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*Research article*

# Demand forecast and influential factors of cold chain logistics based on a grey model

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**Abstract:** Due to high requirements of storage, operation and delivery conditions, it is more difficult for cold chain logistics to meet the demand with supply in the course of disruption. And, accurate demand forecasting promotes supply efficiency for cold chain logistics in a changeable environment. This paper aims to find the main influential factors of cold chain demand and presents a prediction to support the resilience operation of cold chain logistics. After analyzing the internal relevance between potential factors and regional agricultural cold chain logistics demand, the grey model GM (1, N) with fractional order accumulation is established to forecast future agricultural cold chain logistics demand in Beijing, Tianjin, and Hebei. The following outcomes have been obtained. (1) The proportion of tertiary industry, per capita disposable income indices for urban households and general price index for farm products are the first three factors influencing the cold chain logistics demand for agricultural products in both Beijing and Tianjin. The GDP, fixed asset investment in transportation and storage, and the proportion of tertiary industry are three major influential factors in Hebei. (2) Agricultural cold chain demand in Beijing and Hebei will grow sustainably in 2021–2025, while the trend in Tianjin remains stable. In conclusion, regional developmental differences should be considered when planning policies for the Beijing-Tianjin-Hebei cold chain logistics system.

**Keywords:** demand forecasting; grey relation model; FGM (1, N) model

## 1. Introduction

In supply chain management, cost, quality and price are the three core issues [1]. However, besides seeking to achieve the critical goals of minimum cost, quality service and maximum profit, supply chain managers nowadays are faced with challenges and changes such as supply risk and resilience [2]. A resilient supply chain has a strong predictive ability to meet the demand with the supply even in the course of disruption [3]. Unfortunately, most businesses are often caught short due to the lack of accurate demand forecasting.

Cold chain logistics is a special logistics network that handles perishable produce, including agricultural products, meat, milk and dairy products, pharmaceutical products, etc. [4]. The storage and transportation of perishable assets are sensitive to various operational and environmental factors like temperature and humidity [5]. The global cold chain logistics market is expected to soar from USD 160 billion in 2018 to USD 585.1 billion by 2026, with a compound annual growth rate (CAGR) close to 10% during the period. In 2020, the market size of China's cold chain logistics reached 383.2 billion yuan, a year-on-year increase of 13%, and the total demand for fresh food cold chain logistics exceeded 265 million tons, a year-on-year growth of 13.69%. The statistics from the China Cold-Chain Logistics Association indicate that the market size for cold chain logistics in China will reach RMB 897 billion in 2025, with a CAGR close to 18%, demonstrating the dramatic potential of the market demand [6]. However, the mismanagement of operations within the cold chain network may cause from 20 to 30% of damage to the fresh goods in any given situation [7]. Therefore, in order to reduce the deterioration of fresh goods during transportation, operations like cross-docking [8,9], intermodal freight network application [10] and path optimization [11,12] have been well and widely studied in practice and research. However, due to higher technical requirements, the cold chain logistics is more difficult to manage than a general supply chain, which makes it difficult for replenishment when there is a supply shortage. Consequently, accurate demand forecasting for cold chain logistics and its influential factors analysis will significantly improve operation efficiency and bring information and communication resilience into the cold chain network [13].

The rest of this work is structured as follows. Section 2 reviews literature relevant to this study. Section 3 presents the modelling methods and materials used in this paper. In Section 4, the grey relation model, FGM (1,1) model and FGM (1, N) model are applied to forecast the demand of agricultural cold chain logistics in Beijing, Tianjin and Hebei. Finally, Section 5 concludes this paper.

## 2. Literature review

Diverse approaches to forecasting the cold chain logistics demand have sparked extensive discussions, and some well-honed techniques are presented below. To predict the cold chain logistics demand for fresh agricultural products, Liu et al. proposed a secondary exponential smoothing model [14]. He et al. used a back-propagation neural network to forecast the size of China's cold chain market, using residents' per capita disposable income and per capita consumption expenditure as exogenous influential factors [15]. Wang et al. developed and tested a multivariate linear regression prediction model to analyze the demand for fruit cold chain logistics. The influential factors tested in the experiment included the disposable income of urban residents, mileage of transportation lines, cold chain circulation rate and retail price index [16]. To construct a demand forecasting model of aquatic cold chain logistics, Xu et al. proposed a gray wolf optimizer-support vector machine [17]. Wang et al. used a metabolic GM

(1,1) model to forecast the demand for the cold chain logistics of agricultural products in China [18]. Lu et al. discovered that the circulation rate of aquatic products in the cold chain, the corrosion rate of aquatic products and the added value of the tertiary industry were the first three factors influencing the Dalian aquatic products cold chain demand by using a grey relation model; they then used a combination of an improved GM (1,1) model and back propagation (BP) neural network model to predict demand [19].

The above-mentioned research methods for demand forecasting are of practical value and have a certain forecasting accuracy; moreover, they have laid a good foundation for this work to forecast the demand for cold chain logistics. However, there are many factors that affect the demand of cold chain logistics, and there is a nonlinear correlation between each influential factor and the demand of cold chain logistics; what's more, most of the forecasting models need a large amount of sample data to fit the relationship between factors [20]. Using a multiple regression forecasting method has drawbacks that lead to multicollinearity problems while using a time-series forecasting method has the requirement of strict continuity timeline data [21]. The statistical system of cold chain logistics in China is unsound and lacks historical data, which have affected the prediction accuracy of cold chain logistics demand. In other words, when dealing with issues characterized by multicollinearity and insufficient input data, most models appear to fail. Considering the characteristics of cold chain logistics demand forecasting, the multi-variable grey forecasting model GM (1, N) was proposed to address this issue, providing an innovative way to analyze small batches of low-quality uncertain data [22].

A system's characteristic sequence and (N-1) related factor sequences make up GM (1, N). The modeling process fully considers the impact of various influential factors on system change and makes full use of the information contained in the associated series [23]. Although the GM (1, N) model has distinct advantages, it still has some inherent flaws in terms of achieving high predicting accuracy, because it does not reflect the priority of new information [24]. As a result, a new grey system model with fractional order accumulation was proposed; it can effectively reflect the priority of new information [25]. For small sample sizes, practical studies on the novel fractional grey model have demonstrated remarkable prediction performance when compared to the traditional grey model [26–28].

Based on the analysis presented above, due to a lack of historical data on cold chain logistics demand, as well as uncertainty and nonlinear linkages in the system, traditional forecasting methods are insufficiently precise and subjective, making them unsuitable for forecasting cold chain logistics demand. While there is a large body of literature on forecasting cold chain logistics demand, fractional grey models with multi-variables for estimating cold chain demand have received little attention; what's more, there are few that focus on various factors influencing regional development. Regional differences in economy and resource distribution have a great impact on the regional development level of agricultural cold chain logistics [29]. Consequently, this paper takes demand forecasting and its influential factors for agricultural cold chain logistics in Beijing-Tianjin-Hebei region as the research objective by using an FGM (1, N) model. This work's contributions are summarized as follows. 1) Grey correlation analysis is used to determine the three main factors influencing cold chain logistics demand for agricultural products in Beijing, Tianjin, and Hebei. 2) An FGM (1, N) model is proposed to forecast agricultural product cold chain logistics demand. 3) The proposed method can accurately forecast the future trend of agricultural cold chain demand logistics in Beijing, Tianjin and Hebei. Furthermore, the prediction results can serve as a policy guide for the integrated and coordinated development of agricultural cold chain logistics in the Beijing-Tianjin-Hebei region.

## 3. Methods and materials

### *3.1. Methods*

#### 3.1.1. Grey relation analysis

Through the fitting degree of the curve geometry, grey relation analysis determines whether the correlation between the influential factor series and the characteristic series is close. The greater the degree of curve fitting, the greater the degree of correlation between the sequences, and the greater the importance of the influential factor [30]. The following is a description of the grey relation analysis process.

If $X_i$ is a system influential factor, and its observation data on the *k*th serial number is $x_i(k), k = 1,2,\cdots,n$, then $X_i = \{x_i(1), x_i(2), \cdots, x_i(n)\}$ is the behavioral sequence of $X_i$.

Let $X_0 = \{x_0(1), x_0(2), \cdots, x_0(n)\}$ be the system's character behavioral sequence; then the sequences of relevant influencing factors are:

$$\begin{cases} X_1 = \{x_1(1), x_1(2), \cdots, x_1(n)\} \\ X_2 = \{x_2(1), x_2(2), \cdots, x_2(n)\} \\ \quad\vdots \\ X_m = \{x_m(1), x_m(2), \cdots, x_m(n)\} \end{cases},$$

where *m* is the number of influential factors.

Therefore, the relation degree for a relevant factor sequence and feature sequence can be calculated by using the below formula:

$$\gamma(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_0(k), x_i(k)) \tag{1}$$

where,

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|} \tag{2}$$

$\xi$ is the resolution coefficient and $\xi \in (0,1)$ per work [22] according to Deng; if the sequence data are relatively stable, we generally set $\xi = 0.5$ to improve the significance of the difference between correlation coefficients.

#### 3.1.2. Fractional order GM (1,1) forecasting model

The FGM (1,1) model is used in this study to predict the factors influencing cold chain logistics demand. The modeling procedure is described in detail below [23].

(a) Assume the non-negative sequence $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}$. $X^{(0)}$ represents the annual data series for a cold chain demand influential factor index. The *r*th-order accumulated generation sequence of the original sequence $X^{(0)}$ is

$$X^{(r)} = \{x^{(r)}(1), x^{(r)}(2), \cdots, x^{(r)}(n)\} \tag{3}$$

where $x^{(r)}(k) = \sum_{i=1}^{k} C_{k-i+r-1}^{k-i} x^{(0)}(k)$, and $C_{k-i+r-1}^{k-i} = \frac{(k-i+r-1)(k-i+r-2)\cdots(r+2)(r+1)r}{(k-i)!}$.

And $C_{r-1}^{0}$=1. $C_{k}^{k+1}$=0 and $x^{(r)}(1) = x^{(0)}(1)$.

The superscript ($r$) indicates an $r_{\text{th}}$-order accumulation sequence, while a superscript (0) indicates an original sequence in Eq (3). In this work, the particle swarm algorithm is used to calculate the optimal order $r$ of the prediction model.

(b) The corresponding whitening equation for the newly generated sequence $X^{(r)}$ is as follows:

$$\frac{dx^{(r)}}{dt} + ax^{(r)} = b \tag{4}$$

where $a$ is the development coefficient and $b$ represents the grey action quantity.

(c) The least squares method is used to compute the values of the parameters $a$ and $b$.

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{5}$$

where the $Y$ and $B$ matrices are as follows:

$$Y = \begin{bmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{bmatrix}, \; B = \begin{bmatrix} -Z^{(r)}(2) & 1 \\ -Z^{(r)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(r)}(n) & 1 \end{bmatrix}$$

Where,

$$Z^{(r)}(k) = \frac{\left(x^{(r)}(k) + x^{(r)}(k+1)\right)}{2} \tag{6}$$

(d) The time response formula of the whitening equation is

$$x^{(r)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \tag{7}$$

Then the response time series $X^{(r)}$ is obtained as below:

$$X^{(r)} = \left\{x^{(r)}(1), x^{(r)}(2), \cdots, x^{(r)}(n), \cdots\right\} \tag{8}$$

The $r$-order reduction of $X^{(r)}$ is as below:

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n), \cdots\right\} \tag{9}$$

where $x^{(0)}(1) = x^{(0)}(1)$ and $x^{(0)}(k) = x^{(r)(1-r)}(k) - x^{(r)(1-r)}(k-1)$. Therefore, the fitting values for the cold chain demand influential factors index data are $\left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\}$, and the predicted values are $\left\{x^{(0)}(n+1), x^{(0)}(n+2), \cdots\right\}$.

### 3.1.3. Fractional order GM (1, N) forecasting model

An FGM (1, N) model is proposed to predict the cold chain logistics demand while taking into account various influential factors [31].

(a) Assume the system's characteristic data sequence $X_0 = \{x_0(1), x_0(2), \cdots, x_0(n)\}$, where $X_0$

represents the annual data series for the cold chain demand and the formula below expresses the annual data series for the influential factors:

$$\begin{cases} X_1 = \{x_1(1), x_1(2), \cdots, x_1(n)\} \\ X_2 = \{x_2(1), x_2(2), \cdots, x_2(n)\} \\ \vdots \\ X_m = \{x_m(1), x_m(2), \cdots, x_m(n)\} \end{cases} \tag{10}$$

The sequence after *r*-order accumulation is $X_i^{(r)} = \left\{x_i^{(r)}(1), x_i^{(r)}(2), \cdots, x_i^{(r)}(n)\right\}, i = 1,2,\cdots,m,$ where

$$x_i^{(r)}(k) = \sum_{i=1}^{k} C_{k-i+r-1}^{k-i} x_i^{(0)}(k), k = 1,2,\cdots,n$$

$$C_{k-i+r-1}^{k-i} = \frac{(k-i+r-1)(k-i+r-2)\cdots(r+2)(r+1)r}{(k-i)!}$$

Let $C_{r-1}^{0}$=1,$C_k^{k+1} = 0$ and $x^{(r)}(1) = x^{(0)}(1)$. Then, $x_0^{(r)}(k) + az_0^{(r)}(k) = \sum_{i=1}^{n} b_i x_i^{(r)}(k)$ is the FGM (1, N) model.

(b) For the newly generated sequence $X^{(r)}$, the corresponding whitening equation can be expressed as:

$$\frac{dx_0^{(r)}}{dt} + ax_0^{(r)}(k) = \sum_{i=1}^{n} b_i x_i^{(r)}(k) \tag{11}$$

(c) The values of the parameters *a* and *b* are calculated by using the least square method:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y$$

where the matrices of *Y* and *B* are as follows:

$$Y = \begin{bmatrix} x_0^{(r)}(2) - x_0^{(r)}(1) \\ x_0^{(r)}(3) - x_0^{(r)}(2) \\ \vdots \\ x_0^{(r)}(n) - x_0^{(r)}(n-1) \end{bmatrix}, B = \begin{bmatrix} -z_0^{(r)}(2) & x_1^{(r)}(2) & \cdots & x_n^{(r)}(2) \\ -z_0^{(r)}(3) & x_1^{(r)}(3) & \cdots & x_n^{(r)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ -z_0^{(r)}(n) & x_1^{(r)}(n) & \cdots & x_n^{(r)}(n) \end{bmatrix}$$

where, $z_0^{(r)}(k) = \frac{(x_0^{(r)}(k) + x_0^{(r)}(k+1))}{2}$ $k = 2,3,\cdots,n.$

(d) The time response formula of the whitening equation is

$$x^{(r)}(k) = \left(x_0^{(r)}(1) - \frac{1}{a}\sum_{i=1}^{n} b_i x_i^{(r)}(k+1)\right) e^{-a(k-1)} \frac{1}{a}\sum_{i=1}^{n} b_i x_i^{(r)}(k+1) \tag{12}$$

Then the response time series $X^{(r)}$ is obtained as below:

$$X_0^{(r)} = \left\{x_0^{(r)}(1), x_0^{(r)}(2), \cdots, x_0^{(r)}(n), \cdots\right\}$$

The $r$-order reduction of $X_0^{(r)}$ is as below:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n), \cdots\} \tag{13}$$

where,

$$x^{(0)}(1) = x^{(0)}(1), x^{(0)}(k) = x^{(r)(1-r)}(k) - x^{(r)(1-r)}(k-1), k = 2,3,\cdots,n,\cdots$$

Therefore, the fitting values for the cold chain demand logistics index data are $\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}$, and the predicted values are $\{x^{(0)}(n+1), x^{(0)}(n+2), \cdots\}$.

(e) There are various criteria for evaluating the precision of the grey model. For example, the mean absolute percentage error (MAPE), absolute mean error, and mean square error are widely used [32]. In addition, the $R^2$ coefficient of determination is validated for fitting a linear model. In this work, the MAPE and $R^2$ coefficient of determination are used to assess the precision of the models involved. The larger the value of $R^2$, the better the performance of the model. Table 1 displays the MAPE criteria [25].

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n} \frac{\left|\hat{x}^{(0)}(k) - x^{(0)}(k)\right|}{x^{(0)}(k)} \times 100\%$$

**Table 1.** MAPE evaluation criteria.

| MAPE | Prediction Ability |
|---|---|
| <10% | Good |
| 10%-20% | Qualified |
| 20%-50% | Barely enough |
| >50% | Unqualified |

$$R^2 = 1 - \frac{SSE}{SST}$$

where $SSE = \sum_{k=1}^{n}(x^{(0)}(k) - \hat{x}^{(0)}(k))^2$ and $SST = \sum_{k=1}^{n}(x^{(0)}(k) - \overline{x^{(0)}(k)})^2$.

Additionally, where $x^{(0)}(k)$ is the actual value at time $k$, and $\hat{x}^{(0)}(k)$ is the prediction value at time $k$.

### *3.2. Materials*

#### 3.2.1. Selection of influential factors

Five influential factors were preliminarily selected to investigate their impact on the cold chain logistics for agricultural products in Beijing, Tianjin and Hebei; they are the regional GDP, proportion of tertiary industry, fixed assets investment in transport and storage, per capita disposable income indices for urban households, and general price index for farm products; this was done by summarizing existing literature.

The GDP measures a region's level of economic development; it is commonly suitable for estimating logistics efficiency [33]. The larger the total GDP, the higher the level of economic development, and the greater the demand for logistics services such as cargo transportation, warehousing, distribution, and logistics information processing [34]. Therefore, the economy and cold chain logistics benefit from mutual and coordinated growth.

Logistics is a critical component of the tertiary industry. The stabilization of the tertiary industry means continuous requirements for logistics services and the optimization of the economy's structure [35]. The development of the tertiary industry drives the prosperity of the service industry which generates huge potential demand for logistics services [36].

Fixed assets investment in transportation and storage improves infrastructure such as roads, waterways, railways, and cold storage capacity [21]. Cold chain products are mainly distributed in urban areas via road transport; high requirements for time and infrastructure stimulate substantial investment to increase cold chain storage and transportation capacity [37]. As a result, it has a positive impact on cold chain logistics demand.

The consumption level of urban households is represented by per capita disposable income indices. Consumers have higher expectations for food quality and safety as their consumption level rises, and the demand for cold chain services will rise as well [38].

From the standpoint of supply, the general price index for farm products influences the demand for agricultural cold chain logistics. The effective supply of agricultural products ensures that there are enough commodities in the market to meet the needs of consumers, and the reasonable price of agricultural products balances the supply and demand, influencing the demand for agricultural cold chain logistics [39].

### 3.2.2. Data sources

**Table 2.** Factors influencing agricultural cold chain logistics in Beijing.

| Year | GDP ($10^8$ yuan) | Proportion of Tertiary Industry (%) | Fixed Assets Investment in Transport and Storage ($10^8$ yuan) | Per Capita Disposable Income Indices for Urban Households | General Price Index for Farm Products |
|---|---|---|---|---|---|
| 2014 | 22926 | 80.6 | 756.5 | 108.9 | 99.7 |
| 2015 | 24779.1 | 92.6 | 827 | 120.38 | 99.8 |
| 2016 | 27041.2 | 86.9 | 973 | 108.35 | 99.7 |
| 2017 | 29883 | 89.5 | 1327 | 108.96 | 99.6 |
| 2018 | 33106 | 90.2 | 1341.6 | 108.95 | 103.6 |
| 2019 | 35445.1 | 89.6 | 1218.17 | 108.62 | 109.9 |
| 2020 | 36102.6 | 72.6 | 1093.92 | 102.4 | 110.9 |

The data used for the influential factors in Beijing, Tianjin and Hebei are all from the regional statistics department. Tables 2–4 summarize data from the Statistical Yearbooks of Beijing, Tianjin and Hebei for these five influential factors from 2014 to 2020. The proposed grey model is stable when the sample data size is small in theory, which is a difference between the grey model and the traditional statistical model [40]; therefore, we only use recent data. Because logistics demand is not separately recorded in China's statistical reports, the method described in [39] was employed to calculate cold chain logistics demand for agricultural products; in this method, the number of urban permanent residents is multiplied by the urban per capita consumption of fresh agricultural products. In this paper, the agricultural products include vegetables, fruits, meat, fresh eggs, aquatic products, milk, and dairy products. Table 5 shows the calculation results for the cold chain logistics demand for agricultural products in Beijing, Tianjin, and Hebei from 2014–2020.

**Table 3.** Factors influencing agricultural cold chain logistics in Tianjin.

| Year | GDP ($10^8$ yuan) | Proportion of Tertiary Industry (%) | Fixed Assets Investment in Transport and Storage ($10^8$ yuan) | Per Capita Disposable Income Indices for Urban Households | General Price Index for Farm Products |
|---|---|---|---|---|---|
| 2014 | 10640.62 | 55.1 | 769.71 | 101.9 | 98.3 |
| 2015 | 10879.51 | 57.2 | 860.77 | 101.7 | 97.8 |
| 2016 | 11477.2 | 60.5 | 787.5 | 102.1 | 102.2 |
| 2017 | 12450.56 | 62 | 670.95 | 102.1 | 101 |
| 2018 | 13362.92 | 62.5 | 621.3 | 102 | 100.2 |
| 2019 | 14055.46 | 63.5 | 784.7 | 102.7 | 103.7 |
| 2020 | 14083.73 | 64.4 | 1079.75 | 102 | 104.5 |

**Table 4.** Factors influencing agricultural cold chain logistics in Hebei.

| Year | GDP ($10^8$ yuan) | Proportion of Tertiary Industry (%) | Fixed Assets Investment in Transport and Storage ($10^8$ yuan) | Per Capita Disposable Income Indices for Urban Households | General Price Index for Farm Products |
|---|---|---|---|---|---|
| 2014 | 29421.2 | 37.30 | 2025.90 | 108.61 | 100.23 |
| 2015 | 29806.1 | 40.19 | 2035.70 | 108.33 | 97.5 |
| 2016 | 31827.9 | 41.71 | 2081.30 | 106.33 | 96.35 |
| 2017 | 36964 | 41.82 | 2116.30 | 108.14 | 96.19 |
| 2018 | 32494.61 | 50.01 | 2581.89 | 107.95 | 104.65 |
| 2019 | 35104.52 | 51.65 | 2646.43 | 117.02 | 101 |
| 2020 | 36206.9 | 51.73 | 3048.69 | 126.38 | 113.67 |

**Table 5.** Cold chain logistics demand for agricultural products in Beijing, Tianjin and Hebei (unit: $10^4$ tons).

| Year | Beijing | Tianjin | Hebei |
|---|---|---|---|
| 2014 | 744.79 | 332.35 | 798.44 |
| 2015 | 765.2 | 339.42 | 845.2 |
| 2016 | 793.67 | 353.15 | 980.5 |
| 2017 | 816.34 | 358.02 | 974.4 |
| 2018 | 893.89 | 367.90 | 1094.78 |
| 2019 | 965.4 | 367.68 | 1187.84 |
| 2020 | 1033.95 | 392.82 | 1280.49 |

## 4. Demand forecast for agricultural cold chain logistics in Beijing-Tianjin-Hebei

### *4.1. Determination of influential factors*

A grey correlation analysis is performed for the agricultural product cold chain logistics demand and five influential factors in Beijing, Tianjin and Hebei, respectively. Table 6 and Figure 1 show the results.

According to Table 6, the first three factors influencing the cold chain logistics demand for agricultural products in Beijing and Tianjin are the proportion of tertiary industry, per capita disposable income indices for urban households and general price index for farm products. In Hebei, the GDP, fixed assets investment in transport and storage, and proportion of tertiary industry are the three major influential factors.

The results in Table 6 also indicate that the five influential factors selected in this study have significant effects on the cold chain logistics for agricultural products in Beijing, Tianjin and Hebei. This further displays that the economy, the supply to demand, the transportation capacity and people's living standards promote the development of cold chain logistics [41]. The ranking of influential factors does vary from region to region. Therefore, it is more relevant to forecast demand based on the influences of local differences.

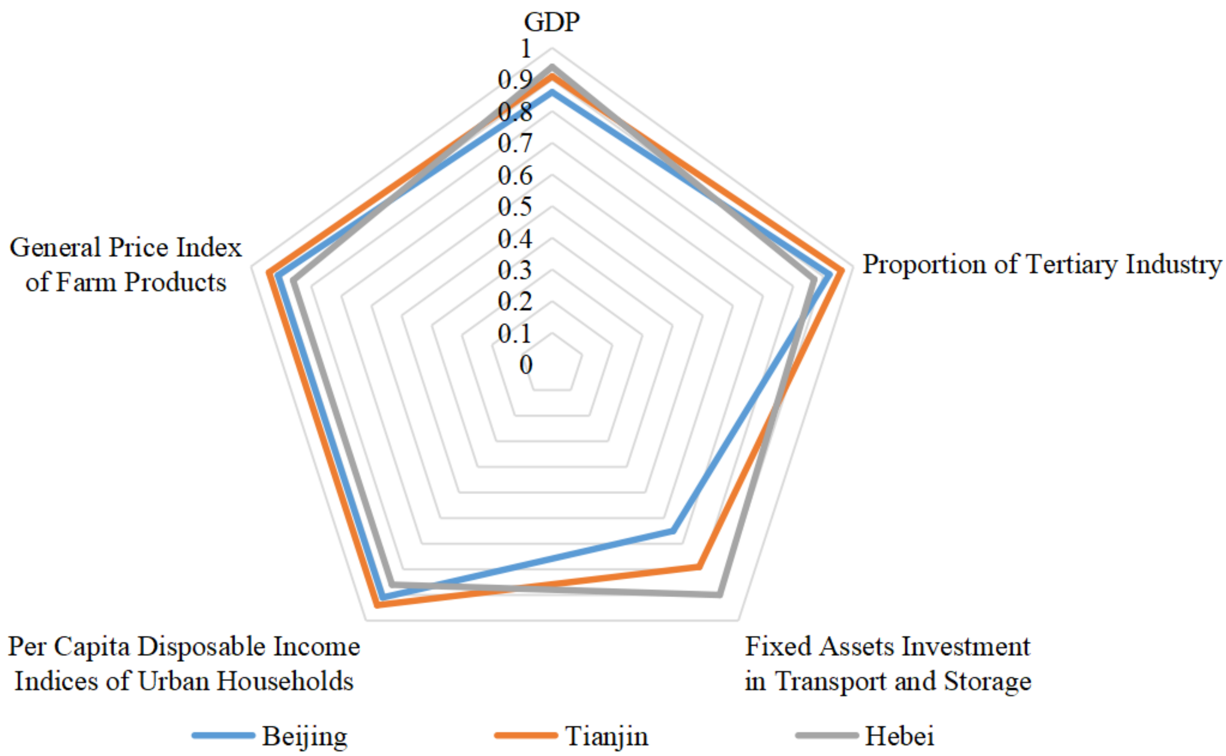


**Figure 1.** Grey relation results for agricultural product cold chain logistics demand and influential factors in the Beijing-Tianjin-Hebei region.

**Table 6.** Grey relation results for agricultural product cold chain logistics demand and influential factors in the Beijing-Tianjin-Hebei region.

| Influencing Factors | Grey Relation Degree | | |
|---|---|---|---|
| | Beijing | Tianjin | Hebei |
| GDP | 0.86 | 0.91 | 0.94 |
| Proportion of Tertiary Industry | 0.92 | 0.96 | 0.87 |
| Fixed Assets Investment in Transport and Storage | 0.65 | 0.79 | 0.90 |
| Per Capita Disposable Income Indices for Urban Households | 0.91 | 0.94 | 0.86 |
| General Price Index for Farm Products | 0.91 | 0.94 | 0.86 |

### 4.2. *FGM (1,1) forecasting results for the influential factors*

To predict the main sequence, the prediction results for the relevant influential factors must first be obtained. In this section, the FGM (1,1) model is used to predict the sequence of influential factors from 2021 to 2025, and the results are summarized in Tables 7–9.

According to Tables 7–9, the MAPE values of the simulation results for the first three influential factors for the agricultural products cold chain logistics in Beijing, Tianjin and Hebei are less than 5%. Furthermore, the $R^2$ coefficient of determination values are also relatively high.

According to Table 1, if the MAPE value is less than 10%, the model's prediction accuracy is high, the prediction results are accurate and persuasive. As a result, it is reasonable to predict the influential factors using a FGM (1,1) model.

**Table 7.** Forecasts of the factors influencing agricultural cold chain logistics demand in Beijing.

| Year | Proportion of Tertiary Industry (%) | | Per Capita Disposable Income Indices for Urban Households | | General Price Index for Farm Products | |
|---|---|---|---|---|---|---|
| | Fitted Value | Error | Fitted Value | Error | Fitted Value | Error |
| 2014 | 80.6 | 0.00 | 108.90 | 0.00 | 99.70 | 0.00 |
| 2015 | 89.94 | −2.66 | 115.43 | −4.95 | 98.70 | −1.10 |
| 2016 | 92.20 | 5.30 | 111.95 | 3.60 | 99.94 | 0.24 |
| 2017 | 90.48 | 0.98 | 109.41 | 0.45 | 102.01 | 2.41 |
| 2018 | 86.83 | −3.37 | 107.56 | −1.39 | 104.61 | 1.01 |
| 2019 | 82.31 | −7.29 | 106.13 | −2.49 | 107.61 | −2.29 |
| 2020 | 77.47 | 4.87 | 104.96 | 2.56 | 110.96 | 0.06 |
| MAPE | 4.09% | | 1.99% | | 0.98% | |
| $R^2$ | 0.62 | | 0.74 | | 0.92 | |
| 2021 | 72.63 | | 103.97 | | 114.65 | |
| 2022 | 67.96 | | 103.12 | | 118.68 | |
| 2023 | 63.55 | | 102.37 | | 123.04 | |
| 2024 | 59.46 | | 101.70 | | 127.74 | |
| 2025 | 55.69 | | 101.09 | | 132.80 | |

**Table 8.** Forecasts of the factors influencing agricultural cold chain logistics demand in Tianjin.

| Year | Proportion of Tertiary Industry (%) | | Per Capita Disposable Income Indices for Urban Households | | General Price Index for Farm Products | |
|---|---|---|---|---|---|---|
| | Fitted Value | Error | Fitted Value | Error | Fitted Value | Error |
| 2014 | 55.10 | 0.00 | 101.90 | 0.00 | 98.30 | 0.00 |
| 2015 | 57.20 | 0.00 | 101.70 | 0.00 | 98.66 | 0.86 |
| 2016 | 60.16 | -0.34 | 101.97 | -0.13 | 99.77 | -2.43 |
| 2017 | 61.96 | -0.04 | 102.16 | 0.06 | 101.00 | 0.00 |
| 2018 | 63.06 | 0.56 | 102.22 | 0.22 | 102.22 | 2.02 |
| 2019 | 63.71 | 0.21 | 102.17 | -0.53 | 103.39 | -0.31 |
| 2020 | 64.04 | -0.36 | 102.07 | 0.07 | 104.48 | -0.02 |
| MAPE | 0.34% | | 0.14% | | 0.80% | |
| $R^2$ | 0.99 | | 0.62 | | 0.73 | |
| 2021 | 64.13 | | 101.92 | | 105.49 | |
| 2022 | 64.05 | | 101.75 | | 106.42 | |
| 2023 | 63.83 | | 101.57 | | 107.27 | |
| 2024 | 63.51 | | 101.39 | | 108.06 | |
| 2025 | 63.09 | | 101.21 | | 108.77 | |

**Table 9.** Forecasts of the factors influencing agricultural cold chain logistics demand in Hebei.

| Year | GDP ($10^8$ yuan) | | Proportion of Tertiary Industry (%) | | Fixed Assets Investment in Transport and Storage ($10^8$ yuan) | |
|---|---|---|---|---|---|---|
| | Fitted Value | Error | Fitted Value | Error | Fitted Value | Error |
| 2014 | 29421.20 | 0.00 | 37.30 | 0.00 | 2025.90 | 0.00 |
| 2015 | 30335.69 | 529.59 | 39.85 | -0.34 | 1923.93 | -111.77 |
| 2016 | 31860.05 | 32.15 | 42.48 | 0.77 | 2052.39 | -28.91 |
| 2017 | 33254.37 | -2709.63 | 45.01 | 3.19 | 2246.98 | 130.68 |
| 2018 | 34425.90 | 1931.29 | 47.41 | -2.60 | 2479.50 | -102.39 |
| 2019 | 35378.73 | 274.21 | 49.68 | -1.97 | 2741.73 | 95.30 |
| 2020 | 36138.11 | -68.79 | 51.81 | 0.08 | 3031.17 | -17.52 |
| MAPE | 2.33% | | 2.78% | | 3.03% | |
| $R^2$ | 0.76 | | 0.91 | | 0.95 | |
| 2021 | 36732.57 | | 53.82 | | 3347.52 | |
| 2022 | 37188.87 | | 55.70 | | 3691.55 | |
| 2023 | 37530.56 | | 57.47 | | 4064.68 | |
| 2024 | 37777.84 | | 59.13 | | 4468.73 | |
| 2025 | 37947.74 | | 60.69 | | 4905.87 | |

### *4.3. Fractional order GM (1, N) model predicts cold chain demand*

In this section, the first three factors influencing the agricultural cold chain demand logistics in the Beijing-Tianjin-Hebei region are identified by grey correlation analysis. As a result, an FGM (1,3) model with three related factor sequences is used for forecasting agricultural cold chain logistics demand in Beijing, Tianjin and Hebei. Besides, in order to validate the FGM (1, N) model's good performance in terms of forecasting accuracy and efficiency when reflecting the priority of new information, a comparison to the GM (1, N) model [25] is presented. Table 10 displays the comparison of the predicted fitting value and error results for the GM (1,3) and FGM (1,3) models.

**Table 10.** Fitting and error results for the cold chain logistics demand for agricultural products in Beijing-Tianjin-Hebei (unit: $10^4$ tons).

| Year | Beijing | | Tianjin | | Hebei | |
|---|---|---|---|---|---|---|
| | GM (1,3) | FGM (1, 3) | GM (1,3) | FGM (1,3) | GM (1,3) | FGM (1,3) |
| 2014 | 744.79 | 744.79 | 332.35 | 332.35 | 798.44 | 798.44 |
| 2015 | 660.19 | 752.92 | 271.59 | 314.73 | 785.95 | 838.58 |
| 2016 | 896.37 | 786.22 | 363.92 | 359.78 | 1095.56 | 979.88 |
| 2017 | 840.02 | 836.34 | 361.28 | 365.01 | 1075.16 | 1044.88 |
| 2018 | 885.11 | 891.00 | 362.44 | 364.86 | 1172.99 | 1205.44 |
| 2019 | 985.07 | 948.01 | 373.93 | 375.67 | 1194.78 | 1246.31 |
| 2020 | 1030.47 | 1029.53 | 384.24 | 382.47 | 1303.27 | 1335.58 |
| MAPE | 4.7% | 1.26% | 4.19% | 2.79% | 5.51% | 4.57% |
| $R^2$ | 0.777 | 0.988 | 0.545 | 0.762 | 0.904 | 0.972 |

According to Table 10, the MAPE values of cold chain logistics demand for agricultural products in Beijing, Tianjin, and Hebei from 2021–2025, as predicted by the FGM (1,3) model, are 1.26, 2.79 and 4.57%, respectively, and the $R^2$ values are 0.988, 0.762 and 0.972, respectively, which are very close to 1. In comparison to the results in Table 1, the MAPE and $R^2$ values for the two models meet the requirements, but the MAPE of FGM (1,3) is much lower than that of GM (1,3), and $R^2$ is closer to 1. What's more, the growth rate of FGM (1,3) is extremely consistent with the actual situation. In other words, the comparison indicates that the FGM (1,3) model predicts future values better than the GM (1,3) model. As a result, the FGM (1,3) model is used to forecast the agricultural cold chain demand logistics in the Beijing-Tianjin-Hebei region from 2021 to 2025; the results are summarized in Table 11, and the corresponding trend chart is shown in Figure 2.

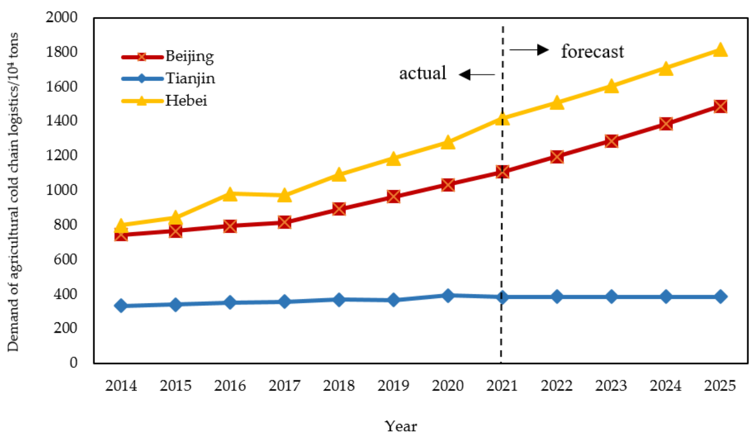


**Figure 2.** Trend of agricultural cold chain logistics demand in Beijing-Tianjin-Hebei from 2011–2025.

**Table 11.** Prediction results for the cold chain logistics demand for agricultural products in Beijing-Tianjin-Hebei. (unit: $10^4$ tons)

| Year | Beijing | Tianjin | Hebei |
|---|---|---|---|
| 2021 | 1108.98 | 383.33 | 1418.48 |
| 2022 | 1195.60 | 385.14 | 1509.67 |
| 2023 | 1288.25 | 386.15 | 1606.23 |
| 2024 | 1386.23 | 386.58 | 1708.47 |
| 2025 | 1488.85 | 386.37 | 1816.88 |

According to the forecasting results, agricultural cold chain demand in Beijing-Tianjin-Hebei region could exceed 36 million tons in 2025, up from 18.75 million tons in 2014. As shown in Figure 2, the growth trends of demand for cold chain logistics for agricultural products in Beijing, Tianjin, and Hebei from 2011 to 2025 differ due to differences in economic, industrial, and population conditions. Among them, the cold chain logistics demand for agricultural products in Beijing and Hebei has been steadily increasing since 2017, and this high growth rate is expected to continue during the forecast period of 2021 to 2025. Although the demand in Tianjin fluctuated slightly between 2014 and 2020, the demand is predicted to remain flat and stable during the forecast period from 2021 to 2025, with a growth rate of nearly 0.

In general, Beijing and Tianjin have high consumption levels and a large floating population, which ensures a demand for fresh agricultural products [36]. At the same time, people's understanding of the health benefits of eating fresh agricultural products has gradually increased, fueling demand for cold chain logistics [42]. In the Beijing-Tianjin-Hebei region, Hebei is the primary producer of fresh agricultural products. At the same time, the general price index for farm products will continue to rise (Tables 7 and 8), which is also very consistent with China's current strategy of vigorously developing agricultural economy and Rural Revitalization [27]. Therefore, all of these factors will lead to a high claim for cold chain logistics in the Beijng-Tianjin-Hebei region. Furthermore, increasing the fixed assets investment in transport and storage in Hebei Province (Table 9) will promote a convenient transportation system, resulting in a more prosperous logistics industry in the Beijing-Tianjin-Hebei region [14]. As a result, government assistance in the construction of logistics networks in Hebei, such as roads and railways, will help to promote the integrated development of the cold chain logistics industry in the Beijing-Tianjin-Hebei region.

## 5. Conclusions

This paper analyzes the demand forecast and its influential factors based on the use of a grey model. A cold chain logistics demand forecast case study for agricultural products in Beijing, Tianjin and Hebei was conducted taking into account regional differences. The following conclusions can be made based on the above research. 1) There are many factors influencing the demand for cold chain logistics, but the main influential factors vary slightly from region to region. Identification of the main influential factors for each region can better respond to the needs of cold chain logistics. 2) The FGM (1,3) model was successfully implemented to forecast based on the use of various input data demonstrating better performance than the GM (1,3) model. 3) From 2021 to 2025, the agricultural cold chain logistics demand in Beijing and Hebei will continue to rise, while it will remain stable in Tianjin. According to the prediction results, Beijing, Tianjin and Hebei could take targeted measures based on their specific developing trends and influential factors.

The economic development of the different regions differs, and this inconsistency contributes to the cold chain logistics industry's low efficiency. Cold chain logistics, no matter how many regions are involved, should be seen as a unified system. Hence, a cold chain network, as so many other forms of logistics networks, should form a systematic and dynamic approach to achieve its objectives of meeting the demand with supply efficiently. Given the major factors influencing agricultural product cold chain logistics in Beijing, Tianjin, and Hebei, fully utilizing the comparative advantages of various regions and constructing an efficient agricultural product cold chain logistics system will contribute to the integrated development of the agricultural product cold chain logistics industry in Beijing, Tianjin and Hebei.

The limitations and future research direction of this work are listed as follows. First, though the fractional order accumulation model shows higher accuracy and stability of prediction in the application, there are not enough other cases to test the forecasting model; furthermore, it is suggested to adopt other intelligent optimization algorithms to search for more optimal values for the fractional order, which will improve forecast accuracy. Second, there was no assessment of influencing factors on cold chain logistics as comprehensively as possible, a certain criterion for systematic assessment of cold chain influencing factors is to set to select independent variables. Last but not least, one of the most crucial works is to build a simulation model by using a technique such as a system dynamics approach or discrete-event dynamic system, incorporating it into the forecast model. The incorporation with such techniques will not only provide a graphical visualization of a supply chain network and an analysis of system behavior, but it will also improve the management and prediction of how the disruption in a supply chain is propagated, which will improve the performance in terms of cost, quality and time, and thus the resilience of a supply chain network system [43,44].

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## Data availability

The research data used to support the findings of this study are included within the article, the data used are shown in Tables 2–5.

## Conflict of interest

The authors declare no conflicts of interest.

## References

1. D. Samson, Operations/supply chain management in a new world context, *Oper. Manage. Res. Adv. Pract. Theory*, **13** (2020), 1–3. https://doi.org/10.1007/s12063-020-00157-w

2. O. Theophilus, M. A. Dulebenets, J. Pasha, Y. Lau, A. M. Fathollahi-Fard, A. Mazaheri, Truck scheduling optimization at a cold-chain cross-docking terminal with product perishability considerations, *Comput. Ind. Eng.*, **1** (2021), 107240. https://doi.org/10.1016/j.cie.2021.107240
3. J. Wang, R. R. Muddada, H. Wang, J. Ding, Y. Lin, C. Liu, et al., Toward a resilient holistic supply chain network system: Concept, review and future direction, *IEEE Syst. J.*, **10** (2016), 410–421. https://doi.org/10.1109/JSYST.2014.2363161
4. J. Blackburn, G. Scudder, Supply chain strategies for perishable products: The case of fresh produce, *Prod. Oper. Manage.*, **18** (2009), 129–137. https://doi.org/10.1111/j.1937-5956.2009.01016.x
5. R. Haass, P. Dittmer, M. Veigt, M. Lütjen, Reducing food losses and carbon emission by using autonomous control-A simulation study of the intelligent container, *Int. J. Prod. Econ.*, **164** (2015), 400–408. https://doi.org/10.1016/j.ijpe.2014.12.013
6. J. Fu, D. Yang, The current situation, dilemma and policy suggestions of China's cold chain logistics development, *China Econ. Trade Herald*, **9** (2021), 20–23. https://doi.org/10.3969/j.issn.1007-9777.2021.13.006
7. C. Mena, L. A. Terry, L. Ellram, Causes of waste across multi-tier supply networks: Cases in the UK food sector, *Int. J. Prod. Econ.*, **152** (2014), 144–158. https://doi.org/10.1016/j.ijpe.2014.03.012
8. F. Zheng, Y. Pang, Y. Xu, M. Liu, Heuristic algorithms for truck scheduling of cross-docking operations in cold-chain logistics, *Int. J. Prod. Res.*, **59** (2021), 6579–6600. https://doi.org/10.1080/00207543.2020.1821118
9. F. Pan, T. Fan, X. Qi, J. Chen, C. Zhang, Truck scheduling for cross-docking of fresh produce with repeated loading, *Math. Problems Eng.*, **2021** (2021). https://doi.org/10.1155/2021/5592122
10. M. A. Dulebenets, E. E. Ozguven, R. Moses, M. B. Ulak, Intermodal freight network design for transport of perishable products, *Open J. Optim.*, **5** (2016), 120–139. https://doi.org/10.4236/ojop.2016.54013
11. C. Qi, L. Hu, Optimization of vehicle routing problem for emergency cold chain logistics based on minimum loss, *Phys. Commun.*, **40** (2020), 101085. https://doi.org/10.1016/j.phycom.2020.101085
12. M. A. Dulebenets, E. E. Ozguven, Vessel scheduling in liner shipping: Modeling transport of perishable assets, *Int. J. Prod. Econ.*, **184** (2017), 141–156. https://doi.org/10.1016/j.ijpe.2016.11.011
13. M. Wang, X. Li, Demand forecasting of agricultural cold chain logistics based on metabolic GM (1,1) model. *IOP Conf. Series Earth Environ. Sci.*, **831** (2021). https://doi.org/10.1016/10.1088/1755-1315/831/1/012018
14. T. Liu, S. Li, S. Wei, Forecast and opportunity analysis of cold chain logistics demand of fresh agricultural products under the integration of Beijing, Tianjin and Hebei. *Open J. Social Sci.*, **5** (2017), 63–73. https://doi.org/10.4236/jss.2017.510006
15. B. He, L. Yin, Z. Ernesto, Prediction modelling of cold chain logistics demand based on data mining algorithm, *Math. Probl. Eng.*, **2021** (2021). https://doi.org/10.1155/2021/3421478
16. S. Wang, C. Wei, Demand prediction of cold chain logistics under B2C E-Commerce model, *J. Adv. Comput. Intell. Intell. Inf.*, **22** (2018), 1082–1087. https://doi.org/10.20965/jaciii.2018.p1082

17. R. Xu, H. Lan, Demand forecasting model of aquatic cold chain logistics based on GWO-SVM, in *Conference Proceedings of the 8th International Symposium on Project Management*, (2020), 1088–1093. https://doi.org/10.26914/c.cnkihy.2020.029466
18. M Wang, X. Li, Demand forecasting of agricultural cold chain logistics based on metabolic GM (1, 1) model, *IOP* Conf. S*er. Earth Environ. Sci.*, **831** (2021). https://doi.org/10.1088/1755-1315/831/1/012018
19. J. Lv, Y. Chen, Dalian aquatic products cold chain logistics demand forecast and analysis of influencing factors, *Math. Pract. Theory*, (2020), 72–80
20. B. Ya, Study of food cold chain logistics demand forecast based on multiple regression and AW-BP forecasting method on system order parameters, *J. Comput. Theor. Nanosci.*, **13** (2016), 4019–4024. https://doi.org/10.1166/jctn.2016.4930
21. C. Bu, L. Chen, Demand forecast of cold chain logistics of fresh agricultural products in Jiangsu province based on GA-BP model, *World Sci. Res. J.*, **7** (2021), 210–217. https://doi.org/10.6911/WSRJ.202108_7(8).0034
22. J. L. Deng, *An introduction to grey mathematics-grey hazy set*, Huazhong University of Science and Technology Press, 1992
23. L. Wu, S. Liu, L. Yao, S. Yan, D. Liu, Grey system model with the fractional order accumulation, *Commun. Nonlinear Sci. Numer. Simul.*, **18** (2013), 1775–1785. https://doi.org/10.1016/j.cnsns.2012.11.017
24. L. Wu, S. Liu, Z. Fang, H. Xu, Properties of the GM (1, 1) with fractional order accumulation, *Appl. Math. Comput.*, **252** (2015), 287–293. https://doi.org/10.1016/j.amc.2014.12.014
25. Z. X. Wang, P. Hao, An improved grey multivariable model for predicting industrial energy consumption in China, *Appl. Math. Model.*, **40** (2016), 5745–5758. https://doi.org/10.1016/j.apm.2016.01.012
26. H. Chen, Y. Tong, L. Wu, Forecast of energy consumption based on FGM (1, 1) model, *Math. Probl. Eng.*, **2021** (2021). https://doi.org/10.1155/2021/6617200
27. Y. Xu, T. S. Lim, K. Wang, Prediction of farmers' income in Hebei province based on the fractional grey model (1, 1), *J. Math.*, **2021** (2021). https://doi.org/10.1155/2021/4869135
28. S. Mao, X. Xiao, M. Gao, X. Wang, Nonlinear fractional order grey model of urban traffic flow short-term prediction, *J. Grey Syst.*, **30** (2018), 1–17
29. X. Qin, H. Tian, Comprehensive evaluation of cold chain logistics level of agricultural products in China based on grey cluster analysis, *Preserv. Process.*, **19** (2019),170–177
30. S. Liu, Y. Yang, L. Wu, *The grey system theory and application*, Science Press, 2014.
31. J. Wang, N. Li, Influencing factors and future trends of natural gas demand in the eastern, central and western areas of China based on the grey model, *Nat. Gas Ind.* B, **7** (2020). https://doi.org/10.1016/j.ngib.2020.09.005
32. L. Wu, S. Liu, Z. Fang, H. Xu, Properties of the GM (1, 1) with fractional order accumulation, *Appl. Math. Comput.*, **252** (2015), 287–293. https://doi.org/10.1016/j.amc.2014.12.014
33. S. Lan, C. Yang, G. Q. Huang, Data analysis for metropolitan economic and logistics development, *Adv. Eng. Inf.*, **32** (2017), 66–76. https://doi.org/10.1016/j.aei.2017.01.003
34. W. Zhang, X. Zhang, M. Zhang, W. Li, How to coordinate economic, logistics and ecological environment? Evidences from 30 provinces and cities in China, *Sustainability*, **12** (2020), 1058. https://doi.org/10.3390/su12031058

35. R. Xie, H. Huang, Y. Zhang, P. Yu, Coupling relationship between cold chain logistics and economic development: A investigation from China, *PloS one*, **17** (2022), e0264561–e0264561. https://doi.org/10.1371/JOURNAL.PONE.0264561
36. J. Li, L. Sun, Demand forecast of the cold chain logistics based on the multiple linear regression analysis, *J. Anhui Agric. Sci.*, **39** (2011), 6519–6520. https://doi.org/10.13989/j.cnki.0517-6611.2011.11.142
37. T. Rossi, R. Pozzi, G. Pirovano, R. Cigolini, M. Pero, A new logistics model for increasing economic sustainability of perishable food supply chains through intermodal transportation, *Int. J. Logistics Res. Appl.*, **24** (2020), 1–18. https://doi.org/10.1080/13675567.2020.1758047
38. M. Li, J. Wang, Prediction of demand for cold chain logistics of aquatic products based on RBF nueral network, *Chin. J. Agric. Resour. Reg. Plann.*, **41** (2020), 10. https://doi.org/10.7621/cjarrp.1005-9121.20200612
39. X. Wang, K. Zhao, Forecast of logistics demand of agricultural products based on neural network, *J. Agrotechnical Econ.*, **2** (2010), 62–68. https://doi.org/10.13246/j.cnki.jae.2010.02.006
40. L. Wu, S. Liu, L. Yao, S. Yan, The effect of sample size on the grey system model, *Appl. Math. Model.*, **37** (2013), 6577–6583. https://doi.org/10.1016/j.apm.2013.01.018
41. C. Magazzino, M. Mele, On the relationship between transportation infrastructure and economic development in China, *Res. Transp. Econ.*, **88** (2020), 100947. https://doi.org/10.1016/j.retrec.2020.100947
42. J. Li, Research on development strategy of cold chain logistics based on food safety, *Front. Econ. Manage.*, **2** (2021), 214–225. https://doi.org/10.6981/FEM.202103_2(3).0028
43. B. Mary, O. Akinola, W. Zhang, A systems dynamics approach to the management of material procurement for engineering, procurement and construction industry, *Int. J. Prod. Econ.*, **244** (2022). https://doi.org/10.1016/J.IJPE.2021.108390
44. J. W. Wang, W. H. lp, R. R. Muddada, J. L. Huang, W. J. Zhang, On Petri net implementation of proactive resilient holistic supply chain networks, *Int. J. Adv. Manuf. Technol.*, **69** (2013), 427–437. https://doi.org/10.1007/s00170-013-5022-x

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