Research on the Demand Forecasting Method of Sichuan Social Logistics Based on Positive Weight Combination

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Abstract

The macro-social logistics demand forecast is of great strategic significance to optimize the national or regional economic structure, improve the investment environment and improve the overall competitiveness of regional economy. In this study, the total amount of social logistics in Sichuan province was selected to reflect the social logistics demand, the factors influencing the social logistics demand in Sichuan province were analyzed, and eight economic indicators were summarized. This study first USES the time series prediction model (including the time response model GM (1, 1)), an exponential smoothing model, causal relation model (including multidimensional prediction model GM (1, n) and BP neural network model), to build four methods combination model, weight given solution of linear programming each forecast model, the forecasting result of combination forecast model deviation is minimal. The posterior difference test was applied to the above five models to compare the prediction results of each prediction method.

Key words: Social logistics demand forecasting; Total social logistics; Combined prediction model

INTRODUCTION

Regional logistics demand refers to the human production and living in this area is greater than the demand for all kinds of things can provide the number of items or people demand in this area is not production, need from other areas and cause the transfer of all kinds of physical items in time or space configuration of the behavior area and the country's logistics development planning to optimize the economic structure(2017), improve the investment environment and enhance the competitiveness of regional economy as a whole has important strategic significance, and related macro logistics, such as national or regional logistics demand forecasting is the premise of regional logistics planning.

Logistics demand has two categories, converting and value measurement indicators, converting generally embodied in the various functional requirements of the logistics, such as freight, freight turnover volume of transportation environment, storage of inventory, in-out warehouse work, etc., in the planning and design of infrastructure facilities for the purpose of logistics demand forecasting, generally choose the converting of measurement indicators. Goods demand value measurement refers to the monetary form of logistics demand, such as stock take fund, freight turnover, total social logistics and social logistics cost and so on, can reflect the value of a country or region form scale, commonly used in logistics project planning, investment, for the purpose of logistics demand forecasting.

Logistics demand forecasting has two kinds of qualitative and quantitative methods, qualitative prediction methods including the Delphi method, business personnel evaluation method, quantitative method is more, can be summed up in three types: time series prediction method (including the moving average, exponential smoothing method and the change of seasons forecast method, etc.), causality prediction method (including regression analysis method, multi-factor neural network prediction, multi-factors grey prediction, etc.), combination forecasting method.

Many scholars have made research on regional logistics demand forecasting and planning. Yang Jinwei

through physical value conversion, storage, packaging, circulation processing capacity, loading and unloading amount distribution of predicted value conversion into volumes, and calculate its sum is an area of regional logistics demand, application method for GM and the BP neural network combination. Sun Jianqing (2011) analysis gross index, industrial structure and economic indexes, domestic trade and the influence of human development indexes of logistics demand by other parts work with freight volumes of the physical value conversion relation instead of logistics demand of measurement indicators. The method applied is a combination of grey prediction and BP neural network prediction. Zhao Congcong choose freight as logistics demand, through the analysis of GDP, the total gross primary industry, secondary industry and tertiary industry GDP, population size, disposable income, residents' consumption level, the district total retail sales of consumer goods, import and export trade, investment in fixed assets, transportation, total mileage of the eight indicators for freight to analyze the influence of logistics demand, methods for genetic gray neural network(2017). Li Shangji to tal social logistics, Ren Xueting scholarsused in place of the logistics demand, social investment in fixed assets, gross domestic product, total imports and exports, wholesale and retail trade of the influence factors of logistics demand, the application of the method is given.it is analyzed(2008). Sun Xun, Liu and other scholars (2008) to choose freight volume as the measurement indicators, economic analysis of population density and the density of land economy, put forward a kind of based on the density of urban logistics demand comprehensive prediction method (Sun, ed., 2008).

Scholars take the freight, freight turnover similar converting metrics to forecast logistics demand is more, to value such as total social logistics and social logistics costs as a logistics demand forecasting amount less; there are many researches on forecasting national or regional logistics demand using a forecasting model than combined forecasting model. The development potential of logistics in SICHUAN province is huge and the market is vast. Portfolio model is applied in this article forecasts the total social logistics in Sichuan Province as object to analyze the forecasting logistics demand of SICHUAN province, the development of regional logistics forecasting theory and future actual logistics planning in SICHUAN Province has a certain significance.

1. MODEL ESTABLISHMENT

In the actual forecast process, usually by a variety of different models to choose from, and every prediction model of different level contains a certain sample information, if the simple with the size as the judgment standard error, and some methods of error will abandon, may lose some valuable information of the sample, want to consider using combination forecast method in such a case, namely the use of certain means to each single

prediction method of organic combination. The prediction method can make full use of the information of each single prediction method, reduce the randomness and improve the accuracy of prediction.

1.1 Time Series Prediction Method

1.1.1 The Data Processing

In order to reduce the randomness of the original sequence, eliminate the influence of different unit dimensions, before the forecast method of initial value change formula will be initialized raw data processing, with regularity and comparability of the data. Set existing sequence $X = \left(X_i^{(0)}(1), X_i^{(0)}(2), \cdots, X_i^{(0)}(3) \right)$, the data processing method is $f\left(X_i^{(0)}(k) \right) = X_i^{(0)}(k)/X_i^{(0)}(1)$.

1.1.2 Establish One-Dimensional GM (1,1) Time Response Function

Step 1: construct the cumulative generation sequence

$$X^{(1)} = \{ X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \cdots, X^{(0)}(n) \} \tag{1-1}$$

Step 2: construct the data matrix X and Y

$$X = \begin{pmatrix} -\frac{1}{2}[X^{(1)}(1) + X^{(1)}(2)] & 1 \\ -\frac{1}{2}[X^{(1)}(2) + X^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[X^{(1)}(5) + X^{(1)}(6)] & 1 \end{pmatrix}, \quad Y = \begin{pmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ X^{(0)}(4) \\ \vdots \\ X^{(0)}(n) \end{pmatrix} \tag{1-2}$$

Step 3: estimate the parameter vector B

$$\hat{B} = \begin{pmatrix} \hat{a} \\ \hat{b} \end{pmatrix} = (X^T X)^{-1} X^T Y \tag{1-3}$$

Step 4: get the prediction model

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{1-4}$$

$$\hat{X}^{(1)}(t+1) = \left[X^{(0)}(1) - \frac{\hat{b}}{\hat{a}} \right] e^{-\hat{a}t} + \frac{\hat{b}}{\hat{a}} \tag{1-5}$$

Step 5: subtract and generate the sequence

Reduction generation is the inverse operation of accumulation generation, the data obtained by subtracting the two data before and after the original sequence. The accumulative and subtraction operation can restore the accumulative generated sequence to the original sequence. In the process of modeling, the increase information can be obtained. The cumulative reduction is:

$$\hat{x}_1^0(1) = \hat{x}_1^1(1); \ \hat{x}_1^0(k+1) = \hat{x}_1^1(k+1) - \hat{x}_1^1(k) \tag{1-6}$$

Step 6: sequence validation

This article USES is posterior deviation test, according to the model calculation $\hat{X}^{(0)}(k)$, to calculate $\hat{X}^{(0)}(k)$ as the original sequence $X^{(0)}(k)$ residual error sequence:

$$\varepsilon^{(0)}(k) = X^{(0)}(k) - \hat{X}^{(0)}(k), \ k = 1, 2, \cdots, n \tag{1-7}$$

The mean and variance of the original sequence are:

$$\bar{x} = \frac{1}{n} \sum_{k=1}^{n} X^{(0)}(k) \tag{1-8}$$

$$s_1^2 = \frac{1}{n} \sum_{k=1}^{n} \left(X^{(0)}(k) - \bar{x} \right)^2 \tag{1-9}$$

The mean and variance of the residual error are:

$$\bar{\varepsilon} = \frac{1}{n}\sum_{k=1}^{n}\varepsilon(k) \tag{1-10}$$

$$s_2^2 = \frac{1}{n}\sum_{k=1}^{n}(\varepsilon(k) - \bar{\varepsilon})^2 \tag{1-11}$$

Calculate the mean variance ratio C，Small residual error probability P

$$C = s_2 / s_1 \tag{1-12}$$

$$p = P\{|\varepsilon(k) - \bar{\varepsilon}| < 0.6745 s_1\} = \sum k/n \tag{1-13}$$

By calculating the mean variance ratio and small residual probability of a set of values, the accuracy of the prediction model can be determined, and its precision grade is shown in Table 1.

Table 1
Accuracy Test Class Reference Table

C	p	Model accuracy
<0.35	>0.95	Level 1 (excellent)
<0.50	>0.80	Level 2 (qualified)
<0.65	>0.70	Level 3 (barely qualified)
>0.65	<0.70	Level 4 (unqualified)

Note: model accuracy level = Max (p level, C level)

Step 7: data restoration and data prediction

$$x(k) = \hat{x}_i^0(1) * \hat{x}_i^0(k) \text{(after the normalization of}$$
data with each element of the first data multiplication)
$$\tag{1-14}$$

1.1.3 Establish a Primary Exponential Smoothing Model
Exponential smoothing method is a time series analysis and prediction method, which can predict the future of phenomena by calculating the exponential smoothing value and combining with a certain time series prediction model. The principle is that the exponential smoothing of any period is a weighted average of the actual observed value of the period and the exponential smoothing of the previous period.

The prediction formula of single exponential smoothing method is:

$$F_{t+1} = ax_t + (1-a)F_t \tag{1-15}$$

Where, t -- the time of the period;

a -- exponential smoothing coefficient, whose value is

between 0 and 1;

x_t-- the actual observation value of period t;

F_t -- predicted value of period t;

F_{t+1}-- predicted value of period t+1

The inspection method adopts the posterior difference method

1.2 Causal Forecasting Methods

1.2.1 Establish GM (1, n) Causality Function
Step 1: list the corresponding columns of each variable in the system

$$X_i^{(0)} = \{X_i^{(0)}(1)，X_i^{(0)}(2)，X_i^{(0)}(3)，\cdots，X_i^{(0)}(n)\} \tag{1-16}$$

The second step:$X_i^{(0)}$ make a accumulation generation

$$X^{(1)} = \{X^{(1)}(1)，X^{(1)}(2)，\cdots，X_i^{(0)}(n)\} \tag{1-17}$$

Where

$$x^{(1)}(k) = \sum_{i=1}^{k}x^{(0)}(i)，k = 1，2，\cdots，n \ Z_1^{(1)} \text{ for}$$

$X_1^{(1)}$ (adjacent to generate sequence: (1))

$$Z_1^{(1)}(k) = 0.5(X_1^{(1)}(k) + X_1^{(1)}(k-1)k = 2,3,\cdots,n) \tag{1-18}$$

Step 3: establish the first order grey differential equation of N variables

$$X_1^{(0)}(k) + aZ_1^{(1)}(k) = \sum_{i=2}^{N}b_i X_i^{(1)}(k) \tag{1-19}$$

In the equation, a and b_i are parameters, $I = 2, 3\cdots$，n.

Step 4: find the approximate value of equation parameters

Remember equation parameters as $(a,b_2,b_3\cdots,b_N)^T$, according to the least square method can calculate the parameter value of the column, its formula is: $u = (B^T B)^{-1}B^T Y$

Where B and Y are respectively expressed as:

$$\begin{pmatrix} -Z_1^{(1)}(2) & X_2^{(1)}(2) & \cdots & X_N^{(1)}(2) \\ -Z_1^{(1)}(3) & X_2^{(1)}(3) & \cdots & X_N^{(1)}(3) \\ \cdots & \cdots & \cdots & \cdots \\ -Z_1^{(1)}(n) & X_2^{(1)}(n) & \cdots & X_N^{(1)}(n) \end{pmatrix} \tag{1-20}$$

$$\{X_1^{(0)}(2)，X_1^{(0)}(3)，\cdots，X_1^{(0)}(n)\} \tag{1-21}$$

Step 5: solve the differential equation and get the prediction model

$$\hat{X}^{(1)}(k+1) = \left[X_1^0(1) - \frac{1}{a}\sum_{i=2}^{N}b_{i-1}X_i^0(k+1)\right]e^{-\hat{a}t} + \frac{1}{a}\sum_{i=2}^{N}b_{i-1}X_i^0(k+1) \ \text{其中}k = 1,2,\cdots,n \tag{1-22}$$

Step 6: restore the model and generate the subtraction

Reduction generation is the inverse operation of accumulation generation, the data obtained by subtracting the two data before and after the original sequence. The accumulative and subtraction operation can restore the accumulative generated sequence to the original sequence. In the process of modeling, W can obtain the increase information. The cumulative reduction is:

$$\hat{x}_1^0(1) = \hat{x}_1^1(1)；\hat{x}_1^0(k+1) = \hat{x}_1^1(k+1) - \hat{x}_1^1(k) \tag{1-23}$$

Step 7: data test is the same as GM (1,1) model. The posterior difference test is adopted in this study.

1.2.2 BP Neural Network Prediction Model Was Established
Step 1: data normalization processing

In BP network, because the original input data variable units provided to it are not uniform, and the data between different indicators are too different. In order to accelerate the training of network convergence, prevent neurons output saturation phenomenon, improve the accuracy of prediction, the need to convert raw data into dimensionless expression, namely, all the data into a number between 0 and 1. Sigmoid function and logarithm function training effect in close to 0 or 1 will be significantly lower, $x_i' = \dfrac{x_i - n}{m - n}$. Type o x_i' for the value of the normalized after x_i for raw data values; N is 0.7 times the minimum value in x_i; M is the maximum of 1 in x_i 1.3 times.

Step 2: design the topology of the network

In this paper, a typical three-layer neural network is used to simulate the model. It was determined that the number of input layer, output layer and hidden layer of BP neural network were n, m and l respectively. The choice of the number of nodes in the hidden layer has great influence on the network prediction results. According to kolmogorov theorem, the number of neurons in the hidden layer is preliminarily determined. L = square root of m+n +a, n is the number of input neurons, m is the number of output neurons, and a ranges from 1 to 10. This article tansig function is chosen as the transfer function of the hidden layer, select purelin function as transfer function of the output layer, and the model of the number of iterations is set to 100, vector set it to 0.1, the error of the target limit set at 0.0001. A BP neural network model with 4 to 13 nodes in the hidden layer was established. Then, the models of different hidden layer nodes were run 10 times respectively to find the number of neuron nodes with the minimum relative error mean of the test data and take it as the optimal number of hidden layer nodes.

Step 3: MATLAB simulation process

MATLAB provided neural network functions, neural network programming, using the code to establish the above requirements of BP network.

1.3 A Combined Prediction Model is Established

For the same prediction problem, there are n prediction methods: $f_1, f_2, f_3, \cdots, f_n$ can be applied, then the combined prediction model composed of these n models is:

$$f(x_i) = \sum_{j=1}^{n} w_j f_{ij}(x) \quad i = 1, 2, \cdots, m \quad m \text{ s stands for}$$

m groups of sample data （1-24）

$$w_1 + w_2 + w_3 + , \cdots , + w_n = 1$$

$w_1 + w_2 + w_3 +, \cdots, + w_n = 1$ n means there are n prediction methods   (1-25)

$f(x_i)$ i=1,2,3,4……, 9 $f(x_i)$ The predicted value after applying the composite method   (1-26)

w_i, i=1,2,3,4 w represents the weight of each prediction method

Set ei as the prediction error of model I and variable weight combination model in a certain year, and its expression is

$$e_i = Y_i - f(x_i) = Y_i - \sum_{j=1}^{n} w_j f_{ij}(x)$$ (1-27)

Y_i is the actual observed value of the ith value, and e_i is the difference between the actual value of the ith group of data and the predicted value.

$$E_t = \sum_{i=1}^{m} e_i$$ (1-28)

E_t is the error of all data.

Optimization combination model, weight w_i, make the observation value of the combination forecast model and the actual value of the minimum value difference, the obtained Y_i, can compare the combination forecast model and the rest of the n kinds of single forecasting model of the effect.

$$\begin{cases} min E_t^2 = \sum_{i=1}^{m} e_i^2 & i = 1, 2, \cdots, m \\ s.t \sum_{i=1}^{n} w_j = 1 & j = 1, 2, \cdots, n \end{cases}$$ (1-29)

In this study, four prediction methods are adopted: time series prediction model includes two kinds, one-dimensional grey prediction GM (1,1) model and exponential smoothing model. Causal relationship affect the logistics demand forecast analysis of the eight indicators, respectively set up multidimensional grey prediction GM (1, 8) model and BP neural network model, and then four kinds of prediction model together, given certain weights to each model, finally it is concluded that the best model of logistics demand forecasting.

2. THE EMPIRICAL ANALYSIS

2.1 The Original Data

Table 2
Total Social Logistics In Sichuan Province from 2009 to 2017 and Its Influencing Factors

		Indicators							
Year	Indicators of regional economic aggregate	Regional industrial structure indicators				Regional and external trade indicators		Regional consumption level	Regional fixed asset investment indicators	Social logistics demand
	Regional GDP (billion yuan)	Total output value of primary industry (billion yuan)	Total output value of secondary industry (billion yuan)	Total output value of tertiary industry (billion yuan)	Total retail sales of consumer goods ($100 million)	Total regional foreign trade (RMB 100 million)	Per capita consumption level (yuan)	Fixed asset investment (100 million yuan)	Total social logistics (100 million yuan)	
	t	X1	X2	X3	X4	X5	X6	X7	X8	Y
2009	1	14151.28	2206.53	6123.53	5821.22	5779.89	1654.72	6863.00	12017.28	28153.90
2010	2	17185.48	2443.20	7902.18	6840.10	6884.84	2218.92	8182.00	13581.96	33779.92
2011	3	21026.68	2937.70	10045.72	8043.26	8290.84	3086.30	9903.00	15124.09	35190.00
2012	4	23872.80	3245.94	11240.02	9386.84	9622.00	3732.29	11280.00	18038.90	45949.80
2013	5	26392.07	3368.66	12378.71	10644.70	11001.00	4000.34	12548.00	21049.20	51284.40
2014	6	28536.66	3531.05	12836.60	12166.01	12459.99	4315.45	13755.00	23577.20	54804.70
2015	7	30053.10	3677.30	13248.08	13127.72	13961.40	3213.42	14774.00	2573.70	57314.50
2016	8	32680.50	3924.08	13924.73	14831.69	15601.87	3277.94	16024.00	29126.00	60878.80
2017	9	36980.20	4282.80	14294.00	18403.40	17480.50	4605.90	20580.00	32097.30	63909.50

Source: Sichuan statistical yearbook

2.2 Time Series Model

2.2.1 Data Processing

According to the formula $f(X_i^{(O)}(k))=X_i^{(O)}(k)/X_i^{(O)}(1)$ for data processing, are shown in table3 with regularity and comparable relevant data.

Table 3
Related Data After Initialization

	T	Y	X1	X2	X3	X4	X5	X6	X7	X8
2009	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2010	2	1.200	1.214	1.107	1.290	1.175	1.191	1.341	1.192	1.130
2011	3	1.250	1.486	1.331	1.641	1.382	1.434	1.865	1.443	1.259
2012	4	1.632	1.687	1.471	1.836	1.613	1.665	2.256	1.644	1.501
2013	5	1.822	1.865	1.527	2.021	1.829	1.903	2.418	1.828	1.752
2014	6	1.947	2.017	1.600	2.096	2.090	2.156	2.608	2.004	1.962
2015	7	2.036	2.124	1.667	2.163	2.255	2.416	1.942	2.153	0.214
2016	8	2.162	2.309	1.778	2.274	2.548	2.699	1.981	2.335	2.424
2017	9	2.270	2.613	1.941	2.334	3.161	3.024	2.783	2.999	2.671

2.2.2 GM (1,1) Time Response Function

Step 1: construct the cumulative generation sequence

$$X^{(1)} = \{1.000，2.200，3.450，5.082，6.903，8.850，10.886，13.048，15.318\} \tag{2-1}$$

Step 2: construct the data matrix X and Y

Step 3: estimate the parameter vector B

$$\hat{B} = \begin{pmatrix} \hat{a} \\ \hat{b} \end{pmatrix} = \begin{pmatrix} -0.08724 \\ 0.97533 \end{pmatrix} \tag{2-3}$$

$$X = \begin{pmatrix} -1.60 & 1 \\ -2.82 & 1 \\ -4.27 & 1 \\ -5.99 & 1 \\ -7.88 & 1 \\ -9.87 & 1 \\ -11.97 & 1 \\ -14.18 & 1 \end{pmatrix}, Y = \begin{pmatrix} 2.200 \\ 3.450 \\ 5.082 \\ 6.903 \\ 8.850 \\ 10.886 \\ 13.048 \\ 15.318 \end{pmatrix} \tag{2-2}$$

Step 4: get the prediction model

$$\frac{dX^{(1)}}{dt} - 0.08724X^{(1)} = 0.97533 \tag{2-4}$$

$$\hat{X}^{(1)}(t+1) = \left[1 - \frac{0.97533}{-0.08724}\right]e^{0.08724t} + \frac{0.97533}{-0.08724} = 12.17985e^{1.04292t} - 11.1798 \tag{2-5}$$

Step 5: residual test

Formula $\hat{X}^{(1)}(t+1) = \left[X^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right]e^{-\hat{a}t} + \frac{\hat{b}}{\hat{a}} = 12.17985e^{1.04292t} - 11.17985$ is used to calculate the cumulative sequence

of predicted values, as shown in the Table 4:

Table 4
Time-Based GM (1,1) Model Predicts Cumulative Values

t	0	1	2	3	4	5	6	7	8
	1	2.30189	3.72055	5.266429	6.95094	8.78651	10.78670	12.96626	15.34129

The cumulative generation sequence is calculated and the original value is restored, and the results are shown in Table 5.

Table 5
GM (1, 1) Model Of Sichuan Province Total Social Logistics Predicted Value

Year	The actual value	Predictive value	Absolute value of error
2009	28153.9	28153.9	0
2010	33779.92	36653.56	2873.64
2011	35190	39940.53	4750.53
2012	45949.8	43522.27	2427.53
2013	51284.4	47425.53	3858.87
2014	54804.7	51678.74	3125.96
2015	57314.5	56313.15	1001.35
2016	60878.8	61363.11	484.31
2017	63909.5	66866.08	2956.58

It is calculated that $C=s_2/s_1=1308.251497/10819.59765=0.1209<0.5$, *p=87.5%,* so the prediction level of this time response model is grade 1 and the prediction effect is excellent.

The actual value, predicted value and error of the GM (1,1) prediction model were obtained by restoring the data, as shown in the figure below:
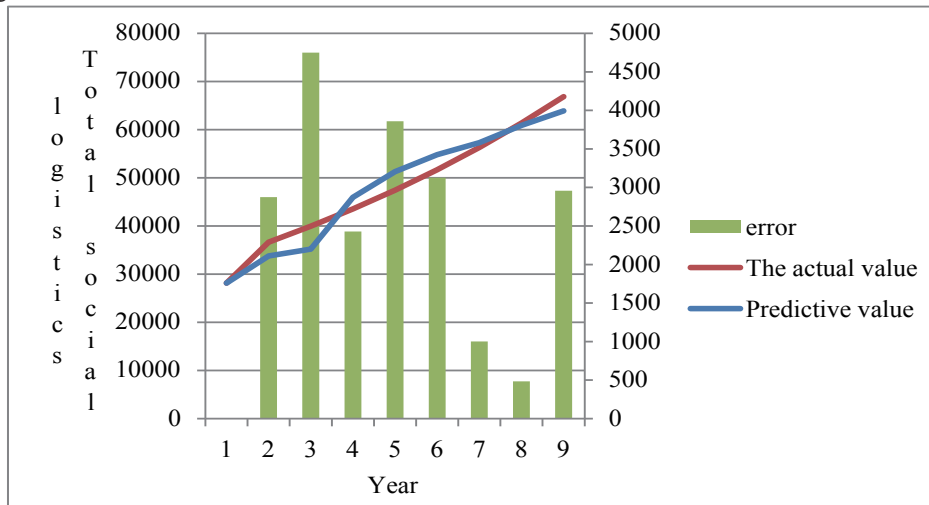

Figure 1 GM (1, 1) Model Prediction

2.2.3 Establish a Primary Exponential Smoothing Model

The initial results of this study were set by SPSS, and the prediction results of Sichuan's total social logistics were shown in table 5 below:

Table 5
Total Predicted Value of Social Logistics in Sichuan Province in the First Exponential Smoothing Model

Year	The actual value	Predictive value	Absolute value of error
2009	28153.90	28750.43	596.53
2010	33779.92	33197.75	3455.81
2011	35190.00	37993.34	1947.19
2012	45949.80	41788.59	1733.68
2013	51284.40	47641.69	216.16
2014	54804.70	53341.61	1662.87
2015	57314.50	58397.53	2084.38
2016	60878.80	62701.13	1338.02
2017	63909.50	66786.28	79.8

The variance test after exponential smoothing model is obtained $C = s_2/s_1 = \dfrac{1057.0594}{12374.8082} = 0.0854 < 0.5$, Small error probability $p = P\{|\varepsilon(k) - \bar{\varepsilon}| < 0.6745 s_1\} = 100\%$, indicating the model accuracy level to level, the prediction accuracy for the best, can be used as a prediction of the total amount of social logistics. This model can be used to predict the total amount of social logistics.
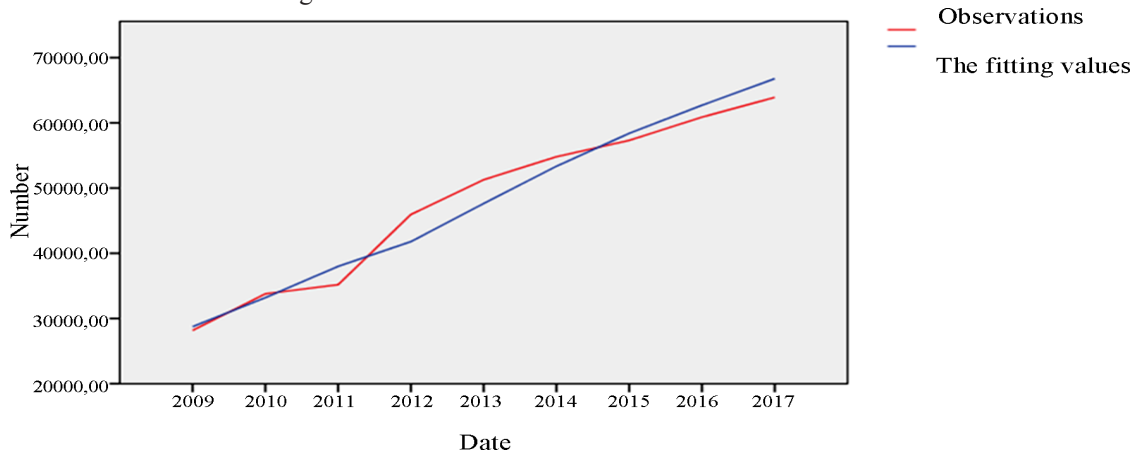

Figure 2
Prediction Results of Spss Time Series Exponential Smoothing Method

2.3 Causal Model

2.3.1 Establish GM (1, n) Causality Function

Table 6
Cumulative Data of Grey Prediction Model

	T	Y	X1	X2	X3	X4	X5	X6	X7	X8
2009	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2010	2	2.200	2.214	2.107	2.290	2.175	2.191	2.341	2.192	2.130
2011	3	3.450	3.700	3.439	3.931	3.557	3.626	4.206	3.635	3.389
2012	4	5.082	5.387	4.910	5.767	5.169	5.290	6.462	5.279	4.890
2013	5	6.903	7.252	6.436	7.788	6.998	7.194	8.879	7.107	6.641
2014	6	8.850	9.269	8.037	9.884	9.088	9.349	11.487	9.111	8.603
2015	7	10.886	11.392	9.703	12.048	11.343	11.765	13.429	11.264	8.817
2016	8	13.048	13.702	11.482	14.322	13.891	14.464	15.410	13.599	11.241
2017	9	15.318	16.315	13.423	16.656	17.052	17.489	18.194	16.598	13.912

Step 1: data accumulation. After the initial independent and dependent variables in the system are accumulated once, a more regular sequence model is obtained. As shown in table 6.

$z^{(1)}$ as the sequence $y^{(1)}$ adjacent to the mean of the sequence, are:

$z^{(1)}$=(1.60 2.82 4.27 5.99 7.88 9.87 11.97 14.18)

$$(2\text{-}6)$$

Let the grey difference equation of GM (1,8) be:

$$y^{(0)}(k) + aZ_1^{(1)}(k) = \sum_{i=2}^{8} b_i X_i^{(1)}(k) \tag{2-7}$$

a, bi (I =2,3... , 8) is the parameter of the model

$$Y_8 = \left(y(2)，y(3)，\cdots，y(9)\right)^T = \left(1.20，1.25，1.63，1.82，1.95，2.04，2.16，2.27\right)^T \tag{2-8}$$

$$B = \begin{pmatrix} -1.60 & 2.21 & 2.11 & 2.29 & 2.18 & 2.19 & 2.34 & 2.19 & 2.13 \\ -2.82 & 3.70 & 3.44 & 3.93 & 3.56 & 3.63 & 4.21 & 3.64 & 3.39 \\ -4.27 & 5.39 & 4.91 & 5.77 & 5.17 & 5.29 & 6.46 & 5.28 & 4.89 \\ -5.99 & 7.25 & 6.44 & 7.79 & 7.00 & 7.19 & 8.88 & 7.11 & 6.64 \\ -7.88 & 9.27 & 8.04 & 9.88 & 9.09 & 9.35 & 11.49 & 9.11 & 8.60 \\ -9.87 & 11.39 & 9.70 & 12.05 & 11.34 & 11.76 & 13.43 & 11.26 & 10.76 \\ -11.97 & 13.70 & 11.48 & 14.32 & 13.89 & 14.46 & 15.41 & 13.60 & 13.19 \\ -14.18 & 16.32 & 13.42 & 16.66 & 17.05 & 17.49 & 18.19 & 16.60 & 15.86 \end{pmatrix} \tag{2-9}$$

The following values

$$u = \left(a，b_1，b_2，\cdots，b_N\right)^T = (B^T B)^{-1} B^T Y_8 \text{ obtained: (1) B}$$

Thus, the GM (1,8) model is obtained.

a=10.0994 *b*1=4.8106.*b*2=-6.6872.*b*3=-2.5074.*b*4=-24.7294.
*b*5=15.4154,*b*6=2.8662.*b*7=10.1076.*b*8=8.1317

$$y(k + 1) = \left[X_1^{(0)}(1) - \frac{1}{10.0994}\left(4.8106X_1^{(1)}(k + 1) - 6.6872X_2^{(1)}(k + 1) - 2.5074X_3^{(1)}(k + 1) - 24.7294X_4^{(1)}(k + 1) + 15.4154X_5^{(1)}(k + 1) + 2.8662X_6^{(1)}(k + 1) + 10.1076X_7^{(1)}(k + 1) + 8.1317X_8^{(1)}(k + 1)\right)\right]e^{-10.0994k} + \frac{1}{10.0994}\left(4.8106X_1^{(1)}(k + 1) - 6.6872X_2^{(1)}(k + 1) - 2.5074X_3^{(1)}(k + 1) - 24.7294X_4^{(1)}(k + 1) + 15.4154X_5^{(1)}(k + 1) + 2.8662X_6^{(1)}(k + 1) + 10.1076X_7^{(1)}(k + 1) + 8.1317X_8^{(1)}(k + 1)\right) \tag{2-10}$$

Type, $y(k)$ is a total social logistics forecast, $Z_1^{(1)}(k)$ is a sequence of $y^{(1)}(k)$ adjacent to the mean sequence, $X_1^{(1)}(k), X_2^{(1)}(k), X_2^{(1)}(k)\cdots, X_2^{(1)}(k)$ for various influence factors after an accumulation of data, $k = 2, 3,...,8$.

Predictive fruit analysis

The established GM (1,8) model was used to predict the freight volume in Beijing over the years. After obtaining the predicted results, the corresponding predicted values were obtained after another reduction and reverse normalization treatment. The prediction data of grey GM (1,8) model were compared with the actual data, and the prediction results shown in table 7 were obtained.

Step 2: prediction results

The established GM (1,8) model was used to predict the freight volume in Beijing over the years. After obtaining the predicted results, the corresponding predicted values were obtained after another reduction and reverse normalization treatment. The prediction data of grey GM (1,8) model were compared with the actual data, and the prediction results shown in table 7 were obtained.

Table 7
Grey Multidimensional Model Prediction Results

Year	The actual value	Predictive value	Absolute value of error
2009	28153.90	28153.9	-
2010	33779.92	19230.55326	14549.37
2011	35190.00	34119.94233	1070.06
2012	45949.80	41105.5678	4844.23
2013	51284.40	48691.64022	2592.76
2014	54804.70	52906.42367	1898.28
2015	57314.50	55795.11818	1519.38
2016	60878.80	58835.02201	2043.78
2017	63909.50	61849.27273	2060.23

For GM (1, 8) variance after inspection, get $C = s_2/s_1 = \dfrac{4190.38}{10819.60} = 0.3873 < 0.5$, small error probability $p = P\{|\varepsilon(k) - \bar{\varepsilon}| < 0.6745 s_1\} = 87.5\%$, shows that the model precision for the secondary grade, prediction accuracy of qualified, can be used as a prediction of the total amount of social logistics.

The actual value, predicted value and error of GM (1,8) prediction model are shown in figure 3:
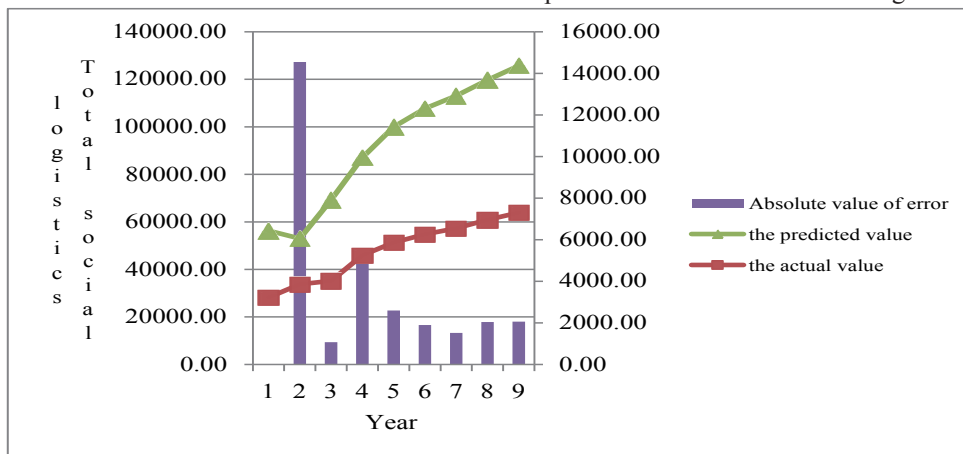

Figure 3
GM (1, 8) Prediction Model

2.3.2 Establish BP Neural Network Prediction Model
Sichuan province total social logistics is closely associated with the level of economic development elements, use BP neural network to build function relation between the two, using the neural network learning rate for the *Effficiency = 0.035*, the target error *Direction = 0.00065*, adopt measure to obtain network structure for the 8-10-1, that a given node values of 8, hidden layer is 10, node results is 1, application MATLAB software coding, the prediction results of 8 listed in the table below:

Table 8
Prediction Effect Of BP Neural Network

Year	The actual value	Predictive value	Absolute value of error
2009	28153.90	28267.22	21.10
2010	33779.92	33185.45	3324.56
2011	35190.00	35395.90	4632.53
2012	45949.80	45710.12	2304.73
2013	51284.40	51572.59	3991.47
2014	54804.70	54729.10	3141.26
2015	57314.50	57487.12	1124.85
2016	60878.80	60860.53	437.11
2017	63909.50	64031.05	2870.08

Variance after inspection of BP neural network model

for $C = s_2/s_1 = \dfrac{592.27}{4479.71} = 0.1287 < 0.35$, small error

probability, $p = P\{|\varepsilon(k) - \bar{\varepsilon}| < 0.6745s_1\} = 66.7\%$ shows that this model is precision grade level, can be used

as a prediction of the total amount of social logistics. The comparison between the actual value and predicted value of BP neural network and the error figure are shown in figure 4 below.
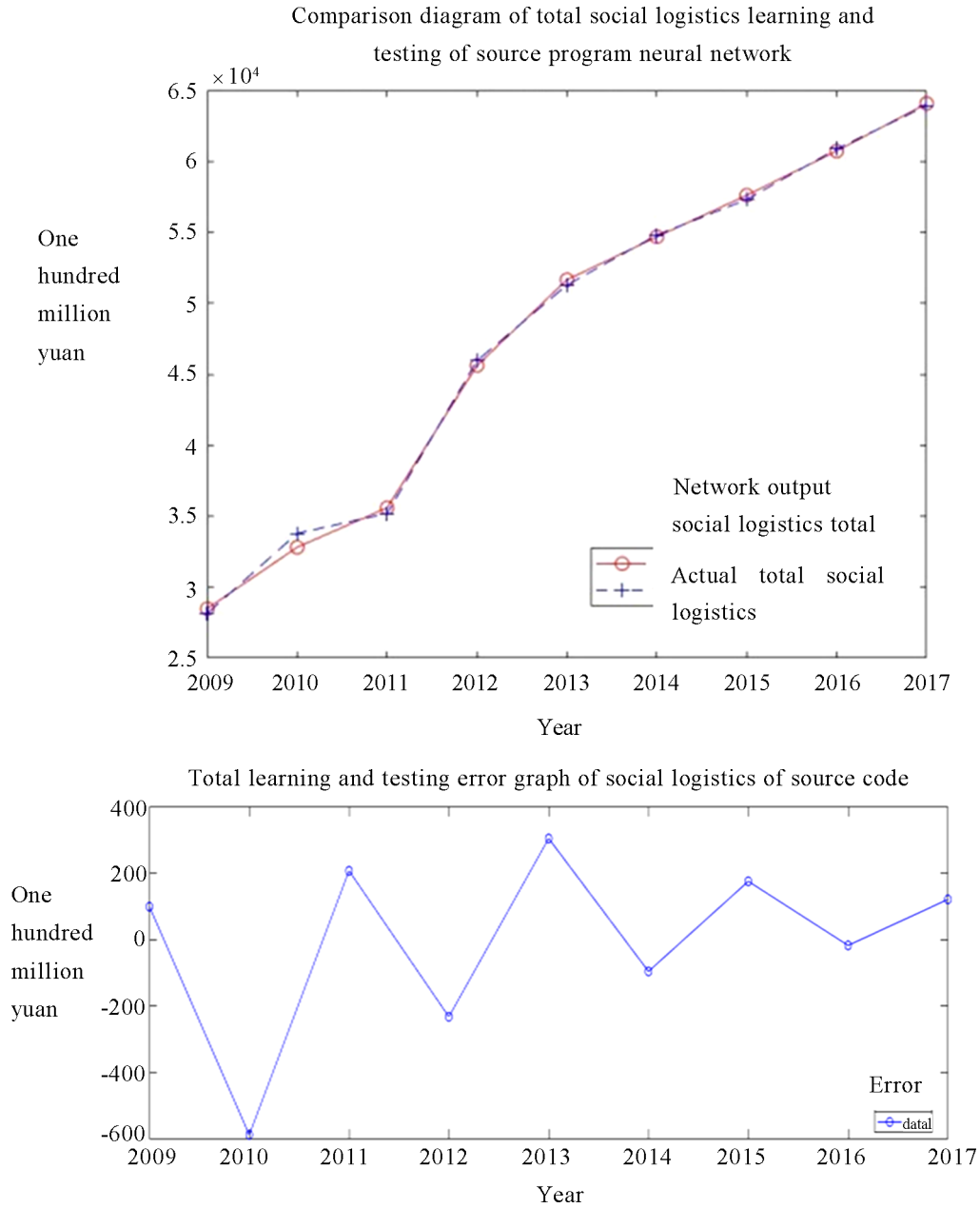
Comparison diagram of total social logistics learning and testing of source program neural network

Total learning and testing error graph of social logistics of source code

Figure 4
Comparison and Error of Total Learning and Testing Of BP Neural Network Social Logistics

2.4 Establish a Combined Prediction Model

In this paper, 9 groups of data and 4 prediction methods are given, $i = 1,2,……, 9, j = 1,2,3, 4$. The prediction results

of the four models are shown in the following table.

The combined prediction model was applied to obtain the final prediction results, as shown in table 9:

Table 9
Comparison and Analysis of Predicted Values by Various Methods

Year		The first method	The second method	The third method	the fourth method	
	Weight	0	0.01963525	0	0.9803648	
	The actual value	Exponential smoothing	GM(1,1)	GM(1,N)	BP neural network	Combined predictive value
2009	28153.90	28750.43	28153.90	28153.90	28267.22	28265.00
2010	33779.92	33197.75	36653.56	19230.55	33185.45	33253.55
2011	35190.00	37993.34	39940.53	34119.94	35395.90	35485.14
2012	45949.80	41788.59	43522.27	41105.57	45710.12	45667.16
2013	51284.40	47641.69	47425.53	48691.64	51572.59	51491.16
2014	54804.70	53341.61	51678.74	52906.42	54729.10	54669.20
2015	57314.50	58397.53	56313.15	55795.12	57487.12	57464.07
2016	60878.80	62701.13	61363.11	58835.02	60860.53	60870.40
2017	63909.50	66786.28	66866.08	61849.27	64031.05	64086.72
c	——	0.1020	0.1231	0.3400	0.0131	0.0108

The final predicted result is

$$f(x_i)=0.01964f_{i2}(x)+0.98036f_{i4}(x) \qquad (2\text{-}11)$$

The posterior difference test was applied to the combined prediction model, and the c value was calculated as 0.0108, and the prediction effect was better than the other four single prediction models.

CONCLUSION AND DISCUSSION

In the regional logistics demand forecasting, on behalf of the regional logistics demand indicators is not unified, and due to the randomness of logistics and highly nonlinear, simply use a kind of prediction method, it is difficult to get satisfactory forecasting results. This study adopts the total social logistics, as the representative of the Sichuan provincial social logistics demand weight combination forecast method, the one-dimensional grey forecasting, grey prediction, exponential smoothing solution weights, neural network algorithm is given, and a posteriori difference test separately for each model, found that the combination forecast method compared the prediction results and the actual result, deviation is small, the agricultural cold chain logistics compared with the actual result is more close to. The combination of this model provides a new method for forecasting regional logistics demand. Due to the combined model is larger than a single model of computation, when the forecast data further increase, further complicate economic impact factors, how to choose a more suitable model and combination method, to meet the needs of real-time traffic flow forecasting, is worth studying further.

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