Chapter 11
Industrial Area Power Load Forecasting Based on Seasonal Kalman Filter

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Abstract The stable and economic operation of the power system depends on accurate regional electricity load forecasting. This article proposes a seasonal Kalman filter prediction model based on Fourier transform spectrum maximization period analysis, which solves the problem of electricity load prediction in regions with different data distributions. The results indicate that the seasonal Kalman filter model has good predictive ability, low volatility, and stable error.

11.1 Introduction

Economic development has led to an increasing demand for electricity, and at the same time a rising demand for power quality. This leads to the rapid development of intelligent power systems. One of the decisive factors for the stable economic operation of the power system is the prediction of power demand [1]. Due to the influence of many random factors, such as society, society, economy, and natural conditions, the power load variation curve has a very complex nonlinear form. How to use historical data to make reasonable power demand forecasts has become one of the keys to intelligent power grid research. Zhou Xie made a detailed analysis of the main external factors affecting the load characteristic index of the power grid, studied the impact of climate factors, economic factors, holiday factors, and other factors on the power grid load, and sorted out the internal relationship of the load characteristic index. The research shows that the influence of various factors on power load has a

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certain randomness [2]. By studying the current situation at home and abroad, Wang Huizhong et al. briefly described the characteristics of short-term load forecasting and various factors affecting the forecasting accuracy, expounded the intelligent methods of short-term load forecasting for power systems, and analyzed and compared the advantages and disadvantages of various methods [3].

Due to the randomness of relying on external data for power load forecasting, and the power load of the same industry always being a certain periodicity, it is predictable. Therefore, many researchers tend to use the information of the power load curve directly to predict electricity consumption behavior. For example, Wang Jianjun et al., based on the historical data of China's electricity consumption from 1973 to 2004, fitted a similar exponential regression curve according to its trend chart, and then analyzed and identified its residual series using time series [4]. Kalman filter is a linear model based on minimized covariance estimation error, which has the advantages of simple calculation and a solid theoretical foundation. Yu Jingwen et al. briefly introduced the power quality problem and its analysis and detection methods. Then, the basic principles of three Kalman filters, namely conventional Kalman filter, extended Kalman filter, and untraced Kalman filter, are summarized systematically and their applications in power quality analysis are compared and analyzed [5]. Huang Z discusses the feasibility of applying Kalman filtering techniques, including estimating state models in dynamic variables. In the large and small interference tests of a multi-machine system, the Kalman filtering of the dynamic model is proposed, and the sensitivity analysis of the sampling rate and noise level shows that the dynamic state estimation performance is good [6]. Considering the characteristics of the power system itself, Ma Jingbo et al. built a load system model, observation model, and system parameter model with a time-varying coefficient based on the historical electricity consumption data at the same time on different dates. The time-varying noise statistical estimator is used to perform adaptive estimation of noise covariance, and the predictive equation is used to predict the load of the next day. The research shows that the predictive ability of the predictive equation of the adaptive time-varying noise estimator considering historical data is stronger than the general Kalman prediction model [7]. However, the study is based on the assumption that the electricity load is a stationary series at the same time every day. When generalized to the forecast of the total load of the whole day, the original assumption may not be valid, that is, the total load of the whole day does not necessarily constitute a stationary series with the load of the same period of the previous week or month. In the real production environment, the cycle rule is more complicated. Even for individual manufacturers in the same industry, the cycle of the electricity load is not the same.

Therefore, an adaptive Kalman filter prediction model (FFT-KF) combined with fast Fourier algorithm is proposed in this paper. Based on the fast Fourier model, the period of the power load time series curve is identified, the periodic shock factor is established, and the daily power load of various industries in each station area in the region is adaptively predicted, and then the daily power load in the whole region is obtained through linear combination. In order to analyze the adaptability of the FFT-KF model in theory and practice, this paper will compare the generalization ability of the FFT-KF model and classical Kalman filter in terms of prediction ability, in order to estimate the gap between the FFT-KF model and classical Kalman filter. Considering the influence of industry factors, this paper studies the generalization ability of the FFT-KF model under the influence of industry factors by analyzing the residual distribution and cumulative error of the FFT-KF model in power estimation of different industries.

11.2 Classic Kalman Filter Load Forecasting Model

The core idea of the classical Kalman filter is that according to the measured value at this moment and the predicted value and error at the previous moment, the weighted average is obtained at this moment, and the value of the next moment is predicted [8]. The errors are prediction errors and measurement errors, which exist independently and are not affected by measurement data. The predicted value of the previous time and the measured value of the current time are normal distributions, and the fusion of the two normal distributions can obtain the desired value more accurately. Kalman filtering first constructs a hidden Markov model for the system. Generally, the state of hidden Markov model cannot be directly observed, which needs to be divided into a state transition equation and observation equation, and then implemented by Bayes' theorem. First, estimate a prior probability based on previous experience, that is, Kalman's posterior estimate, and then add new information, that is, the measurement value, so that with the new information, the prediction of the value is more accurate [9, 10].

The Kalman filter model believes that the world is full of noise, and even the signal from the sensor will have various biases due to electromagnetic interference. In the power system, because the power load is composed of a certain sampling point, the sampling point itself is also affected by the accuracy of the power instrument. Based on the principle of minimum estimated mean square error, the Kalman filter model uses a recursive method to solve the linear filtering problem of discrete data [11].

The Kalman filter consists of a system state equation and a measurement equation, and follows the linear unbiased minimum mean square error estimation criterion to achieve recursive prediction using prediction and correction [12].

For a linear constant system state equation xk and measurement equation $y_{k,}$

$$x_k = \Phi_{k|k-1} x_{k-1} + \omega_{k-1} \tag{11.1}$$

$$y_k = H_k x_k + v_k \tag{11.2}$$

Among them, x_k and x_{k-1} are the electricity load values at time k and $k-1$, $\Phi_{k|k-1}$ is the correlation coefficient between k-1 and the electricity load at time k, and for stationary loads $\Phi_{k|k-1}$ is the identity matrix I, ω_{k-1} is the normal distribution process noise with the mean value of 0; y_k is the measured value of the electricity load at time k, and H_k is the measurement matrix, ν_{k-1} is the measurement noise of normal distribution with mean value of 0.

Because ω_{k-1}, ν_{k-1} is the normal distribution white Gaussian noise with the mean of 0, there is

$$\hat{x}_k = \Phi_{k|k-1}\hat{x}_{k-1} \tag{11.3}$$

$$\hat{y}_k = H_k \hat{x}_k \tag{11.4}$$

$\hat{x}_k$, $\hat{x}_{k-1}$, $\hat{y}_k$, are the estimated values of x_k, x_{k-1} and y_k, respectively.

By using the actual measurement value y_k at time k to correct the estimated electricity load $\hat{x}_k$, there is

$$\begin{aligned} \hat{x}_k &= \Phi_{k|k-1}\hat{x}_{k-1} + K_k(y_k - \hat{y}_k) \\ &= \Phi_{k|k-1}\hat{x}_{k-1} + K_k(y_k - H_k\Phi_{k|k-1}\hat{x}_{k-1}) \end{aligned} \tag{11.5}$$

where K_k is the gain matrix that minimizes the mean square deviation P_k of $(x_k - \hat{x}_k)$, i.e.

$$\begin{aligned} P_k &= E[(x_k - \hat{x})(x_k - \hat{x})^T] \\ &= \Phi_{k|k-1}P_{k-1}\Phi_{k|k-1}^T + Q_{k-1} \end{aligned} \tag{11.6}$$

$$K_k = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1} \tag{11.7}$$

Among them, R_k is the measurement noise variance, and Q_{k-1} is the process noise variance.

Equations (11.3)–(11.7) constitute the recursive equation system of the Kalman filter prediction model. The classic Kalman filter load prediction model is aimed at predicting the electricity load in a stationary time series, but has poor performance for periodic fluctuations in load [13].

11.3 Seasonal Kalman Filter Electricity Load Forecasting Model

The classic Kalman filter load forecasting method is based on a stationary time series of daily load values at the same time, and the predicted duration is usually daily or weekly [14]. However, for non-stationary data, this algorithm is not suitable. In fact, in the medium to long term, the load has cyclical fluctuations, especially in the industry's electricity load, which fluctuates greatly with seasonal changes. For individual manufacturers in the same industry, the cycle of their electricity load is different. It is necessary to identify the period of historical electricity load data and add a period factor to the Kalman filter prediction [15].

The data collection of power load in the production process of power enterprises is carried out, and the power load curve in the industrial manufacturing process of power enterprises is collected and recorded, and the collected power load curve is self-adaptive cycle identification. Perform a fast Fourier transform on the power load identification data to obtain the spectrum sequence s_j. Take the subscript of the sequence with the largest spectrum as the period T, and T is equal to j corresponding to the maximum value of the spectrum sequence s_j. Then

$$s_j = \sum_{k=0}^{n-1} e^{-\frac{2\pi}{n} j^k} h_k \tag{11.8}$$

Among them, $h_k \in (h_0, h_2, h_3, \ldots, h_{n-1})$ is the true value sequence of power load, $k = 1, 2, 3, \ldots, n$, $j = 0, 1, 2, \ldots, n-1$.

In order to incorporate periodic factors and introduce a prediction model with two parameters, the state equation and measurement equation are as follows:

$$x_k = \Phi_{k|k-1} x_{k-1} + \Psi_{k|k-1} u_k + \omega_{k-1} \tag{11.9}$$

$$y_k = H x_k + v_k \tag{11.10}$$

where $u_k = x_{k-T}$, that is, the power load data at T before k is taken as the cycle factor, and Ψ_k is the correlation coefficient of the load at k and $k-T$. Since the cycle is T, Ψ_k is taken as the identity matrix I.

Let $A_{k|k-1} = [\Phi_{k|k-1}\ \Psi_{k|k-1}]$, $X_{k-1} = [x_{k-1}\ u_k]^T$, then there is

$$x_k = A_{k|k-1} X_{k-1} + \omega_{k-1} \tag{11.11}$$

Similarly, a recursive formula can be obtained by minimizing the minimum mean square error.

Prediction estimation equation:

$$\hat{x}_k = A_{k|k-1} X_{k-1} + K_k \left[y_k - H_k A_{k|k-1} X_{k-1} \right] \tag{11.12}$$

Prediction gain equation:

$$K_k = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1} \tag{11.13}$$

Prediction covariance equation:

$$P_k = A_{k|k-1} P_{k-1} A_{k|k-1}^T + Q_{k-1} \tag{11.14}$$

In practice, it is difficult to accurately grasp the initial states x_0 and P_0. However, due to the continuous use of new information in the recursive process of Kalman filtering to correct the state, when the filtering time is sufficiently long, the influence of the initial state value x_0 on x_k will decay to zero, and the influence of the initial covariance P_0 on the filtering estimation covariance matrix P_k will also decay to nearly zero. Therefore, the initial conditions for filtering can be approximately determined. In this model, both the state value and the measured value are power load values, so the measurement matrix H_k is taken as the identity matrix I [9, 10].

The Kalman filtering model quantifies the common periodic phenomena in real production by adding periodic factors, thereby enhancing the predictive ability of classical Kalman filtering methods.

11.4 Case Study

This article selects the load data of representative electricity consumption units in the non-ferrous metal smelting and rolling processing industry, chemical raw material and chemical product manufacturing industry, and cement manufacturing industry in Guangxi region from 2014 to 2015 as examples. The classic Kalman filter and seasonal Kalman filter are used to estimate the electricity load day by day, and the advantages and disadvantages of the Kalman model with seasonal factors are analyzed, and the degree to which industry factors affect seasonal Kalman filtering.

Taking the non-ferrous metal smelting and rolling processing industry as an example, taking the data of the industry in 2014 as training data, and bringing it into Eq. (11.8), the spectral period of the industry's data in 2014 is 106 days, equivalent to about 3 and a half months.

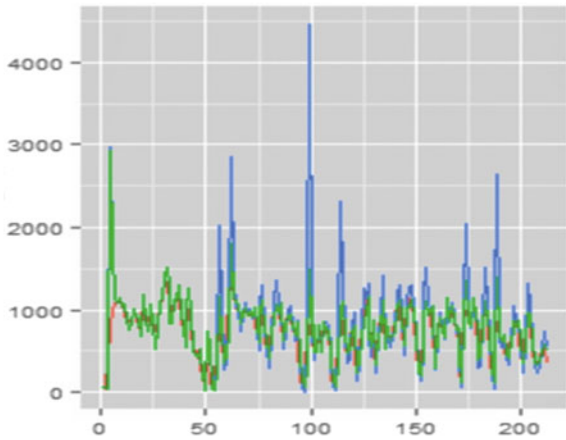
H is initialized to [0.5, 0.5]; initialize process noise variance Q_1 to 4, measure noise variance R_1 to 4, and calculate the predicted value for 2015.

Figure 11.1 is a comparative diagram of using classical Kalman filtering and seasonal Kalman filtering to predict the smelting and rolling industries of non-ferrous metals, respectively.

The randomness of the classical Kalman filter in Fig. 11.1 is strong. For example, at points with a number of days equal to 52,100,110,190, there is a significant difference between the predicted results of the classical Kalman filter and the actual measured values. This indicates that the classical Kalman filter is susceptible to noise interference, resulting in significant errors in the predicted results. The Kalman filter incorporating seasonal factors avoids the situation of excessive prediction error, allowing the prediction error to converge to a smaller range. Figure 11.2 shows the cumulative probability distribution of classical Kalman filtering and seasonal Kalman filtering.

The image on the left of Fig. 11.2 represents the cumulative error distribution of classical Kalman filtering, while the image on the right represents the cumulative distribution of seasonal Kalman filtering. From the graph, it can be observed that

Fig. 11.1 Comparison of classical Kalman filter and seasonal Kalman filter predictions



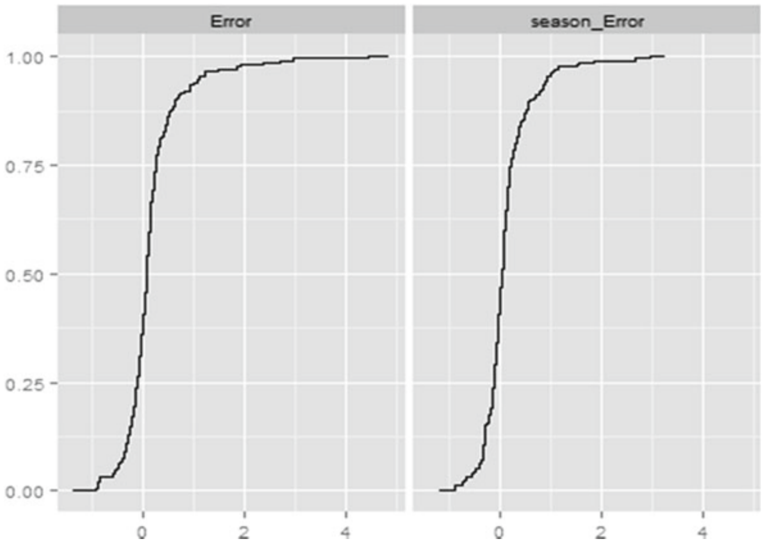


Fig. 11.2 Cumulative probability distribution of classical Kalman filter and seasonal Kalman filter

compared to classical Kalman filtering, seasonal Kalman filtering has a steeper cumulative distribution curve and converges at a lower upper bound. This fully demonstrates that seasonal Kalman filtering has stronger predictive ability than classical Kalman filtering.

The magnitude and patterns of electricity consumption vary among different industries. Therefore, it is necessary to consider whether the algorithm can maintain good predictive ability after incorporating industry factors. Using the non-ferrous metal smelting and rolling processing industry, chemical raw material and chemical

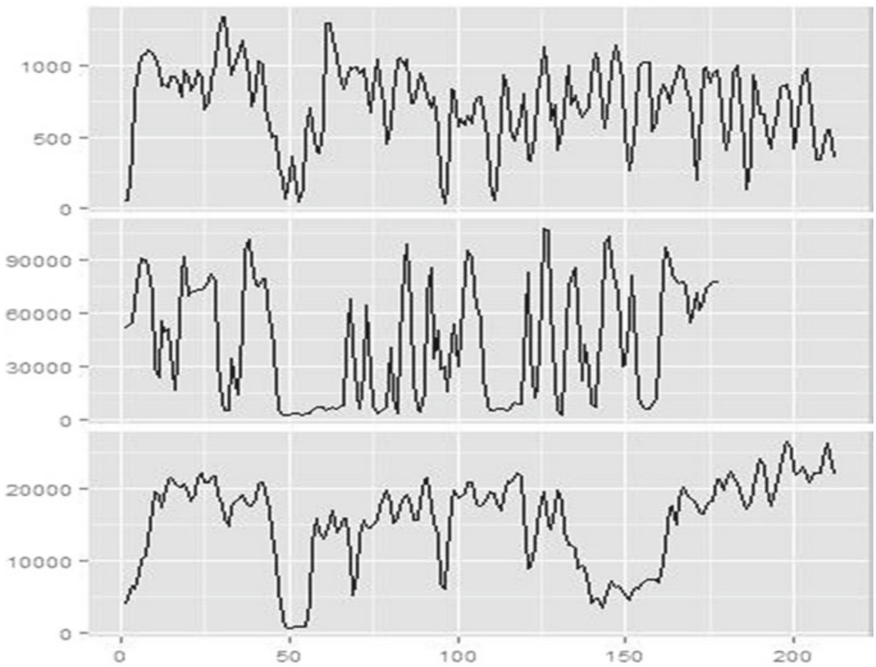


Fig. 11.3 Time series diagram of industry's electricity load to be predicted

product manufacturing industry, and cement manufacturing industry as control variables, analyze the generalization ability of seasonal Kalman filter models. Figure 11.3 is a time series comparison chart of the predicted electricity load for three industries.

From Fig. 11.3, it can be observed that the fluctuation of the power load curve shows weak periodicity, and the data fluctuation range is relatively large. The power load range of different industries is completely different, with a value of cement > non-ferrous metals > chemical engineering, and a variance of cement > non-ferrous metals > chemical engineering. Figure 11.4 shows the frequency distribution of generalization error of seasonal Kalman model for three industries.

From Fig. 11.4, it can be observed that the probability distribution of errors is basically similar, with a nearly bell-shaped distribution centered around 0. From the graph, it can be analyzed that the Kalman filter prediction model still has good predictive ability. However, for different industries, the generalization ability of seasonal Kalman filter prediction models varies significantly. The degree of concentration serves as the dividing line for distinguishing the generalization ability of the model, and its generalization ability is ranked as Nonferrous Metals > Chemical Industry > Cement Manufacturing. Research has shown that seasonal Kalman has good generalization ability for predicting electricity load, but industry factors have a certain influence on the stability of the model.

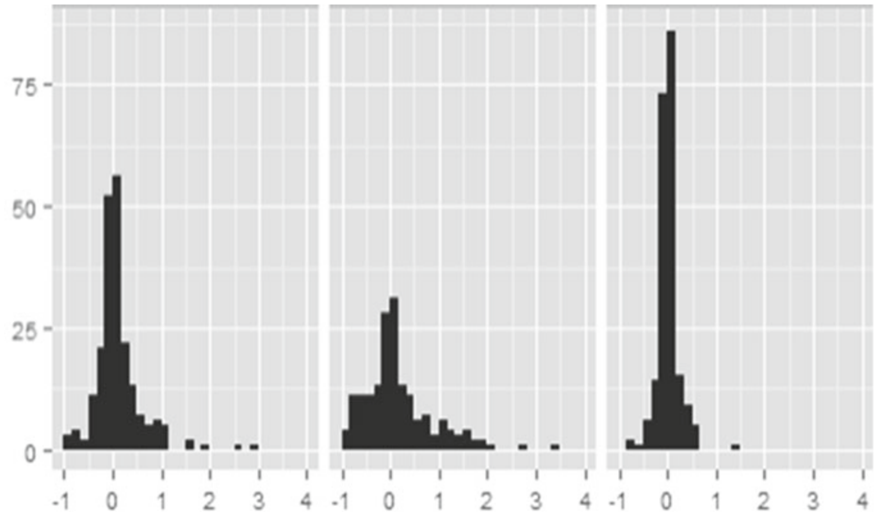


Fig. 11.4 Multiple industry prediction error frequency pairs

11.5 Conclusion

Regional electricity load forecasting is a key factor in determining the stable and economic operation of the power system. Based on the periodic characteristics of industry electricity load data, this article improves the common time-varying Kalman filter by incorporating seasonal factors. Taking the non-ferrous metal smelting and rolling processing industry, chemical raw material and chemical product manufacturing industry, and cement manufacturing industry as examples, the generalization ability of classic time-varying Kalman filtering and seasonal Kalman filtering was compared and analyzed. Research shows.

(1) In terms of model stability, seasonal Kalman filtering is superior to classical Kalman filtering models, and its upper bound of error is narrower than classical Kalman filtering.
(2) The error distribution of seasonal Kalman filtering is a bell-shaped curve centered around 0, and industry factors have a certain impact on the predictive ability of seasonal Kalman filtering.

The seasonal Kalman filtering method studied in this paper can use the recurrence method to continuously revise the state estimation according to the new information. When the time series is long enough, the influence of the state value of the initial state and the covariance matrix on the estimation will decay to zero. Therefore, the Kalman filter model can update the state information continuously and obtain more accurate estimates. This method can be used not only for short-term load forecasting, but also for ultra-short-term load forecasting.

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