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China's dependency on foreign oil will exceed 80% by 2030: Developing a novel NMGM-ARIMA to forecast China's foreign oil dependence from two dimensions

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ABSTRACT

China is the world's largest net importer of oil and the second largest oil consumer; consequently, changes of China's foreign oil dependence significantly impact both the Chinese and the international oil market. To enhance the forecasting ability of China's foreign oil dependence, this study combines the nonlinear metabolic grey model (NMGM) with the linear autoregressive integrated moving average model (ARIMA), thus obtaining the combined NMGM-ARIMA model. The proposed technique uses the linear ARIMA to correct NMGM forecasting residuals, thus improving forecasting accuracy. The proposed technique achieves a mean absolute error of 2.1–2.3%, reflecting its high reliability. The proposed NMGM-ARIMA was used to forecast China's foreign oil dependence for the period of 2017–2030 from two dimensions. For the first dimension, the gap between China's oil demand and supply was forecast. To fill this gap, China has to import oil; therefore, this gap is responsible for China's foreign oil dependence. For the second dimension, the change of China's foreign oil dependence level was directly forecast. Both dimensions indicate a similar conclusion, namely that the Chinese foreign oil dependence level will increase from 65% in 2016 to over 80% in 2030. A high level of 80% dependence on foreign oil would bring major concern to China. The policy recommendations given at the end of the paper will help China's decision makers respond appropriately.

1. Introduction

In 1993, the economic expansion of China outpaced its oil production capability, resulting in China becoming a net oil importer for the first time since the 1970s. China's extent of dependence on oil imports had reached 6.7% in 1993 [1]. Since then, China has continued to become more dependent on foreign oil. In 2009, China's dependence on oil imports reached 52%, which was the first time this level exceeded 50%. In 2011, China surpassed the United States and became the world's largest net oil importer and in 2016, China's foreign oil dependence reached 65.5%. From 1993 to 2016, the proportion of China's foreign oil dependence has increased nearly 10-fold [2].

With roughly 1.4 billion inhabitants, China is the world's most populated country and currently, the second largest oil consumer, followed by the United States. Thus, the increasing dependence on oil imports and the frequent fluctuations in oil prices will put China's oil imports at great risk. An improved ability to forecast the future trend of China's foreign oil dependence will help ensure China's oil supply security. This study developed a combination of the metabolic nonlinear grey model with the autoregressive integrated moving average model (NMGM-ARIMA), which better predicts China's foreign oil dependence from 2017 to 2030. The proposed NMGM-ARIMA effectively combines the advantages of a nonlinear forecasting model (the NMGM) and a linear forecasting model (the ARIMA).

The remainder of this paper is organized as follows: Section 2 reviews previous publication on petroleum forecasting and the existing research on forecasting methods. Section 3 introduces the modeling steps and principles of the NMGM-ARIMA model. In Section 4, the fitting steps and forecasting results of China's oil foreign dependence degree are illustrated. The conclusion and policy suggestions are presented in Section 5.

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Nomenclature/abbreviations

GM (1,1)	grey model with first order and one variable
ARIMA	Autoregressive Integrated Moving Average
NGM	non-linear grey model
NMGM	non-linear metabolic grey model
MSE	mean square error
MAPE	mean absolute percent error
RMSE	root mean square error
1-AGO	first-order accumulated generation sequence

2. Literature review

The existing studies of energy prediction have a wide range of research. In terms of research object, forecasting studies on power consumption, oil consumption, and carbon emissions are common. With regard to forecasting models, the most used energy prediction methods mainly include: time series prediction model, artificial neural network prediction model, econometric prediction model, and input-output model. Considering the research objects and forecasting models in this work, the literature review will cover the following aspects: (i) Overview of the forecasting oil-related research. (ii) Overview of the forecasting technique based on grey model and ARIMA.

2.1. Overview of the forecasting oil-related research

In previous studies, scholars have conducted oil-related prediction research. Fiévet et al. [3] used a new Monte-Carlo method to predict the crude oil production of both Norway and the United Kingdom. The addition of the back-test period of 2008–2014 achieved more accurate forecasting. The results showed that the decline in oil production of Norway and the United Kingdom was likely much slower than expected by standard inferences. Wang et al. [4] predicted the total output of China's oil under three price scenarios. The results showed that even if prices increased, China's oil production would begin to decline during the next few years. The obtained results showed that the TCM-NNCT model, optimized by artificial intelligence algorithms, was an effective tool for the analysis of the energy market. In the context of different ultimately recoverable resources (URR), Saraiva et al. [5] applied the improved multi-Hubbert model to estimate the Brazilian oil production. The authors reported that Brazil's oil peak should range between 2.3702 Million barrel/day (2015), 3.3302 Mb/d (2022), and 6.5902 Mb/d (2035). Nashawi et al. [6] obtained a more accurate prediction of the world's crude oil supply using the multicyclic Hubbert model. This multicyclic extension overcomes the limitations of the original Hubbert model and incorporates the production cycle of oil reserves into new ideas for prediction. The obtained conclusions showed that the world crude oil reserves were depleted at a rate of 2.1% per year. Soleng [7] used an optimized genetic algorithm to assess the uncertainty of the future total oil production. This method of optimization can effectively overcome the drawbacks of rock physical properties, and thus provide reliable help for the prediction of oil production. The oil supply closely influences the changes in crude oil prices and these oil prices in turn affect the economic stability of many countries.

In addition to the prediction of oil production, many studies have therefore focused on the prediction of crude oil prices. Naser [8] forecasted the crude oil prices of West Texas Intermediate (WTI) and used the dynamic model averaging (DMA) method to provide a better forecast of the price spot index. He et al. [9] proposed a new multivariate empirical mode decomposition (EMD)-based model that can forecast the crude oil price with the help of the heterogeneity of price changes. By comparing gene expression programming (GEP), artificial neural network (NN) models, and the ARIMA model, Mostafa et al. [10] predicted the oil prices between 1986 and 2012. The results indicate that the GEP model can better explain the actual changes of crude oil prices. By considering the prediction of risk value, Lux et al. [11] reported that the new MSM model was more applicable for this type of forecasting research. Wang et al. [12] adopted combination forecasting over time-varying parameter (TVP) models to predict the price of crude oil. The results of their study indicate that this benchmark model is more suitable for predictions that exceed three months. Lee et al. [13] used the Bayesian method to integrate the structural changes and influencing factors of the oil market. Based on informative priors, the long-term crude oil price was forecast to increase to $ 169.3 per bbl by 2040. In order to clearly show the relationship between these researches, Table 1 classified those studies.

2.2. Overview of the forecasting technique based on grey model and ARIMA

Based on the research model used in this paper, the literature review of time-series forecasting models (Section 2.2) can be divided into three subsections. The first subsection reviews the research progress of grey forecasting techniques, the second subsection reviews the research progress of ARIMA forecasting techniques, and the third subsection reviews the research progress of combined forecasting techniques based on a combination of the grey model and the ARIMA model.

2.2.1. Overview of the grey forecasting model and its applications

In addition to the prediction of oil consumption, the development of prediction methods also developed to an advanced state. Among the utilized techniques, the grey theory provides useful ideas for the construction of the NMGM-ARIMA model. With regard to its developmental process, the grey model was first proposed by Professor Deng in 1982 [14]. During the construction of the NMGM-ARIMA model, the grey model was widely used in the field of energy prediction due to its good extrapolation [15,16].

During the later application of energy consumption prediction, Wang et al. [17] applied the traditional grey model to the field of hydrogeology and water resources. Li et al. [18] applied the traditional grey model for the prediction of energy consumption in Shandong, China. During the further developmental process, many improved grey models have been proposed and applied. Zhao et al. [19] developed a new hybrid optimized grey model. This Rolling-ALO-GM (1,1) model was optimized using a rolling mechanism and was then applied for the prediction of the annual electricity consumption of China and Shanghai. A self-adapting intelligent grey prediction model, which can automatically optimize model parameters based on characteristics of the modeling data, was proposed by Zeng and Li [20]. The results of data fitting of 2002–2014 and data prediction for 2015–2020 show that the demand for natural gas will rapidly increase in the future. Due to unknown variables in the time response function, Xu et al. [21] constructed a nonlinear optimization method based on a particle swarm algorithm and applied this to forecast China's electricity system. The data of shale gas in China is currently very limited and contains a large amount of uncertainty. Because of this, Zeng et al. [22] proposed an unbiased grey prediction model called the UGM (1,1). By greying down the buffering operator, this model achieves an accurate prediction of the shale gas production in China for the period of 2017–2025.