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PREDICTION OF LOGISTICS DEMAND IN GUANGZHOU BASED ON GREY MARKOV MODEL

YongXin Peng, SiMei Pan*, YuJing Huang, LianHua Liu, WenChao Pan
School of Management, Guangzhou Huashang College, Guangzhou 511300, Guangdong, China.
Corresponding Author: SiMei Pan, Email: 324827824@qq.com; pansm@gdhsc.edu.cn

Abstract: This paper selects the logistics data of Guangzhou from 2015 to 2019, using grey theory model and grey Markov model to forecast the logistics development data of Guangzhou from 2015 to 2019. Based on the actual data and forecast data of Guangzhou logistics from 2015 to 2019, the grey Markov model with high forecasting accuracy is selected to calculate the logistics demand of Guangzhou from 2020 to 2024, the empirical results show that there are two characteristics of logistics demand growth in Guangzhou in the future: First, the total demand of logistics industry in Guangzhou shows a continuous growth trend; Second, the structure of logistics demand in Guangzhou has changed slightly. According to the results of empirical research, this paper puts forward two countermeasures: First of all, under the background of new infrastructure, Guangzhou needs to strengthen the construction of logistics infrastructure, focusing on the development and improvement of infrastructure construction such as Internet of Things and logistics big data. Secondly, in view of the changes in the logistics demand structure in Guangzhou, we should continue to optimize the structure of the logistics industry, drain the highway logistics with higher carbon emissions, and pay attention to the development of clean, efficient and low-energy logistics methods to help achieve the goals of peak carbon dioxide emissions and carbon neutrality.
Keywords: Grey prediction model; Grey Markov model; Guangzhou; Logistics demand forecast

1 INTRODUCTION

Logistics plays an increasingly important role in the economic and social system[1-4]. There is a positive circular relationship between economic development and logistics development, and logistics and economic development complement each other. Under the background of the integrated development of Guangdong-Hong Kong-Macao Greater Bay Area, Guangzhou, as an important node city of Guangdong-Hong Kong-Macao Greater Bay Area, is particularly important to improve the level of Guangzhou's logistics industry with the highest global efficiency, the lowest cost and the most competitive under the background of the new development pattern of the domestic circulation as the main body and the mutual promotion of the domestic and international circulation. Guangzhou' s logistics industry has shown a good development trend. According to the National Economic Statistical Bulletin of Guangzhou in 2019, Guangzhou' s freight volume in 2019 was 136.165 million tons, an increase of 6.6 % compared with 2018, and the turnover of goods was 218.29 billion tons of kilometers, an increase of 1.6 % compared with the previous year. As an important logistics hub in Guangdong-Hong Kong-Macao Greater Bay Area, Guangzhou' s high-quality development of modern logistics promotes the economic integration process of Guangdong-Hong Kong-Macao Greater Bay Area, and is also conducive to Guangzhou' s development as the economic growth pole of transportation hub in Guangdong-Hong Kong-Macao Greater Bay Area. Therefore, the prediction of the development trend of Guangzhou' s logistics industry is conducive to Guangzhou' s mastery of the market supply and demand development of logistics industry development, and is conducive to Guangzhou' s early development planning for logistics infrastructure construction, promoting the high-quality development of logistics industry, and meeting the development of logistics demand in Guangzhou.

In recent years, logistics development prediction has become a hot topic of research for scholars. The methods commonly used by scholars include exponential smoothing [5-7], linear models [8], BP neural network methods [5-9], multiple regression analysis [5,9], seasonal autoregressive models [10-13], discrete wavelet techniques [14], vector autoregressive methods [15], Markov model theory [16], and other widely used methods for predicting logistics and freight development. In addition to conventional prediction methods, scholars have also innovated prediction methods, such as a genetic algorithm and a backpropagation (GA-BP) prediction model an optimized backpropagation neural network model using genetic algorithms, for predicting freight demand with small errors [17]. We applied the L-OD logistics demand forecasting method and constructed a new dual constraint gravity model to predict logistics distribution, achieving good prediction results. Introducing the State Travel Demand Model (STDM) [18], a new hybrid multi criteria decision model combining Delphi, Analytic Network Process (ANP), and Quality Function Deployment (QFD) methods in a fuzzy environment is used for freight forecasting [19]. Grey system theory is an effective method for studying and modeling systems composed of small samples, which contains limited information and has wide applications in many fields [20]. Extract valuable information by processing known information. Further utilize this method to explore the evolutionary laws of the system and establish a predictive model. Due to the many factors that affect the development of freight transportation, such as transportation and logistics environment factors, regional economic environment factors, government policy factors, technological environment factors, etc., it can be regarded as a grey system. Therefore, it can be described using the Grey Model (GM). The GM (1,1) model is the most commonly used grey model. Satisfactory results have been achieved in predicting freight volume using the GM (1,1) model [5,9, 21-25].

In conclusion, this paper selects the logistics data of Guangzhou from 2015 to 2019 for modeling analysis, and uses grey theory model and grey Markov model to predict the logistics development data of Guangzhou from 2015 to 2019. On the basis of the actual logistics data and prediction data of Guangzhou from 2015 to 2019, this paper selects the prediction model with high prediction accuracy to calculate the logistics demand of Guangzhou from 2020 to 2024, which provides reference for Guangzhou to further make reasonable planning and construction of high quality modern logistics.

2 RESEARCH METHODS

2.1 Grey System Theory and GM (1,1) Model

2.1.1 Overview of grey system theory

The grey system theory was established in 1982 by Professor Deng Julong, a Chinese scholar. At the cognitive level, the system is divided into black, white and grey three-color systems. Black means that information is scarce and completely insufficient. When the information of the object of study is not clear and the data is very small, it should be expressed by ‘black’. White means that information is rich and sufficient. When the information of the object of study is clear and the data is sufficient, it can be expressed by ‘white’, and gray is between them. The grey system theory aims at the situation that some information in the system is known, while some information is incomplete. Now grey system theory has been widely used, which plays an important role in national economy and social development.

2.2.2 Establishment of GM (1,1) model

Grey GM (1,1) model is a process of data collection and analysis, grey modeling and model solving for grey system. GM (1,1) model is the most commonly used gray theory model, and its modeling principle is as follows:

Firstly, a set of primitive numbers is set as

$$X^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x(3),\cdots x^{(0)}(n)\right\}\text{, among } X^{(0)}(k)\geq 0,k=1,2,\cdots n$$

Then, the original sequence is cumulatively generated, and the generated new number is listed as $X^{(1)}=\left\{x^{(1)}(1),x^{(1)}(2),x^{(1)}(3),\cdots x^{(1)}(n)\right\}$, where, $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)$, k=1,2,$\cdots$ n

Thirdly, the moving average matrix B and vector Y_n are constructed.

$$\begin{bmatrix} -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(3)) & 1 \\ \cdots & \cdots \\ -\frac{1}{2}(x^{(1)}(n-1)+x^{(1)}(n)) & 1 \end{bmatrix}$$

$Y_n=(x^{(0)}(2),x(3),\cdots x^{(0)}(n))^T$, the undetermined coefficients a and u are calculated by the least square method.

$$\hat{a}=[a,u]^T=(B^TB)^{-1}B^TY_n$$

$$\hat{x}^{(1)}(k+1)=(x^{(0)}(1)-\frac{u}{a})e^{-ak}+\frac{u}{a} \tag{1}$$

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k) \tag{2}$$

Formulas (1) and (2) are the prediction equations of GM (1,1) model, where $\hat{x}^{(0)}(k+1)$ is the predicted value, − a is the development coefficient, and u is the grey effect.

2.1.3 GM (1,1) model test

We conduct residual test on the GM (1,1) model, and the posterior residual test is adopted in this paper.

① Calculate the original sequence mean

$$\bar{x}_0=\frac{1}{n}\sum_{k=1}^{n}x^{(0)}(k) \tag{3}$$

② Mean square deviation of original series

$$S_1=\sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(x^{(0)}(k)-\bar{x})^2} \tag{4}$$

③ Residual mean

$$\bar{\varepsilon}=\frac{1}{n}\sum_{k=1}^{n}\varepsilon(k) \tag{5}$$

④ Mean square error of residuals

$$S_2=\sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(\varepsilon(k)-\bar{\varepsilon})^2} \tag{6}$$

⑤ Posterior residual ratio C

$$C=\frac{S_2}{S_1} \tag{7}$$

⑥ Probability of small error

$$P=P\{|\varepsilon(k)-\bar{\varepsilon}|<0.6745S_1\} \tag{8}$$

Finally, according to the ratio C and probability P, the accuracy of the model is determined by comparing the accuracy level table of the grey prediction model (Table 1).

Table 1 Table of Prediction Accuracy

Grade	C	P
Good	≦0.35	≧0.95
Qualified	≦0.50	≧0.80
Barely qualified	≦0.65	≧0.70
Unqualified	>0.65	<0.70

2.2 Grey Markov Theory and Model

2.2.1 Overview of grey markov theory

Markov model was first proposed by Russian mathematician Markov in 1906, Markov prediction model is based on the current situation to predict the future moment of development. Given the current knowledge or information, the past (that is, the current previous historical state) is irrelevant to predicting the future (that is, the current future state). Time and state are discrete Markov processes called Markov chains, which are abbreviated as $\{X_n, n=1,2,\dots\}$. The Markov model is based on the data predicted by the grey GM(1,1) model. According to the calculated relative values, the state transition matrix is divided, and the optimal state is found from the steps of the state transition matrix, so as to estimate the future change trend.

2.2.2 Grey markov model

(1) Division of State Intervals

The ratio between the original data and the grey prediction value is calculated, and the space is divided into n intervals according to the calculated value. Each interval represents a state and is represented by E_i, $E_i \in [l_i, m_i]$, i= 1, 2,…, n. Where l_i and m_i are the upper and lower limits of the state interval.

(2) Establishment of State Transition Probability Matrix

Since there are more than one state at each different time, there are several cases of transition from the previous state to the current state, then all conditional probabilities form a matrix called the transition probability matrix. State transition probability from state E_i to state E_j is represented by $p_{ij(k)}$:

$$p_{ij(k)}=\frac{n_{ij(k)}}{n_i} \tag{9}$$

The state transition probability matrix is obtained:

$$P=\begin{pmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{pmatrix} \tag{10}$$

(3) Optimized Predictive Value of Markov Chain Model

An event is currently in state E_n, according to the state transition probability matrix, the state transition probability vector is V_n, and then the large probability transition direction and its fluctuation range of the next state of the event can be obtained by using $V_n *$ p. The possible prediction value of the system in the future is :

$$\hat{x}'^{(0)}=\frac{1}{2}(l_i+m_i)\hat{x}^{(0)} \tag{11}$$

In which l_i and m_i are the upper and lower limits of the next state interval, and $\hat{x}^{(0)}$ is the predicted value of the grey prediction model GM(1,1).

3 ESTABLISHMENT OF GM (1,1) PREDICTION MODEL FOR LOGISTICS DEMAND IN GUANGZHOU

3.1 Source and Overview of Data

The data are from the Guangzhou Statistical Yearbook from 2015 to 2019 on the website of Guangzhou Bureau of Statistics. The data are six groups of data including the freight volume, railway freight volume, highway freight volume, waterway freight volume, air freight volume and pipeline freight volume in Guangzhou. For convenience of calculation, the following are respectively expressed by Freight volume (F), Railway freight volume (R), Highway freight volume (H), waterway freight volume (w), Air freight volume (A) and Pipeline freight volume (P). Statistics the development of logistics demand in Guangzhou every year, including the freight volume (F), railway freight volume (R), highway freight volume (H), waterway freight volume (W), aviation freight volume (A), pipeline freight volume (P), the total value of the six index system, as shown in table 2, and as the original data to predict the development of logistics demand in Guangzhou from 2020 to 2024.

Table 2 Annual Data of Logistics Demand Development Indicators in Guangzhou from 2015 to 2019 Unit: (10000 tons)

	Freight volume (F)	Railway freight volume (R)	Highway freight volume (H)	Waterway freight volume (W)	Air freight volume (A)	Pipeline freight volume (P)
2015	100124	4811	71284	23007	116	905
2016	107992	4884	71860	30212	125	910
2017	120737	5121	77099	37506	132	879
2018	127752	1989	82032	42608	137	985
2019	136165	2105	88352	44571	140	997

Data Source: Guangzhou Statistical Yearbook, website of Guangzhou Bureau of Statistics.

3.2 Class Ratio Checking

3.2.1 Calculate the grade ratio

$\lambda(k)F=(0.9271,0.8944,0.9451,0.9382)$
$\lambda(k)R=(0.9851,0.9537,2.5747,0.9449)$
$\lambda(k)H=(0.9920,0.9320,0.9399,0.9285)$
$\lambda(k)W=(0.7615,0.8055,0.8803,0.9560)$
$\lambda(k)A=(0.9280,0.9470,0.9635,0.9786)$
$\lambda(k)P=(0.9945,1.1111,0.8924,0.9880)$

3.2.2 Judgment grade ratio

$\lambda(k)\in\left(e^{-\frac{2}{n+1}},e^{\frac{2}{n+1}}\right)$ When n is 5, $\lambda(k)\in(0.7165,1.3956)$. When the $\lambda(k)$ value falls in the above range, it is s uitable to use GM (1,1)modeling. $\lambda(k)F\in(0.8944,0.9451)$, $\lambda(k)H\in(0.9285,0.9920)$, $\lambda(k)W\in(0.7615,0.9560)$, $\lambda(k)A\in(0.9280,0.9786)$, $\lambda(k)P\in(0.8924,1.1111)$, K=2,3,4,5 , the ratio of stages is in the region $\lambda(k)\in(0.7165,1.3956)$, so GM(1,1) modeling can be done with $X_F^{(0)}$, $X_H^{(0)}$, $X_W^{(0)}$, $X_A^{(0)}X_P^{(0)}$. However, there is a grade ratio of $\lambda(k)R\in(0.9449,2.5747)$ that is not in the region, so it is not suitable for GM(1,1) modeling with $X_R^{(0)}$, and it is not suitable for prediction. Therefore, the railwayf reightvolume will no longer be predicted below.

3.3 GM (1,1) Model Construction

According to the original sequence, a cumulative sequence is generated, and the differential equation is constructed. On the basis of solving the values of a and b, the time response sequence is obtained as shown in Equations (12 – 16). The predicted values are calculated according to the time response series (12 – 16), as shown in Table 3 and Table 4.

$$\widehat{X}^{(1)}(k+1)_F=\left(X^{(0)}(1)_F-\frac{u}{a}\right)e^{-ak}+\frac{u}{a}=1435664.583e^{0.074k}-1335540.583 \tag{12}$$

$$\widehat{X}^{(1)}(k+1)_H=\left(X^{(0)}(1)_T-\frac{u}{a}\right)e^{-ak}+\frac{u}{a}=1016465.393e^{0.068k}-945181.393 \tag{13}$$

$$\widehat{X}^{(1)}(k+1)_W=\left(X^{(0)}(1)_W-\frac{u}{a}\right)e^{-ak}+\frac{u}{a}=249449.092e^{0.121k}-226442.092 \tag{14}$$

$$\widehat{X}^{(1)}(k+1)_A=\left(X^{(0)}(1)_A-\frac{u}{a}\right)e^{-ak}+\frac{u}{a}=3326.1e^{0.037k}-3210.1 \tag{15}$$

$$\widehat{X}^{(1)}(k+1)_P=\left(X^{(0)}(1)_P-\frac{u}{a}\right)e^{-ak}+\frac{u}{a}=22170.147e^{0.039k}-21265.147 \tag{16}$$

Table 3 Actual and Predicted Values of Logistics Demand Development Indicators in Guangzhou (unit: 10,000 tons)

Year	Freight volume (F)		Highway freight volume (H)	
	$X_F^{(0)}$	$\widehat{X}_F$	$X_H^{(0)}$	$\widehat{X}_H$
2015	100124	100124	71284	71284
2016	107992	109844	71860	71823
2017	120737	118249	77099	76897
2018	127752	127296	82032	82331
2019	136165	137035	88352	88148

Table 4 Actual and Predicted Values of Logistics Demand Development Indicators in Guangzhou (unit: 10,000 tons)

Year	Waterway freight volume (W)		Air freight volume (A)		Pipeline freight volume (P)	
	$X_W^{(0)}$	$\widehat{X}_W$	$X_A^{(0)}$	$\widehat{X}_A$	$X_P^{(0)}$	$\widehat{X}_P$
2015	23007	23007	116	116	905	905

Year	Waterway freight volume (W)		Air freight volume (A)		Pipeline freight volume (P)	
	$X_W^{(0)}$	$\hat{X}_W$	$X_A^{(0)}$	$\hat{X}_A$	$X_P^{(0)}$	$\hat{X}_P$
2016	30212	31996	125	126	910	888
2017	37506	36100	132	131	879	923
2018	42608	40731	137	136	985	960
2019	44571	45955	140	141	997	999

3.4 Accuracy Test of GM (1,1) Forecasting Model for Guangzhou Logistics Demand

3.4.1 Posterior residual test

According to the above modeling results of GM (1,1) model, the model accuracy test will be carried out below. This paper uses the posterior residual test method to test.

First, get the standard deviation of the original sequence $X_F^{(0)}, X_H^{(0)}, X_W^{(0)}, X_A^{(0)}, X_P^{(0)}$, S_{1F}=14583.696 S_{1H}=7193.023 S_{1W}=8955.949, S_{1A}=9.670, S_{1P}=52.452.

Secondly, the standard deviation of residual sequence $\varepsilon(k)_F, \varepsilon(k)_H, \varepsilon(k)_W, \varepsilon(k)_A, \varepsilon(k)_p$ is calculated, S_{2F}=1625.963, S_{2H}=205.574, S_{2W}=1627.531, S_{2A}=1.000, S_{2P}=27.608.

Then the posterior residual ratio C is calculated, C_F=0.111, C_H=0.029, C_W=0.182, C_A=0.103, C_P=0.526

The value of C_P is greater than 0.5 and less than 0.65, and the posterior residual test results are barely qualified. The values of C_F, C_H, C_W, C_A are less than 0.35, and the posterior residual test results are good.

3.4.2 Small probability error test

The values of small probability error S_{0F}, S_{0H}, S_{0W}, S_{0A}, S_{0P} are as follows: S_{0F} =9836.7, S_{0H} =4851.694, S_{0W}=6040.788, S_{0A}=6.522, S_{0P}=35.379.

The small probability error $|\varepsilon(k)-\bar{\varepsilon}|$ is calculated as follows:

$|\varepsilon(k)_F-\bar{\varepsilon}_F|$=(44.4,1896.4,2443.6,411.6,914.4) each value is less than S_{0F}, so P=1>0.95.

$|\varepsilon(k)_H-\bar{\varepsilon}_H|$=(28.8,8.2,173.2,327.8,175.2) each value is less than S_{0H},so P=1>0.95.

$|\varepsilon(k)_W-\bar{\varepsilon}_W|$=(23,1807,1383,1854,1407) each value is less than S_{0W},so P=1>0.95.

$|\varepsilon(k)_A-\bar{\varepsilon}_A|$=(0,1,1,1,1) each value is less than S_{0A},so P=1>0.95.

$|\varepsilon(k)_P-\bar{\varepsilon}_P|$=(0.2,21.8,44.2,24.8,2.2), P=0.8， qualified.

In summary, the freight volume (F), highway freight volume (H), waterway freight volume (W), air freight volume (A) of the four indicators of logistics demand development in Guangzhou meet the posterior residual test standard of C < 0.5, P ≧ 0.8， Pipeline freight volume (P) meets the posterior residual test standard of C < 0.65, P ≧ 0.8, indicating that the model accuracy is qualified, therefore, it is feasible and scientific to use GM (1,1) model to predict the development of logistics demand in Guangzhou.

4 ESTABLISHMENT OF GREY MARKOV FORECASTING MODEL FOR LOGISTICS DEMAND IN GUANGZHOU

4.1 The State Interval is Divided according to Equations (12 – 16)

The state interval is divided according to the relative residual percentage between the original data value and the grey prediction value. The relative residual percentage sequence is

$\{\Delta(k)_F\}$={0%, -1.71%,2.06%,0.36%, -0.64%} The corresponding interval length of $\{\Delta(k)_F\}$ is 1.5%, and it is divided into three state intervals, in order from small to large for [-2%,-0.5%] ,[-0.5%, 1%] ,[1%, 2.5%]

$\{\Delta(k)_H\}$={0%,0.05%,0.26%, -0.36%,0.23%} The corresponding interval length of $\{\Delta(k)_H\}$ is 0.3%, and it is divided into three state intervals, in order from small to large for [-0.4%,-0.1%] ,[-0.1%, 0.2%] ,[0.2%, 0.5%]

$\{\Delta(k)_W\}$={0%, -5.90%,3.75%,4.41%, -3.11%} The corresponding interval length of $\{\Delta(k)_W\}$ is 4%, and it is divided into three state intervals, in order from small to large for [-6%,-2%] ,[-2%, 2%] ,[2%, 6%]

$\{\Delta(k)_A\}$={0%, -0.8%,0.76%,0.73%, -0.71%} The corresponding interval length of $\{\Delta(k)_A\}$ is 0.6%, and it is divided into three state intervals, in order from small to large for [-1%,-0.4%] ,[-0.4%, 0.2%] ,[0.2%, 0.8%]

$\{\Delta(k)_P\}$={0%,2.42%, -5.01%,2.54%, -0.20%} The corresponding interval length of $\{\Delta(k)_P\}$ is 3%, and it is divided into three state intervals, in order from small to large for [-5.5%,-2.5%] ,[-2.5%, 0.5%] ,[0.5%, 3.5%]

4.2 Grey Prediction State Segmentation

After dividing the state interval, the next step can divide the state of each grey prediction value of the grey prediction model. The state results are shown in Table 5-9:

Table 5 Status Table of Grey Forecast Value of Freight Volume

Year	Raw data (10000 tons) $X_F^{(0)}$	Grey prediction value(10000 tons)$\hat{X}_F$	Residual error (10000 tons)	Relative residuals(%)$\Delta(k)_F$	Belonging status
2015	100124	100124	0	0	2
2016	107992	109844	-1852	-1.71	1

Year	Raw data (10000 tons) $X_F^{(0)}$	Grey prediction value(10000 tons)$\widehat{X}_F$	Residual error (10000 tons)	Relative residuals(%)$\Delta(k)_F$	Belonging status
2017	120737	118249	2488	2.06	3
2018	127752	127296	456	0.36	2
2019	136165	137035	-870	-0.64	1

Table 6 Status Table of Grey Forecast Value of Highway Freight Volume

Year	Raw data (10000 tons) $X_H^{(0)}$	Grey prediction value(10000 tons) $\widehat{X}_H$	Residual error (10000 tons)	Relative residuals(%)$\Delta(k)_H$	Belonging status
2015	71284	71284	0	0	2
2016	71860	71823	37	0.05	2
2017	77099	76897	202	0.26	3
2018	82032	82331	-299	-0.36	1
2019	88352	88148	204	0.23	3

Table 7 Status Table of Grey Prediction Value of Waterway Freight Volume

Year	Raw data (10000 tons) $X_W^{(0)}$	Grey prediction value(10000 tons) $\widehat{X}_W$	Residual error (10000 tons)	Relative residuals(%)$\Delta(k)_W$	Belonging status
2015	23007	23007	0	0	2
2016	30212	31996	-1784	-5.90	1
2017	37506	36100	1406	3.75	3
2018	42608	40731	1877	4.41	3
2019	44571	45955	-1384	-3.11	1

Table 8 Status Table of Grey Prediction Value of Air Freight Volume

Year	Raw data (10000 tons) $X_A^{(0)}$	Grey prediction value(10000 tons)$\widehat{X}_A$	Residual error (10000 tons)	Relative residuals(%)$\Delta(k)_A$	Belonging status
2015	116	116	0	0	2
2016	125	126	-1	-0.8	1
2017	132	131	1	0.76	3
2018	137	136	1	0.73	3
2019	140	141	-1	-0.71	1

Table 9 Status Table of Grey Prediction Value of Pipeline Freight Volume

Year	Raw data (10000 tons) $X_P^{(0)}$	Grey prediction value(10000 tons) $\widehat{X}_P$	Residual error (10000 tons)	Relative residuals(%)$\Delta(k)_P$	Belonging status
2015	905	905	0	0	2
2016	910	888	22	2.42	3
2017	879	923	-44	-5.01	1
2018	985	960	25	2.54	3
2019	997	999	-2	-0.20	2

4.3 Calculation of State Transition Probability Matrix

The state transition probability matrix can be calculated according to the state-owned table:

$$P_F=\begin{bmatrix}0 & 0 & 1\\ \frac{2}{3} & \frac{1}{3} & 0\\ 0 & 1 & 0\end{bmatrix} \qquad P_H=\begin{bmatrix}0 & 0 & 1\\ 0 & \frac{2}{3} & \frac{1}{3}\\ 1 & 0 & 0\end{bmatrix}$$

$$P_W=\begin{bmatrix}0 & 0 & 1\\ \frac{1}{2} & \frac{1}{2} & 0\\ \frac{1}{2} & 0 & \frac{1}{2}\end{bmatrix} \qquad P_A=\begin{bmatrix}0 & 0 & 1\\ \frac{1}{2} & \frac{1}{2} & 0\\ \frac{1}{2} & 0 & \frac{1}{2}\end{bmatrix} \qquad P_P=\begin{bmatrix}0 & 0 & 1\\ 0 & \frac{1}{2} & \frac{1}{2}\\ \frac{1}{2} & \frac{1}{2} & 0\end{bmatrix}$$

4.4 Markov Chain Test

Whether the grey prediction value sequence can be analyzed by Markov model needs Markov test. According to the calculation, the marginal probabilities of the five indexes are as follows

F: $p_{.j}=\{p_{.1},p_{.2},p_{.3},p_{.4}\}=\{0.4,0.4,0.2\}$

H: $p_{.j}=\{p_{.1},p_{.2},p_{.3},p_{.4}\}=\{0.2,0.4,0.4\}$

W: $p_{.j}=\{p_{.1},p_{.2},p_{.3},p_{.4}\}=\{0.4,0.2,0.4\}$

A: $p_{.j}=\{p_{.1},p_{.2},p_{.3},p_{.4}\}=\{0.4,0.2,0.4\}$

P: $p_{.j}=\{p_{.1},p_{.2},p_{.3},p_{.4}\}=\{0.2,0.4,0.4\}$

The x^2 statistic can be further calculated by the combination formula of one-step transition frequency, one-step probability transition matrix and marginal probability. The value is shown in table 10-14:

Table 10 Calculation Table of Freight Volume $\frac{x^2}{2}$Statistics

state	$f_{i1}\|ln\frac{p_{i1}}{p_{.1}}\|$	$f_{i2}\|ln\frac{p_{i2}}{p_{.2}}\|$	$f_{i3}\|ln\frac{p_{i3}}{p_{.3}}\|$	total
1	0	0	1.6094	1.6094
2	1.0216	0.1823	0	1.2039
3	0	0.9163	0	0.9163
total	1.0216	1.0986	1.6094	3.7296

According to Table 10, $x^2=7.4592$. When the number of state partition m = 3, given the significance level α, α = 0.01, according to the x^2 distribution table can be seen, x_α^2 (($-1)^2$)=0.297, x_α^2 (($-1)^2$)< x^2 holds, indicating that the sequence$\widehat{X}^{(0)}(k+1)_F$ has Markov property, and Markov prediction model can be used.

Table 11 Calculation Table of Highway Freight Volume $\frac{x^2}{2}$Statistics

state	$f_{i1}\|ln\frac{p_{i1}}{p_{.1}}\|$	$f_{i2}\|ln\frac{p_{i2}}{p_{.2}}\|$	$f_{i3}\|ln\frac{p_{i3}}{p_{.3}}\|$	total
1	0	0	0.9163	0.9163
2	0	1.0216	0.1823	1.2039
3	1.6094	0	0	1.6094
total	1.6094	1.0216	1.0986	3.7296

According to Table 11, $x^2=7.4592$. When the number of state partition m = 3, given the significance level α, α = 0.01, according to the x^2 distribution table can be seen, x_α^2 (($-1)^2$)=0.297, x_α^2 (($-1)^2$)< x^2 holds, indicating that the sequence$\widehat{X}^{(0)}(k+1)_H$ has Markov property, and Markov prediction model can be used.

Table 12 Calculation Table of Waterway Freight Volume $\frac{x^2}{2}$Statistics

state	$f_{i1}\|ln\frac{p_{i1}}{p_{.1}}\|$	$f_{i2}\|ln\frac{p_{i2}}{p_{.2}}\|$	$f_{i3}\|ln\frac{p_{i3}}{p_{.3}}\|$	total
1	0	0	0.9163	0.9163
2	0.2231	0.9163	0	1.1394
3	0.2231	0	0.2231	0.4462
total	0.4462	0.9163	1.1394	2.5019

According to Table 12, $x^2=5.0038$. When the number of state partition m = 3, given the significance level α, α = 0.01, according to the x^2 distribution table can be seen, x_α^2 (($-1)^2$)=0.297, x_α^2 (($-1)^2$)< x^2 holds, indicating that the sequence$\widehat{X}^{(0)}(k+1)_W$ has Markov property, and Markov prediction model can be used.

Table 13 Calculation Table of Air Freight Volume $\frac{x^2}{2}$Statistics

state	$f_{i1}\|ln\frac{p_{i1}}{p_{.1}}\|$	$f_{i2}\|ln\frac{p_{i2}}{p_{.2}}\|$	$f_{i3}\|ln\frac{p_{i3}}{p_{.3}}\|$	total
1	0	0	0.9163	0.9163
2	0.2231	0.9163	0	1.1394
3	0.2231	0	0.2231	0.4462
total	0.4462	0.9163	1.1394	2.5019

According to Table 13, $x^2=5.0038$. When the number of state partition m = 3, given the significance level α, α = 0.01, according to the x^2 distribution table can be seen, x_α^2 (($-1)^2$)=0.297, x_α^2 (($-1)^2$)< x^2 holds, indicating that the sequence$\widehat{X}^{(0)}(k+1)_A$ has Markov property, and Markov prediction model can be used.

Table 14 Calculation Table of Pipeline Freight Volume $\frac{x^2}{2}$Statistics

state	$f_{i1}\|ln\frac{p_{i1}}{p_{.1}}\|$	$f_{i2}\|ln\frac{p_{i2}}{p_{.2}}\|$	$f_{i3}\|ln\frac{p_{i3}}{p_{.3}}\|$	total
1	0	0	0.9163	0.9163
2	0	0.2231	0.2231	0.4462
3	0.9163	0.2231	0	1.1394
total	0.9163	0.4462	1.1394	2.5019

According to Table 14, $x^2 = 5.0038$. When the number of state partition m = 3, given the significance level α, α = 0.01, according to the x^2 distribution table can be seen, $x_\alpha^2\ ((\quad - 1)^2)=0.297$, $x_\alpha^2\ ((\quad - 1)^2)< x^2$ holds, indicating that the sequence$\widehat{X}^{(0)}(k+1)_P$ has Markov property, and Markov prediction model can be used.

4.5 Markov Prediction Model Optimization

Through the prediction value selection formula under each state, combined with the state of grey prediction value, five freight volume indexes from 2015 to 2019 are predicted by grey Markov prediction. The prediction results are as follows: Table 15-19 shows:

Table 15 Grey Markov Forecast Optimization Table for Freight Volume

Year	Raw data (10000 tons) $X_F^{(0)}$	Markov prediction optimization value(10000 tons)	Residual error(10000 tons)	Relative residuals(%)$\Delta(k)_F$	Belonging status
2015	100124	100124	0	0	2
2016	107992	108494	-502	-0.46	1
2017	120737	120362	375	0.31	3
2018	127752	127622	130	0.10	2
2019	136165	135350	815	0.60	1

Table 16 Grey Markov Forecast Optimization Table for Highway Freight Volume

Year	Raw data (10000 tons)$X_H^{(0)}$	Markov prediction optimization value(10000 tons)	Residual error(10000 tons)	Relative residuals(%)$\Delta(k)_H$	Belonging status
2015	71284	71284	0	0	2
2016	71860	71859	1	0.00	2
2017	77099	77167	-68	-0.09	3
2018	82032	82126	-94	-0.11	1
2019	88352	88458	-106	0.12	3

Table 17 Grey Markov Forecast Optimization Table for Waterway Freight Volume

Year	Raw data (10000 tons) $X_W^{(0)}$	Markov prediction optimization value(10000 tons)	Residual error(10000 tons)	Relative residuals(%)$\Delta(k)_W$	Belonging status
2015	23007	23007	0	0	2
2016	30212	30777	-565	-1.87	1
2017	37506	37620	-114	-0.30	3
2018	42608	42447	161	0.38	3
2019	44571	44204	367	0.82	1

Table 18 Grey Markov Forecast Optimization Table for Air Freight Volume

Year	Raw data (10000 tons) $X_A^{(0)}$	Markov prediction optimization value(10000 tons)	Residual error(10000 tons)	Relative residuals(%)$\Delta(k)_A$	Belonging status
2015	116	116	0	0	2
2016	125	125	0	0	1
2017	132	132	0	0	3
2018	137	137	0	0	3
2019	140	140	0	0	1

Table 19 Grey Markov Forecast Optimization Table for Pipeline Freight Volume

Year	Raw data (10000 tons) $X_P^{(0)}$	Markov prediction optimization value(10000 tons)	Residual error(10000 tons)	Relative residuals(%)$\Delta(k)_P$	Belonging status
2015	905	905	0	0	2
2016	910	906	4	0.44	3
2017	879	888	-9	-1.02	1
2018	985	980	5	0.51	3
2019	997	997	0	0	2

5 GUANGZHOU LOGISTICS INDUSTRY DEVELOPMENT TREND PREDICTION MODEL SELECTION AND PREDICTION RESULTS

According to tables 5-9 and 15-19, the grey prediction model and grey Markov model for 2015-2019 are compared and analyzed, as shown in tables 20 and 21.

Table 20 Comparative Analysis of Prediction Results of Grey Prediction Model and Grey Markov Model

	Freight volume(F)		Highway freight volume(H)	
	Grey prediction model	Grey Markov model	Grey prediction model	Grey Markov model
Relative residual range	(0,2.06%)	(0,0.6%)	(0,0.36%)	(0,0.12%)
Average relative residual	0.954%	0.294%	0.18%	0.064%
Model precision	99.046%	99.706%	99.82%	99.936%

Table 21 Comparative Analysis of Prediction Results of Grey Prediction Model and Grey Markov Model

	Water freight volume(W)		Air freight volume (A)		Pipeline freight volume(P)	
	Grey prediction model	Grey Markov model	Grey prediction model	Grey Markov model	Grey prediction model	Grey Markov model
Relative residual range	(0,5.90%)	(0,1.87%)	(0,0.8%)	(0,0)	(0,5.01%)	(0,1.02%)
Average relative residual	3.434%	0.674%	0.6%	0	2.034%	0.394%
Model precision	96.566%	99.326%	99.4%	100%	97.966%	99.606%

After the optimization of grey Markov model, the relative residual of five indexes of Guangzhou logistics industry development can be greatly reduced, the prediction accuracy has been significantly improved, and the prediction reliability has been greatly improved. Therefore, the results predicted by the grey Markov model are more valuable and appropriate.

According to the grey Markov model, the total demand forecast of freight volume in 2019 is in state 1, and the initial state transition probability vector is $V_0 = (1,0,0)$. From $V_0 * p = (0,0,1)$, it is concluded that the state in 2020 is most likely to be state 3. Based on the grey Markov model, the demand forecast results of total freight volume in 2020-2024 are obtained. The results are shown in table 22:

Table 22 Grey Markov Forecast Optimization Table of Freight Volume in 2020-2024

Year	Belonging status	Grey prediction value(10000 tons) $\hat{X}_F$	Markov prediction optimization value (10000 tons)
2020	3	147520	150156
2021	2	158807	159214
2022	1	170957	168856
2023	3	184038	187327
2024	2	198119	198627

According to the grey Markov model, the total demand forecast of highway freight volume in 2019 is in state 3, and the initial state transition probability vector is $V_0 = (0,0,1)$. From $V_0 * p = (1,0,0)$, it is concluded that the state in 2020 is most likely to be state 1. Based on the grey Markov model, the demand forecast results of total freight volume in 2020-2024 are obtained. The results are shown in table 23:

Table 23 Grey Markov Forecast Optimization Table of Highway Freight Volume in 2020-2024

Year	Belonging status	Grey prediction value(10000 tons) $\hat{X}_H$	Markov prediction optimization value (10000 tons)
2020	1	94377	94142
2021	3	101045	101400
2022	1	108185	107915
2023	3	115830	116237
2024	1	124014	123705

According to the grey Markov model, the total demand forecast of waterway freight volume in 2019 is in state 1, and the initial state transition probability vector is $V_0 = (1,0,0)$. From $V_0 * p = (0,0,1)$, it is concluded that the state in 2020 is most likely to be state 3. Based on the grey Markov model, the demand forecast results of total freight volume in 2020-2024 are obtained. The results are shown in table 24:

Table 24 Grey Markov Forecast Optimization Table of Waterway Freight Volume in 2020-2024

Year	Belonging status	Grey prediction value(10000 tons) $\hat{X}_W$	Markov prediction optimization value (10000 tons)
2020	3	51850	54034
2021	3	58500	60964
2022	3	66004	68784
2023	3	74470	77607
2024	3	84022	87561

According to the grey Markov model, the total demand forecast of air freight volume in 2019 is in state 1, and the initial state transition probability vector is $V_0 = (1,0,0)$. From $V_0 * p = (0,0,1)$, it is concluded that the state in 2020 is most likely to be state 3. Based on the grey Markov model, the demand forecast results of total freight volume in 2020-2024 are obtained. The results are shown in table 25:

Table 25 Grey Markov Forecast Optimization Table of Air Freight Volume in 2020-2024

Year	Belonging status	Grey prediction value(10000 tons)$\widehat{X}_A$	Markov prediction optimization value (10000 tons)
2020	3	146	147
2021	3	152	153
2022	3	158	159
2023	3	164	165
2024	3	170	171

According to the grey Markov model, the total demand forecast of pipeline freight volume in 2019 is in state 3, and the initial state transition probability vector is $V_0 = (0,0,1)$. From $V_0 * p^2 = (0,\frac{1}{4},\frac{3}{4})$, it is concluded that the state in 2020 is most likely to be state 3. Based on the grey Markov model, the demand forecast results of total freight volume in 2020-2024 are obtained. The results are shown in table 26:

Table 26 Grey Markov Forecast Optimization Table of Pipeline Freight Volume in 2020-2024

Year	Belonging status	Grey prediction value(10000 tons)$\widehat{X}_P$	Markov prediction optimization value (10000 tons)
2020	3	1039	1060
2021	1	1080	1039
2022	3	1124	1147
2023	2	1169	1158
2024	3	1215	1240

According to the demand forecast of Guangzhou logistics industry in 2024, compared with the basic data in 2019, the change trend of Guangzhou logistics structure is shown in Figure 1.

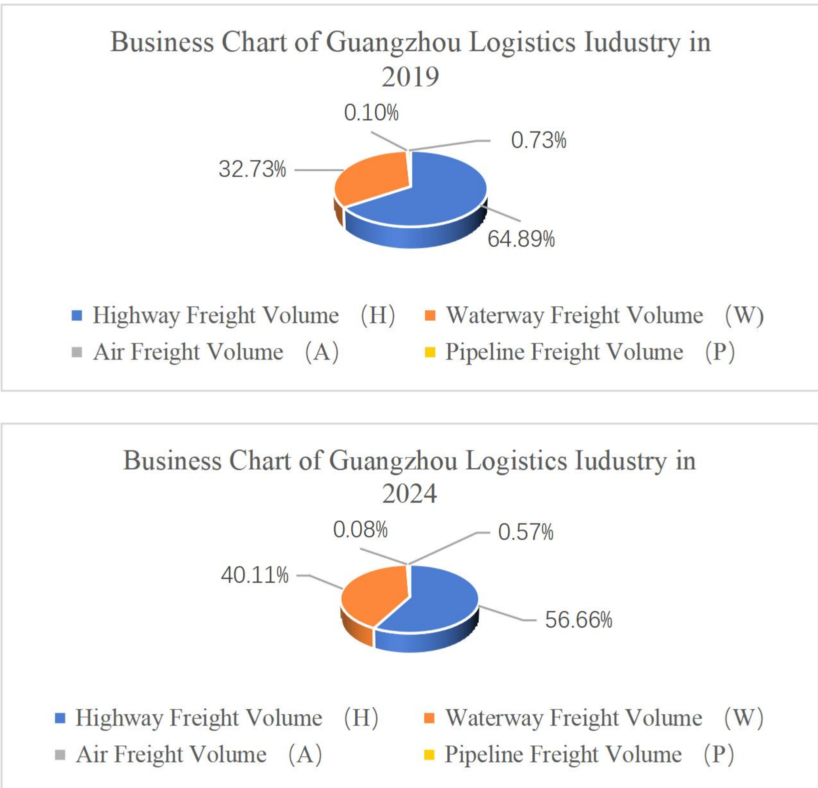

Figure 1 Comparison of Business Structure between Guangzhou Logistics Industry in 2019 and Guangzhou Logistics Industry in 2024

According to the prediction results, highway freight in 2024 is still the main business of the logistics industry in Guangzhou. It is expected that the highway freight volume will still show a trend of moderate growth in the future, while the proportion of waterway freight volume is higher than that in 2019, and the future development potential will be improved. The other two freight volume indicators will slowly rise. From the forecast trend, the total freight volume in the future shows a gradual growth trend. Under the construction of Guangdong-Hong Kong-Macao Greater Bay Area, each freight index of Guangzhou will be improved to varying degrees, which brings greater opportunities to the development of logistics industry in Guangzhou. The logistics demand is very large in 2020-2024, and the total freight volume increases at the rate of 10 million tons per year.

6 CONCLUSION AND STRATEGY

This paper selects the logistics data of Guangzhou from 2015 to 2019, and uses the grey theory model and the grey Markov model to predict the logistics development data of Guangzhou from 2015 to 2019. On the basis of the actual data and prediction data of Guangzhou' s logistics from 2015 to 2019, this paper selects the grey Markov model with high prediction accuracy to measure the logistics demand of Guangzhou from 2020 to 2024. The empirical results show that the two characteristics of the future growth of Guangzhou' s logistics demand First, the total demand of Guangzhou' s logistics industry shows a continuous growth trend. Second, Guangzhou logistics demand structure slightly changed.

According to the results of empirical research, this paper puts forward two coping strategies. Firstly, in view of the increasing demand for logistics in Guangzhou, Guangzhou should strengthen the construction of logistics infrastructure in the context of new infrastructure construction, and improve the infrastructure such as roads, railways, ports, airports, circulation centers and network communication. In particular, the construction and improvement of public information platform related to the development of the logistics industry and the Internet of Things infrastructure related to smart logistics are the most important, so as to give full play to the maximum potential of logistics development to help improve the overall economic level. The increase in infrastructure construction in logistics should provide corresponding policy support for the development of the logistics industry, vigorously develop the modern logistics system, improve the related logistics facilities as soon as possible and introduce corresponding policies, so as to provide conditions for the rapid economic development of Guangzhou and even the whole Guangdong-Hong Kong-Macao Greater Bay Area in the future. Secondly, in view of the changes in the development of logistics demand structure in Guangzhou, we should continue to optimize the structure of the logistics industry, drain road logistics with high carbon emissions, and pay attention to the development of clean and efficient logistics with low energy consumption, such as water transportation and pipeline transportation. The logistics industry helps to achieve carbon peak and carbon neutrality.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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