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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, LE_1, which reflects the construction of regional logistics infrastructure.

(2) Fixed asset investment in logistics, LE_2, which reflects the development potential of regional logistics industry.

(3) Number of logistics employees, LE_3, which measures regional logistics development from the angle of manpower.

(4) Volume of freight traffic, LE_4, which reflects the development scale of regional logistics.

(5) Total output of logistics industry, LE_5, which reflects the contribution of logistics to regional economy.

(6) Growth rate of added value of logistics, LE_6, which reflects the development speed and overall trend of regional logistics.

(7) Growth rate of logistics investment, LE_7, which reflects the ability and trend of regional logistics attracting internal/external investment.

(8) Logistics development environment, LE_8, which comprehensively reflects the development expectation of regional logistics.

(9) Logistics user satisfaction, LE_9, which influences the subsequent development of regional logistics.

(10) Logistics talent cultivation, LE_{10}, which reflects the training situation of professional talents.

(11) Regional gross domestic product (GDP), LE_{11}, which reflects the overall level of regional economic development.

(12) Tertiary industry as a proportion of GDP, LE_{12}, which reflects the advanced level of regional economic development.

(13) Total retail sales of consumer goods, LE_{13}, 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

$$\mathrm{LE}_i = \frac{\mathrm{LE}_i - \mathrm{LE}_{\min}}{\mathrm{LE}_{\max} - \mathrm{LE}_{\min}}. \quad (1)$$

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

$$\delta_i(i) = \frac{\Delta \min + \delta_{\Delta \max}}{\Delta_i(i) + \delta_{\Delta \max}}. \quad (2)$$

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

$$e_i = \frac{1}{M}\sum_{l=1}^{M} \delta_i(l). \quad (3)$$

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

$$ST_{ZF} = \{ZF_1, ZF_2, ZF_3 \cdots ZF_m, IR, h\}, \quad (4)$$

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; $ZF_m(h-1)$ 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

$$ZF_i(h) = g_i[ZF_1(h), ZF_2(h), ZF_3(h), \ldots, ZF_m(h), ZF_m(h-1), YS_m(h)] \quad (i = 1, 2, \ldots, m). \quad (5)$$

Let $\varepsilon_i(h)$ 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 $\theta_i(h)$ be the weight of $\varepsilon_i(h)$. According to the definition of the coordination degree of the composite system, the coordinated development of the composite system can be quantified by

$$\max ZF(h) = \sum_{i=1}^{m} \theta_i \varepsilon_i(h). \quad (6)$$

Formula (6) shows that the better the development state and the higher the benefit of a system, the greater the value of $\varepsilon_i(h)$. Meanwhile, $\theta_i(h)$ 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

$$PA(V_{ij}) = \begin{cases} \dfrac{A_{ij} - UL_{ij}}{LL_{ij} - UL_{ij}} i = [1, k], \\[2ex] \dfrac{LL_{ij} - A_{ij}}{LL_{ij} - UL_{ij}} i = [1, m]. \end{cases} \quad (7)$$

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

$$\mu_l = \frac{a^{(0)}(l-1)}{a^{(0)}(l)}, \quad l = 2, 3, \ldots, m. \quad (8)$$

If the index data meet the interval

$$A = \left(e^{-2/m+1}, e^{2/m+1}\right), \quad (9)$$

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

$$b^{(0)}(l) = a^{(0)}(l) + d, \quad l = 1, 2, \ldots, m, \quad (10)$$

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

$$a^{(1)}(h) = \sum_{l=1}^{h} a^{(0)}(l), \quad l = 1, 2, \ldots, m. \quad (11)$$

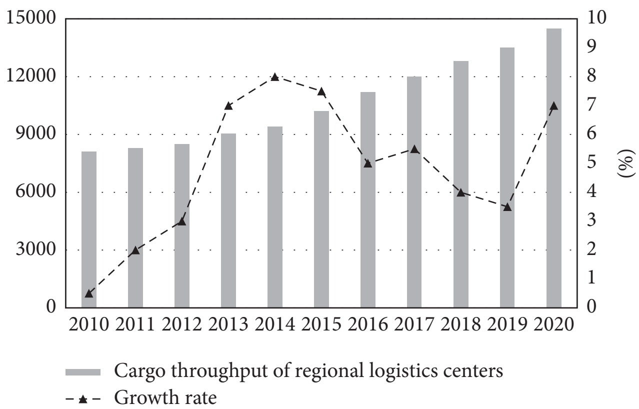

Figure 1: Cargo throughput and its growth rate at regional logistics centers.

Let DQ be the development coefficient that measures the trends of target series $a'^{(0)}$ and $a'^{(1)}$, 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 $a^{(1)}$:

$$\frac{\mathrm{d}a^{(1)}}{\mathrm{d}h} + \mathrm{DQ} \cdot a^{(1)} = v. \tag{12}$$

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

$$a^{(1)}(h+1) = \left\{ a^{(0)}(1) - \frac{v}{\mathrm{DQ}} \right\} e^{-\mathrm{DQ}\cdot t} + \frac{v}{\mathrm{DQ}}. \tag{13}$$

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

$$O = \begin{bmatrix} -\frac{1}{2}\left[a^{(1)}(1) + a^{(1)}(2)\right] & \cdots & 1 \\ -\frac{1}{2}\left[a^{(1)}(2) + a^{(1)}(3)\right] & \cdots & 1 \\ \vdots & \ddots & 1 \\ -\frac{1}{2}\left[a^{(1)}(m-1) + a^{(1)}(m)\right] & \cdots & 1 \end{bmatrix} B_m = \begin{bmatrix} a^{(0)}(2) \\ a^{(0)}(3) \\ \vdots \\ a^{(0)}(m) \end{bmatrix}. \tag{14}$$

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

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

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

$$a'^{(0)}(h+1) = \left(1 - e^{\mathrm{DQ}}\right)\left[a^{(0)}(1) - \frac{v}{\mathrm{DQ}}\right] e^{-\mathrm{DQ}\cdot h}. \tag{16}$$

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

$$\mathrm{ZB}_1 = \sqrt{\frac{\sum_{l=1}^{m}\left(\sigma_{(l)}^{(0)} - \widehat{\sigma}^{(0)}\right)^1}{m-1}}. \tag{17}$$

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

$$\mathrm{ZB}_2 = \sqrt{\frac{\sum_{l=1}^{m}\left(a_{(l)}^{(0)} - \widehat{a}^{(0)}\right)^2}{m-1}}, \tag{18}$$

where

$$\begin{aligned} \widehat{a} &= \frac{1}{m}\sum_{l=1}^{m} a_{(l)}^{(0)}, \\ \widehat{\sigma} &= \frac{1}{m}\sum_{l=1}^{m} \sigma_{(l)}. \end{aligned} \tag{19}$$

The posterior error can be calculated by

$$\mathrm{HE} = \frac{\mathrm{ZB}_1}{\mathrm{ZB}_2}. \tag{20}$$

The small error probability can be calculated by

$$\mathrm{GV} = \mathrm{GV}\left\{\left|\sigma_{(l)}^{(0)} - \widehat{\sigma}^{(0)}\right| < 0.67 S_2\right\}, \tag{21}$$

where

$$\sigma_{(l)}^{(0)} = \left|a_{(l)}^{(0)} - a'^{(0)}_{(l)}\right|. \tag{22}$$

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 ξ, training accuracy ε, and maximum number of learning iterations N were configured. Then, the input samples $\mathrm{LE}_l = (\mathrm{LE}^l{}_1, \mathrm{LE}^l{}_2, \ldots, \mathrm{LE}^l{}_m)$ and the expected output samples $O_0 = (O^l{}_1, O^l{}_2, \ldots, O^l{}_m)$ were provided to the established neural network.

Let ω_{ij} be the connection weight between the input layer and the hidden layer and φ_j 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:

$$\begin{aligned} r_j &= \sum_{i=1}^{m} \omega_{ij}\mathrm{LE}_i - \omega_j, \\ d_j &= g\left(r_j\right), \quad j = 1, 2, \ldots, t. \end{aligned} \tag{23}$$

Let u_{jh} be the connection weight between the hidden layer and the output layer and η_h be the output threshold of each output layer node. Then, the input SR_h of each output layer node can be given by

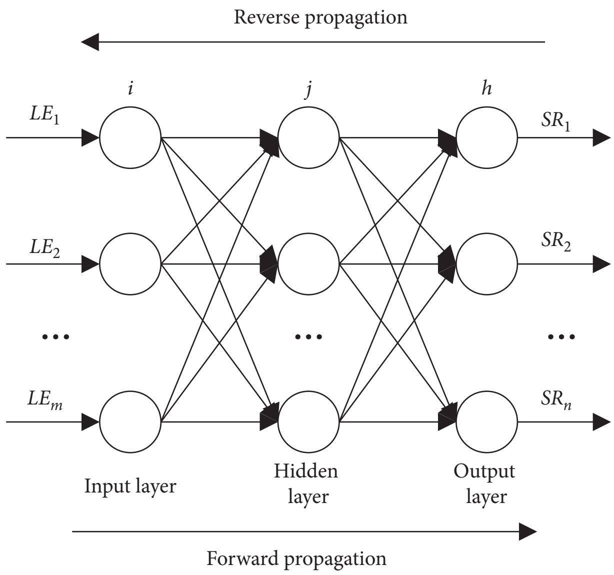

Figure 2: Structure of BP neural network.

$$\mathrm{SR}_h = \sum_{j=1}^{m} u_{jh} d_j - \eta_t. \tag{24}$$

The output SC_h of each output layer node can be calculated by

$$\begin{aligned} \mathrm{SC}_h &= g(\mathrm{SR}_h), \\ h &= 1, 2, \ldots, w. \end{aligned} \tag{25}$$

The error function can be given by

$$\zeta = \frac{1}{2} \sum_{h=1}^{w} (\xi_h - c_h)^2. \tag{26}$$

Based on the calculated error, the partial derivative of the error function for output layer nodes could be obtained. Then, the neural network error will be backpropagated to the input layer. According to the error signal, each layer will update its weight. Thus, the errors of all layers could be iteratively adjusted. The iteration will stop when the error falls below the preset training accuracy, or the number of training iterations reaches the maximum number of learning iterations.

3.3. Composite Prediction Model. Considering the complexity of regional logistics system, it is very difficult to obtain historical development data over a long time. If GM (1, 1) and BP neural network could be combined, the composite prediction model would fit well with the features of regional logistics heat problem.

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 θ_i be the weight of the i-th prediction method; ζ_h be the error of the composite series at time h; and $\zeta_{i(h)}$ be the error corresponding to the i-th prediction method at time h. Then, we have

$$\zeta_h = K_{(h)} - a_{(h)} = \sum_{i=1}^{I} \theta_i \zeta_{i(h)}. \tag{27}$$

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

$$\mathrm{MinFH} = \sum_{h=1}^{m} \left|\zeta_h^2\right| = \sum_{h=1}^{m} \left|\sum_{i=1}^{I} \theta_i \zeta_{i(h)}\right|, \tag{28}$$

where θ_i satisfies the following equation:

$$\sum_{i=1}^{I} \theta_i = 1, \quad 0 \leq \theta_i \leq 1. \tag{29}$$

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

$$b_h = \theta_1 K_1(h) + \theta_2 K_2(h) + \ldots + \theta_I K_I(h). \tag{30}$$

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 $h_1 < h_2 < \ldots < h_{m+1}$, $h_i\in\psi$, $1 \leq i \leq m+1$, the conditional distribution of $A(h_{m+1})$ relative to $A(h_1)$, $A(h_2)$, …, $A(h_m)$ can be given by

$$\begin{aligned} &\mathrm{GV}\left(A\left(h_{m+1}\right) \leq a \middle| A\left(h_m\right) = a_m, \ldots, A\left(h_1\right) = a_1\right) \\ &\quad = \mathrm{GV}\left(A\left(h_{m+1}\right) \leq a \middle| A\left(h_m\right) = a_m\right). \end{aligned} \tag{31}$$

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:

$$\mathrm{GV}_{ch} = \mathrm{GV}\{a_i = h | a_{i-1} = c\}. \tag{32}$$

The predicted regional logistic heat has multiple states, ST_1, ST_2, …, 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

$$GV = \begin{bmatrix} GV_{11} & GV_{12} & \cdots & GV_{1m} \\ GV_{12} & GV_{22} & \cdots & GV_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ GV_{m1} & GV_{m2} & \cdots & GV_{mm} \end{bmatrix}. \tag{33}$$

The elements GV_{ij} in matrix GV need to satisfy

$$\begin{aligned} &0 \leq GV_{ij} \leq 1, \\ &\sum_{j=1}^{m} GV_{ij} = 1, \quad (i = 1, 2, \ldots, m). \end{aligned} \tag{34}$$

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

$$\begin{aligned} A^{(m+1)} &= GV \cdot A^{(m)}, \\ A^{(m)} &= GV^{(m)} A^{(0)}. \end{aligned} \tag{35}$$

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 $ZB_1 = 1957421$, $ZB_2 = 15144284$, posterior error was $HE = 0.145$, and small probability error was $GV > 0.9$. 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 $8.94 * 10^{-7}$, 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.

Table 1: Grey correlations between regional logistics and economy.

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

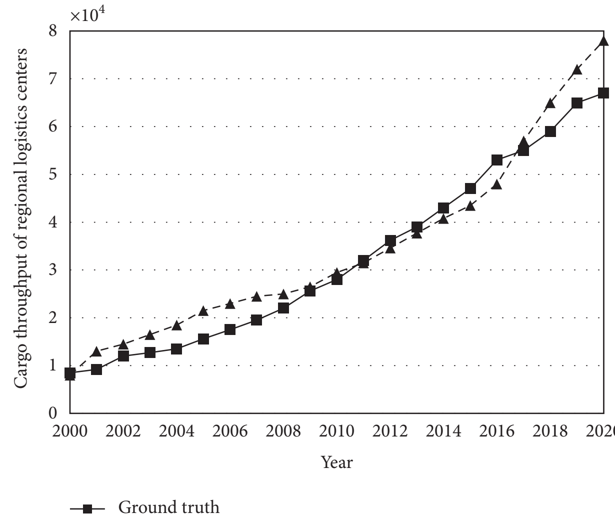

Figure 3: Training results of GM (1, 1) model.

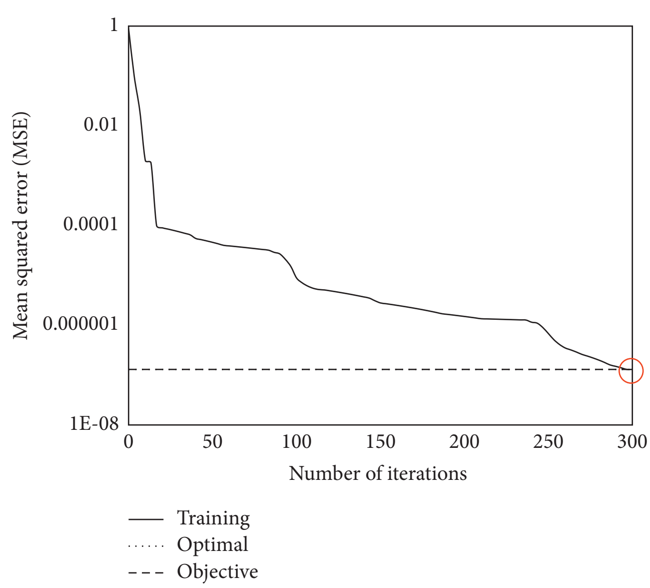

Figure 4: Change curve of training error of BP neural network.

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

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

Table 3: Prediction results and errors of different models.

Year	Ground truth	GM (1, 1)		BP neural network		Composite model	
		Prediction	MSE	Prediction	MSE	Prediction	MSE
2010	8635	8672.25	0.431	8689.71	0.634	8676.64	0.482
2011	10478	12603.72	20.287	9919.56	−5.330	11632.12	11.015
2012	12534	17521.83	39.794	10819.24	−13.681	11941.36	−4.728
2013	14912	18654.31	25.096	11728.61	−21.348	12896.65	−13.515
2014	16253	20156.74	24.019	14849.68	−8.634	15794.72	−2.820
2015	18165	22513.95	23.941	16952.75	−6.674	18984.24	4.510
2016	22789	23891.56	4.838	24195.63	6.172	23673.36	3.881
2017	26453	25234.79	−4.605	28442.12	7.519	27984.21	5.788
2018	31916	27919.32	−12.522	29891.48	−6.343	28561.25	−10.511
2019	32453	30917.08	−4.733	34972.61	7.764	33849.64	4.304
2020	36351	32156.26	−11.540	37156.25	2.215	36894.76	1.496

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 ST_1[4%, 8%], ST_2[2%, 4%), ST_3[2%, 0.5%), ST_4[−0.5%, −2%), ST_5[−2%, −4%), and ST_6[−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 ST_3 and ST_4. In 2021, 2022, and 2023, the regional logistics heat was $4.577 * 10^4$, $4.948 * 10^4$, and $5.689 * 10^4$, respectively. Through Markov chain analysis, the maximum probability intervals of the composite prediction model in the three years were $[5.015 * 10^4, 5.215 * 10^4]$, $[5.205 * 10^4, 5.626 * 10^4]$, and $[5.694 * 10^4, 6.079 * 10^4]$, respectively. The ground truth of 2021 fell within $[5.015 * 10^4, 5.215 * 10^4]$, testifying the credibility of the predictions for 2022–2023.

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

Year	Ground truth	Composite prediction model	
		Relative error	State
2000	1536	−0.236	ST_5
2001	2109	−7.205	ST_6
2002	3512	1.895	ST_3
2003	4173	7.823	ST_1
2004	5236	2.215	ST_2
2005	6014	3.546	ST_2
2006	6531	−3.592	ST_5
2007	7983	4.194	ST_1
2008	8324	3.682	ST_2
2009	8542	2.918	ST_2
2010	8635	1.812	ST_3
2011	10478	−7.613	ST_6
2012	12534	−4.782	ST_6
2013	14912	−3.319	ST_5
2014	16253	−3.842	ST_5
2015	18165	−1.389	ST_4
2016	22789	−0.914	ST_4
2017	26453	−0.237	ST_4
2018	31916	−1.589	ST_4
2019	32453	−1.791	ST_4
2020	36351	−2.985	ST_5

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

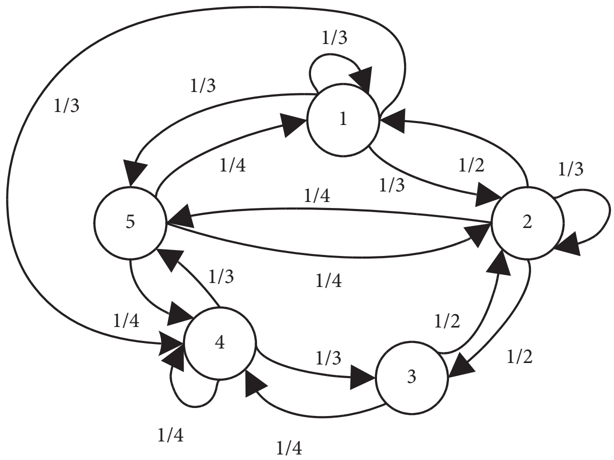

Figure 5: One-step transfer Markov chain.

Table 5: Markov chain analysis results of the composite prediction model.

Year	Prediction result	State	Prediction interval		Probability
2021	45,771.489	ST_1	46,849.152	48,416.052	16.72%
		ST_2	48,496.545	49,894.156	12.34%
		ST_3	49,981.925	50,893.525	21.93%
		ST_4	50,156.513	52,156.063	21.02%
		ST_5	52,950.258	55,892.158	11.64%
		ST_6	53,214.245	56,412.245	15.32%
2022	49,489.315	ST_1	49,985.491	52,819.564	20.75%
		ST_2	52,895.987	53,478.157	12.68%
		ST_3	53,892.562	54,314.156	22.74%
		ST_4	52,059.364	56,265.131	20.38%
		ST_5	56,652.895	59,491.564	15.42%
		ST_6	57,112.54	31,245.23	14.57%
2023	56,894.784	ST_1	53,897.252	56,792.256	20.63%
		ST_2	56,394.956	57,697.563	13.12%
		ST_3	57,623.561	58,318.395	20.51%
		ST_4	56,948.213	60,796.462	21.16%
		ST_5	60,156.332	64,983.567	16.38%
		ST_6	62,558.356	67.412	9.28%

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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