Medium and long-term coal demand for electricity sector forecasting based on improved seasonal adjustment model

The electrical coal consumption in our country presents non-stationary characteristics of seasonal periodicity and circular trend while seasonal adjustment can decompose this sequence into trend cycle element, season element and irregular component with practical economic meaning. Before seasonal adjustment, we need to eliminate the impact of outlier, workday and leap year in the sequence in original electrical coal consumption and then we can conduct decomposition on the trend cycle sequence after seasonal adjustment applying H-P filtering method. After that, we can select appropriate model to conduct electrical coal demand forecasting based on different characteristics like long-term trend, periodic cycle, seasonal factor and irregular component after decomposition. Through the empirical test of electrical coal consumption in our country for 192 months, the results indicate that the precision has been improved significantly in long-term electrical coal demand forecasting by using the improved seasonal adjustment model and method.

Keywords: Electrical coal demand; time sequence; seasonal adjustment; H-P filter; forecasting.

1. Introduction

The electrical coal consumption in thermal power generation accounts for the major proportion of coal consumption in our country. Similar to electric load, electrical coal demand is often influenced by non-linear factors and uncertain factors like feature of thermal power generation, fluctuation of coal price, adjustment of industrial structure, climatic change and sudden natural disaster, which leads to the non-stationary characteristics like tendency, cyclicity and seasonality in electrical coal consumption statistical data that serves as time sequence [1-3]. Therefore, it is very difficult to conduct high-precision electrical coal demand forecasting.

In recent years, some scholars apply various models and methods to conduct forecast analysis on the electrical coal demand in our country. Zhu Fagen et al. applied X-12-ARIMA model to forecast the short-term electrical coal demand in China [4-5]; Zhang Dong et al. conducted quantitative analysis on the long-term development situation of coal power in our country [6-7]. However, because of the periodic variation of seasonal factors, it is difficult for the measured monthly and quarterly electrical coal consumption time sequence to reflect the economic change in time. Meanwhile, fluctuation may occur in the electrical coal consumption time sequence due to the impact of non-linear factors, leading to the abnormal increase or decrease of individual data in the sequence. Therefore, it is very difficult to grasp the varying regulation in the electrical coal consumption sequence, making it harder making to conduct forecasting.

On this basis, this paper first conducts preliminary adjustment on the monthly electrical coal consumption data, eliminating the outlier effect and workday effect in the electrical coal consumption sequence; after that, three time sequences of trend cycle, seasonal component and irregular component can be obtained after seasonal adjustment; then, we can apply H-P method to separate the long-term trend sequence and periodic cycle sequence from the trend circular sequence. On this basis, directing at the characteristics of each sequence separated, this paper establishes appropriate forecasting models respectively; finally, this paper combines the forecasting results of each sequence and obtains the final forecasting results of electrical coal consumption. The empirical test of fire power supply standard coal consumption in our country for 192 months is conducted and the forecasting results are compared to traditional SARIMA and Holt-Winters method. The results indicate that we can obtain superior forecasting results by using the improved seasonal adjustment model.

2. Establishment, improvement and forecasting of seasonal adjustment model

2.1 Establishment of seasonal time sequence model

Statistics show that electrical coal demand presents non-stationary seasonal variation rule on a quarterly or monthly period [8-9]. The time sequence $\{y_t\}$ of non-stationary electrical coal consumption on the basis of X-11-ARIMA (p, d, q) measurement model can be transformed into $(p, d, q)\times(P, D, Q)_s$ order seasonal time sequence model (SARIMA) after "D" seasonal difference. The X12-SARIMA models [10-11]

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established are

$$\Phi_p(L)A_P(L^s)(1-L)^d(1-L^s)^d(y_t-\sum_{i=1}^{r}\beta_i x_{it}) = \Theta_q(L)B_Q(L^s)v_t \quad ... \quad (1)$$

In this equation, $\Phi(L)=1-\phi_1 L-\phi_2 L^2-\cdots-\phi_p L^p$ is the auto-regressive operator; $\Theta(L)=1+\theta_1 L+\theta_2 L^2+\cdots+\theta_q L^q$ is the moving-average operator; "L" is the lag operator ; $D_s = 1$-L^s is the seasonal difference operator; "D, d" represents the number of seasonal and non-seasonal difference respectively; "P, Q, p, q" represents the maximum lag order of seasonal auto-regression, non-seasonal auto-regression and moving average operator respectively; parameter "f_p, q_q" represents the coefficient of p-order auto-regressive model and the coefficient of p-order moving average model respectively; "e_t" is the white noise of 0 mean value and s^2 variance; c_{it} is the regressor variable of outliers, i = 1,..., r; b_i is regression coefficient; v_t is white noise process. The determination of p, d, q and P, D, Q order in Census X12-SARIMA model is conducted according to the order determination process of SARIMA model and the monthly period is taken as "s = 12".

2.1.1 Outlier effect

The existence of outliers often leads to the fluctuation in the time sequence [12-14]. When constructing the forecasting model of electrical coal demand, the failure to recognize the variation rule of the sequence may lead to the wrong setting of forecasting model or the increasing error of model parameters, influencing the precision of forecasting. Therefore, before seasonal adjustment, we should eliminate the regression effect of outliers in the electrical coal consumption sequence.

In the electrical coal consumption sequence, outliers are mainly divided into three categories:

(1) AO

AO refers to a single jump point, which only exerts impact on a single observed value in the sequence [15-16]. The definition of regression explanatory variables is shown in formula (2), representing the outlier point at t_0 moment.

AO outlier: $$AO_t^{t_0}=\begin{cases}-1 & for \quad t<t_0\\ 0 & for \quad t\geq t_0\end{cases} \quad ... \quad (2)$$

(2) Longitudinal shift

Longitudinal shift (LS) refers to the longitudinal enduring changes in the sequence, whose impact comes from all the observed value of fixed time points [17-18]. The manifestation is the sudden increase or constant reduction of all observed value on a specific time point, which is longitudinal shift. The definition of regression explanatory variables is shown in formula (3), representing that the variables change to a new level suddenly and maintain at this level from t_0 moment.

LS outlier: $$LS_t^{t_0}=\begin{cases}-1 & for \quad t<t_0\\ 0 & for \quad t\geq t_0\end{cases} \quad ... \quad (3)$$

(3) AE

AE refers to that after jumping in the time sequence, it will smoothly return to single jumping point in the initial path. This outlier influences several observed values [20]. The definition of regression explanatory variables is shown in formula (4), and a refers to the rate of exponential decay to original level (0< <1).

AE outlier: $$AE_t^{t_0}=\begin{cases}0 & for \quad t<t_0\\ a^{t-t_0} & for \quad t\geq t_0\end{cases} \quad ... \quad (4)$$

2.1.2 Weekday effect

Weekdays and weekends exist in every week and the number of weekdays and weekends in every week is different, thus posing different impact on electrical coal consumption data [21]. To identify the development law of electrical coal consumption, this impact should be eliminated before seasonal adjustment. Assume the impact of weekday effect is the same and the impact of Saturday and Sunday is the same, then we can use the variables in formula (5) to construct the regression effect of trading days.

$$ZD_i = No_{wi}-\frac{5}{2}No_{hi} \quad ... \quad (5)$$

In this equation, No_{wi} represents the number of weekdays in a month and represents No_{hi} the number of Saturday and Sunday in a month.

2.1.3 Leap year effect

There are 29 days in the February in leap years and there are 28 days in the February in non-leap years. We can use the variables in formula (6) to construct leap year regression effect.

$$LY_t=\begin{cases}0.75 & \text{(February in leap years)}\\ -0.25 & \text{(February in non - leap years)}\\ 0 & \text{(other months)}\end{cases} \quad ... \quad (6)$$

2.2 Seasonal adjustment of electrical coal consumption sequence

We can use Census X12 seasonal adjustment method to decompose the electrical coal consumption sequence into trend component, circular component, seasonal component and irregular component. The core of seasonal adjustment is to use Henderson moving average method [22] to conduct component decomposition. For additive model, the seasonal adjustment is shown in formula (7). After seasonal adjustment, three sequences including trend cycle TC_t, seasonal component s_t and irregular component I_t will be formed.

$$Y_t = TC_t + S_t + I_t \quad ... \quad (7)$$

2.3 H-P filter

The trend cycle sequence TC_t formed after seasonal adjustment includes long-term trend component and periodic cycle variation component. We can use H-P filter to separate long-term trend component and periodic cycle component so as to build appropriate forecasting model based on characteristics of the sequence separated, as is shown in formula (8).

$$TC_t = T_t + C_t \quad \text{...} \quad (8)$$

T represents long-term trend component and C represents periodic cycle component. The basic principle of H-P filter [23] is to reach the minimal value of loss function in formula (9).

$$\min\left\{\sum_{i=1}^{n}(TC_t - T_t)^2 + \lambda\sum_{i=1}^{n}\begin{bmatrix}(T_{t+1} - T_t)\\ -(T_t - T_{t-1})\end{bmatrix}^2\right\} \quad \text{...} \quad (9)$$

2.4 Forecasting of component electrical coal demand sequence

2.4.1 Long-term trend sequence

Seasonal factor and periodic cycle component are not included in the long-term trend sequence, so we can use the Holt-Winters non-seasonal factor modulus to conduct forecasting. m_i and b_i are the current longitudinal smoothed value and trend smoothed value respectively.

$$\begin{aligned} m_i &= \alpha y_i + (1-\alpha)(m_{i-1} + b_{i-1}) \\ b_i &= \beta(m_i - m_{i-1}) + (1-\beta)b_{i-1} \end{aligned} \quad \text{...} \quad (10)$$

We can use Holt-Winters method to conduct forecasting and we need to calculate the initial value and a, b parameter values [7]. For the calculation of initial value, we can use the ordinary least square method in formula (11). Assume the first i data is selected, and then the m_i and b calculated through the regression equation are initial longitudinal smoothed value and trend smoothed value respectively.

$$m_i = c + b_i \quad \text{...} \quad (11)$$

For a, b parameter values, we can use Newton tangential method in the non-linear programming in formula (12) to find the solution, which is based on the idea that the mean square error sum of forecasting one phase in advance when eliminating the first i data is the smallest.

$$\min \frac{\sum (m_i - \hat{m}_i)^2}{n}$$

St:

$$\begin{aligned} 0 \le \alpha \le 1 \\ 0 \le \beta \le 1 \end{aligned} \quad \text{...} \quad (12)$$

2.4.2 Seasonal component forecasting

Run the regression equation of s dummy variables without intercept in formula (13) and the parameters S_1, S_2,..., S_s estimated are the required seasonal component forecasting value.

$$S_i = S_1 D_{1t} + S_2 D_{2t} + \cdots + S_s D_{st} + e_t \quad \text{...} \quad (13)$$

2.4.3 Periodic cycle component and irregular component forecasting

The periodic cycle sequence C_t and irregular component sequence I_t both fluctuate between 0 and trend and seasonal elements are not included. The sequence should be stable at this time, so we can use ARIMA model in formula (14) to conduct forecasting.

$$y_t = c + \varphi_1 y_{t-1} + \cdots + \varphi_2 y_{t-p} + u_t + \delta_1 u_{t-1} + \cdots + \delta_q u_{t-q} \quad \text{...} \quad (14)$$

2.5 Final forecasting result

We can use formula (15) to combine the forecasting of each component together and then we can obtain the final forecasting results. K is the number of periods of forecasting ahead.

$$\hat{Y}_{t+k} = \hat{T}_{t+k} + \hat{C}_{t+k} + \hat{S}_{t+k} + \hat{I}_{t+k} \quad \text{...} \quad (15)$$

If weekday and leap year effect exists in a month in the forecasting period, then we need to conduct corresponding modification on the forecasting in this month.

3. Empirical test of medium and long-term electrical coal demand forecasting

To verify the validity of this model method, we select the monthly statistics of fire power supply standard coal consumption from Jan 2001 to Dec 2016 (192 months) in China to conduct modelling of sequence $\{y_t\}$ and the unit of coal consumption data is ten thousand tonnes. The monthly statistics of fire power supply standard coal consumption from Jan 2001 to Dec 2015 (180 months) is taken as □ part, which is used for time sequence modelling, identification order determination and forecasting. The monthly statistics of fire power supply standard coal consumption from Jan 2016 to Dec 2016 is taken as □ part, which is used for test and evaluation of models and comparison of forecasting precision

3.1Electrical coal consumption sequence

The original electrical coal consumption sequence is shown in Fig.1, we can see that the original sequence presents certain trend and seasonal periodicity and the fluctuation of electrical consumption is more obvious in July 1999, second half of 2008 and first half of 2010.

3.2 Impact of outlier

To eliminate the impact of outliers, we can use X12-SARIMA model to conduct detection of outliers and the results are shown in Table 1. Feb 2013 and Jan 2016 are single point outlier; temporary variation occurs in March 2008 and Jan 2015; longitudinal shift occurs in Nov 2008 and Feb 2009.

3.3 Weekday and leap year effect

We conduct measurement on trading days and leap year effect and the results are shown in Table 2. We can see from the statistical results that the statistical magnitude of weekday/weekend is below the significant level at 0.05 significance level but above the significant level at 0.10

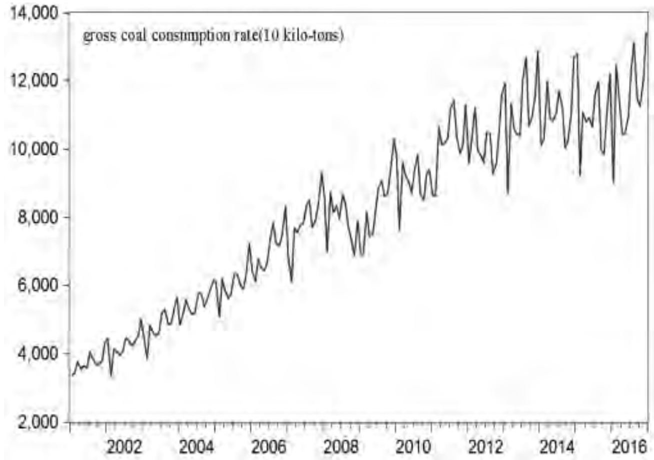

Fig.1 Original series

TABLE 1: TYPE OF OUTLIERS AND STATISTICS

Type of outliers	Estimated value of parameters	Standard error	T value
AO2013.02	-17.2961	4.60660	5.96
AO2016.01	-19.3967	4.15069	4.78
AE2015.01	20.1342	2.93181	5.31
LS2008.11	-12.2819	2.41360	-5.36
LS2009.02	-12.7522	2.39829	-5.31

TABLE 2: EFFECTS OF TRADING DAY AND LEAP YEAR

	Estimated value of parameters	Standard error	T value
Weekday	-0.1347	0.07924	-2.09
Weekend	0.3613	0.22371	1.59
Leap year	2.1707	1.79654	1.13

significance level, which shows that the impact of weekday and weekend is different. The leap year effect reaches the significant level at 0.15 significance level. The P value of chi-square statistics of joint distribution is 0.14. Therefore, we can eliminate the impact of weekday and leap year effect from the original sequence.

3.4 SEASONAL ADJUSTMENT DECOMPOSITION

We can obtain periodic cycle, seasonal factor and irregular component sequence through the seasonal decomposition conducted on the sequence after preliminary adjustment. Compared to original sequence, the trend circular sequence is smoother and the trend characteristics are more obvious. Apparent seasonal factors can be observed in the seasonal component sequence, usually peaking at August and December and bottoming at February. For irregular component sequence, we can observe that it fluctuates between 0.

3.5 H-P FILTER

Both long-term trend component and periodic cycle component exist in the trend circular component sequence, so we can apply H-P filter method to conduct further decomposition. The long-term trend sequence and periodic cycle sequence are shown in Fig.2.

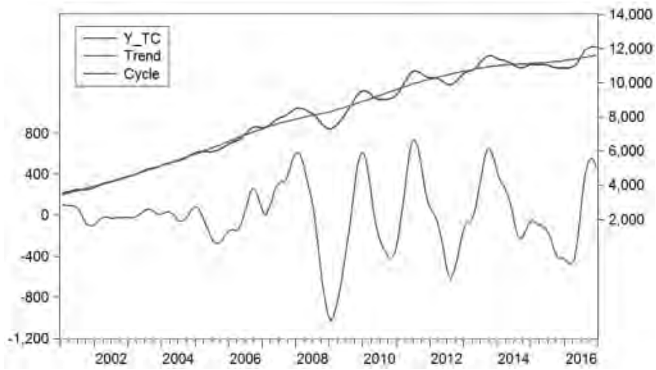

Fig.2 Series after decomposed on trend and cycle series

We can see from this figure that the trend sequence is smoother after decomposition while periodic cycle component fluctuates between 0. Moreover, the electrical coal consumption fluctuates wildly from the end of 2007 to 2013.

3.6 FORECASTING OF DECOMPOSITION SEQUENCE

The characteristics of each sequence after decomposition are different, so we need to select appropriate models to conduct forecasting.

The improved Holt-Winters method is adopted to conduct modelling on trend time sequence. We select the first 24 data to establish the regression model and obtain the initial value and slope, which is 19.19 and 0.13 respectively; then, we adopt linear programming and the parameter value of α and β, which is 1. This indicates that degradation occurs in the model.

Dummy variable regression is adopted to obtain the value of seasonal factor in each month for seasonal component sequence. The value of each month is above the significant level at 0.01 significance level except January and August; the value of January is below the significant level at 0.10 significance level while value of August is below the significant level at 0.10 significance level

For irregular component and periodic cycle sequence, we need to conduct unit root test to examine the stability of the sequence. The DF test statistics of periodic cycle sequence is t = -3.98 and P = 0.00; the DF test statistics of irregular component sequence is t = -13.02 and P = 0.00. This indicates that the sequence is stable, and thus we can establish SARIMA model. Through correlation diagram analysis, the equation of periodic cycle component sequence can be established

$$C_t = 0.89u_{t-1} + 0.83u_{t-2} + 0.72u_{t-3}$$

The equation of irregular component sequence can be established

$$I_t = 0.69 I_{t-1} - 0.55 u_{t-2} - 0.23 u_{t-3}$$

The estimated value of each parameter all reaches the significant level.

3.7 Forecasting results

Based on the established model of each component sequence, we can conduct earlier forecasting for the period between Jan 2016 and Dec 2016. After that, we can sum the forecasting results of each component, which is the preliminary forecasting results. The weekday and leap year effect is eliminated during the preliminary adjustment stage, so we need to adjust for the months with weekday and leap year effect when forecasting. And we can obtain the final forecasting results after the adjustment of corresponding months.

To verify the practical effect of this forecasting method, we adopt seasonal Holt-Winters model and X12-SARIMA model to conduct forecasting at the same time and compare the forecasting results. The percentage error of each forecasting result, the mean absolute percentage error of 12 months $MAPE = \frac{100}{k} \sum_{t=T+1}^{T+k} \left| \frac{\hat{y}_t - y_t}{y_t} \right|$ and forecasting sample period $t = T+1, \cdots, T+k$ are shown in Table 3.

We can know from Table 3 that the MAPE% of forecasting results of the 12 months selected obtained by the forecasting method proposed in this paper is the lowest. The second is Holt-Winters model while the last is seasonal X12-SARIMA model, which shows that the forecasting effect of the method in this paper is superior than that of Holt-Winters model and seasonal X12-SARIMA model and the forecasting results are more stable.

Table 3: Comparative of results by different methods

Time	X12-SARIMA	Holt-Winters	Method in this paper
2016.1	9.59	6.49	5.65
2016.2	-7.19	-6.06	-4.96
2016.3	2.99	2.52	1.31
2016.4	3.76	2.95	2.03
2016.5	3.04	3.22	2.27
2016.6	3.55	3.08	2.99
2016.7	4.87	3.98	3.01
2016.8	10.47	7.56	6.77
2016.9	3.41	3.59	1.59
2016.10	4.87	3.17	3.48
2016.11	1.93	2.63	0.83
2016.12	7.29	5.38	3.19
MAPE%	5.25	4.22	3.17

4. Conclusions

For the forecasting method based on seasonal adjustment, this paper proposes to investigate the impact of outliers and weekday in the electrical coal consumption sequence and then to conduct preliminary adjustment; after that, directing at the periodic cycle characteristics of electrical coal consumption sequence after seasonal adjustment, we adopt H-P filter method to obtain the trend sequence and periodic cycle sequence after decomposition; and then, due to the differences of characteristics and meaning of each component sequence after decomposition, we need to select appropriate models to conduct modelling; finally, we eliminate weekday and leap year effect when conducting the preliminary adjustment of electrical coal demand in several months.

Through the analysis of electrical coal consumption sequence of 192 months in our country and the forecasting of electrical coal demand of 12 months, the forecasting results of the forecasting method proposed in this paper is stable and the forecasting precision is relatively high, proving the practicability of the forecasting method.

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