Research and application of a novel grey multivariable model in port scale prediction under the impact of Free Trade Zone

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Abstract

Purpose – Considering the impact of the Free Trade Zone (FTZ) policy on forecasting the port cargo throughput, this paper constructs a fractional grey multivariate forecasting model to improve the prediction accuracy of port cargo throughput and realize the coordinated development of FTZ policymaking and port construction.

Design/methodology/approach – Considering the effects of data randomization, this paper proposes a novel self-adaptive grey multivariate prediction model, namely FDCGM(1,N). First, fractional-order accumulative generation operation (AGO) is introduced, which integrates the policy impact effect. Second, the heuristic grey wolf optimization (GWO) algorithm is used to determine the optimal nonlinear parameters. Finally, the novel model is then applied to port scale simulation and forecasting in Tianjin and Fujian where FTZs are situated and compared with three other grey models and two machine learning models.

Findings – In the Tianjin and Fujian cases, the new model outperforms the other comparison models, with the least mean absolute percentage error (MAPE) values of 6.07% and 4.16% in the simulation phase, and 6.70% and 1.63% in the forecasting phase, respectively. The results of the comparative analysis find that after the constitution of the FTZs, Tianjin's port cargo throughput has shown a slow growth trend, and Fujian's port cargo throughput has exhibited rapid growth. Further, the port cargo throughput of Tianjin and Fujian will maintain a growing trend in the next four years.

Practical implications – The new multivariable grey model can effectively reduce the impact of data randomness on forecasting. Meanwhile, FTZ policy has regional heterogeneity in port development, and the government can take different measures to improve the development of ports.

Originality/value – Under the background of FTZ policy, the new multivariable model can be used to achieve accurate prediction, which is conducive to determining the direction of port development and planning the port layout.

Keywords Port cargo throughout, Free Trade Zone policy, FDCGM(1,N) model, Dummy variable, Fractional order, Grey wolf optimizer

Paper type Research paper

1. Introduction

China has been deepening its basic state policy of open-door to the outside world and exploring establishing a Free Trade Zone (FTZ) for the past few years. It aims to facilitate investment and foreign trade through the construction of multifunctional special economic zones, probe new ways and accumulate new experiences for the comprehensive deepening of reform (Yao and Whalley, 2016). Since 2013, China has laid out 21 FTZs across the country through multiple batches, initially forming a basic pattern of "1 + 3+7 + 1+6 + 3." Each FTZ is situated in a significant economic region, serving specific economic zones and having

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distinct development positioning. With the gradual improvement of the construction layout of the FTZ, a reform and opening-up innovation pattern covering the east, west, north, south and centre has been formed. Bold exploration and remarkable results have been achieved in areas such as investment, foreign trade and financial services for the real economy (Chen *et al.*, 2022; Wang *et al.*, 2022a).

Ports are important transportation hubs and open gateways and play an essential role in accelerating international trade and creating economic benefits (Gonzalez Aregall *et al.*, 2018). Its development is of great significance to the construction of FTZs while establishing FTZs will be conducive to port improvement. Port development studies indicate port cargo throughput as an essential indicator of port production capacity and operation. It is also the basis for port planning and construction, which can reflect the modernization level of ports and the degree of foreign trade (Wiegmans *et al.*, 2015). However, due to the persistent global economic downturn, the size of Chinese ports has been saturated, and their development prospects face many challenges and risks (Chen *et al.*, 2020; Wan *et al.*, 2021). Then, in the context of FTZ policy, improving the prediction exactness of port cargo throughput and realizing precise forecasting are conducive to determining port development direction, planning the port layout and better planning of the port logistics industry. Thus, policy formulation and port construction in the FTZs can be realized through synergistic development.

In summary, considering that the port cargo throughput data is difficult to obtain and affected by many factors, this paper constructs a fractional grey multivariate forecasting model considering the impact of the FTZ policy to forecast the port cargo throughput. The three main contributions of this study are as follows:

(1) Although the traditional grey multivariate model has good forecasting performance for time series data, the problem of forecasting time series with randomness has not been perfectly solved. In this paper, a new grey multivariate forecasting model (FDCGM(1,N)) is constructed based on the GM(1,N) model by introducing the fractional-order AGO and a generalized time response function with a forecasting function is derived. Meanwhile, optimal nonlinear parameters of the new model are obtained by the GWO algorithm, which significantly enhances the description of the new model.

(2) FDCGM(1,N) model is used to simulate and forecast port cargo throughput of Tianjin and Fujian Province implementing FTZ policy. Importantly, compared with three other grey models and two machine learning models, the new model has the smallest mean absolute percentage errors (MAPEs) in the in-sample prediction interval, which are 6.70% and 1.63%, respectively.

(3) This paper applies the FDCGM(1,N) model to forecast and analyse the port cargo throughput of Tianjin and Fujian Province from 2022 to 2025. It is found that port development under the FTZ policy is regionally heterogeneous. It is estimated that in 2025, the port cargo throughput of Tianjin will reach 762,348,800 tons and Fujian province's port cargo throughput will reach 1,017,638,300 tons.

The rest of the paper is organized as follows. Section 2 details previous studies on FTZS and ports as well as grey models. Section 3 introduces the model evaluation method, the parameter solution algorithm and the research framework. Section 4 applies the FDCGM(1,N) model to the port cargo throughput forecasts of Tianjin and Fujian province implementing FTZ policy and discusses the port cargo growth rates and the forecast results. Section 5, then, presents the conclusions and the future outlook.

2. Literature review

As a functional node for the flow of goods trade, ports are the ligament of the entire supply chain of FTZs and the centre of the flow of goods, capital and information (Wan *et al.*, 2014).

Consequently, many scholars have explored the impact of FTZ policy on port development. For example, Chen *et al.* (2018) constructed a system to assess the development performance of typical FTZs. They conducted an empirical study on six selected distinctive FTZs. Liu *et al.* (2021) evaluated port efficiency in the context of FTZ policy, identified its influencing factors and proved that the scale of port operation significantly positively impacts port efficiency. Li *et al.* (2021) studied the impact of FTZ policy on the evolution of port-listed companies in FTZs. They found that port-listed companies' development performance continuously grew under the FTZ policy. Considering the port throughput and the scale of urban import and export trade, Fan *et al.* (2022) selected four ports established earlier in FTZs and used the allometric growth model and linear scale factor to empirically test the FTZ policy's impact on the ports.

In addition, a lot of scholars have also conducted in-depth research on the prediction of port cargo throughput. At present, the prediction methods of port cargo throughput mainly include traditional econometric model, artificial intelligence model and grey model. In terms of traditional econometric models, Sanguri *et al.* (2022) proposed an intertemporal forecasting model based on exponential smoothing to forecast container throughput at the Port of Los Angeles. In terms of the artificial intelligence model, Cuong *et al.* (2022) utilized a neural network predictive controller and adaptive fractional-order supervision sliding mode control to handle throughput under external disturbances. In the meantime, some scholars have also used the decomposition integration method (Du *et al.*, 2019; Jin *et al.*, 2023), SARIMA and machine learning hybrid method (Huang *et al.*, 2022; Mo *et al.*, 2018) for forecasting container throughput prediction. In fact, port cargo throughput data is usually provided by port authorities, customs, shipping companies, etc., and its availability is limited especially when some ports may be unwilling or unable to disclose it. As a result, the accuracy of the model predictions mentioned above, which require a large amount of data support, may be compromised. For this reason, some scholars have used grey forecasting models to predict port cargo throughput. For example, Hsu *et al.* (2020) proposed a new model combining grey share prediction with Markov chain and grey residual correction, and proved that the model has good prediction performance.

Deng (1982) first proposed the grey theory. Based on this theory, later scholars optimized the grey univariate prediction model from various perspectives, such as model structure (Yang and Wang, 2022; Zeng *et al.*, 2020c), initial value optimization (Zeng *et al.*, 2020b), background value (Wu *et al.*, 2020a) and cumulative generation operator (Wang *et al.*, 2022c; Zeng *et al.*, 2023a, b), and achieved better prediction results. Currently, grey prediction models have been widely used to deal with the prediction problems in the fields of energy price (Duan *et al.*, 2022; Duan and Liu, 2021), air quality (Du *et al.*, 2021; Shi and Wu, 2020; Zeng *et al.*, 2021), food production (Zeng *et al.*, 2020a, b, c), new energy vehicle sales (Liu *et al.*, 2022), energy consumption (Liu and Wu, 2021; Moonchai and Chutsagulprom, 2020; Wu *et al.*, 2020b), output of high-technology industries (Ding *et al.*, 2022) and epidemic disease transmission (Saxena, 2021). However, considering the influence of external factors, the multivariable grey model is gradually being used more and more to compensate for the shortcomings of univariate models. As the most basic multivariate grey model, the GM(1,N) model is widely used (Duan and Luo, 2022; Zeng *et al.*, 2023a, b; Zhang *et al.*, 2022). Unfortunately, the model also has some problems in the modelling process (Ren *et al.*, 2023; Zeng *et al.*, 2019). Therefore, many scholars optimize the GM(1,N) model from different perspectives to enhance the applicability of the model.

In terms of dummy variables, Ding *et al.* (2018) added dummy variables into the GM (1,N) model, gave a specific modelling approach, and verified the availability of the neoteric model by examples. Wan *et al.* (2022) introduced dummy variables' interactions into Ding's model to establish a new grey multivariate model, which improved the model's prediction accuracy. Meanwhile, considering the impact of fractional-order accumulative generation, they introduced fractional-order into the new model to enhance the model's simulation and forecasting performance for time series with randomness. For instance, Wang *et al.* (2022b) introduced a new kind of fractional order, namely Grünwald-Letnikov fractional-order calculus, to enhance model adaptability. Yan *et al.* (2022) introduce fractional-order cumulative generation into the multivariable time-delayed grey model to reduce the impact of randomness of online public opinion data on the prediction results and optimize the modelling parameters using particle swarm optimization.

3. Methods

3.1 The existing GM(1,N) model

In this paper, the GM(1,N) model is selected as the benchmark model. In order to fully demonstrate the new model proposed, the GM(1,N) model is briefly introduced at first.

Definition 1. Zeng *et al.* (2016) Let the original sequences $X_1^{(0)}$ and $X_i^{(0)}(i=2,3,\cdots,N)$ denote the system behaviour sequences and driver sequences, respectively, and their 1-order accumulative generation sequences $X_1^{(1)}$ and $X_i^{(1)}$, respectively, and $Z_1^{(1)}$ is called the background value and is generated by $X_1^{(1)}$ where $Z_1^{(1)}(k)=\frac{1}{2}\times[X_1^{(1)}(k)+X_1^{(1)}(k-1)], k=2,3,\cdots,n.$

Then,

$$x_1^{(0)}(k)+az_1^{(0)}(k)=\sum_{i=2}^{N}b_ix_i^{(1)}(k) \tag{1}$$

is the GM(1,N) model. Where a is the system development factor, $b_ix_i^{(1)}(k)$ is the driving term, and b_i is the driving coefficient.

Definition 2. Let $\widehat{a}=[a,b_2,\cdots,b_N]^T$ be the parameter column of the model. Then,

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=\sum_{i=2}^{N}b_ix_i^{(1)}(k) \tag{2}$$

is the whitening equation of the GM(1,N) model.

3.2 The proposed FDCGM(1,N) model

In this section, a new grey multivariate model is proposed, referred to as the FDCGM(1,N) model. Before the new model is introduced, the fractional-order cumulative generating series and the cumulative-decreasing generating series are first introduced.

Definition 3. Let sequence $X_i^{(0)}$ be as described in Definition 1. Then, the sequence $X_i^{(r)}=(x_i^{(r)}(1),x_i^{(r)}(2),\cdots,x_i^{(r)}(n))$ is known as the r-order accumulation of $X_i^{(0)}$, and the sequence $X_i^{(-r)}=(x_i^{(-r)}(1),x_i^{(-r)}(2),\cdots,x_i^{(-r)}(n))$ is known as the r-order inverse accumulation of $X_i^{(0)}$. Specifically,

$$x_i^{(r)}(k)=\sum_{s=1}^{k}\frac{\Gamma(r+k-s)}{\Gamma(k-s+1)\Gamma(r)}x_i^{(0)}(s), k=1,2,\cdots,n. \tag{3}$$

$$x_i^{(-r)}(k)=\sum_{s=0}^{k-1}(-1)^s\frac{\Gamma(r+1)}{\Gamma(s+1)\Gamma(r-s+1)}x_i^{(0)}(k-s), k=1,2,\cdots,n. \tag{4}$$

Definition 4. Let the sequences $X_i^{(0)}$ and $X_i^{(r)}$ be as described in Definition 1 and Definition 3, respectively, and the sequence of dummy variables $D_j^{(0)} = (d_j^{(0)}(1), d_j^{(0)}(2), \cdots, d_j^{(0)}(n)), d_j^{(0)}(k) = 0 \text{ or } 1,$ which the r-order accumulative generation sequence is $D_j^{(r)}(j = M+1, M+2, \cdots, N)$. $Z_1^{(r)}$ is the background value sequence of $X^{(r)}$, which is $Z_1^{(r)} = (z_1^{(r)}(1), z_1^{(r)}(2), \cdots, z_1^{(r)}(n)), z_1^{(r)}(k) = \frac{1}{2} \times [x_1^{(r)}(k) + x_1^{(r)}(k-1)]$.

Then,

$$x_1^{(r)}(k) - x_1^{(r)}(k-1) + az_1^{(r)}(k) = \sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k) \tag{5}$$

is basic form of FDCGM(1,N) model.

$\sum_{i=2}^{M} b_i x_i^{(r)}(k)$ is the quantified variable driver; $\sum_{j=M+1}^{N} b_j d_j^{(r)}(k)$ is the dummy variable driver, which takes into account the influence of qualitative factors on the dependent variable; b_j is the driving coefficient of the accumulative generation term of the dummy variable.

Theorem 1. Let $X_i^{(0)}, X_i^{(r)}, D_j^{(0)}$ and $D_j^{(r)}$ be as described in Definition 1, Definition 3 and Definition 4. The model parameters are listed as $\widehat{b} = [a, b_2, \cdots, b_M, \cdots, b_N]^T$ are known. Where,

$$Y = \begin{pmatrix} x_1^{(r)}(2) - x_1^{(r)}(1) \\ x_1^{(r)}(3) - x_1^{(r)}(2) \\ \vdots \\ x_1^{(r)}(n) - x_1^{(r)}(n-1) \end{pmatrix}$$

$$B = \begin{pmatrix} -z_1^{(r)}(2) & x_2^{(r)}(2) & \cdots & x_M^{(r)}(2) & d_{M+1}^{(r)}(2) & \cdots & d_N^{(r)}(2) \\ -z_1^{(r)}(3) & x_2^{(r)}(3) & \cdots & x_M^{(r)}(3) & d_{M+1}^{(r)}(3) & \cdots & d_N^{(r)}(3) \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -z_1^{(r)}(n) & x_2^{(r)}(n) & \cdots & x_M^{(r)}(n) & d_{M+1}^{(r)}(n) & \cdots & d_N^{(r)}(n) \end{pmatrix} \tag{6}$$

Then, the least squares of the parameter columns satisfy:

(1) When $n = N+1, \widehat{b} = B^{-1}Y, |B| \neq 0$;

(2) When $n > N+1, \widehat{b} = (B^TB)^{-1}B^TY, |B^TB| \neq 0$;

(3) When $n < N+1, \widehat{b} = B^T(B^TB)^{-1}Y, |B^TB| \neq 0$.

Proof. Bringing $k = 2, 3, \cdots, n$ into the FDCGM(1,N) model, we get

$$\begin{aligned} x_1^{(r-1)}(2) &= -ax_1^{(r-1)}(2) + \sum_{i=2}^{M} b_i x_i^{(r)}(2) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(2) \\ x_1^{(r-1)}(3) &= -ax_1^{(r-1)}(3) + \sum_{i=2}^{M} b_i x_i^{(r)}(3) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(3) \\ &\vdots \\ x_1^{(r-1)}(n) &= -ax_1^{(r-1)}(n) + \sum_{i=2}^{M} b_i x_i^{(r)}(n) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(n) \end{aligned} \tag{7}$$

That is, from the least squares method, we have $Y = B\widehat{b}$.

(1) When $n = N + 1$ and $|B| \neq 0$, the inverse matrix of B exists and the system of equations has a unique solution, we can obtain $\widehat{b} = B^{-1}Y$.

(2) When $n > N + 1$ and B is column-full rank, there is a column-full rank solution of B to $B = DC$. In turn, the generalized matrix B^{+} of B can be obtained as

$$B^{+} = C^{T}\left(CC^{T}\right)^{-1}\left(D^{T}D\right)^{-1}D^{T}, \widehat{\beta} = C^{T}\left(CC^{T}\right)^{-1}\left(D^{T}D\right)^{-1}D^{T}Y$$

Since B is a full-rank matrix, C can be taken as a unit matrix, $B = DI_N$, $B = D$, we get

$$\widehat{b} = C^{T}\left(CC^{T}\right)^{-1}\left(D^{T}D\right)^{-1}D^{T}Y = \left(D^{T}D\right)^{-1}D^{T}Y = \left(B^{T}B\right)^{-1}B^{T}Y$$

(3) When $n < N + 1$ and B is a row full-rank matrix, D can be taken as a unit matrix, $B = I_{n-1}C$, $B = C$, then we gain

$$\widehat{b} = C^{T}\left(CC^{T}\right)^{-1}\left(D^{T}D\right)^{-1}D^{T}Y = C^{T}\left(CC^{T}\right)^{-1}Y = B^{T}\left(BB^{T}\right)^{-1}Y$$

Theorem 2. Let $X_i^{(0)}, X_i^{(r)}, D_j^{(0)}$ and $D_j^{(r)}$ be as described in Definition 1, Definition 3 and Definition 4, we have:

(1) The solution of the whitening differential equation of the FDCGM(1,N) model is

$$\begin{aligned} x_1^{(r)}(t) = e^{-at}\Bigg[x_1^{(r)}(0) - t\left(\sum_{i=2}^{M} b_i x_i^{(r)}(0) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(0)\right) + \\ \sum_{i=2}^{N} \int \left(\sum_{i=2}^{M} b_i x_i^{(r)}(t) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(t)\right) e^{at} dt \Bigg] \end{aligned} \tag{8}$$

(2) When the magnitude of change in the driver sequence $X_i^{(1)}(i=2,3,\cdots,N)$ is small, the model drivers $\sum_{i=2}^{M} b_i x_i^{(1)}(t)$ and $\sum_{j=M+1}^{N} b_j d_j^{(1)}(t)$ can be considered as grey constants. The approximate time corresponding function sequence of the grey differential equation of the FDCGM(1,N) model is:

$$\hat{x}_1^{(r)}(k) = e^{-a(k-1)}\left[x_1^{(r)}(1) - \left(\sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k)\right)\frac{1}{a}\right] + \left(\sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k)\right)\frac{1}{a} \quad (9)$$

(3) The time response equation of $\hat{x}_1^{(r)}(k)$ can be obtained by the r-order accumulative generation of $\hat{x}_1^{(0)}(k)$:

$$\hat{x}_1^{(0)}(k) = \begin{cases} x_1^{(0)}(1)\, k=1 \\ \left(\hat{x}_1^{(r)}\right)^{(-r)}(k) = \sum_{j=0}^{k-1}(-1)^j \frac{\Gamma(r+1)}{\Gamma(j+1)\Gamma(r-j+1)}\hat{x}_1^{(r)}(k-j)\, k=2,3,\cdots,n \end{cases} \quad (10)$$

Proof.

(1) From the whitening equation, we can obtain the general solution equation:

$$x_1^{(r)}(t) = e^{-at}\left[\sum_{i=2}^{N}\int\left(\sum_{i=2}^{M} b_i x_i^{(r)}(t) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(t)\right)e^{at}dt + e\right] \quad (11)$$

Where e is a constant to be determined. Bringing $x_i^{(r)}(0)$ into the above equation yields, we can get

$$e = x_1^{(r)}(0) - \sum_{i=2}^{N}\int\left(\sum_{i=2}^{M} b_i x_i^{(r)}(t) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(t)\right)e^{at}dt \quad (12)$$

Then, Eq. (8) is proved.

(2) Let the model drivers $\sum_{i=2}^{M} b_i x_i^{(1)}(t)$ and $\sum_{j=M+1}^{N} b_j d_j^{(1)}(t)$ be considered as grey constants, and then the approximate time corresponding function sequence of the grey differential equation of the FDCGM(1,N) model is

$$\hat{x}_1^{(r)}(k) = e^{-a(k-1)}\left[x_1^{(r)}(1) - \left(\sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k)\right)\frac{1}{a}\right] + \left(\sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k)\right)\frac{1}{a}$$

(3) Based on (2),

When $k=1$, $\hat{x}_1^{(0)}(1) = x_1^{(0)}(1)$.

When $k = 2, 3, \cdots, n$, by the r-order inverse accumulative generation operator (I-AGO)

$$x_i^{(-r)}(k) = \sum_{s=0}^{k-1} (-1)^s \frac{\Gamma(r+1)}{\Gamma(s+1)\Gamma(r-s+1)} x_i^{(0)}(k-s), k = 1, 2, \cdots, n.$$

We can get

$$\widehat{x}_1^{(0)}(k) = \left(\widehat{x}_1^{(r)}\right)^{(-r)}(k) = \sum_{s=0}^{k-1} (-1)^s \frac{\Gamma(r+1)}{\Gamma(s+1)\Gamma(r-s+1)} \widehat{x}_1^{(r)}(k-s) \tag{13}$$

In summary, Eq. (10) is proved.

Theorem 3. When b_j and r in the FDCGM(1,N) model take disparate values, it can be transformed into existing grey models, including GM(1,N) model, FGM(1,N) model and DVCGM(1,N) model.

Proof.

(1) When $b_j = 0$ and $r = 0$, the new model can be transferred to the GM(1,N) model (Zeng *et al.*, 2016).

$$\frac{dx_1}{dt} + ax_1(t) = \sum_{i=2}^{M} b_i x_i(t) \tag{14}$$

(2) When $b_j = 0$ and $r \neq 0$, the new model can be turned to the FGM(1,N) model (Wang and Li, 2020).

$$\frac{dx_1^{(r)}}{dt} + ax_1^{(r)}(t) = \sum_{i=2}^{M} b_i x_i^{(r)}(t) \tag{15}$$

(3) When $b_j \neq 0$ and $r = 0$, the new model can be the DVCGM(1,N) model (Ding *et al.*, 2018).

$$\frac{dx_1}{dt} + ax_1(t) = \sum_{i=2}^{M} b_i x_i(t) + \sum_{j=M+1}^{N} b_j d_j(t) \tag{16}$$

3.3 Optimization of the fractional order based on GWO

In the FDCGM(1,N) model, the fractional order r needs to be optimized. It can be solved by constructing a nonlinear optimization problem and choosing MAPEs as the objective function. The objective function and each constraint condition can be expressed as:

$$\min_r MAPE_S = \frac{1}{m-1} \sum_{k=1}^{m} \left| \frac{x_1^{(0)}(k) - \widehat{x}_1^{(0)}(k)}{x_1^{(0)}(k)} \right| \times 100\% \tag{17}$$

$$
s.t.\begin{cases}
\widehat{b} = [a, b_2, \cdots, b_M, \cdots, b_N]^T \\
B = \begin{pmatrix} -z_1^{(r)}(2) & x_2^{(r)}(2) & \cdots & x_M^{(r)}(2) & d_{M+1}^{(r)}(2) & \cdots & d_N^{(r)}(2) \\ -z_1^{(r)}(3) & x_2^{(r)}(3) & \cdots & x_M^{(r)}(3) & d_{M+1}^{(r)}(3) & \cdots & d_N^{(r)}(3) \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -z_1^{(r)}(n) & x_2^{(r)}(n) & \cdots & x_M^{(r)}(n) & d_{M+1}^{(r)}(n) & \cdots & d_N^{(r)}(n) \end{pmatrix} \\
Y = \begin{pmatrix} x_1^{(r)}(2) - x_1^{(r)}(1) \\ x_1^{(r)}(3) - x_1^{(r)}(2) \\ \vdots \\ x_1^{(r)}(n) - x_1^{(r)}(n-1) \end{pmatrix} \\
\widehat{x}_1^{(r)}(k) = e^{-a(k-1)}\left[x_1^{(r)}(1) - \left(\sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k)\right)\frac{1}{a}\right] + \left(\sum_{i=2}^{M} b_i x_i^{(r)}(k) + \sum_{j=M+1}^{N} b_j d_j^{(r)}(k)\right)\frac{1}{a} \\
\widehat{x}_1^{(0)}(k) = \left(\widehat{x}_1^{(r)}\right)^{-r}(k)
\end{cases}
$$

The above objective function and constraints suggest that parameter optimization of FDCGM(1,N) model is a nonlinear optimization problem with multiple nonlinear constraints. In this paper, we will apply the grey wolf optimization (GWO) algorithm to find new model's optimal fractional order r. According to previous studies (Mirjalili *et al.*, 2014), the steps of GWO include social stratification, follow the prey, and find prey and attack it.

3.4 Performance metrics

This section will define the following two metrics to estimate the exactness of the FDCGM(1,N) model.

The first one is absolute percentage error (APE), which is set to be represented concretely:

$$
APE(k) = \left|\frac{x_1^{(0)}(k) - \widehat{x}_1^{(0)}(k)}{x_1^{(0)}(k)}\right| \times 100\% \tag{18}
$$

The second one is the MAPE. It can reflect the difference between fitting and original values that APE cannot measure. Suppose there is a total of raw data used as modelling data to judge the model's simulation accuracy. The remaining data are applied as prediction data to evaluate the model's prediction veracity. The following two equations can express the average percentage error of simulation and prediction:

$$
MAPE_S = \frac{1}{m-1}\sum_{k=1}^{m}\left|\frac{x_1^{(0)}(k) - \widehat{x}_1^{(0)}(k)}{x_1^{(0)}(k)}\right| \times 100\% \tag{19}
$$

$$MAPE_{\mathrm{P}} = \frac{1}{n-m}\sum_{k=m+1}^{n}\left|\frac{x_1^{(0)}(k)-\widehat{x}_1^{(0)}(k)}{x_1^{(0)}(k)}\right| \times 100\% \tag{20}$$

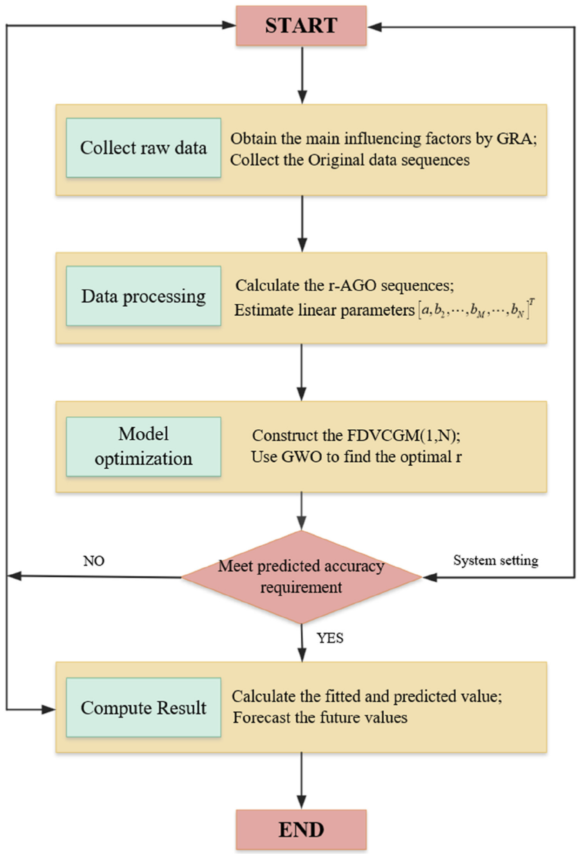
In the above equation, $x^{(0)}(k)$ and $\widehat{x}^{(0)}(k)$ represent the actual and predicted values of the original data, respectively.

3.5 Modelling process

According to the modelling idea of the FDCGM(1,N) model, this section elaborates on the modelling steps (see Figure 1).

Step 1: Selection of model variables. Based on practical application cases, policy dummy variables are identified, and three main influencing factors of port cargo throughput are decided by grey correlation analysis.

Step 2: Based on the selected variables, the original data sequence $X_i^{(0)}$ is created and the corresponding r-order accumulating generation sequence is $X_i^{(r)}$.



Source(s): Figure created by authors

Figure 1. Modelling step diagram of the FDCGM(1,N) model

Step 3: The FDCGM(1,N) model is developed according to Theorem 1, and the model parameters are estimated. The time response equation is calculated according to Theorem 2 and used for subsequent simulations and predictions.

Step 4: The nonlinear parameter optimization problem is established, and GWO obtains the optimal fractional order with the minimization of the mean percentage error of the simulation as the objective function.

Step 5: Sequence $X_1^{(r)}$ is generated by r-order I-AGO to obtain the original data sequence's simulated and predicted sequence $X_1^{(0)}$. If the new model's MAPEs and MAPEp meet the prediction accuracy requirements, they can be used for out-of-sample prediction for practical applications. Otherwise, the model needs to be improved.

Step 6: The new model through evaluation is applied to predict the port cargo throughput of Tianjin and Fujian, which implements the policy of FTZ from 2022 to 2025, and at the same time prediction results and the growth rate are compared and analysed, and corresponding policy recommendations are put forward.

4. Empirical analysis

This article selects the Tianjin and Fujian provinces that have established FTZs and have relatively unabridged index data as objects of study. Given that more and more factors influence port cargo throughput, grey correlation analysis is applied to ascertain port cargo throughput's main influencing factors in two coastal provinces (cities). Specifically, the main influencing factors of Tianjin's port cargo throughput are the secondary industry-added value, road freight volume and total import and export volume, among which the secondary industry-added value has the most significant influence, with a correlation value of 0.6798. The correlation between port throughput and total import and export volume, GDP and water freight volume is strong in Fujian province, and total import and export volume is most closely related to port cargo throughput. The data on port cargo throughput (measured in millions of tons) and the influencing factors are from statistical yearbooks published by the National Bureau of Statistics and local statistical bureaus from 2005 to 2021.

4.1 Case 1: simulation and prediction of Tianjin's port cargo throughput

4.1.1 Model comparison and analysis of port cargo throughput in Tianjin. Tianjin FTZ was established in 2015. Benefiting from the FTZ policy dividend, Tianjin's ports actively carry out offshore trade, which helps port development. Through grey correlation analysis, the secondary industry-added value, road freight volume, and total import and export volume are identified as the three main influencing factors of port cargo throughput in Tianjin. The data can be seen in Table 1.

The optimal order of the new model is -0.6195 after optimization by the GWO. According to the modelling steps, the data in Table 1 are modelled, and the calculation formula of the FDCGM(1,N) model can be obtained as follows:

$$\widehat{x}_1^{(-0.6195)}(k) = e^{-0.6687*(k-1)} * x_1^{(-0.6195)}(1) + \frac{1}{0.6687} * \left(1 - e^{-0.6687*(k-1)}\right)$$
$$\left(7.3537x_2^{(-0.6195)}(k) - 0.0315x_3^{(-0.6195)}(k) - 3.5034x_4^{(-0.6195)}(k) - 2018.7736d_5^{(-0.6195)}(k)\right)$$

From Table 2 and Figure 2, the port cargo throughput of Tianjin in 2005–2021 fluctuates relatively smoothly and shows a stable upward trend overall. Compared with the other three grey and two machine learning models, the new model best fits the original data. Especially

Year	Port cargo throughput (10000 tons)	Secondary industry-added value (100 million yuan)	Road freight volume (10000 tons)	Total import and export volume (USD 100 million)	D
2005	24069.00	1630.53	19850.00	533.87	0
2006	25760.00	1834.54	20290.00	645.73	0
2007	30946.00	2123.63	23500.00	715.50	0
2008	35593.00	2659.71	18160.00	805.39	0
2009	38111.00	2808.74	19800.00	639.44	0
2010	41325.00	3259.74	20855.00	822.01	0
2011	45338.00	3756.26	23505.00	1033.91	0
2012	47697.00	4134.03	27735.00	1156.23	0
2013	50063.00	4407.10	28206.00	1285.28	0
2014	54002.00	4615.50	31130.00	1339.12	0
2015	54051.00	4489.59	30551.00	1143.47	1
2016	55056.00	4367.97	32841.00	1026.51	1
2017	50056.00	4564.06	34720.00	1129.45	1
2018	50774.00	4835.30	34711.00	1225.11	1
2019	49220.00	4947.18	31250.00	1066.45	1
2020	50290.00	4911.77	32261.00	1059.31	1
2021	52954.00	5854.27	34527.00	1325.65	1

Source(s): Table created by authors

Table 1. Observations of Tianjin's port cargo throughput and the related factors from 2005 to 2021

for the simulations and forecasts of recent years, the simulated and forecasted values are approximate to raw values. Meanwhile, other comparison models have large deviations from the actual values. Figure 3 shows that the new model has the least APE fluctuation and is more stable, while the Backpropagation Neural Network (BPNN) and Long Short-Term Memory (LSTM) models will have a larger APE and poor stability at a certain time.

In terms of model analysis, DVCGM(1,N) model's MAPEs and MAPEp are smaller than those of the GM(1,N) and DGM(1,N) model. It implies that FTZ policy does have an impact on Tianjin's port cargo throughput. Meanwhile, the FDCGM(1,N) model's MAPEs and MAPEp are smaller than those of the DVCGM(1,N) model. It means that the impact of port cargo throughput in previous years needs to be considered when forecasting port cargo throughput in Tianjin. Figure 4 shows that the FDCGM(1,N) model performs well in simulation and forecasting. Its simulation and in-sample prediction errors are the smallest, at 6.07% and 6.70%, respectively. These indicate that the new model effectively identifies serial trends of port cargo throughput in Tianjin. It may be due to the inclusion of policy dummy variables, and fractional-order AGO in the new model, significantly improving the time series' estimated performance and stability.

4.1.2 Forecast Tianjin's port cargo throughput in 2022–2025. The FDCGM(1,N) model performs well in the Tianjin simulation and forecasting port cargo throughput. Thus, using all the data from 2005 to 2021, the new model is used to predict Tianjin's port cargo throughput in 2022–2025. As seen from Table 3, the port cargo throughput of Tianjin shows a stable growth trend from 2022 to 2025. In recent years, Tianjin has taken advantage of FTZ's innovation and used its strategic port resources and hard-core benefits to refine the port. Tianjin's port carrying capacity has been significantly improved; port cargo throughput and infrastructure capacity have been substantially improved; and the construction of intelligent, green and safe ports has been practical. Tianjin will further enhance the port collection and distribution network, strengthen the role of shipping hubs and accelerate the formation of Tianjin port as the centre of the northern international shipping hub. At the same time, the port must implement the "smart supervision" mode of operation, build an innovative, green world-class port, upgrade the port economy, better serve the Jing-Jin-Ji region and strengthen

Year	Real data	FDCGM(1,N) Fitting	FDCGM(1,N) APE (%)	GM(1,N) Fitting	GM(1,N) APE (%)	DGM(1,N) Fitting	DGM(1,N) APE (%)
2005	24069.00	24069.00	0.00	24069.00	0.00	24069.00	0.00
2006	25760.00	30675.87	19.08	20491.44	20.45	30160.82	17.08
2007	30946.00	33332.43	7.71	42782.88	38.25	34948.59	12.93
2008	35593.00	37530.32	5.44	32569.68	8.49	40914.02	14.95
2009	38111.00	38849.72	1.94	−20409.11	153.55	43078.52	13.03
2010	41325.00	41735.30	0.99	−72633.17	275.76	46508.49	12.54
2011	45338.00	45085.77	0.56	−131536.77	390.12	51600.03	13.81
2012	47697.00	47705.36	0.02	−210393.26	541.10	57274.70	20.08
2013	50063.00	49447.65	1.23	−325222.87	749.63	66167.11	32.17
2014	54002.00	50853.86	5.83	−482056.20	992.66	77471.52	43.46
2015	54051.00	47116.76	12.83	−962511.82	1880.75	89805.59	66.15
2016	55056.00	45950.00	16.54	−1483889.66	2795.24	104767.59	90.29
2017	50056.00	47188.05	5.73	−2043942.04	4183.31	126557.57	152.83
2018	50774.00	49415.61	2.68	−3039098.03	6085.54	157853.43	210.89
2019	49220.00	51414.89	4.46	−5658615.41	11596.58	198566.41	303.43
MAPE(%)					2122.25		71.69
2020	50290.00	50813.97	1.04	−8051467.56	16110.08	256814.57	410.67
2021	52954.00	59494.88	12.35	−12530458.38	23762.91	337972.18	538.24
MAPE(%)					19936.49		474.45

Year	Real data	DVCGM(1,N) Fitting	DVCGM(1,N) APE(%)	BPNN Fitting	BPNN APE(%)	LSTM Fitting	LSTM APE(%)
2005	24069.00	24069.00	0.00	27713.64	15.14	40860.31	69.76
2006	25760.00	22200.93	13.82	29163.72	13.21	38510.61	49.50
2007	30946.00	45838.99	48.13	33256.09	7.46	39740.87	28.42
2008	35593.00	45361.15	27.44	35690.49	0.27	40716.24	14.39
2009	38111.00	55502.68	45.63	38374.81	0.69	41472.66	8.82
2010	41325.00	57147.69	38.29	40777.12	1.33	42813.84	3.60
2011	45338.00	61507.75	35.66	43406.07	4.26	44634.28	1.55
2012	47697.00	74595.34	56.39	48446.28	1.57	46526.28	2.45
2013	50063.00	73482.43	46.78	51094.68	2.06	48528.15	3.07
2014	54002.00	84352.85	56.20	56204.62	4.08	50402.47	6.67
2015	54051.00	47996.13	11.20	44611.86	17.46	50791.54	6.03
2016	55056.00	61230.66	11.22	42131.81	23.47	50789.08	7.75
2017	50056.00	65221.31	30.30	35914.62	28.25	50490.43	0.87
2018	50774.00	58988.18	16.18	35697.13	29.69	50080.16	1.37
2019	49220.00	41848.41	14.98	52226.56	6.11	49286.40	0.13
MAPE(%)			32.30		10.34		13.63
2020	50290.00	46496.59	7.54	49623.49	1.33	48365.36	3.83
2021	52954.00	39175.33	26.02	43590.60	17.68	47917.65	9.51
MAPE(%)			16.78		9.50		6.67

Source(s): Table created by authors

Table 2. Fitting and forecasting results of six models to Tianjin's port cargo throughput

Tianjin FTZ's functional positioning. In 2025, the port cargo throughput of Tianjin will reach 762,348,800 tons.

4.2 Case 2: simulation and prediction of Fujian province's port cargo throughput

4.2.1 Model comparison and analysis of port cargo throughput in Fujian province. Fujian FTZ is based on promoting cross-strait economic and trade cooperation. The correlation between port cargo throughput and its influencing factors in Fujian province is obtained through grey correlation analysis, and then three main influencing factors are obtained, namely

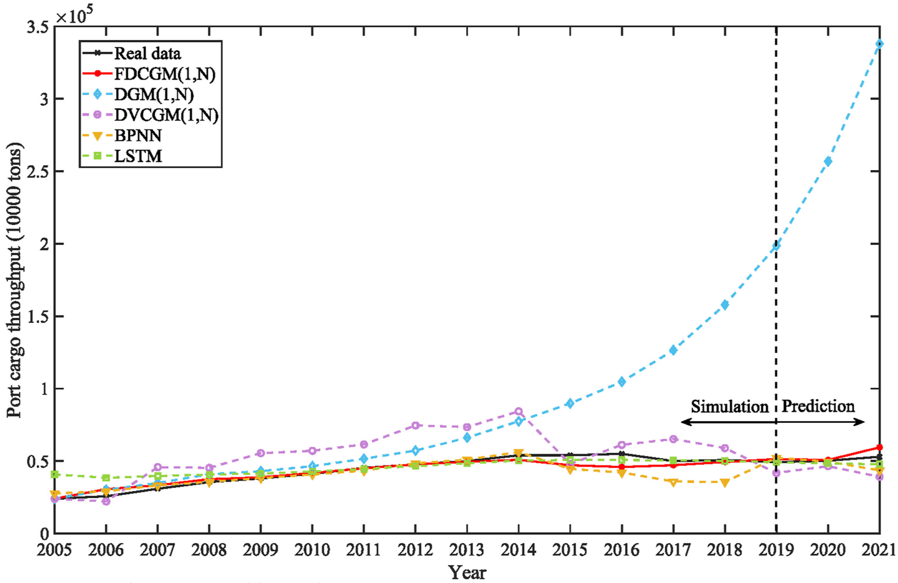


Figure 2.
Fitting curves of five models to Tianjin's port cargo throughput

Source(s): Figure created by authors

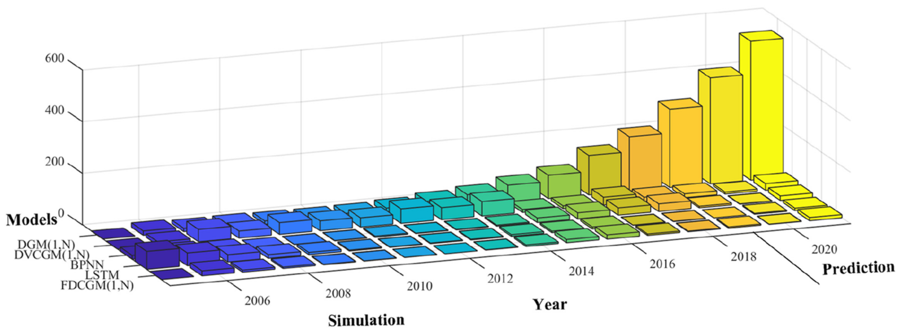


Figure 3.
APE(%) of Tianjin's port cargo throughput amongst five models

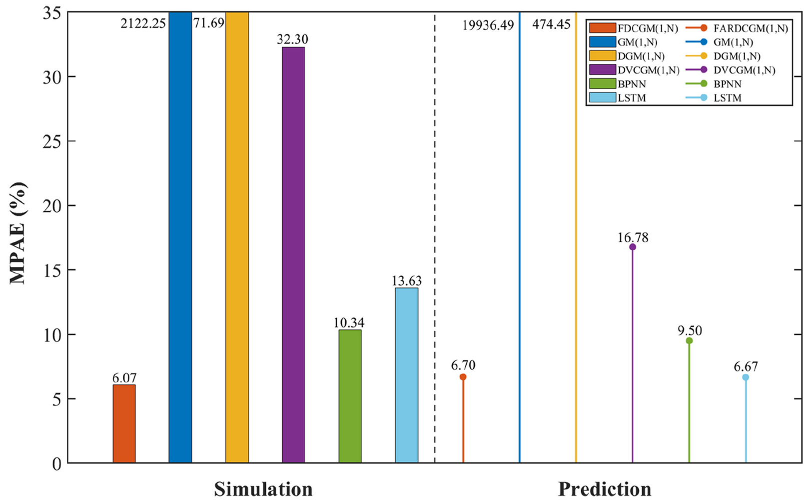
Source(s): Figure created by authors

total import and export volume, GDP and water freight volume. Table 4 manifests the required data.

FDCGM(1,N) model's optimal order is −0.9396, obtained by GWO. According to the modelling steps, the data in Table 4 are modelled, and the calculation formula of the FDCGM(1,N) model can be obtained as follows:

$$\widehat{x}_1^{(-0.9396)}(k) = e^{-1.1345*(k-1)} * x_1^{(-0.9396)}(1) + \frac{1}{1.1345} * \left(1 - e^{-1.1345*(k-1)}\right)$$

$$\left(7.4598x_2^{(-0.9396)}(k) + 0.1488x_3^{(-0.9396)}(k) + 0.7167x_4^{(-0.9396)}(k) - 778.0284d_5^{(-0.9396)}(k)\right)$$



Source(s): Figure created by authors

Figure 4. MAPE(%) of six models to Tianjin's port cargo throughput

Table 3. Tianjin's port cargo throughput predicted by the FDCGM(1,N) model from 2022 to 2025

	2022	2023	2024	2025
Port cargo throughput (10000 tons)	64516.28	68172.36	72074.35	76234.88

Source(s): Table created by authors

Table 4. Observations of Fujian province's port cargo throughput and the related factors in 2005–2021

Year	Port cargo throughput (10000 tons)	Total import and export volume (USD 100 million)	GDP (100 million yuan)	Water freight volume (10000 tons)	D
2005	19809.25	544.11	9210.00	6415.50	0
2006	23865.61	626.59	10841.00	7468.60	0
2007	23880.90	744.51	12130.00	9325.60	0
2008	27422.06	848.21	15193.00	10931.80	0
2009	30831.81	796.49	14272.00	12418.10	0
2010	33069.01	1087.80	16803.00	15002.50	0
2011	37695.95	1435.22	18871.00	17917.70	0
2012	41359.23	1559.38	21100.00	20190.70	0
2013	45911.19	1693.22	23162.00	22503.80	0
2014	49541.24	1774.08	25782.00	24942.10	0
2015	50652.09	1688.46	28419.00	26819.50	1
2016	51140.09	1568.19	31664.00	29609.40	1
2017	51995.49	1710.35	33453.00	33842.40	1
2018	56130.88	1875.76	36854.00	38687.80	1
2019	59483.99	1930.86	42263.00	42326.60	1
2020	62132.47	2033.17	45018.00	43608.60	1
2021	69190.28	2852.50	50224.00	48810.40	1

Source(s): Table created by authors

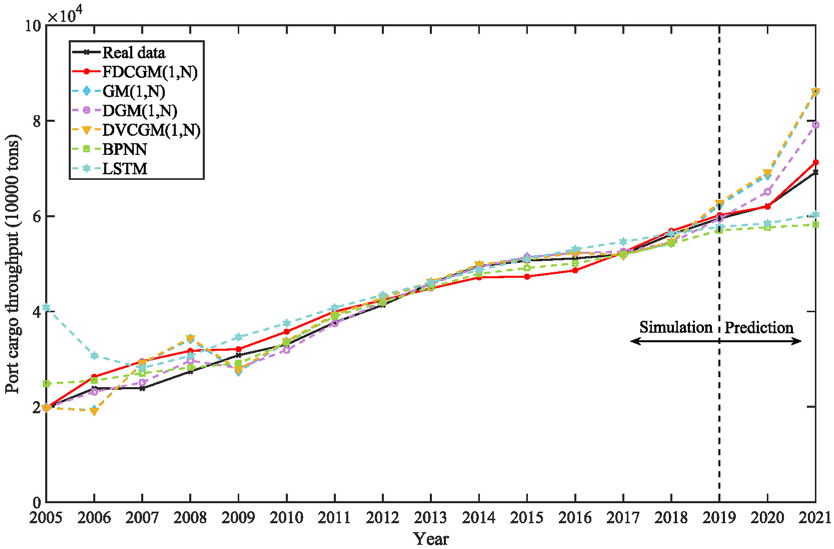
Table 5 shows the raw data and six models' simulation and forecast results. Fujian province's port cargo throughput of achieved more than three times growth from 2005 to 2021. Figure 5 shows that the new model is not only closer to actual values in terms of simulation and forecasting results but also very consistent with the actual situation in terms of change trends, which all show an upward trend overall and can reflect the actual state of port throughput in Fujian province. Especially for the in-sample prediction stage, the predicted values of other models have a significant deviation from the true value.

		FDCGM(1,N)		GM(1,N)		DGM(1,N)	
Year	Real data	Fitting	APE(%)	Fitting	APE(%)	Fitting	APE(%)
2005	19809.25	19809.25	0.00	19809.25	0.00	19809.25	0.00
2006	23865.61	26309.45	10.24	19321.50	19.04	23143.58	3.03
2007	23880.90	29560.23	23.78	29117.78	21.93	25146.88	5.30
2008	27422.06	31762.80	15.83	34213.01	24.76	29705.88	8.33
2009	30831.81	32104.63	4.13	27472.86	10.89	28152.03	8.69
2010	33069.01	35783.11	8.21	33601.99	1.61	31917.44	3.48
2011	37695.95	39996.33	6.10	39281.88	4.21	37505.14	0.51
2012	41359.23	42382.29	2.47	42829.68	3.56	41939.52	1.40
2013	45911.19	44856.43	2.30	46087.66	0.38	45775.67	0.30
2014	49541.24	47151.69	4.82	49619.81	0.16	49354.31	0.38
2015	50652.09	47328.13	6.56	51379.51	1.44	51382.08	1.44
2016	51140.09	48629.83	4.91	52447.81	2.56	52286.24	2.24
2017	51995.49	52386.95	0.75	51794.85	0.39	52563.63	1.09
2018	56130.88	56902.79	1.38	54437.78	3.02	54430.19	3.03
2019	59483.99	60200.70	1.20	62314.38	4.76	59466.07	0.03
MAPE(%)					7.05		2.80
2020	62132.47	61977.45	0.25	68586.82	10.39	65107.76	4.79
2021	69190.28	71271.52	3.01	86089.33	24.42	79119.11	14.35
MAPE(%)					17.41		9.57

		DVCGM(1,N)		BPNN		LSTM	
Year	Real data	Fitting	APE(%)	Fitting	APE(%)	Fitting	APE(%)
2005	19809.25	19809.25	0.00	24863.60	25.52	40870.00	106.32
2006	23865.61	19180.86	19.63	25521.59	6.94	30766.25	28.91
2007	23880.90	29221.16	22.36	27081.11	13.40	28160.56	17.92
2008	27422.06	34453.96	25.64	28256.75	3.04	30734.86	12.08
2009	30831.81	27817.36	9.78	29134.12	5.51	34638.12	12.35
2010	33069.01	33806.58	2.23	33494.81	1.29	37534.54	13.50
2011	37695.95	39311.85	4.29	39021.02	3.52	40799.68	8.23
2012	41359.23	42915.81	3.76	41955.43	1.44	43458.64	5.08
2013	45911.19	46221.49	0.68	45083.91	1.80	46087.97	0.39
2014	49541.24	49887.45	0.70	47922.43	3.27	48717.44	1.66
2015	50652.09	50835.20	0.36	49129.09	3.01	50991.79	0.67
2016	51140.09	52307.97	2.28	50113.41	2.01	53065.70	3.77
2017	51995.49	51808.85	0.36	51992.74	0.01	54630.18	5.07
2018	56130.88	54663.14	2.61	54233.13	3.38	56350.72	0.39
2019	59483.99	62858.31	5.67	57019.61	4.14	57737.66	2.94
MAPE(%)			7.17		5.22		14.62
2020	62132.47	69172.23	11.33	57628.06	7.25	58461.78	5.91
2021	69190.28	86211.78	24.60	58242.12	15.82	60340.63	12.79
MAPE(%)			17.97		11.54		9.35

Source(s): Table created by authors

Table 5.
Fitting and forecasting results of six models to Fujian province's port cargo throughput



Source(s): Figure created by authors

Figure 5.
Fitting curves of five models to Fujian province's port cargo throughput

[Figure 6](#) exhibits that the APE of the FDCGM(1,N) model is within 5% except for a few years, and the degree of fluctuation is the most stable among all the comparison models. It indicates that new model has more durable and accurate performance and more robust adaptability than the comparison models. Meanwhile, Figure 7 shows that the MAPEs of the FDCGM(1,N) model is 4.16%, a little bit higher than that of the DGM(1,N) model. The LSTM model has the largest MAPEs of 14.62%. The FDCGM(1,N) model performs well with the smallest MAPEp among the six models at 1.63%. The new model considering the fractional-order AGO can overcome the limitations of other models in the simulation and forecasting process and has better forecasting accuracy and stable performance. It can perform out-of-sample forecasting of cargo throughput in Fujian province.

4.2.2 Forecast Fujian's port cargo throughput in 2022–2025. A new model is used to forecast Fujian province's port cargo throughput in 2022–2025. From Table 6, in the next four years, Fujian province's port cargo throughput will continue to grow and reach 1,017,638,300

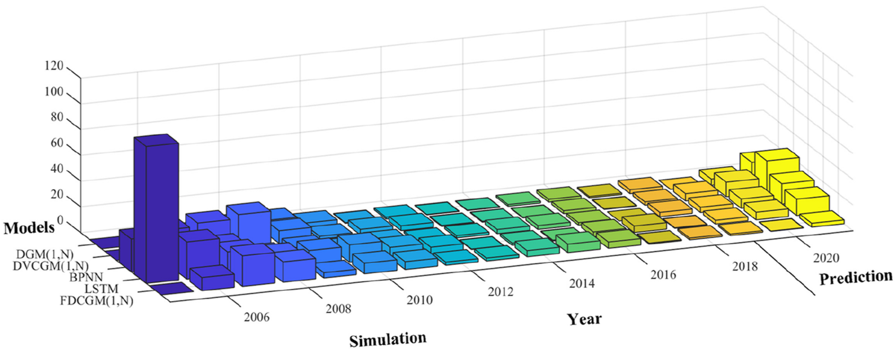


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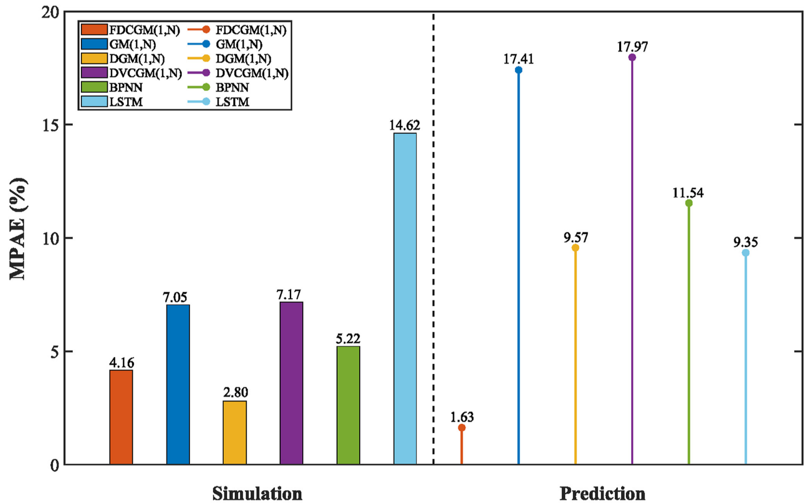
Figure 6.
APE(%) of Tianjin's port cargo Fujian province's amongst six models



Source(s): Figure created by authors

Figure 7. MAPE(%) of six models to Fujian province's port cargo throughput

Table 6. Fujian province's port cargo throughput predicted by the FDCGM(1,N) model from 2022 to 2025

	2022	2023	2024	2025
Port cargo throughput (10000 tons)	78720.28	85580.92	93231.36	101763.83

Source(s): Table created by authors

tons in 2025. The construction of Fujian FTZ provides an endogenous impetus for developing ports. With a series of preferential policies brought by the FTZ, Fujian provincial ports have been significantly strengthened, the disadvantages of "one bay and two ports" management have been effectively solved, and the level of port intensification, scale and modernization have been significantly improved. The free trade and convenient investment brought by Fujian FTZ have accelerated port development and enhanced port enterprises' competitiveness. In the future, Fujian province will continue to promote port integration actively, clarify the scope of port areas, functional positioning and development goals of each port, strengthen cross-strait industrial docking and promote advantageous industrial cooperation.

4.3 Comprehensive contrastive analysis

Figures 8 and 9 show the growth rates of port cargo throughput from 2005 to 2025, and the port cargo throughput prediction results from 2022 to 2025 for Tianjin and Fujian provinces. From them, the effects of the FTZ policy on port cargo throughput differ from region to region.

Tianjin's port cargo throughput has shown a growth trend after the constitution of the Tianjin FTZ, but the growth rate has slowed. It may be because Tianjin FTZ strives to develop its transit transport business, which diverts part of the import and export cargo flow. Meanwhile, the cargo throughput mainly comes from the Beijing-Tianjin-Hebei region. After establishing the FTZ, Tianjin port faces more and more competition from the Bohai Seaport group. The growth rate will be reduced as a result. Overall, the FTZ policy has brought stable development to Tianjin's ports. In 2022–2025, the cargo throughput of Tianjin ports will continue to grow, and its growth rate will remain stable. It indicates that the Tianjin FTZ policy will continue to fuel the development of Tianjin's ports.

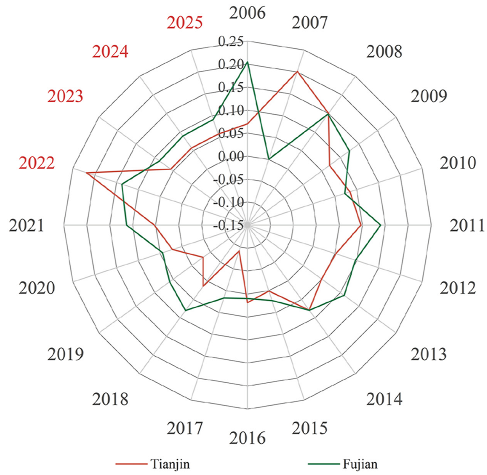


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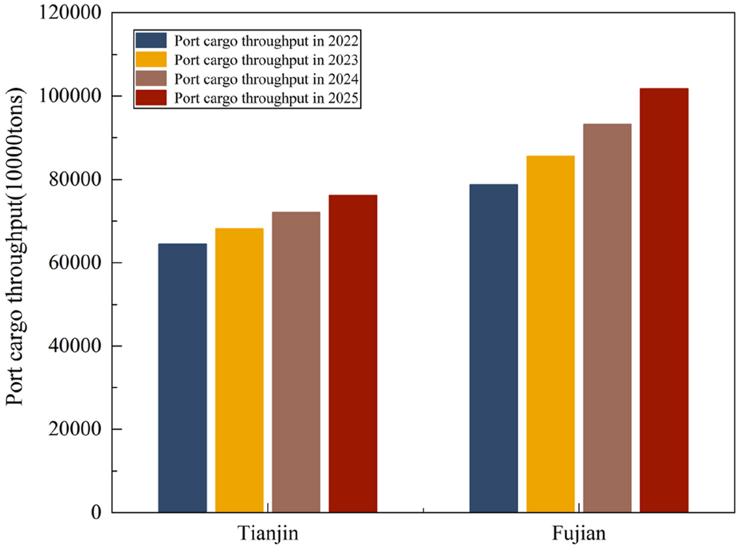
Figure 8.
The growth rate of port cargo throughput of Tianjin and Fujian from 2006 to 2025



Source(s): Figure created by authors

Figure 9.
Port cargo throughput of Tianjin and Fujian from 2022 to 2025

Meanwhile, the Fujian FTZ policy has contributed significantly and continuously to the port cargo throughput. With the preferential policies of the Fujian FTZ, easier market access has attracted many enterprises to move in, driving import and export business. It has directly caused the rapid growth of port cargo throughput in Fujian province, thus maintaining a stable growth rate. The port cargo throughput continues its growth trend in 2022–2025, reaching 1,017,638,300 tons in 2025. Its growth rate increases and then decreases, indicating that Fujian needs to strengthen port infrastructure construction, improve port productivity and realize the boosting effect of the FTZ on port development in the long term.

5. Conclusions

The establishment of the FTZs has advanced port production and development. As an essential indicator of port production capacity and operation, accurate prediction of port cargo throughput is vital for policymakers in formulating port development plans. This paper forecasts and analyses the port cargo throughput under the FTZ policy by constructing a new model and obtains the following conclusions:

(1) By introducing the fractional-order AGO and considering the policy effect, this paper proposes a new grey multivariate forecasting model, which enhances the adaptability and forecasting performance of the new model and compensates for the shortcomings of the traditional multivariate model. Further, the GWO algorithm is employed to track the optimal introduced fractional-order AGO, which weakens the randomness of the original data series and improves the ability of the FDCGM(1,N) model to mine the information of the original data series.

(2) By simulating and forecasting port cargo throughput from 2005 to 2021 for Tianjin where FTZs are located, the results show that the new model curve can fit the raw data curve well. Compared with five comparison models, GM(1,N), DGM(1,N), DVCGM(1,N), BPNN and LSTM, the new model has good performance with MAPE values of 6.07% in the simulation phase and 6.70% in the forecasting phase, respectively. It indicates that the FDCGM(1,N) model is a practical tool for forecasting port cargo throughput. It can be used for out-of-sample forecasting and port cargo throughput of Tianjin will reach 762,348,800 tons in 2025. Meanwhile, comparative analysis reveals that Tianjin's port cargo throughput has shown a slow growth trend under the influence of FTA policy.

(3) The port cargo throughput of Fujian province where FTZs are located is simulated from 2005 to 2021, and the results show that the new model curve can better reflect the changing trend of the original data. Compared with the five comparison models GM(1,N), DGM(1,N), DVCGM(1,N), BPNN and LSTM, the MAPE value of the new model is 4.16% in the simulation stage and 1.63% in the prediction stage. It shows that the FDCGM(1,N) model can be used to predict the port cargo throughput in Fujian province out of sample. Through the forecast, it is found that the cargo throughput of ports in Fujian province will reach 1,017,638,300 tons in 2025. In addition, the results of the comparative analysis show that, thanks to the FTZ policy, Fujian's port cargo throughput has exhibited rapid growth.

The grey multivariate model proposed in this paper, which considers the effects of both policy and fractional order, has better simulation and forecasting performance than the traditional grey forecasting and machine learning models. In the future, other intelligent optimization algorithms can be considered to improve the new model's performance. The autoregressive time-lag term can be also introduced to improves the new model's performance. In addition, the FDCGM(1,N) model can also be used to predict the port cargo throughput of other provinces (cities) implementing FTZ policy, providing a reliable basis for decision-makers to make port development plans.

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