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A novel grey wave forecasting method for predicting metal prices

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ABSTRACT

The evolution of metal prices shows severe fluctuations and irregular cycles which bring difficulties to accurate forecasting. This paper proposes a novel grey wave forecasting method with unequal-interval contour lines and contour time sequences filtrating to predict metal prices. In the proposed model unequal-interval contour lines are determined by the quantiles of data, which considers the intensity of data. Contour time sequences are filtrated based on autocorrelation characteristics of time series. Furthermore, we use monthly prices of two metals - aluminum and nickel-to assess the performance of our novel grey wave forecasting model with a multi-step-ahead prediction. The empirical analysis indicates the modified grey wave forecasting method is much better than basic grey wave forecasting method in terms of prediction accuracy and it can also achieve better forecasting results than ARMA and random walk.

1. Introduction

The fluctuations of metal price impact global economy and the corporation performance in the mineral industry. Many countries earn huge portion of revenues from exporting metal, so metal price have significant impact on the economy of these countries. Since metal is an important primary resource for manufacturing process, many corporations in metal smelting and processing industry are impacted by the unexpected movement of metal price. Metal price is also very important for the project valuation during the capital budgeting process (Dooley and Lenihan, 2005). For these reasons, forecasting metal price is meaningful to corporation managers, related government sectors and business investors. However, the accurate and effective prediction of metal price remains an open research question since the movement of metal price, often highly complex and nonlinear in nature, is subject to complicated influence factors from the industrial sectors to the financial sectors. As a result, there is rising demand for modeling and forecasting metal price movement more accurately. Dooley and Lenihan (2005) found that the performance of ARIMA model was marginally better than that of lagged forward price model to forecast monthly metal price. Arouri et al. (2012) analyzed the long-memory characteristics and structural breaks of precious metals' prices and used a ARFIMA–FIGARCH model to forecast the volatility of precious metals. In recent years, many researchers presented an advance of using non-traditional techniques to forecast metal prices, for example, Kriechbaumer et al. (2014) used an improved combined wavelet-autoregressive integrated moving average(ARIMA) to forecast monthly price of aluminum, copper, lead and zinc. He et al. (2015) considered the chaotic and multiscale data characteristics of metal prices and used a multi-scale curvelet method to forecast metal prices. Lasheras et al. (2015) forecasted COMEX copper spot price by neutral network. To explore new techniques in metal prices forecasting, grey wave forecasting method is introduced in this paper to predict metal prices just using the information of the time series graph of metal prices. Empirical studies in the literature also provided numerous evidences about the existence of cycles in the metal price movements. For example, Labys et al. (1998) presented initial evidence of existence of cycles in metal price movement; Jerrett and Cuddington (2008) used the band-pass filter to extract cyclical components in the historical metal price data successfully; Roberts (2009) found metal prices indicated some degree of cyclicality. Labys et al. (1998) also indicated that perceived cycles was confounded by stochastic shocks, moreover, Roberts (2009) suggested the amplitude of price changes did not show regularity. Irregular fluctuations are always difficult to measure with mathematical method, so this paper uses graphical method to predict metal prices.

Grey system theory, proposed by Professor Julong Deng, is a theory of describing and dealing with uncertain information. It can use a few data to establish models without considering the

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distribution of data (Deng, 1982; Liu and Lin, 2006), and it has been widely used in the field of image processing, time series prediction, system optimization, control and decision etc. (Olson and Wu, 2006; Bai and Sarkis, 2010; Xiong et al., 2010; Wei, 2011). Grey system forecasting is one of the most important components in grey system theory and it finds development rules of system through certain data processing procedures in order to forecast system's future scientifically and quantitatively. Grey system forecasting is also very popular in academia, for example Li et al. (2012) used it to predict short-term electricity consumption of Asian countries; Wei et al. (2015) used it to predict mining and commercial casualties, highway traffic accidents, railway traffic accidents, fire disasters, and all fatal casualties of mainland China. Most of the previous researches used GM(1,1) or GM(1,N) model for forecasting purpose (Kung et al., 2006; Deng et al., 2012). But GM(1,1) or GM(1,N) model performs most effectively for data series increasing with time and it is not suitable for time series with periodic fluctuations and irregular large ranges (Liu et al., 2010). As a result grey wave forecasting model is proposed to forecast time series with such characteristics.

Grey wave forecasting conducts prediction based on the graph of time series, therefore, it belongs to a category of graphical prediction method. This method begins with identifying a set of contour lines. It then constructs GM(1,1) models based on contour time sequences, which consist of the intersections of contour lines and time series graph. Grey wave forecasting method not only has the advantage of grey system forecasting models, which can predict middle and long term developing trend of system based on a small amount of data, but also conducts prediction making few assumptions about the underlying data distribution and the stationarity of data (Liu and Lin, 2006; Liu et al., 2010). In practice, grey wave forecasting method performs well in forecasting time series with large fluctuation ranges, for example Wan et al. (2009) forecasted Shanghai Composite Index weekly data and found the forecasting wave and the actual wave had the same fluctuating mode. However, compared to the explosive researches on GM(1,1) or GM(1,N) (Kayacan et al., 2010; Deng, Hu et al., 2012; Xie et al., 2013; He et al., 2015), few researches applied grey wave forecasting method in time series prediction, not to mention the improvement of grey wave forecasting methods. The only work involved in this field is Wan et al. (2009) and they chose contour lines according to the crests and troughs of time series graph to fix the limitation that basic (equal-interval) grey wave forecasting method is only effective for time series data with regular fluctuation ranges. However, this method is not efficient since finding all the crests and troughs involves exponentially increasing level of computational complexity. To overcome the short coming that basic grey wave forecasting method is not suitable for time series with irregular fluctuation range, this paper uses unequal-contour lines and contour time sequences filtrating to improve existing method.

The major contribution in this paper is the proposition of a novel grey wave forecasting method with unequal-interval contour lines and contour time sequences filtrating to forecast metal prices. In this paper, we propose to use quantile to identify the contour lines which are actually consistent with the intensity of original data. Moreover, we suggest filtrating contour time sequences to find qualified ones and unqualified ones. Finally, we establish GM(1,1) models based on qualified contour time sequences for forecasting purpose. We introduce this method to forecast monthly price of aluminum and nickel, which usually shows irregular and large fluctuation ranges. The second contribution is the multi-step-ahead forecasting of metal prices in this paper, since most of previous researches (Dooley and Lenihan, 2005; Kriechbaumer et al., 2014; He et al., 2015) focused on one-step-ahead forecasting rather than multi-step-ahead forecasting. Xiong et al. (2013) argued that one-step-ahead prediction provides no information as to the long-term future behavior and multi-step-ahead forecasting extrapolates price series without the availability of outputs in the horizon of interest. So this paper explores multi-step-ahead metal prices forecasting based on our proposed method. The last contribution in this paper is the introduction of graphical prediction method to metal prices forecasting, which will extend the quantitative metal price forecasting literature.

The organization of the paper is as follows: in Section 2, we introduce the procedures of the novel method. In Section 3, we describe the data used in this paper, elaborate the forecasting process for metal prices, compare the results with basic grey wave forecasting methods and other benchmark models. In Section 4 we discuss the robust of the model. In the last section we provide a brief summary and potential directions of future research.

2. Methodology

Grey wave forecasting mainly includes three steps: choosing contour lines, identifying contour time sequences, establishing GM (1,1) models for contour time sequences (Liu et al., 2010). Choosing contour lines and identifying contour time sequences are used to capture the information of time-series graph. This paper adds a new step, called filtrating contour time sequences, after the second step. The new step aims to divide contour time sequences into two types (qualified and unqualified) according to certain rules, in this paper the rules is based on the autocorrelation characteristic of time series. Qualified contour time sequences are used for in-sample fitting and out-of-sample forecasting, whereas unqualified contour time sequences are just used for in-sample fitting with GM(1,1), the third step of basic grey wave forecasting method.

2.1. Choosing contour lines

The first step of grey wave forecasting is to choose contour lines. Basic method uses equally spaced contour lines obtained from averaging the maximum and minimum of original data, which only performs well for time series with similar swing ranges and regular fluctuations, such as time series show sine wave approximately. In this case, since the numbers of intersections of every contour line and original time series are almost same(or the numbers of elements in every contour time sequences are almost same), the predicted time series is likely to intersect with each contour line regularly. However, for the time series with irregular fluctuation ranges, equally spaced contour lines can't capture graph information accurately, because averaging may set more contour lines in the ranges which actually just include a few original data (shown in Fig. 1(a)). In order to capture more information in the range with frequent fluctuations and less information in the range with few fluctuations, this paper suggests choosing unequally spaced contour lines based on the quantiles of original data. Quantiles divide the data set with equal probabilities, so in the range with intensive data, the space between two quantiles is small and vice versa. Thus, determining contour lines with quantiles can capture more information in the range that original data is intensive and less information in the range that original data is not intensive (shown in Fig. 1(b)).

Definition 1. (unequal-interval contour lines contour lines): Let the original time series to be $X = (x(1), x(2), \cdots, x(n))$. Sort the original series in ascending order to get $X^a = (x^a(1), x^a(2), \cdots, x^a(n))$.

Let $\xi_0 = x^a(1)$, $\xi_s = x^a(n)$, and let $(\xi_1, \xi_2, \cdots, \xi_{s-1})$ to be the s-quantile of the data, in which the *iths*-quantileis.