Bayesian Optimization - LSTM Modeling and Time Frequency Correlation Mapping Based Probabilistic Forecasting of Ultra-short-term Photovoltaic Power Outputs

Jie Shi, Yuming Wang, Yue Zhou, Yan Ma, Jie Gao, Shude Wang, Zuan Fu

***Abstract*—Due to the fluctuation and randomness of photovoltaic power over time, accurate and reliable ultra-short-term photovoltaic power forecasting is significant for real-time dispatch and frequency regulation of power grids. In this paper, the improved BO-LSTM forecasting frame considering frequency correlation mapping is proposed. Firstly, the features of photovoltaic power are extracted and resolved according to power series frequency segments. Then, the established BO-LSTM forecasting model is adjusted based on the above extracted features in separate segment, and the results of deterministic forecasting are obtained. Furthermore, in order to obtain the reliable performance, the time-correlation algorithm is employed into the above deterministic forecasting model, which offers the base for probabilistic power forecasting. Finally, the above algorithms and forecasting framework are applied to the measurement data from a commercial photovoltaic power station in North China. Compared to the benchmark models, the Power Interval Normalized Average Width (PINAW) error of the proposed ultra-short-term forecasting algorithm has shown satisfied improvements. The PINAW has reduced by 8.4% (v.s. Adam-LSTM), 48.9% (v.s. Sgd-LSTM), 52.8% (v.s. Adagrad-LSTM), 9.1% (v.s. Rmsprop-LSTM), 97.2% (v.s. Adadelta-LSTM), 86.8% (v.s. Adam-mlp), 87.4% (v.s. Sgd-mlp), 90.9% (v.s. Adagrad-mlp), 86.5% (v.s. Rmsprop-mlp), and 99.7% (v.s. Adadelta-mlp).**

***Index Terms*— time frequency correlation; BO-LSTM; photovoltaic power forecasting; feature extraction; deep learning.**

I. INTRODUCTION

Large-scale centralized photovoltaic power is developing greatly. However, due to the fluctuation and randomness of photovoltaic (PV) power over time, it will bring much challenge when integrating more photovoltaic to grid. This situation is crucial especially in large centralized PV farms, and highly reliable power output forecasting is one of the effective solutions[1].

This work was supported by National Key R&D Program of China (Intergovernmental Special Projects, 2019YFE0118400) and the program of Chinese Scholarship Council. *Corresponding author: Jie Shi.*

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Nomenclature

$V(t)$	Auxiliary white noise sequences	D	The power data set
$X(t)$	Original photovoltaic power sequence	$r_{0,0}$	The daily PV power data series in the forecasting day
$H_m^+(t)$	Component elements	$r_{i,j}$	The daily PV power data series in the j^{th} day before (negative) or after (positive) forecast moment of the previous i^{th} year
$f(x)$	The mean absolute error between the true PV power and the model forecasting power	$C(r_0, r_i)$	The correlation coefficient between $r_{0,0}$ and $r_{i,j}$
$E(f(x))$	The mathematical expectation of $f(x)$	T	The periodicity scale coefficient
$k(x,x)$	The covariance function of historical power x	L	Similarity scale coefficient
$\Phi(Z)$	The probability density function of the standard normal distribution	R	Reference matrix
$\phi(x)$	The distribution function of the standard normal distribution	E_{ref}	Reference PV power data value

The power data series of different dates which are in similar time slots have a strong respective correlation with each other. On the contract, the PV power fluctuation expresses a randomness due to nature feature coming from various meteorological elements. Hence how to figure out the above two issues is crucial to improve the accuracy and reliability of forecasting results[1].

According to the report from International Research Center for Renewable Energy (IRCRE), the time duration of ultra-short-term forecasting is focusing on a range between a few minutes and one hour[2]. For centralized PV power forecasting, mess of contributions have been obtained. The forecasting methods can be classified into deterministic forecasting and probabilistic forecasting. On one hand, in deterministic forecasting, studies on the time scale and time-frequency distribution of photovoltaic power, have been attracted much attention. Firstly, to analyze the influence of time scale on forecasting, current research mainly focuses on improving the forecasting accuracy of photovoltaic power at different time scales. To tackle the deficiencies of conventional artificial intelligence modeling methods such as over fitting problem and insufficient generalization ability to complex nonlinear modeling, a day-ahead PV power forecasting model assembled by fusing deep learning modeling and time correlation principles under a partial daily pattern prediction (PDPP) framework is proposed in [3]. A hybrid forecasting method based on multi-scale similarity day and an improved Archimedes algorithm optimized for ESN-

KELM dual-core forecasting is proposed[4]. This method aims to improve short-term forecasting accuracy. A reliable PV power forecasting model based on neural network (NN), convolutional neural network (CNN) and long short-term memory (LSTM) model is proposed[5, 18, 20]. The model utilizes CNN-LSTM to extract internal features of photovoltaic data trends and seasonal variables to achieve more accurate forecasting results. Time-sharing prediction (TSP) model combining variation modal decomposition (VMD) and Bayesian regularized neural network (BRNN) is proposed[6]. Secondly, the characteristics and frequency segments of power data series are studied, and current research mainly focuses on how the features of photovoltaic power are extracted. There is a proposed PV power spatial temporal forecasting model[7]. The temporal shift correction and a multi-station information fusion strategy are taken account. The model applies the forecasting results of multiple reference power plants into the data processing module for time-shift analysis and spatial correlation information fusion correction. That model is able to effectively address data gaps in the target power station for forecasting. In addition, an accurate PV power forecasting interval method based on frequency domain decomposition and hybrid deep learning (DL) model is proposed[8]. The study utilizes Ensemble Empirical Mode Decomposition to decompose and reconstruct the original energy time series data into sub-sequences, followed by statistical feature extraction. In [9], considering the multi-period error distribution (MPED), EEMD-LSTM-BP model is proposed. The study utilizes ensemble empirical mode decomposition (EEMD) to investigate the fluctuation characteristics within various frequency domains.

On the other hand, in probabilistic forecasting, the reliability is an important concern for evaluating model performance, hence diverse evaluation indicators are needed[21-24]. In [10], the forecasting accuracy of the model is evaluated using three evaluation metrics: normalized root mean squared error (nRMSE), mean relative error (MRE), and normalized mean absolute error (nMAE). In [11], the reliability of the forecasting intervals is evaluated using the average bandwidth metric. What's more, new artificial intelligence probabilistic models are needed to improve the forecasting reliability. In [12], a new approach called SVR2D which directly computes the 2D-interval forecasts from previous historical solar power and meteorological data is proposed. A novel interval forecasting method based on generalized weather conditions is proposed [13]. The uncertainty of PV power under different weather conditions is firstly analyzed, then a generalized weather classification method based on solar irradiance reduction index K is performed. Aiming at the uncertainty of power and kernel density estimation, a power interval forecasting method based on hybrid semi-cloud model and non-parametric kernel density estimation is proposed[14]. To address the problem of low traditional power interval forecasting accuracy, a new interval method is proposed based on PSR-BLS-QR with adaptive rolling error correction[15]. The optimal correction index is used as the objective function to determine the optimal error correction power for different power interval segments of the interval upper and lower boundaries.

However, there are still much room for improvement. Firstly, the quantitative impact of distribution characteristics in different time periods on the forecasting model framework has not yet been figured out. Due to the fluctuation and randomness of PV power over time, temporal characteristics are essential factor that must be considered in the forecasting model framework. Secondly, the numerical mapping relationship which is between time-frequency distribution of photovoltaic power and the forecasting results is unclear. Currently, most research focuses on using historical power data or weather data to forecast photovoltaic output. However, multiple studies have shown the significance of studying the effect of PV power time-frequency distribution features on the forecasting results in improving the accuracy of forecasting models[25,28].

To solve the above problems, an ultra-short short-term PV power probability forecasting model considering time-frequency analysis is proposed in this paper. Initially, the features of photovoltaic power are extracted and resolved according to power series frequency segments, and it is applied in the established deterministic forecasting framework BO-LSTM to obtain respective model in every time-frequency segment. Then, the improved BO-LSTM model is employed to individually forecast each component to improve the accuracy and stability of PV forecasting. Thus, the Time Correlation model (TC) is applied to correct the deterministic forecasting result. Finally, photovoltaic power interval probabilistic forecasting is conducted under 80%, 90%, and 95% confidence conditions, respectively.

The contributions of this paper can be summarized below:

(1) Considering the numerical mapping relationship between the time-frequency distribution of photovoltaic power and the forecasting results, a novel pre-processing method for PV power data is proposed. The features of photovoltaic power are extracted and resolved according to power series frequency segments during the data pre-processing stage, thereby improving the accuracy of subsequent forecast.

(2) Considering the quantitative impact of distribution features in different time periods within the same photovoltaic power station on the model framework, a statistical model for correcting the forecasting results of artificial intelligence is proposed. The BO-LSTM model-based forecasting results are corrected using a time correlation model, thus improving the reliability of the model.

The organizational structure of the method in this paper is as follows: Section 2 introduces algorithms and principles which are used in this paper for model construction. Section 3 is the modeling process, focusing on building up the hybrid model for ultra-short-term PV power forecasting. Section 4 is case studies along with results discussion, followed by conclusions.

II. Principles

A. Photovoltaic power feature extraction

Since PV power is significantly affected by environment and time, it is inevitable to encounter some abnormal values in the power output data. These values can interfere with the normal operation of forecasting models and impact the model accuracy. Currently, EEMD method has been widely used to handle nonlinear and non-stationary signals, such as the photovoltaic power data sequence. According to [4], the number of components is positively related to forecasting accuracy and workload. It can be observed that when the number of components is set to 6, both of the forecasting accuracy and workload are acceptable. Therefore, in this paper, the raw power data is decomposed into six Intrinsic Mode Function (IMF) components.

Adding *M* sets of auxiliary white noise sequences *V(t)* with different amplitudes and phase differences of π to the original photovoltaic power sequence *X(t)*, *H(t)* containing the photovoltaic power information are obtained.

$$\begin{cases} H_m^+(t) = X(t) + V_m(t) \\ H_m^-(t) = X(t) - V_m(t) \end{cases}, m = 1, 2, \cdots, M \tag{1}$$

Next, the local extreme points of *H(t)* are found, and the envelopes are drawn using interpolation. Then, the *M* sets of signals *H(t)* are decomposed using Empirical Mode Decomposition (EMD), obtaining *2M* component elements $H_m^+(t)$ of the IMF.

$$\begin{cases} H_m^+(t) = \sum_{i=1}^{N} C_i^{m+}(t) + r^{m+}(t) \\ H_m^-(t) = \sum_{i=1}^{N} C_i^{m-}(t) + r^{m-}(t) \end{cases}, i = 1, 2, \cdots, N \tag{2}$$

Finally, the overall average of the decomposition results is calculated to obtain the IMF components and margins of the original power sequence.

$$\begin{cases} C_i(t) = \dfrac{1}{2M} \sum_{m=1}^{M} [C_i^{m+}(t) + C_i^{m-}(t)] \\ r_i(t) = \dfrac{1}{2M} \sum_{m=1}^{M} [r_i^{m+}(t) + r_i^{m-}(t)] \end{cases} \tag{3}$$

EEMD is one of the unique methods of reducing mode mixing by adding white noise. Because of solid adaptability and the capability to effectively analyze non-linear data, EEMD stands out from other forms. By integrating multiple noise perturbations, it ensures the robustness of results. Moreover, its ability to offer a time-frequency representation allows for simultaneous observations of signal changes in both time and frequency, which is suitable for pre-processing power data.

B. BO-LSTM power forecasting frame

The Bayesian optimizer estimates the posterior distribution of the objective function based on Bayes theorem[11]. Then, based on the evaluation results, the following combination of hyper-parameters that minimizes the value of the objective function is found by building up alternative functions[16]. In this paper, it makes full use of the information from the PV power in previous time, and its optimization works by learning the shape of the objective function of power forecasting and finding the parameters that provide the maximum improvement to the forecasting results. The core of the Bayesian optimizer consists of a probabilistic agent model and a sampling function[1].

$$f(x) \sim GP(\mu(x), k(x, x)) \tag{4}$$

Where, *f(x)* denotes the mean absolute error between the true PV power and the model forecasting power, $\mu(x)=E(f(x))$, *E(f(x))* is the mathematical expectation of *f(x)*, *k(x,x)* denotes the covariance function of historical power *x*.

Through the Gaussian process, the mean absolute error between the real PV power and the model forecasting power can be obtained[17]. The optimal local solution will be found by the sample calculation. The commonly used sampling function is the *EI* sampling function. The design idea of the *EI* sampling function lies in finding the next power point x_{t+1} of the maximum improvement expectation and the function is:

$$EI(x) = \begin{cases} (\mu(x) - f(x^+))\Phi(Z) + \sigma(x)\phi(Z) & \sigma(x) > 0 \\ 0 & \sigma(x) = 0 \end{cases} \tag{5}$$

Where, *Φ(Z)* is the probability density function of the standard normal distribution and *φ(x)* is the distribution function of the standard normal distribution, where *Z* can be expressed as:

$$Z = \frac{\mu(x) - f(x^+)}{\sigma(x)} \tag{6}$$

During the training of the model, the working process of the Bayesian optimizer is classified into four steps:

Step 1: The initialized sample points of PV power are generated randomly according to the range of hyper-parameters of the LSTM network. The initialized sample points are fed into the Gaussian process and the LSTM model is trained. The Gaussian model is corrected using the loss values output by the objective function, thus making the Gaussian model closer to the actual distribution of the power.

Step 2: Use the sampling function to select the next set of power points *x* to be evaluated in the modified Gaussian model. New sample points are applied into the LSTM model as input. The new output value y of the PV power is obtained, which is used to update the power data set $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_t, y_t)\}$ and the Gaussian model.

Step 3: The newly selected sample point is compared with the true value. The error between the sample point and the true value is the loss value. The comparison index used in this paper is the standard score. Sort the standard scores of all the sample points and output the smallest one. The algorithm is terminated and exits, outputting the best combination of parameters currently selected and the corresponding loss value (*x*, *y*) of the objective function.

Step 4: If the loss value of the objective function does not meet the requirement of the modelling, (*x*, *y*) is updated to the power data set. Skip to step 2 and continue to correct the Gaussian model until the requirement is met.

C. Time Correlation Algorithm

The PV power output is closely related to the surface solar irradiance, and the surface irradiance exhibits an annual periodicity, so the PV power output is close to the data value within adjacent historical time. Therefore, the reference value of PV power generation for the forecast moment can be calculated via the generation data from the corresponding historical period.

Suppose the daily PV power data series in the forecasting day is $r_{0,0}$, and the daily PV power data series in the j^{th} day before (negative) or after (positive) forecast moment of the previous i^{th} year is $r_{i,j}$. The correlation coefficient between $r_{0,0}$ and $r_{i,j}$, can be calculated according to the following formula[15].

$$C\left(r_0, r_i\right) = \frac{\operatorname{cov}\left(r_0, r_i\right)}{\sqrt{Var\left(r_0\right)Var\left(r_i\right)}} \tag{7}$$

To determine the reference value of PV power output at a specific time, the periodicity scale coefficient T and similarity scale coefficient L are defined to describe the needed data scope [31]. The periodicity scale coefficient T determines the yearly value of historical data The similarity scale coefficient L determines the days of historical data at the forecast time. T and L are both positive integers. Then according to the determined values of scale coefficients, a reference matrix R of PV power at a definitive forecast moment can be created using historical data. According to the reference matrix R, the reference PV power data value E_{ref} can be calculated as the average of all the elements in matrix R[19,26]. It is important to note that the value of E_{ref} can characterize the primary trend of irradiance, which can either be used as an individual PV power forecast result or modify the forecast results of other machine learning method.

III. Bayesian Optimization - LSTM and Time Frequency Correlation Mapping Based Probabilistic Forecasting

A. Overall Framework

Aiming at improving accuracy and reliability of forecasting performance, the PV power output features in time scale are fully considered in this paper. The overall framework which includes three stages is shown in Fig. 1.

Stage 1: Photovoltaic power feature extraction in time and frequency domain: to deal with the volatility and randomness of power output, the data series is decomposed into various frequency bands.

Stage 2: Deterministic forecasting model adjustment: in each frequency band, the deterministic forecasting model is optimized based on the extracted power features obtained from Stage 1. The data series is classified into a training set (90% of the data samples) and a testing set (10% of the data samples). In the deep learning algorithms, the larger the number of small batch samples, the higher the computational cost. Choosing an appropriate number of small batch samples can balance computational efficiency and result quality. Therefore, the number of small batch samples is selected as 10. In order to improve the generalization ability of the model while maintaining its stability, the discard rate is set to 0.5.

Stage 3: Probabilistic forecasting model considering time correlation analysis: the time correlation model is applied to correct the model forecasting results to calculate the photovoltaic power probability forecasting intervals, which are at 80%, 90%, and 95% confidence levels, respectively.

To evaluate the forecasting effect, the evaluation index, which is Power Interval Normalized Average Bandwidth (PINAW) is selected. The performance of the proposed algorithm is compared with that of multiple benchmark models by case studies.

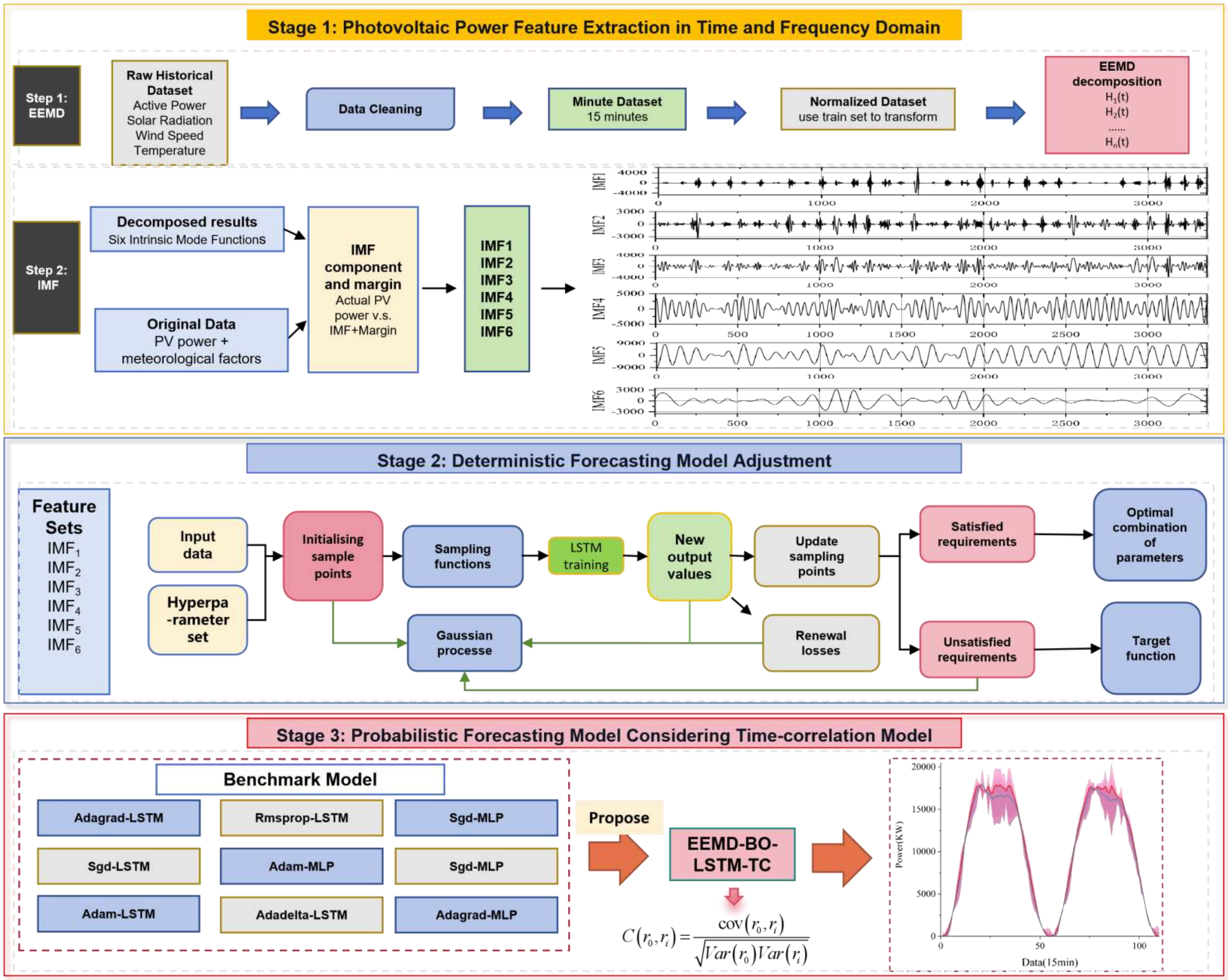

Fig.1. Overall Framework.

B. Data Segment in Frequency Domain

Before performing the decomposition, a suitable decomposition segment quantity should be figured out. If the value is too small, it may result in larger deviation from original data series, indicating that the power sequence decomposition is insufficient causing model mixing. That deviation decreases along with increasing segment quantity. However, if the value is too large, it can lead to excessive decomposition, which is also affecting the performance. According to the conclusion of reference [27], the optimal decomposition segment quantity is selected as 6 in the PV power forecasting model, which is like the one in this paper.

Through the above analysis, the original data is decomposed according to time and frequency. The specific decomposition diagram is shown in fig.1. EEMD decomposes the power into multiple modal components with different frequency characteristics, which facilitates to analyze hidden information of the power data and enables the model to have better forecasting accuracy.

To verify whether the decomposition of modal components is consistent with the original power data, the IMF components are reconstructed to obtain a series data. In Fig. 2 the chart in black is the original power data and the line in red with dashed line shows the reconstruction result. From the figure, it can be concluded that the reconstructed power data basically accords with the original power data, retaining most of the original data information. If the deviation between original power and reconstructed power is defined as the absolute deviation, meanwhile the standardized absolute deviation is defined as the coincidence rate, then the average coincidence rate between the reconstructed power and the original power is 98.3%, retaining most of the original data information. Therefore, the original power data is decomposed by using the decomposition method, which is beneficial to extract different features in the power data, and then it can forecast the PV power based on the feature information more accurately.

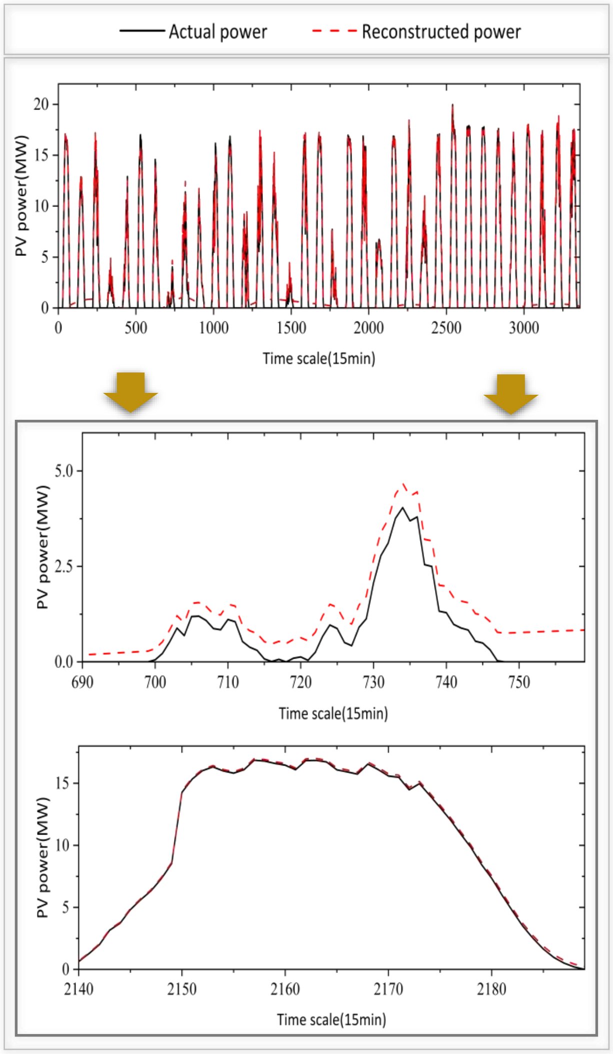

Fig. 2. Comparison of power time series with the reconstructed results after EEMD decomposition.

C. Probabilistic Forecasting

The parameter settings of the LSTM can lead to poor network fitting, to solve that problem, a Bayesian optimizer is introduced to optimize the learning rate, the number of hidden layer nodes and the regularization factor of the network in the paper. The randomness of the network brought by relying on empirical determination of network parameters is avoided, and the forecasting accuracy of the network is relatively improved. Furthermore, the Time Correlation model (TC) is applied to correct the deterministic forecasting results of the hybrid forecasting model based on deep learning. Finally, based on the forecasting results, photovoltaic power interval probability forecasting is conducted under the 80%, 90%, and 95% confidence levels, respectively.

IV. Case Study

A. Data

The data samples used in this paper are obtained from the measured data taken in a photovoltaic power plant which is in northern China (time duration: from 0:00 01/01/2017 to 23:59 31/12/2017). Because PV power output has an annual periodicity feature based on the solar radiation and motivation, a one-year data set is selected in this paper. Referring to the Reference [2], normally a one-year data set can cover all similar scenarios of the model. The time step of data is 15 minutes, and the installation capacity of power plant is 20MW, including total radiation, direct radiation, diffuse radiation, temperature, ambient temperature, air pressure, ambient humidity, and measured power data, which the details are shown below.

There are some relationships between PV power performance and some meteorological values which includes solar irradiance, ambient temperature, relative humidity, wind speed, wind direction, and air pressure. The correlation coefficient between meteorological factors and PV power is shown in Fig. 3. As the above meteorological factors are extremely random, the specific effect of each factor on PV power cannot be determined appropriately. To obtain a more definite quantitative relationship between meteorological factors and PV power, data pre- processing is required.

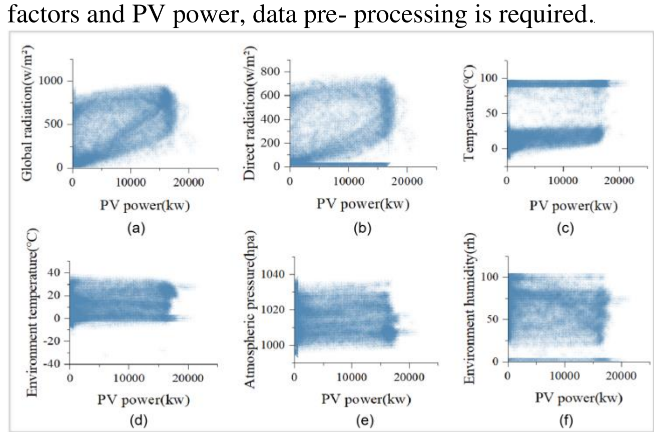

Fig. 3. Scatter plots between PV power and various meteorological factors. (a. global radiation; b. direct radiation; c. panel temperature; d. environment temperature; e. atmospheric pressure; f. environment humidity.)

As can be seen from the figure, the power generation curve has the same trend with total radiation, direct radiation, panel temperature, and environment temperature, so there is a positive correlation between power generation and the above factors.

B. Initial selection of the correlated deep learning model

Deep learning is widely used for both deterministic and probabilistic photovoltaic power forecasting [17]. In this paper, an improved BO-LSTM deep learning forecasting algorithm based on output power data time-frequency analysis and feature extraction algorithms is proposed. Other deep learning algorithms are applied for performance comparison with respect to the proposed forecasting model.

To save time and computational resources, it is necessary to select some algorithms with better performance from many commonly used algorithms. Therefore, the power forecasting results generated by models are compared with actual operational data in this section based on the case PV power station. In this paper, the correlations between actual power and the forecasting models (BO-LSTM, Adam-LSTM, Sgd-LSTM, Adagrad-LSTM, Rmsprop-LSTM, Adadelta-LSTM, Adam-mlp, Sgd-mlp, Adagrad-mlp, Rmsprop-mlp, Adadelta-mlp) are compared, which is shown in the heat map.

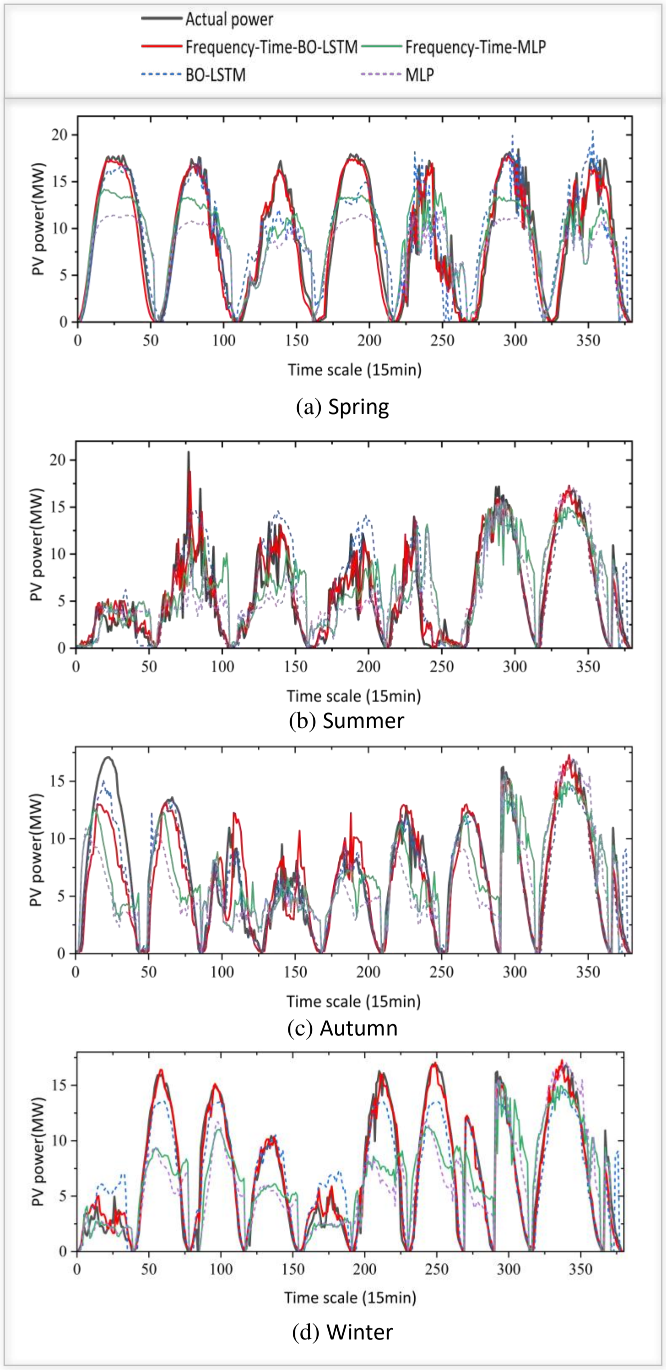

Fig. 4. Performance comparison of different forecasting models according to four seasons.

Performance comparison of different forecasting models is shown in Fig. 4. The solid line in red in the figure represents the forecasting results of the decomposed BO-LSTM model. As can be seen from the figure, the accuracy is significantly higher than that of other benchmark models in the ultra-short-term forecasting of PV power. Particularly, when there are fluctuations in photovoltaic power, the decomposed BO-LSTM can respond more quickly and make timely adjustments, thereby enhancing the accuracy of photovoltaic power forecasting. From the table, the forecasting accuracy is significantly improved by time-frequency decomposition on the original power data. This is because time-frequency decomposition can eliminate the outliers in the photovoltaic power data sequence.

TABLE I Mean Absolute Error based on the decomposed forecasting method and benchmark methods according to different weather types (unit: MW)

Forecasting Models	Sunny days	Cloudy days	Rainy days
Frequency-Time-BO-LSTM	**0.59**	**0.88**	**0.76**
Frequency-Time-MLP	1.41	0.96	1.01
BO-LSTM	1.96	1.27	2.46
MLP	2.26	1.43	1.98

C. The Performance of the Frequency-Time Feature Mapping Method

The variation features of solar radiation differ according to four seasons over a year. For example, summer has large solar radiation and long daytime while it is opposite in winter. To evaluate the model performance across the whole year, 4 months are selected for representation of different seasons.

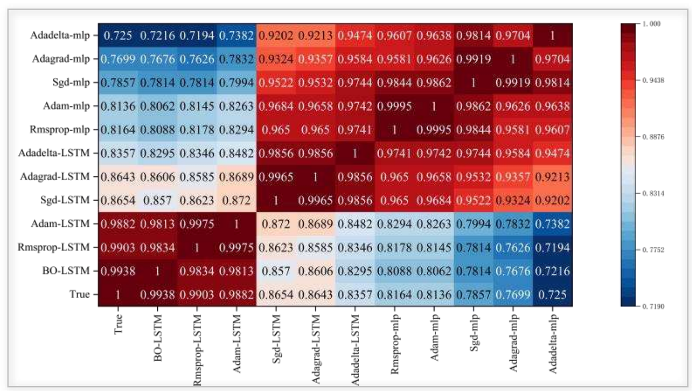

Fig. 5. Graph of deterministic forecasting results.

Fig. 5 illustrates the correlation coefficients of the real values and the forecasting results of different algorithms. The color represents the values of the correlation coefficients, with cooler colors indicating smaller values and warmer colors representing larger values. To save time and computational resources, forecasting algorithms with a correlation coefficient of over 0.9 are selected for the case analysis in this paper. Therefore, Bo-LSTM， RMSPROP-LSTM， ADAM-LSTM are selected for the following power forecasting.

D. The Performance of the Proposed BO-LSTM-TC Neural Network Model

To obtain the optimal weight coefficients, Multiple Linear Regression is employed to calculate the weights between Time Correlation Model and improved BO-LSTM model. Thus the hybrid BO-LSTM-TC model is constructed, and the forecasting results are illustrated in Fig. 6 and Table II.

It can be observed that in every deputy month, the results of the time-correlated model are all closer to the actual data trend, while the BO-LSTM model tracks the fluctuations closely in photovoltaic power output. The integrated model which is shown in red combines the advantages of both models and obtains higher accuracy compared to the individual models.

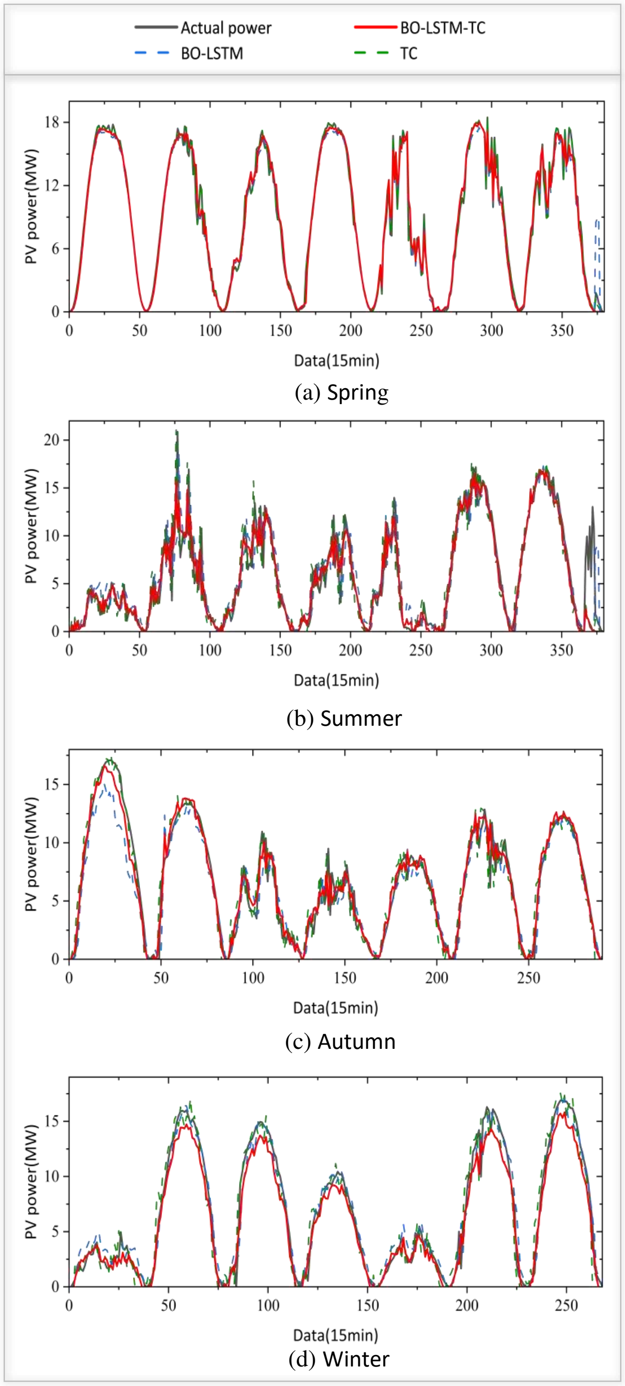

Fig. 6. Forecasting results after incorporating time-correlation models.

TABLE II Mean Absolute Error (unit: MW) based on the integrated method and other selected benchmark methods

Forecasting Models	Sunny	Cloudy	Rainy
BO-LSTM-TC	**0.76**	**0.52**	**0.57**
BO-LSTM	1.22	0.70	0.59
TC	0.83	0.88	0.91

E. The Performance of the Proposed BO-LSTM-TC Probabilistic Forecasting

Confidence intervals show the probability that the actual value falls around the measurement result. Based on the forecasting results of the above comprehensive forecasting model framework, photovoltaic power probabilistic forecasting is conducted Confidence Conditions (CC) under 80%, 90%, and 95%, respectively. As seen from the figure, the forecasting accuracy of the LSTM network is higher than that of the multi-layer perceptron for the same optimizer. The reason why the accuracy of the LSTM network is higher is that PV power is more regular on the time scale than on the spatial scale.

From the figure, the proposed model has higher forecasting accuracy based on the same case data. The Bayesian optimizer can fully use historical information when selecting the optimal combination of parameters, thus obtaining the optimal combination of hyper-parameters.

F. Probabilistic Forecasting Error Analysis

The performance of the proposed approach is evaluated by a metric, named as Power interval normalized average width (PINAW).

$$PINAW = \frac{1}{N_t R} \sum_{i=1}^{N_t} (U_i - L_i) \tag{8}$$

Where, N_t denotes the sample size, R denotes the range of target value variation, U_i denotes the interval's upper limit and L_i denotes the lower limit of the interval. The proposed model is compared with the other common models mentioned in terms of PINAW. The comparison results are shown in Fig. 8.

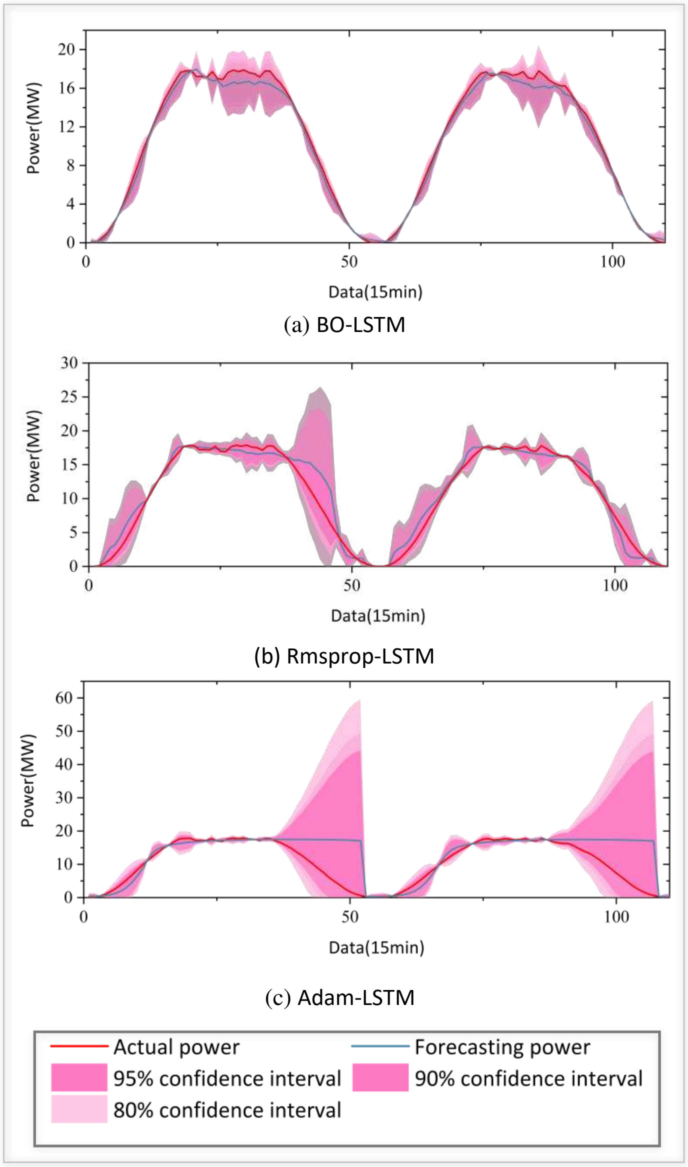

Fig. 7. Comparison of probabilistic forecasting results based on different algorithms.

The BO-LSTM-TC is the model proposed in this paper. From Fig. 8 and Table III, the standard deviation of the proposed BO-LSTM-TC model is significantly smaller than that of other models. The BO-LSTM-TC shows the model's superiority by its high probabilistic forecasting accuracy. Table I expresses the forecasting errors of the proposed model and two benchmark models with confidence conditions of 80%, 90% and 95%. Based on the correlation analysis which is shown in Fig.7, the model performances of Rmsprop-LSTM and Adam-LSTM are much more related with actual measurement power output. Hence, they are selected as the benchmark models. According to all the three confidence intervals, the proposed model gains better performance with lower errors which are 0.08, 0.10, and 0.13, respectively.

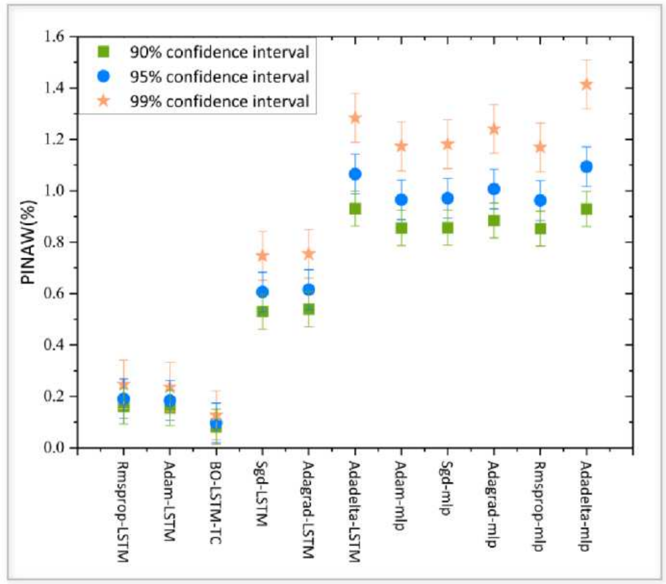

Fig. 8. Performance Comparison of LSTM and multi-layer perceptron.

TABLE III Forecasting Power deviation based on the proposed method and other selected benchmark methods of power forecasting method

Forecasting Model / Confidence Conditions	80%	90%	95%
Rmsprop-LSTM	0.16	0.19	0.23
Adam-LSTM	0.15	0.18	0.24
BO-LSTM-TC	**0.08**	**0.10**	**0.13**

V. Conclusions

Time correlation and time-frequency analysis of power data are crucial for improving the reliability of centralized photovoltaic power forecasting. In this paper, an improved BO-LSTM model incorporating time correlation (TC) weight analysis is proposed to achieve ultra-short-term probabilistic forecasting of centralized photovoltaic power. Firstly, the features of photovoltaic power are extracted and resolved according to power series frequency segments, thus obtaining the power components. Then, the constructed BO-LSTM model is improved according to each component to forecast each component power, respectively. Furthermore, the BO-LSTM-TC model is developed to correct the deterministic forecasting results. Finally, based on the results from the integrated forecasting model framework mentioned above, probabilistic photovoltaic power forecasting is performed. The specific conclusions are as follows.

(1) A novel BO-LSTM model with time and frequency mapping is proposed. Parameters for modeling are optimized through analyzing different power segment characteristics, thereby enhancing the accuracy of deterministic photovoltaic power forecasting. Case study illustrates an average accuracy improvement throughout the year of 39.5%.

(2) The hybrid model (BO-LSTM-TC) fully consider the effect of time-continuous characteristics on the forecasting model framework, thereby enhancing the forecasting reliability. Compared to benchmark models, the forecasting

power deviation of the proposed probabilistic forecasting is reduced by 37%.

ACKNOWLEDGMENT

This work was supported by National Key R&D Program of China (Intergovernmental Special Projects, 2019YFE0118400) and the program of Chinese Scholarship Council.

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