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Short-term prediction of photovoltaic power generation based on LMD-EE-ESN with error correction

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Abstract: Considering the instability of the output power of photovoltaic (PV) generation system, to improve the power regulation ability of PV power during grid-connected operation, based on the quantitative analysis of meteorological conditions, a short-term prediction method of PV power based on LMD-EE-ESN with iterative error correction was proposed. Firstly, through the fuzzy clustering processing of meteorological conditions, taking the power curves of PV power generation in sunny, rainy or snowy, cloudy, and changeable weather as the reference, the local mean decomposition (LMD) was carried out respectively, and their energy entropy (EE) was taken as the meteorological characteristics. Then, the historical generation power series was decomposed by LMD algorithm, and the hierarchical prediction of the power curve was realized by echo state network (ESN) prediction algorithm combined with meteorological characteristics. Finally, the iterative error theory was applied to the correction of power prediction results. The analysis of the historical data in the PV power generation system shows that this method avoids the influence of meteorological conditions in the short-term prediction of PV output power, and improves the accuracy of power prediction on the condition of hierarchical prediction and iterative error correction.

Key words: photovoltaic (PV) power generation system; short-term forecast; local mean decomposition (LMD); energy entropy (EE); echo state network (ESN)

0 Introduction

With the development of clean energy, the proportion of photovoltaic (PV) power generation is gradually increasing. Due to the influence of different meteorological conditions, its output power is uncertain, and the resulting technical problems also need to be solved urgently[1,2]. At the present stage, the power output regulation of the PV power generation system generally adopts a real-time grid-connected configuration[3]. On one hand, this regulation mode causes voltage instability of carrier load in grid-connected operation[4]; on the other hand, in the face of extreme weather, it causes certain resource waste in emergency regulation capacity[5]. If the PV power can be predicted in advance, it will be reasonably scheduled in a grid-connected configuration, which is conducive to improving the stability of the entire power system and realizing efficient energy conversion between traditional energy and PV energy [6-8].

As for the predictability of the output power of PV power generation, some scholars have proposed a series of methods from different perspectives[9,10].

From the perspective of factors affecting PV power generation and mainly considering different lighting conditions, Hui et al.[11,12] integrated the neural network algorithm into weather forecast information to achieve power prediction through curve fitting of historical power generation data. Zhang et al.[13,14] used the Markov chain algorithm to train similar meteorological conditions. When the similarity of meteorological conditions is high, the PV power sequence corresponding to similar days is the predicted power sequence. Considering the mutability of weather conditions and the difference in geographical conditions, the adaptability of taking meteorological conditions as reference quantity is poor, which has certain limitations.

From the perspective of historical power data of PV power generation, Wang et al.[15,16] proposed a short-term prediction of PV power output based on a genetic algorithm and made up for the lack of prediction accuracy by using the dynamic correction method. Li et al.[17,18] used the improved support vector machine algorithm for analysis and took the historical power generation, meteorological conditions, temperature, and humidity as the input feature set. While realizing the prediction of PV power generation, there are problems such as redundancy of feature information and too large a training dimension.

Through the above analysis, considering the influencing factors of PV power generation and historical power generation data, we proposed a short-term prediction method for PV power generation based on LMD-EE-ESN algorithm with iterative error correction. Firstly, using the advantages of the local mean decomposition (LMD) algorithm in extracting small features of unstable signals[19], the power generation under different meteorological conditions was quantitatively analyzed, and energy entropy (EE) was taken as the quantization feature. Then, after LMD processing of the generation power curve, the echo state network (ESN) algorithm was used for hierarchical prediction. Finally, the rolling prediction method was used to calculate the iteration error. Based on the LMD-EE-ESN prediction model, the iterative error analysis can significantly reduce the prediction error, which proves the effectiveness of the method in the short-term prediction of PV power generation.

The main contributions and innovations of this study include the following three aspects: 1) To achieve the hierarchical prediction of power series and the extraction of detail components, the LMD algorithm was used to decompose power series into decomposition components with different frequency characteristics. 2) The meteorological conditions were quantified with the energy entropy algorithm, and the different decomposition components are predicted by the ESN network. 3) The iterative error theory was used to modify the graded prediction results to optimize the power prediction results.

1 Output power characteristics

The output power of the PV power generation system not only is affected by its own installed capacity, but also increases randomly under the condition of sunshine imbalance. To accurately judge the output power characteristics of PV power generation system under different sunshine conditions, the amount of sunshine must be divided first, and the main factor affecting the amount of sunshine is the difference in meteorological conditions.

Based on the fuzzy clustering analysis of different meteorological conditions under the GB/T22164—2008 standard[20] from the China Meteorological Administration, the meteorological conditions are classified: sunny, rainy or snowy, cloudy, and changeable weather. Under these four typical meteorological conditions, the power output curve of a PV power generation system under sunshine conditions is shown in Fig.1, with the sampling period of 15 min.

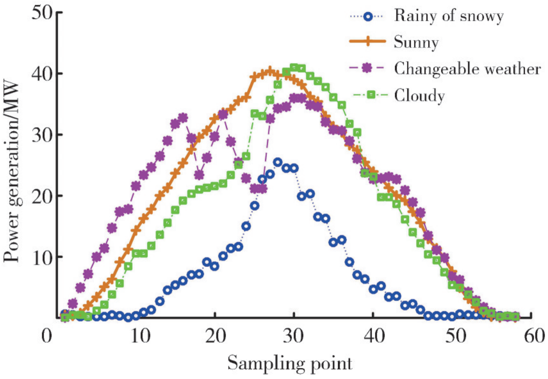


Fig. 1 PV output power curve under different meteorological conditions

As can be seen from Fig.1, when it is rainy or snowy, the PV power decreases significantly, while with the improvement of meteorological conditions, the amount of light received by solar panels increases gradually, and the PV power also rises gradually. It can be seen that for the prediction of real PV power generation, in addition to considering the characteristics of the PV power generation power curve, the influence of meteorological conditions should also be considered.

2 Algorithm analysis

2.1 LMD

As an adaptive decomposition method, the LMD algorithm does not need a basis function compared with empirical mode decomposition and wavelet decomposition and solves the problems of mode aliasing, endpoint effect, and so on. LMD was first proposed by Smith et al. In 2005[17]. Based on the theories of envelope function and local mean, the LMD process of initial signal $x(t)$ is shown in Fig.2.

The specific algorithm flow can be described as follows:

1) Calculating local mean function m_{ik} and envelope estimation function a_{ik}

Taking i as the decomposition level and k as the number of cycles, it is assumed that the local extreme point of the initial signal sequence $x(t)$ is R_j, and its functions m_{ik} and a_{ik} are calculated by

$$m_{ik}(t)=\frac{(R_{j+1}+R_j)}{2},\tag{1}$$

$$a_{ik}(t)=\frac{|R_{j+1}-R_j|}{2}.\tag{2}$$

2) Calculating frequency modulation (FM) signal $s_{ik}(t)$ and local envelope estimation function $h_{ik}(t)$ as

$$h_{ik}(t)=x(t)-m_{ik}(t),\tag{3}$$

$$s_{ik}(t)=h_{ik}(t)/a_{ik}(t).\tag{4}$$

When FM signal $s_{ik}(t)$ does not satisfy the pure frequency modulation signal, the corresponding number of cycles is increased by 1, and Step 1 is repeated until $h_{i(k+1)}(t)=1$ is satisfied.

3) Solving production function component $F_i(t)$

The envelope signal of the envelope estimation function $a_{ik}(t)$ is expressed as

$$a_i(t)=a_{i1}(t)a_{i2}(t)\cdots a_{ik}(t).\tag{5}$$

The product function component $F_i(t)$ is obtained by multiplying it with pure FM signal $s_{ik}(t)$, and the remaining component $u_i(t)$ is calculated by

$$F_i(t)=s_{ik}(t)a_i(t),\tag{6}$$

$$u_i(t)=x(t)-F_i(t).\tag{7}$$

The decomposition ends until the remaining component $u_i(t)$ satisfies the monotone signal, that is, there are not enough extreme points. Otherwise, i adds 1, and Step1 is repeated to continue the decomposition. After the initial signal $x(t)$ is decomposed by LMD, the final decomposition form is shown as

$$x(t)=\sum_{i=1}^{Z}F_i(t)+u_i(t),\tag{8}$$

where z is the total number of decomposition layers.

2.2 EE

The EE is used to measure the randomness of signals at different product functions $F_i(t)$. For the initial signal sequence $x(t)$ decomposed by LMD, the energies of its different product function components $F_i(t)$ can be expressed as

$$E_i=\int_{-\infty}^{+\infty}[F_i(t)]^2\mathrm{d}t.\tag{9}$$

For different components of the energy probability p_i can be expressed as

$$P_i=E_i\Big/\sum_{i=1}^{Z}E_i,\tag{10}$$

where $E=\sum_{i=1}^{Z}E_i$, that is, the energy of the initial signal sequence is equal to the sum of the decomposition components. After the initial signal sequence is processed by LMD, the energy entropy W can be represented as

$$W=-\sum_{i=1}^{Z}p_i\lg p_i.\tag{11}$$

EE represents the randomness of the signal, and the greater the entropy, the stronger the randomness of the signal.

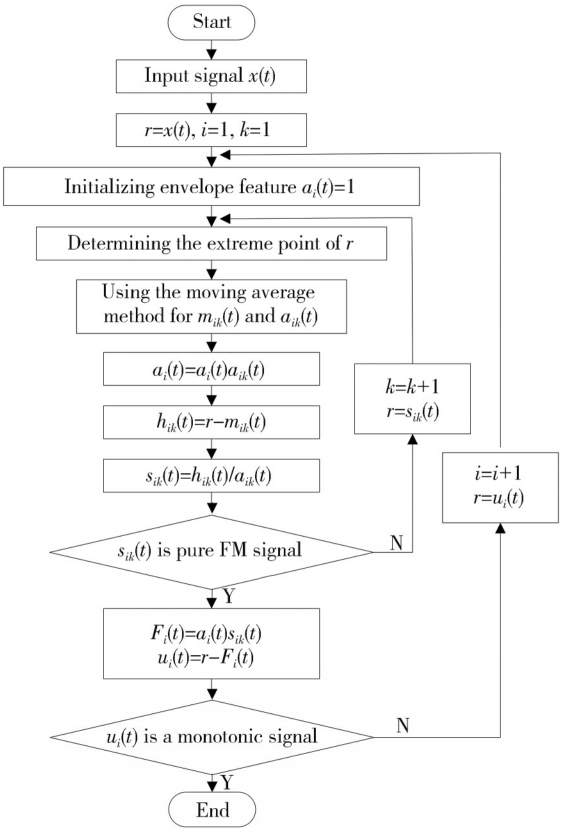


Fig. 2 Flow chart of LMD algorithm

2.3 ESN

The ESN, as a kind of neural network[18], is similar in that it also includes three parts: input, hidden, and output. The difference is that the hidden part is replaced by the reserve pool. The algorithm of ESN takes advantage of its short-term memory and is often used for short-term prediction, and its characteristic is that it only trains for the weight parameters of the output part, while the weight parameters of the input part and the reserve pool are fixed, thus simplifying the structural model and achieving global optimization. The network structure model of the ENS algorithm is shown in Fig.3.

The signal dimension of the output part is assumed to be K, the signal dimension of the reserve pool is assumed to be N, and the signal dimension of the output part is assumed to be L. According to Eq. (12), the input value of the ESN algorithm network is $\boldsymbol{u}(n)$, the intermediate value of the reserve pool is $\boldsymbol{f}(n)$, and the output value is $\boldsymbol{y}(n)$.

$$\begin{cases} \boldsymbol{u}(n)=(u_1(n),u_2(n),\cdots,u_K(n)), \\ \boldsymbol{f}(n)=(f_1(n),f_2(n),\cdots,f_N(n)), \\ \boldsymbol{y}(n)=(y_1(n),y_2(n),\cdots,y_L(n)). \end{cases} \tag{12}$$

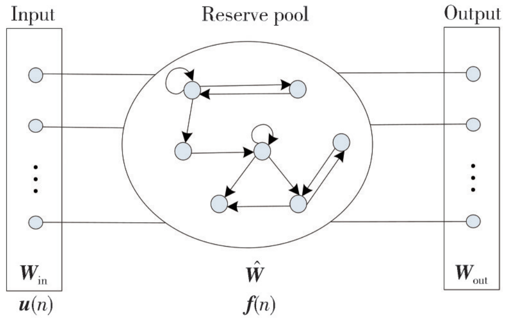


Fig. 3 Network structure model of ENS algorithm

As shown in Fig. 3, the weight parameter matrix of the input part is $\boldsymbol{W}_{\text{in}}$, the sparse connection matrix of the reserve pool is $\hat{\boldsymbol{W}}$, the weight parameter matrix of the output part is $\boldsymbol{W}_{\text{out}}$, and the weight parameter matrix of the output feedback part is $\boldsymbol{W}_{\text{back}}$. Taking time n as an example, the state equation of the reserve pool and the output equation of ESN are expressed as

$$\boldsymbol{f}(n+1)=\tanh[\boldsymbol{W}_{\text{in}}\boldsymbol{u}(n+1)+\hat{\boldsymbol{W}}\boldsymbol{f}(n)+\boldsymbol{W}_{\text{back}}\boldsymbol{y}(n)], \tag{13}$$

$$\boldsymbol{y}(n+1)=\boldsymbol{W}_{\text{out}}[\boldsymbol{u}(n+1),\boldsymbol{f}(n+1),\boldsymbol{y}(n)], \tag{14}$$

where $\tanh(\bullet)$ is the activation function, $\boldsymbol{W}_{\text{in}}\in\mathrm{R}^{N\times K}$, $\hat{\boldsymbol{W}}\in\mathrm{R}^{N\times N}$, $\boldsymbol{W}_{\text{back}}\in\mathrm{R}^{N\times L}$, and $\boldsymbol{W}_{\text{out}}\in\mathrm{R}^{L\times(K+N+L)}$. The spectral radius of ESN algorithm is between 0 and 1, that is, the range of eigenvalues is $[-1, 1]$. The algorithm flow mainly includes the following steps:

1) Determining the dimensions of the ESN, that is, the values of K, N, and L.

2) Initializing $\boldsymbol{W}_{\text{in}}$, $\hat{\boldsymbol{W}}$, and $\boldsymbol{W}_{\text{back}}$.

3) ESN network training is carried out through Eqs. (13) and (14).

4) Finally, the predicted output value $\boldsymbol{y}(n+1)$ at $n+1$ is obtained from the input value $\boldsymbol{u}(n+1)$ at $n+1$.

ESN algorithm establishes the connection between the input value and output value through the constantly updated state space in the reserve pool for the purpose of short-term prediction of the ESN.

3 Short-term prediction based on iterative error

Due to the influence of weather changes, climate conditions, geographical factors, and other external factors, it is difficult to guarantee the accuracy of PV power prediction when the input feature is simply historical data. To further improve the reliability of prediction, we adopted the following three methods to revise the predicted value.

In terms of weather factors, the PV power curves under different weather conditions were quantitatively analyzed. The energy entropy of different product function components was extracted with LMD algorithm, and the prediction result was corrected as the input feature of ESN algorithm.

In terms of the prediction of the historical output PV power curve, LMD algorithm was used to predict the historical power curve, and ESN short-term prediction was carried out for different product function components respectively. Finally, the historical power prediction results were obtained through decomposition and reconstruction.

In terms of iteration error correction, the iteration error was updated progressively, and the historical generation power was corrected by using the iteration error sequence of different levels.

3.1 Iterative error analysis

According to the iterative error analysis theory[21], based on the short-term prediction algorithm, the error analysis was carried out on the prediction results and the initial sequence of its training set. Based on the error results of the first generation, the error sequence was predicted again, to obtain the error sequence of the second generation, and so on until the error sequence no longer changed. Finally, the iteration error sequences of generation 1, generation 2, and generation 3 were added, and the short-term prediction results of generating power in the test set were brought into the sum, to realize the correction of the prediction results. The iterative error analysis is shown in Fig.4.

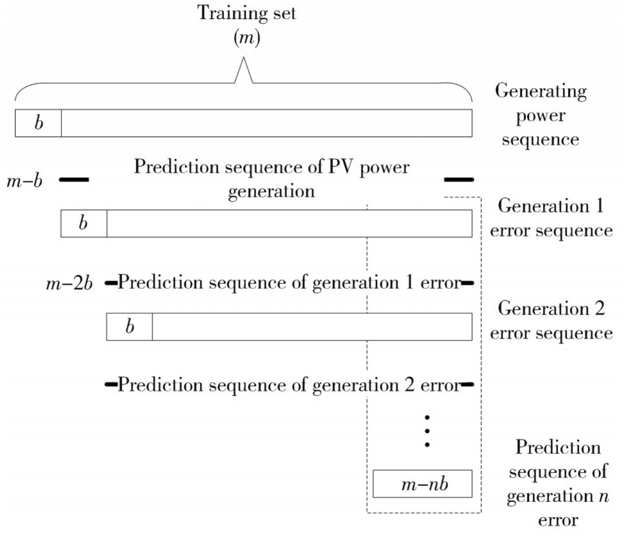


Fig. 4 Schematic diagram of iterative error analysis

Firstly, it is assumed that the number of sampling points in the PV power sequence in the training set is m. The rolling method is used to predict sampling point b of the initial power generation sequence, that is, when the sampling point $b+1$ is predicted, the sampling point b is the real power generation. For the prediction of sampling point $b+2$, sampling point $b+1$ is the real power generation. And so on until the signal sequence of centralized power generation after training is predicted.

Then, the first generation error sequence e_1 is obtained by comparing the initial power of the training set with the prediction sequence. The error sequence e_1 is continued for rolling prediction to obtain the prediction sequence of the first-generation error, and the second-generation error sequence e_2 is obtained by comparing it with the error sequence e_1.

Finally, error iteration is continued to obtain error sequences of different grades. In field practice, when the value between error sequences is satisfied $|e_n - e_{n-1}| < e_{n-1}/10$ as to the iteration termination condition[18], the number of iterations $n \leqslant 3$.

3.2 Short-term prediction process

In this study, based on the LMD theory and ESN algorithm, and considering the influence of different weather types on the randomness of power generation, the energy entropy of different weather types was added as the input feature of the ESN network, to improve the prediction accuracy. To realize the correction of short-term prediction results, based on the LMD-EE-ESN prediction model, we utilized the iterative error theory to modify the prediction results to improve their reliability of the prediction results. The corresponding short-term prediction process of PV power is shown in Fig.5.

1) The original signal sequence $x(t)$ is decomposed by LMD, and then the ESN algorithm is used to predict the different $F_i(t)$ by the rolling method, and the different decomposition components are reconstructed, to obtain the initial prediction sequence of PV power generation.

2) Combined with the EE extraction method in Section 2.2, PV power generation under typical weather types is selected as the reference sequence. The reference sequence is decomposed by LMD and its energy entropy is extracted as the input feature of ESN.

3) In combination with the iterative error analysis theory in Section 3.1, the LMD-EE-ESN prediction model is modified, and $\boldsymbol{y} = y(t) + e_1 + e_2 + e_3$ will eventually serve as the output result of the short-term prediction of PV power generation.

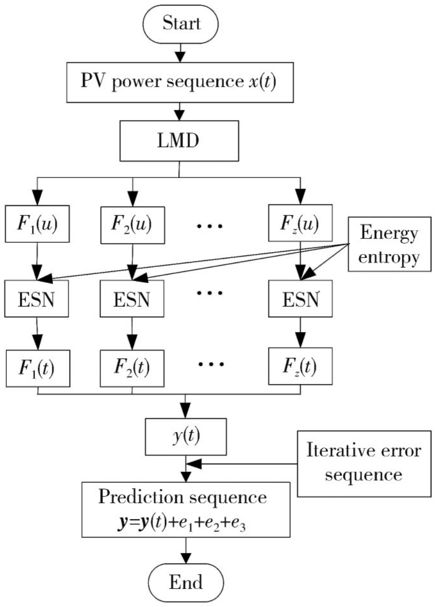


Fig. 5 Flow chart of short-term prediction of PV power generation

3.3 Prediction result standard

To verify the validity of the prediction results, mean square error and root mean squared error are used as the standards of the prediction results, and the calculations are expressed as

$$M = \frac{1}{T}\sum_{t}^{T}(x_t - y_t)^2, \tag{15}$$

$$R = \sqrt{\frac{1}{T}\sum_{t}^{T}(x_t - y_t)^2}, \tag{16}$$

where M is the root mean square value; R is the root mean squared error; t is the sampling point of the test set; T is the size of the test set; x_t is the true value of concentrated PV power generation; and y_t is the predicted value of PV power generation. The larger the values of M and R, the more effective the prediction results.

4 Instance analysis

4.1 EE calculation under different meteorological conditions

Under different weather conditions, the output power of PV power generation varies greatly under the influence of sunshine conditions. To measure the characteristics of average daily power generation under different weather types, LMD was first performed according to the PV power sequence within 24 h of a day in Fig. 1. Then, the EE values of output power under meteorological conditions of sunny, rainy or snowy, cloudy, and changeable weather were calculated according to the EE calculation method in Section 2.2. Finally, to improve the stability of the energy entropy representation, the mean value of the EE of the phase near the same meteorological conditions was calculated as a part of the input characteristics of the prediction model to improve the prediction accuracy of the same meteorological conditions.

In this study, the historical electric power of a PV power station with an installed capacity of 50 MW was investigated as a reference and the EE of power generation power in 24 h under typical meteorological conditions was calculated. The calculation results are shown in Table 1. Among them, when the meteorological conditions are sunny, the EE is the highest; however, under the conditions of rain and snow, the EE is the lowest. It can be seen that different sunshine has a great impact on PV output power.

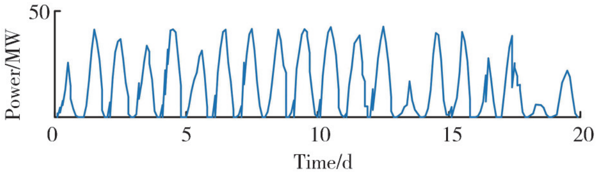
Table 1 Energy entropy under different meteorological conditions

Date	Meteorological conditions	Similar date	EE
Aug. 23	Sunny	Aug. 20, 21, 24	0.568
Dec. 30	Rainy or snowy	Dec. 2, 8, 20	0.213
Jun. 2	Cloudy	Jun. 3, 6, 22	0.335
Jul. 15	Changeable weather	Jul. 1, 5, 19	0.467

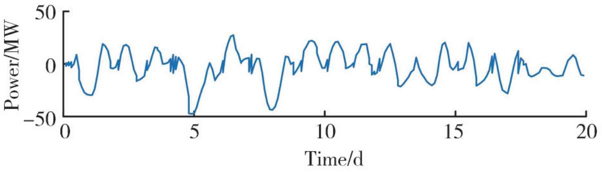
4.2 LMD processing

Partial data of historical power generation of a PV power station are taken as sample objects and decomposed by the LMD algorithm, as shown in Fig. 6. Fig. 6(a) is the output power curve of PV power generation within 20 d, and Fig. 6(b) — (f) are the product function components $F_i(t)$ ($i=1, 2, \cdots, 5$) after corresponding LMD processing.

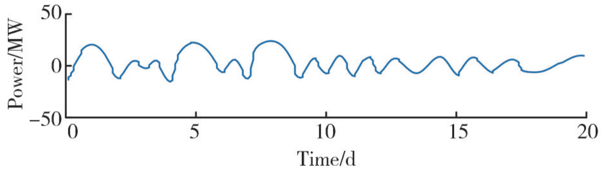
As shown in Fig. 6, the output power curve within 20 d presents uneven changes. For example, the generation power on the 19th day is significantly lower than that on other days. After consulting relevant meteorological conditions, the generation power is reduced on the 19th day due to rain and snow and insufficient sunshine amount. After the power output curve is processed by LMD, the output power curve of PV power generation is decomposed into different product function components, and component $F_5(t)$ does not have enough extreme points to meet the end condition of decomposition of the LMD algorithm. When the product function components are predicted separately, the characteristics of the original power output signal are fully guaranteed, and the prediction accuracy is also improved.



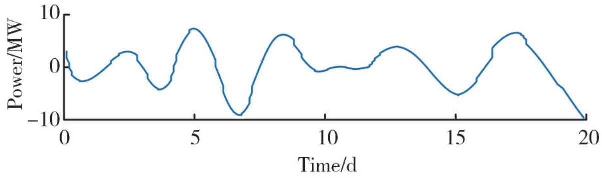
(a) PV power output within 20 d



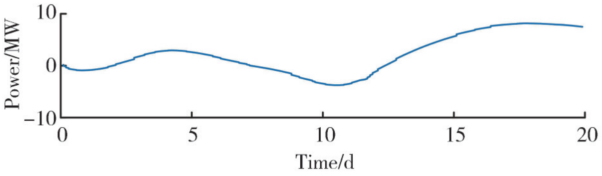
(b) $F_1(t)$



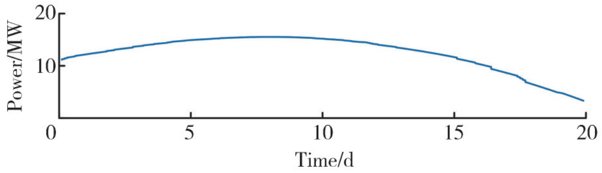
(c) $F_2(t)$



(d) $F_3(t)$



(e) $F_4(t)$



(f) $F_5(t)$

Fig. 6 Output power curves and LMD processing

4.3 Short-term prediction based on LMD-EE-ESN algorithm

4.3.1 Example demonstration and result analysis

Short-term prediction of output power by PV power generation system is the key to realizing grid-connected operation and guaranteeing the stable output of the power grid. Under different meteorological conditions, the EE of the power curve was extracted based on the LMD algorithm as the input feature of the prediction model. In terms of short-term prediction, LMD hierarchical prediction method was used to predict and reconstruct different frequency components. To improve the prediction accuracy, the iterative error theory was used to modify the prediction results.

To verify the effectiveness of the proposed algorithm in the short-term prediction of PV power generation, the PV power output curve in the first 20 d in Fig.6(a) was used as a training data set. After meteorological prediction, the EE of sunny weather on the 21st day was taken as the input feature, and the training set was processed by LMD to predict the PV power outputs of $F_1(t)-F_5(t)$ on the 21st day. The prediction results reconstructed by decomposition components were added to the iteration error e_1-e_3, and the final prediction result is shown in Fig.7.

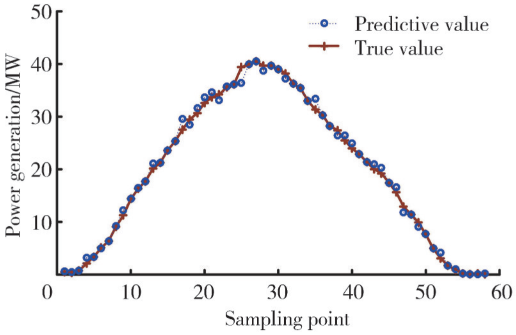


Fig. 7 Power prediction with iterative error based on LMD-EE-ESN algorithm

The predicted results show that the predicted value of PV power follows closely with the true value of the signal sequence, and M in the predicted result standard is 1.78%, and R is 3.34%. The effectiveness of the algorithm is verified by example analysis.

4.3.2 Comparative analysis of short-term forecasts

To further verify the effectiveness of the algorithm, the LMD-EE-ESN prediction model is used for analysis without iterative error analysis based on Section 4.3.1, and the prediction results are shown in Fig.8.

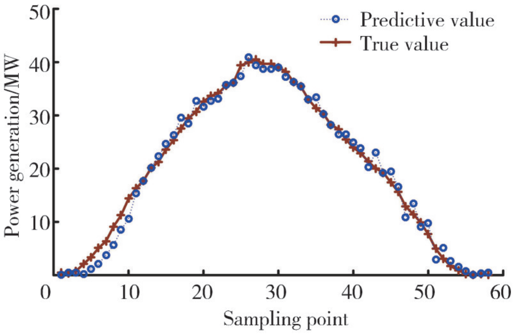


Fig. 8 Power prediction without iterative error based on LMD-EE-ESN algorithm

According to the standard analysis of the prediction results from Fig.8, M is 2.45%, and R is 5.78%, which is higher than the standard value of prediction results after adding iteration error, thus proving the correction effect of adding iteration error on LMD-EE-ESN prediction model.

In the case of multiple samples, LMD-EE-ESN prediction model, LMD-ESN prediction model, and ESN prediction model were verified, respectively. In this study, the historical power of a PV power station with an installed capacity of 50 MW was selected to analyze, and the output power within 20 d was taken as the training set. After standard analysis of the prediction results on the 21st to 30th day, the prediction errors are shown in Table 2.

Table 2 Error analysis under different prediction models

Prediction model	M/%	R/%
ESN	7.23	9.04
LMD-ESN	5.43	6.19
LMD-EE-ESN	2.98	5.03

Under different prediction models, the error analysis shows that the error of LMD-EE-ESN prediction model is lower than that of LMD-ESN and ESN models, and the error of the LMD-ESN prediction model is lower than that of the ESN model. It is proved that the reliability of prediction can be improved when the EE of different weather types is used as the character input. LMD algorithm is helpful to improve the accuracy of prediction.

To verify the effectiveness of the ESN algorithm in the short-term prediction of PV power generation, we compared the ESN algorithm with SSVM and ELM algorithm under prediction models of ESN, LMD-ESN, and LMD-EE-ESN. The prediction error is shown in Table 3.

Table 3 Error analysis under different prediction algorithms

Prediction model	M/%	R/%
SSVM/ELM	12.31/11.80	15.10/14.28
LMD-SSVM/LMD-ELM	9.15/8.23	10.06/11.72
LMD-EE-SSVM/LMD-EE-ELM	4.28/4.86	5.04/5.62

Compared with Table 2 and Table 3, it can be seen that the M and R values of ESN algorithm are lower than those of the SSVM and ELM algorithm in the short-term prediction of PV power generation. The validity of the ESN algorithm in short-term power prediction is proved.

5 Conclusions

Since the output power of PV power system is affected by meteorological conditions, latitude, humidity, solar angle of attack, unstable phenomenon appears due to the influence of such factors on its power output. Therefore, we proposed a short-term prediction algorithm of PV power generation based on LMD-EE-ESN with iterative error correction, and draws the following conclusions through example comparison tests:

1) LMD can decompose the PV output power curve into product function components with different frequency characteristics, and realize the hierarchical prediction of power generation based on fully extracting the characteristics of the power generation sequence.

2) To cope with the influence of different meteorological conditions, the reliability of power prediction can be improved when EE is used to quantify its characteristics as part of the predicted input characteristics.

3) The iterative error theory is introduced into the correction of prediction results to further improve the accuracy of prediction.

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Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

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基于LMD-EE-ESN在误差修正下的光伏发电功率短期预测

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摘　要：针对光伏发电系统输出功率的不稳定现象，为提高光伏电能在并网运行时对其功率的调节能力，在对气象条件进行量化分析的基础上，提出了基于LMD-EE-ESN算法在迭代误差修正下实现光伏发电功率短期预测的方法。首先，通过对气象条件的模糊聚类处理，以晴朗、雨天或雪天、多云和多变天气四种典型天气下的光伏发电功率曲线为参考，分别进行局部均值分解（Local mean decomposition，LMD），并以各自的能量熵（Energy entropy，EE）作为气象特征。其次，利用LMD算法对历史发电功率序列分解，以回声状态网络（Echo state network，ESN）预测算法结合气象特征实现功率曲线的分级预测。最后，将迭代误差理论用于功率预测结果的修正。分析光伏发电系统历史数据，结果表明，该方法用于光伏输出功率短期预测，可避免气象条件的影响，且在分级预测和迭代误差修正的情况下，可提高功率预测的精准度。

关键词：光伏发电系统；短期预测；局部均值分解；能量熵；回声状态网络

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