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Forecasting material flows of modern logistics centres of railway freight stations exemplified by Xi'an (the People's Republic of China)

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ABSTRACT The purpose of the study is to create a more accurate material flow forecasting model of Xi'an freight railway station in China. The combined forecasting model is more validated for forecasting freight flows of regional logistics compared to three methods: grey forecasting, Markov chains, entropy weighting. Through the creation of the combined model, the grey forecasting method is combined with Markov chain correction, and the projected data is compared with the actual data to obtain higher accuracy of the forecasting model.

A combined model using the grey forecasting method combined with Markov chain correction is created, with the forecast data compared with the actual data to obtain high accuracy of the forecasting model.

The practical significance is that in the context of the present post-pandemic economic development, the logistics enterprises that do not operate in accordance with the modern logistics methods may be displaced by competitors. If the railway does not improve its logistics infrastructure, logistics equipment, railway logistics network platform, etc., it will lose out to other modes of transport. In order to meet the needs of logistics and improve the market competitiveness, the main indicator of a freight station is loading and logistics flow. Therefore, exact prediction of future changes in the logistics flow of a freight station can help to determine whether the station needs to be upgraded as a railway station or transformed into a certain type of a logistics centre.

KEYWORDS: rail freight; regional logistics; grey forecasting; GM (1,1) grey model; Markov chain; combined forecasting

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Научная статья

Прогнозирование материальных потоков современных логистических центров железнодорожных грузовых станций на примере Сианя (Китайская Народная Республика)

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АННОТАЦИЯ Цель исследования — создание более точной модели прогнозирования материальных потоков грузовой железнодорожной станции Сиань в Китае.

Комбинированная модель прогнозирования является более обоснованной в прогнозировании грузопотоков региональной логистики по сравнению с тремя методами: серого прогнозирования, цепей Маркова, взвешивания энтропии. Благодаря созданию комбинированной модели метод прогнозирования серого сочетается с коррекцией цепи Маркова, а прогнозируемые данные сравниваются с фактическими данными, чтобы получить более высокую точность модели прогнозирования.

Создана комбинированная модель с использованием метода прогнозирования серого в сочетании с коррекцией цепей Маркова, при этом прогнозируемые данные сравниваются с фактическими данными для получения высокой точности модели прогнозирования. Практическая значимость — в условиях современного постпандемийного экономического развития логистические предприятия, которые не работают в соответствии с современными методами логистики, могут быть вытеснены конкурентами.

Если железная дорога не усовершенствует логистическую инфраструктуру, логистическое оборудование, платформу железнодорожной логистической сети и т.д., она проиграет конкурентную борьбу другим видам транспорта. Для удовлетворения потребностей логистики и, таким образом, повышения рыночной конкурентоспособности, основным показателем грузовой станции является погрузка и логистический поток. Поэтому точное прогнозирование будущих изменений в логистическом потоке грузовой станции может позволить определению, нуждается ли станция в модернизации, как железнодорожная станция, или преобразовании в определенный тип логистического центра.

КЛЮЧЕВЫЕ СЛОВА: железнодорожные перевозки; региональная логистика; серое прогнозирование; серая модель GM (1,1); цепь Маркова; комбинированный прогноз

Для цитирования: *Ван Хэлинь, Коровяковский Е.К.* Прогнозирование материальных потоков современных логистических центров железнодорожных грузовых станций на примере Сианя (Китайская Народная Республика) // Транспорт БРИКС. 2024. Т. 3. Вып. 3. Ст. 2. https://doi.org/10.46684/2024.3.2.

INTRODUCTION

With the continuous process of increasing the complexity of forecasting models and improving algorithm technology, the accuracy of forecasting various economic indicators has also undergone great changes. Most forecasting methods are currently based on the input data to create a forecasting model with high accuracy according to time series, and the maximum goodness of fit can be achieved by repeated use of the model, which ensures the accuracy of forecasting results. Logistics flow forecasting is mainly organised chronologically based on the actual logistics flow over a period of time to establish a mathematical model that fits the actual distribution law of the random variable. The single modelling approach has limitations for certain situations, while the creation and use of the model also has certain limitations; therefore, to improve the accuracy of the forecast, it is necessary to compensate for the shortcomings of the single model by creating highly specialised models.

Forecasting of transport and logistics indicators and an attempt to prove the prospectivity and validity of applying artificial neural networks (ANN) compared to other forecasting methods are presented in [1, 2]. Forecasting freight traffic in the traditional way is exponential smoothing, least squares analysis, time series and other methods. However, obtaining reliable forecasting results, even for short-term periods, is quite complicated for such difficult to forecast and dynamically changing indicators as the volume of transportations of production, trade, transit or other cargoes, because flows are heterogeneous in time and space; therefore, this requires their easily accessible validation which can be carried out indirectly by several methods of comparison of forecasting results [3, 4]. Even in this case, direct validation may be only considered to be comparison of formulated forecasts combined with actual data which are only obtained at the end of the preparation period [4, 5]. Therefore, the decision was made to use two methods for forecasting, one of them being the exponential smoothing method, and the other being the grey forecasting method with Markov chain correction not so often used for traffic volumes forecasting.

PROBLEM OF TRANSFORMATION OF RAILWAY FREIGHT STATIONS

Definition of a railway logistics centre

A railway logistics centre is usually an element of a transport hub of a large agglomeration, has full information support, carries out logistics activities for the economy and society and performs such functions as providing logistics services, has sufficient storage capacity, throughput and processing capacity [6].

Analysis of the issues of transforming freight railway stations into modern logistics centres

At present, the number of railway freight stations in China is huge, and the scope, location and main functions of freight stations are not uniform. If the transformation and modernisation is carried out without a prior comprehensive analysis, it will be both impossible to develop modern logistics and may lead to waste of resources. Based on the analysis of some information sources and relevant literature on freight stations and railway logistics centres and with account of the key factors, it is outlined that the railway freight station turns into a modern logistics centre that adapts to various functional services.

The railway freight station is an important railway network junction. This junction has a certain coverage. Therefore, this attribute should be used as one of the elements of transformation analysis [7]. The factors under study are large volume of commercial operations, large freight flows and large-scale industrial parks, presence of large industrial units within the radius, with the decision on the possibility of transformation made based on the analysis of these factors.

Geographical features

Railway freight stations and railway transport lines form the railway transport network. The development of railway freight hubs and the development of regional cities go together. However, when they develop in an uncoordinated manner, freight stations become a significant obstacle to urban development. Due to the scarcity of land resources, freight stations may also be relocated to urban fringes in the urban development process.

At present, the central freight yards in many cities are gradually reducing their freight business and shifting their main business to urban fringes [8]. Therefore, when selecting a freight station for transformation, it is necessary to consider the geographical position of the existing freight station, and for modernisation, a freight station with expansion and construction capabilities should be selected, so that the newly built railway logistics park should further promote the development of urban economy. This both promotes the expansion of the city size and facilitates the development of the railway logistics centre.

Scale conditions

A modern railway logistics centre should have complete logistics equipment in terms of scale, and can provide basic logistics services, such as co-storage, handling, distribution; therefore, the choice of transformation usually involves selection of a freight yard with a relatively large freight handling volume [9]. At the same time, other auxiliary transport functions of the freight yard should also be relatively complete, while its area, existing scale and operating yard should meet certain conditions, and the freight yard should have a certain reserved space [10].

Problems of station allocation and coordination in large agglomerations

Given the current development of modern logistics, there still are various ungrounded problems in its planning. Take Xi'an railway junction as an example. This area has 16 freight stations with large annual traffic volume. The decentralised structure of small freight stations does not allow for economies of scale, and it is difficult to change to meet the market requirements (*Fig. 1*).

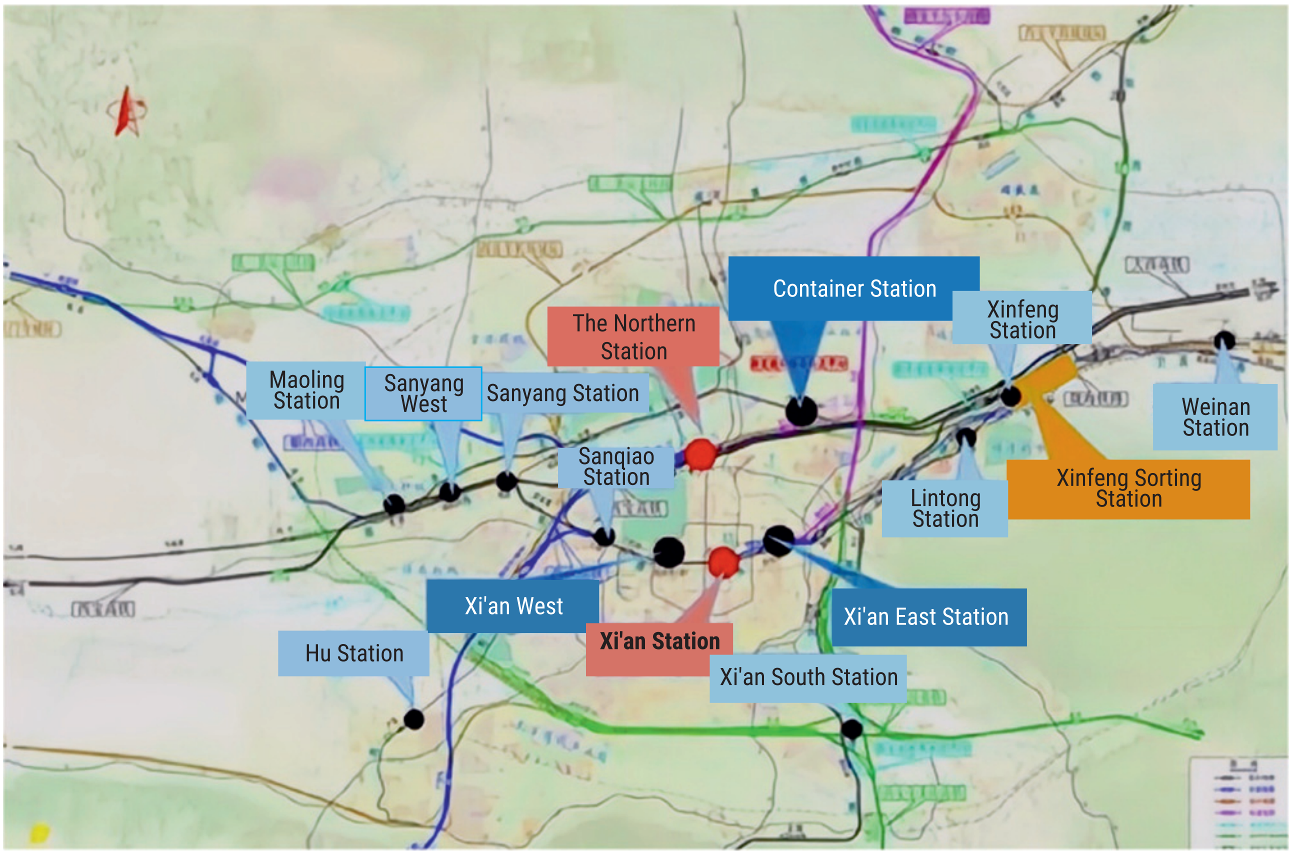

Fig. 1. Distribution scheme of freight railway stations in Xi'an agglomeration area
(URL: https://shidian.baike.com/wikiid/86385658282055880?anchor=2)

Fig. 2. Xi'an East Railway Station (URL: https://m.thepaper.cn/baijiahao_20513940)

The development of Dongcheng high-speed railway area relies on the Xi'an East Station Transport Hub, which is connected to the core area in east Xi'an, but also enhances the business development in central Xi'an through industrial upgrading, space renovation, infrastructure improvement and environmental improvement. *Fig. 2* shows the design of Xi'an East Station Hub.

Xi'an East Railway Station will become a large-scale integrated transport hub combining high-speed railway, conventional railway, intercity transport, underground and public transport. Once its reconstruction is completed and put into operation, the annual passenger traffic is expected to reach 36.5 million people. This will improve the urban transport capacity and directly contribute to the economic development of eastern Xi'an.

FORECASTING TECHNOLOGY FOR TRANSFORMING RAILWAY FREIGHT YARDS INTO MODERN LOGISTICS CENTRES

Transformation of railway freight yards into modern logistics centres has become a key task for the development of modern logistics in the railway transport industry. The necessity and feasibility of modernisation were analysed previously, and an important factor driving the conversion is the change in freight volumes and modernisation of transport functions; therefore, it is necessary to forecast the volumes of freight handled at terminals [11].

A grey combination forecasting method based on Markov chain correction with entropy is proposed, with the accuracy of the forecasting method verified by comparing the relevant data.

Overview of forecasting methods

The key forecasting methods include the field method, market research method and brainstorming method; quantitative forecasting is mainly based on the correlation of things and time and is divided into causal forecasting and time series forecasting due to the many correlations affecting the development of events and the difficulty of determining the correlations, with the time series being the main parameter in forecasting [12].

The freight flow is a combination of several data, which mainly includes the superposition of transportation, storage and distribution demand data. But in practice, there is still no clear definition of the freight flow; so in this paper, we will define the freight flow as a simple superposition of freight volume, storage, distribution and processing, due to the transformation and upgrading of railway freight yards into modern logistics centres The function expansion is also mainly focused on increasing the warehouse function and distribution function, and the loading and unloading volume is a key indicator of the location of the facilities and equipment in the fleet; therefore, it is easy to determine, which provides accurate data to make effective forecasts [13].

Study of material flow forecasting technology model

Model overview

It follows from the basic composition of material flow that if a single forecasting model is used for forecasting, its own shortcomings and application limitations will increase, which will affect the accuracy of forecasting results, and the meaning of forecasting will be lost; therefore, the combined model of GM (1,1) and Pierre F. Verhulst is introduced. To integrate the model, use is made of the entropy weighting method to ensure the effective integration of the combined model, and a Markov chain is introduced to adjust the obtained values of the forecasting model, so that the forecasting results are transformed from single data into material flow intervals, and the probability of interval formation is effectively estimated, which improves the reliability of forecasting [1].

GM (1,1) model building process

The model is built for training and adjustment of the existing data series to find a mathematical function with some kind of law according to certain criteria to improve the degree of "whiteness", so as to bring the forecasting effect to the expected results. The model is usually a first-order multivariate model. Especially widely usd is the GM (1,1) model wih the following forecasting stages:

1. Based on the initial values, the following values are determined

$$x^{(1)}(t) = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)) \text{ i.e.}$$

$$x^{(1)}(t) = \sum_{k=1}^{t} x^{(0)}(k), \quad t = 1, 2, ..., n. \tag{1}$$

2. The matrix B and the constant vector Y_n are constructed

$$B = \begin{pmatrix} -0.5\left(x^{(1)}(1) + x^{(1)}(2)\right), 1 \\ -0.5\left(x^{(1)}(2) + x^{(1)}(3)\right), 1 \\ \dots \\ -0.5\left(x^{(1)}(n-1) + x^{(1)}(n)\right), 1 \end{pmatrix};$$

$$Y_n = (x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n))^T. \tag{2}$$

3. The following is solved for grey parameters using the least squares method

$$\left(\frac{a}{u}\right) = (B^TB)^{-1}(B^TY_n). \tag{3}$$

4. Substitution of elements of the grey parameter vector into the time function

$$x^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{u}{a}\right)^{e^{-at}} + \frac{u}{a}. \tag{4}$$

5. $x^{(1)}(t)$ is differentiated to obtain

$$x^{(0)}(t+1) = -a\left(x^{(0)}(1) - \frac{u}{a}\right)e^{-at}. \tag{5}$$

6. $e^{(0)}(t)$ balance is calculated and relative error $q(x)$ is calculated.

7. Verification of errors, the verification criteria are
A. $q(x) \le 0.01$, accuracy for class 1;
B. $q(x) \le 0.05$, accuracy for class 2;
C. $q(x) \le 0.10$, accuracy for class 3;
D. $q(x) \le 0.20$, accuracy for class 4.

8. Using the model for forecasting and results.

Building a Pierre Verhulst model

Let $x^{(0)}$ is initial data sequence; $x^{(t)}$ is single accumulation $x^{(0)}$ to generate the sequence 1-AGO

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(k), ..., x^{(0)}(n)); \tag{6}$$

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(k), ..., x^{(1)}(n)), \tag{7}$$

where $x^{(1)}(k) = \sum_{k=1}^{k} x^{(0)}(i)$, $k = 1, 2, 3, ..., n$; $Z^{(1)}$ is average generating sequence $X^{(1)}$ in close proximity, i.e.

$$Z^{(1)} = (Z^{(1)}(1), Z^{(1)}(2), ... Z^{(1)}(k), ..., Z^{(1)}(n)), \tag{8}$$

where $Z^{(1)}(1) = X^{(1)}(1)$

$$Z^{(1)}(k) = \frac{1}{2} x^{(1)}(k) + x^{(1)}(k-1), \quad k = 2, 3, ..., n.$$

Then formula

$$X^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))\delta \tag{9}$$

is said to be a model of GM (1,1, a) order.

Then we transform equation 9 into the form of a differential equation

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b(x^{(1)})^{\alpha}. \tag{10}$$

Let's call this the whitening equation for the "GM (1,1 a) order" model.

Solution of the equation

$$x^{(1)}(t) = \left(e^{-(1-a)at}(1-a)\int be^{(1-a)at}dt + c\right)^{\frac{1}{1-a}}. \tag{11}$$

When a = 2, the formula is called the Pierre Verhulst model:

$$x^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^2. \tag{12}$$

This formula is the differential equation of the Pierre Verhulst model:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b(x^{(1)})^2. \tag{13}$$

Let's solve the differential equation 13 to get:

$$x^{(1)}(t) = \frac{ax^{(1)}(1)}{bx^{(1)}(1) - \left(a - bx^{(1)}(1)\right)e^{at}}. \tag{14}$$

Thus, the forecasting model of the discrete Pierre Verhulst model has the following form:

$$x^{(\hat{1})}(k+1) = \frac{ax^{(1)}(1)}{bx^{(1)}(1) - \left(a - bx^{(1)}(1)\right)e^{ak}}. \tag{15}$$

EXAMPLE OF A MATERIAL FLOW FORECASTING STUDY

Example and process

To check the validity and reliability of the model, the freight flow of Xi'an freight railway station from 2008 to 2019 was selected as an example for the empirical study *(Table 1)*.

Table 1

Xi'an's cargo turnover in 2008–2019

Years	Actual cargo turnover, thousand tonnes	Symbols in the mathematical model
2008	11,250	$x^{(0)}(1)$
2009	12,300	$x^{(0)}(2)$
2010	14,030	$x^{(0)}(3)$
2011	15,660	$x^{(0)}(4)$
2012	18,450	$x^{(0)}(5)$
2013	20,380	$x^{(0)}(6)$
2014	21,780	$x^{(0)}(7)$
2015	23,530	$x^{(0)}(8)$
2016	23,830	$x^{(0)}(9)$
2017	25,230	$x^{(0)}(10)$
2018	26,720	$x^{(0)}(11)$
2019	31,230	$x^{(0)}(12)$

GM (1.1) grey model forecast formula of Xi'an freight railway station flow from 2008 to 2019.

$$x^{(\mathrm{i})}(t+1) = 1.54839.2756e^{0.0801t} - 14315.276. \quad (16)$$

Pierre Verhulst's forecasting formula:

$$x^{(1)}(t+1) = \frac{-104.3281}{-0.0024 - 0.0891e^{-0.08984t}}. \quad (17)$$

Let's calculate the forecast value of the freight station logistics flow according to the forecasting formula and compare the results. The results are shown in *Table 2*, where the formula for calculating the error is as follows

$$\varepsilon_1 = \frac{\left(x_1 - \widehat{x_{ij}}\right)100}{x_1}, \quad i = 1, 2, ..., m; \; t = 1, 2, ..., n. \; (17)$$

Combined forecasting models

Suppose that the initial sequence of data is $x = (x_1, x_2, ..., x_n)^T$, the forecast value of the ith single forecasting model at time t is equal to $\widehat{x_{it}} = (i = 1, 2, ..., m;$ $t = 1, 2, ..., m)$, the vector consisting of weight coefficients of each individual model has the following form $\omega = (\omega_1, \omega_2, ..., \omega_n)$, the resulting grey combination forecasting model is

$$\widehat{y_t} = f\left(\widehat{x_{it}}, \omega_i\right), \quad i = 1, 2, ..., m; \; t = 1, 2, ..., n. \quad (18)$$

Determining the model weights for each combined forecasting model

Establishing effective model weights for each particular forecasting model is a key step in ensuring the accuracy of the combined forecasting results [1]. In this study, the weights for each particular forecasting model are determined based on the information entropy theory and the degree of variation of relative errors of different models.

1) Let the relative error of the ith forecasting method at time t be

$$e_{it} = \begin{cases} 1, & \left(x_t - \widehat{x_{it}}\right)/x_t \geq 1 \\ \left(x_t - \widehat{x_{it}}\right)/x_t, & 0 \leq \left(x_t - \widehat{x_{it}}\right)/x_t \leq 1 \end{cases}. \quad (18)$$

Table 2

Comparison of forecast results for 2009–2019

Years	Forecast data / 10,000 tonnes		Actual cargo turnover / 10,000 tonnes	Error limit ε_1, %	
	GM (1,1)	Pierre Verhulst		GM (1,1)	Pierre Verhulst
2009	1414.5	1330.84	1230	−12.5294	−0.0668
2010	1498.07	1346.31	1403	−6.8903	3.9730
2011	1625.57	1472.30	1566	−3.6118	5.9841
2012	1756.79	1609.67	1845	4.7210	13.339
2013	1903.30	1810.21	2038	7.0023	13.9524
2014	2109.50	2002.46	2178	5.5562	10.3456
2015	2345.82	2137.97	2353	6.1573	9.4236
2016	2414.27	2293.07	2383	−1.3119	3.7443
2017	2613.98	2503.96	2523	−3.6468	0.7555
2018	2830.10	2730.93	2672	−5.9204	−2.2056
2019	3064.32	2978.34	3123	1.8793	4.6325

2) Normalization of errors

$$f_{it} = e_{it} / \sum_{t=1}^{n} e_{it}, \quad i = 1, 2, ..., m; \quad t = 1, 2, ..., n. \tag{19}$$

3) Calculation of entropy values for the ith forecasting method

$$H_i = -1/Inn \sum_{t=1}^{n} f_{it} Inf_{it}, \quad i = 1, 2, ..., m; \quad t = 1, 2, ..., n. \tag{20}$$

It follows that for the ith model, if f_{it} are equal, i.e. $f_{it} = 1/n$, $t = 1, 2, ..., n$. Then H_i takes on big value 1, and we have $0 \le H_i \le 1$.

4) Let's calculate the coefficient of variation for the ith forecasting method:

$$V_i = 1 - H_i, \quad i = 1, 2, ..., m. \tag{21}$$

5) Let's determine the weight coefficient for the ith forecasting method

$$\omega_i = \frac{1}{m-1}\left(1 - V_i \,/\, \sum_{i=1}^{m} v_i\right), \quad i = 1, 2, ..., m. \tag{22}$$

6) Let's build a combined forecasting model

$$\widehat{y_t} = \sum_{i=1}^{m} \omega_i \widehat{x_{it}}, \quad t = 1, 2, ..., n. \tag{23}$$

According to the forecast results in *Table 2*, in conjunction with the relevant entropy method principle, the correlation weight coefficient of each forecasting model is calibrated, the vector of weight coefficients calculated by the formula (3.1)–(3.10), is:

$$\omega = (0,6731, 0.3269).$$

Thus, the corresponding model of the combination of entropy methods is obtained as follows

$$\widehat{y_t} = \left(0.6731\widehat{x_{1t}} + 0.3269\widehat{x_{2t}}\right). \tag{24}$$

The forecast compliance value obtained using the combined forecasting model is written as $\widehat{y_t}$.

COMPARISON OF ACCURACY OF THE RESULTS

Let's define the forecasting accuracy indicator as the average relative error of the forecasted values in order to compare the accuracy of forecasting models. Formula for calculating the average relative forecast error

$$\Delta_i = \frac{1}{n}\sum_{t=1}^{n} \frac{|x_t - x_{it}|}{x_t} 100, \quad i = 1, 2, ..., m. \tag{25}$$

Let's enter the accumulated data into the formula and the calculation results are shown in *Table 3* and *Fig. 3*.

Table 3

Average relative error of different models

Forecasting models	GM (1,1)	Pierre Verhulst	Combined forecast models
Relative error, %	6.4266	5.2416	4.0653GM

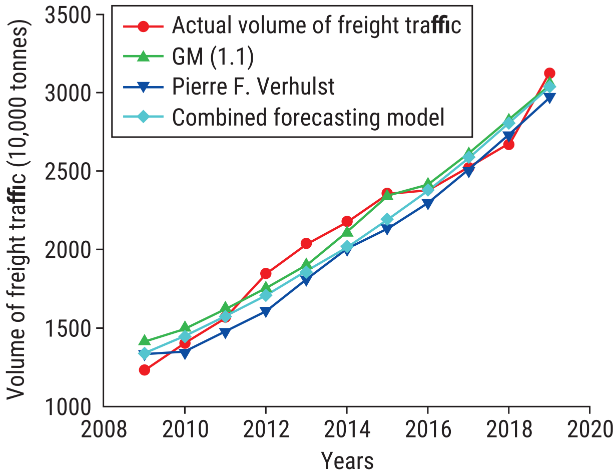

Fig. 3. Graph of forecast results for different forecasting methods

CORRECTION OF MODEL FORECAST RESULTS

Markov chain correction forecast results

The forecast result of the grey combination model is a single value; this forecast result will give a certain error with respect to the actual value. To ensure the accuracy of the forecast result we use Markov chain methods to accurately combine the forecast values into a small range of intervals, on this basis we calculate both the probability [14, 15] and the probabilistic problem of its interval generation.

The central aspect of the Markov chain approach is to determine a probabilistic approximation of the number of transitions m_i from sample state S_i into state S_j as m_{ij}, i.e.

$$P_{ij} = m_{ij}/m_i, \tag{26}$$

where P_{ij} is the probability of transition of Markov chain state S_i to state S_j.

The properties of P_{ij} value are:

$$0 \le P_i \le 1; \quad \sum_{j=1}^{n} P_{ij} = 1. \tag{27}$$

The state transition matrix is built in the form

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_n \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}. \quad (28)$$

According to the method, the results of the combined forecast are categorised into three states when compared with the actual freight volume values: First, the residuals as a percentage of the actual freight volume less than –15 % and greater than –5 % are overestimated states (E1); the forecast residuals from –5 % to 5 % of the actual freight flows are normal (E2); the forecast residuals as a proportion of the actual freight flows in the range from 5 to 15 are called underestimated states (E3). Based on this classification criterion, the occurrence of each state in the combined forecast scenario is shown in *Table 4*.

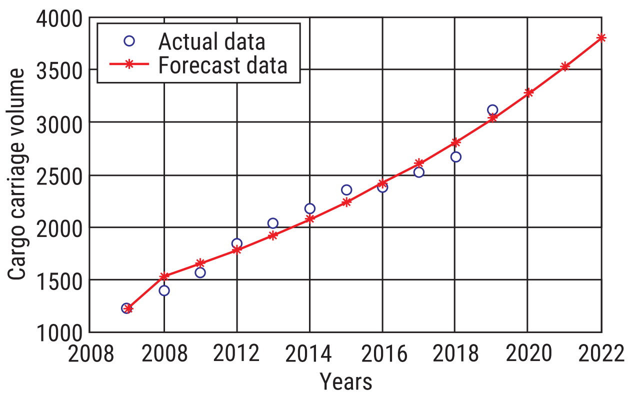

Fig. 4. Optimised graph of forecast data of freight traffic volume

Table 4

The forecast value and classification status of the combined forecasting model from 2009 to 2019

Years	Combined forecasting model / 10,000 tonnes	Actual cargo turnover / 10,000 tonnes	Error limit ε_1, %	State
2009	1336.48	1230	−8.6571	E1
2010	1451.28	1403	−3.5150	E2
2011	1575.87	1566	−0.6303	E2
2012	1711.07	1845	7.2088	E3
2013	1857.76	2038	8.8438	E3
2014	2016.88	2178	7.3974	E3
2015	2189.47	2353	6.9501	E3
2016	2376.60	2383	0.2684	E2
2017	2579.48	2523	−2.2790	E2
2018	2799.36	2672	−4.7660	E2
2019	3037.60	3123	2.7348	E2

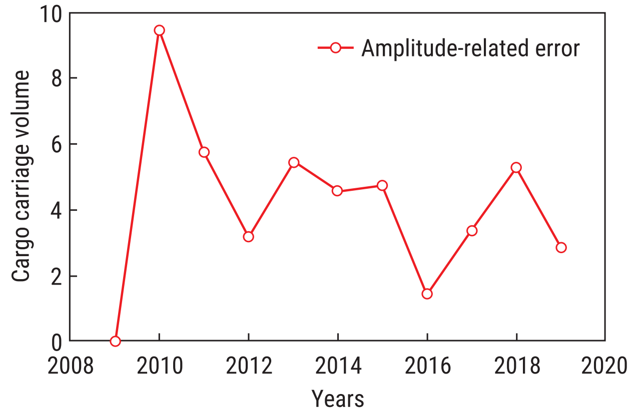

Fig. 5. Relative error in forecasting the freight traffic volume

Table 5

Forecasting results after Markov chain correction

Years	Combined forecast results	Forecasting results after Markov chain improvement		
		Status space	Probability	Range of forecast values
2020	3357.16	E1	0.0000	[239.05, 3024.35)
		E2	0.8000	[3024.35, 3423.68)
		E3	0.2000	[3423.68, 3642.68)
2021	3572.09	E1	0.0000	[3125.28, 3403.56)
		E2	0.6900	[3403.56, 3870.65)
		E3	0.3100	[3870.65, 4234.90)
2022	3874.21	E1	0.0000	[3312.07, 3700.49)
		E2	0.6295	[3700.49, 4086.92)
		E3	0.3705	[4086.92, 4395.34)

Based on the Markov correction principle, the algorithm of the combined forecasting model on MATLAB can be improved to increase the accuracy of the forecasting results, as well as the subsequent output of the forecast state vectors, as shown in *Figs. 4*, *5* and *Table 5*.

Comparing the forecast data for 2020 and 2021 in *Table 5* with the actual traffic volume data of Xi'an Station, we can conclude that the results forecast by the model better reflect the development trend of the future traffic volume and can more accurately forecast the future traffic volume, and the model itself is more efficient.

CONCLUSION

Most existing methods for forecasting regional flows require the collection of a multitude of diverse data affecting flows. The variety of statistical methods leads to complex causal analyses, making the data difficult to use. Using the combined forecasting model and Markov chain to improve and adjust the forecasting results, the traffic volume of Xi'an railway station and the development of Xi'an's logistics demand were forecasted, and the probability situation of the occurrence of the corresponding intervals of logistics demand for the forecast year was obtained. Logistics flow forecasting plays an important role in the development of macro-logistics initiatives of the government. Based on the statistical data of Xi'an city freight turnover of Shaanxi Province from 2008 to 2019, the freight flows for 2020–2022 are forecasted, and the combined forecasting model is more validated for forecasting the logistics scale of the region compared to the GM model (1.1).

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