current time step depends only on the current and historical inputs, thereby satisfying the causality requirement in time-series forecasting tasks. The causal convolution can be expressed as follows:

$$y_t = \sum_{k=0}^{K} w_k x_{t-k} \tag{9}$$

where K denotes the kernel size and w_k represents the convolution kernel parameter.

To further enlarge the receptive field and enhance long-term dependency learning capability, TCN introduces a Dilated Convolution structure, which can be formulated as:

$$y_t = \sum_{k=0}^{K} w_k x_{t-dk} \tag{10}$$

where d denotes the dilation factor.

In addition, to alleviate the gradient degradation problem during deep network training, a residual connection structure is further introduced:

$$H(x)=F(x)+x \tag{11}$$

where $F(x)$ represents the output feature of the convolution layer and x denotes the input feature.

Through the joint construction of causal convolution, dilated convolution, and residual connections, the TCN can effectively learn long-term temporal dependency relationships in the error sequence and improve the stability of error forecasting.

3.4. Attention-Based Error Correction Layer

Although TCN can effectively learn long-term dependency relationships, the importance of error features at different time intervals is not identical for the final forecasting results. Therefore, to further improve the model's ability to focus on critical error fluctuation intervals, an Attention mechanism is introduced after the TCN to construct a dynamic error correction layer.

The Attention mechanism dynamically assigns weights to different temporal features, thereby enhancing the model's capability of learning key temporal characteristics and improving forecasting accuracy under complex error patterns. First, the input features are mapped into Query, Key, and Value vectors:

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V \tag{12}$$

Then, the attention weights are calculated to measure the correlations among different temporal features:

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{13}$$

where d_k denotes the feature dimension. Finally, the Attention output is utilized to generate the error compensation term:

$$\Delta e_t = f_{att}(X_t) \tag{14}$$

Through the dynamic error learning mechanism of Attention, the proposed model can more accurately identify critical error fluctuation intervals and further enhance the error correction performance.

3.5. Rolling Iterative Forecasting Strategy

In multi-step short-term photovoltaic power forecasting tasks, prediction errors tend to gradually propagate and accumulate as the forecasting horizon increases. Therefore, relying solely on single-step forecasting results is insufficient for long-term continuous forecasting tasks. To improve the stability of multi-step forecasting, a rolling iterative forecasting strategy is further introduced in this paper.

This method incorporates the current forecasting result into the input sequence of the next time step and continuously updates the input window, thereby achieving continuous multi-step forecasting. The rolling forecasting process can be expressed as follows:

$$X_{t+1} = [x_{t-n+2}, x_{t-n+3}, \ldots, \hat{y}_t] \tag{15}$$

The final corrected forecasting result is formulated as:

$$\hat{y}_t^{'} = \hat{y}_t + \Delta e_t \tag{16}$$

Through the rolling iterative mechanism, the proposed model can dynamically correct prediction errors during continuous forecasting, thereby reducing the performance degradation caused by error accumulation and further improving the accuracy and stability of short-term photovoltaic power forecasting.

4. Experimental Results and Analysis

4.1. Experimental Settings

To verify the effectiveness and stability of the proposed ST-CNN-TCN-Attention model in short-term photovoltaic power prediction, this paper conducts experimental research based on a publicly available photovoltaic power generation dataset. The dataset mainly includes historical photovoltaic power output and corresponding meteorological variables, including features such as temperature, solar irradiance, wind speed, and humidity. The data temporal resolution is set to 15 minutes.

In the experiment, the dataset was first divided chronologically, with the training, validation, and test sets accounting for 70%, 20%, and 10% respectively. Regarding model parameter settings, the initial Stacking prediction model used XGBoost, LightGBM, Random Forest, and SVR as base learners, and Linear Regression as the meta-learner. The error correction network consisted of CNN layers, TCN layers, and attention layers. The CNN kernel size was set to 3, and the TCN used a dilated causal convolution structure with dilation coefficients of 1, 2, and 4 to expand the model's receptive field. The attention module employed a multi-head attention mechanism to enhance the model's dynamic learning ability for key error fluctuation ranges.

During model training, the Adam optimizer was used for parameter updates, with an initial learning rate of 0.0001, a batch size of 64, and 100 epochs.

To more comprehensively evaluate the model's predictive performance, this paper uses root mean square error (RMSE) and mean absolute error (MAE) as the main evaluation metrics, defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{17}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{18}$$

where y_i denotes the actual photovoltaic output power, $\hat{y}_i$ represents the predicted value, and n denotes the number of testing samples.

Furthermore, to further verify the effectiveness of the proposed model, this paper also compares and analyzes the proposed method with several typical prediction models such as SVM, Bi-LSTM, GRU, TCN, and Transformer.

4.2. Error Correction Effectiveness Analysis

To verify the effectiveness of the CNN-TCN-Attention error correction module, this paper compares and analyzes the initial and corrected prediction results of the Stacking model. The Stacking model can fit the overall trend of photovoltaic power change, but local biases still exist during the rapid rise, peak fluctuation, and decline phases. After CNN-TCN-Attention error correction, the predicted curve's fit with the actual power curve is further improved, the offset in the peak region is reduced, and the prediction results for short-term fluctuation ranges are more stable.

As shown in Figure 2, this paper compares and analyzes the photovoltaic power prediction results before and after error correction. Figure 2(a) shows the initial prediction results of Stacking. It can be seen that the initial prediction curve can basically follow the overall trend of the actual power change, but there are still some deviations in the power rise segment, near the peak, and in the fall segment, indicating that relying solely on the initial prediction model is difficult to fully characterize the local fluctuation characteristics. Figure 2(b) shows the prediction results after CNN-TCN-Attention error correction. The corrected curve is closer to the actual power curve, the prediction offset in the peak region is significantly reduced, and the overall fluctuation trend is more consistent. It can be seen that the proposed error correction module can effectively learn the dynamic change law in the initial prediction error and further improve the accuracy of short-term photovoltaic power prediction.

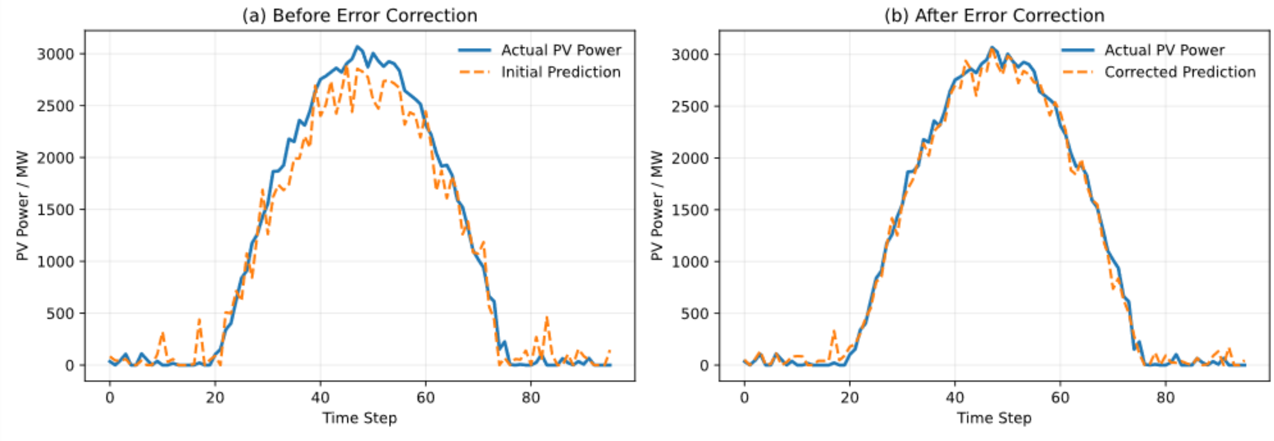

Figure 2: Prediction comparison before and after error correction.

After analyzing the error correction effect, this paper further compares the prediction curves of different models at 200 consecutive time points. Figure 3 shows the prediction results of SVM, Bi-LSTM, GRU, TCN, Transformer, and the proposed ST-CNN-TCN-Attention model. It can be seen that all models can fit the overall trend of photovoltaic power change to a certain extent, but the prediction performance of different models differs significantly during the rapid rise, peak fluctuation, and decline phases. SVM has relatively weak tracking ability for nonlinear fluctuations, Bi-LSTM and GRU have some lag near the peak, and TCN and Transformer have improved fitting performance, but still have deviations in local fluctuation ranges. In contrast, the prediction curve of the proposed ST-CNN-TCN-Attention model is closest to the actual power curve, showing better tracking ability in the peak region and rapid change phases, indicating that this model can effectively improve the accuracy of short-term photovoltaic power prediction.

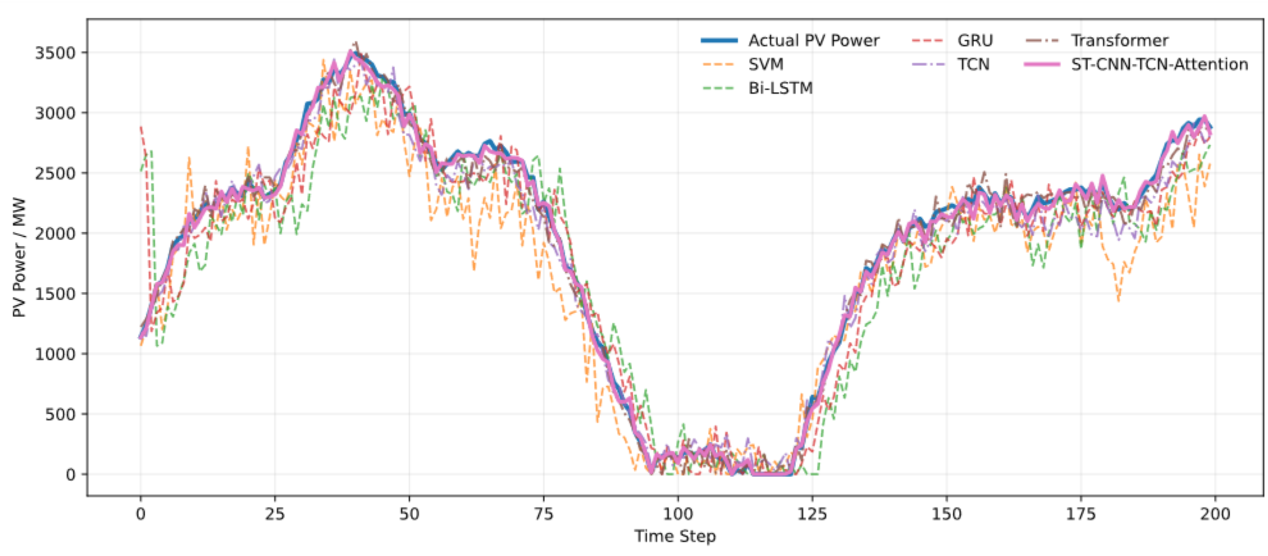

Figure 3: Prediction curves of different models over 200 time points.

Table 1 presents the comparison results of different forecasting models on the photovoltaic power prediction task. It can be observed that the traditional machine learning model SVM achieves the largest prediction error, with RMSE and MAE values of 214.37 and 168.42, respectively. This indicates that SVM has limited capability in modeling highly nonlinear and non-stationary photovoltaic power sequences, especially under rapid power fluctuation conditions.

Table 1: Comparison Results of Different Forecasting Models.

Model	**RMSE**	**MAE**
SVM	214.37	168.42
Bi-LSTM	176.85	139.76
GRU	158.29	124.53
TCN	131.47	102.64
Transformer	118.92	91.35
ST-CNN-TCN-Attention	72.48	56.17

Compared with SVM, the deep learning models Bi-LSTM and GRU achieve lower prediction errors due to their ability to capture temporal dependencies in time-series data. Among them, GRU performs slightly better than Bi-LSTM, demonstrating stronger temporal feature learning efficiency and improved parameter update capability.

The TCN model further improves the forecasting performance, reducing RMSE and MAE to 131.47 and 102.64, respectively. This improvement is mainly attributed to the dilated causal convolution structure, which enlarges the receptive field and enhances long-term dependency learning capability in photovoltaic power sequences.

Transformer achieves better prediction performance than TCN, with RMSE and MAE values of 118.92 and 91.35, respectively. Benefiting from the self-attention mechanism, Transformer can dynamically learn global temporal relationships among different time steps, thereby improving the overall forecasting accuracy. However, certain deviations still exist in local fluctuation regions and peak variation intervals.

Among all compared models, the proposed ST-CNN-TCN-Attention model achieves the best forecasting performance, with RMSE and MAE reduced to 72.48 and 56.17, respectively. Compared with Transformer, the proposed model reduces RMSE by approximately 39.05% and decreases MAE by approximately 38.51%. The experimental results demonstrate that the proposed model can more accurately fit photovoltaic power variation trends and maintain better prediction stability in peak fluctuation intervals and rapidly changing stages.

4.3. Typical-Day Forecasting Results

To further verify the model's predictive capabilities under different weather conditions and seasons, this paper selects typical daily photovoltaic power data from spring, summer, autumn, and winter for predictive analysis.

As shown in Figure 4(a) of the prediction results for a typical spring day, all models can fit the overall trend of photovoltaic power change well, but errors of varying degrees still exist during the rapid power increase phase and near the peak. LSTM and BiGRU exhibit some lag in the peak region, while TCN and Transformer, although able to track the overall trend well, still show some deviation in local fluctuation regions. In contrast, the proposed ST-CNN-TCN-Attention model has the highest fit with the actual power curve and can more accurately reflect the photovoltaic power change pattern.

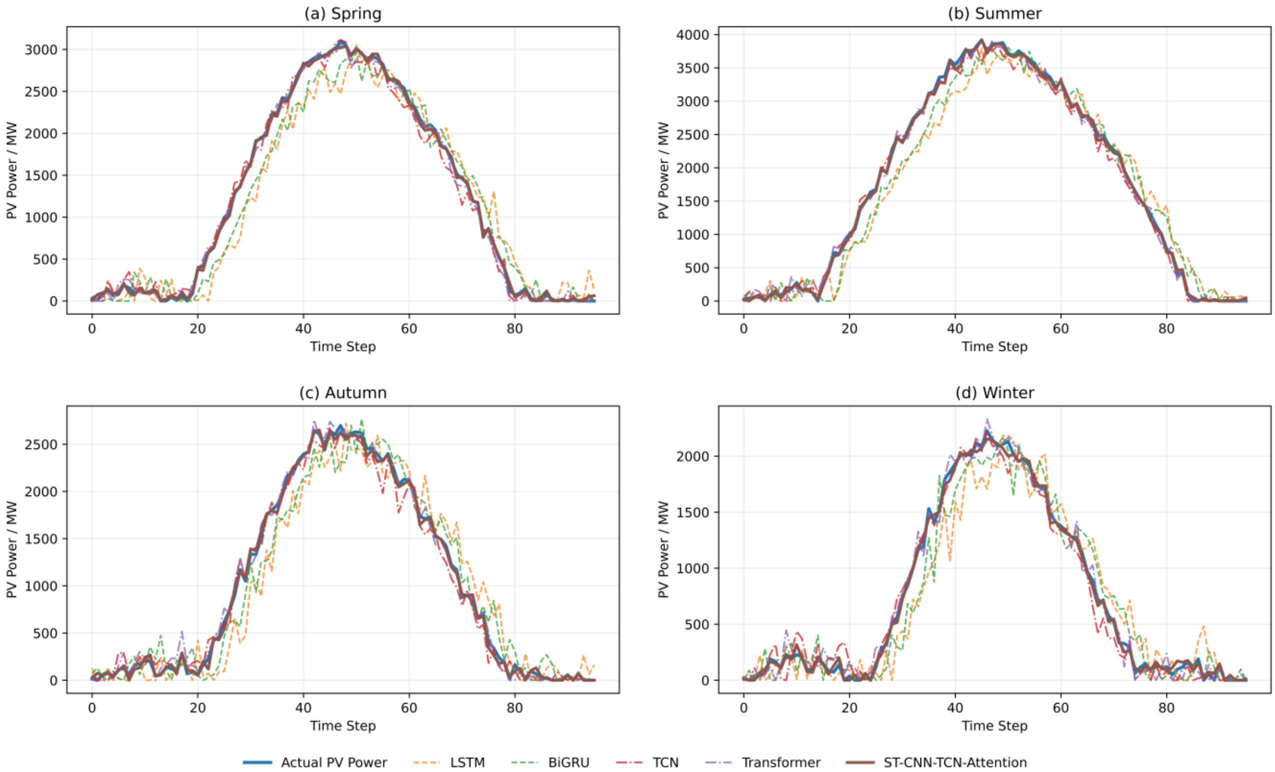

Figure 4: Prediction curves of different models over 200 time points.

Under the conditions of a typical summer day (Figure 4(b)), due to strong solar irradiance, the overall photovoltaic output power is high, and local fluctuations are more pronounced. Experimental results show that traditional recurrent neural network models are prone to prediction bias in the high-peak region, while the proposed method can effectively track peak changes and maintain good prediction stability. This indicates that the error correction mechanism can effectively alleviate the problem of local prediction bias under complex weather conditions.

Figure 4(c) of the prediction results for a typical autumn day further shows that as the frequency of weather changes increases, the prediction errors of all models increase. Among them, LSTM and BiGRU showed weak response to local fluctuations, with noticeable smoothing of the predicted curves. TCN and Transformer improved the prediction performance, but still had some errors in the rapid fluctuation phase. The proposed method, however, maintained better consistency between the predicted and actual power curves, indicating that the proposed model has a stronger adaptability to complex dynamic changes.

Figure 4(d) shows that the overall prediction difficulty is further increased due to lower irradiance and more complex weather changes on a typical winter day. Experimental results show that most models are prone to large fluctuation errors in the low-power region, while ST-CNN-TCN-Attention still maintains high prediction accuracy. This is mainly due to the CNN module's ability to extract local features, the TCN's ability to learn long-term temporal dependencies, and the Attention's ability to dynamically focus on key error regions.

4.4. Monthly Error Distribution Analysis

To further analyze the predictive stability of the model under long-term operating conditions, this paper statistically analyzes the changes in RMSE and MAE of each model in different months and comprehensively evaluates the predictive performance of the model throughout the year. Figure 5 shows the error distribution results under different monthly conditions.

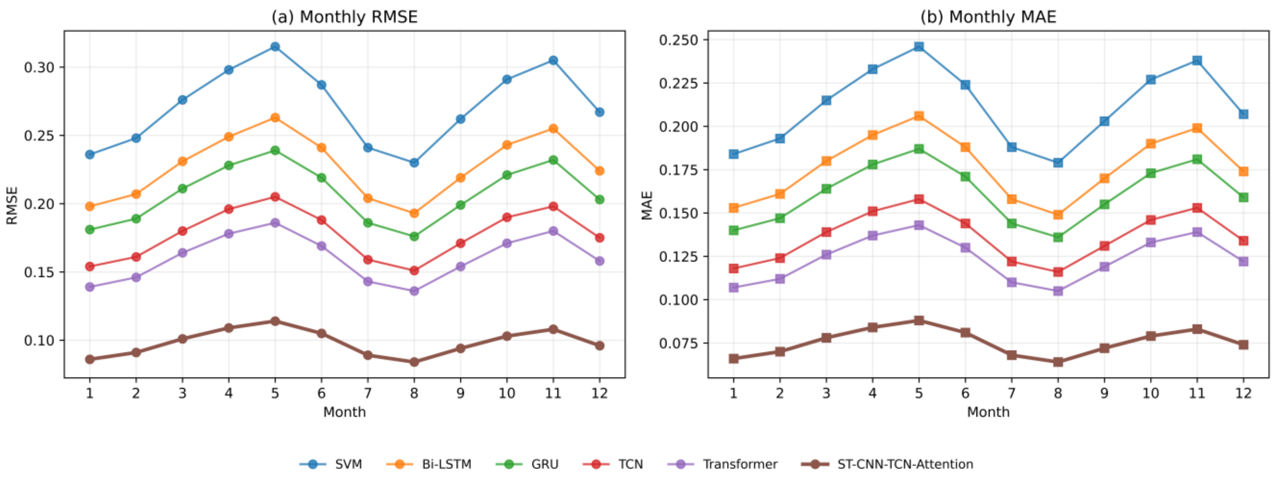

Figure 5: Monthly Error Analysis.

Experimental results show that there are significant differences in photovoltaic power prediction errors in different months. In spring and autumn, due to frequent weather changes and strong cloud disturbances, the overall errors of each model are relatively high; while in summer, due to relatively stable solar irradiance conditions, the overall model prediction errors decrease. In winter, due to lower light intensity and increased weather instability, the prediction errors show an upward trend again.

Compared with traditional models, the proposed ST-CNN-TCN-Attention model maintains lower RMSE and MAE values in all months of the year, indicating that the model has good cross-seasonal generalization ability and long-term operational stability. Especially in months with significant complex weather changes, the error growth rate of the proposed method is significantly smaller than that of other comparative models, further demonstrating that the error correction network can effectively mitigate the prediction bias caused by weather changes.

Furthermore, the annual error trend reveals that traditional machine learning models are prone to significant error fluctuations during months with complex weather conditions. While deep learning models show overall improved prediction performance, they still exhibit some instability in locally dynamic regions. In contrast, the method presented in this paper maintains high prediction accuracy across different monthly conditions, demonstrating better robustness and stability.

5. Conclusion

This paper addresses the challenges of strong random fluctuations, significant local nonlinear changes, and the accumulation of errors in multi-step rolling predictions during short-term photovoltaic (PV) power forecasting. A novel PV power forecasting method based on ST-CNN-TCN-Attention is proposed. First, a stacking ensemble learning model is used for initial PV power forecasting to improve the overall generalization ability of the model. Then, a CNN-TCN-Attention error correction network is introduced to dynamically learn and compensate for the initial prediction error. CNN is used to extract local fluctuation features, TCN is used to learn long-term temporal dependencies, and the Attention mechanism is used to dynamically focus on key error regions. Finally, a rolling iterative prediction strategy is combined to achieve multi-step continuous PV power forecasting.

Experimental results show that the proposed method maintains high prediction accuracy under different seasons, weather conditions, and prediction step sizes. Compared with models such as SVM, Bi-LSTM, GRU, TCN, and Transformer, ST-CNN-TCN-Attention achieves the best results in terms of RMSE and MAE, especially demonstrating better prediction stability in peak fluctuation ranges and rapid change phases. Meanwhile, analysis of typical daily forecast results and monthly error distribution reveals that the proposed method effectively reduces forecast bias even under complex weather conditions, demonstrating good robustness and generalization ability.

Future research could further incorporate numerical weather prediction (NWP) data, multi-site spatial information, and probabilistic prediction mechanisms into the model building process to enhance the model's adaptability to complex meteorological environments. Furthermore, combining the Transformer long-sequence modeling structure with graph neural network methods could construct a multi-source collaborative prediction framework for regional-level new energy scenarios, thereby providing more reliable forecast support for new energy grid-connected scheduling and intelligent energy management.

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