An Effective And Efficient Renewable Energy Generation Forecasting Via Meteorological Assistance

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Accurate signal pattern mining of renewable energy generation forecasting (REGF) is important to the days-ahead power scheduling of renewable energy power systems. Despite achieving excellent performance with current methods, two issues still persist. (1) They solely utilize historical meteorological signal data to assist in power signal forecasting and neglect valuable information in future information of meteorological signals, consequently limiting their performance. (2) They pursue predictive performance by designing complex architectures and mechanisms, which may lead to insufficient model generalization. To this end, an effective and efficient MLP architecture is proposed to mine REGF signal patterns in renewable energy power systems (SPM-REPS), which contains power signal forecast architecture and meteorological signal forecast architecture. Two architectures seamlessly collaborate in forecasting power generation patterns, which achieves better performance. Meanwhile, time-correlation and feature-correlation strategies are devised within MLP networks to capture both intra-sequence and inter-sequence correlations of signal variables like transformer- and RNN-based methods. Furthermore, a theoretical analysis of linear architecture is given to prove the progressiveness of SPM-REPS. Finally, numerous experiments, conducted on common datasets (CSG-PV and CSG-wind) from Chinese State Grid, demonstrate SPM-REPS sets a new benchmark in mining REGF signal patterns of REPS.

Keywords: Power forecasting; meteorological assistance; time- and feature-correlations

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1. Introduction

With the continuous advancement of technology and the increasing awareness of environmental protection, high-proportion renewable energy power systems have been widely promoted and applied globally, providing effective solutions for addressing climate change and reducing dependence on fossil fuels [1–4]. However, renewable energy signals are susceptible to various factors such as weather fluctuations, seasonal changes, and geographical differences, exhibiting high levels of randomness, volatility, and intermittency. For example, the output power of wind energy production fluctuates due to rapid changes in wind speed, while solar energy generation is influenced by factors such as duration of sunlight and cloud cover. Due to complex characteristics of these signals, renewable energy power systems are incapable of effectively extracting and processing signal patterns, leading failures in grid scheduling and management [5, 6].

Machine-learning-based signal pattern mining methods utilize big data mining and analysis techniques to identify complex patterns and correlations within renewable energy signals from historical data derived from renewable energy power systems, which have gained significant progress in renewable energy generation forecasting (REGF). These machine-learning-based signal processing methods in REGF can be partitioned into two branches: traditional-based REGF methods [7–9] and deep-based REGF methods [1, 10, 11]. Traditional-based REGF methods typically build generation forecasting models by training supervised learning algorithms. They utilize historical electricity signals and relevant meteorological signals (such as temperature, wind speed, humidity, etc.) to establish regression or classification models. Common traditional-based REGF methods include LR, SVMs, DTs, and RFs, which are relatively easy to implement, computationally efficient, and can achieve satisfactory prediction accuracy when the data volume is small and the feature relationships are relatively simple. Deep-based REGF methods aims to construct sophisticated neural network structures to capture more complex nonlinear relationships. Common deep -based REGF methods include CNNs, RNNs, and LSTMs, which can handle high-dimensional input signals and automatically extract important features through the training of large datasets, adapting to complex meteorological and temporal signal patterns. Deep-based REGF methods usually perform excellently when dealing with large-scale data and complex patterns.

Current methods have achieved excellent performance, but two issues still persist: Despite these methods exploring the relationship between meteorological signals and renewable energy signals, their researches are limited to historical weather signal, neglecting the potential impact of future meteorological information on renewable energy generation. Predicting and modeling future weather conditions can provide more accurate guidance and optimization for renewable energy generation. Additionally, they do not sufficiently balance the relationship between model complexity and prediction accuracy. In other words, in the pursuit of higher prediction accuracy, the models and algorithms become overly complex, leading to increased computational resource requirements in extracting and processing signal patterns.

To this end, an effective and efficient MLP architecture is proposed to mine REGF signal patterns in renewable energy power systems (SPM-REPS), which contains power signal forecast architecture and meteorological signal forecast architecture. Specifically, the power signal forecast architecture consists of an alignment projection component (APC), an information aggregation component (IAC), and a power forecasting component (PFC). APC utilizes a linear layer along the time dimension to align historical signal data and future meteorological signal data, providing a foundation for subsequent integration. IAC designs time correlation and feature correlation strategies to model the intra-sequence temporal patterns and cross-feature dependencies of signal variables, achieving deep integration of information. PFC uses a fully connected layer to obtain the final power prediction. Similarly, to simplify the model, the meteorological signal forecast architecture still uses MLP networks to obtain future meteorological signal prediction. Additionally, we discuss how the linear architecture can effectively capture periodic and smooth trend patterns in time series data. Finally, extensive experiments on the publicly available datasets CSG-PV and CSG-wind from Chinese State Grid demonstrate that SPM-REPS significantly enhances the accuracy and reliability in mining REGF signal patterns in the renewable energy power systems.

The contributions of SPM-REPS are three-fold: (1) An effective and efficient MLP architecture is introduced for REGF signal pattern mining, enhancing the model generalization and applicability while ensuring prediction accuracy. (2) A meteorological signal forecast architecture is designed to provide more accurate guidance and optimization for the power signal forecasting via modelling future meteorological characteristics. (3) Numerous experiments demonstrate SPM-REPS sets a new benchmark in mining REGF signal patterns.

2. Related works

2.1. Traditional-based REGF methods

This type of method is a data-driven predictive technique that analyzes historical signal using statistical models to learn generation patterns and trends. For example, Kim et al. constructed an adaptive knowledge integration framework for solar power generation forecasting by introducing selective weighting factors to base learners such as support vector regression, naive Bayes classification, and hourly logistic regression, effectively improving robustness to outliers and noise in the generation forecasting [7]. Zhou et al. devised a mixed framework rooted in extreme learning machines, genetic algorithms, and customized similar-day analysis, to forecast solar power generation [8]. They utilize the Pearson correlation coefficient to model the correlations among five meteorological signals and power signals, and then introduce the genetic algorithm to search for the optimal values of the hidden layer parameters of the ELM for enhancing solar power generation forecasting. Li et al. utilized a mixed enhanced multivariable optimizer to perform a global search in the support vector parameter space [9]. Such a manner effectively captures patterns and relationships between electricity and meteorological signals and greatly enhances both the accuracy and speed of solar power generation forecasts. Wang et al. designed an extreme learning machine wind power forecasting model relying on the predator-prey optimization algorithm [5]. They employed partial least squares variable importance projection and NMI to explore the correlation among wind speed and power generation, and then applied the predator-prey optimization with adaptive inertia weight to seek for the best parameters of the extreme learning machine, achieving high-precision predictions of wind power output.

2.2. Deep-based REGF methods

This type of method uses neural network with multi-layer structures, such as CNNs, RNNs, and LSTMs, to process and analyze signal patterns, which can automatically extract complex features from the signals and make predictions by learning the deep relationships between these features and power generation [12]. For example, Wang et al. introduced a mixed wind power deep prediction architecture combining CEEMDAN decomposition, a transformer, and a Bi-GRU attention mechanism [1]. They first used CEEMDAN to differentiate high- and low-frequency sequences based on sample entropy, then applied the transformer and Bi-GRU attention models for generation prediction, and finally aggregates the results in a voting manner to improve prediction accuracy. Alhussan et al. developed a dual-integrated wind power prediction architecture by dynamically coupling LSTM, GRU, and Bi-LSTM where a whale optimization algorithm and a throat optimization algorithm were designed to optimally weight the outputs of the sub-models [13]. Zang et al. proposed a solar power forecasting method that combines variational mode decomposition with CNNs [14]. First, different frequency components are decomposed from historical photovoltaic power time series signals and structured into a two-dimensional data format. Then, these components are integrated with meteorological features for training to boost the forecasting accuracy. Han et al. analyzed the season distribution of photovoltaic power output fluctuations over time and established a seasonal multi-model based on ELM to predict photovoltaic power, which obtains more accurate photovoltaic power forecasting performance comparing with a single prediction model [10]. Widodo et al. used LSTM networks to capture the correlations between meteorological signals, such as irradiance, air temperature, panel temperature, wind speed, wind direction, and precipitation, and solar power generation, which effectively captures the nonlinear long-term dependencies between signals and achieves accurate extraction of solar power generation patterns [11].

Current methods for renewable energy generation forecasting face several challenges. Traditional approaches often struggle with limited historical data, affecting their ability to generalize and predict accurately, especially in dynamic environments. They also may not adequately handle errors or conflicts in probabilistic forecasts, and their complexity can lead to inefficiencies. On the other hand, deep-based methods, while powerful, are prone to overfitting, especially with limited or noisy data, making it difficult to understand feature impacts. Additionally, integrating diverse data sources and signals poses challenges, complicating the achievement of optimal forecasting accuracy. These issues highlight the need for improvements in data handling, model interpretability, and computational efficiency to enhance forecasting performance in renewable energy systems.

3. An effective and efficient renewable energy generation forecasting via meteorological assistance

An effective and efficient MLP architecture is proposed to mine REGF signal patterns in renewable energy power systems via deeply coupling dual architectures, i.e., power signal forecast architecture and meteorological signal forecast architecture, as shown in Fig. 1.

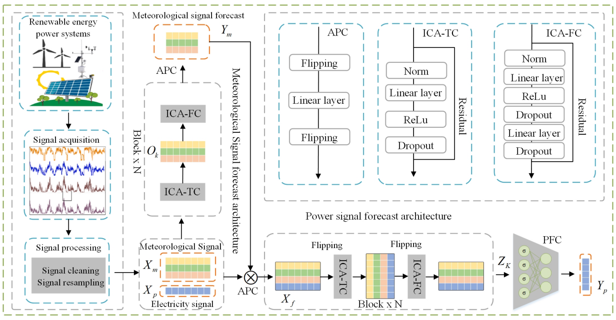

Fig. 1. Overview of the SPM-REPS architecture for renewable energy generation forecasting: integration of meteorological and power signals with time-correlation and feature-correlation learning mechanisms.

3.1. Problem definition

SPM-REPS performs generation forecasting via modelling correlations between future power outputs and relevant input signal including historical power signal data, historical meteorological signal data, and future meteorological signal data. Mathematically, given a historical power signal data matric $X_p \in R^{L\times 1}$ and a historical meteorological signal data matric $X_m \in R^{L\times C}$, where L is backtracking window length and C is the number of meteorological variables, SPM-REPS utilizes meteorological signal forecast architecture $g(\cdot)$ to obtain meteorological signal prediction $Y_m \in R^{T\times C}$ where T is the future window length, and then it devises power forecast main architecture $f(\cdot)$ to aggregate information among historical power signal data, historical and future meteorological signal data for forecasting future power Y_p :

$$Y_p = f\left(X_p, X_m, g\left(X_m\right)\right) \in R^{T\times 1} \tag{1}$$

3.2. Power signal forecast architecture

To avoid overcomplicating the model, an effective and efficient MLP network is used to conduct the power signal forecast architecture, which consists of an alignment projection component, an information aggregation component, and a power forecasting component.

The alignment projection component (APC) is designed to align the temporal dimensions of historical data and future meteorological data. Specifically, given historical data matric $X \in R^{L\times(C+1)}$ $\left(X = \left[X_p, X_m\right]\right)$, APC utilizes a linear layer to map the time series from L to T along the dimension of time:

$$APC_{L\to T}\left(X_{pm} \in R^{T\times(C+1)}\right) = W_1 X + b_1 \tag{2}$$

where W_1 and b_1 denote the weight and bias of the layer, respectively. Then, fusion data $X_f \in R^{T\times(2C+1)}$ can be obtained via concatenating X_{pm} and Y_m along the dimension of feature.

Clearly, future meteorological information significantly impacts energy power predictions, yet this crucial aspect is often overlooked by current forecasting methods. Meteorological conditions directly influence the operation and efficiency of energy systems. For instance, solar and wind energy outputs are directly affected by factors such as sunlight intensity and wind speed, effectively utilizing future meteorological information can help improve forecasts for renewable energy generation.

The information aggregation component (IAC) is devised to fuse information among historical power data, historical and future meteorological data. To model both intra- and inter-sequence correlations of variables like transformer- and RNN- based methods, IAC devises time-correlation and feature-correlation strategies.

Firstly, the time-correlation (TC) is implemented via a nonlinear layer with the activation function Relu to capture temporal pattern information within variables. For the fusion data matric $X_f \in R^{T\times(2C+1)}$, the process is designed along the dimension of time as follows:

$$\begin{aligned} &TC_{T\to T}\left(X_f\right) \\ &= \text{Norm}\left(X_f + \text{Drop}\left(\text{Relu}\left(APC_{T\to T}\left(X_f\right)\right)\right)\right) \end{aligned} \tag{3}$$

where Norm $(\cdot)$ denotes the batch normalization that is used on the data along the dimensions of feature and time. Drop $(\cdot)$ denotes the dropout operation, a regularization technique used to prevent overfitting. Then, the feature-correlation (FC) is implemented via a nonlinear layer with the activation function Relu to capture dependencies between variables. the process is designed along the dimension of feature as follows:

$$\begin{aligned} &FC_{2c+1\to h}\left(TC\left(X_f\right)\right) = \\ &\text{Norm}\left(W_h TC\left(X_f\right) + \text{Drop}\left(\text{Relu}\left(W_2\left(TC\left(X_f\right) + b_2\right)\right)\right)\right) \end{aligned} \tag{4}$$

where W_2 and b_2 denote the weight and bias, respectively. $W_h TC\left(X_f\right)$ denotes the residual terms. h denotes the dimension of latent representations. To fully captures intra-sequence and inter-sequence correlations of variables, the time-correlation and the feature-correlation are sealed into the block for loop operation:

$$Z_1 = FC_{2c+1\to h}\left(TC\left(X_f\right)\right) \tag{5}$$

$$Z_k = FC_{h\to h}\left(TC_{T\to T}\left(Z_{k-1}\right)\right), \forall k = 2, \ldots, K \tag{6}$$

where K denotes the loop number. Z_k denotes latent representations generated by the k-th block. Network parameters between blocks are not shared.

The power forecasting component (PFC) uses a linear layer to map fully aggregated latent representations into future power outputs:

$$Y_p = PFC\left(Z_K\right) = PFC\left(ICA\left(X_f\right)\right) \in R^{T\times 1} \tag{7}$$

Where Y_p denotes power forecasting of SPM-REPS.

3.3. Meteorological signal forecast architecture

Meteorological forecast is a common long-term series forecasting task and can be implemented using time series forecasting methods. To simplify the model, the MLP networks are selected to construct meteorological signal forecast auxiliary architecture.

Specifically, given the historical meteorological signal data matric $X_m \in R^{L\times C}$, the prediction process of the meteorological forecast auxiliary architecture is defined as follows:

$$O_1 = FC_{C\to C}\left(TC_{L\to L}\left(X_f\right)\right) \tag{8}$$

$$O_k = FC_{C\to C}\left(TC_{L\to L}\left(O_{k-1}\right)\right), \forall k = 2, \ldots, K \tag{9}$$

$$Y_m = APC_{L\to T}\left(O_k\right) \tag{10}$$

where O_k denotes latent representations of meteorological data. Notably, the network parameters between the power forecast main architecture and the meteorological signal forecast auxiliary architecture are not shared.

3.4. Model loss

SPM-REPS employs a two-stage training strategy to enhance the accuracy of power prediction while mitigating the impact of inaccurate meteorological forecasts. The specific strategy is as follows:

In the first stage, we train the meteorological signal forecast architecture with the Mean Squared Error between meteorological predictions and meteorological labels:

$$L_m = \frac{1}{N_m} \sum_{i=1}^{N_m} \left(y_m^i - g_m^i \right)^2 \tag{11}$$

where N_m denotes the number of the meteorological samples. g_m^i denotes labels of the meteorological samples.

In the second stage, we fix the parameters of the meteorological signal forecast architecture and do not adjust them further. Subsequently, we train the power signal forecast architecture with the Mean Squared Error between power predictions and power labels:

$$L_p = \frac{1}{N_p} \sum_{i=1}^{N_p} \left(y_p^i - g_p^i \right)^2 \tag{12}$$

where N_p denotes the number of the power samples. g_p^i denotes labels of the power samples. By employing this phased training strategy, we can ensure the accuracy of meteorological predictions while optimizing the performance of the power prediction network, thereby improving the overall accuracy and reliability of the predictions.

3.5. Theoretical analysis of SPM-REPS

The Complexity Analysis: The time complexity analysis of SPM-REPS is as follows: For the Meteorological Signal Forecast Architecture, given the historical meteorological signal matrix $X_m = R^{L \times C}$, the time complexity of the $TC_{L \to L}$ operation is $O\left(NLC^2\right)$, where N denotes the number of samples. The $FC_{C \to C}$ operation has a time complexity of $O\left(NLC^2\right)$, and with K loops, the total complexity is $O\left(NKLC^2\right)$. The final $APC_{L \to T}$ operation has a time complexity of $O\left(NTC^2\right)$. Hence, the total time complexity for the Meteorological Signal Forecast Architecture is $O\left(NKLC^2 + NLC^2\right)$. For the Power Signal Forecast Architecture, given the fused data matrix $X_f = R^{T \times (2C+1)}$, the time complexity of the $TC_{T \to T}$ operation is $O\left(NT(2C+1)^2\right)$. The $FC_{2C+1 \to h}$ operation has a time complexity of $O(NTh)$, and with K loops, the total complexity is $O\left(NKL(2C+1)^2 + NKL(2C+1)h\right)$. The final PFC operation has a time complexity of $O(NTh)$. Combining these, the overall time complexity of SPM-REPS is $O\left(NKTC^2\right)$, which is linear in the number of samples N. That is, SPM-REPS is a linear architecture.

Progressiveness of Linear Architecture: The time series of renewable energy generation often exhibit smoothness or periodicity, characteristics that are essential for maintaining predictability and ensuring the reliability of predictive models. To facilitate analysis, we initially adopt the assumption that the time series of renewable energy power generation is periodic.

Considering a periodic function $x(t) = x(t - w)$ in which w denotes the period of time series and $w < l$, a linear solution can be formulated that precisely predicts future values, as expressed by:

$$w_{ij} = \begin{cases} 1, & \text{if} \quad j = L - w + (i \bmod w) \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where w_{ij} denotes the parameter of the linear architecture. This solution indicates that the linear model can fully capture the periodic pattern in the time series. Furthermore, for the affine-transformed periodic series $x(t) = \alpha x(t - w) + \beta$ where α, β are constants, a perfect solution is still provided:

$$w_{ij} = \begin{cases} \alpha, & \text{if} \\ 0, & \text{otherwise} \end{cases}, L - w + (i \bmod w), b_i = \beta \tag{14}$$

In this case, the linear model adjusts its parameters to accommodate the scaling and shifting introduced by the affine transformation, maintaining perfect prediction accuracy. A broader framework posits that the time series can be decomposed into both a periodic component $\pi(t)$ and an underlying smooth trend component $\mu(t)$, i.e., $x(t) = \pi(t) + \mu(t), \pi(t)$ is subject to the constraint $|\pi(a) - \pi(b)| \le K \left| \frac{a-b}{a+b} \right|$, there exists a linear architecture with a lookback window size $L \ge w + 1$ that ensures the prediction error remains bounded:

$$|y_i - \bar{y}_i| \le K(i + \min(i, w)), \quad i = 1, 2, \ldots, T \tag{15}$$

This result demonstrates that linear models are powerful tools for capturing temporal relationships, particularly in time series with periodic or smooth trends. Even for non-periodic patterns, as long as the series remains smooth, the prediction error will be constrained, provided the lookback window is sufficiently large. This makes linear models a strong candidate for practical time series forecasting tasks.

Differences from current methods: Compared to current LSTM-, RNN-, and Transformer-based methods, SPM-REPS has three advantages in the renewable energy generation forecasting task:

1. Simplified Model Complexity: In the context of REGF, where data volatility and uncertainty are prominent—such as in wind and solar power generation affected by weather changes—traditional models like LSTM and RNN may become excessively complex due

to their recurrent structures. Transformer models, despite their ability to manage long-range dependencies, often suffer from overfitting due to their large parameter space. SPM-REPS addresses this by leveraging MLPs, reducing complexity and mitigating overfitting risks.

2. Efficient Correlation Extraction: SPM-REPS excels in efficiently integrating information across both time steps and feature dimensions, which is crucial for forecasting renewable energy volatility. While LSTM and RNN struggle with long-term dependencies and Transformer models face high computational costs, SPM-REPS utilizes alternating time-correlation and feature-correlation learning to adeptly capture complex patterns and long-term dependencies.
3. Future Meteorological Integration: Renewable energy generation is significantly influenced by meteorological conditions. SPM-REPS integrates future meteorological data directly into forecasting models, offering a substantial advantage over traditional methods like LSTM, RNN, and Transformer. This integration provides critical insights, such as future wind speeds and precipitation levels, essential for accurate energy production predictions.

4. Results

4.1. Setup

Dataset and metric: SPM-REPS uses PV and wind power dataset [15] provided by Chinese State Grid from 2019-1-1 to 2020-12-31, i.e., CSG-PV1, CSG-PV2, CSG-Wind1, and CSG-Wind2, to verify effectiveness and preeminence in the REGF tasks. Each dataset contains 70176 time series, with training data of 55565 and testing data of 13461. The statistical information of the dataset. Meanwhile, to evaluate performance, two common metrics, MAE and MSE, are utilized in the experiments where the smaller the metric value and the better the performance. Implementation Details: SPM-REPS is implemented via PyTorch and performed on a platform with an NVIDIA Tesla V100 GPU on Windows 10. In the experiments, each variable undergoes independent standardization, and the data remains unaltered during performance evaluation. The training number is set as 200 epochs and early stopping is employed if the loss is not improved during 5 epochs. The backtracking window length L and the prediction window length T are set as 480 and 96, respectively. The learning rate, the loop number, and dropout are set as 0.0001, 4, and 0.7, respectively. The dimension of latent reorientations is set as 8. The batch size is set as 128.

4.2. Comparison results

Eight baselines are compared with our methods for fully validating performance in REGF tasks, including four universal time series prediction methods, i.e., Autoformer [16], TFT [17], FEDformer [18] and Informer [19], four customized REGF methods IEDN-RNET [20], IAMFN [21], CNN-RNN [22] and CNN-BiLSTM [23]. The experimental results in Table 1 demonstrate the superior performance of SPM-REPS compared to eight baseline models for 24-hour power prediction across four datasets. SPM-REPS consistently outperforms all baseline models in both MSE metrics. For instance, on the CSG-PV1 dataset, SPM-REPS achieves an MAE of 0.1128 and an MSE of 0.0580, significantly lower than the second-best model, FEDformer, which has an MAE of 0.2021 and an MSE of 0.1867. Similar trends are observed across the other datasets, with SPM-REPS showing marked improvements over models like Autoformer, TFT, and Informer. SPM-REPS achieves superior forecasting accuracy due to two main factors. Firstly, it effectively utilizes future meteorological data, crucial for forecasting renewable energy generation. By integrating anticipated weather conditions that directly influence solar and wind power outputs, SPM-REPS produces predictions less susceptible to the uncertainties of weather-dependent energy sources. Secondly, SPM-REPS excels in efficiently mixing information across different time steps and feature dimensions. This capability allows the model to explore inherent patterns and dependencies hidden in the data, essential for understanding the dynamics of renewable energy generation. By blending information in this way, SPM-REPS can accurately identify and leverage the relationships between various factors affecting energy production, thereby enhancing the precision of its forecasts.

4.3. Effects of backtracking window length

To further investigate the capability of SPM-REPS in handling sequences, analytical experiments are conducted via using different backtracking window lengths on the four methods. The prediction window T is fixed at 96. The experiment results are shown in Fig. 2. From these experiments, two main observations can be drawn: (1) The performance of SPM-REPS significantly improves as the backtracking window size increases from 96 to 480 and appears to reach a convergence point at 720. (2) Complex models based on multivariate Transformers and LSTMs do not benefit from backtracking window sizes larger than 480 and tend to overfit as the window size increases. These two observations demonstrate that the proposed method exhibits superior robustness and is not adversely affected by the increase in backtracking window length.

Table 1. The comparison results with eight baselines within 24-hour power prediction.

Method	CGS-PV1		CGS-Wind1		CGS-PV2		CGS-Wind1	
	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
Autoformer	0.3134	0.1960	0.3420	0.2360	0.3758	0.2278	0.3569	0.2259
TFT	0.3768	0.2951	0.3412	0.3387	0.4700	0.4586	0.3489	0.3100
FEDformer	0.2021	0.1867	0.3110	0.1975	0.2941	0.2121	0.2847	0.1968
Informer	0.3930	0.3044	0.4127	0.3516	0.4795	0.4268	0.4897	0.3965
IEDN-RNET	1.0301	0.9987	1.3670	1.2569	1.7258	1.3245	1.6379	1.4546
IAMFN	2.8709	2.2564	2.2709	2.0415	3.0648	2.5656	2.9878	2.5415
CNN-RNN	1.4902	1.3115	1.9902	1.6115	1.7812	1.5189	1.2912	1.0120
CNN-BiLSTM	0.4487	0.3548	0.8902	0.6315	0.5689	0.2544	0.5123	0.3564
MSF-net	**0.1128**	**0.0580**	**02485**	**0.1454**	**0.2119**	**01244**	**0.2345**	**0.1559**

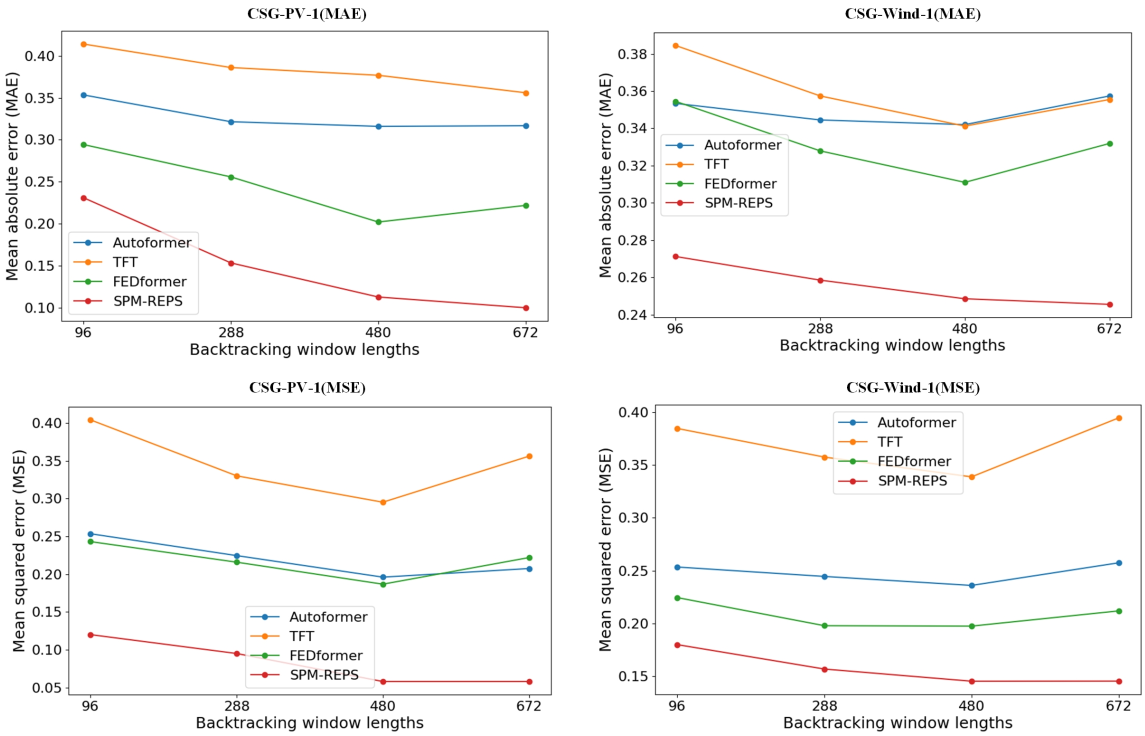

Fig. 2. Effects of backtracking window length on CSG-PV1 and CSG-Wind1 about MAE and MSE.

4.4. Ablation Study

To validate the justification and effectiveness of each component in SPM-REPS, the ablation study is conducted on CSG-PV1 with MSE and MAE. Specifically, there are three (1) SPM-REPS_1 uses the time-correlation strategy to aggregate information of power data, and then obtains power forecasting. (2) SPM-REPS_2 uses the time-correlation strategy and the feature-correlation strategy to aggregate information of history power and meteorological data, and then obtains power forecasting. (3) SPM-REPS_3 trains the power signal forecast architecture and the meteorological signal forecast architecture in an end-to-end manner. There are three observations from Table 2: (1) SPM-REPS_1 shows higher MSE and MAE compared to the other variants and the full SPM-REPS model. This indicates that while the time-correlation strategy alone can capture some temporal patterns, it is not sufficient for achieving low prediction errors. (2) SPM-REPS_2 significantly improves over SPM-REPS_1 in both MSE and MAE. This highlights the importance of the feature-correlation strategy in capturing dependencies between historical power and meteorological data, leading to better performance. (3) SPM-REPS_3, which trains both architectures simultaneously, shows some improvements over SPM-REPS_1 but performs worse than SPM-REPS_2 and the full SPM-REPS. This suggests that while end-to-end training can be beneficial, it may also lead to suboptimal performance due to the increased complexity and potential overfitting.

Table 2. Ablation study of SPM-REPS on CSG-PV1.

Metric	SPM-REPS_1	SPM-REPS_2	SPM-REPS_3	SPM-REPS
MSE	0.5134	0.2015	0.5856	0.0580
MAE	0.6692	0.2471	0.4315	0.1128

Table 3. Computational cost on CSG-PV1.

	Autoformer	FEDformer	TFT	SPM-REPS
NP	471 K	1.7 M	2.9 M	435 K
Time	5.9700	27.67	50.98	5.1200
MSE	0.1960	0.1867	0.2951	0.0580
MAE	0.3134	0.2021	0.3768	0.1128

4.5. Qualitative Evaluation

Fig. 3 illustrates a high degree of overlap between predicted and actual values, showcasing the model's superior accuracy in daily solar and wind power forecasts. This close alignment confirms the model's effectiveness in capturing both short-term and long-term variations in power generation. The model demonstrates excellent performance across both solar and wind energy predictions, highlighting its robustness in managing complex data patterns. Its ability to maintain high precision even during rapid changes in power data underscores its reliability for practical applications. The model's stability and consistent performance are particularly valuable for optimizing energy management and decision-making, proving its practical utility in enhancing energy efficiency and reducing operational costs. Furthermore, the model's high accuracy facilitates more reliable energy forecasts, leading to better planning and resource allocation. Its versatility across different types of renewable energy makes it a valuable tool for diverse energy management scenarios. Overall, the model's strong performance supports its adoption for improving operational efficiency and supporting sustainable energy practices.

4.6. Further Evaluation

The computational cost of each method is evaluated using their optimal hyperparameters on the CSG-PV dataset. As demonstrated in Table 3, the proposed method is outperformed by models based on transformers. Specifically, significantly fewer model parameters are required by SPM-REPS, and lower MSE and MAE errors are achieved. This indicates that an effective balance between model complexity and prediction accuracy is struck in our study, highlighting the robustness and efficiency of SPM-REPS.

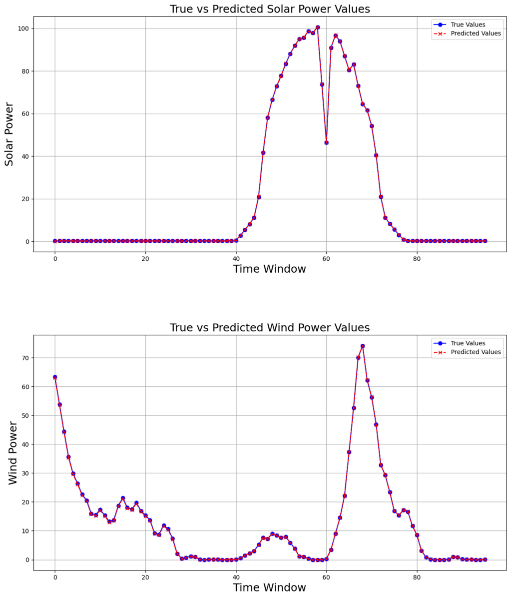

Fig. 3. True v.s. Prediction.

5. Conclusions

This paper proposes an effective and efficient meteorology-assisted signal pattern mining method for renewable energy generation forecasting, named SPM-REPS, via constructing power signal forecast main architecture and meteorological signal forecast auxiliary architecture within a MLP network. Moreover, SPM-REPS captures intra-sequence and cross-sequence correlations of signal variables in the MLP network through designed strategies for time and feature correlations. Extensive experiments on the publicly available datasets CSG-PV and CSG-wind from Chinese State Grid demonstrate that SPM-REPS greatly boosts the accuracy and robustness of renewable energy generation forecasting. By effectively utilizing future meteorological signal data and efficiently blending information across different time steps and feature dimensions, SPM-REPS provides robust support for day-ahead power scheduling in renewable energy power systems. Future challenges remain in advancing this approach. These include enhancing the model's adaptability to varying weather conditions and integrating more diverse data sources to further improve forecasting precision.

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