

Forecast Analysis of Cold Chain Logistics Demand Based on Different Models

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Abstract: With economic development and the improvement of residents' consumption capacity, public awareness of pursuing healthy lifestyles has been continuously strengthened, leading to rising expectations for the variety and quality of fresh food products. Cold chain logistics, as a key link in ensuring the circulation quality of fresh products, has gained increasing importance. Henan Province, a major agricultural base in China, boasts abundant production of fresh agricultural products but suffers significant losses during circulation, largely due to an underdeveloped cold chain logistics system. Although Henan possesses advantages in output and geographical location for developing cold chain logistics for fresh agricultural products, its current development still faces multiple challenges. Based on an analysis of the development status of cold chain logistics for fresh agricultural products in Henan Province, this paper constructs five forecasting models: Wavelet Neural Network, BP Neural Network, GA-BP Neural Network, PSO-BP Neural Network, and LSTM. After comparing their prediction accuracy, the LSTM model with the best performance is selected to forecast the demand for cold chain logistics of fresh agricultural products in Henan, providing a decision-making basis for optimizing the allocation of regional cold chain logistics resources. Based on the forecast results, this paper further proposes countermeasures to promote the high-quality development of fresh agricultural product cold chain logistics in Henan Province, aiming to balance supply and demand, alleviate operational pressure, and drive the industry towards greater efficiency, sustainability, and intelligence.

Keywords: Henan Province; Fresh agricultural products, Cold chain logistics, Demand forecast.

1. Introduction

In the context of global trade integration, an efficient and reliable cold chain logistics system is key to enhancing the international competitiveness of agricultural products, helping to expand international markets and strengthen national soft power [1]. The circulation loss rate of fresh agricultural products in China is higher than the average level of developed countries. Therefore, developing cold chain logistics is crucial for ensuring quality and safety and reducing circulation losses. In addition, a sound cold chain logistics system can promote the upgrading of the agricultural industrial structure, increase farmers' income, and support the implementation of the rural revitalization strategy [2].

In recent years, the state has introduced a series of policies to support the development of cold chain logistics for agricultural products. For example, the "14th Five-Year Plan for Cold Chain Logistics Development" issued in 2021 clearly proposed building a national cold chain logistics backbone corridor network with "four horizontal and four vertical" corridors [3], and planned to initially form a three-tier cold chain logistics node system covering about 90% of counties nationwide by 2025, with a focus on building full-chain temperature control capacity for categories such as meat, fruits, and vegetables. Subsequently, the "Three-Year Action Plan for County-Level Commerce (2023-2025)" further focused on addressing weaknesses in cross-regional cold chain logistics facilities, aiming to significantly reduce agricultural product circulation losses by 2025. Through technological upgrading, financial support, and network improvement, these policies have provided systematic support for the high-quality development of agricultural cold chain logistics.

As a major agricultural province and a pilot for building a strong modern logistics province, Henan Province has actively responded to these policies. In 2024, it issued the "Notice on Carrying Out the Establishment of Provincial Backbone Cold Chain Logistics Bases," planning to form a "5+15" backbone cold chain logistics facility network by 2025, with a focus on supporting the integration of cold chain resources in advantageous production areas for meat, fruits, and vegetables. At present, Henan Province has four national backbone cold chain logistics bases in Zhengzhou, Shangqiu, Xinxiang, and Luohe [4]. Supporting policies provide priority guarantees in terms of land use quotas, central government budget investment, and local government special bonds, and a dynamic monitoring and exit management mechanism has been established. The 20th National Congress of the Communist Party of China emphasized high-quality development [5]. Against this background, continuously improving the cold chain logistics service capacity for fresh agricultural products and promoting its high-quality development have urgent practical significance for safeguarding people's livelihoods, promoting circulation, and serving national strategies.

The construction of an agricultural cold chain logistics system is not only an important part of the modern service industry, but also an important carrier of a green and low-carbon economic development model, occupying a strategic position in promoting high-quality economic development. By effectively connecting the production and consumption ends, cold chain logistics hubs not only optimize the efficiency of agricultural product resource allocation, but also become a core engine driving agricultural supply-side structural reform and industrial upgrading. For Henan Province, the innovative development of its cold chain logistics system has a direct effect on promoting the integration of primary, secondary, and tertiary industries in

rural areas and increasing farmers' income. At the same time, it can provide solid industrial support for the construction of a logistics hub economy, and plays an indispensable role in comprehensively promoting rural revitalization and the building of a modern socialist country.

This paper aims to review the current development status of cold chain logistics for fresh agricultural products in Henan Province, construct and compare multiple machine learning and deep learning prediction models, and select the optimal model to forecast regional cold chain logistics demand. On this basis, by combining the prediction results with existing problems, it proposes countermeasures and suggestions to promote the high-quality development of fresh agricultural product cold chain logistics in Henan Province, so as to achieve a dynamic balance between supply and demand, alleviate operational pressure on the industry, and further promote comprehensive rural revitalization.

Scholars at home and abroad have conducted extensive research in the field of cold chain logistics demand forecasting and have achieved a series of results. Tang Qian et al. [6] constructed and validated a high-precision hybrid forecasting model, effectively solving the problem of large errors in traditional methods for regional cold chain logistics demand forecasting and providing a scientific tool for related decision-making. Liu Shuai et al. [7] developed a combined gray-BP neural network model, demonstrating its superiority in cold chain logistics demand forecasting for aquatic products in the post-pandemic era and providing data support for policy formulation and resource allocation. He Bo and Yin Lvjiang [8] compared neural network and gray forecasting models, verifying the effectiveness of data mining technology in cold chain logistics demand forecasting and providing a methodological reference for optimizing resource allocation in the industry. Wang Meng and Li Xin [9] used a metabolic GM(1,1) model to improve the limitations of traditional gray forecasting in agricultural cold chain demand analysis, providing a dynamic forecasting tool. In domestic research, Zhang Xiaoyan [10] used statistical analysis methods to screen significant variables and established a multiple linear regression model for logistics demand forecasting. Chen Liangyun [11] used a GM(1,1) model to forecast the cold chain logistics demand for agricultural products in Fujian Province. Zhu Chuang and Sun Qingfeng [12] proposed using the MIV algorithm to screen key influencing indicators in order to improve model forecasting accuracy. Wang Xiaoping and Yan Fei [13] used principal component analysis to reduce dimensionality, and then combined BP neural network and RBF neural network for forecasting, finding that averaging the prediction results of the two neural network models can effectively improve the accuracy and stability of cold chain logistics demand forecasting for urban agricultural products in Beijing. Zeng Yu and Zhu Zhihao [14] also confirmed through comparison of multiple models that the RBF neural network performs excellently in regional logistics demand forecasting.

A review of the existing literature shows that research on agricultural product cold chain logistics demand forecasting

presents a trend of multi-method integration. Scholars have comprehensively used multiple regression, gray forecasting, neural networks and their hybrid models to construct forecasting systems from multiple dimensions, significantly improving model accuracy. These studies not only provide scientific evidence for optimizing cold chain resource allocation and reducing agricultural product losses, but also provide decision-making support for government planning of cold chain infrastructure and promoting the modernization of the agricultural industry chain. On the basis of existing research, this paper will construct and compare multiple advanced forecasting models according to the specific situation of Henan Province, in order to obtain more accurate demand forecasting results.

2. Model Construction

(1) Wavelet Neural Network Model

The Wavelet Neural Network (WNN) combines the good time-frequency localization characteristics of wavelet transform with the strong nonlinear fitting capability of neural networks. Its hidden layer neurons use wavelet basis functions as the activation function. The output of the o -th hidden layer node is expressed as:

$$h_o(x) = \prod_{j=1}^t g\left(\frac{x_j - b_{jo}}{a_{jo}}\right)$$

Where g is the mother wavelet function, and a_{jo} and b_{jo} are the scale factor and translation factor of the o -th node corresponding to the j -th input variable, respectively. The final output of the network is the linear weighted sum of the outputs of all hidden layer nodes:

$$y_k(x) = \sum_{o=1}^p w_{jo} h_o(x)$$

This model is suitable for the multi-scale decomposition and prediction of non-stationary and nonlinear time series data.

(2) BP Neural Network Model

The BP (Back Propagation) neural network is a typical multilayer feedforward network that adjusts connection weights and thresholds through the error back-propagation algorithm. The BP network constructed in this paper consists of an input layer, a hidden layer, and an output layer [15]. The number of neurons in the input layer corresponds to the number of influencing factors, and the output layer has one neuron (cold chain logistics demand). The BP neural network model is shown in Equation (1-3), and the number of neurons in the hidden layer is calculated using an empirical formula:

$$n_h = \sqrt{n_i + n_o} + l$$

Where n_i is the number of neurons in the input layer, n_o is the number of neurons in the output layer ($n_o=1$), and l is a constant between 1 and 10. The network structure is shown in Fig. 1.

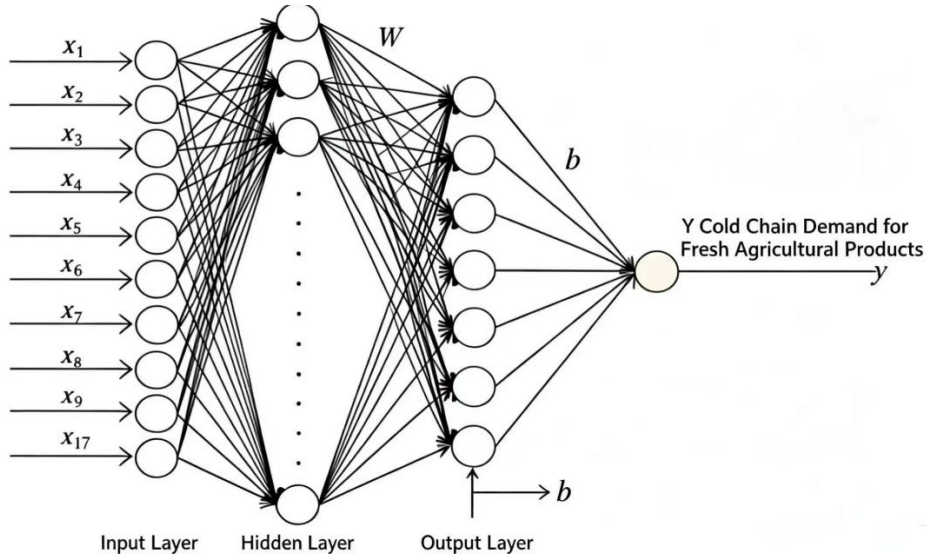


Figure 1. Structure of the BP neural network

(3) GA-BP Neural Network Model

The Genetic Algorithm optimized BP neural network (GA-BP) uses the global search capability of the genetic algorithm to optimize the initial weights and thresholds of the BP neural network, so as to prevent the model from falling into local optimal solutions. The basic process is as follows: the weights and thresholds of the BP network are encoded as chromosomes, the reciprocal of the network prediction error is used as the fitness function, and the population is iteratively evolved through genetic operations such as selection, crossover, and mutation. Finally, the optimal individual is decoded as the initial parameters of the BP network.

(4) PSO-BP Neural Network Model

The Particle Swarm Optimization optimized BP neural network (PSO-BP) introduces the particle swarm optimization algorithm to optimize the parameters of the BP network. Each particle represents a set of network weights and thresholds, and its position is updated according to the individual historical best position and the group historical best position. The parameter settings in this paper are as follows: particle number 30, learning factors $c_1 = c_2 = 2$, dynamically adjusted inertia weight, and maximum iteration number 100 [16].

(5) LSTM Model

The Long Short-Term Memory (LSTM) network is a variant of the recurrent neural network (RNN). By introducing a gating mechanism, it effectively solves the vanishing or exploding gradient problem in long sequence training and is particularly suitable for processing time series data with long-term dependencies. The calculation process of its core computing unit at time t is as follows:

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Candidate cell state:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

Update of the cell state:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Hidden state:

$$h_t = o_t \odot \tanh(C_t)$$

Where σ denotes the sigmoid activation function, $\odot$ represents element-wise multiplication, and W and b are the weight matrices and bias vectors, respectively.

3. Analysis of Factors Influencing the Demand for Fresh Agricultural Products in Henan Province

(1) Prediction Indicators

Since the official statistical system lacks a direct indicator for “cold chain logistics demand for fresh agricultural products,” this paper follows common practice and uses the total consumption of various fresh agricultural products as a proxy variable for cold chain logistics demand. The specific calculation formula is: total agricultural product consumption by residents = per capita consumption of urban residents $\times$ urban permanent population + per capita consumption of rural residents $\times$ rural permanent population. The data mainly come from the China Statistical Yearbook and the Henan Statistical Yearbook from 2001 to 2024, covering major categories such as vegetables and edible fungi, melons and fruits, meat, poultry eggs, milk, and aquatic products.

(2) Influencing Factor Indicators

Based on literature research and current situation analysis, 17 secondary indicators were preliminarily selected as potential influencing factors from five dimensions: economic development level, residents' living standard, logistics development level, product supply level, and transportation and informatization level, as shown in Table 1.

Table 1. Influencing factor indicators of cold chain logistics demand for fresh agricultural products in Henan Province

Primary indicator	Secondary indicator	Unit
Economic development level	Per capita GDP	yuan
	Total retail sales of consumer goods	100 million yuan
	Total import and export volume	100 million yuan
	Per capita consumption expenditure of urban residents	yuan
	Contribution of the tertiary industry	%
Logistics development level	Freight volume	10,000 tons
	Freight turnover	100 million ton-km
	Total operating mileage of highways and railways	km
Product supply level	Urban permanent population	10,000 persons
	Per capita consumption of fresh agricultural products by urban residents	kg
	Total output of fresh agricultural products	10,000 tons
Transportation and informatization level	Internet broadband access ports	10,000 ports
	Fixed asset investment in agriculture, forestry, animal husbandry and fishery	100 million yuan
	Fixed asset investment in the logistics industry	100 million yuan
	Number of urban employees in the logistics industry	10,000 persons
	Express delivery volume	10,000 pieces
	Research funding investment	100 million yuan

(3) Data Sources

This paper selects a total of 17 factors influencing cold chain logistics demand in Henan Province as the research indicators, and names the variables as follows [17]: fresh agricultural product cold chain logistics demand y , per capita GDP X_1 , total retail sales of consumer goods X_2 , total import and export volume X_3 , per capita consumption expenditure of urban residents X_4 , contribution rate of the tertiary industry X_5 , freight volume X_6 , freight turnover X_7 , total operating mileage of highways and railways X_8 , urban permanent population X_9 , per capita consumption of fresh agricultural products by urban residents X_{10} , total output of fresh agricultural products X_{11} , internet broadband access ports X_{12} , fixed asset investment in agriculture, forestry, animal husbandry and fishery X_{13} , fixed asset investment in the logistics industry X_{14} , number of urban employees in the logistics industry X_{15} , express delivery volume X_{16} , and research funding investment X_{17} . Their specific values are shown in Table 2.

7, total operating mileage of highways and railways X_8 , urban permanent population X_9 , per capita consumption of fresh agricultural products by urban residents X_{10} , total output of fresh agricultural products X_{11} , internet broadband access ports X_{12} , fixed asset investment in agriculture, forestry, animal husbandry and fishery X_{13} , fixed asset investment in the logistics industry X_{14} , number of urban employees in the logistics industry X_{15} , express delivery volume X_{16} , and research funding investment X_{17} . Their specific values are shown in Table 2.

Table 2. Indicators influencing cold chain logistics demand in Henan Province from 2001 to 2024

Year	Fresh agricultural product demand / 10,000 tons	Per capita GDP / yuan	Total retail sales of consumer goods / 100 million yuan	Total import and export volume / 100 million yuan
t	y	X_1	X_2	X_3
2001	558.64	5867	2057.80	231.13
2002	614.84	6359	2275.39	265.25
2003	645.29	7279	2518.19	390.52
2004	713.99	8763	2923.73	547.59
2005	694.26	10682	3362.58	626.54
2006	768.63	12758	3908.68	780.91
2007	864.95	15756	4658.58	980.39
2008	875.03	18672	5772.92	1223.80
2009	911.24	20170	6689.09	917.98
2010	863.90	23892	7922.66	1204.40
2011	876.65	27788	9337.22	2071.20
2012	909.93	30410	10767.69	3260.27
2013	971.79	33103	12243.51	3716.51
2014	846.01	36020	13777.41	3994.36
2015	929.94	38042	15475.80	4600.19
2016	1012.67	41242	17274.50	4714.70
2017	1047.13	45480	19289.11	5232.79
2018	1110.57	51057	21267.96	5512.71
2019	1209.56	54378	23476.13	5711.63
2020	1278.38	54592	22502.77	6654.80
2021	1406.30	58320	24381.70	8202.07
2022	1432.22	59537	24407.41	8524.14
2023	1461.68	61592	26004.25	8107.88
2024	1422.55	64854	27596.69	8201.72

Table 2. (Continued)

Per capita consumption expenditure of urban residents / yuan	Contribution rate of tertiary industry / %	Freight volume / 10,000 tons	Freight turnover / 100 million ton-km
X4	X5	X6	X7
4110	37.8	65191	1573.28
4505	5.9	68397	1649.22
4942	35.2	69689	1891.73
5294	28.3	73796	2107.26
6038	29.5	78827	2282.60
6658	28.6	86608	2415.89
7827	31.8	101410	2729.30
8837	29.7	138392	5215.84
9567	35.0	169643	6146.09
10838	29.7	202470	7141.82
12336	33.5	240965	8530.79
13733	34.1	272240	9490.26
14822	36.0	184669	7259.81
16184	37.0	200626	7401.12
17154	44.2	192715	6948.05
18088	52.4	205385	7383.54
19422	51.5	229458	8228.70
20989	52.4	259461	8982.12
21972	49.5	218647	8658.54
20645	70.9	219072	8833.22
23178	64.9	254624	10674.57
23539	32.4	260014	11751.16
25570	46.2	283086	12228.82
26509	41.7	293441	12856.77

Table 2. (Continued)

Total operating mileage of highways and railways / km	Urban permanent population / 10,000 persons	Per capita consumption of fresh agricultural products by urban residents / kg	Total output of fresh agricultural products / 10,000 tons	Internet broadband access ports / 10,000 ports
X8	X9	X10	X11	X12
72360	2334	239.35	6315.97	185.56
75088	2480	247.92	6874.19	208.42
77241	2629	245.45	6419.86	245.81
79470	2808	254.27	7481.04	269.17
83506	2994	241.48	8391.20	274.28
240339	3189	252.01	8303.41	230.80
242665	3389	269.12	8838.48	321.40
244634	3573	257.20	8952.21	497.30
246212	3758	254.25	9234.80	693.20
249313	4193	238.09	9656.58	875.80
251790	4420	228.60	9746.47	1104.10
254471	4590	227.92	9660.06	1435.70
254653	4813	232.29	9613.05	1747.00
254965	5001	194.71	9668.74	2016.40
255789	5274	203.89	9846.48	3241.90
272907	5546	212.30	10175.67	4345.80
273275	5752	210.69	10565.24	4475.80
274049	5978	215.52	10236.34	4780.80
276299	6204	226.47	10317.77	4752.80
276790	6389	232.01	10480.24	4934.50
278089	6510	252.07	10471.01	5631.00
284201	5634	254.21	10781.44	6228.60
287863	5701	259.63	11008.36	6624.90
290920	5795	246.50	12234.29	6877.80

Table 2. (Continued)

Fixed asset investment in agriculture, forestry, animal husbandry and fishery / 100 million yuan	Fixed asset investment in the logistics industry / 100 million yuan	Number of urban employees in the logistics industry / 10,000 persons	Express delivery volume / 10,000 pieces	Research funding investment / 100 million yuan
X13	X14	X15	X16	X17
106.05	244.62	42.41	539	30.72
113.35	342.10	42.73	761	32.43
149.06	368.94	32.94	945	36.66
128.20	415.01	33.34	1105	44.81
166.56	541.43	32.91	1163	59.60
215.42	696.68	31.51	1136	83.71
286.01	508.38	30.96	2940	107.11
538.14	485.48	36.38	3442	129.60
761.57	583.89	28.78	4080	184.37
824.14	791.54	29.15	5765	220.30
670.50	665.31	30.24	8378	275.49
825.88	927.25	38.65	12503	323.22
962.02	1201.45	49.70	19444	366.30
1343.18	1427.56	52.03	29484	409.11
1738.89	1937.81	55.25	51450	444.25
2159.76	1944.56	49.70	83875	505.92
2574.42	2487.54	76.78	107378	596.66
2277.38	2989.07	74.92	152632	688.70
2170.37	3309.81	41.16	211093	816.04
2433.47	3848.28	42.14	310005	926.08
2188.14	4021.45	39.28	435553	1046.39
2082.34	4417.09	36.25	445289	1171.82
1671.93	5583.00	35.88	604600	1211.66
1822.40	4935.37	32.82	905257	1275.10

(4) Grey Relational Analysis

To eliminate dimensional influence and screen out key influencing factors, grey relational analysis is used to calculate the correlation between the influencing factors and

demand Y. The closer the relational degree is to 1, the stronger the consistency between the factor and the change trend of demand. A threshold of 0.6 is set, and indicators with relational degrees below this value will be eliminated. The calculation results are shown in Table 3.

Table 3. Grey relational degrees of influencing factors with demand

Primary indicator	Secondary indicator	Variable	Grey relational degree
Economic development level	Per capita GDP	X1	0.8491
	Total retail sales of consumer goods	X2	0.8382
	Total import and export volume	X3	0.8512
	Per capita consumption expenditure of urban residents	X4	0.8327
	Contribution of the tertiary industry	X5	0.7277
Logistics development level	Freight volume	X6	0.7563
	Freight turnover	X7	0.8099
	Total operating mileage of highways and railways	X8	0.6727
Product supply level	Urban permanent population	X9	0.7707
	Per capita consumption of fresh agricultural products by urban residents	X10	0.533
	Total output of fresh agricultural products	X11	0.7607
Transportation and informatization level	Internet broadband access ports	X12	0.8318
	Fixed asset investment in agriculture, forestry, animal husbandry and fishery	X13	0.7527
	Fixed asset investment in transportation, warehousing and postal services	X14	0.8322
	Number of urban employees in transportation, warehousing and postal services	X15	0.6061
	Express delivery volume	X16	0.7977
	Research funding investment	X17	0.8846

According to Table 3, the grey relational degree of indicator X10 (per capita consumption of fresh agricultural products by urban residents) is 0.533, which is lower than the

threshold of 0.6, so it is eliminated. The remaining 16 indicators have strong correlations with cold chain logistics demand and are finally determined as the input variables for

modeling.

4. LSTM-Based Cold Chain Demand Forecasting in Henan Province

(1) Parameter Settings and Training

The data from 2001 to 2019 are used as the training set, and the data from 2020 to 2023 are used as the test set. All indicator data are normalized to accelerate model convergence. Through multiple experiments and adjustments, the final parameters of each model are determined to ensure accuracy while avoiding overfitting. For example, the BP

neural network is set with 16 nodes in the input layer, the number of hidden layer nodes is determined as 12 according to Equation (3-3), the learning rate is 0.05, and the maximum number of iterations is 70,000. The LSTM network is set with 64 hidden units, 250 iterations, and a learning rate of 0.005.

(2) Comparison of Model Prediction Performance

To objectively evaluate model performance, the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) are used to compare the models on the test set. The results are shown in Table 4.

Table 4. Prediction error comparison of the five models on the test set

Model	Mean Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE/%)	Root Mean Square Error (RMSE)
Wavelet Neural Network	228.714	16.3620	228.7319
BP Neural Network	112.714	8.0890	113.0219
GA-BP Neural Network	14.714	1.0602	14.9263
PSO-BP Neural Network	1.718	0.1255	2.0428
LSTM Neural Network	0.246	0.0178	0.2776

It can be clearly seen that the LSTM model has the lowest error, with an MAE of 0.246, significantly outperforming the other models. The PSO-BP model ranks second, and its performance is significantly better than that of the basic BP neural network and the WNN model, indicating that the optimization algorithm effectively improves the prediction capability of the neural network. The GA-BP model also performs well, but its accuracy is slightly lower than that of PSO-BP. The fitting performance of each model is shown in Figs. 2-6, and the prediction curve of the LSTM model coincides with the actual value curve.

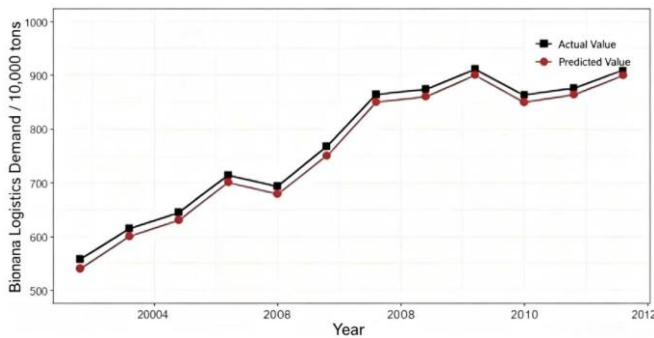


Figure 2. Visualization of predicted and actual values of the wavelet neural network model

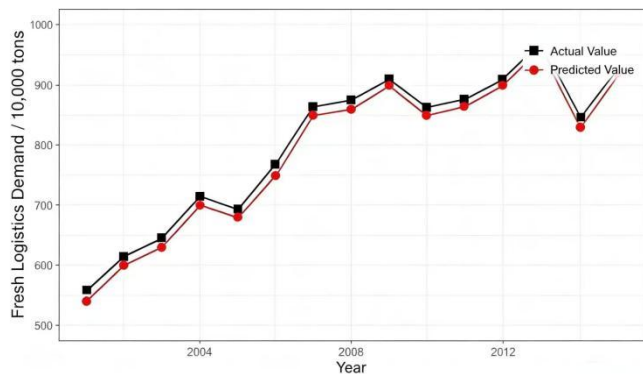


Figure 3. Visualization of predicted and actual values of the BP neural network model

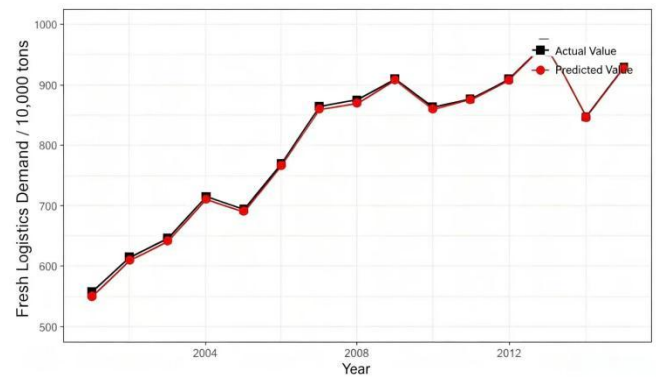


Figure 4. Visualization of predicted and actual values of the GA-BP model

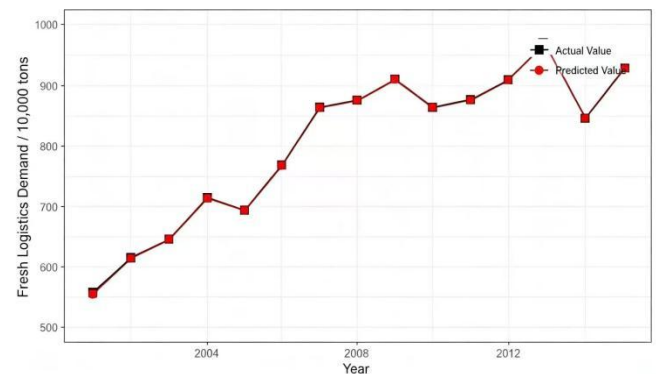


Figure 5. Visualization of predicted and actual values of the PSO-BP model

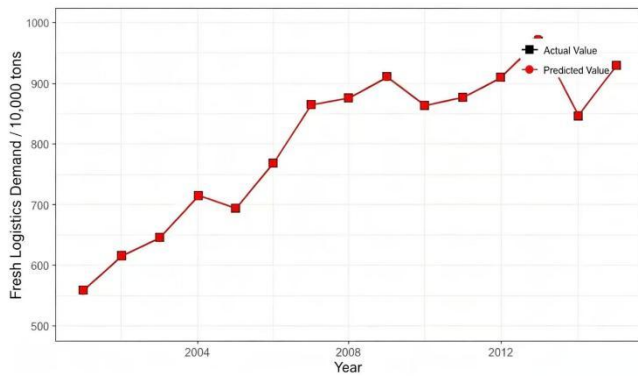


Figure 6. Visualization of predicted and actual values of the LSTM model

(3) Forecasting of Agricultural Product Cold Chain Logistics Demand in Henan Province

The best-performing LSTM model was selected and retrained using all data from 2001 to 2024, and then used to forecast the cold chain logistics demand for fresh agricultural products in Henan Province from 2025 to 2029. The prediction results are shown in Table 5.

Table 5. Forecast of cold chain logistics demand for fresh agricultural products in Henan Province from 2025 to 2029

Year	LSTM predicted demand /10,000 tons
2025	1459.26
2026	1493.88
2027	1528.55
2028	1563.12
2029	1597.80

According to the prediction results shown in Table 5, the cold chain logistics demand for fresh agricultural products in Henan Province will maintain a steady growth trend over the next five years, while the annual growth rate will show a slight slowdown. This reflects that, against the background of consumption upgrading and demographic changes, the total demand continues to expand, but the growth rate may gradually stabilize. These prediction results provide an important quantitative reference for Henan Province to plan cold chain infrastructure in advance and rationally allocate logistics resources.

5. Conclusion

This paper systematically analyzes the development status and influencing factors of cold chain logistics for fresh agricultural products in Henan Province, and constructs and compares five prediction models: wavelet neural network, BP neural network, GA-BP, PSO-BP, and LSTM. The results show that the LSTM model has the highest accuracy and stability in forecasting cold chain logistics demand in Henan Province. The LSTM-based prediction indicates that the cold chain logistics demand for fresh agricultural products in Henan Province will continue to grow steadily from 2025 to 2029. In view of future demand and current challenges, this paper proposes countermeasures and suggestions to promote high-quality development from four aspects: technology application, facility construction, talent cultivation, and policy support.

This study still has certain limitations. For example, the prediction model is mainly based on historical macro data.

Future research can integrate multi-source information such as real-time market data and consumer behavior data to improve the timeliness and refinement of prediction. In addition, emerging issues such as carbon emissions from cold chain logistics and emergency support capacity need to be further explored. Looking ahead, with the deep integration of the digital economy and the real economy, smart, green, and resilient development will become the core directions of cold chain logistics development. Henan Province should seize opportunities, continue to innovate, and continuously improve the modern cold chain logistics system, so as to provide more solid support for ensuring national food security, promoting rural revitalization, and boosting consumption upgrading.

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