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The Analysis of Differential High-Quality Development of Economy by Deep Neural Network and Internet of Things

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ABSTRACT This study solves the problems of insufficient objectivity and a large amount of calculation in traditional regional economic development level evaluation methods. The conventional Back Propagation (BP) neural network can easily fall into local extremes and slow convergence speed. Firstly, an improved BP algorithm is proposed. The LM (Levenberg-Marquardt) algorithm optimizes the BP neural network. Secondly, the evaluation model of Henan County's economic development level is constructed based on the improved BP algorithm. Finally, Matlab software is used to design simulation experiments. The BP model is used to evaluate the comprehensive economic development level of 107 counties in Henan Province. The results show that the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE) of the output of the proposed BP model are 0.9, 1.72, and 3, respectively. This is far lower than other popular algorithms and is more suitable for estimating the comprehensive development level of the region. The overall economic development level of counties in Henan Province is relatively balanced but partially uneven. The polarization of development is more serious. The middle-level and middle- and lowlevel development counties account for a relatively large area, and the overall distribution characteristics are "convex". This study aims to provide necessary technical support for a more accurate analysis of Henan counties' comprehensive economic development level distribution and then to promote the coordinated development of counties in the province.

INDEX TERMS Neural network, county economic development level, evaluation system, high-quality development.

I. INTRODUCTION

At present, China's economy has already shifted from rapid growth to a stage of high-quality development [1]. Highquality product improves the quality of economic development on the premise of stable growth. Therefore, China should not blindly pursue the speed of action but should pay attention to the quality of the product [2]. In recent years, with the rapid development of the Internet of Things (IoT), the popularity of online payment and shopping has undoubtedly extensively promoted the development of China's economy [3]. In addition, people can directly obtain statistical

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data related to economic growth from the IoT. On this basis, some methods can be used to analyze the problems in the region's development and make improvements to achieve a "qualitative" change in the regional economic growth [4]. Stoyanova *et al.* [5] pointed out that data can be transmitted through the network based on IoT technology without interaction between people and computers or between people. A large amount of data information obtained in the network brings convenience to people [5]. Al Hayajneh *et al.* [6] proposed a system model that effectively combines software-defined networking with the IoT to improve the security of the IoT. For the IoT, which can only use Hyper Text Transfer Protocol (HTTP), they proposed solutions to mitigate man-in-the-middle attacks. Finally, through simulation experiments,

the effectiveness of the proposed technology is proven [6]. As China's third most populous province, Henan Province ranks fifth in the country's Gross Domestic Product (GDP) in 2020 and has played an essential role in China's economic development [7]. Therefore, analyzing and researching the overall economic development level of Henan Province, and optimizing and adjusting its economic layout and structure on this basis, have solid practical significance for promoting the high-quality economic development of China.

There have been corresponding research results for evaluating the regional economic development level. Lin et al. [8] established a comprehensive evaluation system for the sustainable development of agriculture. They used gray correlation analysis and macro-level data to evaluate the sustainable development level of agriculture in Zhejiang Province and compared the sustainable development level of county agriculture in different terrains [8]. Zhao and Xiao [9] used the concept of green development to build an evaluation system to develop a green marine economy in Guangdong Province. They used the entropy method to calculate the index weights, scored the green development level of the maritime economy in the coastal cities of Guangdong Province, and analyzed the differences in the green development level of each city based on the scoring results [9]. Zhang et al. [10] used Analytic Hierarchy Process (AHP) to improve the entropy method and combined with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to establish the Evaluation of the competitiveness of the development of high-quality manufacturing in the Yangtze River Economic Zone Model [10].

The traditional economic development level evaluation methods mainly include the gray correlation analysis, entropy weight, and AHP. However, these methods can only evaluate the level of regional development by calculating the consequences of relevant indicators and ranking them. The resulting scores are relative evaluations within all objects, rather than reflecting absolute levels and lack of objectivity. In addition, it is impossible to deal with the non-linear problems in the data and to perform index prediction by extracting and learning the traditional knowledge in the relevant historical data; when the amount of information is large, the use of these methods will have the defect of excessive calculation. The Back Propagation neural network (BPNN) can effectively solve the above problems. Luo [11] discussed the application of the BP neural network in macro and microeconomic management in coastal areas, taking the application of BP neural network in enterprise order forecasting and performance evaluation as an example. The research results fully prove that BP neural network is a good tool for coastal economic management [11]. Huang et al. [12] used the BP neural network algorithm under deep supervised learning to construct an intelligent evaluation model for land use growth. They conducted an empirical analysis based on actual urban development data in the Yangtze River Economic Belt. The results show that the proposed BPNN model of intelligent growth evaluation based on deep supervised learning has

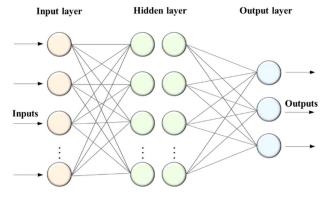


FIGURE 1. Structure diagram of BPNN.

good evaluation accuracy, and the error is within the preset range [12].

The traditional BP neural network also has shortcomings, such as falling into the local extremum and a slow convergence rate [13]. This study proposes an improved BP algorithm, which uses the Levenberg-Marquardt (LM) algorithm to optimize BPNN. By this improved algorithm, an evaluation model for the level of economic development of Henan counties is constructed. The innovation lies in the proposal of an optimized BP algorithm. This algorithm can more accurately analyze the distribution of Henan counties' comprehensive economic development level, which is significant to promoting the coordinated development of counties in the province.

II. METHOD OF MODEL CONSTRUCTION

A. IMPROVED BP NEURAL NETWORK

BPNN, the full name, is the backpropagation model. It is a typical representative of Artificial Neural Network (ANN) and is currently the most widely used ANN [14]. BPNN is produced by simulating the structure of the human brain neuron network. It is a complex network composed of many interconnected nodes [15], which has the advantages of self-learning, self-organization, and parallel processing. BPNN is a multi-layer perceptron structure that mainly contains a three-layer system of input, hidden, and output [16]. The network of BPNN is shown in Figure 1.

The input layer and output layer mainly store and transmit external information. All networks contain an input layer and an output layer. The main difference lies in the number of hidden layers in the middle [17]. The hidden layer does not directly communicate with the outside world, but its changes will directly impact the relationship between the input layer and the output layer [18]. The BPNN algorithm is abbreviated as BP algorithm, which can be realized through the following specific process:

a. Select appropriate input data and target data as the sample data for training BPNN;

b. Establish a neural network model and initialize the network parameters;

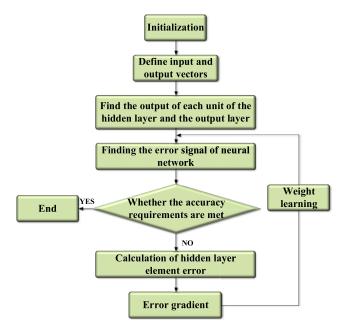


FIGURE 2. Flow chart of BP algorithm.

c. Through the constructed network training sample data, it is automatically completed by the computer program and continuously loops until it reaches the preset value;

d. Complete the network training, determine the weights and thresholds, and output the results. The specific process is shown in Figure 2.

In short, the BP algorithm can transform the signal input and output problems into non-linear optimization problems. Combined with the gradient descent method, an iterative algorithm is used to solve the weights. It is hoped that the optimal solution can be obtained using the added hidden layer nodes to increase the adjustable parameters of the optimization problem [19]. BPNN has simple learning rules and a non-linear solid fitting ability. The trained neural network can also give appropriate output for the input near the samples not in the sample set. BP algorithm includes two signal forward and backward propagation processes in the learning process.

1) FORWARD TRANSMISSION

The forward propagation is carried out from the input to the hidden layer and then to the output layer. The input α_i of the *i*-th node in the hidden layer can be expressed as Eq. (1):

$$\alpha_i = \sum_{j=1}^m w_{ij} x_j + \theta_i, \quad j = 1, 2, 3, \cdots, m$$
(1)

Among them:

 x_i : is the input of the j-th node of the input layer;

 w_{ij} : is the weight between the i-th node in the hidden layer and the j-th node in the input layer;

 θ_i : is the threshold of the i-th node in the hidden layer.

The output β_i of the *i*-th node in the hidden layer can be expressed as Eq. (2):

$$\beta_i = \phi(\alpha_i) = \phi\left(\sum_{j=1}^m w_{ij}x_j + \theta_i\right)$$
(2)

Among them: $\phi(\alpha_i)$ represents the activation function of the hidden layer.

The input δ_k of the *k*-th node in the output layer can be expressed as Eq. (3):

$$\delta_k = \sum_{i=1}^q w_{ki} \beta_i + a_k = \sum_{i=1}^q w_{ki} \phi \left(\sum_{j=1}^m w_{ij} x_j + \theta_i \right) + a_k,$$

$$i = 1, 2, 3, \cdots, q \quad (3)$$

Among them:

 w_{ki} : is the weight between the *k*-th node in the output layer and the *i*-th node in the input layer;

 a_k : is the threshold of the *k*-th node in the output layer.

The output y_k of the *k*-th node of the output layer can be expressed as equations (5) and (6):

$$y_k = \psi(\delta_k) = \psi\left(\sum_{i=1}^q w_{ki}\beta_i + a_k\right)$$
(4)

$$=\psi\left(\sum_{i=1}^{q}w_{ki}\phi\left(\sum_{j=1}^{m}w_{ij}x_{j}+\theta_{i}\right)+a_{k}\right)$$
(5)

Among them: $\psi(\delta_k)$ represents the excitation function of the output layer. If the error between the actual and expected output signals is too large, it must enter the backpropagation process.

2) BACKPROPAGATION

Backpropagation is to pass the output error back layer by layer in the direction of the input layer through the hidden layer, distribute it to all units in each layer, and adjust the weight of each unit using the error signal obtained by each layer. Meanwhile, the connection strength and threshold between the input, output, and hidden layers are adjusted, and the gradient reduces the error. Repeat this process until the error tends to the allowable range or reaches the present practice frequency. It will stop learning [20].

The quadratic error criterion function E_p of each sample p can be expressed as equation (6):

$$E_p = \frac{1}{2} \sum_{k=1}^{l} (T_k - y_k)^2$$
(6)

 T_k represents the expected output; y_k represents the actual output.

The model's total error criterion function for P training samples can be expressed as equation (7):

$$E = \frac{1}{2} \sum_{P=1}^{P} \sum_{k=1}^{l} \left(T_k^P - y_k^P \right)^2$$
(7)

According to the error gradient descent method, the weights and thresholds of the output layer and the hidden layer are sequentially modified. The weight correction amount Δw_{ki} of the output layer, the threshold correction amount Δa_k , the weight correction amount Δw_{ij} of the hidden layer, and the threshold correction amount $\Delta \theta_i$ are obtained, as shown in equations (8)-(11).

$$\Delta w_{ki} = -\eta \frac{\partial E}{\partial w_{ki}} \tag{8}$$

$$\Delta a_k = -\eta \frac{\partial E}{\partial a_k} \tag{9}$$

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \tag{10}$$

$$\Delta \theta_i = -\eta \frac{\partial E}{\partial \theta_i} \tag{11}$$

 η represents the learning rate. Finally, equations (12)-(15) are obtained:

$$\Delta w_{ki} = -\eta \sum_{P=1}^{P} \sum_{k=1}^{l} \left(T_k^P - y_k^P \right) \cdot \psi \left(\delta_k \right) \cdot \beta_i \qquad (12)$$

$$\Delta a_k = \eta \sum_{P=1}^{P} \sum_{k=1}^{l} \left(T_k^P - y_k^P \right) \cdot \psi \left(\delta_k \right) \tag{13}$$

$$\Delta w_{ij} = \eta \sum_{P=1}^{P} \sum_{k=1}^{l} \left(T_k^P - y_k^P \right) \cdot \psi \left(\delta_k \right) \cdot w_{ki}$$
$$\cdot \phi \left(\alpha_i \right) \cdot x_j \tag{14}$$

$$\Delta \theta_{i} = \eta \sum_{P=1}^{P} \sum_{k=1}^{l} \left(T_{k}^{P} - y_{k}^{P} \right)$$
$$\cdot \psi \left(\delta_{k} \right) \cdot w_{ki} \cdot \phi \left(\alpha_{i} \right)$$
(15)

The network architecture only contains one input layer, one output layer and one hidden layer. The number of nodes is generally determined in the input and output layers to improve accuracy, reduce network errors, and avoid the "overfitting" phenomenon.

Traditional BP neural network has defects such as being easy to fall into local extreme value and slow convergence speed. The LM algorithm is used to optimize the BP neural network. The LM algorithm obtains the extreme importance of the function through iteration and is the product of the combination of the Gauss-Newton method and the gradient descent method. It combines the local convergence of the former and the global characteristics of the latter. Generally, the gradient descent method declines quickly at the beginning. As the target approaches the optimal value, the gradient tends to 0, and the objective function declines slowly. The Gauss-Newton method can produce the optimal search direction near the optimal value. Therefore, the LM algorithm used to optimize BPNN can solve the problem of quickly falling into local extreme values and effectively reduce the computational complexity, thereby reducing the number of network iterations and speeding up the convergence speed [21].

 x_k and x_{k+1} are two points in the function f(x), as shown in equation (16):

$$x_{k+1} = x_k + \Delta x \tag{16}$$

Newton's method is shown in equation (17):

$$\Delta x = -\left[\nabla^2 E(x)\right]^{-1} \nabla E(x) \tag{17}$$

E(x): the error-index function; $\nabla^2 E(x)$: the *Hessian* matrix of E(x);

 $\nabla E(x)$: the gradient.

E(x) is expressed as equation (18):

$$E(x) = \frac{1}{2}e^{2}(x)$$
 (18)

e(x) represents the error, as shown in equations (19)-(21):

$$\nabla E(x) = J^T(x) e(x) \tag{19}$$

$$\nabla^2 E(x) = J^T(x) e(x) + S(x)$$
 (20)

$$S(x) = \sum e_i(x) \nabla^2 e_i(x)$$
(21)

S(x) represents the *Jacobian* (J) matrix, and the matrix J is shown in equation (22):

$$J(x) = \begin{bmatrix} \frac{\partial e_{1(x)}}{\partial x_1} & \frac{\partial e_{1(x)}}{\partial x_2} & \cdots & \frac{\partial e_{1(x)}}{\partial x_n} \\ \vdots & \ddots & \cdots & \vdots \\ \frac{\partial e_{n(x)}}{\partial x_1} & \frac{\partial e_{n(x)}}{\partial x_2} & \cdots & \frac{\partial e_{n(x)}}{\partial x_n} \end{bmatrix}$$
(22)

The calculation rule of the Gauss-Newton method is shown in equation (23):

$$\Delta x = \left[J^T(x) J(x)\right]^{-1} J(x) e(x) \tag{23}$$

The improved Gauss-Newton method is the LM algorithm, as shown in equation (24):

$$\Delta x = \left[J^T(x) J(x) + \mu I \right]^{-1} J(x) e(x)$$
 (24)

 μ represents the proportionality coefficient, a constant greater than 0; I represents the identity matrix.

B. EVALUATION MODEL OF HENAN COUNTY ECONOMIC DEVELOPMENT LEVEL

1) DATA SOURCE

In constructing the Henan County economic development level evaluation model, 107 counties in Henan Province (including 21 county-level cities and 86 counties) were used as research units. All the data used are from the *Henan Province Statistical Yearbook 2020, China County Statistical Yearbook 2020,* and the government statistical bulletins of cities, counties, and districts at various levels.

2) CONSTRUCTION OF EVALUATION INDEX SYSTEM

The use of multiple indicators to build an evaluation system often covers more comprehensive information. Therefore, for the Evaluation of the economic development level of Henan counties, a multi-index evaluation index system is constructed. The vast economic development level of the

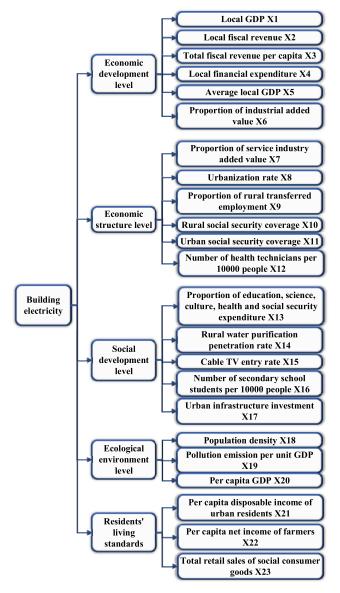


FIGURE 3. Evaluation index system of comprehensive economic development level of Henan counties.

county is mainly reflected in the comprehensive development of a people-centered society, economy, and ecology at the county scale, following the principles of scientific, representativeness, systemic, independence, accessibility, and regionality. Comprehensively analyze and make choices, and five items are established: economic development level, economic structure level, social development level, ecological environment level, and urban and rural people's living standards. These five items are all first-level indicators. The first-level indicators correspond to 23 second-level evaluation indicators. The specific index content is shown in Figure 3.

3) CONSTRUCTION OF BP EVALUATION MODEL a: DATA STANDARDIZATION

Due to the enormous amount of data, the sample data should be standardized to speed up the training rate of BPNN and reduce the influence of singular samples on the network performance. The processed data range should fall within [0, 1]. Data standardization is the dimensionless processing of all the data obtained, which can improve the convergence speed and accuracy of the model. Generally, the maximum value method is adopted, and the calculation of the positive index is shown in Eq. (25), and the measure of the negative index is shown in Eq. (26).

$$T_{ij} = \frac{X_{ij}}{T_{imax}}$$
(25)

$$T_{ij} = \frac{T_{imin}}{X_{ij}} \tag{26}$$

Among them: X_{ij} represents the original data; T_{imax} represents the maximum value of each sequence; T_{imin} represents the minimum value of each sequence; T_{ij} represents the standardized data.

b: DATA GRADING

The 23-index data of the counties in Henan Province are used as the input of the BP model. According to the maximum and minimum intervals of the sample data, Natural Breaks (NB) [22] is adopted to divide the data sample into five levels. Among them, 1 represents a high level of comprehensive economic development, 2 represents a medium-to-high level, 3 represents a medium level, 4 represents a medium-low level, and 5 represents a low level. The natural breakpoint method is a statistical method that is classified according to the numerical statistical distribution law. It can maximize the difference between classes. The algorithm believes that any statistical sequence has some natural turning points and characteristic points, and these points can be used to divide the research objects into groups with similar properties. The natural breakpoint classification method (Jenks) in Arcgis 9.2 software is used for data classification. On this basis, the training sample data of BPNN is constructed, and the specific data is shown in Table 1.

C. EXPERIMENTAL METHOD

1) IMPLEMENTATION OF BP NEURAL NETWORK

The 23 sets of index data (independent variables) collected from 107 counties in Henan Province and the numerical values (dependent variables) representing the economic development level of each county are integrated to construct a data set. The data of 100 randomly selected counties are used as the training set, and the data of the remaining seven counties are used as the test set to verify the model.

Matlab 7.0 software programming is used to design the neural network, and then the entire experimental process is simulated. The training method of the BP model is as follows: the training set is input into the model for the learning and training process until the error of the network output is reduced to a preset value. The maximum number of training times is 5000, and the maximum error of network convergence is 0.01. When the model is trained to reach the preset accuracy, the test set is input to the model to start the formal Terminet

Input		Output layer			
layer	1	2	3	4	5
\mathbf{X}_1	1	0.6180	0.4017	0.2136	0.0865
X_2	1	0.6461	0.4020	0.2700	0.1497
X_3	1	0.4310	0.2615	0.1133	0.0449
X_4	1	0.4622	0.3067	0.2210	0.1425
X_5	1	0.5030	0.2282	0.1161	0.0584
X_6	1	0.6583	0.2938	0.1800	0.0836
X_7	1	0.5310	0.2247	0.1175	0.0488
X_8	1	0.4456	0.2526	0.1378	0.0813
X_9	1	0.5643	0.3017	0.1059	0.0387
\mathbf{X}_{10}	1	0.6931	0.4431	0.2994	0.1524
\mathbf{X}_{11}	1	0.7157	0.5343	0.3464	0.1944
X_{12}	1	0.6259	0.4757	0.4019	0.3268
X_{13}	1	0.7628	0.5755	0.4620	0.3065
X_{14}	1	0.8521	0.7406	0.6079	0.4924
X15	1	0.4185	0.2786	0.1934	0.1363
X_{16}	1	0.7143	0.6071	0.5179	0.4107
X_{17}	1	0.8233	0.7203	0.6586	0.5961
X_{18}	1	0.6617	0.5433	0.4677	0.4189
X_{19}	1	0.7842	0.6888	0.5864	0.4758
X_{20}	1	0.7652	0.5800	0.3963	0.2527
X_{21}	1	0.5002	0.2500	0.1300	0.0714
X ₂₂	1	0.8379	0.7158	0.6259	0.5228
X ₂₃	1	0.8315	0.7018	0.5127	0.2516

 TABLE 1. Evaluation Criteria for Comprehensive Economic Development

 Level of Henan County.

Output love

experiment. Long Short-Term Memory (LSTM) is selected as a control to compare the performance of the proposed improved BP neural network.

2) BP NEURAL NETWORK PARAMETER OPTIMIZATION

The model parameter determination is mainly divided into optimizing network structure, activation function, and learning rate parameters. The number of input indicators of the BP model is 23, and the number of input layer nodes is 23. The level of economic development is taken as the network's output, and the number of nodes in the output layer is 1. Therefore, the optimal number of hidden layer nodes can be found. The calculation of the number of hidden layer nodes is shown in equation (27):

$$M = \sqrt{NL} + \alpha \tag{27}$$

M: is the number of layer nodes; N: is the number of layer nodes; L: is the number of out-layer nodes; α : is an integer of [1, 10]. The number of hidden layer nodes is 5-11, respectively. During the training process, the model's RMSE, MAE, and MSE are used as indicators to perform verification

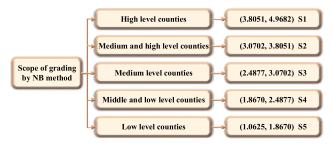


FIGURE 4. Scope of NB law classification.

experiments to determine the number of nodes in the optimal hidden layer.

Sigmoid and Tanh are selected as the activation function for comparative experiments to determine the best activation function. If the learning rate is too low during the training process, it will cause the training to stop before finding the best parameters. Excessive learning rate may cause shock or divergence, failing to find the best point. RMSE, MAE, and MSE are shown in equations (28), (29), and (30):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}$$
(28)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i|$$
(29)

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(\hat{y}_i - y_i \right)^2$$
(30)

 \hat{y}_i : is the predicted value; y_i : is the actual value; n: is the total number of samples.

3) SPECIFIC EXPERIMENTAL METHODS

After the optimal parameter combination of the BP model is obtained, 2461 standardized sample indicators corresponding to 107 counties in Henan Province are input into the trained BPNN. Through a series of calculations, the comprehensive economic development level scores of the counties in Henan Province are output. The NB method is used to classify the scores of each county. The range of each level is shown in Figure 4.

In Figure 4, the number of regions included in each evaluation level, the average value, the standard deviation between groups, and the standard deviation within the group are calculated. S1S2 represents the standard deviation between the high and medium-high levels; S2S3 represents the standard deviation between the medium-high and medium levels; and so on S3S4, S4S5. Among them, the calculation of the standard deviation between groups [23] is shown in Eq. (31):

$$T = \sqrt{\frac{n\sum x^2 - (\sum x)^2}{n^2}}$$
(31)

where: x represents the overall average of the sample; n represents the total number of pieces. The calculation of the

TABLE 2.	The be	st parameter	table of	f BP neura	l network.
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Parameters	Value
Number of input layer nodes	23
Number of output layer nodes	1
Number of hidden layer nodes	8
Activation function	Tanh
Learning rate	0.0015

standard deviation within the group [24] is shown in eq. (32):

$$T = \sqrt{\frac{n\sum x^2 - (\sum x)^2}{n^2}}$$
(32)

x represents the overall average of a sample; *n* represents the total number of pieces.

III. EXPERIMENTAL RESULTS

A. MODEL PARAMETER OPTIMIZATION AND PERFORMANCE TEST RESULTS

Under different hidden layer node numbers, activation functions, and learning rate parameters, the model's performance test results are shown in Figure 5.

In Figure 5, when the number of hidden layer nodes is 8, the activation function is Tanh function, and the learning rate is 0.0015, the model's performance reaches the best. Therefore, the optimal network parameter settings are shown in Table 2.

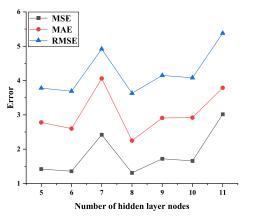
Under the same conditions, the error comparison of the output results of the improved BP model and the LSTM model on the test set is shown in Figure 6.

In Figure 6, the MSE, MAE, and RMSE between the output of the LSTM model and the accurate data are 4.27, 5.4, and 6.54, respectively. The improved BP model's MSE, MAE, and RMSE are 0.9, 1.72, and 3, respectively. This is much lower than the LSTM model. The reason may be that more weights need to be trained in LSTM, but the BP network only needs to train two consequences; the more weights, the more training times are required. The convergent error function can be obtained after multiple training. Moreover, the improved BP algorithm has lower computational complexity than the traditional BP algorithm, faster network convergence, and better performance.

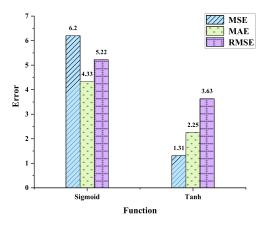
B. EVALUATION RESULTS OF THE ECONOMIC DEVELOPMENT LEVEL OF HENAN COUNTIES

The error curve and BP evaluation model training are shown in Figures 7 and 8.

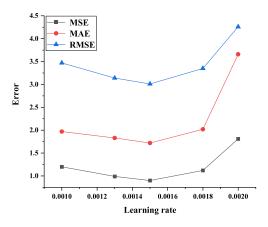
Figure 7-8 shows that BPNN has reached the preset convergence accuracy after 2968 times of training. Its correlation coefficient is 0.9995, the high degree of fit, and the network performance can meet the actual requirements. The statistics



(a) The result of optimizing the number of hidden layer nodes



(b) The result of activation function optimization



(c) Results of learning rate optimization FIGURE 5. Performance test results of BP model under different parameter conditions.

of the regions included in each evaluation level of the comprehensive economic development level of counties in Henan Province, the average value of each station, the standard deviation between groups, and the standard deviation within groups are shown in Figures 9-12.

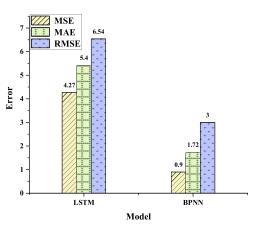


FIGURE 6. BPNN training error curve.

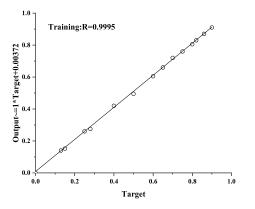


FIGURE 7. BPNN training error curve.

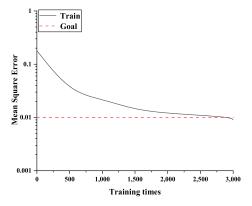


FIGURE 8. Analysis of BPNN training results.

In Figure 9, the comprehensive economic development levels of the counties in Henan Province have certain differences. This includes counties in descending order: S3 medium-level counties (28), S4 medium-low-level counties (25), S2 medium-high-level counties (20), S5 low-level counties (19), S1 high-level counties (15). High-level counties are relatively small, accounting for only 14% of all counties.

In Figure 10, the average scores of the counties at each level are sorted from highest to lowest: S1 (4.7123), S2 (3.5796), S3 (2.8845), S4 (2.3012), S5 (1.6365). The difference

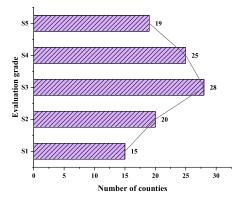


FIGURE 9. Statistics of counties included in each evaluation level.

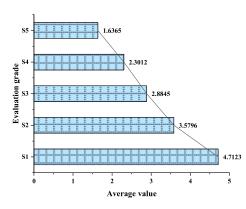


FIGURE 10. Statistical graph of average value of each evaluation grade.

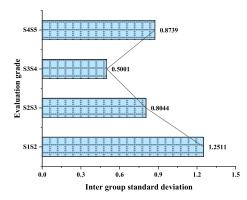


FIGURE 11. Statistical graph of standard deviation between groups of each evaluation level.

between the average score of high-level counties and low-level counties is as high as 3.0758.

In Figure 11, comparing the deviations between groups of each evaluation level, the standard deviations are sorted from largest to smallest: S1S2 (1.2511), S4S5 (0.8739), S2S3 (0.8044), S3S4 (0.5001). This shows that the differentiation between high-level and middle-high-level counties in Henan Province is the most obvious, followed by middle-low-level and low-level counties. The weakest difference is middle-level counties and middle-low-level counties.

From the comparison of intra-group deviations of each evaluation level in Figure 12, the intra-group standard deviations are sorted from large to small: S1 (0.4235), S5 (0.3438),

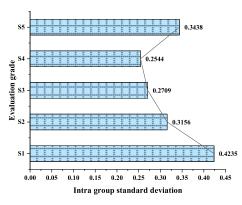


FIGURE 12. Statistical graph of standard deviation within each evaluation level group.

S3 (0.2709), S2 (0.3156), S4 (0.2544). It shows that the highlevel counties in Henan Province have the most apparent intra-group differentiation; the low-level counties are second. The middle and low-level counties have the most little intragroup differentiation, which means their development is the most balanced.

C. RESULT DISCUSSION

An improved BP algorithm optimized by the LM algorithm is proposed. The Henan County economic development level evaluation model is constructed based on this algorithm. Matlab 7.0 software is used to design simulation experiments to evaluate the comprehensive economic development level of 107 counties in Henan Province. The experimental results show that: (1) there are 15 high-level counties in Henan Province, 20 middle-high levels, 28 middle-level ones, 25 middle-low levels, and 19 low-level counties. The overall development level of the counties is mainly concentrated in the middle and low-medium classes, and the number of highlevel counties is relatively small, accounting for only 14% of all counties. (2) The average score of high-level counties is 4.7123, and the average score of low-level counties is 1.6365. The difference between the two is as high as 3.0758. This shows that the comprehensive economic development level of the counties in Henan Province presents a polarized pattern of differentiation. (3) The differentiation between high-level counties and middle-high-level counties in Henan Province is the most obvious; the difference between low-medium and low-level counties is the second; the weakest is the middlelevel counties and low-medium-level counties.

In summary, the overall development level of the county is not high, and the polarization is more serious. It presents a "convex" distribution characteristic of stronger strong ones, weak ones, and relatively concentrated middle and low levels. According to the status quo, the current economic development model has been further improved.

IV. CONCLUSION

As an essential part of China's economic development, Henan Province has important practical significance to analyze and study its comprehensive economic development level. The traditional evaluation method of regional economic development level can only obtain relative Evaluation but cannot reflect the absolute level, and the objectivity is insufficient. On the above problems, with 107 counties in Henan Province as the research unit, the evaluation model of Henan County economic development level using improved BP algorithm and the measurement model of residents' disposable income are constructed. And the distribution characteristics of the overall economic development level of Henan County are analyzed and studied. The analysis results show that the MSE, MAE, and RMSE of the output of the proposed BP model are 0.9, 1.72, and 3, respectively. This is far lower than other popular algorithms and is more suitable for estimating the comprehensive development level of the region. The overall economic development level of the counties in Henan Province is relatively balanced on the whole and unbalanced locally. The polarization of development is more serious; the counties with medium and low levels of development account for a rather large proportion, and the overall distribution characteristics are "convex".

The limitations are as follows: it only analyzes the distribution characteristics of the economic development level of Henan counties and the differences between counties at various levels. It does not carry out relevant development model optimization research. Future work can be carried out mainly for the optimization research of the Henan County economic development model and the direction of expanding the data set to improve the model. The purpose is to more accurately analyze the distribution of comprehensive economic development levels in Henan counties and to promote the coordinated development of counties in the province to provide necessary technical support.

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