Forecasting the Coke Price Based on the Kalman Filtering Algorithm

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Abstract: Research on coke price forecasting is of theoretical and practical significance. Here, the Kalman filtering algorithm was used to analyze the price of coke. As the only state variable, the historical coke price is sorted out to build the state space model. The algorithm makes use of innovation composed of the difference between observed and predicted values, and allows us to obtain the optimal estimated value of the coke price via continuous updating and iteration of innovation. Our results show that this algorithm is effective in the field of coke price tracking and forecasting.

Key words: coke price; forecasting; state space model; Kalman filtering algorithm

1 Introduction

As an important basic industry, the energy industry has great influence on the development of the Chinese economy. Price fluctuations in energy poses a real threat to industrial structure, patterns of production, employment and the price level. At the same time, the rational allocation of energy resources has a marked impact on the efficiency of economic development, such as for resource-poor countries that have larger obstacles to economic development. Under a market economy, the most important tool to distribute energy resources is a price mechanism. However, the monopoly of the energy industry is obvious, and the energy market generally does not work well when only depending on adjustment by the market itself; energy allocation policy also plays a positive role.

The energy industry and Chinese economy can be effective and healthy, only under the the condition that the ‘visible hand’ of government and “invisible hand” (according to Adam Smith) function simultaneously. Coal dominates energy consumption in China, such a pattern will not change in the short term, and coal price prediction research is of great significance to reduce the risks associated with large energy price fluctuations. For example, Radchenko (2005) constructed long-term forecasts of energy prices using a reduced form model of shifting trend developed by Pindyck (1999). Ming and Hua (2007) used multivariate linear regression and time series analysis techniques to construct a model for forecasting coal mean prices. Patzek and Croft (2010) developed a base-case scenario for global coal production based on physical multi-cycle Hubbert analysis of historical production data. Last, Zhao et al. (2011) forecasted coal demand in China using a variable weight combination forecasting model.

The coke price is affected by many factors, such as the imbalance between supply and demand, energy consumption expectations, the development of alternative consumables, energy industry technology, financial markets, economic booms, changes in international environments and adjustment of industrial structure. Traditional economic forecasting methods are theoretical and many kinds of factors have to be taken into account when the structural model is established. In the process of modeling, superfluous variables or omitted variables are inevitable, so the model is inefficient and parameters biased. Because variables abound, there are huge difficulties in data collection. Traditional forecasting methods are unable to improve regarding coke price forecasting and are of poor precision.
The Kalman filter has a wide range of applications and Kalman (1960) proposed a new approach to linear filtering and prediction problems. Julier and Uhlmann (1997) used the Extended Kalman Filter (EKF), which simply linearises all nonlinear models so that the traditional linear Kalman filter can be applied. Chen and Liu (2000) proposed a special sequential Monte Carlo method, the mixture Kalman Filter, which uses a random mixture of the Guassian distribution to approximate a target distribution. Lefebvre et al. (2004) compared the performance of different Kalman filters such as the EKF, Iterated Extended Kalman Filter (IEKF), Central Difference Filter (CDF), first order Divided Difference Filter (DDF) and Unscented Kalman Filter (UKF). Daum (2005) showed that nonlinear filters are vastly superior to extended Kalman filters for some important practical applications.

The Kalman filtering algorithm has obvious advantages over other methods in the study of price forecasting. Its competitive superiority lies in two aspects: operability and prediction accuracy. In terms of operability, first of all, the approach cannot figure in those facts that play a role in the coke price. The Kalman filtering algorithm deduces the future value of coke price on the basis of the historical data itself, and the course of constructing a model is simplified. Second, the algorithm needs fewer data, no special requirements for their distribution and is easily calculated. The data does not need to be preprocessed, so the approach solves the problem of possible data loss, and all features of the data are maintained. In terms of prediction accuracy, the Kalman filtering algorithm is effective and offers a new method to forecast coke prices because information loss is low and innovation can be considered instantaneously.

2 Analysis of coke price fluctuation

Coke price movement is regular. If information regarding future coke price is obtained in time, coke enterprises can change and adjust their business strategies in order to avoid operational risk as much as possible and the government can predict the movement characteristics of coke pricing so as to form energy-sector policy effectively. The producer price index of coal and the coking industry from 1980 to 2012 compiled by the Chinese National Bureau of Statistics was selected to study coke price movements (Fig. 1).

Coke price movement in China since 1980 can be divided into two phases. The two periods are 1980–1999 and 1999–2012 and during these the coke price movement was similar. The movement of the coke price is a key aggregate index which directly reflects the state of the national economy. In the first cycle: at the end of 1984 China’s economy overheated and the coke price index reached 117.60 by 1985. With rapid development of the economy, the coke price rose after 1987. The coke price index reached 139.70 which is the peak of the first cycle in 1993. The Asian Financial Crisis in July 1997 resulted in a serious impact on China’s economic development and there was a decrease in exports and weakening of consumption and investment in China after 1997. By 1999, the coke price index dropped dramatically to 94.80.

In the second cycle: China’s economy began to develop rapidly after 1999 and remained in a state of rapid development until the 2008 Global Financial Crisis. The economic development of China bottomed out in 2009, and the coke price index fell to 98.50. Considering the severe downturn in the economy, China issued the Four Trillion Economic Stimulus Plan and other measures to boost the domestic economy. The stimulus package had certain effects in the short term, but has resulted in secondary economic problems. For example, Chinese economic development has relied heavily on fixed asset investment. Data from the Chinese National Bureau of Statistics shows that fixed asset investment has experienced exponential growth since 2000 which has caused a rapid growth of energy consumption and resulted in serious environmental pollution. The stimulus package has created excess capacity, especially in the coke, steel and cement industries. In 2012, the coke price index plunged to 88.28 and reflected the consequences of the economic stimulus package. Usually the coke price rises when the economy develops rapidly, and tends to decline when the economic environment is sluggish.

3 The Kalman filtering algorithm

3.1 Theoretical background

Kalman filtering is extremely useful in diverse real world applications including communication systems, GPS, inertial navigation, chemical plant control and predicting the weather. The theory of Kalman filtering originates from Wiener filtering. The theory of Wiener filtering was proposed in the 1940s and is also known as linear filtering. Kalman introduced the state model into the theory of linear filtering and the recurrence of the state model overcomes the defect of infinite historical data in Wiener filtering and expands the application field gradually. Kalman filtering, also known as linear unbiased recursive filtering, is a method of optimal estimation, and abides by the estimation criterion of linear minimum mean square error. State
equation and observation equation of state space model describe the filter together, estimated value at \( k \) time and observed value at \( k+1 \) time update the estimated state variables continuously; the value at \( k+1 \) time without noise is estimated.

For a dynamic process, according to the known state equation (or dynamic equation), the future state can be forecasted by the current status. If the random disturbance or noise is added to the dynamic system, the forecasted future state will be under the influence of random factors, and as a result the forecast error will be problematic. If the real observation can measured at \( k+1 \) time, we can improve the accuracy by taking a weighted average of the real measured value at \( k+1 \) time and the forecasted value at \( k \) time, even if measurement error exists. If the initial values of state equation, state error and measurement error are known, we can find the optimal weight matrix in the following process of forecasting and measuring gradually with the known equation of state.

### 3.2 The algorithm

Suppose the state model could be expressed as follows:

\[
x_{k+1} = a_kx_k + B_kU_k + \omega_k
\]

\[
z_k = H_kx_k + V_k
\]

Equation (1) is the state equation and Equation (2) is the observation equation. In the state equation, \( x_k \) is the state variable at \( k \) time; \( x_{k+1} \) is the state variable at \( k+1 \) time; \( a_k \) is the state-transition matrix; \( U_k \) is the control variable; \( B_k \) is the coefficient matrix; and \( \omega_k \) is the random disturbance term at \( k \) time. From the state equation, we can conclude that \( \omega_k \) exercises a great influence on \( x_{k+1} \), not \( x_k \). In the observation equation, \( z_k \) is the observed value at \( k \) time; \( H_k \) is the observation matrix that reflects that observations are a linear combination of state vector; and \( V_k \) is the measurement noise. We suppose that \( \omega_k \) and \( V_k \) are Gaussian series, \( E(V_k) \) and \( E(\omega_k) \) are close to zero, \( Q(k) \) and \( R(k) \) are covariance matrices which are positive definite matrixes.

The aim of state estimate is to obtain the optimal price estimator from price observation, on condition that the statistic characters of initial state variable are known (e.g., the initial expectation of state variable \( E(x_0) \) and the initial covariance \( P_0 \)). Here, our object of study is a single time series. The given initial value of \( \phi \) (state transfer coefficient) is 1, and indicates that coke price at \( k \) time is consistent with the price at \( k+1 \) time. Control variable is given as zero. The residual term \( \omega_k \) is random white noise, so its expectation is zero and variance is \( Q(k) \). Considering that the initial value of state variable and disturbance have trivial effect on the system we are studying, all initial values are set according to the attribute of the system. Here, the initial value of state variable is zero, the expectation of state variable is 2000, and the covariance is 4.

We assume that the observed value and the actual value have a one-to-one relationship; moreover, the observed value could represent the real value directly to a great extent. We have the assumption that observation coefficient—\( H \) is 1, expectation of disturbance term is zero, covariance—\( R(k) \) is random white noise.

### 4 The Kalman filtering algorithm of coke price forecast

#### 4.1 State equation of coke price

The state equation of price is defined as:

\[
x_{k+1} = \phi x_k + \omega_k
\]

The aim of state estimate is to obtain the optimal price estimator from price observation, on condition that the statistic characters of initial state variable are known (e.g., the initial expectation of state variable \( E(x_0) \) and the initial covariance \( P_0 \)). The given initial value of \( \phi \) (state transfer coefficient) is 1, and indicates that coke price at \( k \) time is consistent with the price at \( k+1 \) time. Control variable is given as zero. The residual term \( \omega_k \) is random white noise, so its expectation is zero and variance is \( Q(k) \). Considering that the initial value of state variable and disturbance have trivial effect on the system we are studying, all initial values are set according to the attribute of the system. Here, the initial value of state variable is zero, the expectation of state variable is 2000, and the covariance is 4.

#### 4.2 Observation equation of coke price

The observation equation of price is defined as:

\[
z_k = H_kx_k + \nu_k
\]

We assume that the observed value and the actual value have a one-to-one relationship. Moreover, the observed value could represent the real value directly to a great extent. We have the assumption that observation coefficient \( H \) is 1, expectation of disturbance term is zero, and covariance \( R(k) \) is random white noise.

#### 4.3 The algorithm for Kalman filtering

After setting about the state space model, the coke price could be represented by above recursive programs as implemented in MATLAB.

The forecast equation of coke price is:

\[
\hat{x}_{k+1} = \alpha \hat{x}_{k}
\]

where, \( \alpha \) is the forecast coefficient. The research object is a single time series, in view of stability of coke price, the value of \( \alpha \) is set to 1.

There is a difference between the real observed value and the forecast value which can be deduced from state value at \( k-1 \) time. The difference is the innovation of coke price in the paper. The innovation is critical in the iteration algorithm of Kalman filtering. Through the dynamic adjustment of innovation, we can use all of information
as far as possible and obtain the perfect Kalman filtering estimator eventaully. The equation of innovation is:
\[ \hat{z}_{k+1} = \tilde{z}_{k+1} - \hat{x}_{k+1|k} \]  
(6)

Both the covariance of filtering prediction error at \( k \) time and the covariance of random noise at \( k \) time determine the covariance of prediction-estimation error. The equation of prediction-estimation error is:
\[ P(k+1|k) = aP(k) + Q(k) \]  
(7)

The optimal weight matrix is the best weight coefficient matrix, which can minimize the covariance of the filtering prediction error, also known as the gain matrix. The equation of optimal weight matrix is:
\[ K_{k+1} = P(k+1|k)H_{k+1}^t [H_{k+1}P(k+1|k)H_{k+1}^t + R(k)]^{-1} \]  
(8)

In the study of coke price, we know the nature of the Kalman filtering estimator is the weighted average of estimated value and observed value. The theory of innovation expresses the idea briefly, meanwhile, innovation uses all the information at great extent. The coke price equation of Kalman filtering estimation is:
\[ x_{k+1} = \hat{x}_{k+1} + K_{k+1}\tilde{z}_{k+1} \]  
(9)

The process of Kalman filtering estimation determines the least-mean-error criterion and the following iteration process abided by the rule all the time. This criterion ensures minimum covariance of Kalman filtering estimation at every time in the study of coke price. The covariance equation of Kalman filtering estimation is:
\[ P(k+1) = [I-K_{k+1}H_{k+1}]P(k+1|k) \]  
(10)

5 Predicting coke prices

This study is based on datum for the daily coke price between 18 December 2009 to 1 February 2013 from the Bohai Commodity Exchange, and results show that the short-term prediction of coke price is efficient. The coke price is affected by many factors which are hard to obtain and where validity is weak. For this reason, we did not analyze coke based on numbers of influencing factors, but based on the coke price itself. Through the Kalman filtering algorithm and the single time series, we built a space model with a single variable and reduced noise from the polluted data to gain the real movement trace in coke price.

The results shows that the estimated value by Kalman filtering and real observed value fit well (Fig. 2). The estimated value by Kalman filtering mirrors the entire movement of coke price, that is, the Kalman filtering algorithm is effective in tracking.

The Kalman filtering algorithm abides by criteria for linear minimum variance estimation. According to these criteria, we know the state vector of coke price is the linear function of observation. This result shows that the Kalman filtering estimation is unbiased, and the covariance is minimum.

The covariance of Kalman filtering estimation error has good character in stability in the study on coke price. The range of covariance fluctuation is \([0,1.5]\), and most of the value is within \([0,0.5]\) (Fig. 3). The good character shows that the fitting error is rather small, and the estimation precision is reliable.

Kalman filtering belongs to the Markov process, i.e., coke price at \( k \) time is closely related to the price at \( k-1 \) time, however, it has nothing to do with historical price. The above specific iterative Kalman filtering algorithm and update process confirm this idea. Through Kalman filtering, we can one-step forward forecast only. According to the established state space model and Kalman filter algorithm we forecasted the coke price on 4 February 2013. The forecast price at that moment is 1772.70 CNY ton\(^{-1}\), and the real coke price is 1790 CNY ton\(^{-1}\) (Bohai Commodity Exchange) so the prediction error is small. All of the above results show that the Kalman filtering algorithm is valid in the field of short-term coke price prediction.

![Fig. 2 Observed value and estimated value by Kalman filtering.](image1)

![Fig. 3 Covariance of Kalman filtering estimation error.](image2)
6 Conclusions

Many factors influence the coke price and there are two kinds of difficulties when forecasting. First, traditional forecast methods struggle to consider all factors and as a result some useful factors are omitted and the forecast accuracy remains inadequate. Second, the relationship between coke price and external influence is complex. The traditional forecast method makes an assumption that the relationship is linear and the coefficient matrix does not reflect the real relationship between variables; simultaneously, the accuracy is low.

Here, we forecast the coke price using the Kalman filtering algorithm and select the coke price itself as a single variable. In the short term the movement of the coke price is relatively stationary (e.g., if the step size is one day, coke price is consistent to a great extent), so linear Kalman filtering has advantages when forecasting the coke price. Our empirical results show that the Kalman filtering algorithm can promote forecast accuracy and the forecast values hold each time.

The Kalman filtering algorithm has remarkable advantages in predicting coke prices. The algorithm is simple and fast and in general it does not require sample pretreatment. Information from data is retained which promotes the prediction accuracy as much as possible. Furthermore, all innovation at any time can be added into the prediction model so as to minimize information loss. The Kalman filtering algorithm is a usable method in the field of prediction and can be applied broadly to the prediction of other energy prices.

References


基于卡尔曼滤波算法的焦炭价格预测

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摘 要：焦炭价格预测研究具有重要的理论和实践意义，本文利用卡尔曼滤波算法对焦炭价格进行预测研究。建立状态空间模型时，选取焦炭价格作为唯一的状态变量，通过每一时刻变量观测值与预测值形成的新息，不断更新和迭代，以寻求最优估测值。实证分析表明，该算法对焦炭价格的跟踪和预测效果较好。

关键词：焦炭价格; 预测; 状态空间模型; 卡尔曼滤波算法