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Forecasting iron ore import and consumption of China using grey model optimized by particle swarm optimization algorithm

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ABSTRACT

The iron and steel industry plays a fundamental role in a country's national economy, especially in developing countries. China is the largest iron ore consumption market in the world. However, because of limited domestic iron ore resources, a large proportion of iron ore is imported from other countries. Faced with the conflict between the iron ore supply shortage and the growing demand, it is necessary for the government to predict imports and total consumption. This paper develops a high-precision hybrid model based on grey prediction and rolling mechanism optimized by particle swarm optimization algorithm. We use the China Statistical Yearbook (1996–2011) as our database to test the efficiency and accuracy of the proposed method. According to the experimental results, the proposed new method clearly can improve the prediction accuracy of the original grey model. Future projections have also been done for iron ore imports and total consumption in China in the next five years.

Introduction

This paper develops a high-precision hybrid model based on grey prediction and rolling mechanism optimized by particle swarm optimization algorithm (PSO) to forecast iron ore imports and consumption in China. The iron and steel industry is an essential foundation for economic growth in developing countries. China's growth, even during the global economic crisis that began in 2008, was largely attributable to the 4 trillion Yuan (about 570 billion US$) stimulus to boost the economy, with a focus on real estate, infrastructure construction, and related manufacturing sectors. These activities account for a large proportion of the consumption of steel in China. Iron is an indispensable factor across these industries.

China accounts for one-third of the world's total iron ore consumption, and also ranks first in the world in iron ore import and crude steel output. Ghosh (2006) and Evans (2010) investigated the positive correlation between steel consumption and economic growth activity. China's iron ore consumption rose 784% between 2000 and 2010 and has ranked first in the world since 2003 (World Steel Association, 2009). However, China is not full of iron ore, and the domestic ore grade in China is very poor (only half of the average world level). To meet its iron ore needs, China relies increasingly on imports from countries like Brazil, Australia and India. Meanwhile, the variation in China's iron ore consumption affects the world price trend of iron ore. Thus, an accurate projection of China's import volume and consumption of iron ore would be profoundly instructive to the economic development of China and valuable to the world.

Table 1 shows China's iron ore imports and the world's marine iron ore trade from 1999 to 2009. We further use Fig. 1 to visually represent the data trend in Table 1. From Fig. 1, we can see that, over the past ten years, China's iron ore imports account for an increasing percentage of the world's total iron ore imports. The decrease in total world imports in 2009 can be explained by the 2008 global financial crisis. The visible increase of China's iron ore imports in 2009 can be explained by the stimulus described above.

Because iron ore demand is generally represented as following an exponential trend, short-term data may have advantages in explaining a country's macro-policy tendencies. Traditional forecasting models, such as regression analysis method needs plenty of sample data. Sample size would limit the predictive accuracy of these methods. Thus, for short-term data with an exponential trend, it is helpful to establish new models that can use limited samples to forecast iron ore imports and consumption in China.

Grey system theory, originally proposed by Deng (1982), aims to deal with situations that have uncertain and insufficient

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Table 1
China' iron ore import and the world's marine iron ore trade (10,000 t).
(*Data source*: China statistical yearbook (2000–2010); Steel statistical yearbook 2010).

Year (1999–2009)	World' total iron ore trade	China's iron ore import	The ratio of China's import in world's total import (%)
1999	44,355	5,527	12.46
2000	51,078	6,997	13.69
2001	50,672	9,231	18.21
2002	53,130	11,149	20.98
2003	58,302	14,812	25.40
2004	66,990	20,808	31.06
2005	75,249	27,523	36.58
2006	80,301	32,629	40.63
2007	85,551	38,309	44.78
2008	93,324	44,356	47.53
2009	81,545	62,778	76.99

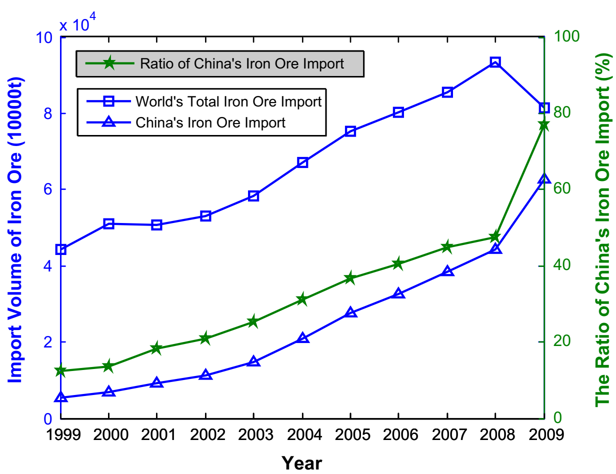

Fig. 1. The percentage of China's iron ore import in the world.

information. Grey theory employs an accumulated generating operation (AGO) to reduce the randomness of raw data to a monotonically increasing series. Due to its convenience in use, grey theory has been widely and successfully applied in forecasting, systems analysis, data processing, decision-making and so on (Li et al., 2011). In addition, grey forecasting methods can be used to forecast a system with uncertain factors and can find regularity from low volume, discrete, disorderly and unsystematic data in a timely manner. Thus, grey forecasting methods have been used in many applications (Jiang et al., 2004; Li et al., 2010; Tsaur and Liao, 2007; Zhao et al., 2012). GM(1,1) is a primary forecasting model in grey systems which only needs the recent year's data for reliable and acceptable accuracy in prediction, and this is one of the considerable advantages of GM(1,1) over previous methods. The potency of the original series in GM(1,1) has been proven to be as few as four (Akay, 2007). In many practical applications, however, the GM(1,1) model sometimes cannot fit the actual data very well, so how to improve the accuracy of the GM(1,1) model is an issue of concern to many researchers. Akay (2007) employed a rolling mechanism to increase the forecasting accuracy of GM in the case of exponential and chaotic data. Pi et al. (2010) applied a grey prediction approach to forecasting energy demand in China. Wang et al. (2011) proposed an optimized NGBM(1,1) model which can realistically reflect the feature of non-linearity in data, as evidenced by high simulation and forecasting accuracy. Li et al. (2012) used an adaptive grey-based approach to forecast short-term electricity consumption of Asian countries. Zhou (2009) optimized a nonlinear grey Bernoulli model by using PSO algorithm. Zhao et al. (2012) improved the GM(1,1) model with DE algorithm.

Evolutionary algorithm (EA) has been applied in many fields and proved to be efficient and fast at performing well approximating solutions in fields such as engineering, economics, marketing, operations research, etc. EA may not get the optimal solution to a problem, but it takes little efforts to reach a near-optimal solution. As a typical evolutionary algorithm based on Swarm Intelligence (SI), PSO has been successfully applied in many research and application areas in past several years for its simple expression, convenience to program and fast convergence (Yu et al., 2012; Assareh et al., 2010; Boonchuay and Ongsakul, 2012; Nezhad and Mahlooji, 2011) since it was proposed by Kennedy and Eberhart (1995). It has been demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust.

This paper utilizes PSO algorithm to optimize the parameter λ of grey model GM(1,1). Furthermore, the PSO-rolling GM(1,1) was constructed by introducing rolling mechanism. We use data from the China Statistical Yearbook (1996–2011) as our database to test the efficiency and accuracy of the proposed method. According to the experimental results, the proposed new method clearly can improve the accuracy of prediction compared to the original grey model. Future projections have also been done for the iron ore imports and total consumption of China in the next five years.

The remainder of the paper is organized as follows. In the next section, a brief description of the grey prediction model is given. Particle swarm optimization section introduces the basic PSO. In PSO based GM(1,1) prediction model section, PSO based GM(1,1) model and PSO based rolling GM(1,1) model are presented. Empirical results section presents numerical results. Finally, discussion and conclusion section contains the concluding remarks.

Overview of grey prediction model

Classical grey model GM(1,1)

GM(1,1) model is constituted by a univariate first order differential equation.

Step 1: Assume that the original non-negative series with n historical observed values is expressed as

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \tag{1}$$

where $x^{(0)}(k)$ is the value of the behavior series at k, $k = 1, 2, \ldots, n$.

Step 2: Using accumulated generating operator (AGO), $X^{(0)}$ is converted into a monotonically increasing series

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)) \tag{2}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$.

Step 3: The grey differential equation of the GM(1,1) model is:

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2, 3, \ldots, n \tag{3}$$

where

$$z^{(1)}(k) = \lambda x^{(1)}(k-1) + (1-\lambda)x^{(1)}(k), \quad k = 2, 3, \ldots, n \tag{4}$$

where a is the development coefficient, b is the grey actor. $z^{(1)}(k)$ in Eq. (4) is called the background value of GM(1,1) model, where λ denotes a horizontal adjustment coefficient. λ is in the range of 0–1, which traditionally equals to 0.5. The selection criterion of the value λ is to yield the smallest forecasting error rate (Wen et al., 2000).