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Study on the forecast of coalmine electricity consumption based on holt-winters model

The coal industry has a larger demand for electricity consumption, therefore the forecast of coalmine electricity consumption has become an urgent problem for the electric power company and large-scale coal enterprise. Through the analysis of available coalmine electricity consumption data, a weak increasing trend can be observed from the electricity consumption longitudinal analysis curve. A periodic and seasonal pattern can also be shown in the monthly electricity consumption comparative analysis curve. In other words, we find the time series examples of the coalmine electricity consumption show a linear, seasonal and stochastic pattern. In this study, a popular forecasting model based on Holt-Winters method is employed to estimate the trend of coalmine electricity consumption. Meanwhile, two other forecasting models, the classical linear regression (CLR) model and the quadric exponential smoothing (QES) model are utilized in the same data sets. Forecasted results indicate that the Holt-Winters model is outperforms the CLR and the QES models in terms of forecasting evaluation measures. Thus, the Holt-Winters model is an effective and feasible method for the coalmine electricity consumption forecasting.

Keywords: *Coalmine electricity consumption, Forecast evaluation, Seasonality, Holt-Winters model.*

1. Introduction

Electricity plays an important role in the sustainable development of every enterprise. Due to employ many electrical equipment, the coal enterprise has a larger demand for electricity. According to statistics, if the annual coal output of a coal enterprise is 1.5 million tons, then the electricity consumption of this enterprise equals to the lighting electricity consumption of a medium-sized city. Meanwhile, many coalmines do not pay attention to energy conservation, so the overall energy consumption is too large. In recent years, since the situation of electric power supply and demand is grim, electricity conservation becomes more and more important. For the electric power company and large-scale coal enterprise, selecting the appropriate model for the forecast of coalmine electricity consumption is of great significance in making power management policies and electricity marketing strategies.

In common forecasting methods, there are two types: regression analysis method and time series analysis method. Regression analysis is a statistical methodology, which can be used to predict values of one or more dependent variables from a collection of independent variable values [1]. Time series analysis is a statistics method, which is based on random process theory and mathematical statistics method and can be used to process dynamic data [2]. As a forecasting technique that have the simplicity and robustness, exponential smoothing method is widely applied to the time series analysis [3]. For forecasting a collection of time series variables, the different methods and techniques have been extensively applied in various fields.

In this article, the statistical Holt-Winters model is employed to forecast coalmine electricity consumption through combining the cross-sectional and longitudinal data analysis of coalmine electricity consumption. The basic idea of Holt-Winters forecasting model is firstly to separate the level factor, the linear factor and the seasonal factor from time series data, then these factors are combined to forecast. Holt-Winters method has been extensively used for various forecasting researches. In [4], Holt-Winters method was employed to predict the changes of organic water pollutions emissions. In [5], an exponential smoothing method was used to forecast prices in real-time electricity markets. In [6], autoregressive integrated moving average was compared with Holt-Winters models on forecasting electricity consumption, and the results showed that Holt-Winters model is suitable method. In [7], Holt-Winters model was used to predict the time series data of electricity demand. In [8], the volunteer grid workload was forecasted by using Holt-Winters method. In [9], a combination method of Holt-Winters model and Markov model was utilized to predict the partial ionospheric delay.

The remainder of this paper is arranged as follows. The necessary data analysis and model evaluation are discussed in Section 2. In Section 3, a popular forecasting technique

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based on Holt-Winters model is described. In Section 4, the forecasted results of different models are analyzed and compared. Finally, the conclusions are made in Section 5.

2. Data analysis and model evaluation

2.1 Data analysis

The available power consumption data of Jiangzhuang coalmine cover a period of 4 years from 2012 to 2016. These data are divided into two parts. One is the historical period data sets, which are used to build up the models and select the parameters of the forecasting models. The other is the extended period data sets, which are utilized to analyze the performance of different forecasting models. For comparing the accuracy of forecasting results, the same data sets are examined by different forecasting models.

Fig.1 shows the monthly electricity consumption from January 2012 to April 2016 of Jiangzhuang coalmine. Fig.2 shows electricity consumption longitudinal analysis curve of Jiangzhuang coalmine. In Fig.2, a weak increasing trend can be observed. The monthly electricity consumption of every year are plotted in Fig.3 respectively. Fig.3 shows a periodic and seasonal pattern. Through analysis, we find time series examples of the coalmine electricity consumption take on the characteristics of linearity, seasonality and stochasticity.

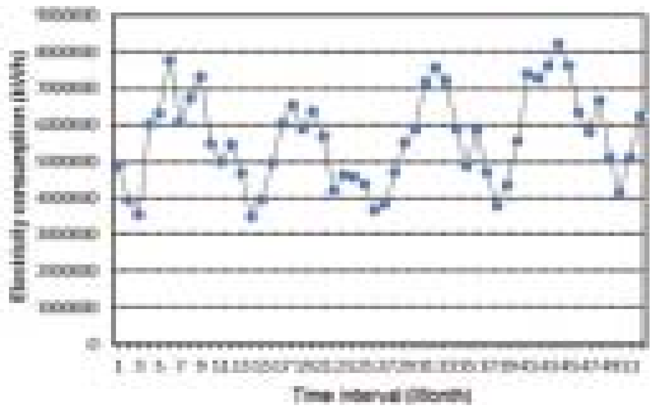

Fig.1 The monthly electricity consumption of coalmine from January 2012 to April 2016

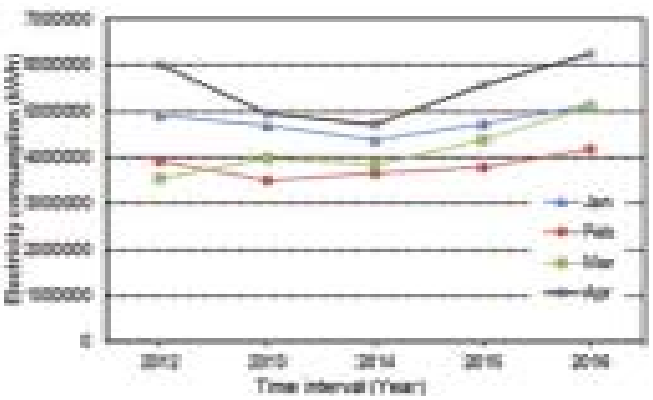

Fig.2 The electricity consumption longitudinal comparative analysis curve

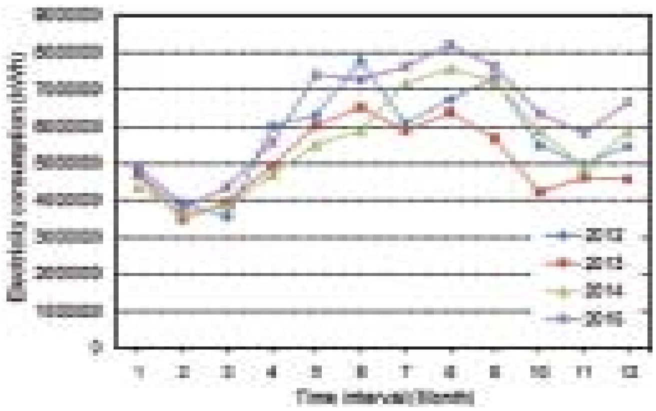

Fig.3 The monthly electricity consumption comparative analysis of every year

2.2 Model evaluation

The important criterion for examining the suitability and accuracy of a forecasting model is error measure. The following equations are widely used in model evaluation measure [10], [11]:

(1) Mean Error (ME)

$$ME = \frac{\sum (A_t - F_t)}{n} \quad \text{... 1}$$

(2) Mean Absolute Error (MAE)

$$MAE = \frac{\sum |(A_t - F_t)|}{n} \quad \text{... 2}$$

(3) Mean Percentage Error (MPE)

$$MPE = \frac{\sum [(A_t - F_t)/A_t]}{n} \times 100 \quad \text{... 3}$$

(4) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{\sum |(A_t - F_t)/A_t|}{n} \times 100 \quad \text{...4}$$

(5) Mean-Squared Error (MSE)

$$MSE = \frac{\sum (A_t - F_t)^2}{n} \quad \text{... 5}$$

(6) Root-Mean-Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\Sigma (A_t - F_t)^2}{n}} \quad \text{... 6}$$

where A_t, F_t are the actual value and the forecasting value of the time series at period t, n is the total number of forecasting periods.

The smaller errors show that the forecast are more accurate. Since the positive value and negative values can be cancelled out each other, the ME and MPE are not widely used to forecast evaluation measures. The ME and MPE may be zero in a relatively poor prediction model. In measuring prediction deviation, the ME and MPE are valuable. The positive value of ME and MPE indicate the predictions are relatively small. On the contrary, the positive value of ME and MPE show that the prediction results are larger. In this study, we calculate the value of MPE, MAPE and RMSE, which are applied to validate the optimum forecast model [12].

3. Forecasting models

As above discussed, the Holt-Winters model is suitable for the described characteristics of data sets. The Holt-Winters model was firstly presented in early 1960s [13], and the exponentially weighted moving averages method was used to forecast sales in this model. Holt-winters forecasting model is widely applied to predict data that show some forms of trend or seasonal pattern. Meanwhile, the stochastic time series can be effectively forecasted by Holt-Winters forecasting model. A time trend forecast can be constructed by Holt-Winters model, and is able to flexible adjust previous errors and prepare next forecasts. The data containing both trend and seasonality can be forecasted by Holt-Winters exponential smoothing method, which is evolved from Holt's method. Therefore, the Holt-Winters model was applied to forecast the coalmine electricity consumption by using the following equations:

$$S_t = \alpha \frac{y_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1}) \quad \text{... 7}$$

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \quad \text{... 8}$$

$$I_t = \gamma \frac{y_t}{-s_t} + (1-\gamma)I_{t-L} \quad \text{... 9}$$

$$\hat{y}_{t+m} = (S_t + mb_t)I_{t-L+m}$$

where, y_t is the actual value at period t;

α is the level smoothing coefficients, $\alpha \in [0, 1]$;

β is the trend smoothing coefficients;

γ is the seasonal smoothing coefficients;

S_t is the level factors of time series;

b_t is the trend factors of time series;

I_t is the seasonal factors of time series;

L is the seasonal duration;

m is the number of forecasted periods;

$\hat{y}_{t+m}$ is forecasted value at period $t + m$.

Given an original coalmine power consumption time series, the process of Holt-Winters model is as follows:

Step 1: the average increments of the first and second periods are calculated respectively.

$$V_1 = (1/L)\sum_{i=1}^{L} y_t \quad \text{... 11}$$

$$V_2 = (1/L)\sum_{i=1}^{L} y_{i+L} \quad \text{... 12}$$

Step 2: The mean value (b0) of the V_1 and V_2 is calculated as follows.

$$b_0 = (V_2 - V_1)/L \quad \text{... 13}$$

Step 3: The initial value of the trend and level factors are calculated respectively.

$$b_{2L+1} = b_0 \quad \text{... 14}$$

$$S_{2L+1} = S_0 = V_2 + (L-1)b/2 \quad \text{... 15}$$

Step 4: The seasonal factors for each period is calculated respectively.

$$I_t = \frac{y_t}{V_1 - \left(\frac{L+1}{2} - t\right)b_0} \quad \text{... 16}$$

$$I_{L+t} = \frac{y_{L+t}}{V_2 - \left(\frac{L+1}{2} - t\right)b_0} \quad \text{... 17}$$

where, $t \in [1, 2,3, \ldots, L]$

Step 5: The average factors for two period is calculated by applying the following equations:

$$I''_{L+t} = \frac{I'_t + I'_{L=t}}{2} \quad \text{... 18}$$

Step 6: normalizing seasonal factor.

$$\overline{I''_{L+t}} = \frac{I''_{L+t} + I'_{L=t}}{\sum_{t=1}^{L} I''_{L+t}} . L \quad \text{... 19}$$

Step 7: the corresponding prediction for the third period is calculated respectively.

$$\hat{y}_{t+m} = (S_{2L+1} + mb_{2L+1})\bar{I}_{t+m-L} \quad \text{... 20}$$

where, $t = 2L$, m = 1, 2, 3, ..., L.

Step 8: The value of S_t , b_t and I_t are updated according to the Eq (7), Eq (8) and Eq (9).

Step 9: Repeating step 6 after all factors of the next period are updated.

4. Results and discussion

In order to compare the Holt-Winters forecasting model with the others, the CLR model and the QES model were employed in the same data sets. For the given examples, the forecasted results and performances of different models are showed in Table 1.

In Fig.4, we make the point-to-point comparisons of actual values and predicted values of example in different models. The results show that the RMSE and MAPE of Holt-Winters forecasting model are minimum when confronted with other forecasting models in Tables 1. In other words, the obtained results on the testing data indicate that the Holt-Winters

TABLE 1. THE FORECASTED RESULTS AND PERFORMANCES OF DIFFERENT MODELS

Time	Actual value	CLR model	QES model	Holt-Winters model
201501	4722765	4135333	4128570	5067381
201502	3786002	3435981	3647914	4099795
201503	4372974	4063679	3863380	4234422
201504	5559898	3935286	4276110	5627831
201505	7389914	5150346	5117260	6666347
201506	7275673	4862703	5168039	7505795
201507	7616202	7452718	7877195	7872224
201508	8221581	7738586	8201481	8285135
201509	7620395	6651457	7680404	8016250
201510	6354443	5594181	6524268	6305880
201511	5819327	4727319	4933318	5682043
201512	6669606	5701984	6378074	6563934
MPE		15.62 %	10.30 %	-0.97 %
MAPE		15.62 %	11.45 %	3.91 %
RMSE		1222918	1035132	299472.1

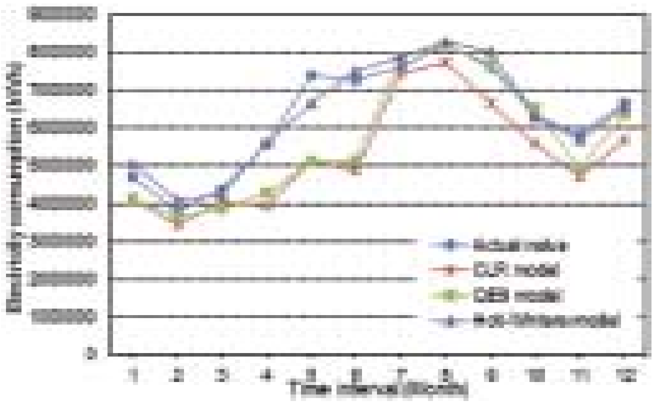

Fig.4 Comparison of actual values and predicted values of example in different models

forecasting model outperforms the CLR model and the QES model by the forecasting graphs and the forecasting performances.

Comparing the MPE, MAPE and RMSE between the CLR model and the QES model, what they both have in common is the forecast results are low. However, for the accuracy of the forecasting, the QES model is superior to the CLR model. The MPE of Holt-Winters model is equal to –0.31%, the forecasted results are high. Considering MAPE and RMSE of Holt-Winters model, we can observe that the Holt-Winters model forecasts more accurately than other models except for the fifth month.

As shown in Fig.4, the CLR model and the QES model cannot efficiently capture the seasonal trend of data. On the contrary, the Holt-Winters forecasting model can efficiently follow the data trend and can make accurate forecast.

5. Conclusions

In this study, through the analysis of available coalmine electricity consumption data sets, Holt-Winters forecasting model is employed to forecast coalmine electricity consumption at Jiangzhuang coalmine. The comparison of the forecasted results and performances of different models indicate that Holt-Winters forecasting model is suitable and provide more accurate data than the CLR model and the QES model. Meanwhile, the results show that excluding a small number of forecasted point, a majority of predicted results of Holt-Winters forecasting model are relatively accurate. The reason is the Holt-Winters forecasting model considered the level factor, the trend factor and the seasonal factor, while the other reference models are obviously inadequate to deal with this kind of data. So, the Holt-Winters forecasting model is a useful tool to forecast coalmine electricity consumption with similar stochastic behavior.

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