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*Research Article*

# Estimation of the Student Employment in the Aviation Industry Based on Novel Fractional Error Accumulation Grey Model

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To improve the employment forecasting accuracy of traditional grey models, the grey model with the fractional error accumulation is proposed. The estimation error is accumulated. The proposed model can make use of the initial value $x(1)$ and can give more attention to the error of new data. The monotonicity of the simulative value by the proposed model is data-driven and uncertain. The comparison results show that the proposed model can enhance the forecasting accuracy of traditional grey model. It deserves to be applied to employment forecasting.

## 1. Introduction

High-quality personnel are very important for the entire aviation industry. Based on the investigation and analysis of the university student employment in the aviation industry, the training countermeasures, the curriculum system, and the improvement of teaching methods can be worked out. Therefore, it is essential to predict the university student employment of a school in the aviation industry. The methods of forecasting employment can be divided into two kinds: qualitative forecasting and quantitative forecasting [1]. At present, the forecast of the future human resource demand is analyzed from the quantitative point of view, such as the multiple regression model [2], the grey forecast model, and the neural network model [3]. Because the student employment in the aviation industry is a complex grey system, the influencing factors are uncertain and variable. In this paper, the grey model is used to predict the student employment in aviation industry for a university.

Due to the limitation of cost and time, it is difficult to obtain the adequate information in many forecasting scenarios [4, 5]. To address this problem, Deng Julong put forward the grey system theory in 1982 [6, 7]. To enhance the predictive accuracy of the traditional grey forecasting models, the grey model has been developed. The review of previous studies is listed in Table 1.

However, the methods mentioned above cannot give larger weight to the new information than that of the old information, and cannot get rid of the limitation of the development coefficient in the grey forecast model. In this paper, considering the memory superiority of fractional order accumulation [22–28], the fractional error accumulation grey model (FAGM(1, 1)) is proposed to give larger weight to the new information than that of the old information. The recent data can reflect the recent situation. The future employment situation is very similar to the recent information. Thus, the employment prediction must give more attention to the recent data. The real cases also demonstrated that FAGM(1,1) can obtain accurate forecasting results.

The rest of this paper is as follows. The FAGM(1,1) model is put forward in Section 2. The monotonicity and the effectiveness of the initial value by FAGM(1,1) is proved. Its new information priority is discussed. The validity of the FAGM(1,1) model is demonstrated in Section 3. The employment data of students in two universities are selected to explain the application of FAGM(1,1) in Section 4. The conclusion is given in Section 5.

## 2. FAGM(1, 1) and Its Properties

In most cases, the larger the weight of new information, the better the forecasting results of the grey model. A non-negative sequence is $X = \{x(1), x(2), \cdots, x(n)\}$. For the model,

$$x(k+1) = ax(k) + b. \tag{1}$$

To estimate the parameters $a$ and $b$ and pay more attention to recent data in the meantime, we put forward the definition.

*Definition 1.* For the actual data, $\varepsilon_i\,(i = 1, 2, \cdots, n-1)$ is the error. We can obtain

$$\begin{gathered} x(2) = ax(1) + b + \varepsilon_1, \\ x(3) = ax(2) + b + \varepsilon_2, \\ M, \\ x(n-1) = ax(n-2) + b + \varepsilon_{n-2}, \\ x(n) = ax(n-1) + b + \varepsilon_{n-1}. \end{gathered} \tag{2}$$

To frequently use the error of new data, we can obtain

$$\begin{gathered} \sum_{i=2}^{n} x(i) = a\sum_{i=1}^{n-1} x(i) + (n-1)b + \sum_{i=1}^{n-1} \varepsilon_i, \\ \sum_{i=3}^{n} x(i) = a\sum_{i=2}^{n-1} x(i) + (n-2)b + \varepsilon_2 + \sum_{i=2}^{n-1} \varepsilon_i, \\ x(n-1) + x(n) = a[x(n-2) + x(n-1)] + 2b + \varepsilon_{n-2} + \varepsilon_{n-1}, \\ x(n) = ax(n-1) + b + \varepsilon_{n-1}. \end{gathered} \tag{3}$$

Equation (3) is called the one-order error accumulation. Similarly, we can give the two-order error accumulation. Without loss of generality, the FAGM(1, 1) with the fractional r-order error accumulation is

$$\begin{aligned} &\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} x(k+1) \\ &= a\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} x(k) + b\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} + \sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} \varepsilon_k, \quad i = 1, 2, \cdots, n-1. \end{aligned} \tag{4}$$

From Equation (3), we can see that all equations can memorize the error $\varepsilon_{n-1}$, and only $\sum_{i=2}^{n} x(i) = a\sum_{i=2}^{n-1} x(i) + (n-1)b + \sum_{i=2}^{n-1} \varepsilon_i$ can memorize the error $\varepsilon_1$. Thus, the bigger $r$ can give more weight to the error of new data. To give more weight to the new information, its modelling process is as follows.

*Step 1.* For the $r$-order error accumulation $\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} \varepsilon_k$, positive error and negative error may be neutralized. The neutralized error may be smaller than the error of the positive error and negative error, because the error $\varepsilon_i\,(i = 1, 2, \cdots, n-1)$ may be negative, and the error $\varepsilon_i\,(i = 1, 2, \cdots, n-1)$ may be positive. Therefore, the FAGM (1, 1) model is written as

$$\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} x(k+1) = a\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i} x(k) + b\sum_{k=i}^{n-1} \binom{k+r-i-1}{k-i}, \quad i = 1, 2, \cdots, n-1. \tag{5}$$

$r$ is a fraction. When $r = 1$, FAGM (1, 1) model is [29]

$$\sum_{k=i}^{n-1} x(k+1) = a\sum_{k=i}^{n-1} x(k) + b(n-i), \quad i = 1, 2, \cdots, n-1. \tag{6}$$

To minimize the sum of the squared residuals, the unknown parameters, $\hat{a}, \hat{b}$, is solved by the following least squares estimation:

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = \left(D^T D\right)^{-1} D^T Y, \tag{7}$$

where

$$D = \begin{bmatrix} \sum_{k=1}^{n-1}\binom{k+r-2}{k-1}x(k) & \sum_{k=1}^{n-1}\binom{k+r-2}{k-1}k \\ \sum_{k=1}^{n-2}\binom{k+r-3}{k-i}x(k) & \sum_{k=1}^{n-2}\binom{k+r-3}{k-i}k \\ \vdots & \vdots \\ x(n-1) & 1 \end{bmatrix},$$

$$Y = \begin{bmatrix} \sum_{k=2}^{n}\binom{k+r-2}{k-i}x(k) \\ \sum_{k=3}^{n-1}\binom{k+r-3}{k-i}x(k) \\ \vdots \\ x(n) \end{bmatrix}. \quad (8)$$

*Step 2.* For $X = \{x(1), x(2), \cdots, x(n), \cdots\}$, the predictive sequence is

$$\widehat{X} = \{\widehat{x}(1), \widehat{x}(2), \cdots, \widehat{x}(n), \widehat{x}(n+1), \cdots\}, \quad (9)$$

where $\widehat{x}(k+1) = \widehat{a}x(k) + \widehat{b}$, $\widehat{x}(1) = x(1)$, $\widehat{x}(k)$ is the fitting value at time $k$.

*Step 3.* The mean absolute percentage error (MAPE) and root mean square error (RMSE) are the performance criteria of the model, where

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{\widehat{x}(k) - x(k)}{x(k)}\right| \times 100\%,$$

$$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^{n}[\widehat{x}(k) - x(k)]^2}{n}}. \quad (10)$$

The forecasting function of FAGM(1, 1) is $\widehat{x}(k+1) = \widehat{a}x(k) + \widehat{b}$. The simulative data $\widehat{x}(k)$ is not always an exponential model. Therefore, the monotonicity of the simulative value by FAGM(1, 1) is uncertain and data-driven.

The original sequence is

$$X = \{347.839, 273.021, 289.014, 285.208, 288.818, 297.078\}. \quad (11)$$

The simulative value of the traditional GM(1, 1) model is

$$\widehat{X} = \{347.839, 277.152, 281.811, 286.540, 291.362, 296.263, 301.245, 306.307, 311.452\}. \quad (12)$$

$r = 1.15$, and the simulative value of the FAGM(1, 1) model is

$$\widehat{X} = \{347.839, 269.143, 296.533, 286.999, 290.318, 289.163, 286.810, 290.384, 289.140\}. \quad (13)$$

Thus, the first value of original data by FAGM(1, 1) is effective. The first value of original data in traditional GM (1, 1) is not effective, i.e. the first value of original data in the traditional GM(1, 1) does not affect the simulated value.

*The New Information Priority of the FAGM(1, 1) model.* It is proved that the multivariable grey model can make use of the new information to some extent [30]. According to Lemma 1 in Reference [31], we can obtain the following theorem.

**Theorem 1.** *Assume that* $D \in C^{n\times n}, \Delta D \in C^{n} \times n, Y \in C^{n}, \Delta Y \in C^{n}$, *the vector norm* $\|\bullet\|$ *is compatible with the matrix norm* $\|\bullet\|$. *If there is* $C^{n\times n}$ *for a matrix norm* $\|\bullet\|$ *on* $\|D^{-1}\|\|\Delta D\| < 1$, *then, the solutions of the nonhomogeneous linear equations* $DX = Y$ *and* $(D + \Delta D)(x + \Delta x) = Y + \Delta Y$ *satisfy*

$$\frac{\|\Delta x\|}{\|x\|} \leq \frac{\|D\|\|D^{-1}\|}{1 - \|D\|\|D^{-1}\|\|\Delta D\|/\|D\|}\left(\frac{\|\Delta D\|}{\|D\|} + \frac{\|\Delta Y\|}{\|Y\|}\right). \quad (14)$$

*Proof.* When a disturbance $\widetilde{x}(1) = x(1) + \varepsilon$ occurs,

$$\widetilde{D} = D + \Delta D,$$
$$\widetilde{Y} = Y + \Delta Y,$$
$$\Delta D = \begin{bmatrix} \varepsilon & 0 \\ 0 & 0 \\ \vdots & \\ 0 & 0 \end{bmatrix},$$
$$\Delta Y = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{15}$$
$$\frac{\|\Delta x\|}{\|x\|} \leq \frac{\|D\|\left\|D^{-1}\right\|}{1 - \|D\|\left\|D^{-1}\right\|\|\Delta D\|/\|D\|} \cdot \left(\frac{\|\Delta D\|}{\|D\|} + \frac{\|\Delta Y\|}{\|Y\|}\right) = \frac{\|D\|\left\|D^{-1}\right\||\varepsilon|}{\|D\| - \|D\|\left\|D^{-1}\right\||\varepsilon|}.$$

In other words, the changing boundary of the solution is

$$L[x(1)] = \frac{\|D\|\left\|D^{-1}\right\||\varepsilon|}{\|D\| - \|D\|\left\|D^{-1}\right\||\varepsilon|}. \tag{16}$$

When a disturbance $\widetilde{x}(2) = x(2) + \varepsilon$ occurs,

$$\widetilde{D} = D + \Delta D,$$
$$\widetilde{Y} = Y + \Delta Y,$$
$$\Delta D = \begin{bmatrix} r\varepsilon & 0 \\ \varepsilon & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix},$$
$$\Delta Y = \begin{bmatrix} \varepsilon \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{17}$$
$$\frac{\|\Delta x\|}{\|x\|} \leq \frac{\|D\|\left\|D^{-1}\right\|}{1 - \|D\|\left\|D^{-1}\right\|\sqrt{r^2+1}|\varepsilon|/\|D\|} \cdot \left(\frac{\sqrt{r^2+1}\,|\varepsilon|}{\|D\|} + \frac{|\varepsilon|}{\|Y\|}\right).$$

In other words, the changing boundary of the solution is

$$L[x(2)] = \frac{\|D\|\left\|D^{-1}\right\|}{1 - \|D\|\left\|D^{-1}\right\|\sqrt{r^2+1}|\varepsilon|/\|D\|}\left(\frac{\sqrt{r^2+1}\,|\varepsilon|}{\|D\|} + \frac{|\varepsilon|}{\|Y\|}\right). \tag{18}$$

When a disturbance $\widetilde{x}(3) = x(3) + \varepsilon$ occurs,

$$\Delta D = \begin{bmatrix} \frac{r(r+1)}{2}\varepsilon & 0 \\ r\varepsilon & 0 \\ \varepsilon & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix},$$
$$\Delta Y = \begin{bmatrix} r\varepsilon \\ \varepsilon \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{19}$$
$$\frac{\|\Delta x\|}{\|x\|} \leq \frac{\|D\|\left\|D^{-1}\right\|}{1 - \|D\|\left\|D^{-1}\right\|r\sqrt{r^2+2r+5}|\varepsilon|/2\|D\|} \left(\frac{r\sqrt{r^2+2r+5}\,|\varepsilon|}{2\|D\|} + \frac{\sqrt{r^2+1}\,|\varepsilon|}{\|Y\|}\right).$$

In other words, the changing boundary of the solution is

$$L[x(3)] = \frac{\|D\|\left\|D^{-1}\right\|}{1 - \|D\|\left\|D^{-1}\right\|r\sqrt{r^2+2r+5}|\varepsilon|/2\|D\|} \left(\frac{r\sqrt{r^2+2r+5}\,|\varepsilon|}{2\|D\|} + \frac{\sqrt{r^2+1}\,|\varepsilon|}{\|Y\|}\right). \tag{20}$$

Thus, $L[x(3)] > L[x(2)] > L[x(1)]$.

Similarly, when a disturbance $\widetilde{x}(i) = x(i) + \varepsilon (i = 4, 5, \cdots, n-1)$ occurs, we can obtain. $L[x\ (n-1)] > \cdots > L[x(5)] > L[x(4)]$.

Thus, we have $L[x(n-1)] > \cdots > L[x(5)] > L[x(4)] > L[x(3)] > L[x(2)] > L[x(1)]$.

According to the calculation above, $L[x(i)]$ is an increasing function of $i$, i.e., the weight of new information in the FAGM(1, 1) is larger than the old information. Also, the FAGM(1, 1) model can give more weight to the new data.

As $i$ increases, $L[x(i)]$ also increases. In other words, the sensitivity of $x(i)$ to the results will increase with the number of the sample. This means that the FAGM(1, 1) is more stable when the sample data are small.

Table 1: The review of previous studies.

| Reference | Model form | Sequence accumulation | Parameter optimize |
|---|---|---|---|
| Reference [8] | Self-adaptive intelligence grey model | Fractional order | Particle swarm optimization |
| Reference [9] | Grey Bernoulli model | Fractional order | Particle swarm optimization |
| Reference [10] | Riccati equation | 1-accumulating generation operator | Simulated annealing algorithm |
| Reference [11] | Verhulst-GM(1,N) model | 1-accumulating generation operator | Least squares estimate |
| Reference [12] | Traditional grey model | 1-accumulating generation operator | Artificial intelligence |
| Reference [13] | Grey model envelopment learning procedure | 1-accumulating generation operator | Least squares estimate |
| Reference [14] | Traditional grey model | Fractional order | Least squares estimate |
| Reference [15] | Grey model with fourier series | Fractional order | Least squares estimate |
| Reference [16, 17] | Nonlinear grey Bernoulli model | Fractional order | Genetic algorithm |
| Reference [18] | Grey Lotka-volterra system | Fractional order | Least squares estimate |
| Reference [19] | Grey multivariable model | Fractional order | Lingo software |
| Reference [20] | Grey Bernoulli model | Fractional order | Particle swarm optimization algorithm |
| Reference [21] | Traditional grey model | Conformable fractional order | Quantum inspired evolutionary algorithm |

Table 2: The results of three models: Case 1.

| Year | Actual value | FAGM(1, 1) | Even GM(1, 1) | Discrete GM(1, 1) |
|---|---|---|---|---|
| 2007 | 14.1 | 14.1 | 14.1 | 14.1 |
| 2008 | 15.5 | 14.9 | 13.9 | 13.9 |
| 2009 | 15.9 | 16.8 | 15.7 | 15.7 |
| 2010 | 16.7 | 17.3 | 17.7 | 17.7 |
| 2011 | 19.5 | 18.4 | 20.0 | 20.0 |
| 2012 | 22.0 | 22.1 | 22.6 | 22.6 |
| 2013 | 25.3 | 25.5 | 25.5 | 25.6 |
| 2014 | 30 | 30.0 | 28.8 | 28.9 |
| MAPE | | 2.92 | 4.01 | 4.04 |
| RMSE | | 0.59 | 0.84 | 0.83 |
| 2015 | 38.6 | 36.3 | 32.6 | 32.7 |
| 2016 | 48.3 | 44.7 | 36.8 | 36.9 |
| 2017 | 56.1 | 56.2 | 41.6 | 41.7 |
| 2018 | 66.6 | 71.6 | 47.0 | 47.1 |
| MAPE | | 5.26 | 23.60 | 23.49 |
| RMSE | | 3.29 | 13.81 | 13.71 |

Table 3: The results of three models: Case 2.

| Time | Actual value | FAGM(1, 1) | Even GM(1, 1) | Discrete GM(1, 1) |
|---|---|---|---|---|
| 1 | 862.17 | 862.17 | 862.17 | 862.17 |
| 2 | 1140.84 | 1144.29 | 1113.60 | 1124.13 |
| 3 | 1541.38 | 1538.34 | 1517.36 | 1535.53 |
| 4 | 2088.53 | 2088.73 | 2067.52 | 2097.51 |
| 5 | 2855.94 | 2857.47 | 2817.15 | 2865.15 |
| 6 | 3930.31 | 3931.21 | 3838.58 | 3913.74 |
| MAPE | | 0.12 | 1.73 | 0.60 |
| RMSE | | 2.01 | 44.12 | 11.21 |
| 7 | 5524.43 | 5430.93 | 5230.35 | 5346.08 |
| 8 | 7590.21 | 7525.65 | 7126.75 | 7302.64 |
| 9 | 10678.29 | 10451.43 | 9710.73 | 9975.26 |
| 10 | 14635.61 | 14537.96 | 13231.59 | 13625.99 |
| MAPE | | 1.33 | 7.52 | 5.12 |
| RMSE | | 137.93 | 895.65 | 637.98 |

Table 4: The criteria for MAPE.

| MAPE (%) | Forecasting ability |
|---|---|
| <10 | Excellent |
| 10–20 | Good |
| 20–50 | Reasonable |
| >50 | Weak |

Table 5: The forecasting results of two models: Case 3.

| Year | Actual data | FAGM(1, 1) | GDGM(1, 1) [33] |
|---|---|---|---|
| 2007 | 137.86 | 132.15 | 129.81 |
| 2008 | 157.81 | 148.96 | 142.76 |
| 2009 | 171.75 | 168.39 | 155.09 |
| 2010 | 191.09 | 190.83 | 165.77 |
| 2011 | 218.09 | 216.77 | 173.62 |
| 2012 | 245.65 | 246.75 | 250.89 |
| 2013 | 269.55 | 281.38 | 176.46 |
| MAPE | | 2.47 | 17.29 |
| RMSE | | 6.15 | 41.20 |

Table 6: The employment data from Nanjing University of Aeronautics and Astronautics in the aerospace and other defense-related industry.

| Year | Graduate student | Undergraduate student |
|---|---|---|
| 2015 | 672 | 633 |
| 2016 | 742 | 640 |
| 2017 | 740 | 649 |
| 2018 | 787 | 580 |
| 2019 | 875 | 531 |

Table 7: The forecasting employment data from Nanjing University of Aeronautics and Astronautics in the aerospace and other defense-related industry.

| Year | Graduate student | Undergraduate student | Actual value of graduate employment | Actual value of undergraduate employment |
|---|---|---|---|---|
| 2020 | 936 | 480 | 985 | 504 |
| 2021 | 1001 | 414 | 1032 | 443 |
| 2022 | 1071 | 331 | - | - |
| 2023 | 1147 | 224 | - | - |
| 2024 | 1228 | 88 | - | - |

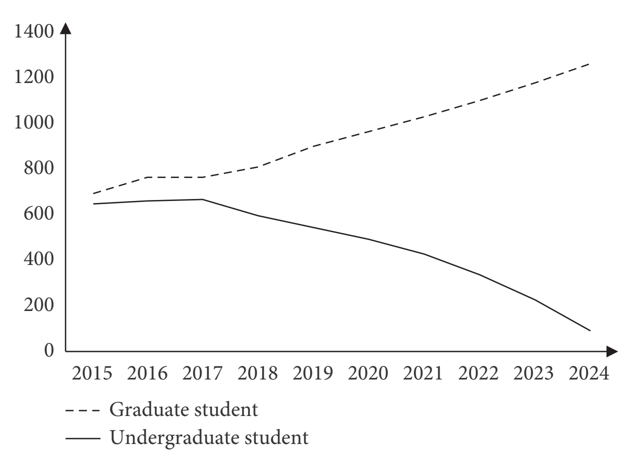


Figure 1: The employment trend in the aerospace and other defense-related industry.

Table 8: The employment data from Harbin Engineering University in the aerospace and other defense-related industry.

| Year | Graduate student | Undergraduate student |
|---|---|---|
| 2016 | 851 | 512 |
| 2017 | 816 | 431 |
| 2018 | 999 | 397 |
| 2019 | 1073 | 365 |

Table 9: The forecasting employment data from Harbin Engineering University in the aerospace and other defense-related industry.

| Year | Graduate student | Undergraduate student | Actual value of graduate employment | Actual value of undergraduate employment |
|---|---|---|---|---|
| 2020 | 1311 | 338 | 1238 | 322 |
| 2021 | 1453 | 316 | 1350 | 301 |
| 2022 | 1612 | 298 | — | — |
| 2023 | 1792 | 282 | — | — |
| 2024 | 1995 | 269 | — | — |

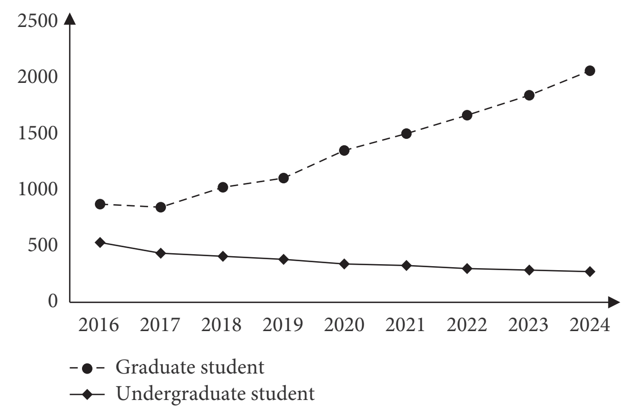


Figure 2: The employment trend of Harbin Engineering University in the aerospace and other defense-related industry.

The grey system theory claims that the traditional grey forecasting model can address the small sample, but this claim lacks the theorem proof. The FAGM(1, 1) is more stable when the sample data is small in theory. This is a difference between the FAGM(1, 1) and the traditional grey forecasting model. □

## 3. Verification of FAGM(1, 1) Model

The adaptability of the FAGM(1, 1) model is proved in three cases in this section.

*Case 1.* Take the nuclear energy consumption in China as an example [32], the data from 2007 to 2014 is the in-sample data, and the data from 2015 to 2018 is the out-of-sample data. The results of three models are given in Table 2.

In Table 2, both the MAPE (RMSE) of the in-sample data and the MAPE (RMSE) of the out-of-sample data are smaller than those of Even GM(1, 1) and Discrete GM(1, 1). Thus, the proposed model can enhance the traditional grey forecasting models.

*Case 2.* The data are from Reference [33]. The data from 1 to 6 are the in-sample data, and the data from 7 to 10 are the out-of-sample data. The results of three models are given in Table 3.

In Table 3, both the MAPE (RMSE) of the in-sample data and the MAPE (RMSE) of the out-of-sample data are smaller than that of Even GM(1, 1) and Discrete GM(1, 1). Thus, the proposed model is an excellent model according to the Lewis's scale of MAPE values in Table 4 [7, 8].

*Case 3.* The data of the disposable income per capita of urban households in China is the same as in Reference [34]. The data from 1997 to 2006 are used to forecast the data for the next seven years. The forecasting results are listed in Table 5. In Table 5, the MAPE (RMSE) of FAGM(1, 1) is much smaller than that of the traditional GM(1, 1) in the out-of-sample data. The forecasting results show that the FAGM(1, 1) model has a better prediction performance.

In other words in this paper, Firstly, the monotonicity of the FAGM(1, 1) value are data-driven. Secondly, the FAGM(1, 1) can make full use of original data (including the initial value). Thirdly, the FAGM(1, 1) can pay more attention to the recent data. Fourthly, FAGM(1, 1) can overcome the limitation of the development coefficient in grey forecast model. Thus, the prediction results of FAGM(1, 1) are more accurate.

## 4. Application

To test the proposed forecasting model, the employment data of graduate students and undergraduate students are respectively predicted. These data are from the Student Affairs Office of Nanjing University of Aeronautics and Astronautics in China. We select the employment data in the aerospace and other defense-related industry. The data from 2015 to 2019 are the samples and are listed in Table 6. The forecasting results of the FAGM(1, 1) model are listed in Table 7 and plotted in Figure 1.

As can be seen in Figure 1, more and more graduate students will work in the aerospace and other defense-related industry. However, fewer and fewer undergraduate students will work in this industry. This result is consistent with the actual situation.

Like the employment situation at Nanjing University of Aeronautics and Astronautics, the employment data of Harbin Engineering University are listed in Table 8. These data are from the Student Affairs Office of Harbin Engineering University in China. We cannot obtain the data of 2015. The data from 2016 to 2019 are the samples. The forecasting results of the FAGM(1, 1) model are listed in Table 9 and plotted in Figure 2.

As can be seen in Figure 2, the forecasting trends are the same as Figure 1. Because the aerospace and other defense-related industry is usually more knowledge- and technology-intensive, it needs more and more high-level talented people. The high-level talented people are the base of the aerospace and other defense-related industry. The students who have a master's degree can find a job in this field after graduation. Therefore, the departments in two universities must enhance the knowledge- and technology-intensive in the process of teaching and learning.

## 5. Conclusion

The fractional error accumulation grey model is proposed and its properties are analyzed. The real cases demonstrated that the proposed model can obtain accurate forecasting results. The forecasting results indicate that the undergraduate students must pursue a master's degree if they want to enroll in the aerospace and other defense-related industry. This model can also predict the employment data in the aerospace and other defense-related industry in the other universities. It can be applied to the employment forecasting in the other regions and the other industries in order to test the model performance.

## Data Availability

The data sources are given in this paper.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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