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Forecasting the potential of global marine shipping carbon emission under artificial intelligence based on a novel multivariate discrete grey model

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Abstract

Purpose – To achieve sustainable development in shipping, accurately identifying the impact of artificial intelligence on shipping carbon emissions and predicting these emissions is of utmost importance.

Design/methodology/approach – A multivariable discrete grey prediction model (WFTDGM) based on weakening buffering operator is established. Furthermore, the optimal nonlinear parameters are determined by Grey Wolf optimization algorithm to improve the prediction performance, enhancing the model's predictive performance. Subsequently, global data on artificial intelligence and shipping carbon emissions are employed to validate the effectiveness of our new model and chosen algorithm.

Findings – To demonstrate the applicability and robustness of the new model in predicting marine shipping carbon emissions, the new model is used to forecast global marine shipping carbon emissions. Additionally, a comparative analysis is conducted with five other models. The empirical findings indicate that the WFTDGM (1, N) model outperforms other comparative models in overall efficacy, with MAPE for both the training and test sets being less than 4%, specifically at 0.299% and 3.489% respectively. Furthermore, the out-of-sample forecasting results suggest an upward trajectory in global shipping carbon emissions over the subsequent four years. Currently, the application of artificial intelligence in mitigating shipping-related carbon emissions has not achieved the desired inhibitory impact.

Practical implications – This research not only deepens understanding of the mechanisms through which artificial intelligence influences shipping carbon emissions but also provides a scientific basis for developing effective emission reduction strategies in the shipping industry, thereby contributing significantly to green shipping and global carbon reduction efforts.

Originality/value – The multi-variable discrete grey prediction model developed in this paper effectively mitigates abnormal fluctuations in time series, serving as a valuable reference for promoting global green and low-carbon transitions and sustainable economic development. Furthermore, based on the findings of this paper, a grey prediction model with even higher predictive performance can be constructed by integrating it with other algorithms.

Keywords Carbon emission of marine shipping, Artificial intelligence, Sustainable development, Multivariate discrete grey model, Grey wolf optimization

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1. Introduction

1.1 Background and motivation

Carbon emission management has emerged as a critical aspect in the development of an ecological civilization and in participating in international climate regulation. The transportation sector is a significant contributor to carbon emissions, with marine shipping being a substantial component. Over the past half-century, seaborne trade has expanded at an approximate annual rate of 3%, representing roughly 80–85% of the global total trade volume (Chen and Lv, 2015). Despite its vital role in enabling global commerce, marine shipping has attracted considerable public criticism (Zhu *et al.*, 2023). On March 14, 2020, the European Environment Agency (EEA) issued a report stating that the maritime sector is "currently one of the most unregulated sources of air pollution." This is primarily due to its heavy reliance on fossil fuel combustion, which results in the release of copious amounts of carbon dioxide. Due to the continued growth of global shipping trade, emissions from international shipping are likely to increase by 40% from 2008 levels by 2050 (Liu *et al.*, 2019a). The maritime industry must also embrace the responsibility of emission reduction and has made commendable strides under the guidance of the International Maritime Organization.

Studies have demonstrated that artificial intelligence technology exerts a complex dual impact on carbon emissions. On one hand, the development and application of AI technology could escalate potential energy demand (Wang *et al.*, 2023), leading to substantial carbon emissions. The development and operation of AI necessitate considerable computing resources and power support, which predominantly originate from fossil-fuel power stations, thereby contributing to overall carbon emissions. Conversely, the integration of AI technology with low-carbon technology can alter production and consumption patterns, consequently mitigating carbon emissions (Chen *et al.*, 2022; Liu *et al.*, 2019b). The deployment of AI enables the planning of more rational shipping routes and enhances shipping efficiency, ultimately diminishing shipping-related carbon emissions. Moreover, industrial intelligence facilitates the precise detection and prediction of shipping carbon emissions. The establishment of a carbon emission trading platform grounded in digital information technology can curtail total carbon emissions, fostering reductions in carbon footprints.

Based on this, under the influence of artificial intelligence technology, the development trend of marine shipping carbon emission belts needs to be verified. However, traditional time series forecasting methods are often inadequate for achieving accurate predictions of shipping carbon emissions due to constraints related to large sample sizes and stringent distribution requirements. The advantage of grey prediction models in processing small samples and managing poor information systems aligns with the characteristics of shipping carbon emission data. Given this compatibility, it is necessary to propose a more extensive, practical, and stable grey prediction model to comprehensively examine the impact of artificial intelligence development on carbon emissions from marine shipping. This would enable more accurate predictions of global shipping carbon emissions and provide a scientific basis for formulating effective emission reduction policies. This not only has important implications for reducing carbon emissions from marine shipping and creating a low-carbon world, but also offers research support for policies aimed at promoting intelligent manufacturing.

1.2 Literature review

1.2.1 Research on carbon emission of marine shipping. As the largest ecosystem on Earth, the ocean serves as a reservoir for carbon dioxide and plays a pivotal role in the global carbon cycle. Nevertheless, current measures and policies aimed at mitigating climate change predominantly focus on terrestrial environments, overlooking the significant potential of ocean-based solutions in curtailing CO2 emissions (Cooley *et al.*, 2019). Evidence suggests that marine ecosystems possess the capacity to sequester carbon (Serrano *et al.*, 2019; Wang *et al.*, 2019). The decarbonization of marine shipping essentially entails the adoption of clean energy sources. With the advancement of low-carbon marine shipping and the anticipated increase in global marine trade, clean energy is poised to make an increasingly substantial contribution to diminishing carbon emissions (Feng *et al.*, 2021).

In September 2020, the European Parliament resolved to incorporate marine shipping emissions into the EU ETS (Cariou *et al.*, 2021). Recent studies have addressed CO2 emissions from shipping, focusing on the implications of these emissions (Wang *et al.*, 2015), their mitigation efficacy (Gu *et al.*, 2019), and the repercussions for other sectors (Cariou *et al.*, 2021). Many scholars have conducted in-depth research on strategies and models for reducing carbon emissions from ships. Psaraftis *et al.* (2021) evaluated various smoke reduction models for ships to diminish greenhouse gas emissions. Lagouvardou *et al.* (2022) examined a fuel tax's potential for prompting CO2 emission reductions and devised a model to optimize ship load and speed. The ramifications of integrating marine affairs into the EU ETS were discussed by Lagouvardou and Psaraftis (2022), considering CO2 emissions and the costs incurred by shipping companies both within and beyond the European Economic Area (EEA). From an economic standpoint, Wang *et al.* (2015) appraised the ETS's impact on international shipping. Gritsenko (2017) reviewed literature on the shipping industry's response to global ETS, regional ETS, and local policies, advocating a multicentric regulatory approach. Wu *et al.* (2022) scrutinized research on ETS in transportation and analyzed the drivers, challenges, and outcomes of Market-Based Measures (MBMs) within this framework. Chen *et al.* (2014) determined that governmental measures, encompassing environmental policies and financial incentives, could substantially curtail carbon emissions from shipping. In the realm of marine shipping carbon emission measurement, various scholars have developed distinct Emission Assessment Models, such as the Ship Emission Inventory Model (SEIM) to gauge ocean-going vessel emissions' impact on East Asia (Liu *et al.*, 2016). This model was further refined by Chinese researchers (Wang *et al.*, 2021). Li *et al.* (2023a) proposed a Geographically-based Emission Estimation Model (GEEM) to estimate carbon emissions across the global high seas. In terms of the prediction of marine shipping carbon emissions, different scholars have used different models for prediction analysis, such as activity weighting method (Mou *et al.*, 2024), improved integrated scheduling model for multiple heterogeneous coded genetic algorithms (Wang *et al.*, 2020), and the construction of a carbon reduction assessment model from multiple dimensions (Feng *et al.*, 2021). These models are adapted to different scenarios and requirements.

1.2.2 Research on relationship between carbon emission of marine shipping and artificial intelligence. With the ongoing technological advancements, escalating market investments, and augmented government support, the role of artificial intelligence as a pivotal factor of production has been unequivocally established. As a vanguard technology in the current technological revolution, AI has significantly enhanced the intelligence and applicability of industrial robots. It has emerged as an essential tool for global economies to alleviate labor shortages in production and to augment productivity. Data from the International Federation of Robotics (IFR) indicates that the global annual installation of industrial robots reached 514,700 units in 2021, marking a 31% increase from the previous year. Experts forecast that there is a 90% likelihood that AI will possess greater human work capabilities within this century, with the potential for AI technology to be integrated into over 70% of enterprises by 2030 (Bughin *et al.*, 2018).

Marine shipping constitutes a significant contributor to carbon emissions. However, the advent of digital technology within the industrial sector presents a potential solution to mitigate these high emissions from marine shipping. The amalgamation of cutting-edge technologies such as Industry 4.0 and artificial intelligence with economic and social activities has emerged as a crucial catalyst for sustainable societal development (Vinuesa *et al.*, 2020). In China, industrial robots, being a pivotal component of Industry 4.0 and artificial intelligence, have experienced rapid advancements. The extensive integration of new energy sources, novel materials, and industrial robotics fosters industrial technological evolution, augmenting the environmental advantages conferred by industrial robots and facilitating the transition towards a low-carbon economy. The substitution and augmentation of human labor with intelligent processes is likely to influence the distribution of factors and marginal output between capital and labor (Acemoglu and Restrepo, 2019). Existing research has predominantly concentrated on the repercussions of industrial robots on the labor market (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Moreover, Kromann *et al.* (2020) examined the implications of industrial robots on economic growth and the disparity in residents' income.

As general-purpose technologies advance, a limited body of literature has begun to examine the influence of Information and Communication Technologies (ICT) on carbon emissions and energy intensity (Zhou *et al.*, 2019; Lange *et al.*, 2020; Sun and Kim, 2021). However, there remains a paucity of research exploring the impact of artificial intelligence on carbon emissions within the shipping industry. Empirical studies by Li *et al.*, 2022 and Wang *et al.* (2022), utilizing cross-national data, have identified that the carbon emission reduction attributable to industrial robots is subject to industry and country heterogeneity. Zhao *et al.* (2024) employed the generalized moment estimation model and discovered that artificial intelligence can significantly mitigate disparities in carbon emissions. Furthermore, under the regulatory influence of green innovation, the carbon reduction efficacy of artificial intelligence has been augmented (Chen *et al.*, 2022). There is a lack of research on how artificial intelligence affects marine shipping carbon emissions, and little attention is paid to the prediction of carbon emissions from global shipping.

1.2.3 Research on multivariate grey prediction models. The grey prediction model is characterized by its simplicity in operation, ease of verification, and minimal data requirements, making it extensively applicable across various forecasting domains. Notably, it has been employed in areas such as wind power generation (Li *et al.*, 2023c), fishery carbon sinks (Li *et al.*, 2024a), and marine economic resilience (Li *et al.*, 2023a, b, c). Building upon the foundational grey model, numerous scholars have contributed enhancements addressing diverse facets.

In the realm of data preprocessing, various scholars have employed optimized buffer operators to forecast sales volumes for new energy vehicles (He *et al.*, 2020), mobile communication service income (Qu, 2014), and renewable energy sources (Wang *et al.*, 2023). Concerning background value optimization, Wei *et al.* (2018) incorporated an adjusted background value coefficient into the grey polynomial model and developed an algorithmic framework for polynomial order selection, background coefficient search, and parameter estimation. Ye *et al.* (2018) enhanced the traditional grey model by applying the central point triangle whitening weight function to the state division, objectively reflecting the degree of preference under different states, and calculated the possibility of study value under each state, achieving a superior fitting effect. Li *et al.* (2020) introduced the TPBVGM(1,1) model, which increases the number of parameters in the background value, proving the unreasonableness of the two-parameter background value assignment, thus enhancing the smoothness of the background value and mitigating the influence of extreme values in the original sequence. Regarding initial value optimization, Wang *et al.* (2018) devised a matrix-based algorithm to delineate the relationship between initial conditions and development coefficients and to estimate the matrix representation of these two parameters using the least square method, based on the nonlinear algebraic relation between the two parameters, thereby obtaining the parameter relation and error properties between two sequences with multiple relations.

In terms of model application, Ding *et al.* (2018) proposed a new initial condition with variable weighting coefficient according to the principle of "new information priority", combined with new initial conditions and rolling mechanism, and used this model to forecast China's total electricity consumption and industrial electricity consumption from 2012 to 2014. Wu *et al.* (2019) proposed a new nonlinear grey Bernoulli model with fractional order accumulation using fractional order cumulative generation matrix and Bernoulli equation to predict China's short-term renewable energy consumption during the 13th Five-Year Plan period (2016–2020). Li *et al.* (2023b) proposed a novel self-adaptive fractional order grey generalized Verhulst model (SAFGGVM) which was used in energy carbon intensity forecasting for five countries (China, USA, India, Russia and Japan). Wu *et al.* (2018) used grey convex correlation analysis to describe the relationship between power consumption and related factors. A multivariable grey forecasting model considering the total population is proposed for the forecast of electricity consumption in Shandong Province.

1.3 Contributions and organization

In this study, to address the challenge posed by the original data series exhibiting significant fluctuations and its associated influencing factor sequences, we employ a weakening buffer operator in the preprocessing stage for the related sequences. Subsequently, taking into account the fractional order accumulation process and time trend term, we develop a multivariable discrete grey prediction model that incorporates the weakening buffering operator. The potential marginal contribution is as follows:

(1) By incorporating a fractional order accumulation process and a time trend term, a multivariate discrete grey prediction model (WFTDGM) with a weakening buffering operator is formulated. The optimal fractional order effectively mitigates fluctuation range issues within the model segment to a certain extent.

(2) The Grey Wolf algorithm is utilized to optimize the nonlinear parameters of the WFTDGM (1,N) model, thereby enhancing the model's predictive accuracy. Consequently, optimizing the nonlinear parameter not only improves the model's predictive performance but also broadens its applicability.

(3) The WFTDGM model is employed to forecast global marine shipping carbon emissions from 2023 to 2026, followed by an analysis of the forecast results. Subsequently, relevant policy recommendations are derived based on the analytical outcomes. The conclusion offers insights into how artificial intelligence can facilitate the transformation of shipping and reduce its carbon emissions.

The subsequent structure of this paper is organized as follows: Section 2 presents the suggested model along with the algorithm employed in this investigation. Section 3 substantiates the efficacy of the Wavelet-based Forecasting Time Series Decomposition Grey Model (WFTDGM) by utilizing artificial intelligence and marine shipping carbon emission data, and forecasts global marine shipping carbon emissions from 2023 to 2026. Section 4 encompasses the principal conclusions and future outlooks of the research.

2. Methodology

2.1 Defects of traditional DGM(1,N) model

Definition 1. Let $X_i^{(0)} = (x_i^{(0)}(1), x_i^{(0)}(2), \cdots, x_i^{(0)}(m))$, $i = 1, 2, \cdots, N$ represent the original sequence. The first cumulative sequence is denoted as

$X_i^{(1)} = (x_i^{(1)}(1), x_i^{(1)}(2), \cdots, x_i^{(1)}(m)), \quad i = 1, 2, \cdots, N,$ followed by $x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j), i = 1, 2, \cdots, N$. Subsequently,

$$x_1^{(1)}(k+1) + \alpha_1 x_1^{(1)}(k) = \sum_{i=2}^{N} \alpha_i x_i^{(1)}(k+1) + \alpha_{N+1}, k = 1, 2, \cdots, m-1 \tag{1}$$

is referred to as the DGM(1,N) model (Ma *et al.*, 2019), where $\boldsymbol{Q} = (\alpha_1, \alpha_2, \cdots, \alpha_N, \alpha_{N+1})^{\mathrm{T}}$ is the structural parameter.
The predicting formula of the DGM(1,N) model is:

$$\widehat{x}_1^{(1)}(k+1) = -\alpha_1 x_1^{(1)}(k) + \sum_{i=2}^{N} \alpha_i x_i^{(1)}(k+1) + \alpha_{N+1} \tag{2}$$

The parameter vector $\boldsymbol{Q} = (\alpha_1, \alpha_2, \cdots, \alpha_N, \alpha_{N+1})^{\mathrm{T}}$ can be estimated by ordinary least square method (OLS):

$$\boldsymbol{Q} = \left(\boldsymbol{K}^{\mathrm{T}}\boldsymbol{K}\right)^{-1}\boldsymbol{K}^{\mathrm{T}}\boldsymbol{Y}_1 \tag{3}$$

$$\text{where } \boldsymbol{K} = \begin{bmatrix} -x_1^{(1)}(1) & x_2^{(1)}(2) & x_3^{(1)}(2) & \cdots & x_N^{(1)}(2) & 1 \\ -x_1^{(1)}(2) & x_2^{(1)}(3) & x_3^{(1)}(3) & \cdots & x_N^{(1)}(3) & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -x_1^{(1)}(m-1) & x_2^{(1)}(m) & x_3^{(1)}(m) & \cdots & x_N^{(1)}(m) & 1 \end{bmatrix}, \boldsymbol{Y} = \begin{bmatrix} x_1^{(1)}(2) \\ x_1^{(1)}(3) \\ \vdots \\ x_1^{(1)}(m) \end{bmatrix}.$$

In contrast to the conventional multivariable grey prediction model, the discrete multivariable grey model (DGM(1,N)) offers a unified framework that integrates both difference and differential forms of the model, thereby mitigating potential errors during operation and transformation. Nonetheless, DGM(1,N) model still holds considerable potential for further enhancement and optimization.

(1) The conventional DGM(1,N) model demonstrates a commendable simulation effect when applied to original data series characterized by multiple influencing factors. However, its efficacy diminishes when confronted with data series exhibiting pronounced fluctuations and oscillations. Particularly concerning are series with significant volatility, where inadequacies in data preprocessing culminate in suboptimal predictive outcomes.

(2) The model overlooks the complete incorporation of lag and time-varying effects of pertinent influencing factors on the behavior sequence of the original data. It posits a simultaneous relationship between the original data behavior sequence and the impact factor sequence, neglecting any lagged associations.

(3) While the model partially captures the evolution and patterns of the original data series and its influencing factors, it struggles to prioritize new information effectively and leverage the full potential of fresh data. Therefore, there is a need to explore

transitioning the accumulation process from integer to fractional values, thereby enhancing the weighting assigned to novel information.

2.2 Establishment of WFTDGM(1,N) model

2.2.1 The proposed WFTDGM(1,N) model. To address the challenges posed by original data series exhibiting pronounced fluctuation characteristics and their associated influencing factor series, preprocessing involves applying a weakening buffering operator to the correlation sequence. Subsequently, a multivariable discrete grey prediction model with an incorporated weakening buffering operator is developed, taking into account the fractional-order accumulation process and the time trend term.

Definition 2. To enhance the handling of data fluctuations within the original data series, we employ the classical weakening buffer operator $\boldsymbol{B}_1$ for data preprocessing:

$$\boldsymbol{B}_1 = \begin{bmatrix} \frac{1}{m} & 0 & 0 & 0 & 0 \\ \frac{1}{m} & \frac{1}{m-1} & 0 & \cdots & 0 \\ \frac{1}{m} & \frac{1}{m-1} & \frac{1}{m-2} & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & 0 \\ \frac{1}{m} & \frac{1}{m-1} & \frac{1}{m-2} & \cdots & 1 \end{bmatrix}_{m\times m} \tag{4}$$

The buffered sequence is $X_i^{(w)} = (x_i^{(w)}(1), x_i^{(w)}(2), \cdots, x_i^{(w)}(m))$, where $i = 1, 2, \cdots, N$.

To enhance the efficacy of identifying dynamic changes in the data series, we employ the r-order cumulative generating operator, denoted as r-AGO, to accumulate the buffered sequence $X_i^{(w)}$, $i = 1, 2, \cdots, N$. This approach enables the derivation of solutions with heightened model robustness.

Definition 3. The r-AGO accumulation process of sequence $X_i^{(w)}$ is:

$$X_i^{(r)} = (x_i^{(r)}(1), x_i^{(r)}(2), \cdots, x_i^{(r)}(m)), \text{ where}$$
$$x_i^{(r)}(s) = \sum_{j=1}^{s} \frac{\Gamma(s+r-j)}{\Gamma(r)\Gamma(s-j+1)} x_i^{(w)}(j), s = 1, 2, \cdots, m \tag{5}$$

and $\Gamma(1) = 1, x_i^{(r)}(1) = x_i^{(w)}(1)$.

In contrast, the r-IAGO process gives the inverse sequence $X_i^{(r)} = (x_i^{(r)}(1),\ x_i^{(r)}(2),\ \cdots, x_i^{(r)}(m))$, where

$$x_i^{(-r)}(s) = \sum_{j=0}^{s-1} (-1)^j \frac{\Gamma(r+1)}{\Gamma(j+1)\Gamma(r-j+1)} x_i^{(0)}(s-j)\, s = 1, 2, \cdots, m \tag{6}$$

Definition 4. Let the original sequence $X_i^{(0)} = (x_i^{(0)}(1), x_i^{(0)}(2), \cdots, x_i^{(0)}(m))$, $i = 1, 2, \cdots, N$. $X_1^{(r)}$ is its r-AGO, called

$$x_1^{(r)}(k+1) + \beta_1 x_1^{(r)}(k) = \sum_{i=2}^{N} \beta_i x_i^{(r)}(k+1) + \beta_{N+1}(k+1) + \beta_{N+2} \tag{7}$$

as Weakening Fractional Time-varying Discrete Grey Model, abbreviated as WFTDGM(1,N) model, where $k = 1, 2, \cdots, m-1$, r is the fractional order to be optimized, β_i, $i = 1, 2, \cdots, N, N+1, N+2$ indicates the parameter to be estimated.

Theorem 1. The structural parameter vector $\widehat{\beta} = (\widehat{\beta}_1, \widehat{\beta}_2, \cdots, \widehat{\beta}_N, \widehat{\beta}_{N+1}, \widehat{\beta}_{N+2})^{\mathrm{T}}$ in the model can be estimated by OLS, that is,

$$\widehat{\beta} = \left(\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B}\right)^{-1}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{Y} \tag{8}$$

where $\boldsymbol{B} = \begin{bmatrix} -x_1^{(r)}(1) & x_2^{(r)}(2) & x_3^{(r)}(2) & \cdots & x_N^{(r)}(2) & 2 & 1 \\ -x_1^{(r)}(2) & x_2^{(r)}(3) & x_3^{(r)}(3) & \cdots & x_N^{(r)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -x_1^{(r)}(m-1) & x_2^{(r)}(m) & x_3^{(r)}(m) & \cdots & x_N^{(r)}(m) & m & 1 \end{bmatrix}$, $\boldsymbol{Y} = \begin{bmatrix} x_1^{(r)}(2) \\ x_1^{(r)}(3) \\ \vdots \\ x_1^{(r)}(m) \end{bmatrix}$.

Proof

According to Equation (7), it can be obtained:

$$x_1^{(r)}(k+1) = -\beta_1 x_1^{(r)}(k) + \sum_{i=2}^{N} \beta_i x_i^{(r)}(k+1) + \beta_{N+1}(k+1) + \beta_{N+2} \tag{9}$$

Let $k = 2, 3, \cdots, m$ in the above equation respectively, the following equations can be obtained:

$$\begin{cases} x_1^{(r)}(2) = -\beta_1 x_1^{(r)}(1) + \beta_2 x_2^{(r)}(2) + \cdots + \beta_N x_N^{(r)}(2) + \beta_{N+1} \times 2 + \beta_{N+2} \times 1 \\ x_1^{(r)}(3) = -\beta_1 x_1^{(r)}(2) + \beta_2 x_2^{(r)}(3) + \cdots + \beta_N x_N^{(r)}(3) + \beta_{N+1} \times 3 + \beta_{N+2} \times 1 \\ \vdots \\ x_1^{(r)}(m) = -\beta_1 x_1^{(r)}(m-1) + \beta_2 x_2^{(r)}(m) + \cdots + \beta_N x_N^{(r)}(m) + \beta_{N+1} \times m + \beta_{N+2} \times 1 \end{cases} \tag{10}$$

Then convert the above equations into matrix form, we can get:

$$\boldsymbol{Y} = \begin{bmatrix} x_1^{(r)}(2) \\ x_1^{(r)}(3) \\ \vdots \\ x_1^{(r)}(m) \end{bmatrix} \tag{11}$$

$$\boldsymbol{B} = \begin{bmatrix} -x_1^{(r)}(1) & x_2^{(r)}(2) & x_3^{(r)}(2) & \cdots & x_N^{(r)}(2) & 2 & 1 \\ -x_1^{(r)}(2) & x_2^{(r)}(3) & x_3^{(r)}(3) & \cdots & x_N^{(r)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -x_1^{(r)}(m-1) & x_2^{(r)}(m) & x_3^{(r)}(m) & \cdots & x_N^{(r)}(m) & m & 1 \end{bmatrix} \tag{12}$$

$$\widehat{\beta} = \left(\widehat{\beta}_1, \widehat{\beta}_2, \cdots, \widehat{\beta}_N, \widehat{\beta}_{N+1}, \widehat{\beta}_{N+2}\right)^{\mathrm{T}} \tag{13}$$

Make $\boldsymbol{Y} = \boldsymbol{B}\beta$, and minimize the sum of squares of residuals obtained by the WFTDGM(1,N) model, i.e.

$$\boldsymbol{E} = \varepsilon^{\mathrm{T}}\varepsilon = (\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta})^{\mathrm{T}}(\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta}) \tag{14}$$

Based on the above unconstrained linear programming function, combined with the extreme value solving method, it can be obtained

$$\begin{aligned} \frac{\partial \boldsymbol{E}}{\partial \widehat{\beta}} &= \frac{\partial\left[(\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta})^{\mathrm{T}}(\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta})\right]}{\partial \widehat{\beta}} = 2\frac{(\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta})\partial\left[(\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta})^{\mathrm{T}}\right]}{\partial \widehat{\beta}} \\ &= -2\boldsymbol{B}^{\mathrm{T}}(\boldsymbol{Y} - \boldsymbol{B}\widehat{\beta}) = -2\boldsymbol{B}^{\mathrm{T}}\boldsymbol{Y} + 2\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B}\widehat{\beta} = 0 \end{aligned} \tag{15}$$

Theorem 2. Assuming that the structural parameter $\widehat{\beta} = (\widehat{\beta}_1, \widehat{\beta}_2, \cdots, \widehat{\beta}_N, \widehat{\beta}_{N+1}, \widehat{\beta}_{N+2})^{\mathrm{T}}$ and the fractional order parameter r are given, we can obtain:

(1) The initial value is $x_1^{(r)}(1) = x_1^{(0)}(1), k = 1, 2, \cdots, m-1$, and the simulation value of the model is as follows:

$$\widehat{x}_1^{(r)}(k+1) = -\beta_1 x_1^{(r)}(k) + \sum_{i=2}^{N} \beta_i x_i^{(r)}(k+1) + \beta_{N+1}(k+1) + \beta_{N+2} \tag{16}$$

(2) The reduction value of the model is:

$$\widehat{x}_i^{(0)}(k)=\begin{cases} x_i^{(0)}(1), & k=1 \\ \sum_{j=0}^{k-1}(-1)^j\frac{\Gamma(r+1)}{\Gamma(j+1)\Gamma(r-j+1)}\widehat{x}_1^{(r)}(k), k=2,3,\cdots,m \end{cases} \tag{17}$$

Proof

(1) Using mathematical induction to prove:
When $k=1$,

$$\begin{aligned}\widehat{x}_1^{(r)}(2)&=-\beta_1x_1^{(r)}(1)+\sum_{i=2}^{N}\beta_i\times\sum_{j=1}^{2}\frac{\Gamma(1+r-j)}{\Gamma(r)\Gamma(1-j+1)}x_i^{(w)}(j)+\beta_{N+1}\times2+\beta_{N+2}\\ &=-\beta_1x_1^{(r)}(1)+\sum_{i=2}^{N}\beta_ix_i^{(r)}(2)+\beta_{N+1}\times2+\beta_{N+2}\end{aligned} \tag{18}$$

The conclusion is valid.
Assuming that the conclusion is valid when $k=l$, we can obtain:

$$\widehat{x}_1^{(r)}(l+1)=-\beta_1x_1^{(r)}(l)+\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+1)+\beta_{N+1}(l+1)+\beta_{N+2} \tag{19}$$

Then according to Eq.(7) in Definition 4, it can be obtained:

$$x_1^{(r)}(l+2)+\beta_1x_1^{(r)}(l+1)=\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+2)+\beta_{N+1}(l+2)+\beta_{N+2} \tag{20}$$

By bringing the value $\widehat{x}_1^{(r)}(l+1)$ of $k=l$ into the above equation, we can get:

$$\begin{aligned}x_1^{(r)}(l+2)=&-\beta_1\left[-\beta_1x_1^{(r)}(l)+\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+1)+\beta_{N+1}(l+1)+\beta_{N+2}\right]+\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+2)\\ &+\beta_{N+1}(l+2)+\beta\\ &\vdots\\ &=-\beta_1\left[-\beta_l^{l-1}\left(-\beta_1x_1^{(r)}(2)\sum_{i=2}^{N}\beta_ix_i^{(r)}(2)+\beta_{N+1}\cdot2+\beta_{N+2}\right)+\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+1)\right.\\ &\left.+\beta_{N+1}(l+1)+\beta_{N+2}\right]+\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+2)+\beta_{N+1}(l+2)+\beta\\ &=-\beta_1x_1^{(r)}(l+1)+\sum_{i=2}^{N}\beta_ix_i^{(r)}(l+2)+\beta_{N+1}(l+2)+\beta_{N+2}\end{aligned} \tag{21}$$

Therefore, when the conclusion is also true when $k=l+1$, the theorem is proved.

(2) From the inverse process of r-AGO in Definition 3:
When $k>1$,
$\widehat{x}_i^{(0)}(k)=\sum_{j=0}^{k-1}(-1)^j\frac{\Gamma(r+1)}{\Gamma(j+1)\Gamma(r-j+1)}\widehat{x}_1^{(r)}(k)$, where $\widehat{x}_i^{(r)}(k)$ is the simulation value of the model;

When $k=1$, $\widehat{x}_i^{(0)}(k)=x_i^{(0)}(1)$.
To sum up:

$$\widehat{x}_i^{(0)}(k)=\begin{cases} x_i^{(0)}(1), & k=1 \\ \sum_{j=0}^{k-1}(-1)^j\frac{\Gamma(r+1)}{\Gamma(j+1)\Gamma(r-j+1)}\widehat{x}_1^{(r)}(k), k=2,3,\cdots,m \end{cases} \tag{22}$$

The theorem is proved.

2.2.2 Nonlinear parameter optimization based on GWO algorithm. Moreover, within the WFTDGM(1,N) model, the optimal fractional order effectively addresses the issue of fluctuation range within model segments to a certain extent. Thus, optimizing this nonlinear parameter not only enhances the predictive performance of the model but also expands its applicability.

Through the construction of the WFTDGM(1,N) model for estimating the optimal fractional order parameters in the nonlinear constrained optimization model (Eq.(23)), a solution can be effectively sought across various dynamic processes. Notably, the objective function of the constraint focuses on minimizing the Mean Absolute Percentage Error (MAPE) between the predicted and actual values of the model. To achieve this, the Grey Wolf Optimizer (GWO) (Mirjalili *et al.*, 2014) is employed to determine the nonlinear parameters, thereby enhancing the predictive accuracy of the model.

$$\min_{r}\text{MAPE}=\frac{1}{m}\sum_{k=1}^{m}\left|\frac{\widehat{x}_i^{(0)}(k)-x_i^{(0)}(k)}{x_i^{(0)}(k)}\right|\times 100\%$$

$$s.t.\begin{cases} \widehat{\beta}=\left(\widehat{\beta}_1,\widehat{\beta}_2,\cdots,\widehat{\beta}_N,\widehat{\beta}_{N+1},\widehat{\beta}_{N+2}\right)^{\mathrm{T}}=(\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B})^{-1}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{Y} \\ \boldsymbol{B}=\begin{bmatrix} -x_1^{(r)}(1) & x_2^{(r)}(2) & x_3^{(r)}(2) & \cdots & x_N^{(r)}(2) & 2 & 1 \\ -x_1^{(r)}(2) & x_2^{(r)}(3) & x_3^{(r)}(3) & \cdots & x_N^{(r)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -x_1^{(r)}(m-1) & x_2^{(r)}(m) & x_3^{(r)}(m) & \cdots & x_N^{(r)}(m) & m & 1 \end{bmatrix} \\ \boldsymbol{Y}=\begin{bmatrix} x_1^{(r)}(2) \\ x_1^{(r)}(3) \\ \vdots \\ x_1^{(r)}(m) \end{bmatrix} \\ \widehat{x}_1^{(r)}(k+1)=-\beta_1 x_1^{(r)}(k)+\sum_{i=2}^{N}\beta_i x_i^{(r)}(k+1)+\beta_{N+1}(k+1)+\beta_{N+2} \\ \widehat{x}_i^{(0)}(k)=\begin{cases} x_i^{(0)}(1), & k=1 \\ \sum_{j=0}^{k-1}(-1)^j\frac{\Gamma(r+1)}{\Gamma(j+1)\Gamma(r-j+1)}\widehat{x}_1^{(r)}(k), & k=2,3,\cdots,m \end{cases} \end{cases} \tag{23}$$

2.3 Measurement of prediction error

To assess the simulation and prediction performance of each model across different scenarios, fundamental evaluation metrics should be employed. In evaluating the predictive capability of the WFTDGM(1,N) model with buffer operators, we utilized the Absolute Percent Error (APE), Mean Absolute Percent Error (MAPE), and Root Mean Squared Error (RMSE) (Zhou *et al.*, 2021) to gauge the accuracy of model simulation and prediction. The specific calculation equations are as follows:

$$\mathrm{APE}(t)=\left|\frac{\widehat{x}^{(0)}(t)-x^{(0)}(t)}{x^{(0)}(t)}\right|\times 100\%,t=1,2,\cdots,m,m+1,\cdots,m+T \tag{24}$$

$$\mathrm{MAPE}=\frac{1}{m}\sum_{t=1}^{m}\mathrm{APE}(t) \tag{25}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(\widehat{x}^{(0)}(t)-x^{(0)}(t)\right)^2} \tag{26}$$

2.4 Modeling framework of WFTDGM(1,N) model

To elucidate the modeling process and optimization steps of the model effectively, we outline the six modeling steps below, accompanied by the corresponding modeling flowchart depicted in Figure 1.

Step 1: data acquisition. This step involves the collection and organization of relevant original data series pertaining to the research object. Additionally, it entails assessing the change trends and fluctuation characteristics of the original sequence through trend graphs, in preparation for subsequent verification of the effectiveness and applicability of the WFTDGM(1,N) model.

Step 2: data preprocessing. The original data sequence exhibiting significant fluctuation characteristics undergoes preprocessing. This involves applying the weakening buffering operator to derive the buffered sequence $X_i^{(w)}=(x_i^{(w)}(1),x_i^{(w)}(2),\cdots,x_i^{(w)}(m))$, followed by the fractional order accumulation process (r-AGO) to obtain the cumulative sequence $X_i^{(r)}=(x_i^{(r)}(1),x_i^{(r)}(2),\cdots,x_i^{(r)}(m))$;

Step 3: model parameter estimation and optimization. This step involves calculating the structural parameter estimation matrix $\boldsymbol{B}$ and $\boldsymbol{Y}$ of the model, utilizing OLS to estimate parameter $\widehat{\beta}=(\widehat{\beta}_1,\widehat{\beta}_2,\cdots,\widehat{\beta}_N,\widehat{\beta}_{N+1},\widehat{\beta}_{N+2})^{\mathrm{T}}$. The objective function is defined as minimizing the MAPE between the simulated data and the buffered data of the model. To optimize the nonlinear parameter r, a nonlinear optimization constraint model is integrated with the GWO;

Step 4: model construction and simulation. Following the acquisition of the parameters outlined above, the WFTDGM(1,N) model is constructed to derive the corresponding function, simulate, and predict the data series. Subsequently, the reduction value sequence is obtained through the r-IAGO process;

Step 5: model prediction performance evaluation. The model's accuracy is comprehensively assessed using three evaluation indices. Relative prediction errors are compared with those of other comparative models to validate the effectiveness and applicability of the proposed model.

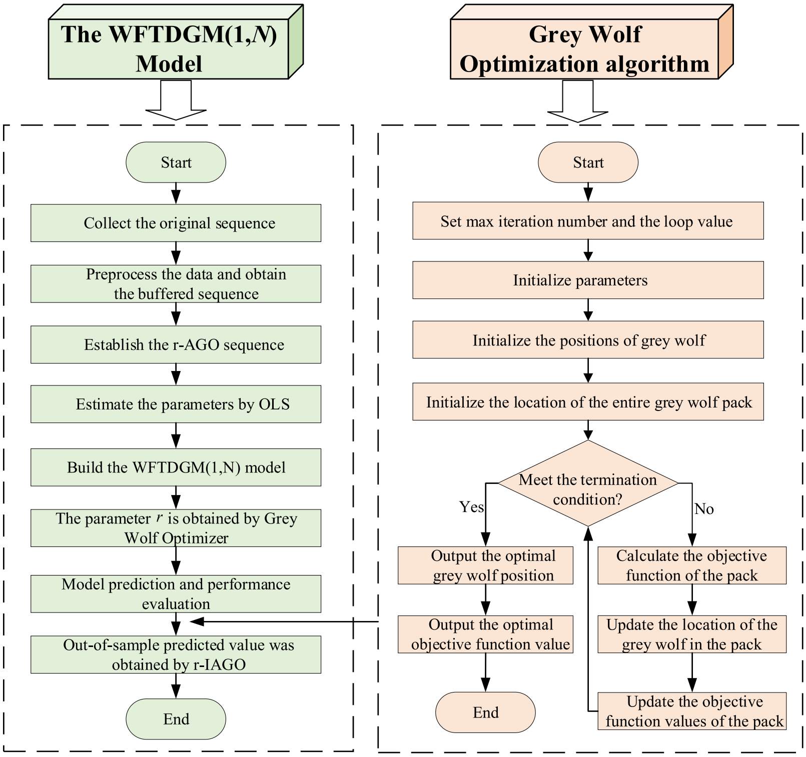


Figure 1.
Modeling flowchart of WFTDGM(1,N) model

Source(s): Authors' own creation

Step 6: effective out-of-sample prediction. In this step, the proposed model is utilized to conduct out-of-sample predictions. The performance of the model is evaluated based on these predictions, enabling the provision of pertinent policy recommendations for real-world scenarios.

3. Empirical analysis

3.1 Data collection and variable selection

In order to investigate the trend and developmental potential of carbon emissions from global maritime shipping using artificial intelligence, our analysis focuses on two variables: Annual installations of industrial robots and carbon emissions from maritime shipping. Notably, the annual installations of industrial robots serve as a proxy for the development of artificial intelligence (Acemoglu and Restrepo, 2020), allowing for an exploration of the impact of the installed amount of industrial robots on the carbon emissions of maritime shipping.

This paper utilizes annual data from 2011 to 2022, with the annual installations of industrial robots sourced from the International Federation of Robotics (IFR) and data on carbon emissions from maritime shipping obtained from the US Energy Information Administration (EIA) (https://www.iea.org/). Subsequently, the original data (Table 1) is analyzed and a model is constructed for empirical research purposes. The paper employs data from 2011 to 2019 as the training set and data from 2020 to 2022 as the test set. As the data in

Table 1.
Original data

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Annual installations of industrial robots (Thousand)	166	159	178	221	254	304	400	423	387	390	526	553
Carbon emissions from maritime shipping (Mt)	663	618	615	636	663	679	706	708	692	633	670	706

Source(s): International federation of robotics (IFR) and US energy information administration (EIA)

Table 1 shows, annual installations of industrial robots show a trend of increasing year by year with slight fluctuations in the middle, which is about the similar trend as carbon emissions from maritime shipping. This study will analyze the impact of annual installations of industrial robots on the development of artificial intelligence as a relevant factor on carbon emissions from maritime shipping.

3.2 Model comparison and analysis

The shipping industry serves as the lifeblood of global trade and transportation, encompassing approximately 80% of these activities. Consequently, carbon emissions from global shipping play a pivotal role in achieving global carbon neutrality or net zero emissions. The advancement of artificial intelligence is fundamental to driving innovation and ensuring the high-quality development of global shipping. Through our research, we aim to establish a robust foundation for facilitating the low-carbon transition within the realm of global maritime shipping.

In order to enhance our understanding of the carbon emission potential of global maritime shipping within the framework of artificial intelligence, this section conducts an empirical analysis on the influence of industrial robot installations on maritime shipping emissions. Additionally, it involves predicting global maritime shipping emissions using the previously developed model in conjunction with the original data. The study compares the simulated and predicted values generated by the WFTDGM(1,N) model with five other models: GM(1,N) and DGM(1,N) in the grey multivariate prediction model, ARIMA in econometrics, BPNN in machine learning, and LSTM in deep learning. Table 2 presents the calculated carbon emissions of global maritime shipping by each model, considering industrial robot installations as a contributing factor, along with their respective error outcomes. Visual comparisons of the results are illustrated in Figures 2–4.

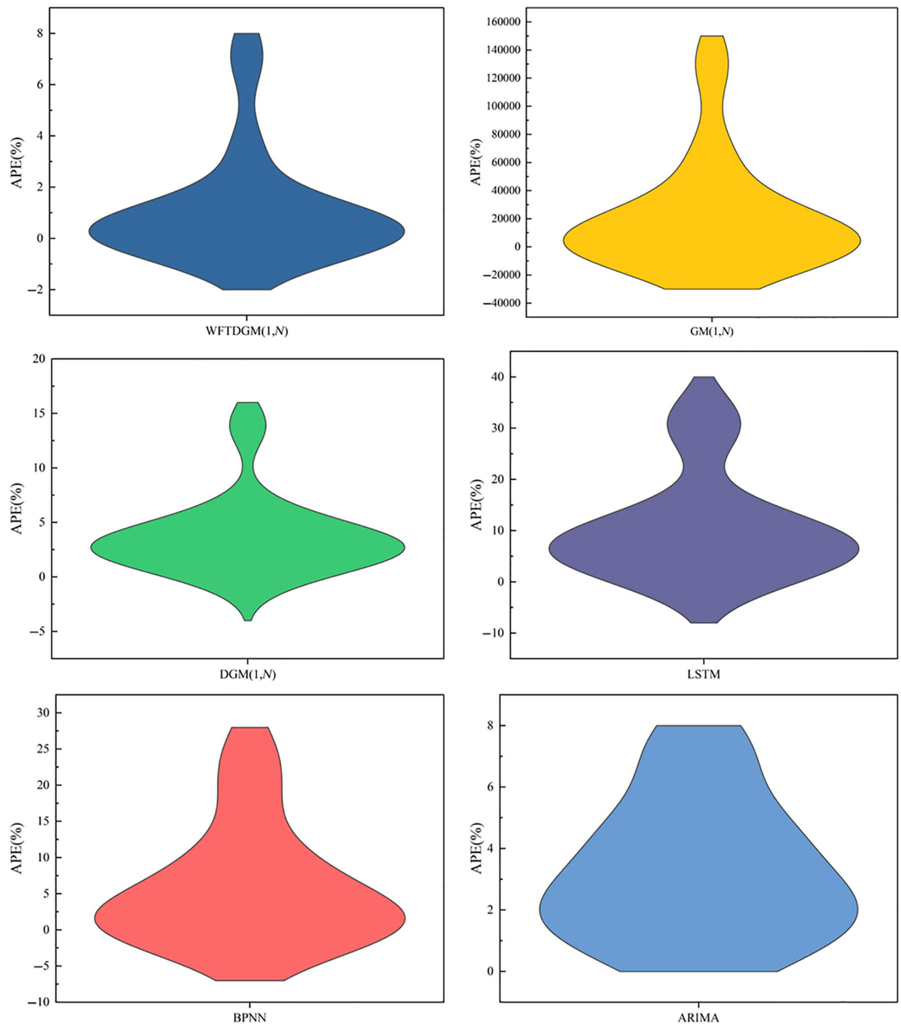
Based on the modeling procedures outlined in Section 2 and the processes of structural parameter estimation and nonlinear parameter optimization, this paper introduces the WFTDGM(1,N) model. The structural parameters of the model, denoted as $\beta_1 = -0.942$, $\beta_2 = 0.232$, $\beta_3 = -5.817$, $\beta_4 = -6.278$ are computed through a combination of structural parameter estimation matrix calculation and OLS method. Subsequently, the GWO intelligent optimization algorithm is applied to optimize the nonlinear parameters. This optimization aims to minimize the MAPE between the predicted and actual values of the model fitting, with the optimal fractional order parameter determined as $r = 0.013$. This optimized model is then constructed for subsequent simulation and prediction tasks.

Analyzing the APE of the simulated values for each model in Figure 2, it is evident that when compared to the other models, the WFTDGM(1,N) model exhibits relatively stable

Table 2.
Simulation values of carbon emissions from global maritime shipping in 6 models and related error values

Year	Shipping carbon emissions (Mt)	WFTDGM(1,N)	APE(%)	GM(1,N)	APE(%)	DGM(1,N)	APE(%)	LSTM	APE(%)	BPNN	APE(%)	ARIMA	APE(%)
Training set													
2011	663	663.000	0.217	663.000	0.000	663.000	0.000	631.060	4.817	634.435	4.308	667.552	0.687
2012	618	666.699	0.312	272.221	55.951	601.443	2.679	570.091	7.752	624.374	1.031	665.443	7.677
2013	615	672.867	0.235	−43.076	107.004	630.161	2.465	538.190	12.489	636.846	3.552	639.562	3.994
2014	636	679.423	0.183	−932.633	246.640	653.926	2.819	561.769	11.672	630.888	0.804	651.891	2.499
2015	663	685.739	0.560	−3379.805	609.774	674.067	1.669	630.543	4.895	663.148	0.022	657.102	0.890
2016	679	692.225	0.578	−8975.252	1421.834	687.098	1.193	681.846	0.419	678.996	0.001	671.482	1.107
2017	706	698.736	0.465	−21914.036	3203.971	683.863	3.136	675.316	4.346	706.000	0.000	672.591	4.732
2018	708	699.829	0.024	−53161.938	7608.748	676.082	4.508	652.436	7.848	773.604	9.266	690.003	2.542
2019	692	691.214	0.114	−113713.932	16532.649	674.105	2.586	632.069	8.661	692.000	0.000	679.660	1.783
MAPE(%)			0.299		3309.619		2.339		6.989		2.109		2.879
RMSE			2.423		42966.286		17.772		50.998		25.086		23.121
Test set													
2020	633	678.298	7.156	−222967.352	35323.910	671.377	6.063	612.888	3.177	694.581	9.728	675.858	6.771
2021	670	692.174	3.310	−437705.285	65429.147	643.444	3.964	471.058	29.693	837.687	25.028	638.695	4.672
2022	706	705.999	0.000	−923831.011	130954.251	607.714	13.922	479.445	32.090	837.687	18.653	688.632	2.460
MAPE(%)			3.489		77235.769		7.983		21.653		17.803		4.634
RMSE			29.118		604686.886		62.818		174.460		128.131		32.241

Source(s): Authors' own creation



Source(s): Authors' own creation

Figure 2.
APE(%) of simulated values for 6 competing models

errors around 0, with a maximum error of less than 8%, indicating a strong fitting performance. The ARIMA model closely follows the performance of the proposed model, with a maximum APE also below 8%. However, the ARIMA model demonstrates more variability around 2% in its errors, ranking second among the six models in terms of fitting effectiveness. Otherwise, the BPNN and LSTM models display maximum errors exceeding 20%, with predominant errors fluctuating between 3% and 5%, showcasing relatively good fitting effects but still falling short compared to the WFTDGM(1,N) model. The two grey multivariate prediction models employed in this study yield contrasting results. DGM(1,N) shows relatively strong fitting effects with error fluctuations of around 3% and a maximum error below 15%. In contrast, GM(1,N) exhibits unsatisfactory forecasting effects, deviating significantly from the original data's development trends.

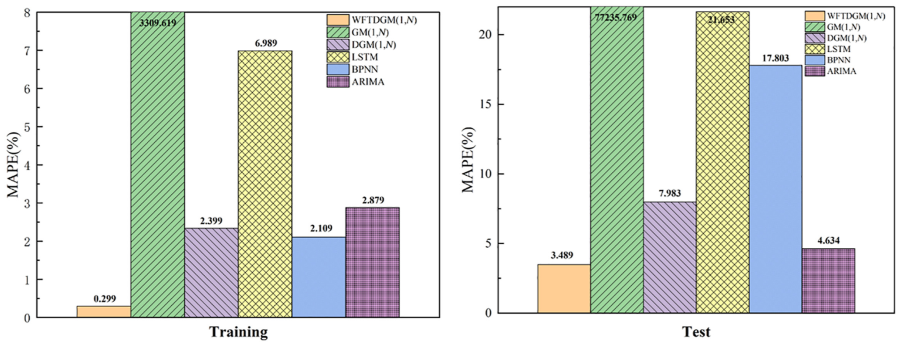


Figure 3.
MAPE(%) of 6 competing model training sets and test sets

Source(s): Authors' own creation

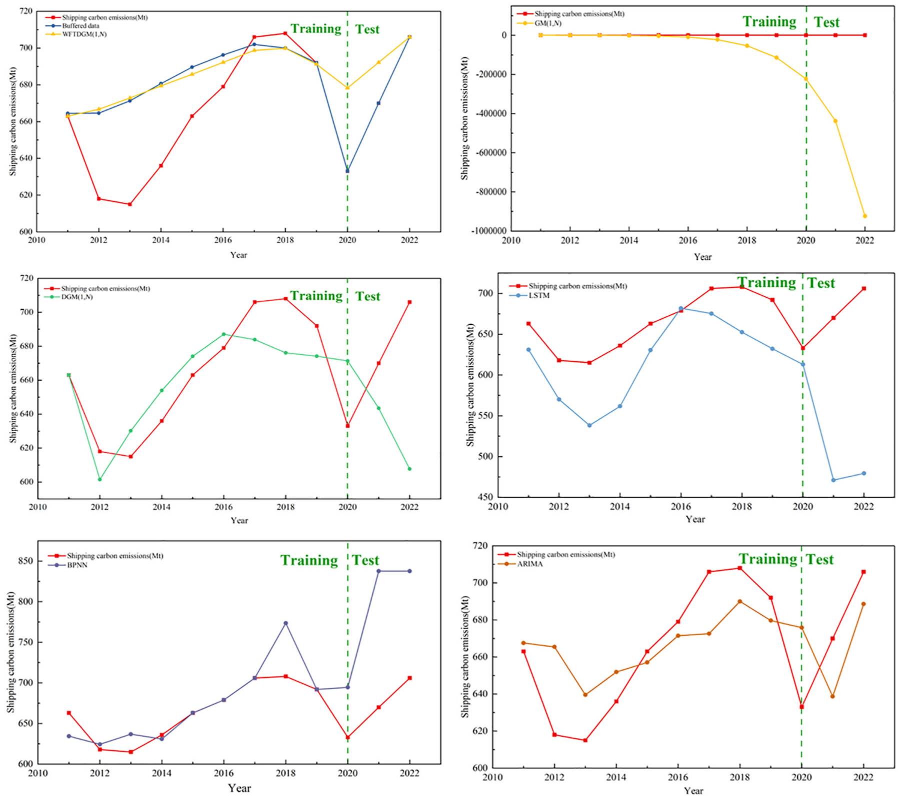


Figure 4.
Comparison between simulated values and real values of 6 competitive models

Source(s): Authors' own creation

Furthermore, a conclusion akin to the preceding analysis can be drawn by evaluating the MAPE for both the training and test sets separately. Figure 3 analysis reveals that the WFTDGM(1,N) model proposed in this paper achieves MAPE values of 0.299% and

3.489% for the training and test sets, respectively, representing the lowest error rates among all models and demonstrating superior fitting and predictive capabilities. Following closely behind is the ARIMA model, showcasing commendable predictive performance. The test set error for the ARIMA model stands at 4.634%, with a training set MAPE of 2.879%, indicating a relatively strong fitting effect. In contrast, both machine learning methods exhibit poor predictive matching characteristics. The training set errors for BPNN and LSTM are 2.109% and 6.989%, respectively. However, the test set errors escalate significantly to 17.803% and 21.653%, highlighting the need for enhanced prediction performance. Among other multivariate grey prediction models, the DGM(1,N) model secures the second-best position with a training set MAPE of 2.339% and a test set error of 7.983%. While slightly trailing the WFTDGM(1,N) model in predictive performance, the DGM(1,N) model still outperforms the GM(1,N) model, which exhibits severely distorted fitting and prediction effects, indicative of significant data processing errors.

The comparison between simulated values and predicted values of the six models can be observed in Figure 4. The WFTDGM(1,N) model, introduced in this paper, employs a novel weakening buffering operator to preprocess the original data before modeling and analyzing the buffered data sequence. Consequently, the fitting effect is best assessed concerning the buffered sequence. Within the WFTDGM(1,N) framework, the training set section emphasizes the comparison between simulated values and the buffered sequence, while subsequent predictions involve fractional order restoration and additional steps, enabling performance comparisons with real values akin to other models, as depicted in Figure 4. Evidently, the simulated sequence generated by the WFTDGM(1,N) model showcases a consistent trend with both the buffered sequence in the training set and the original data sequence in the test set, underscoring its robust fitting and predictive capabilities. Similarly, the ARIMA model's simulated series generally aligns with the original data trend, albeit with larger errors compared to the WFTDGM(1,N) model. Conversely, the DGM(1,N), LSTM, and BPNN models exhibit training set trends similar to the original data but display divergent trends in their test sets, leading to substantial errors. Particularly noteworthy is the GM(1,N) model, demonstrating a continuous and significant decline in the simulation sequence, resulting in a widening gap from the original data and poor fitting and prediction effects. This is because due to the complex and changeable relationship between variables, the traditional GM(1,N) does not have effective mitigation and discrimination ability, so it is prone to data drift, resulting in high prediction errors. The comprehensive analysis of simulation and prediction performance across the six models consistently validates the superior simulation and prediction capabilities of the WFTDGM(1,N) model. Consequently, this model is selected for predicting global maritime shipping carbon emissions and subsequent analysis of carbon emission potential.

Combined with the above empirical results and the characteristics of each model, it can be seen that although the traditional GM(1,N) model can predict the multi-variable small sample data, it is prone to data drift, resulting in poor prediction effect. What's more, DGM(1,N) is difficult to show effective prediction for data with large fluctuation characteristics. However, BPNN and LSTM in machine learning methods are more inclined to deal with the prediction of large sample data, and it is difficult to show good prediction effect for the prediction of small sample data, while the ARIMA model in econometric methods will show a certain lag effect, which is difficult to cope with the time-varying effect of data. Therefore, the WFTDGM(1,N) model proposed in this paper can show excellent fitting and prediction effects in processing multivariate data with large fluctuation characteristics and time-varying effects. Therefore, the WFTDGM(1,N) model will be selected for subsequent prediction.

3.3 Carbon emissions from global maritime shipping forecasts: 2023–2026

Utilizing the WFTDGM(1,N) model, predictions for global maritime shipping carbon emissions from 2023 to 2026 were conducted leveraging artificial intelligence. To ensure greater precision in forecasting, the model employed all annual data from 2011 to 2022. The predicted results are presented in Table 3 and Figure 5. Over the upcoming years, amidst the rapid advancement of artificial intelligence, global maritime shipping carbon emissions are anticipated to experience a gradual increase, rising from 741.688 Mt to 783.777 Mt. The forecast indicates growth rates of 0.679%, 0.700% and 4.233% over the subsequent four years, signifying a progressive escalation in growth rates.

In the era of trade globalization, maritime shipping remains the primary mode of global transportation and is expected to retain this position for the foreseeable future. However, the sustainable development of maritime shipping unavoidably leads to increased carbon emissions, exerting a negative impact on global environmental governance. Over the past decade, as world science and technology have made continuous strides, artificial intelligence has witnessed significant growth. During its early stages, artificial intelligence played a role in facilitating the transformation of maritime shipping, resulting in a temporary reduction in carbon emissions. This signifies that the development of artificial intelligence can contribute to the mitigation of shipping-related carbon emissions. Nevertheless, based on the available data and the projected results presented in this paper, it is evident that global maritime shipping carbon emissions will continue to rise from 2020 onwards. Initially, theoretical analysis suggested that the development of artificial intelligence could lead to a reduction in carbon emissions or, at the very least, curb their growth rate. However, it appears that, at this

Table 3. Predicted carbon emissions from global maritime shipping in 2023–2026

Year	Shipping carbon emissions(Mt)
2023	722.785
2024	739.807
2025	759.601
2026	785.718

Source(s): Authors' own creation

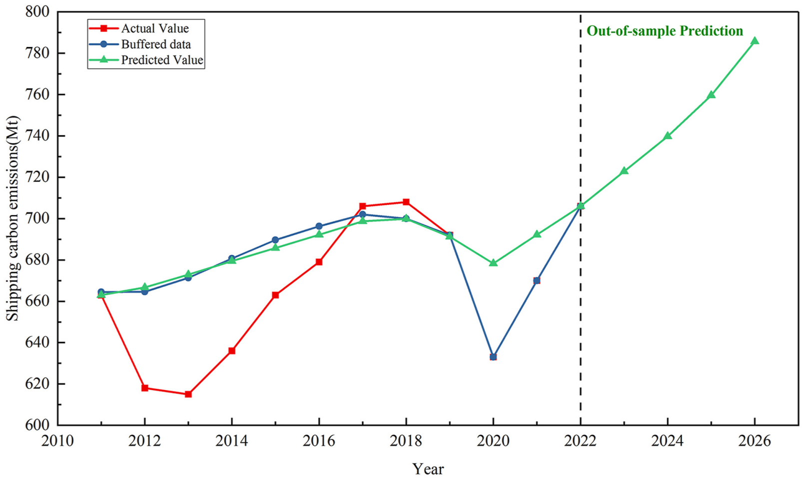


Figure 5. Predicted carbon emissions from global maritime shipping in 2023–2026

Source(s): Authors' own creation

stage, the role of artificial intelligence in addressing shipping-related carbon emissions may not be as impactful as anticipated. Therefore, it is crucial to engage in comprehensive thinking and prioritize this issue in the future. By concurrently advancing artificial intelligence and emphasizing its potential to effectively reduce shipping carbon emissions, we can make substantial contributions towards achieving global carbon neutrality.

4. Conclusions and future discussion

4.1 Conclusions

The advent of artificial intelligence has influenced ship carbon emissions. Accurately forecasting marine shipping carbon emissions is crucial as it serves as a key metric for port production capacity and operational efficiency. Decision-makers rely on these predictions to implement informed ocean management strategies. This study employs the WFTDGM (1,N) model to project and examine the impact of artificial intelligence on shipping carbon emissions, leading to the ensuing conclusions:

(1) A novel grey multivariate prediction model is introduced, which incorporates the weakening buffer operator to enhance its adaptability and prediction performance. This new model compensates for the deficiencies identified in the traditional multivariate model. The use of the GWO (Grey Wolf Optimizer) intelligent optimization algorithm facilitates the optimization of nonlinear parameters, thereby augmenting the fitting accuracy of the WFTDGM (1,N) model.

(2) After simulating and forecasting global shipping carbon emissions from 2011 to 2022, the outcomes indicate that the novel model's curve aligns closely with the original data curve. In comparison to GM(1,N), DGM(1,N), ARIMA, BPNN, and LSTM models, the new model demonstrates superior performance, with a MAPE value of 0.299% during the simulation phase and 3.489% during the prediction phase. This suggests that the WFTDGM (1,N) model is suitable for predicting shipping carbon emissions.

(3) In the out-of-sample predictions for the period from 2023 to 2026, the results obtained from the WFTDGM (1,N) model indicate a gradual increase in global marine shipping carbon emissions. By 2026, these emissions are expected to reach 785.718 million tons. To foster the green development of marine shipping, it is essential that this issue garners widespread global attention. A collective effort is required worldwide to refine the transportation structure and mitigate the carbon footprint of marine shipping. This can be achieved through the implementation of policy incentives and the advancement of technology. Such measures will not only enhance the competitiveness of the shipping industry but also contribute to the promotion of global trade and economic growth. Strengthening international cooperation is crucial for the construction of a sustainable and green marine future.

4.2 Policy suggestions

Based on the analysis results, this paper proposes the following policy recommendations:

(1) Establish a smart shipping supervision system. Establish a unified data platform to realize the sharing of ship operation data, port operation data, cargo information, etc., to provide sufficient data support for AI algorithms. AI technology is used to monitor the shipping process in real time, including the ship's navigation trajectory, emissions, etc., to ensure that the ship meets environmental standards.

(2) Encourage artificial intelligence innovation and application. The government could establish a dedicated fund to bolster research and development in Artificial

Intelligence (AI) aimed at reducing marine shipping emissions. This initiative could encompass the optimization of shipping routes and enhancement of ship energy efficiency. Furthermore, it is advisable for ship manufacturing entities to pursue the development of intelligent vessels, integrating AI technology to streamline ship design and augment operational efficiency.

(3) Optimize the marine shipping logistics system. Optimizing shipping logistics networks through artificial intelligence can significantly reduce unnecessary transportation links and lower overall carbon emissions. Encouraging enterprises to adopt green packaging and transportation methods can further diminish carbon emissions during the shipping process.

(4) Strengthen international cooperation and policy coordination. Engage proactively in international marine shipping emission reduction agreements to foster a collaborative response to climate change within the global shipping sector. Intensify international dialogue and collaboration in the field of artificial intelligence, exchanging insights and technologies related to AI-enabled marine shipping emission abatement, thereby collectively advancing the sustainable growth of the worldwide marine shipping industry.

(5) Develop an artificial intelligence regulatory plan. Develop technical standards and operational norms for the reduction of carbon emissions from artificial intelligence in shipping to ensure the safety and effectiveness of the technology. Establish a sound regulatory mechanism, strengthen the supervision and evaluation of artificial intelligence applications, and ensure that they meet environmental protection requirements.

4.3 Limitations and future work

The WFTDGM (1, N) model proposed in this paper demonstrates superior adaptability compared to the traditional grey prediction model, rendering it suitable for nonlinear and intricate time series modeling. Future considerations may include integrating it with other methodologies, such as machine learning algorithms, to enhance the performance of the new models. Additionally, the incorporation of policy dummy variables into a grey model could be explored to augment the model's predictive accuracy. Furthermore, the WFTDGM (1, N) model can be employed to forecast various carbon emission data types, thereby offering a dependable foundation for achieving a low-carbon transition.

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