Medium and Long-term Load Intelligent Forecasting Method Based on the Comprehensive and Multiple Early Warning Indicators

Yao Wang[1], Zheng Wang[2], Xuxia Li[3], Zhigang Wang[4], Renhui Liu[5], Xing Tong[6]

[1]Planning and Review Center, Economic and Electrical Research Institute of Shanxi Electrical Power Company of SGCC, TaiYuan, ShanXi, 030002, China

[2]Planning and Review Center, Economic and Electrical Research Institute of Shanxi Electrical Power Company of SGCC, TaiYuan, ShanXi, 030002, China

[3]Planning and Review Center, Economic and Electrical Research Institute of Shanxi Electrical Power Company of SGCC, TaiYuan, ShanXi, 030002, China

[4]Planning and Review Center, Economic and Electrical Research Institute of Shanxi Electrical Power Company of SGCC, TaiYuan, ShanXi, 030002, China

[5]R & D department, Shenzhen Orange AI Technology Co., Ltd., ShenZhen, GuangDong, 518000, China

[6]R & D department, Shenzhen Orange AI Technology Co., Ltd., ShenZhen, GuangDong, 518000, China

[*]Corresponding author's e-mail: 779656332@qq.com

Abstract. Medium and long-term load forecast takes the annual and monthly as the main time series, and regards the power demand indicators (such as the monthly power amount, monthly electrical power and so on) as the forecast content, thus being of great significance for reasonably formulating the power system planning, arranging the mid-term operation plan of the power system, reducing operation cost and improving power supply reliability. On the basis of the early warning analysis of power demand, this paper makes some attempts in combining early warning and forecasting work, and proposes a kind of medium and long-term load forecasting method integrating several early warning indicators. The method integrates multiple internal and external factors in the system such as the early warning leading industry and economic factor, uses the principle of minimum information loss to comprehensively utilize multiple early warning information under the unified scale, and can give probabilistic and accurate prediction results. The method has a clear physical background and economic meaning, and it is a new exploration of the medium and long-term load forecasting mechanism.

1. Overview

Medium and long-term load forecast takes the annual and monthly as the main time series, and regards the power demand indicators[1] (such as the monthly power amount, monthly electrical power and so on) as the forecast content, thus being of great significance for reasonably formulating the power system planning, arranging the mid-term operation plan of the power system, reducing operation cost and improving power supply reliability[2-5]. On the basis of the early warning analysis of power demand, this paper makes some attempts in combining early warning and forecasting work, and proposes a kind of medium and long-term load forecasting method integrating several early warning indicators. The method integrates multiple internal and external factors in the system such as the early warning leading industry and economic factor, uses the principle of minimum information loss to comprehensively utilize multiple early warning information under the unified scale, and can give probabilistic and accurate prediction results. The method has clear physical background and economic meaning, and it is a new exploration of the medium and long-term load forecasting mechanism.

Section 2 of this paper summarizes the framework of the forecasting method systematically. Section 3 elaborates on the selection methods and processing methods of early warning indicators. Section 4 illustrates how to use the minimum information loss principle to comprehensively utilize the early warning information provided by multiple indicators. Section 5 discusses how to calculate probabilistic and numerical forecasting results based on the above analysis. Section 6 illustrates the above method with numerical examples. Section 7 summarizes the full paper.

2. Framework of predication method

Different from the traditional relevant factor predication method, this method re-examines the meanings of various early warning indicators from the perspective of probability theory, and comprehensively utilizes various early warning indicators with the method of information theory. The framework of this prediction method is as follows:

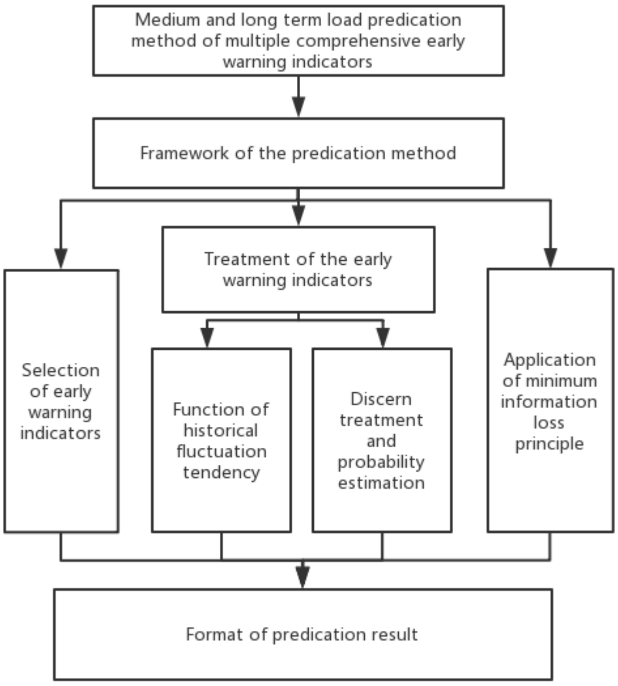

Figure 1. structural diagram of this paper

1. The selection of predictive data form. The data form of the commonly used prediction method is always the prototype form of the electricity consumption. Considering the fact that, as to the medium and long-term prediction, its essential content lies in the accurate prediction of data volatility. At the same time, in order to avoid the influence of seasonal factors, the power consumption data selected here is the cyclic ratio of the de-seasonal component (SA) after X-12-ARIMA seasonal adjustment [6-8]. Therefore, if there is no special Instruction in the subsequent content of this paper, the average value of the electricity consumption is the de-seasonal component (SA) after the X-12-ARIMA seasonal adjustment. The data format of other early warning indicators shall choose the month-on-month value (or growth rate) after removing the seasonal effect as well.

2. Select the early warning indicator used for the predication. The selection of early warning indicators has a direct impact on the forecasting effect, and it must be selected from the internal and external influential factors separately according to the power demand formation reason.

3. Conduct discretization to the early warning indicators and the electricity consumption amount of the whole society separately, and obtain the probability distribution of the corresponding random variables. Firstly, each early warning indicator and the electricity consumption of the whole society are separately discretized in this paper. The advantage of such a manner is that it can enhance the fault tolerance in predicating. Secondly, the discretized early warning indicators and the electricity consumption of the whole society are regarded as discrete random variables. According to each early warning indicator and the joint value sequence of the whole society electricity consumption history, the probability distribution of the early warning indicator random variable is estimated to make several earning warning indicators could be integrated under the unified scale of the information theory.

4. Make comprehensive determination on random variables corresponding to multiple early warning indicators. The principle of minimum information loss in information theory is used to make a comprehensive determination on the random variables of each early warning indicator, and comprehensively judge the value of each early warning indicator before each time to be predicted, so as to obtain the final prediction result. The probability of each discrete result evaluation can be calculated.

5. Put out the prediction results. The predicted result obtained is the probabilistic result of the cyclical value of the seasonal component of the electricity consumption in the whole society. The data can be simply processed to obtain the probabilistic results of the electricity consumption and the numerical prediction results of the whole society.

Combined with the early warning indicators actually selected in this paper, the above framework content can be represented as the block diagram shown in figure 2, in which, the contents of each part will be detailed in the following part in this paper.

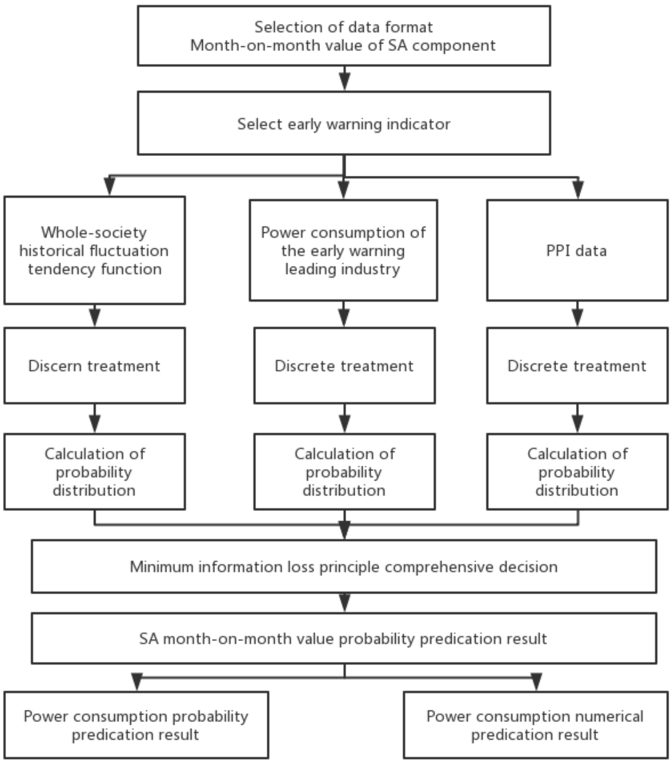

Figure 2. Medium and long term load predication method framework of comprehensive multiple early warning indicator

3. Selection and processing of early warning indicators

3.1. Selection of early warning indicators

The warning indicator used for prediction must have a clear physical background or economic implication, and should be able to indicate the forming reason for the electrical load to a certain extent. In selecting multiple early warning indicators for forecasting in the meanwhile, it is required to pay attention to select from the different perspectives of the cause of the electrical load.

The method selects three early warning indicators, namely: historical fluctuations of electricity consumption in the whole society, electricity consumption in the leading industries of power demand warning, and PPI index (producer price index or industrial product ex-factory price index). These three indicators give early warning information on the electricity consumption of the whole society from different aspects.

The historical fluctuations in electricity consumption in the whole society can reflect the law of fluctuations in electricity consumption in the whole society. Due to the steady growth of power demand, the historical fluctuations in electricity consumption have great similarities with future fluctuations. This is the basis for predicting the historical fluctuations in the electricity consumption of the whole society.

Electricity consumption in the leading industries of power demand warning is to provide the early warning information of the whole society's electricity consumption from the perspective of the whole society's electricity consumption constitution and industry linkage. The selection of this indicator is based on the idea of predicating entity from locality. The specific meaning of the warning information in this indicator is that the indicator should fluctuate in the same direction as the power consumption of the whole society.

PPI index is a kind of economic data. The economic data used in load forecasting is mostly the GDP data. However, GDP data is more affected by the economic environment and so on, compared to it, PPI data can better reflect actual production conditions, thus better reflecting the power consumption which is closely related to the practical production. The specific meaning of the early warning information in this indicator is that the indicator should fluctuate in the same direction as the electricity consumption of the whole society.

The early warning effect of the above three early warning indicators on the electricity consumption of the whole society can be represented by figure 3.

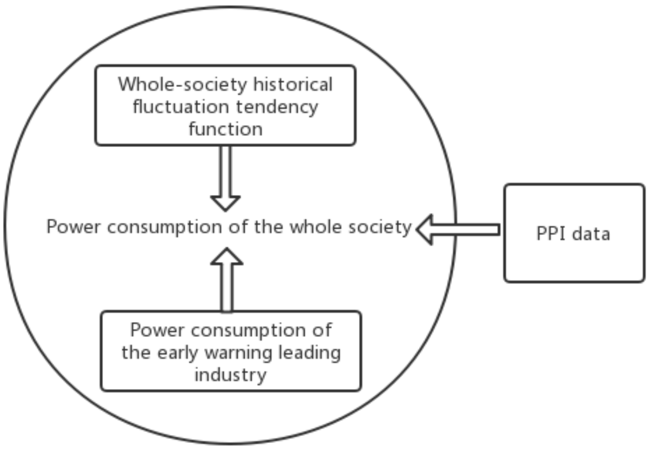

Figure 3. effect of the three early warning indicators selected by the predication method to the power consumption of the whole society

3.2. Potential function of historical fluctuation

The historical fluctuation potential function is a means to quantify the historical fluctuations in the power consumption of the whole society. Before quantifying the historical fluctuation condition of the power consumption, it is firstly required to choose the reference value of the power fluctuation. The reference value selected in the method is the average value of the historical social power consumption cycle data before the period to be predicted. If the period to be measured is k, the average value is marked as $avrg(k)$.The month-on-month value of the power consumption of the whole society at the time period k is marked as $d(k)$, the historical fluctuation function $V(k)$ can constitute the following format:

$$V(k) = -\{\xi r^2[d(k-3) - avrg(k-3)] + r[d(k-2) - avrg(k-2)] \\ +[d(k-1) - avrg(k-1)]\} \quad (1)$$

There are two parameters here. ξ is the 0-1 variable. It determines to consider the situation of 3 time periods or 2 time periods before the period to be measured in considering the historical fluctuation of the power consumption. $r \in [0,1]$ is the attenuation coefficient. It determines the proportion of fluctuations in the previous period that should be attenuated when converted to fluctuations in the current period.

The historical fluctuation function $V(k)$ completes the quantification of the historical power consumption fluctuation condition. The following paragraph shall illustrate its early warning effect. A reasonable assumption for the power consumption loop ratio sequence is made, namely, it is believed that the power consumption loop sequence always fluctuates around the mean. This way, if the overall fluctuation of the power consumption ratio before the time period k is above the historical average, the power consumption of the time period k will have a greater probability of appearing below the historical average. However, the historical fluctuation function $V(k)$ is depicting the general situation of the historical fluctuation of the power consumption loop ratio sequence before the k period (the historical value too far from the time period k has little effect on the time period k, thus can be ignored), so it also depicts the possibility of the power consumption month-on-month value deviating the historical mean at the k time period. According to the formula definition, a higher $V(k)$ will lead to a greater upwards deviation of the valuation from the historical mean at the time period k, otherwise, a greater downward deviation of the valuation from the historical mean at the time period k. In other words, the sequential month-on-month value of the power consumption of the whole society is positively related to $V(k)$ at the k time period. This is exactly the early warning effect of $V(k)$.

3.3. discrete processing of the early warning indicators and predicated probability estimation

Section B quantifies the fluctuations of the power consumption in the whole society, and the power consumption and PPI data of the leading power demand industries are directly available data, which can be directly used in the predication after obtaining the month-on-month value and going through the X-12-ARIMA method treatment.

To this end, the three early-warning indicators selected in this method are consecutively valuated variables. First of all, they are discretized. Given the reference value μ and gradient value Δd of various early-warning indicators, setting the n-level discretized $\mu \pm k\Delta d, k = 1,2\ldots, n$ will discretize the early warning indicators, specifically, setting the indicator value of x, its corresponding discrete variable is X. If $\mu + k\Delta d < x < \mu + (k+1)\Delta d$, $k = 0,1,\ldots, n-1$, making $X = k$. If $\mu - (k+1)\Delta d < x < \mu - k\Delta d$, $k = 0,1,\ldots, n-1$, making $X = -k$. If $x > \mu + n\Delta d$ $x > \mu + n\Delta d$, making $X = n$. If $x < \mu - n\Delta d$, making $X = -n$.

In discretizing three indicators, Δd is taken as the standard deviation of the historical sequence of various indicators. As to $V(k)$, valuing $\mu = 0$. As to the other two indicators, μ is taken as the average value of the historical sequence of the indicator. There are three discrete variables to $V(k)$, power consumption of the power demand leading industry and PPI data, which are respectively marked as X, Y and Z. The power consumption month-on-month value of the power consumption in the whole society is also discretized as the above method. μ is taken as its historical sequence average value. $\Delta d = 1\%$, then the power consumption month-on-month value of the whole society also corresponds to a discrete variable D.

From another perspective, *X*, *Y*, *Z*, *D* can be regarded as four discrete random variables. Historically, each value of each variable can be regarded as a one-time experiment of the random variable. Since all four random variables have clear physical meaning or economic background, the four random variables have a certain probability distribution, and can be approximated by the experimental frequency distribution [9].

The value of each early warning indicator at the time period k is used to conduct a virtual prediction of the value of the power consumption in the whole society at the time period k+1, and each virtual prediction is regarded as an experiment. By counting the virtual prediction results of each indicator, the experimental frequency distribution of the three $(X, D), (Y, D), (Z, D)$ joint random variables can be obtained, which are also the probability distribution estimation of the three joint random variables.

4. Multiple early warning information treatment method based on the minimal information loss principle

Record the valuation collection of the random variable as Φ, $\forall a \in \Phi(X), b \in \Phi(D)$. If it has been known $X = a$ in a certain time period, the information amount according to Shannon information theory [10] decision $D = b$ is:

$$I(D = b|X = a) = ln[\frac{P(D=b|X=a)}{P(X=a)}] \tag{2}$$

The information loss of this decision is:

$$I_{loss}(D = b|X = a) = max\{ I(D = b|X = a)\} - I(D = b|X = a) = ln[\frac{P(b_M/a)}{P(b/a)}] \tag{3}$$

Here, $b_M \in \Phi(D)$, b_M is the valuation of b making $P(D = b|X = a)$ to be the maximum. As to the random variables Y, Z, there are also the same conclusions. Moreover, the information loss when making a decision on the value of D according to each single random variable can be added. In the sense of information theory, the values of X, Y, and Z are known at the same time, and the value of decision D is determined. The best decision result is the solution of the following optimization problem:

$$\min_{b\in\Phi(D)} I_{loss}(D = b|X) + I_{loss}(D = b|Y) + I_{loss}(D = b|Z) \tag{4}$$

This is exactly the minimum information loss (MIL) principle. The MIL theory can be used to integrate the *X*, *Y*, *Z* independent predicated results, thus obtaining the optimal predication of *D*.

5. Format of load predication result

If the result obtained by the direct MIL principle is the final prediction result, the result is an interval prediction concept, that is, the predicted value of the total social power consumption ratio is the interval corresponding to the *D* discrete value.

In order to obtain an accurate load prediction result, we can use the value of the midpoint of the interval as the final load prediction result.

As a matter of fact, in using MIL principle to predicate, in addition to giving the optimal decision value of the final *D*, the information loss when decision *D* takes various possible values is provided as well. In fact, this optimal value of *D* is not the optimal value with the absolute significance. Instead, it means that, compares with other value, if decision *D* takes the value, the loss information is smaller, and the probability of decision error is smaller. It can be seen that the optimal decision of *D* is actually a probabilistic optimal. Then, when the MIL principle is used to predicate, the probabilistic prediction can be performed.

Set $||\Phi(D)|| = n$, $\forall i, j \in \{1,2,\dots,n\}, i \neq j$, there is $b_i \neq b_j$, $\forall i \in \{1,2,\dots,n\}$, there is $b_i \in \Phi(D)$. Assuming at the time period k, the random distribution of D value is $P(D = b_i) = p_i$. Then, according to this random distribution, the information loss difference of *D* at any two values can be calculated.

$$I_{loss}(D = b_i) - I_{loss}(D = b_j) = ln(\frac{p_j}{p_i}) \tag{5}$$

However, $I_{loss}(D = b_i)$ is the known value in using the MIL principle for making decision. Then, it is able to establish the equation set to calculate the p_i value according to the formula, namely, the probability of each load predication interval. Record $I_i = I_{loss}(D = b_i)$, $S = 1/\sum_{i=1}^{n} I_i$, the format of the equation can be:

$$\begin{cases} ln(p_i) - ln(p_{i+1}) = I_{i+1} - I_i \\ \sum_{j=1}^{n} p_j = 1 \end{cases}, i = 1,2,\ldots,n-1 \tag{6}$$

Its solution is:

$$\begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_{n-1} \\ p_n \end{bmatrix} = exp\left(\begin{bmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & -1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 & -1 \\ 1 & 1 & \cdots & 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} -1 & 1 & 0 & \cdots & 0 \\ 0 & -1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -1 & 1 \\ S & S & \cdots & S & S \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_{n-1} \\ I_n \end{bmatrix}\right) \tag{7}$$

The above-mentioned prediction results are the predicted values of the de-seasonal component (SA) after the X-12-ARIMA seasonal adjustment, and it is required to restore it into the power consumption value. Please refer to the following steps:

1. Restore the month-on-month value of the SA component to the value of the SA component;
2. The seasonal component is predicted, and the linear straight-line time series extrapolation can be directly performed by using the annual development sequence of the seasonal component;
3. The holiday component, the leap year component and so on are predicted. The predicted values of this part have already been calculated when using the X-12-ARIMA program for seasonal decomposition, thus could be directly utilized.

Multiplying the above three factors will obtain the final power consumption.

6. Case analysis

The monthly power consumption data of A Province from 1999 to 2008, the monthly power consumption data of various industries from 1999 to 2008, and the PPI monthly indicators from 2004 to 2008 are used to calculate the above prediction methods. This is a virtual forecast of monthly power consumption for the full year of 2008.

Firstly, combined with the early warning leading industry identification method and the total industry influence coefficient and sensitivity coefficient, the monthly electricity consumption data of 50 sub-sectors in A Province from 1999 to 2008 are analyzed, thus obtaining the top 6 early warning leading industries as follows:

Table 1. Power demand early warning leading industry in A province from 1999 to 2008

Industry name
Non-metal mineral industry
Black metal smelting and rolling processing industry
Chemical raw material and chemical product manufacturing industry
Coal mining and washing industry
Textile industry
Accommodation and dining industry

Secondly, the power consumption, historical fluctuation trend function of the whole society, the three types of early warning indicators of PPI data, and the power consumption data of the whole society of the six leading industries are separately discretized, and the number of discretization is 3,1,1,1 respectively.

Finally, based on the discretized data, the monthly power consumption data for the whole year of 2018 is virtually predicted, and the following probabilistic prediction results are obtained. The part with shading and in black font is the interval with the maximum prediction probability:

Table 2. Comparison between several comprehensive early warning factors and the traditional predication method in the predication accuracy

Method name	**Mean relative error of predication**
This method	2.30%
Gray predication method	4.20%

Secondary curve fitting of annual development sequence	5.69%
Indicator function fitting of annual development sequence	10.80%
Predication method based on seasonal decomposition	5.8%

Comparing the method with the commonly used gray predication method, the following comparison diagram can be obtained.

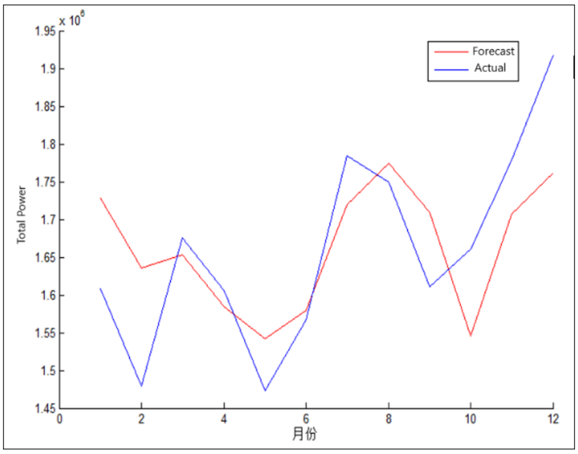

Figure 4. 2018 virtual predication curve diagram of a province

It can be seen from the above prediction results that the prediction method described in this paper has higher precision than the traditional prediction method. It can be seen from the diagram, especially from October to December, when the power consumption presents a great difference to the historical development tendency, the relative error of gray predication is greater. However, the predication error of this method here is lower. This is because the method has a strong physical background and economic significance to support, can obtain information from its constituent factors or external related factors at the "turning point" of electricity consumption, so as to more accurately predicate the power consumption of these periods.

7. Summary of the paper

This paper proposes a medium-term and long-term load forecasting method for comprehensive multiple early warning indicators on the basis of the above-mentioned early warning analysis of power demand. This method has a clear physical background and clear economic implication. In addition, it can accurately predicate through exploring the reason of load fluctuation when the load has a “turning point”, thus it has the advantages not possessed by the general mathematics tools. This method is an exploration of the application of electric power warning indicators to load forecasting. From the perspective of the case predication result, this exploration is beneficial and feasible.

Acknowledgement

Science and technology support project of State Grid Corporation of China, Contract number: SGSXJY00PSJS190003

References

[1] Wang, LY, Wang ZM, Qian W. et.al., (2019)Extended Solow regression model for mid/long-term load forecasting adapted to supply-side structural reform, Power system Protection and Control. Vol. 47(18), pp. 49-59.
[2] Lin JX. Gu HJ, (2019)Analysis of Medium and Long-term Load Forecasting Technology for Power Grid Planning, Electric Power System Equipment, vol. 13, pp. 46-47.
[3] Liu M, Wang HL, Suo LZ, (2019)Medium-and Long-term Load Probability Density Forecasting Based on Variable Weight Combination Model, Proceedings of the CSU-EPSA, vol. 31(7), pp. 88-94.

[4] Luo SX, Lin Y, Ma MH, et.al., (2019)Medium and long term load forecasting method, CN201910355154.5, patent.
[5] Deng YW, Wu GP, Mao WD, et.al., (2019)Research of Multi-Factor Model for Medium and Long-Term Load Forecasting, Inner Mongolia Electric Power. vol. 37(3), pp. 23-28.
[6] Li SX, Li BG. (2018)Comparison of Prediction Method Based on SARIMA Model and X-12-ARIMA Seasonal Adjustment Method, Statistics and Decision, vol. 34(18), pp. 39-42.
[7] Min YY, Ao CL, (2018)Sales Volume Based on X-12-ARIMA and TRAMO /SEATS Season Adjustment Technology, Mathematics in Practice and Theory, vol. 48(8), pp. 68-74.
[8] Zhang Q, Wang Y, Li DR, Zhu WJ, (2017)Monthly Electricity Forecast Based on X-12-ARIMA Seasonal Decomposition and Annual Electricity Correction, Electric Power Construction, vol. 38(1), pp. 76-83.
[9] Xiao TS. (2000)Stochastic mathematics.Beijing, Higher Education Press, in press.
[10] Zhu XL. (2001)Fundamentals of Applied Information Theory, Tsinghua university press, in press.