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Utilizing a Fractional-Order Grey Model to Predict the Development Trends of China's Electronic Commerce Service Industry

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Abstract: Electronic commerce plays a vital role in the digital age, and the creation of a good electronic commerce ecosystem is crucial to maintaining economic growth. The electronic commerce service industry is a leading indicator of electronic commerce development, and its possible changes imply the future trends and innovation directions of the electronic commerce industry. An accurate grasp of the possible future revenue scale of the electronic commerce service industry can provide decision-making information for government policy formulation. Electronic commerce companies must formulate operational plans based on the latest information to determine strategic directions that are reasonable and consistent with the actual situation. Although there exist many prediction methods, they often fail to produce ideal results when the number of observations is insufficient. The fractional-order grey model is a common method used to deal with small data set prediction problems. This study therefore proposes a new modeling procedure for the fractional-order grey model to predict the revenue scale of China's electronic commerce service industry. The results of experiments demonstrate that the proposed procedure can yield robust outputs under the condition of small data sets to reduce decision-making risks. Therefore, it can be regarded as a practical small data set analysis tool for managers.

Keywords: forecasting; fractional-order grey model; small data set; electronic commerce

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1. Introduction

In the digital age, electronic commerce has become an indispensable facet of the business field. It has transformed business models in unique ways and provided countless opportunities for consumers and businesses worldwide. Due to its convenience and efficiency, electronic commerce has reshaped the pattern of shopping behavior [1]; consumers can access online stores at anytime and anywhere to find products, compare prices, and make purchases, which reduces the time and effort required by consumers to find the goods they need. Electronic commerce has also enabled enterprises to open new sales channels, reduce operating costs, and expand their marketing scope [2]. Merchants can sell their products worldwide through the Internet without geographical restrictions. Electronic commerce also plays positive roles in environmental protection and social sustainable development. Online shopping reduces traffic congestion and carbon emissions, which is beneficial to environmental protection. Electronic commerce also provides employment opportunities for vulnerable groups, thereby promoting social equity and economic development. In summary, electronic commerce plays a crucial role in modern business [3].

To maintain sustained economic growth, it is necessary to create a good electronic commerce ecosystem. This requires the government and enterprises to jointly formulate effective policies to guide the orderly development of the industry and positively impact the shopping behavior of consumers. However, the establishment of an ideal economic commerce ecosystem is a long-term and complex process that requires the consideration of many factors, such as optimizing the financial system, setting industry standards, formulating relevant laws, adjusting management mechanisms, cultivating professional talents, and building logistics infrastructure. Any deviation in the policy direction may adversely affect the whole industrial ecosystem. Mastering the possible development of electronic commerce can help enterprises avoid inappropriate decision-making and ensure the sustainable development of electronic commerce [4]. The development trend of electronic commerce provides the public sector with a foundation for decisions regarding the needs of public infrastructure such as computer networks and logistics transportation, the formulation of relevant laws and regulations, and the training of professional talents. Enterprise organizations operating under the economic network structure can also benefit from the prediction of electronic commerce development trends. Therefore, the effective judgement of the development trend of electronic commerce is of great importance to policymakers and practitioners in the electronic commerce and logistics fields.

The electronic commerce service industry is an important component of electronic commerce that covers a series of key areas that support electronic commerce operations. Its common service models include live streaming sales, community group buying, electronic payments, ticketing agents, etc. These service models play a crucial role in the daily operation of electronic commerce, providing necessary support and convenience for electronic commerce enterprises. As a leading indicator of electronic commerce development, the possible changes in electronic commerce service industry trends not only affect the operation of electronic commerce platforms and the shopping experience of consumers but also indicate the future trends and innovation directions of the electronic commerce industry [5]. Therefore, paying attention to the development status of the electronic commerce service industry is significant for the promotion of the sustainable development of electronic commerce.

Common prediction methods for this task are roughly divided into four categories, namely qualitative judgment, time-series modeling, multivariate analysis, and data mining technology. When predicting new market trends or possible new product sales, qualitative judgment based on expert knowledge and subjective identification is a feasible approach in the case of a lack of past experience. Time-series modeling, for which historical data trends are used to determine future demand, is widely used in various predicting problems; however, this method requires a sufficient number of observations to fit a satisfactory model. Multivariate analysis explores the causal relationships between independent and dependent variables to estimate the possible value of the dependent variable. However, the predictive effect depends on whether the main factors affecting the dependent variables are found and whether a reasonable explanatory model is established. Finally, data mining technology uses algorithms to extract hidden information from collected data, but a sufficient number of training samples is necessary to avoid the overfitting phenomenon. One of the key factors affecting the prediction performance of all of these quantitative prediction methods is the number of observations, which limits the applicability of these methods in some prediction situations.

The issue of predicting the revenue trends of China's electronic commerce service industry is an example of an inadequate number of modeling observations. Due to the popularization and rapid development of electronic commerce applications, industrial environment changes and information updating occur very quickly. Electronic commerce enterprises must draw up operational plans according to the latest information to determine a reasonable strategic direction. The reference value of outdated information is worthless; it not only cannot aid the management process but also acts as noise that interferes with operational judgment. To mitigate the risk of decision-making errors, the use of observations with the latest information for data analysis can be more realistic and contribute to effective decisions that are not contrary to the status quo. Therefore, it is of great managerial value to extract useful information from a limited number of recent observations.

Grey system theory is a method for dealing with the problem of incomplete information caused by limited data, via which system behavior is predicted by exploring and utilizing existing data [6]. This theory provides a feasible solution for analysis and decision-making problems under the condition of small data sets and is widely used in different application fields, such as engineering, manufacturing, business, etc. [7–13]. Grey modeling is an important branch of grey system theory and is mainly used for the extraction of pattern trends from small data sets [14]. The original grey model and its extensions have succeeded in solving various prediction problems [15,16]. However, the grey model remains imperfect, and further improvement is possible. In recent decades, many extensions of the grey model have been developed to improve prediction accuracy. Among these extensions, some studies have focused on the optimization of the modeling parameters [17,18], some have sought better background values [19,20], and some have attempted to construct hybrid grey models [3,21]. In addition, some grey models have improved modeling mechanisms, such as the discrete grey model [22], the fractional-order grey model [23], and the extrapolation-based grey model [24], among others.

The fractional-order one-variable grey model, namely the FGM, is one of the most widely used prediction methods in grey system theory [25]. In the face of complex data series characterized by nonlinearity and uncertainty, it is often difficult for traditional models to provide accurate prediction results. The FGM provides a favorable solution to this problem [23]; it can reveal the internal mechanism of data changes to predict future trends and provide a more reliable basis for decision-makers [26]. Due to its convenient use and easy calculation [27], the FGM is adopted in this study to solve the small data set prediction problem encountered in the field of electronic commerce.

To successfully predict the future revenue trend of China's electronic commerce service industry, a clear setting method is provided for the parameters (order) of the FGM. In this study, one practical case is selected for experimental analysis to verify the effectiveness and practical value of the proposed procedure. The revenue scale of the electronic commerce service industry in China compiled by the Ministry of Commerce of the People's Republic of China is adopted as the data used in this study. In addition, a pre-test is performed to confirm the feasibility of the proposed procedure before trend prediction. The results of experiments demonstrate that the proposed procedure generates favorable predictions that can solve small data set problems. Because this procedure yields robust outputs to reduce the decision-making risk, it can be considered a practical small data set analysis tool for managers.

The remainder of this paper is systematically organized as follows. Section 2 introduces the modeling steps of the original FGM and the proposed heuristic order determination method. Section 3 then presents the data analysis and result comparison. Finally, the conclusion is discussed in Section 4.

2. Methodology

The primary challenge faced by small data set analysis is determining how to extract useful information from the collected limited observations for modeling. A parameter determination procedure for the FGM is herein developed to address this issue. The following subsections will introduce the two main components of the modeling process and the detailed steps of the proposed procedure.

2.1. Fractional-Order One-Variable Grey Model

Before analyzing the original random observations, a data preprocessing process is necessary to eliminate the disorder of the numerical series. In grey modeling, the accumulated generating operation (AGO) is generally used to reduce the randomization of the original data [28]. When the order of AGO is not an integer, the established grey model is called an FGM. The original first-order one-variable grey model, namely the GM, is currently one of the most commonly used models; however, one of its disadvantages is that older observations have a greater impact on model establishment, which leads to the phenomenon of larger perturbation intervals in the model solution. Specifically, the higher the order of the AGO, the greater the influence of older observations on the model, which implies that the order of the AGO should not be too high. Therefore, the FGM was developed to address this deficiency. Furthermore, because the order cannot be too high, the order of the AGO in the FGM is generally a proper fraction, which is a number (decimal) between 0 and 1. The detailed calculation steps of the FGM are as follows [23].

1. Consider a non-negative series set with n observations, $X^{(0)} = \left\{x^{(0)}(1),\ x^{(0)}(2), \ldots,\ x^{(0)}(n)\right\}$.
2. Calculate the r-order accumulated generating coefficients series, $O^r = \{o^r(1), o^r(2), \cdots,\ o^r(n)\}$.

$$o^r(1) = 1;\ o^r(k) = \prod_{i=1}^{k-1}\left(\frac{r+i-1}{i}\right),\ k = 2, 3, \ldots, n \quad (1)$$

3. Convert the original series $X^{(0)}$ into a monotonically increasing series $X^{(r)} = \left\{x^{(r)}(1),\ x^{(r)}(2), \ldots,\ x^{(r)}(n)\right\}$ by the r-order AGO. The purpose of the AGO is to discover the change patterns by converting the data dimensions, thus allowing the series to build a better fitted model.

$$x^{(r)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \times o^r(k-i+1),\ k = 1, 2, \cdots, n \quad (2)$$

4. Obtain the background value series $Z^{(r)} = \left\{z^{(r)}(1),\ z^{(r)}(2), \ldots,\ z^{(r)}(n)\right\}$ by calculating the average. The prerequisite for establishing a robust model is that the data cannot be affected by external factors or artificial interference. Therefore, the background value is calculated using an average to reduce randomness.

$$z^{(r)}(k) = \frac{1}{2}\left[x^{(r)}(k-1) + x^{(r)}(k)\right],\ k = 2, 3, \cdots, n \quad (3)$$

5. Construct the grey differential equation.

$$x^{(r)}(k) - x^{(r)}(k-1) + az^{(r)}(k) = b \quad (4)$$

6. Expand Equation (4) into the vector–matrix form of Equation (5), where $\mathbf{Y} = \begin{bmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{bmatrix}$, $\hat{\mathbf{a}} = \begin{bmatrix} a \\ b \end{bmatrix}$, and $\mathbf{B} = \begin{bmatrix} -z^{(r)}(2) & 1 \\ -z^{(r)}(3) & 1 \\ \vdots & \vdots \\ -z^{(r)}(n) & 1 \end{bmatrix}$.

$$\begin{bmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{bmatrix} = \begin{bmatrix} -z^{(r)}(2) & 1 \\ -z^{(r)}(3) & 1 \\ \vdots & \vdots \\ -z^{(r)}(n) & 1 \end{bmatrix} \times \begin{bmatrix} a \\ b \end{bmatrix} \quad (5)$$

7. Calculate the pending coefficient vector $\hat{\mathbf{a}}$ using the ordinary least-squares method.

$$\hat{\mathbf{a}} = \left(\mathbf{B}^T\mathbf{B}\right)^{-1}\mathbf{B}^T\mathbf{Y} \quad (6)$$

8. Solve the ordinary differential equation $dx^{(r)}/dt + ax^{(r)} = b$ to establish a grey prediction model based on the r-order AGO. Via this action, called the whiteness process, the ordinary differential equation is used to replace the source grey differential equation.

$$\hat{x}^{(r)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a} \quad (7)$$

9. Use Equation (7) to output the estimated value of the r-order accumulated generating series $\hat{X}^{(r)} = \left\{\hat{x}^{(r)}(1),\ \hat{x}^{(r)}(2), \ldots,\ \hat{x}^{(r)}(m)\right\}$.
10. Determine the negative r-order accumulated generating coefficients series, $O^{-r} = \{o^{-r}(1), o^{-r}(2), \cdots,\ o^{-r}(n)\}$.

$$o^{-r}(1) = 1;\ o^{-r}(k) = \prod_{i=1}^{k-1}\left(\frac{-r+i-1}{i}\right),\ k = 2, 3, \ldots, m \tag{8}$$

11. Obtain the predicted values $\hat{X}^{(0)} = \left\{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(m)\right\}$.

$$\hat{x}^{(0)}(k) = \sum_{i=1}^{k} \hat{x}^{(r)}(i) \times o^{-r}(k-i+1),\ k = 1, 2, \cdots, m \tag{9}$$

2.2. Heuristic Procedure for Determining Order

In the modeling process of the FGM, the order is the most important factor affecting the applicability and prediction performance of the model. Its value directly influences the entire modeling process and generates different pending coefficients, which impacts the accuracy of the model. However, there is currently no explicit method by which to determine the order. The most common method is to determine the order based on historical data patterns via experience or subjective judgment; when strengthening the importance of the latest data, a smaller order is chosen, and vice versa. However, this approach is not robust and can introduce uncertain risks in practical decision-making applications, thereby weakening the usability of the FGM. Therefore, it is necessary to provide a systematic method for determining the order.

One of the development concepts of the FGM is to weaken the role of older observations in the modeling process. This fact can be easily explained from Equation (1); when the order is between 0 and 1, the composition of the accumulated generating coefficients is the product of a set of proper fractions. As long as the number of multiplications is greater, the coefficient value will be smaller. Therefore, the accumulated generating coefficient of the older observations in the FGM is smaller, and its influence on the modeling process is weakened. Extending this concept, the order should be chosen so that newer data have a greater impact, and vice versa. In addition, because error is one of the most important indicators for measuring prediction models, an appropriate order should minimize the error to the greatest possible extent. Therefore, in the present study, a heuristic objective function is set based on residuals to determine the appropriate order. The following is the process for setting the objective function.

1. After a prediction model is established, there is usually a gap between the actual observation value and the fitting value, which is the residual. The residuals can help analysts to examine the rationality of the model and the reliability of the data. Here, the absolute error (AE) is used as an indicator to measure the residual. If $x^{(0)}(k)$ is the actual observation and $\hat{x}^{(0)}(k)$ is the value fitted by the model, then the calculation formula of AE is as Equation (10).

$$AE(k) = \left|x^{(0)}(k) - \hat{x}^{(0)}(k)\right| \tag{10}$$

2. Because new and old data should have different roles in the modeling process, the data, from newest to oldest, should be given decreasing weights to distinguish the differences between them. The weight is given by the heuristic rank sum weighting method (RSWM). Specifically, the numerator of the weight of the latest observations is the total number of observations; conversely, the numerator of the weight of the oldest observation is 1. In addition, due to the modeling mechanism of the grey model, the residual of the first observation is fixed as 0; thus, the oldest observation here refers to the second observation, and the first observation is not given a weight. If the observations used to establish the model are n, then k is the ordinal number of the

observations, the value of which is larger to imply that the data are newer. Then, the weight formula of the RSWM is as Equation (11).

$$w(k) = \frac{k-1}{\sum_{i=1}^{n-1} i},\ k = 2, 3, \ldots, n \tag{11}$$

3. To determine the order, an objective function based on residuals is designed, as given by Equation (12). The value of the order is limited to the interval between 0 and 1. After an iterative operation, the order r that can minimize the objective function is found, based on which a model for trend prediction is established.

$$\text{Objective function} = \prod\nolimits_{k=2}^{n} w(k) \times AE(k) \tag{12}$$

3. Experimental Analysis

In the following sub-sections, the applicability and feasibility of the proposed procedure are verified by a practical case.

3.1. Data Description and Experimental Design

To evaluate the reliability of the proposed procedure, the revenue scale of the electronic commerce service industry in China released by the Ministry of Commerce of the People's Republic of China "http://www.mofcom.gov.cn/(accessed on 3 January 2024)" was selected as the experimental data. The annual observations from 2013 to 2022 (Table 1) were selected for analysis, and the measurement unit was one trillion Chinese Yuan. Electronic commerce has become a mainstream business model and plays an important role in promoting sustainable economic development. Under the influence of the coronavirus disease 2019 pandemic, electronic commerce has rapidly become an important component of people's lives due to its non-contact transaction characteristics. To create a good industrial environment for electronic commerce, it is essential to accurately predict the future development trend of electronic commerce. In the experiment, four observations were used to build a model to predict the next transaction volume. Specifically, data from 2013 to 2016 were used to build a model that predicted the transaction volume in 2017.

Table 1. Revenue scale of the electronic commerce service industry in China (unit: trillion Chinese Yuan).

Year	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Scale	0.43	1.25	1.98	2.45	2.92	3.52	4.47	5.45	6.40	6.79

3.2. Modeling Example

The first four observations were used as modeling examples to illustrate the details of the proposed procedure, i.e., a model based on the revenue scale data from 2013 to 2016 was established to predict the revenue scale in 2017. Specifically, $X^{(0)} = \{0.43, 1.25, 1.98, 2.45\}$ represents the initial data, and after multiple iterations to optimize the objective function, the fitting order $r = 0.0622$ was obtained, where a and b are 0.19220 and 1.04377, respectively. Therefore, the FGM was $\hat{x}^{(r)}(k+1) = -5.000692e^{-0.1922k} + 5.430692$, and the next output was predicted to be $\hat{x}^{(0)}(5) = 2.860$.

3.3. Comparison and Feasibility Measurement

To confirm the effectiveness of the proposed procedure, two popular grey models and two famous neural networks were selected for comparison; these methods are the GM, the discrete grey model (DGM), the radial basis function network (RBFN), and support vector regression (SVR). The GM is the most typical model in grey system theory and is characterized by convenient application [14]. The DGM proposed by Xie and Liu [22] is the discrete form of the GM and is currently one of the grey models with better prediction accuracy. The RBFN is frequently used in artificial networks; because this method can effectively process nonlinear data and generate prediction models [29], it has been widely used in various fields. Finally, SVR is a non-parametric estimation learning algorithm based on statistical learning theory, which is an alternative to the solution of training problems with limited data [29]. In the experiment, four observations were used for all methods to construct models to predict the next output.

A robust prediction method must be able to obtain accurate results. Therefore, it is necessary to use an error-based indicator to judge the reliability and effectiveness of the method, and only validated methods can be used for practical prediction problems [30,31]. Thus, the mean absolute percentage error (MAPE) was used to evaluate the modeling performance of the prediction methods. The MAPE is a relative indicator presented in percentage form and is not affected by differences in data units, which can help managers evaluate the potential risks of using different prediction methods. Its calculation formula is given by Equation (13), where A_t and F_t are the actual and predicted values, respectively.

$$MAPE = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \tag{13}$$

The experimental results are reported in Tables 2 and 3, which reveal that the proposed procedure produced good predictions. The MAPE of the FGM was 3.69%, which was slightly less than those of the other four models and fell within an acceptable predictive level as compared to the results reported in Table 4 [32]. Moreover, this value was less than that of the GM (6.72%), representing a 45.09% improvement in prediction performance. This result indicates that the proposed order determination procedure that considers the priority of new information can improve the prediction ability of the grey model and is a feasible small data set analysis tool.

Table 2. Actual and predicted values.

Year	Actual Values	Predicted Values				
		GM	DGM	FGM	RBFN	SVR
2017	2.92	3.365	3.408	2.860	2.599	3.046
2018	3.52	3.535	3.552	3.404	3.063	3.386
2019	4.47	4.198	4.216	4.198	3.866	3.856
2020	5.45	5.482	5.518	5.482	5.045	4.584
2021	6.40	6.746	6.791	6.527	5.952	6.012
2022	6.79	7.642	7.674	7.341	6.859	3.046

Table 3. MAPE of the various methods.

Methods	MAPE (%)
GM	6.72
DGM	7.28
FGM	3.69
RBFN	22.56
SVR	8.69

Table 4. MAPE criteria.

MAPE	Prediction Power
<10%	Accurate prediction
10–20%	Good prediction
20–50%	Reasonable prediction
>50%	Inaccurate prediction

3.4. Future Trend of the Revenue Scale in China's Electronic Commerce Service Industry

To effectively grasp the possible revenue scale of China's electronic commerce service industry, the latest four observations were also used to establish a model for trend prediction, based on which the possible values for the next four years were predicted. Table 5 exhibits the predicted revenue scale of China's electronic commerce service industry over the next few years, and Figure 1 displays the revenue trend of China's electronic commerce service industry in recent years. According to the prediction results, the revenue scale of China's electronic commerce service industry is expected to undergo steady growth from 2023 to 2026. Under this trend, the Chinese government should continue to invest in improving the operating environment of electronic commerce. In addition, the trend chart shows that the increase in revenue will gradually shrink in the future. To maintain the development momentum of the industry, enterprises should pay more attention to improving service quality, controlling costs, and increasing operating efficiency. The improvement of the electronic commerce transaction quality will not only enhance user experience but will also promote the market competitiveness of electronic commerce enterprises, thereby contributing to the positive economic growth of the country.

Table 5. Prediction of revenue scale for China's electronic commerce service industry.

Year	2023	2024	2025	2026
Predicted values	7.130	7.322	7.418	7.445

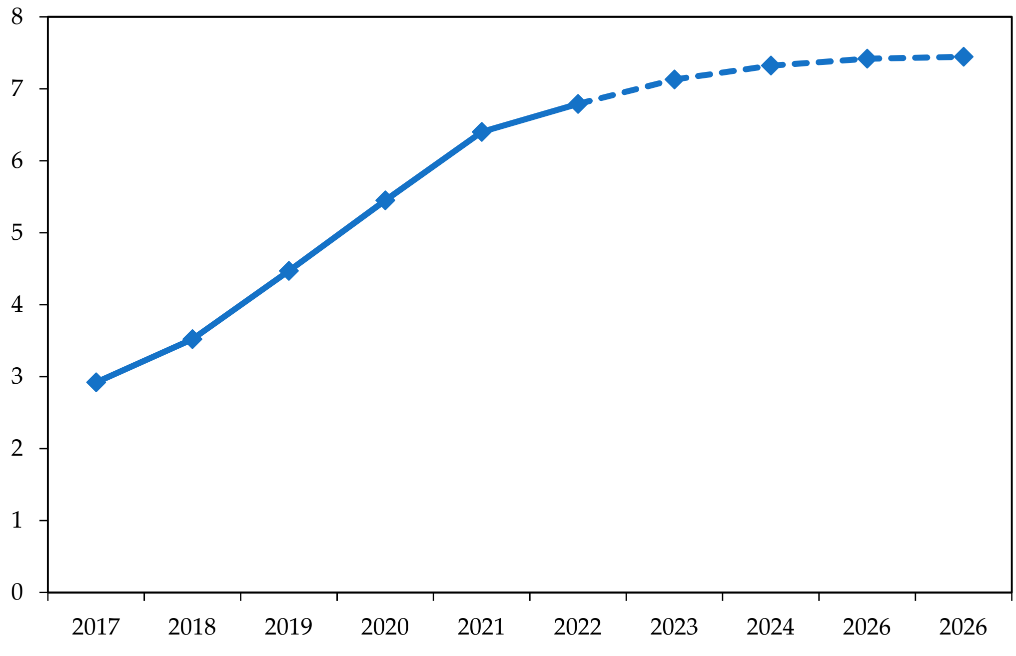

Figure 1. Revenue scale trend of China's electronic commerce service industry.

4. Conclusions and Discussion

Appropriate electronic commerce development planning is crucial for economic development, and the accurate prediction of the electronic commerce transaction volume is a necessary condition for the formulation of profit development strategies. Predictive analysis helps decision-makers grasp future development trends and reduces the impact of uncertainty, thereby aiding in meaningful policy planning. However, to ensure the relevance and effectiveness of electronic commerce policies, it is necessary to plan based on the latest information. Otherwise, if policies are out of touch with reality, industrial development may be negatively impacted. Therefore, a prediction method that is suitable for small amounts of data is significant for governments, industries, and enterprises.

Grey system theory is one of the main methods by which to deal with small data set analysis problems, and its research scope is consistent with the situation considered in the present work. Therefore, the FGM was chosen as the basis for predicting China's economic commerce transaction volume and was used in combination with the proposed heuristic order determination mechanism to improve the prediction efficiency of the traditional grey model. This order determination mechanism is based on minimizing the weighted error in consideration of the importance of new data, i.e., it strengthens the proportion of the influence of new data in the modeling process to fit a more robust prediction model. An experimental analysis revealed that the proposed procedure can yield more favorable prediction results. This method is thus applicable to the prediction of the economic commerce transaction volume in China and has important practical application value.

However, the research was characterized by some limitations. First, it only confirmed the performance of the FGM in small data set analysis, which cannot guarantee that the FGM is suitable for analysis based on other volumes of data. Furthermore, the proposed procedure only solves a specific forecasting problem, and whether it is applicable to other forecasting situations remains to be confirmed. Finally, this work focused on the prediction of time-series data but did not consider possible causal connections between variables. These factors that were not considered in the present analysis can be included in future investigations to increase the overall understanding of the research issue.

The proposed procedure holds promise for addressing prediction challenges in diverse fields. It is also possible to combine the proposed procedure with other data preprocessing methods to further improve its ability to deal with small data set problems. In addition, the development of an order determination mechanism based on the grey incidence degree is another feasible research direction. Finally, the proposed procedure can be expanded into a multivariate model to broaden its application scope.

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