Research Article

Prediction of Regional Logistics Heat and Coupling Development between Regional Logistics and Economic Systems

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The research on logistics heat facilitates the understanding of the drivers of regional logistics development. However, many scholars ignore the difference between prediction methods in terms of attributes and focal points of data analysis during the selection of regional logistics heat prediction model. Regional logistics interacts with regional economy. However, the studies on the coupling development between the two systems fail to make a detailed analysis in the light of their actual situation. Therefore, the evaluation of the coordination degree is often biased. To solve the problem, this paper probes into the prediction of regional logistics heat and the coupling development between regional logistics and economic systems. Firstly, an index system was established to measure the level of coupling development between the two systems, and a grey relational analysis was performed on the indices, leading to the evaluation results on coordination degree. Next, a composite model of GM (1, 1) and back-propagation (BP) neural network was proposed, and the deviation interval of the composite predictions was predicted based on Markov chain prediction model. The proposed algorithm proved effective through experiments.

1. Introduction

The logistics industry is an important support for the flow of economic elements and the junction between various parts of social production. It can promote both social development and economic benefits [1–3]. Logistics heat is the abstraction of specific geographical things, e.g., a logistics warehouse and a delivery point. The concept truthfully reflects the development of regional logistics and demonstrates the real-time logistics distribution with high credibility. Featured by timeliness, accuracy, scientific nature, and wide coverage, logistics heat should be studied to further understand the drivers of regional logistics development [4–6]. Regional logistics interacts with regional economy. Economic development expands the traffic network, improves the integration between transportation methods, and thus boosts the development of logistics industry [7–10].

Logistics heat has always been a hot topic in the research of the logistics industry [11–15]. Lan and Zhong [16] carried out entropy analysis and classification of the data collected from online logistics heat maps, aiming to optimize the spatial pattern of logistics in economic development zones. Wang [17] conducted logistic regression of the logistical network system, which centers on regional economic scale and logistics facilities, and obtained the description and analysis result on spatial logistics pattern, including service ability, service level, and radiation range. Based on logistics heat correlation index, Zhou and Zhang [18] analyzed the spatial pattern of logistics hubs at different levels and compared the internal spatial correlations within a region under different transportation conditions, market economy backgrounds, and policy support intensities. Lacoa et al. [19] summarized the development features of modern logistics packaging and e-commerce logistics against the rapid development of the big data and artificial intelligence (AI) and
regarded green logistics and intelligent logistics as the direction of logistics transformation and upgrading. Ishii et al. [20] surveyed the logistics development state of Yangtze River Economic Belt and depicted the logistics heat distribution features at macro and micro levels. Wang et al. [21] modeled the coupling coordination degree between logistics and economy, identified the drivers of the logistics distribution features, and explored the spatiotemporal evolution law of logistics-economy coupling.

From the perspective of logistics heat, visualization tools can be adopted to analyze the spatiotemporal evolution pattern of regional economy and logistics heat at both macro and micro levels. This helps to discover the problems in regional logistics development and provide objective and authentic data support for relevant studies. Currently, most scholars in the industry refer to relevant research results to select the factors affecting the coupling development of regional logistics heat and economic systems, failing to analyze the specific conditions of the objects. That is why the coordination degree is often evaluated incorrectly [22]. Besides, many scholars ignore the difference between prediction methods in terms of attributes and focal points of data analysis, during the selection of regional logistics heat prediction model. To solve the problem, this paper introduces grey relational analysis and neural network into the prediction of regional logistics heat and the coupling development between regional logistics and economic systems. The main contents of this work are as follows: (1) setting up an index system to measure the level of coupling development between the two systems and carrying out grey relational analysis of all the indices; (2) evaluating the coordination degree of the coupling development between the two systems; (3) combining GM (1, 1) with back-propagation (BP) neural network into a hybrid prediction model for regional logistics heat; (4) estimating the deviation interval of the composite predictions, using the Markov chain prediction model. The proposed algorithm proved effective through experiments.

2. Grey Relational Analysis and Coupling Development Evaluation

2.1. Grey Relational Analysis. Grey relational analysis provides a quantitative metric for the development trend of a system. It is particularly suitable for analyzing dynamic processes. Before grey relational analysis, this paper draws on the existing research and selects the following evaluation indices, forming a systematic, scientific, operable, and stable index system to measure the level of coupling development between regional logistics system and regional economic system quantitatively and qualitatively:

1. Mileage of regional transportation lines, LE1, which reflects the construction of regional logistics infrastructure.
2. Fixed asset investment in logistics, LE2, which reflects the development potential of regional logistics industry.
3. Number of logistics employees, LE3, which measures regional logistics development from the angle of manpower.
4. Volume of freight traffic, LE4, which reflects the development scale of regional logistics.
5. Total output of logistics industry, LE5, which reflects the contribution of logistics to regional economy.
6. Growth rate of added value of logistics, LE6, which reflects the development speed and overall trend of regional logistics.
7. Growth rate of logistics investment, LE7, which reflects the ability and trend of regional logistics attracting internal/external investment.
8. Logistics development environment, LE8, which comprehensively reflects the development expectation of regional logistics.
9. Logistics user satisfaction, LE9, which influences the subsequent development of regional logistics.
10. Logistics talent cultivation, LE10, which reflects the training situation of professional talents.
11. Regional gross domestic product (GDP), LE11, which reflects the overall level of regional economic development.
12. Tertiary industry as a proportion of GDP, LE12, which reflects the advanced level of regional economic development.
13. Total retail sales of consumer goods, LE13, which measures the changes in regional retail market and the prosperity of regional economy.

Indices 1–10 are about regional logistics development, and indices 11–13 are about regional economic development. To prevent some indices from being ignored due to their units or dimensionality, the above index data should be normalized by

\[
LE_i = \frac{LE_i - LE_{min}}{LE_{max} - LE_{min}}.
\]

By (1), all the index data were converted into numbers in [0, 1]. By taking the correlation coefficient between the contrastive series and the reference series as the maximum, the correlation coefficient between a regional logistics development index and a regional economic development index can be calculated by

\[
\delta_i (i) = \frac{\Delta_{\min} + \delta_{\Delta_{\max}}}{\Delta_i (i) + \delta_{\Delta_{\max}}}
\]

The grey correlation between indices equals the mean of the correlation coefficients obtained by (2):

\[
\rho_i = \frac{1}{M} \sum_{l=1}^{M} \delta_i (l).
\]
2.2. Coupling Development Evaluation. With different attributes and relations, regional logistics system and regional economic system constitute a composite system of regional logistics-regional economy. The development states of the two systems determine the development coordination between them. Let $ZF_i$ be the $i$-th system; let $YS_i$, $ST_i$, and $GN_i$ be the environmental, structural, and functional elements of $ZF_i$, respectively. The correlations, IR, between systems or within each system are diverse, interactive, hierarchical, and dynamic. These are natural multidimensional attributes within the systems. Let $h$ be the period measuring the time variation in each system. Then, whether the coordination degree between elements is reasonable can be characterized by

$$ST_{ZF} = \{ZF_1, ZF_2, ZF_3 \cdots ZF_m, IR, h\},$$

where $m$ is the number of systems ($m \geq 2$); $ZF_i \in \{YS_i, ST_i, GN_i\}$.

Let $ZF_i(h)$ be the sum of composite scores between systems in period $h$; $ZF_i(h-1)$ be the composite score of $ZF_i$ in period $h-1$; and $YS_m(h)$ be the composite effect of external environment on $ZF_i$. Then, the relationship between systems can be measured by

$$ZF_i(h) = g_i[ZF_1(h), ZF_2(h), ZF_3(h), \ldots, ZF_m(h), ZF_m(h-1), YS_m(h)],$$

$$l = 1, 2, \ldots, m.$$  

Let $\varepsilon(h)$ be the development state factor of each system in period $h$; $ZF(h)$ be the composite development state of the composite system in period $h$; and $\theta(h)$ be the weight of $\varepsilon(h)$. According to the definition of the coordination degree of the composite system, the coordinated development of the composite system can be quantified by

$$\max ZF(h) = \sum_{i=1}^{m} \theta_i \varepsilon_i(h).$$  

Formula (6) shows that the better the development state and the higher the benefit of a system, the greater the value of $\varepsilon(h)$. Meanwhile, $\theta(h)$ characterizes the development state of that system on the composite system. On this basis, the order parameters of regional logistics system and regional economic system were configured. If the selected order parameters boost the benefits of the composite system, then the composite system has a positive effect; otherwise, the composite system has a negative effect.

Let $PA(V_{ij})$ be the effective contribution of the order parameter $A_{ij}$ to the corresponding system, and let $UL_{ij}$ and $LL_{ij}$ be the upper and lower bounds of the critical point of the order parameter $A_{ij}$ at the stable state of the composite system, respectively; i.e., $LL_{ij} \leq A_{ij} \leq UL_{ij}$. Then, the contribution of an order parameter to the development of the composite system can be described by

$$PA(V_{ij}) = \begin{cases} \frac{A_{ij} - UL_{ij}}{UL_{ij} - LL_{ij}}, & i = 1, k, \\ \frac{LL_{ij} - A_{ij}}{UL_{ij} - LL_{ij}}, & i = 1, m. \end{cases}$$

3. Construction of Prediction Model

3.1. GM (1, 1) Model. Figure 1 shows the cargo throughput and its growth rate at regional logistics centers. The scientific prediction of regional logistics heat is premised on the index system of the coupling development level between regional logistics system and regional economic system. Therefore, it is particularly important to select a suitable prediction method and understand the relevant issues of regional logistics heat. Based on correlation space and smooth discrete function, grey system theory defines grey derivative and grey differential equation and further establishes a dynamic model in the form of differential equation based on discrete data series. Based on the grey relational analysis results in the previous section, and the small sample size and nonlinearity of regional logistics heat, this paper combines GM (1, 1) with BP neural network into a composite prediction model to forecast the regional logistics heat, in the light of the coupling development between regional logistics system and regional economic system.

The applicability of GM (1, 1) model can be verified by the ratio test on the known series. The ratio of the initial values of index data $a^{(0)} = (a^{(0)}(1), a^{(0)}(2), \ldots, a^{(0)}(m))$ can be calculated by

$$\mu_l = \frac{a^{(0)}(l-1)}{a^{(0)}(l)}, \quad l = 2, 3, \ldots, m.$$  

If the index data meet the interval

$$A = (e^{-2/m+1}, e^{2/m+1}),$$

the initial series $a^{(0)}$ can be calculated by setting up a GM (1, 1) prediction model. Otherwise, the index data need to be converted by the rule

$$b^{(l)}(l) = a^{(0)}(l) + d, \quad l = 1, 2, \ldots, m,$$

through accumulative generating operation (AGO) on the original series $a^{(0)} = (a^{(0)}(1), a^{(0)}(2), \ldots, a^{(0)}(m))$:

$$a^{(1)}(h) = \sum_{l=1}^{h} a^{(0)}(l),$$

$$l = 1, 2, \ldots, m.$$
Let DQ be the development coefficient that measures the trends of target series $a^{(0)}$ and $a^{(t)}$, and let $v$ be the grey action of the variation in index data. Then, the first-order linear differential equation can be constructed based on $a^{(1)}$:

$$\frac{da^{(1)}}{dh} + DQ \cdot a^{(1)} = v. \quad (12)$$

Solving the differential equation by least squares method $W^* = (DQ, v)^T = (O^T O)^{-1} O^T B_m$, we can obtain the desired DQ and v:

$$a^{(1)}(h + 1) = \begin{bmatrix} a^{(0)}(1) - \frac{v}{DQ} \cdot e^{-DQ\cdot h} + \frac{v}{DQ} \end{bmatrix}$$

By taking average of cumulative index data, the vector $O$ and constant term vector $B_m$ can be obtained as

$$O = \begin{bmatrix} \frac{1}{2} \left[ a^{(1)}(1) + a^{(1)}(2) \right] & \cdots & 1 \\ \vdots & \ddots & \vdots \\ -\frac{1}{2} \left[ a^{(1)}(m) + a^{(1)}(m) \right] & \cdots & 1 \\ \end{bmatrix}, \quad B_m = \begin{bmatrix} a^{(0)}(2) \\ a^{(0)}(3) \\ \vdots \\ a^{(0)}(m) \end{bmatrix}.$$

Substituting the solution of $a^{(1)}(h + 1)$ to (15), the regional logistics heat can be predicted as

$$a^{(0)}(h + 1) = a^{(1)}(h + 1) - a^{(1)}(h). \quad (15)$$

Then, $a^{(1)}(h + 1)$ can be solved by substituting DQ and v into (11). To obtain the actual prediction $a^{(0)}(h + 1)$ in period $h + 1$, the data imported to the prediction model must go through the inverse AGO (IAGO), because the model has undergone AGO:

$$a^{(0)}(h + 1) = a^{(1)}(h + 1) - a^{(1)}(h). \quad (15)$$

The standard deviation $ZB_1$ of the residual series can be calculated by

$$ZB_1 = \sqrt{\frac{\sum_{i=1}^{m} \left( a^{(0)}(i) - \bar{a}^{(0)} \right)^2}{m - 1}}. \quad (17)$$

The standard deviation $ZB_2$ of the original index data series can be calculated by

$$ZB_2 = \sqrt{\frac{\sum_{i=1}^{m} \left( a^{(0)}(i) - \bar{a}^{(0)} \right)^2}{m - 1}}. \quad (18)$$

where

$$\bar{a} = \frac{1}{m} \sum_{i=1}^{m} a^{(0)}(i), \quad \bar{\sigma} = \frac{1}{m} \sum_{i=1}^{m} \sigma^{(0)}.$$

The posterior error can be calculated by

$$HE = \frac{ZB_1}{ZB_2}. \quad (20)$$

The small error probability can be calculated by

$$GV = GV \left\{ \left| v^{(0)}(i) - \bar{v}^{(0)} \right| < 0.67S_2 \right\}, \quad (21)$$

where

$$\sigma^{(0)} = \left| a^{(0)}(i) - a^{(0)}(i) \right|.$$

The accuracy of the prediction model can be divided into different levels according to indices HE and GV.

### 3.2. BP Neural Network

Figure 2 shows the structure of BP neural network. This paper sets up a BP neural network via the following steps.

Firstly, the connection weights of the neural network were randomly assigned in the interval of $(0, 1)$. Then, the objective training error $\xi$, training accuracy $\varepsilon$, and maximum number of learning iterations $N$ were configured. Then, the input samples $\{L_i = (L_{i1}, L_{i2}, \ldots, L_{im})\}$ and the expected output samples $O_b = (O_{1b}, O_{2b}, \ldots, O_{mb})$ were provided to the established neural network.

Let $w_{ij}$ be the connection weight between the input layer and the hidden layer and $\varphi_i$ be the output threshold of each hidden layer node. Then, the output $d_j$ of each hidden layer node can be calculated from the input $r_j$ of that node, using the activation function $g$:

$$r_j = \sum_{i=1}^{m} \omega_{ij} L_i - \omega_j, \quad (23)$$

$$d_j = g(r_j), \quad j = 1, 2, \ldots, t.$$

Let $w_{jh}$ be the connection weight between the hidden layer and the output layer and $\eta_h$ be the output threshold of each output layer node. Then, the input $SR_h$ of each output layer node can be given by
To improve the prediction effect of the composite model, it is important to assign a suitable weight to GM (1, 1) and to BP neural network. Let $\theta_i$ be the weight of the $i$-th prediction method; $\xi_{ih}$ be the error of the composite series at time $h$; and $\xi_{ih}$ be the error corresponding to the $i$-th prediction method at time $h$. Then, we have

$$
\xi_{ih} = K_{(h)} - a_{(h)} = \sum_{i=1}^{l} \theta_i \xi_{i(h)}.
$$

To minimize the sum of squared errors (SSE) FH, a constrained objective function $QFH$ can be established:

$$
\text{MinFH} = \sum_{h=1}^{m} \left| \xi_{h}^2 \right| = \sum_{h=1}^{m} \left| \sum_{i=1}^{l} \theta_i \xi_{i(h)} \right|,
$$

where $\theta_i$ satisfies the following equation:

$$
\sum_{i=1}^{l} \theta_i = 1, \quad 0 \leq \theta_i \leq 1.
$$

Then, the composite prediction model for regional logistics heat can be expressed as

$$
b_h = \theta_1 K_1 (h) + \theta_2 K_2 (h) + \ldots + \theta_l K_l (h).
$$

### 3.4. Markov Chain Analysis

The Markov chain can predict the state of index data on regional logistics and economic systems at the next moment, according to the state and trend of the data, and mirror the fluctuations and instability of the index data. Taking the prediction error of regional logistics heat as a random variable, this paper estimates the deviation interval of the prediction by the GM (1, 1)–BP neural network composite model, using the Markov chain prediction model.

If the past is not correlated with a future random process $\{A_i(\theta), h \in \psi\}$, i.e., the future $(A(h_{m+1}) < a)$ is independent of the past $(A(h_{m+1}) = a_{m+1}, \ldots, A(h_1) = a_1)$; then, $\{A_i(\theta), h \in \psi\}$ has Markov property, and $\{A_i(\theta), h \in \psi\}$ can be called a Markov process. For any $h_1 < h_2 < \ldots < h_{m+1}, h \in \psi, 1 \leq i \leq m + 1$, the conditional distribution of $(A(h_{m+1})$ relative to $A(h_1), A(h_2), \ldots, A(h_m)$ can be given by

$$
GV \left( A(h_{m+1}) \leq a | A(h_m) = a_m, \ldots, A(h_1) = a_1 \right) = GV \left( A(h_{m+1}) \leq a | A(h_m) = a_m \right).
$$

Time and state are discrete Markov processes, forming a Markov chain of random variables. The chain is stochastic and stationary, with no after-effect. Let $GV_{ch}$ be the probability that the previous state transfers to the current state $h$ under condition $c$. Then, the transfer can be described by the transfer probability GV:

$$
GV_{ch} = GV \{ a_i = h | a_{i-1} = c \}.
$$

The predicted regional logistic heat has multiple states, $ST_1, ST_2, \ldots, ST_m$, at different moments. Therefore, many different situations may occur during the state transfer. The conditional probabilities under different situations constitute a transfer probability matrix. Let $GV_{ij}$ be the state transfer probability from state $ST_i$ to state $ST_j$. Then, the transfer probability matrix $GV$ can be described as
The elements $G_{ij}$ in matrix $G$ need to satisfy $0 \leq G_{ij} \leq 1$.

\[ \sum_{j=1}^{m} G_{ij} = 1, \quad (i = 1, 2, \ldots, m). \tag{34} \]

Since Markov chain has no after-effect, a multistep state transfer probability matrix can be obtained as

\[ A^{(m+1)} = G \cdot A^{(m)}, \]
\[ A^{(m)} = G^{(m)} \cdot A^{(0)}. \tag{35} \]

4. Experiments and Results Analysis

The research data comes from the panel data on Yangtze River Economic Belt in 2000–2020. Table 1 presents the calculated results on the grey correlations between regional logistics and economy. The established GM (1, 1) prediction model was tested by fitting the historical index data on the coupling development between regional logistics and economic systems in 2000–2020. Based on the predicted regional logistics heat, the fitting effect is shown in Figure 3. The prediction error of GM (1, 1) prediction model was 0.0984. The results of posterior error test were $Z_{B1} = 1957421$, $Z_{B2} = 15144284$, posterior error was $HE = 0.145$, and small probability error was $G_{V}>0.9$. Therefore, the proposed GM (1, 1) prediction model has a high accuracy and, to a certain extent, reflects the future trend of logistics heat scale in the study area.

Figure 4 displays the change curve of training error of BP neural network. The training error curve started to converge at around the 300th iteration. When the prediction accuracy of regional logistics heat reached $8.94 \times 10^{-7}$, the preset prediction accuracy was achieved, and the iteration terminated. Table 2 presents the prediction results and errors of our composite prediction model, which makes full use of the predictions by GM (1, 1) and BP neural network. The two prediction models were integrated by least mean squares (LMS) method. In addition, L1 or L2 term was added to the loss function of the neural network, such that the network would try to minimize these terms. Through the additional L1 or L2 regularization, the network would limit the weight increment, because weight is a part of the loss function. Besides, the network became more generalizable, because it always tries to minimize the loss function. The weights of GM (1, 1) and BP neural network were set to 0.1945 and 0.8055, respectively, aiming to minimize the MSE of the fitted prediction error.

To demonstrate its feasibility and effectiveness, our composite model was compared with GM (1, 1) prediction model and BP neural network in terms of the prediction of regional logistics heat in 2010–2020. Table 3 compares the prediction results and errors of the three models. It can be seen that the composite model achieved the smallest error, the highest accuracy, and the most stable results.

| Logistics indices | LE_{11} | LE_{12} | LE_{13} |
|-------------------|---------|---------|---------|
| LE_{1}            | 0.6452  | 0.2356  | 0.6827  |
| LE_{2}            | 0.4589  | 0.1869  | 0.5403  |
| LE_{3}            | 0.3932  | 0.3562  | 0.3426  |
| LE_{4}            | 0.4241  | 0.1725  | 0.4075  |
| LE_{5}            | 0.8318  | 0.2314  | 0.6421  |
| LE_{6}            | 0.2876  | 0.3265  | 0.3028  |
| LE_{7}            | 0.2163  | 0.3476  | 0.2212  |
| LE_{8}            | 0.5231  | 0.1806  | 0.5063  |
| LE_{9}            | 0.4962  | 0.1963  | 0.4256  |
| LE_{10}           | 0.4035  | 0.2418  | 0.4136  |

Table 1: Grey correlations between regional logistics and economy.
This paper treats the range of regional logistics heat as a random variable. The regional logistics heat is stochastic and stationary, with no after-effect. Based on the prediction errors of the three models above, the prediction results were divided by intervals of equal probability, such that the number of transfers between state intervals is reasonable, and the transfer rules are accurate. The state intervals of the specific prediction results were ST1[4%, 8%], ST2[2%, 4%], ST3[2%, 0.5%], ST4[−0.5% −2%), ST5[−2%, −4%), and ST6[−4% −8%). Table 4 shows the prediction results on regional logistics heat and their errors and states.

Based on the states of the prediction results, the fitted results of the composite prediction model could be compiled into a one-step transfer Markov chain (Figure 5).

From the no-after-effect property of Markov chain, the multistep state transfer probability matrix can be obtained to reflect the variation in regional logistics heat. According to the states of prediction results in the years before the target years, the states of prediction results in the target years, number of transfer steps, and state transfer matrix could be derived by the prediction principle of Markov model. Table 5 shows the Markov chain analysis results of the composite prediction model.

As shown in Table 5, the state transfer probabilities in 2021–2023 mostly fell into the two intervals ST3 and ST4. In 2021, 2022, and 2023, the regional logistics heat was $4.577 \times 10^4$, $4.948 \times 10^4$, and $5.689 \times 10^4$, respectively. Through Markov chain analysis, the maximum probability intervals of the composite prediction model in the three years were $[5.015 \times 10^4, 5.215 \times 10^4]$, $[5.205 \times 10^4, 5.626 \times 10^4]$, and $[5.694 \times 10^4, 6.079 \times 10^4]$, respectively. The ground truth of 2021 fell within $[5.015 \times 10^4, 5.215 \times 10^4]$, testifying the credibility of the predictions for 2022–2023.

According to the evolution trend of regional logistics demand predicted by our model, the cargo throughput in the study area will increase continuously. The outbreak of

| Year | Ground truth | Prediction | MSE |
|------|--------------|------------|-----|
| 2015 | 49735        | 49871.6152 | 0.275 |
| 2016 | 51647        | 52995.1563 | 0.261 |
| 2017 | 51596        | 52351.9481 | 0.017 |
| 2018 | 54273        | 54615.1506 | 0.006 |
| 2019 | 61542        | 62362.4857 | 0.013 |
| 2020 | 65131        | 65851.8416 | 0.011 |

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Table 2: Prediction results and errors of our composite model.

Table 3: Prediction results and errors of different models.

Table 4: Prediction results on regional logistics heat and their states.

Table 5: Prediction results and errors of our composite model.

Table 4: Prediction results on regional logistics heat and their errors and states.
COVID-19 has caused the postponement or cancellation of most large-scale logistics activities and a drastic drop in foreign capital utilization in the short term. These negative effects will greatly impact the logistics service in the study area.

5. Conclusions

This paper introduces grey relational analysis and neural network into the prediction of regional logistics heat and the analysis of the coupling between regional logistics system and regional economic system. Specifically, an index system was constructed to measure the coupling development level between the two systems and to evaluate the grey correlations between the indices. Then, the coordination degree of the coupling development between the two systems was evaluated. Next, a composite prediction model for regional logistics heat was constructed by coupling GM (1, 1) with BP neural network. The Markov chain prediction model was employed to estimate the deviation intervals of the composite predictions. Through experiments, the change curve of the training results of GM (1, 1) and the change curve of the training errors of BP neural network were plotted; the prediction results and errors were obtained for the proposed composite prediction model and compared with those of other prediction models. The comparison shows that the composite model achieved the smallest error, the highest accuracy, and the most stable results.

Due to the limitation of paper length and research ability, our research could be further expanded in many aspects. If conditions permit, the authors will split logistics heat into express delivery, logistics park, etc., and explore the factors affecting each component. The index system could also be enhanced and improved to cover more time profiles, yielding richer conclusions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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