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An improved grey multivariable model for predicting industrial energy consumption in China

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ABSTRACT

A grey forecasting model based on convolution integral (GMC(1, n)) is an accurate grey multivariable model, which is derived from the GM(1, n) model by adding a control parameter u. n interpolation coefficients, as unknown parameters, are input into the background values of the n variables so as to improve the adaptability of GMC(1, n) on real data. In addition, a nonlinear optimization model is constructed to obtain the optimal parameters that can minimize the modelling error. The modelling and forecasting results as applied to China's industrial energy consumption show that the optimized grey multivariable model exhibits a higher accuracy than GMC(1, n), SARMA and GM(1, 1). The method proposed for the optimization of the background value can significantly promote the modelling and forecasting precision of GMC(1, n).

1. Introduction

China, as a developing country, is undergoing a process of industrialization. Its industrial economic output mainly relies on a substantial input of production factors (capital, labour, energy, etc.). In recent years, sustainable growth in China's industrial economy has led to a rapid increase in its energy consumption. With its existing economic structure and technology level, an energy shortage will become the bottleneck to the constant development of China's industrial economy. Therefore, the establishment of a corresponding mathematical model for accurately predicting future industrial energy consumption is a significant contribution to the formulation of China's energy security strategy and economic development program.

Energy consumption forecasting is an important issue in the study of energy economics. To investigate this issue, many researchers have adopted different methods. Among them, auto-regressive integrated moving average (ARIMA) [1–3], artificial neural networks (ANNs) [3–5], and support vector regression (SVR) [5–6] are relatively mature ones. However, it is notable that, grey forecasting [7], as a new method of forecasting uncertain system behaviour, is a pioneering approach to energy consumption forecasting [8–12], and shows excellent forecasting ability. It is significant that in existing studies energy consumption is mainly predicted by constructing a single variable grey model GM(1, 1), or its related modified forms. When the behavioural characteristics of the predicted series are apparently affected by exogenous variables, a multivariable grey modelling and forecasting method can produce better results.

In view of the dependence of China's industrial economic growth on energy consumption, and with the current economic structure and technology level, it is important to consider the fact that industrial energy consumption is mainly determined

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Nomenclature

1-AGO	first-order accumulated generation operation
$X^{(0)}$	original series
$X^{(1)}$	first-order accumulated series
GMC(1, n)	grey model with convolution integral
rp	delay period
rf	number of entries to be forecast
1-IAGO	first-order inverse accumulated generation operator
$\hat{X}^{(0)}$	forecasted series of $X^{(0)}$
OGMC(1, n)	optimized grey model with convolution integral
MAPE	mean absolute percentage error
ARMA	auto-regressive moving average model

by industrial economic growth. Accordingly, based on grey theory, a model for forecasting China's industrial energy consumption with industrial economic output value as an associated variable is constructed.

The GM(1, n) model [7], as a basic grey multivariable mode, takes $n-1$ correlative variables as an associated series in addition to the predicted series. It can make full use of the information contained in the associated series in the predicted series. On the other hand, GM(1, 1) only contains the information relating to the predicted series during modelling. In addition, in the view of the available additional information, GM(1, n) is likely to show higher forecasting accuracy compared to GM(1, 1) when related factor data series are tested (excepting the predicted series). The whitening differential equation solved for GM(1, n) is shown to be rough and has been proved to be wrong [13] —it is prone to give rise to great errors in practical forecasting applications. Therefore, it has rarely been applied for practical forecasting. As a matter of fact, previous studies have utilized it to perform forecasting based on the improved models [14–16].

GMC(1, n), as a new model, was put forward by Tien [17] with a view to improve typical GM(1, n) model. Theoretically, the modelling values obtained using GMC(1, n) are taken as the solution of typical GM(1, n) model and the grey control parameter which is input into the model. The GMC(1, n) model tends to descend to GM(1, 1) in the case of $n=1$ which is the number of variables in the model. The approach to significantly improve the forecasting precision of the multivariable grey model using GMC(1, n) has been extensively reported [18–19]. Moreover, aiming to satisfy different application demands, Tien has put forward three improved models based on GMC(1, n) itself. These are: the deterministic GMC(1, n) model [DGDMC(1, n)] [20], the interval GDMC(1, n) model [IGDMC(1, n)] [21], and the first pair-of-data GMC(1, n) model [FGMC(1, n)] [22].

In these extensions, the first derivatives of the 1-AGO data for each relative series are introduced into DGDMC(1, n) [20] to strengthen the indicative significance and evaluate the 1-AGO data modelling for the predicted series based on convolution integral. Meanwhile, the IGDMC(1, n) model extends the forecasting mean of the DGDMC(1, n) model [21] from a point to an interval using a linear regression interval forecasting method. According to hypothesis tests of the system parameters, it is also suggested that certain components need to be removed to make the IGDMC(1, n) model more reasonable. Finally, in constructing the improved FGMC(1, n) model [22], only $n+2$ pairs of history data are required, since the first pair of data has proved to be inconsequential to the modelling result. Hence, the FGMC(1, n) model is usually more satisfactory and stable than the GMC(1, n) model, because it extracts the first pair of the entries information of the original series.

In traditional grey models, the background value of the grey derivative is usually taken as the mean value of the current and previous period values of the first-order accumulative generation data. Like the background value of the traditional GM(1, 1) model it is defined as: $Z^{(1)}(t) = [Z^{(1)}(t) + Z^{(1)}(t-1)]/2$. Detailed arguments on its rationality have been performed by Deng from various perspectives [7, 23, 24]. The current background values for the variables in GMC(1, n) are determined according to the above rule. However, many researchers have put forward methods to improve the traditional method of calculation of grey model background values to increase modelling accuracy. For example, one effective method is to introduce an unknown interpolation coefficient, $\lambda \in [0, 1]$, and is designed to improve the background value according to $Z^{(1)}(t) = \lambda Z^{(1)}(t) + (\lambda - 1)Z^{(1)}(t-1)$. Empirical analysis results show that this method can intensively promote the precision of the grey model in terms of modelling and forecasting applications [14, 15, 25-28]. Hence, this work inputs n interpolation coefficients into the background values for the variables in GMC(1, n). Then, the optimal λ_i $(i = 1, 2, \ldots, n)$ can be derived by minimizing the mean absolute percentage error. Consequently, the applicability and forecasting precision of the GMC(1, n) to real data can be improved. In this work, the optimized GMC(1, n) model performed using this method is denoted as OGMC(1, n).

Comparing with existing researches, the novelty of this paper is shown to be in following three aspects: (1) most of studies on grey forecasting models adopt a single variable grey model or its improved models, such as GM(1, 1) [29-31], DGM(1,1) [32], and Grey Verhulst model [33]. However these models show little concern regarding the influence of relevant factors, which will greatly affect the forecasting accuracy of system behaviours. In this work, the grey multivariable forecasting model GMC(1, n) is taken as an research object in an attempt to achieve more accurate forecasting results than those single variable grey models; (2) although the GMC(1, n) and DGDMC(1, n) proposed by Tien improved the