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Short-Term Load Forecasting Based on Variational Mode Decomposition and Least Square Support Vector Machine

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***Abstract*—**To address the problems of non-linearity and high randomness of the original power load sequence causing the degradation of power load forecasting accuracy, a short-term load forecasting method is proposed. The method is based on the least square support vector machine (LSSVM) optimized by an improved sparrow search algorithm combined with the variational mode decomposition proposed in this paper. The application of the variational mode decomposition technique decomposes the raw power load data into a series of intrinsic mode functions components, which can reduce the complexity and instability of the raw data while overcoming modal confounding; the proposed improved sparrow search algorithm can solve the problem of difficult selection of learning parameters in the LSSVM. Finally, through comparison experiments, the results show that the method can effectively improve prediction accuracy.

***Keywords*—**Load forecasting, variational mode decomposition, improved sparrow search algorithm, least square support vector machine.

I. Introduction

SHORT-term load forecasting refers to the forecasting of power system loads over a short period of time (usually from a few hours to a few days). Its main goal is to help power system operators to better dispatch power resources, optimize generation and transmission plans, and improve system economics and reliability. Short-Term Load Forecasting for power systems [1] are mainly based on historical power loads, weather temperatures, date types and other factors to predict the power loads for the next few hours to days. As current technology is not yet able to achieve large amounts of electrical energy storage, accurate short-term load forecasting is required to ensure the safe and stable operation of the power system [2], [3]. To improve economic efficiency, short-term load forecasting is also important for the economic operation, scheduling and reactive power regulation of power systems [4]-[6].

There are currently two main approaches to short-term load forecasting: single forecasting methods and combined forecasting methods. Single forecasting methods are divided into mathematical statistical model [7] methods and machine learning model [8] methods. For the mathematical statistical model approach, the advantages are simple models, simple calculations and faster forecasting [9]-[11]. For example, the literature [12] considers the load characteristics of different types of holidays and builds a specific Kalman filter model for each. Reference [13] proposed a forecasting model for seasonal exponential smoothing. Reference [14] applies a linear regression algorithm for forecasting electricity load data with different calendars, large data volumes and many features. The above algorithms can obtain more accurate results for electricity load data with low volatility and strong time series [15]. However, for non-linear load data with strong random fluctuations [16], it is difficult to make accurate predictions due to the poor robustness of mathematical statistical models [17], while machine learning algorithms can better handle the non-linearity and achieve better prediction accuracy. However, traditional machine learning algorithms have fewer model parameters and the prediction results depend largely on the quantity and quality of the data. In the face of today's massive and complex power data, it is difficult to mine the internal features, thus failing to obtain satisfactory prediction results.

To address the above problems, this paper applies the variational mode decomposition (VMD) technique to decompose the original load sequence, introduces an improved sparrow search algorithm (ISSA) to optimize the parameter selection in the LSSVM, and uses the VMD technique in combination with ISSA-LSSVM to improve the effect of electricity load forecasting. Finally, the effectiveness of the model is verified by experimental comparison.

II. Improved Sparrow Search Algorithm

The sparrow search algorithm (SSA) is an emerging meta-heuristic algorithm proposed, which is equivalent to particle swarm algorithms and genetic algorithms as a swarm intelligence algorithm for population-based feature optimization. The algorithm simulates the foraging and anti-predatory behavior of sparrows and finds the optimal solution to the objective function by continuously updating the positions of individuals, comparing fitness values and continuously updating the positions of discoverers, joiners and vigilantes. However, the SSA algorithm suffers from poor initial population quality and stability, and is prone to fall into local optimality. This paper proposes an improved sparrow search algorithm.

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A. Gaussian Mapping

The initial position of the individual distribution of the population is crucial to the optimization performance of the swarm intelligence algorithm itself, and uniform initial distribution will effectively improve the speed and accuracy of the population finding high-quality solutions. However, in the SSA, there is a lack of adjustment means to homogenize the population. Only relying on randomness to generate the initial population cannot guarantee the breadth of the search range, and it is easy to cause the algorithm to appear prematurely in the iteration with a fitness value far exceeding the average level. Large aggregations of 'super-sparrows' lead to the phenomenon of 'precociousness' and loss of search diversity. Therefore, the Gauss chaotic map is introduced to initialize the population by using its regularity, randomness, ergodicity, and other characteristics to make the population evenly distributed and improve the convergence speed and optimization accuracy of the algorithm. The mathematical expression for the Gauss map is:

$$x_{k+1} = \begin{cases} 0, x_k = 0 \\ \dfrac{1}{x_k \bmod(1)}, x_k \neq 0 \end{cases} \tag{1}$$

$$\frac{1}{x_k \bmod(1)} = \frac{1}{x_k} - \left[\frac{1}{x_k}\right] \tag{2}$$

where mod is the remainder function, [] represents rounding, $x = (x_1, x_2, \ldots, x_d)$ is the chaotic sequence generated by the Gaussian map, and d represents the dimension. Fig. 1 is a scatter diagram generated by Gauss mapping in the [0,1] interval.

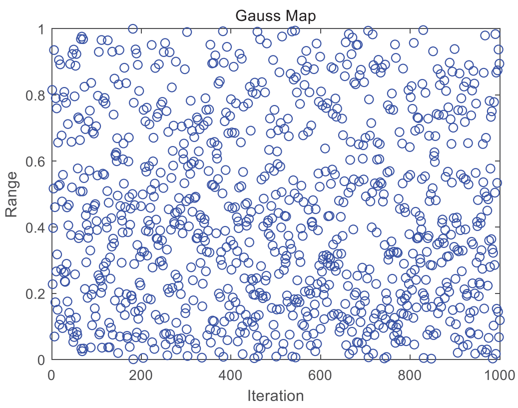

Fig. 1 Gauss chaotic sequence distribution

B. Dynamic Adaptive Weights

In the optimization process of the traditional SSA, the movement process of the finder to the optimal solution is easy to show a "jumping" step state. Although this mode is beneficial to improve the convergence speed of the algorithm and the population in a short time, a large number of internal pooling will reduce the diversity of the search process to a certain extent, and it will lead to local optimal ignoring search blind spots and insufficient search range. At the same time, it is considered that the sparrow finder's lack of use of its location information results in insufficient search accuracy of the algorithm. Therefore, the global search and local development capabilities of a uniformly distributed dynamic adaptive weight coordination algorithm are proposed by referring to the weight idea.

The finder location is updated as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \omega \cdot \exp\left(-\dfrac{i}{\alpha \times iter_{\max}}\right), if \rightarrow R_2 < ST \\ X_{i,j}^{t} + Q \cdot L, if \rightarrow R_2 \geq ST \end{cases} \tag{3}$$

The equation of the uniformly distributed dynamic adaptive weight ω is as follows:

$$\omega = \delta \begin{pmatrix} \omega_{initial} - \left(\omega_{initial} - \omega_{final}\right) \\ \times \dfrac{1}{e-1} \times \left(e^{\frac{t}{T_{iteratiom}}} - 1\right) \end{pmatrix} \tag{4}$$

In the equation, $\omega_{initial}$ and ω_{final} are the initial value and final value of the weight; $\delta \in [0,1]$ is a uniformly distributed random number.

C. Lévy Flight Strategy

When the discoverer iterates a certain number of times and the fitness value remains unchanged, the follower becomes the discoverer. To avoid the algorithm falling into local optimality, the Lévy flight strategy is introduced into the follower update formula to improve the global search capability. The improved formula is as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}\right), if \rightarrow i > m/2 \\ X_{p}^{t+1} + X_{p}^{t+1} \otimes Levy(d) \quad other \end{cases} \tag{5}$$

In (5), X_p^{t+1} is the best position currently occupied by the finder, and the Lévy flight mechanics are as follows:

$$Levy(x) = 0.01 \times \frac{r_3 \times \sigma}{|r_4|^{\left(1/\xi\right)}} \tag{6}$$

In (6), r3 and r4 are both random numbers in the range of [0, 1], and the value of ξ can be 1.5. The calculation method of σ is as follows:

$$\sigma = \left(\frac{\Gamma(1+\xi) \times \sin\left(\pi\xi/2\right)}{\Gamma\left(\left(1+\xi\right)/2\right) \times \xi \times 2^{\left(\left(\xi-1\right)/2\right)}} \right)^{\left(1/\xi\right)} \tag{7}$$

$\Gamma(x) = (x-1)!$ in (7).

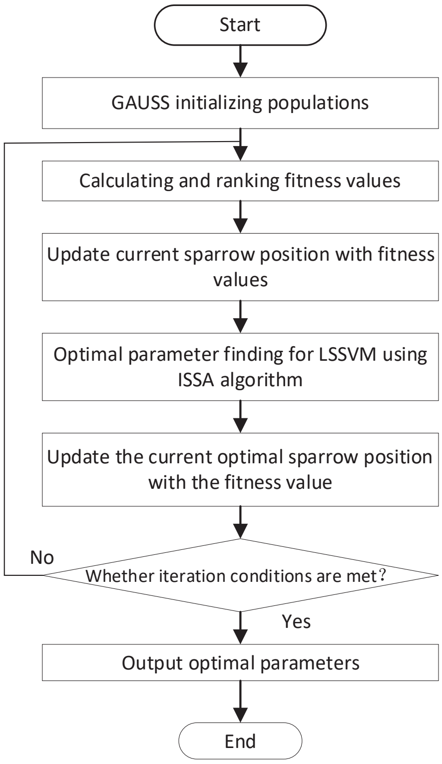

Fig. 2 ISSA advantage search chart

III. VMD Algorithm and ISSA Optimization LSSVM

A. Dynamic Adaptive Weights

The short-term power load sequence can be decomposed by variational mode, and the original complex signal can be adaptively decomposed into k limited bandwidth inherent modal signals using the principle of non-recursion and variable mode, and then subsequences of different frequency scales can be obtained. Each sub-sequence output has better regularity. Using VMD, the original load time series f is decomposed into finite bandwidth modal functions, k = 1,2, … K. The specific steps are the following four steps: solving the frequency band of the modal function, solving the variational problem, unconstrained variational transformation and alternate update.

B. ISSA to Optimize LSSVM

LSSVM is an improvement of the support vector machine. SVM is an effective machine learning method. Its main idea is to map the input vector to a high-dimensional feature space through a non-linear mapping function selected in advance, and to construct an optimal decision function in this space. LSSVM changes the inequality constraint of the SVM optimization problem to the equality constraint, so that the original problem is transformed into the problem of solving linear equations, simplifying the algorithm operation process, improving the convergence accuracy and solving speed, but LSSVM still has learning parameters (penalty factor C, Nuclear parameter). The traditional parameter selection method is the cross-validation method. In order to improve the prediction accuracy, this paper introduces the ISSA algorithm to optimize the hyperparameters of LSSVM. The ISSA search flow is shown in Fig. 2. The specific optimization steps of ISSA-LSSVM are as follows:

1. Set the total number of sparrow groups in the ISSA algorithm n = 30, the maximum number of iterations $iter_{\max}$ = 200. The ratio of discoverers and early warnings are both 0.2, and the value ranges of C and σ are $c \in [0,100]$, $\sigma \in [0.01,0.5]$ initialize sparrow population using Gauss map;
2. Calculate the fitness of each sparrow and sort it to define the population to which each sparrow belongs;
3. Update the position of each sparrow population according to (3) and (5);
4. Re-calculate the fitness of each sparrow after the updated position, compare the fitness before and after the update, and keep the better fitness to continue the update;
5. Determine whether the number of iterations is $iter_{\max}$. If it is not $iter_{\max}$, skip to (2) and continue until it is $iter_{\max}$, and terminate the operation;
6. The position of the optimal fitness X_{best} obtained is the parameters C and σ of LSSVM.

IV. Experiments and Analysis

In this paper, a region in southern China is used, from March 1 to May 31, 2018. The data are obtained from the power company's historical storage records, with a sampling step of 1 hour for the raw data and a total of 2,173 points for the electricity load data. The sliding forecast method is used to forecast the load data for May 31 one step ahead. The raw load is shown in Fig. 3. The mean absolute error MAE (mean) and root mean square error RMSE (root-mean-square error) were selected to evaluate the forecasting effect.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_t - y_t\right| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_t - y_t\right|} \tag{9}$$

Among them, $\hat{y}_t$ and y_t are the predicted value and the true value of the load, respectively.

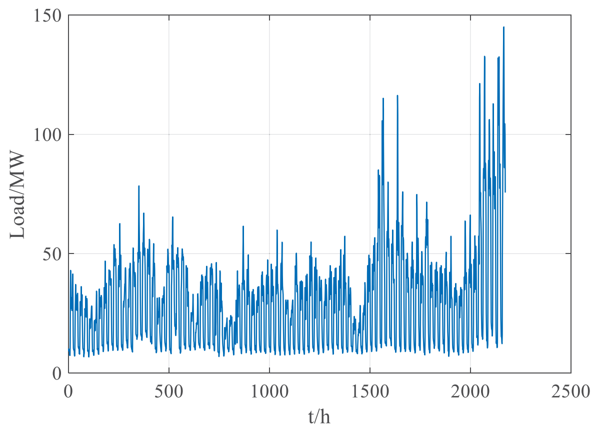

Fig. 3 Original load sequence diagram

A. Variational Modal Decomposition

In the variational modal decomposition of the original load, some parameters need to be set beforehand involving penalty factor alpha, modal number K value, initialized central frequency init, DC component DC, initialized central frequency tol. Because the value of K cannot be reasonably determined by random experiments, this paper uses manual experimental method to search for the optimal number K as 7 according to whether the central frequency is repeated or not. other parameters are uniform as shown in Table I, were configured according to the default values to ensure that the data would not be distorted. The original load sequence was decomposed to obtain the subsequence as shown in Fig. 4.

TABLE I
VMD PARAMETER CONFIGURATION

	alpha	init	DC	tol
Parameter settings	2000	1	0	1.0E-7

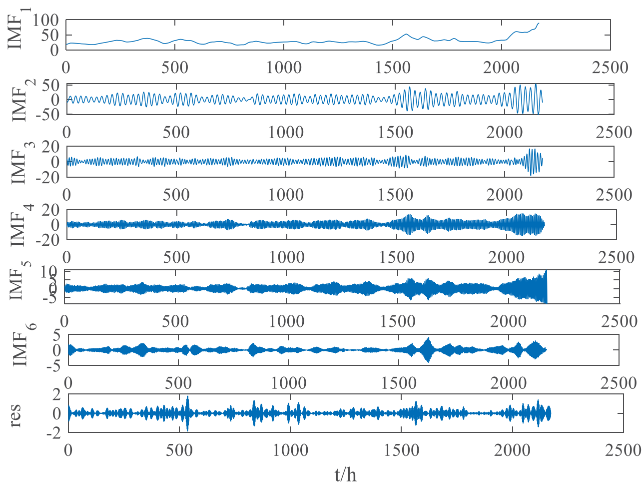

Fig. 4 VMD decomposition structure

B. Forecasting and Analysis

To verify the effectiveness of the proposed model, seven models, including LSSVM, VMD-LSSVM, EMD-LSSVM, VMD-GA-LSSVM, VMD-PSO-LSSVM, VMD-SSA-LSSVM and VMD-ISSA-LSSVM, are constructed under the same conditions in order to fully validate the superiority of the variational modal decomposition technique and the improved sparrow algorithm. Among them, GA is the genetic algorithm and PSO is the particle swarm algorithm, and the maximum population number is set to 30 for all three algorithms, and the number of iterations is 200. The prediction error indexes of different models are shown in Table II, and the prediction effects of each model are shown in Figs. 5 and 6.

As can be seen from Table II, the prediction accuracy of the model loaded with empirical mode decomposition (EMD) and VMD techniques has significantly improved compared with the original single model, and the improvement effect of VMD is significantly better than that of EMD technique, which also fully verifies the improvement effect of VMD on EMD, which can effectively solve the modal mixing problem of EMD and improve the prediction accuracy. Compared with the LSSVM model, the MAE and RMSE indices of the EMD-LSSVM model were reduced by 0.157 MW and 0.668 MW respectively, with a relative improvement of 3.5% and 10.6% respectively. The MAE and RMSE metrics for the VMD-LSSVM were reduced by 0.28 MW and 1.196 MW respectively, with relative percentage improvements of 6.2% and 18.9%.

TABLE II
COMPARISON OF PREDICTION RESULTS OF DIFFERENT MODELS

Models	MAE	RMSE
LSSVM	4.472	6.327
EMD-LSSVM	4.315	5.659
VMD-LSSVM	3.672	5.131
VMD-GA-LSSVM	2.706	3.680
VMD-PSO-LSSVM	1.707	2.758
VMD-SSA-LSSVM	0.580	0.911
VMD-ISSA-LSSVM	0.427	0.715

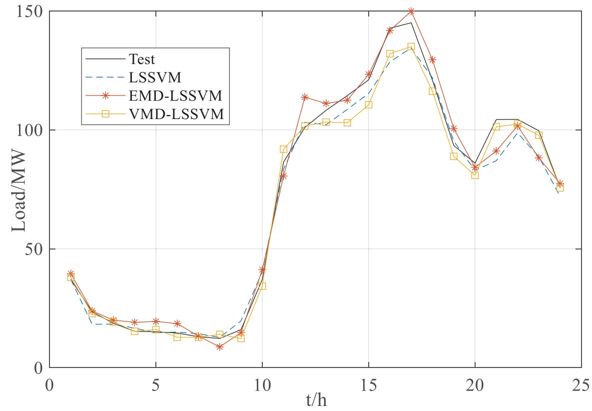

Fig. 5 Load forecasting results for different decomposition techniques

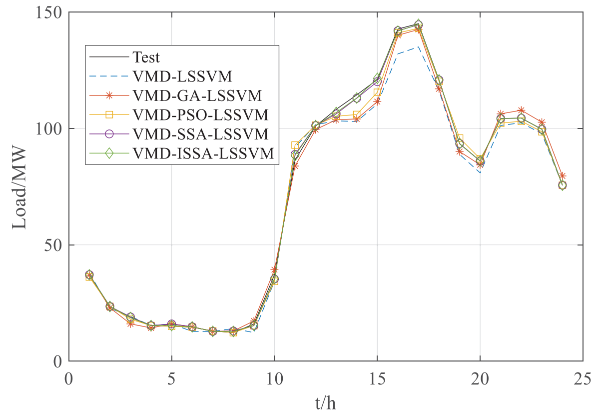

Fig. 6 Load forecasting results for different optimization algorithms

The introduction of different optimization algorithms on the basis of the VMD-LSSVM model will improve the prediction accuracy to varying degrees, with the ISSA algorithm showing the best improvement in prediction accuracy, followed by SSA and PSO, and the GA algorithm showing the worst relative improvement. Compared to the VMD-LSSVM model, the MAE and RMSE metrics of the VMD-GA-LSSVM model were reduced by 0.966 and 1.451 relative improvement percentages of 26.3% and 28.3% respectively, while the MAE and RMSE metrics of the VMD-PSO-LSSVM model were reduced by 1.965 and 2.373 relative improvement percentages of 53.5% and 46.24%, the MAE and RMSE metrics for the VMD-SSA-LSSVM model decreased by 3.092 and 4.22 relative improvement percentages of 84.2% and 82.24%, respectively, and the MAE and RMSE metrics for the VMD-ISSA-LSSVM model decreased by 3.245 and 4.416 relative improvement percentages of 88.37% and 82.24%. In summary, it can be seen that the ISSA algorithm has the best improvement effect, verifying that the ISSA algorithm can effectively solve the problem of difficult selection of learning parameters for LSSVM and substantially improve the prediction accuracy.

The effect of each model can be visualized in Figs. 5 and 6. It is clearly observed that the trend of the VMD-LSSVM model in Fig. 5 best fits the true value, and the predicted results of the VMD-ISSA-LSSVM model in Fig. 6 nearly overlap with the true value. It is also verified that the model proposed in this paper works better.

V. Conclusion

A study on short-term electricity load forecasting is conducted and a short-term load forecasting method based on VMD-ISSA-LSSVM is proposed, with the following conclusions being drawn:

(1) The original load data are processed by the variational modal decomposition technique, which reduces the complexity and instability of the original data and improves the accuracy of load forecasting, and the VMD technique is significantly better than the EMD technique, in addition, the VMD technique can solve the problem of modal mixing that occurs in the EMD technique and deeply explores the data features.

(2) ISSA has good parameter finding ability, which can well solve the problem of difficult selection of learning parameters in LSSVM and improve the prediction accuracy of the model. As well, the improvement effect on the prediction accuracy of the model is more obvious compared with the more classical algorithms GA and PSO algorithms. The MAE of the VMD-ISSA-LSSVM prediction method proposed in this paper is 0.427, and RMSE is 0.715.

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References

[1] Xueying Duan, Xiaoteng Li, Wenjie Chen. Improved particles swarm optimization algorithm-based VMD-GRU method for short-term load forecasting (J). Advanced Technology of Electrical Engineering and Energy, 2022,41(05):8-17.

[2] Qin Yan, Xiaofan Tu. Optimized Operation of an Integrated Electric Vehicle Charging Station with Renewables and Storage under New Power System (J). Journal of Hunan University (Natural Sciences), 2022, 49(02):176-182.

[3] Liang Qi, Yue Wang. Auxiliary Frequency Regulation Control of Power System Considering Operational Reliability (J). Automation of Electric Power Systems, 2022, 46(08):86-94.

[4] Yashan Zhong, Cong Fu, Feng Qian, Bo Bao, Yun Yang, Yunxia Xu, Donghui Zhang. Economic dispatch model of an integrated energy system considering generalized energy storage and conditional value at risk (J). Power System Protection and Control, 2022, 50(09):54-63.

[5] Yan Dong, Junlin Yang, Yongsheng Zhu, Qiuyan Li, Bin Chen, Caijing Nie. Robust optimal dispatch of a power system based on a zero-sum game (J). Power System Protection and Control, 2022, 50(05):55-64.

[6] Xin Ning, Tongxun Wang, Han Chen, Dandan Feng, Lei Han, Hui Wang, Lisheng Li. Reactive Power Voltage Optimization of Distribution Network Based on Goal Planning (J). Power Capacitor & Reactive Power Compensation, 2022,43(03):1-7.

[7] Zhixin Fu, Yan Cao, Junpeng Zhu, Yue Yuan. Research on Hydropower Unit Health Assessment Model Based on MI-GA-BP and Error Statistical Analysis (J). Power System and Clean Energy, 2021, 37(07):97-106.

[8] Yanjun Dong, Xiaotian Wang, Hongming Ma, Libin Wang, Mengyu Li, Fanding Yue, Huan Yuan. Power Load Forecasting Method Based on Random Forest and Long Short-term Memory (J). Journal of Global Energy Interconnection, 2022, 5(02):147-156.

[9] Xuesong Lv, Dong Pan, Kai Wang, BI Jinghu. Markov Modified Grey-time Series Electric Load Forecasting Method (J). Automation technology and applications, 2022,41(03):132-136+176.

[10] Qian Ma, Yumin Zhou, Quan Yuan, Hui Zhou. Research on Power Load Forecasting Method Based on Double Similarity Mechanism During Typhoon (J). Guandong Electric Power, 2022,35(03):79-87.

[11] Yang Guangyu, Li Xiaohang. The short-term power load forecast in wide area learning system based on maximum information mining(J). Electrical Measurement & Instrumentation, 2022,59(03):38-45.

[12] Chen Peiyin, Fang Yanjun. Short-term load forecasting of power system for holiday point-by- point growth rate based on Kalman filtering (J). Engineering Journal of Wuhan University. 2020,53(02):139-144.

[13] Juan F. Rendon-Sanchez, Lilian M.de Menezes. Structural combination of seasonal exponential smoothing forecasts applied to load forecasting (J). European Journal of Operational Research. 2019,275(03):916-924.

[14] Hannah Nano, Savanna New, Achraf Cohen, Bhuvaneswari Ramachandran. Chapter 16 - Load forecasting using multiple linear regression with different calendars (J). Distributed Energy Resources in Microgrids, 2019, 415-417.

[15] Xiaobo Cao, Jin Li, Xin Yang, Shaohua Yang, Benbo Shi, Zhigang Lu. Combined forecasting method of short-term cooling, heating and power load based on weather information correction (J). Journal of Yanshan University, 2022, 46(03):230-238.

[16] Junjie Wu, Qian Zhang, Fan Chen, Guoli Li. Short-term Load Forecasting with Error Correction and Variational Mode Decomposition-Long Short-term Memory (J). Science Technology and Engineering, 2022, 22(12):4828-4834.

[17] Peng Li, Jiahao Wang, Xian Xu, Jianyi Li, Xiaochun Xu, Hui Xia. Robust Reactive Power Partitioning Method for Frequent Power Flow Fluctuation in New Power System (J). Automation of Electric Power Systems. 2022, 46(11):102-110.