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Dynamic Fractional-Order Grey Prediction Model with GWO and MLP for Forecasting Overseas Talent Mobility in China

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Abstract: International students play a crucial role in China's talent development strategy. Thus, predicting overseas talent mobility is essential for formulating scientifically reasonable talent introduction policies, optimizing talent cultivation systems, and fostering international talent cooperation. In this study, we proposed a novel fractional-order grey model based on the Multi-Layer Perceptron (MLP) and Grey Wolf Optimizer (GWO) algorithm to forecast the movement of overseas talent, namely MGDFGM(1,1). Compared to the traditional grey model FGM(1,1), which utilizes the same fractional order at all time points, the proposed MGDFGM(1,1) model dynamically adjusts the fractional-order values based on the time point. This dynamic adjustment enables our model to better capture the changing trends in the data, thereby enhancing the model's fitting capability. To validate the effectiveness of the MGDFGM(1,1) model, we primarily utilize Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) as the evaluation criteria for the prediction accuracy, as well as standard deviation (STD) as an indicator of the model stability. Furthermore, we perform experimental analysis to evaluate the predictive performance of the MGDFGM(1,1) model in comparison to NAÏVE, ARIMA, GM(1,1), FGM(1,1), LSSVR, MLP, and LSTM. The research findings demonstrate that the MGDFGM(1,1) model achieves a remarkably high level of prediction accuracy and stability for forecasting overseas talent mobility in China. The implications of this study offer valuable insights and assistance to government departments involved in overseas talent management.

Keywords: overseas talent; grey model; dynamic fractional order; GWO; MLP

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1. Introduction

1.1. Background

With the reform and opening-up policy, and the continued globalization of China's economy and the increasing importance of education within Chinese families, a notable rise in the number of individuals pursuing overseas studies can be observed [1,2]. In the context of fierce global competition for international talents and the tide of anti-globalization, an increasing number of overseas students have demonstrated their intention to return to their home country for development. Talents, especially high-level talents, are important for China's innovative development [3]. Their return to China significantly impacts technological advancement and economic development [4]. Therefore, attracting more overseas students to contribute to the development of the motherland has become an urgent focus for China's pursuit of high-quality development. It is worth noting that government departments and companies increasingly prioritize managing overseas talents, aiming to comprehensively understand their mobility patterns [5,6].

1.2. Overseas Talent Mobility Prediction

Accurate overseas talent prediction is essential for relevant decision-makers to understand the future trends in overseas talent mobility and develop appropriate policies. Specifically, it can be beneficial for government departments to understand the trends in talent mobility so that they can formulate and adjust policies related to studying abroad, introducing talent, and retaining talent [7]. In addition, understanding the trends in international talent mobility can work in favor of relevant organizations, universities, and enterprises in making effective plans for international exchanges and collaborations [8,9]. Furthermore, since most of the overseas study talent is a high-level talent, accurately predicting talent mobility can help relevant departments to plan the allocation of human resources effectively, thereby rationalizing industrial layouts and developing economic growth [3].

Currently, there are two main categories of research on overseas talent flow trends. In the first instance, some studies analyze the factors that drive talent flow [10], the factors affecting students' willingness to study abroad [11,12], and how to attract [7] and retain talent [13]. A second aspect is to develop models of talent mobility, although this field is relatively understudied.

In the field of overseas talent mobility prediction, the grey model is the most popular model. Based on the limited data available on the number of Chinese students studying abroad, Ke and Wu utilized the GM(1,1) model to establish a prediction model for the number of Chinese students studying abroad [14]. Li employed the GM(1,1) model to forecast Chinese overseas students' development trends [15]. For the prediction of Chinese overseas talent mobility, Ren and Jiang apply four form models of GM(1,1) to predict the number of students studying abroad and returned students [16]. Jiang et al. further proposed a fractional-order grey prediction model based on change-point detection [17]. Additionally, some scholars have applied statistical or machine learning models. For example, Feng and Yu utilized an ARIMA(2,2,2) model to predict the trend of Chinese talent mobility [18]. Olesia constructed five linear trend models based on the different destination countries for Ukrainian students studying abroad [19]. Yang and Duan developed a quadratic curve trend model for predicting the number of Chinese students studying abroad [20]. Yang et al. proposed a hybrid approach, FSDESVR, combining feature selection (FS) and support vector regression (SVR) with differential evolution (DE) for predicting the number of Taiwanese students studying abroad [21]. Bijak et al. compared multiple forecasting models, including AR, ARIMA, Bayesian models, and Autoregressive Distributed Lag (ADL) models. The research findings revealed that no single forecasting method could effectively suit different sets of forecast data [22]. Therefore, some scholars have used combined modeling to predict overseas talent mobility. For instance, Li proposes a combination model combining multiple linear regression, ARIMA, and support vector regression models, which outperformed individual forecasting models [23]. Hu constructs a combined model based on the L1 norm to build the GM(1,3) model and BP neural network model [24]. Also, Wei proposed a combined prediction model integrating GM(1,1) and BP neural networks [25].

Although combination models are superior to single models, single models serve as the foundation for forecast combination [26]. Currently, there are relatively few models for predicting the flow of overseas talent, making it still highly necessary to construct a single predictive model with high accuracy for forecasting the movement of overseas talent. Based on the above analysis, considering the good performance of the grey model in predicting the flow of overseas talent [8], as well as the complexity and limited sample size of China's overseas talent mobility, this paper aims to develop a new grey forecasting model for the flow of overseas talent in China, encompassing the number of Chinese students studying abroad and those returning to China.

1.3. Grey Models

1.3.1. Basic Principles of Grey Forecasting Models

The grey forecasting model is one of the main contents of grey system theory proposed for handling uncertain information [27]. Compared to statistical models requiring data to conform to statistical assumptions, machine learning models require a large sample size for fitting [28]. Grey prediction models achieve nonlinear mapping using a limited number of samples without requiring the data to possess any statistical assumptions [26]. Therefore, grey prediction models are widely used in energy, transportation, water conservancy, economy, tourism, and population [29–32]. The grey prediction model stands out from other prediction models due to its unique approach of utilizing data modeling through the accumulative generation operation (AGO), rather than directly estimating and modeling the original data [33]. The basic grey prediction model, GM(1,1), is primarily based on the first-order AGO (1-AGO). This method generates cumulative sequences, constructs difference models, and derives the final equation for the time response using the least squares method and the inverse 1-AGO [27].

In the GM(1,1) model, the first-order accumulation assigns equal weight to all time point data, which does not comply with the new information priority principle for grey forecasting models [27]. To address the problem of information priority in the accumulation sequence, Wu et al. proposed a grey forecasting model based on fractional-order accumulation, namely FGM(1,1) [34]. The weighting of data during the process of accumulation is influenced by the fractional order, r. As the value of r increases, the weight assigned to old data increases proportionally, while the weight assigned to new data decreases correspondingly, and vice versa [34]. Compared to the integer order, the fractional order can better reveal the intrinsic characteristics and behaviors of objects. Therefore, the grey prediction model based on fractional-order accumulation has gradually attracted the attention of researchers and has been applied in various fields [35–37].

1.3.2. Advancements in Fractional-Order Grey Prediction Models

Improving the forecasting accuracy of the FGM(1,1) model is a primary research focus that entails proposing various fractional-order forms [38–40], constructing prediction models with different fractional-order structures [41–44], investigating the optimal number of modeling samples [17,45], and integrating other optimization algorithms to determine the optimal fractional order of the model [28,39,46], among other approaches. Although existing research has conducted in-depth discussions on the fractional-order grey prediction model, almost all of them have used a fixed fractional-order value. As mentioned above, the fractional order assigns different weights to the accumulated data [34]. While the accumulated data grow over time, the weights determined by the fractional order are also likely to change in accordance with the growth of the data. Thus, the fractional-order values should be dynamically adjusted according to the development of the data. Although there have been several papers discussing the dynamic change in relevant parameters in response to changes in time to improve prediction accuracy [47,48], there is scarce literature exploring the relationship between the time points and the fractional order during the modeling process to adjust the fractional order dynamically. Therefore, we propose a novel FGM(1,1) model in which the fractional order is dynamically adjusted based on different time points.

There are two problems that must be solved in order to achieve a dynamic fractional order. The first is how to determine the fractional order for each time point, and the second is how to determine the fractional order for future time points.

For the first problem, the current method for determining fractional-order values is based on the metaheuristic algorithm [39], and the method is also used in this study in order to calculate the optimal dynamic fractional order. There is no doubt that dynamic fractional optimization with multiple values to optimize is more difficult and complex than fixed fractional-order optimization with only one parameter to optimize. The GWO algorithm has the characteristics of simplicity and flexibility and achieves a proper balance between global search and local optimization [49]. It has been proven to perform well in solving parameters for grey prediction models [39,50]. Therefore, the GWO algorithm is adopted to optimize and solve the dynamic fractional-order values for the proposed model.

For the second problem, we can construct a model based on dynamic fractional-order values and datasets, which can be used to predict future fractional orders. Due to the nonlinear relationship between the optimal fractional order determined by grey wolf optimization and the given dataset, this model should be a nonlinear model. Given that the MLP is renowned as a leading nonlinear time series prediction model for its proficiency in forecasting nonlinear time series [51], the MLP model was thus employed to predict the fractional-order values based on the given dataset.

Basically, this study aims to propose a dynamic fractional-order grey prediction model based on the GWO and MLP, namely MGDFGM(1,1), for the flow of overseas talent in China. The proposed MGDFGM(1,1) model features an adaptive fractional order that adjusts as the time series data changes. It employs the GWO to optimize the dynamic fractional order in order to create the most suitable fitting model, and the MLP to make predictions about future fractional-order parameters in order to prepare an ex-post forecast of overseas talent in China.

1.4. Contributions

The main contribution of this work is that we have proposed a novel grey model MGDFGM(1,1) with a dynamic fractional order based on the MLP and GWO. Compared to the traditional grey model FGM(1,1), which utilizes the same fractional order at all time points, the fractional-order values of MGDFGM(1,1) are dynamically adjusted with the change in the dataset. With the dynamic adjustment, MGDFGM(1,1) is better able to capture the changing trends in the dataset. In addition, the GWO is used in this study for optimizing the dynamic fractional-order values to build the best fitting model. The MLP is applied to predict the fractional-order values to make an ex-post forecast of overseas talents in China. Furthermore, this work takes the flow of Chinese overseas talents as the experimental subject. In comparing different statistical models, grey models, and artificial intelligence models, it is demonstrated that MGDFGM(1,1) has a high degree of predictive accuracy and good predictive stability for predicting Chinese overseas talent mobility, thus offering a novel approach to predict overseas talent mobility.

The remainder of this work is organized as follows. Section 2 introduces the FGM(1,1), GWO algorithm, and MLP method, as well as the proposed MGDFGM(1,1) model. Section 3 examines the proposed model for predicting the flow of overseas talent in China. Section 4 discusses the predictions of MGDFGM(1,1) compared to other grey model predictions and analyzes the advantages of the MGDFGM(1,1) model. The conclusion and future work are briefed in Section 5.

2. Methodology

2.1. FGM(1,1)

The modeling steps for the FGM(1,1) are as follows:

(1) Set $X^{(0)}$ as an original non-negative sequence:

$$X^{(0)} = (x_1^{(0)}, x_2^{(0)}, \cdots, x_n^{(0)}) \tag{1}$$

(2) Convert $X^{(r)}$ to the fractional-order accumulation sequence $X^{(r)}$ by Hausdorff r-order accumulated generating operation (r-AGO):

$$X^{(r)} = \sum_{i=1}^{k} [i^r - (i-1)^r] x_i^{(0)}, \quad k = 1, 2, \cdots, n \tag{2}$$

(3) Set $Z^{(r)}$ as an immediately adjacent mean generating the sequence of $X^{(r)}$

$$Z^{(1)} = 0.5 \times x_k^{(r)} + 0.5 \times x_{k-1}^{(r)}, \quad k = 2, 3, \cdots, n \tag{3}$$

(4) The fractional grey differential equation is constructed as

$$x_k^{(0)} + a \cdot z_k^{(r)} = b, \quad k = 2, 3, \cdots, n \tag{4}$$

(5) Estimate the parameters a and b by the least squares method

$$[a, b]^T = \left(B^T B\right)^{-1} B^T Y \tag{5}$$

where

$$B = \begin{bmatrix} -z_2^{(r)} & 1 \\ -z_3^{(r)} & 1 \\ \vdots & \vdots \\ -z_n^{(r)} & 1 \end{bmatrix}, \ Y = \begin{bmatrix} x_2^{(0)} \\ x_3^{(0)} \\ \vdots \\ x_n^{(0)} \end{bmatrix} \tag{6}$$

(6) Obtain the time response series of the grey differential equation,

$$\hat{x}_k^{(r)} = \left(x_1^{(0)} - \frac{b}{a}\right) \cdot e^{-a(k-1)} + \frac{b}{a}, \quad k = 2, 3, \cdots, n \tag{7}$$

(7) The final prediction value $x_k^{(r)}$ is obtained by reverse r-order AGO:

$$\hat{x}_k^{(0)} = \frac{\left(\hat{x}_k^{(r)} - \hat{x}_{k-1}^{(r)}\right)}{i^r - (i-1)^r}, \quad k = 2, 3, \cdots, n \tag{8}$$

The FGM(1,1) model follows the principle of prioritizing new information when r falls within the range of 0 to 1. The FGM(1,1) model is equivalent to the GM(1,1) model when r is equal to one [34].

2.2. GWO

The GWO algorithm is a metaheuristic optimization algorithm proposed by Mirjalili et al. in 2014, inspired by the social hierarchy and hunting behavior of grey wolves [52].

In the mathematical model of the GWO algorithm, α is considered as the optimal solution, followed by β, δ, and ω in order. The mathematical model equation is as follows:

$$\vec{D} = |\vec{C} \cdot \vec{X}_P(t) - \vec{X}(t)| \tag{9}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A} \cdot \vec{D} \tag{10}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{11}$$

$$\vec{C} = 2 \cdot \vec{r_2} \tag{12}$$

where $\vec{D}$ represents the distance between the grey wolves and the prey, $\vec{A}$ and $\vec{C}$ are vector parameters, $\vec{X}_P$ represents the current position vector of the prey, $\vec{X}$ represents the current position vector of the grey wolves, t denotes the current iteration number. $\vec{a}$ is the convergence factor, which linearly decreases from 2 to 0 during the iteration process. $\vec{r_1}$ and $\vec{r_2}$ are random vectors in the range [0,1].

During the hunting process, grey wolves can identify and surround the prey's location. Let us assume α, β, and δ know the potential prey's location. Based on α, β, and δ, the prey's location can be determined during the hunting process, assisting other grey wolves in updating their positions and gradually approaching the prey. The mathematical model for this phenomenon is expressed below:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|,\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|,\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \tag{13}$$

where $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ represent the distances between α, β, and δ and other grey wolves, respectively. $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ are the current positions of α, β, and δ. The grey wolves adjust their positions based on the three current best solutions, continuously approaching the prey. The average value is used as the new position update target. The formula is as follows:

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha,\ X_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta,\ \vec{X}_3 = \vec{X}_\alpha - \vec{A}_3 \cdot \vec{D}_\delta \tag{14}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{15}$$

When the prey stops moving, the grey wolves begin their attack. If $|\vec{A}| < 1$, then the grey wolves launch their attack. Otherwise, the grey wolves leave the prey and seek an optimal position. At the same time, in the model, C is a random number within the range of [0,2], and this randomness prevents the model from becoming trapped in local optimal solutions, thus obtaining the global optimal solution [53].

2.3. MLP

The MLP is a widely utilized feedforward artificial neural network [54]. The structure of a three-layer MLP comprises an input layer, a hidden layer, and an output layer. The input layer usually consists of a group of nodes through which data are fed into the network. The hidden layer also includes a group of nodes connected to all nodes in the input layer. These nodes apply activation functions to the input data, resulting in nonlinear transformations. The output layer typically contains a node connected to all nodes in the hidden layer, representing the potential output values of the MLP. The mathematical model of the MLP can be represented as:

$$\hat{Y} = \sum_{k=1}^{H} w_k^2 \cdot g(\sum_{j}^{d} w_{kj}^1 X_{i,j}) \tag{16}$$

where $\hat{Y}$ represents the predicted value, H is the number of hidden-layer nodes, d is the input vector dimension, $g(\cdot)$ represents the activation function, $w_{k,j}^1$ and w_k^2 are the weights from the input layer to the hidden layer and from the hidden layer to the output layer, respectively.

2.4. Proposed MGDFGM(1,1)

This study proposes a novel grey model MGDFGM(1,1) with a dynamic fractional order based on MLP and GWO. The main modeling process of MGDFGM(1,1) is as follows:

Step I: Establish a dynamic FGM(1,1). Dynamic parameter adjustment enhances the adaptability of the grey model and improves the accuracy of its predictions [47]; hence, we have established a grey prediction model with dynamic fractional-order parameter adjustment. In the traditional FGM(1,1), the fractional order r is the same at different time points during fractional-order accumulation [34]. However, in the proposed MGDFGM(1,1) model, the fractional order is associated with the actual values at different time points. The fractional order at each time point is denoted as r_j, where $j = 2, 3, \ldots, n$. Thus,

$$X^{(r_j)} = \textstyle\sum_{i=1,j=2}^{k} \left[i^{r_j} - (i-1)^{r_j} \right] x_i^{(0)},\ \ k = 1, 2, \cdots, n \tag{17}$$

The final prediction result can be obtained through a reverse dynamic fractional order,

$$\hat{x}_k^{(0)} = \frac{(\hat{x}_k^{(r_j)} - \hat{x}_{k-1}^{(r_{j-1})})}{i^{r_j} - (i-1)^{r_j}}, \quad k = 2,3,\cdots,n, \quad j = 2,3,\cdots,n \tag{18}$$

Step II: Solve the fractional order r_j. Implement the GWO algorithm to find the optimal r_j by minimizing MAPE as the loss function [39]. The obtained optimal r_j is then used to construct the fitting model in the dynamic FGM(1,1) model. We implement the GWO algorithm using the EvoloPy framework [49]. The GWO algorithm is configured with several search agents = 1000, the maximum number of iterative steps = 1000, and dim = 15. The operator search range is set between the highest value of 1 and the lowest value of 0. Therefore, r_j ranges from 0 to 1, following the principle of prioritizing new information in the proposed model [24].

Step III: Fractional-order prediction. Because the fractional order r_j is related to the data at the corresponding time point, it is not possible to solve the fractional order $r_{j+p} = \{r_{j+1}, r_{j+2}, \ldots, r_{j+p-1}\}$ of the prediction stage by the previous modeling stage. Here, p represents the number of prediction time points. Hence, the MLP method is employed to predict the fractional order r_{j+p} in the prediction stage. The input of the MLP is represented as $input_x = (x_0, x_1, \ldots, x_{n-1}, x_n, \hat{x}_{n+1}, \hat{x}_{n+2}, \ldots \hat{x}_{n+p-1})^T$, and the corresponding output is denoted as $output_r = (r_1, r_2, \ldots, r_j, \hat{r}_{j+1}, \hat{r}_{j+2}, \ldots, \hat{r}_{j+p-1})^T$. Here, $\{\hat{x}_{n+1}, \hat{x}_{n+2}, \ldots \hat{x}_{n+p-1}\}$ represent the predicted values of the case data, and $\{\hat{r}_{j+1}, \hat{r}_{j+2}, \ldots, \hat{r}_{j+p-1}\}$ denote the predicted values of the fractional order. The MLP consists of an input layer, a hidden layer, and an output layer, implemented using Python. The optimal parameters of the MLP are determined using grid search with time series five-fold cross-validation. The "lbfgs" solver is used to optimize the weights. The activation functions can be "identity", "logistic", "tanh", or "relu"; the number of nodes in the hidden layer are set from 2 to 12; the maximum number of iterations are set to 3000.

Step IV: Future value prediction. Bring the fractional-order predicted value obtained in the previous step into the dynamic FGM(1,1) model to obtain the future predicted values.

Based on the above steps, we refer to the dynamic fractional-order grey model that combines the MLP and GWO as MGDFGM(1,1). When all the fractional orders in MGDFGM(1,1) have the same value, MGDFGM(1,1) is equivalent to FGM(1,1). When all the fractional orders equal 1, MGDFGM(1,1) is equivalent to GM(1,1).

The proposed MGDFGM(1,1) model was compared with several forecasting models, including the classic and commonly used time series forecasting models NAÏVE and ARIMA [55], as well as the basic grey models GM(1,1) and FGM(1,1) [34], and three AI-based models, least squares support vector regression (LLSVR) [56], MLP [54], and long short-term memory networks (LSTM) [57], to demonstrate its superior performance. This study adopts NAÏVE as the baseline model for predicting overseas talent mobility. Compared to other models, Naïve forecasting is easier to implement and does not require any parameter optimization. Suppose more complex models perform worse than the Naïve model regarding the prediction performance. In this case, they cannot provide more useful information and are not recommended as predictive models for overseas talent mobility.

2.5. Model Evaluation Criteria

The MAPE is a widely used method for evaluating the prediction accuracy of grey models and is commonly employed to assess the overall performance of models [27,39]. However, relying solely on the MAPE as a performance metric may present certain risks [58]. Therefore, we also included the RMSE, another widely used metric for providing a comprehensive evaluation of model performance [59]. A lower value of the MAPE and RMSE signifies an enhanced predictive accuracy of the model. The respective formulas for the MAPE and RMSE are as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{20}$$

According to the MAPE accuracy criterion [60], a model is deemed to have a high prediction accuracy if the error is below 10%, indicating its suitability for prediction, as shown in Table 1.

Table 1. Accuracy criteria for prediction models (MAPE).

MAPE	Prediction Accuracy
<10%	High
10%~20%	Good
20%~50%	Reasonable
≥50%	Inaccurate

This study applies STD as a measure to test the stability of the models utilized in this paper [30] as follows:

$$STD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(APE_i - MAPE_i)^2} \tag{21}$$

$$APE = \left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \tag{22}$$

3. Empirical Results

3.1. Data Description

The main data used in this study include the number of Chinese students studying abroad and returning to China, which are the two most important predictors for predicting overseas talent mobility. This period covers 2000 to 2019 due to the constraints of data availability. The dataset is from the National Bureau of Statistics of China (https://data.stats.gov.cn/easyquery.htm?cn=C01). Figure 1 presents the dataset employed in this study. Over the past decade, a noteworthy upsurge in the number of Chinese students pursuing education abroad and those repatriating to China has occurred.

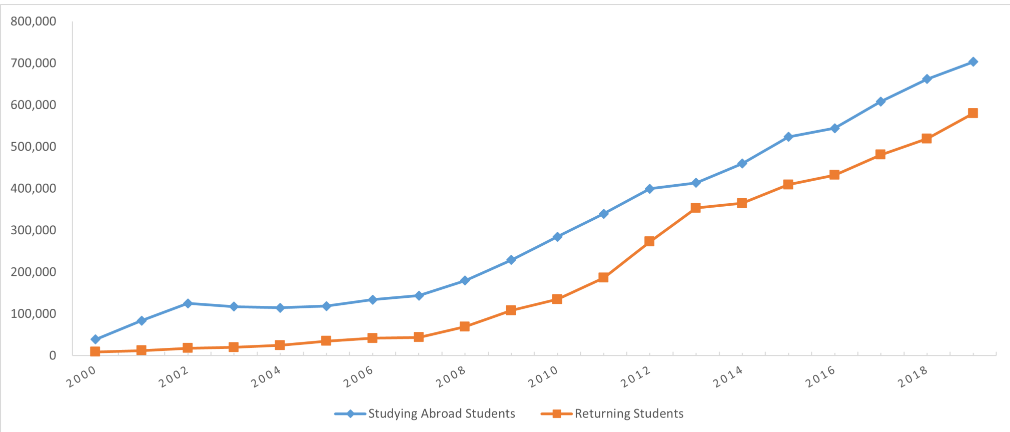

Figure 1. Time series chart of overseas talent mobility (unit: person).

3.2. Experiment 1: Students Studying Abroad

Experiment 1 focuses on forecasting the number of students studying abroad. International students are chosen as the subject of study. The model is constructed using data from 2000 to 2016, and data from 2017 to 2019 are used to validate the predictive accuracy of the model. The specific calculation process using MGDFGM(1,1) in Experiment 1 is as follows.

The number of students studying abroad from 2000 to 2016 is the original sequence $X^{(0)}$:

$$\begin{aligned} X^{(0)} = \; & \{38989, 83973, 125179, 117307, 114682, 118515, 134000, 144000, 179800, \\ & 229300, 284700, 339700, 399600, 413900, 459800, 523700, 544500\} \end{aligned}$$

The GWO algorithm is used to optimize the fractional order of MGDFGM(1,1). After computation, the optimal order r_j is determined to be

$$\begin{aligned} r_j = \; & \{0.980, 0.822, 0.902, 0.947, 0.964, 0.946, 0.948, 0.902, 0.853, \\ & 0.815, 0.790, 0.770, 0.783, 0.777, 0.765, 0.777\} \end{aligned}$$

The corresponding accumulated sequence $X^{(r_j)}$ for the order r_j is

$$\begin{aligned} X^{(r_j)} = \; & \{81695, 87526, 93575, 100251, 107588, 114628, 122791, 131424, \\ & 140505, 150460, 160492, 172243, 184142, 196908, 210520, 226883\} \end{aligned}$$

Based on Formulas (5) and (6), parameters $\hat{a} = -0.068$ and $\hat{b} = 76312.322$ are obtained through the least squares method. Therefore, it can be concluded that

$$\hat{x}_k^{(r_j)} = (38989 + 1126421.153) \cdot e^{0.068 \cdot (k-1)} - 1126421.153, \; k, j = 2, 3, \cdots, n$$

Based on the above time response function, the inverse dynamic fractional order is used to calculate the fitting and predicted value $\hat{X}^{(0)}$.

$$\begin{aligned} \hat{x}_k^{(0)} = \; & \{83967.069, 125020.636, 117267.275, 114508.774, 117995.736, 133996.322, \\ & 143845.767, 179572.535, 229223.394, 284402.673, 340433.924, 399299.278, \\ & 413978.612, 460217.472, 524650.823, 541626.080\} \end{aligned}$$

Finally, using the MLP method for the fractional-order prediction of the next three years, we obtain $r_{j+t} = \{0.782, 0.786, 0.790\}$, and thus, the final predicted values for 2017 to 2019 are $\hat{x}_{k+t}^{(0)} = \{576005.079, 614179.827, 652201.177\}$.

Table 2 shows the predicted results of MGDFGM(1,1) and the comparative models. Figures 2 and 3 represent the predicted performance of all the considered models during the fitting and forecasting stages of Experiment 1, respectively.

During the model fitting stage, all the considered models demonstrated higher prediction accuracy compared to the naive model. However, only the ARIMA, MGDFGM(1,1), and MLP models achieved high prediction accuracy, with MAPE values less than 10%. In comparison, the prediction accuracy of the other models was considered good, with MAPE values ranging from 10% to 20%. In terms of prediction stability, the stability of the other seven models is also superior to that of the NAÏVE model. Therefore, considering the prediction accuracy and stability, the MGDFGM(1,1), ARIMA, and MLP models can be used as fitting models for the number of students studying abroad. However, the MGDFGM(1,1) model outperforms the other models in both aspects.

During the model forecasting stage, the ARIMA, GM(1,1), FM(1,1), and MLP models have a lower accuracy compared to the NAÏVE model. Among these models, the GM(1,1) model exhibits the lowest prediction accuracy and stability. Therefore, the traditional grey prediction models GM(1,1) and FGM(1,1) are not suitable for predicting the number of students studying abroad. In contrast, LSSVR, LSTM, and the proposed MGDFGM(1,1) model demonstrate superior prediction accuracy compared to the naive model, achieving a high level of precision. Specifically, the MGDFGM(1,1) model showcases the highest prediction accuracy. Moreover, regarding the model stability, the STD value of MGDFGM(1,1) is 0.915%, which is smaller than other models, indicating the highest level of prediction stability. Therefore, compared to the other comparative models, MGDFGM(1,1) demonstrates greater suitability for predicting the number of students studying abroad.

Table 2. Comparison results of Experiment 1.

Year	Raw Data	NAÏVE	ARIMA	GM(1,1)	FGM(1,1)$^{0.996}$ *	MGDFGM(1,1)	LSSVR	MLP	LSTM
2000	38,989		38,972	38,989	38,989	38,989			
2001	83,973	38,989	83,925	84,348	83,973	83,967			71,366.6
2002	125,179	83,973	128,957	96,053	95,786	125,021			112,968
2003	117,307	125,179	166,385	109,382	109,181	117,267	121,492		152,380
2004	114,682	117,307	109,435	124,561	124,407	114,509	146,178	131,131	144,757
2005	118,515	114,682	112,057	141,846	141,727	117,996	154,107	135,170	142,203
2006	134,000	118,515	122,348	161,530	161,437	133,996	152,883	134,678	145,932
2007	144,000	134,000	149,485	183,945	183,871	143,846	162,169	156,904	160,957
2008	179,800	144,000	154,000	209,471	209,408	179,573	174,756	163,657	170,785
2009	229,300	179,800	215,600	238,538	238,477	229,223	203,112	216,073	206,504
2010	284,700	229,300	278,800	271,640	271,570	284,403	247,008	269,823	257,169
2011	339,700	284,700	340,100	309,335	309,245	340,434	306,115	330,792	315,399
2012	399,600	339,700	394,700	352,261	352,135	399,299	369,108	386,585	374,476
2013	413,900	399,600	459,500	401,143	400,964	413,979	432,742	449,600	439,746
2014	459,800	413,900	428,200	456,809	456,553	460,217	471,384	437,233	455,448
2015	523,700	459,800	505,700	520,200	519,840	524,651	509,673	505,371	506,007
2016	544,500	523,700	587,600	592,387	591,889	541,626	552,778	569,180	576,499
2017	608,400	544,500	565,300	674,591	673,915	576,005	583,651	568,450	599,465
2018	662,100	608,400	586,100	768,203	767,298	614,180	610,998	600,414	603,235
2019	703,500	662,100	606,900	874,805	873,611	652,201	629,872	629,747	607,004
fit-MAPE		14.926%	7.086%	10.385%	10.365%	**0.140%**	10.288%	6.560%	11.004%
fit-RMSE		39,040.076	22,790.422	25,839.728	25,809.518	**808.903**	23,765.415	18,291.157	22,414.081
fit-STD		12.831%	9.509%	8.414%	8.435%	**0.144%**	8.665%	4.060%	7.811%
pre-MAPE		8.166%	10.765%	17.085%	16.946%	**6.618%**	7.417%	8.789%	8.025%
pre-RMSE		53,792.379	75,200.111	122,453.680	121,513.661	**44,636.843**	53,681.188	60,112.866	65,463.477
pre-STD		1.886%	2.760%	5.550%	5.526%	**0.915%**	2.621%	1.642%	5.038%

* The optimal fractional order of FGM(1,1) is 0.996. The bold font values represent the optimal results.

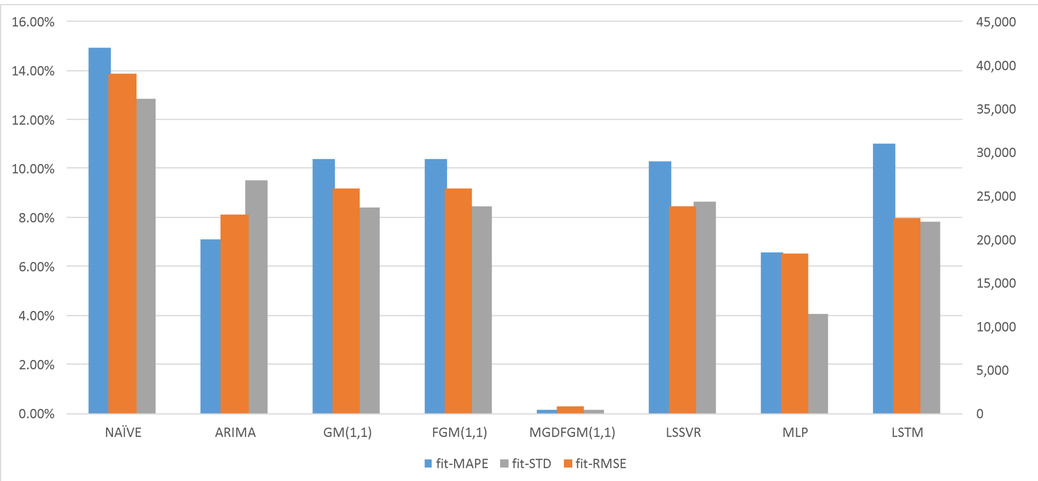

Figure 2. The predicted performance of all considered models during the fitting stages of Experiment 1.

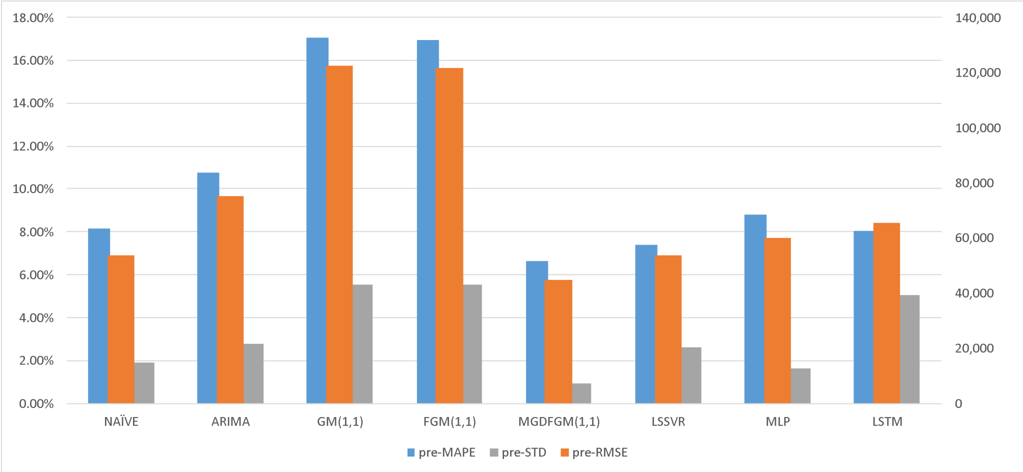

Figure 3. The predicted performance of all considered models during the forecasting stages of Experiment 1.

Figure 4 displays the trend prediction graphs of all the considered models to highlight the disparities in trend prediction among the models. During the fitting stage, all the models demonstrate highly accurate predictions that align closely with the actual values. However, in the prediction stage, the GM(1,1) and FGM(1,1) models produce overestimated predictions that deviate noticeably from the actual value curve. Conversely, the predicted values of the other six models are lower than the actual values, and the MGDFGM(1,1) curve exhibits the closest resemblance to the actual value curve. The predicted value curve of MGDFGM(1,1) demonstrates greater proximity to the actual value curve compared to the other comparative models in both the fitting and prediction stages.

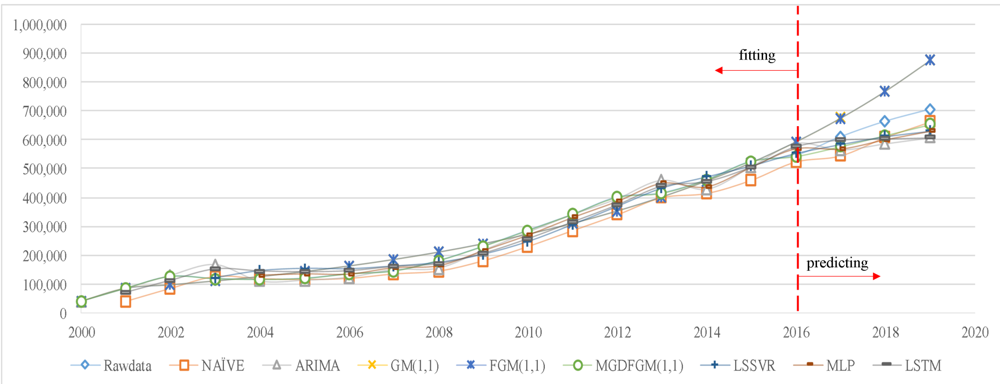

Figure 4. The trend of actual and predicted values in Experiment 1 (unit: person).

In summary, based on the comprehensive comparative analysis of the model accuracy (MAPE and RMSE), model stability (STD), and model trend, it can be inferred that the proposed MGDFGM(1,1) model outperforms the non-grey models NAÏVE, ARIMA, LSSVR, MLP, and LSTM, as well as the grey models GM(1,1) and FGM(1,1) in predicting the number of students studying abroad. Hence, the proposed MGDFGM(1,1) proves to be an effective forecasting tool for the number of students studying abroad.

3.3. Experiment 2: Returned Overseas Students

Experiment 2 uses the number of returned overseas students for prediction to further validate the effectiveness of MGDFGM(1,1) in forecasting overseas talent mobility. The modeling and prediction process in Experiment 2 is similar to Experiment 1, using data from 2000 to 2016 to build the model, while data from 2017 to 2019 are used to validate the accuracy of the model's predictions.

Using the GWO to optimize the order of the model, the calculated optimal order r_j is

$$r_j = \{0.984, 0.874, 0.911, 0.901, 0.840, 0.841, 0.883, 0.798, 0.724, 0.715, 0.680, 0.631, 0.615, 0.651, 0.665, 0.693\}$$

Thus, the obtained time response function is

$$\hat{x}_k^{(r_j)} = (9121 + 61252.834) \cdot e^{0.157\cdot(k-1)} - 61252.834, \quad k, j = 2, 3, \cdots, n$$

We employed the MLP method for predicting the scores in the fractional order for the upcoming three years. The results revealed the values of r_{j+t} = {0.690, 0.724, 0.729}. Utilizing these outcomes, we derived the final projected values for the years 2017 to 2019 as $\hat{x}_{k+t}^{(0)} = \{520592.059, 535105.655, 621055.795\}$.

Table 3 presents the predicted results of the MGDFGM(1,1) model and the comparison models for the number of returned overseas students. Figures 5 and 6 represent the predicted performance of all the considered models during the fitting and forecasting stages of Experiment 2, respectively. For the fitting and forecasting data, the MGDFGM(1,1) model demonstrates lower MAPE and RMSE values compared to the other seven comparison models. Regarding model stability, the MGDFGM(1,1) model is slightly inferior to NAÏVE only during the prediction stage but exhibits the highest stability in all other scenarios.

Table 3. Comparison results of Experiment 2.

Year	Raw Data	NAÏVE	ARIMA	GM(1,1)	FGM(1,1)$^{0.068}$ *	MGDFGM(1,1)	LSSVR	MLP	LSTM
2000	9121		9117	9121	9121	9121			
2001	12,243	9121	12,248	34,537	6789	12,241			
2002	17,945	12,243	15,365	42,486	12,794	17,970			
2003	20,152	17,945	23,647	52,263	20,152	20,132		19,127	
2004	24,726	20,152	22,359	64,291	29,216	24,722	44,202	24,340	37,403
2005	34,987	24,726	29,300	79,087	40,354	35,090	50,551	35,501	45,467
2006	42,000	34,987	45,248	97,288	53,991	42,024	60,850	42,709	55,631
2007	44,000	42,000	49,013	119,678	70,622	44,011	70,737	51,589	65,230
2008	69,300	44,000	46,000	147,221	90,830	69,448	79,232	68,560	78,745
2009	108,300	69,300	94,600	181,102	115,304	108,317	100,032	101,068	97,266
2010	134,800	108,300	147,300	222,781	144,852	134,715	133,752	136,911	119,511
2011	186,200	134,800	161,300	274,052	180,425	185,155	169,655	180,479	153,151
2012	272,900	186,200	237,600	337,123	223,145	271,950	224,884	277,007	212,751
2013	353,500	272,900	359,600	414,708	274,327	350,066	302,361	353,513	282,737
2014	364,800	353,500	434,100	510,149	335,519	360,460	378,376	364,754	351,406
2015	409,100	364,800	376,100	627,554	408,538	407,814	418,206	409,247	420,185
2016	432,500	409,100	453,400	771,979	495,512	431,939	444,275	432,387	472,462
2017	480,900	432,500	455,900	949,642	598,942	520,592	450,457	428,860	500,388
2018	519,400	480,900	479,300	1,168,190	721,753	535,106	454,004	456,216	471,904
2019	580,300	519,400	502,700	1,437,040	867,375	621,056	446,190	455,069	460,205
fit-MAPE		20.69%	11.31%	98.29%	19.20%	**0.28%**	23.17%	2.93%	20.96%
fit-RMSE		37,402.22	23,277.02	120,732.29	30,798.67	**1471.37**	23,955.40	3448.65	31,584.52
fit-STD		10.89%	7.87%	53.73%	16.07%	**0.34%**	24.49%	4.40%	14.99%
pre-MAPE		9.32%	8.76%	123.34%	37.66%	**6.10%**	14.01%	14.86%	11.30%
pre-RMSE		50,111.94	52,455.60	676,917.27	213,925.81	**34,074.24**	87,918.34	86,377.43	75,406.59
pre-STD		**1.36%**	3.42%	20.51%	10.22%	2.23%	6.92%	4.79%	6.96%

* The optimal fractional order of FGM(1,1) is 0.068. The bold font values represent the optimal results.

Figure 7 displays the fitting and forecasting trends of all the considered models for the number of returned overseas students to highlight the differences in model prediction trends. The GM(1,1) model exhibits a significant deviation from the actual values even during the fitting stage. Although the FGM(1,1) model shows a relatively small deviation from the actual values during the fitting stage, it surpasses the actual value curve during the forecasting stage. On the other hand, the NAÏVE, ARIMA, LSSVR, MLP, LSTM, and MGDFGM(1,1) curves closely align with the actual value curve. The MGDFGM(1,1) curve consistently overestimates the values compared to the actual curve, while the other five models consistently underestimate the values. Additionally, the MGDFGM(1,1) curve most closely follows the actual value curve.

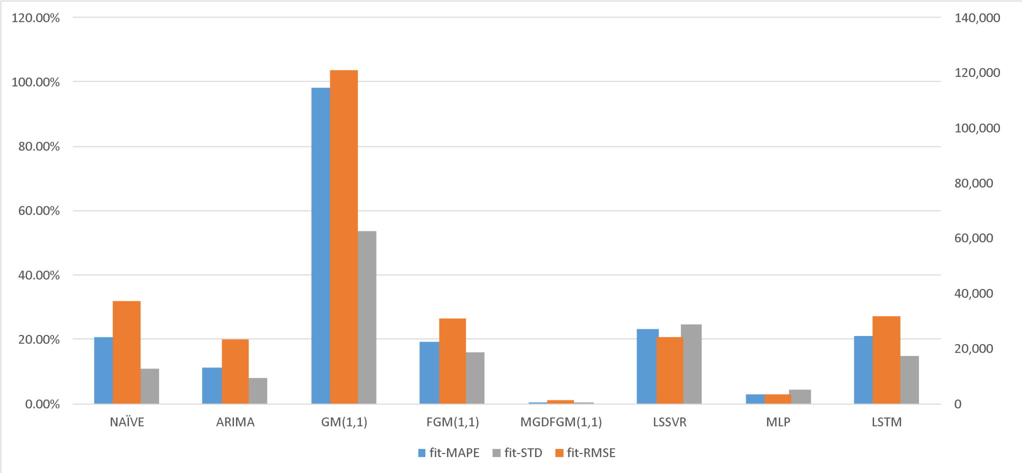

Figure 5. The predicted performance of all considered models during the fitting stages of Experiment 2.

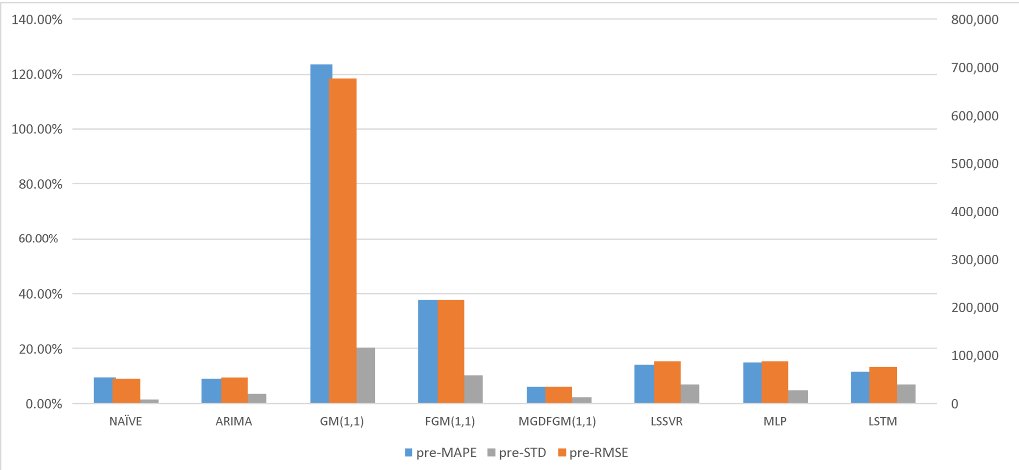

Figure 6. The predicted performance of all considered models during the forecasting stages of Experiment 2.

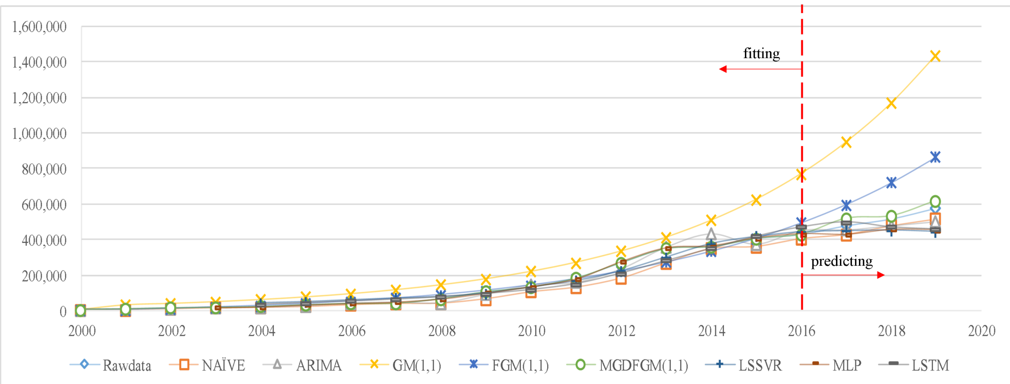

Figure 7. The trend of actual and predicted values in Experiment 2 (unit: person).

The comprehensive comparative analysis combining the model accuracy (MAPE and RMSE), model stability (STD), and model trend indicates that the proposed MGDFGM(1,1) model outperforms the other comparative models in predicting the number of returned overseas students. Therefore, the MGDFGM(1,1) model is shown to be effective in forecasting the count of returned overseas students.

4. Discussion

The results of Experiments 1 and 2 demonstrate that using a dynamic fractional-order grey forecasting model can effectively improve the prediction accuracy of grey forecasting models. In Experiment 1, compared to GM(1,1) and FGM(1,1), MGDFGM(1,1) has improved the MAPE values by 61.264% and 60.946%, and the RMSE values by 63.548% and 63.266%, respectively, elevating the prediction level from good to high accuracy. In Experiment 2, the performance of GM(1,1) in fitting and predicting the returnee students is poor, especially with an MAPE value exceeding 100% in the prediction stage. Although FGM(1,1) improved the prediction accuracy through the optimized fractional order ($r = 0.068$), it still falls short of the desired level and is only considered acceptable. However, with the dynamic accumulation of the fractional order based on the MLP and GWO, the grey prediction model significantly improved the accuracy of predicting returnee students. Compared to GM(1,1) and FGM(1,1), MGDFGM(1,1) has increased the MAPE values by 95.054% and 83.801%, and the RMSE values by 94.966% and 84.072% respectively, elevating the prediction accuracy from acceptable to high. Additionally, from the perspective of model stability, whether in the fitting or prediction stage, the MGDFGM(1,1) model remained stable compared to GM(1,1) and FGM(1,1). Therefore, the proposed dynamic fractional-order model can significantly enhance the prediction accuracy and stability of the grey prediction model.

The proposed MGDFGM(1,1) model has the following advantages compared to other traditional grey models: (1) The implementation of dynamic fractional-order accumulation enables the fitting of distinct trends within the data, enhancing the modeling capability with greater flexibility. (2) The model demonstrates high superiority in prediction accuracy and stability. However, the model still has some limitations, such as the need for assistance from other models for fractional-order prediction in the forecasting stage. In this study, the MLP is utilized for prediction, increasing the model's complexity.

5. Conclusions

As a critical high-quality human resource, effective management of overseas talents is crucial for China's talent strategy and labor internationalization. The accurate prediction of the flow of overseas talents can assist the government and enterprises in formulating more effective policies for talent attraction and retention, maximizing the potential of talents, and promoting sustainable economic and social development. Applying a univariate grey forecasting model is suitable given the limited data and unclear influencing factors in this study. We have introduced a dynamic fractional-order grey forecasting model, MGDFGM(1,1), for predicting the flow of overseas talent in China. In this model, the GWO method is used for fractional-order optimization, and the MLP model is employed for predicting the fractional order. The model exhibits exceptional accuracy in forecasting both studying abroad and returning to study in China, achieving an MAPE value below 7% and stability below 3%, outperforming other comparative models. Therefore, we can conclude that the proposed MGDFGM(1,1) is suitable for predicting the flow of overseas talent in China. In addition, the proposed fractional-order dynamic optimization method can improve the prediction accuracy of the traditional grey model by at least 60% in the case studies of this paper. Therefore, dynamically adjusting the fractional-order accumulation to enhance the prediction accuracy of the grey model has been proven to be effective.

Due to the impact of COVID-19, the Chinese government has not yet released data on the number of international students and returning personnel for 2020 and beyond. This lack of data poses significant challenges and opportunities for predicting the return of overseas talents. The focus of the research lies in obtaining data from recent years or using alternative indicators for forecasting the flow of overseas talent. Although some studies have explored factors influencing the flow of overseas talent, a consensus has not been reached. Therefore, this study adopts a univariate forecasting model to mitigate the influence of other factors on the model. However, exploring multivariate forecasting models that incorporate relevant influencing factors in predicting the flow of overseas talent would be a meaningful step. Therefore, a key research direction in the future will be the development of a multivariable grey forecasting model that incorporates the influence of exogenous variables on the flow of overseas talent.

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Conflicts of Interest: The authors declare no conflicts of interest.

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