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Research on Deep Learning Algorithm Application and Resource Allocation Optimization in Educational Resources Big Data Analysis

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ABSTRACT

The equalization and rationalization of educational resource allocation is of great significance to the coordinated development of education. The study takes the educational resources of 13 districts and counties in Y city in 2023 as an example, and proposes to use the BP neural network-based educational resource allocation evaluation system to analyze it. The results show that only three districts and counties have "very good" and "good" levels of educational resource allocation. Accordingly, this paper constructs a multi-objective optimization model to improve the level of educational resource allocation, reduce the differences between counties, and improve the utilization rate of educational resources. The weights corresponding to the eight indicators of the educational resource allocation evaluation index system are solved by the entropy weight method, after which the preset values of the three objective functions and the weights accounted for by the eight indicators are brought into the model and the artificial raindrop algorithm is used to find the optimal solution. After finding the optimal solution of educational resource allocation, the BP neural network-based educational resource allocation evaluation system is used again to evaluate it, and at this time, the educational resource allocation of a total of 12 districts and counties belongs to the "very good" and "good" grades. The study shows that the optimization method of educational resource allocation designed in this paper can reasonably plan educational resources and realize the coordinated development of education.

Keywords: BP Neural Network, Multi-objective Optimization Model, Artificial Raindrop Algorithm, Resource Allocation Optimization

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1. Introduction

Educational equity has become the theme and basic value orientation of contemporary educational reform. With the acceleration of China's urbanization process and changes in population dynamics, the unbalanced development of educational resources has become a shortcoming and bottleneck that restricts the establishment of a high-quality basic education service system in China [1-2]. Scientific and reasonable planning of educational resources is conducive to its knowledge spillover effect, which is an important embodiment of realizing the equalization of public services, and at the same time is an important content to meet people's needs for a better life [3].

In today's development trend, big data as a collection of massive data that can accommodate trillions of levels of data, which itself often has the characteristics of actuality, objectivity, high-speed readability and diversity, etc. [4]. Educational big data is a collection of data reflecting the current situation, needs and problems of basic education resource allocation, and it is also an effective tool for reshaping the structure of basic education resource allocation and building a good education ecology [5-6]. By collecting and updating basic education big data in real time, the real situation of basic education resource allocation can be revealed, effectively avoiding the problem of insufficient objective basis for resource allocation due to basic education data analysis and lack of scientific decision-making [7-10]. On this basis, combining intelligent technology to optimize the structure of educational resource allocation in real time can solve the problem of mismatch between supply and demand of basic education resources triggered by the roughness of the basic education resource allocation mode, as well as the problem of lack of power and inefficiency in the allocation of basic education resources [11-14]. At the same time, it ensures that the basic education resource allocation strategy can always be compatible with the demand for basic education resources in each region and the development expectations of basic education schools [15-16]. It is not difficult to find that the era of big data puts forward new requirements for the government's educational decision-making process, that is, only by making full use of big data can the government's educational decision-making process be realized intelligently, so as to reduce the adverse effects of traditional government educational decision-making and achieve sustainable development in the field of education [17-18].

The study used the BP neural network-based educational resource allocation evaluation system to assess that the educational resource allocation in Y city is not ideal. Therefore, this paper constructs an educational resource allocation optimization model with the objectives of improving the level of educational resource allocation, reducing the differences between counties, and improving the utilization rate of educational resources. The weights of the indicators affecting the allocation of educational resources are solved by the entropy weight method, after which the preset values of the three objective functions and the weights accounted for by the eight indicators are brought into the model and solved using the artificial raindrop algorithm, so as to optimize the allocation of educational resources in Y city. For the re-planned resource allocation, the educational resource allocation evaluation system is used again for evaluation, and the effectiveness and rationality of the educational resource allocation optimization method of this paper is verified according to the evaluation results.

2. Deep learning-based data analysis of educational resources

Deep learning neural network is a multilayer network including input, hidden and output layers, it can realize the approximation of complex functions by this multilayer neural network structure. Deep learning has the characteristic of fitting any complex function, and different neural network models can extract features from different types of data, which makes deep learning neural networks have stronger recognition ability for input data [19]. And deep learning can store the long-term state in the hidden layer, which can preserve the connection between the data. Deep learning algorithms are more flexible and accurate compared with other data mining methods, and it can make up for the shortcomings of many data mining methods. Accordingly, the study uses BP neural network based educational resource allocation evaluation system to realize the data analysis of educational resources.

2.1. *Indicator system for evaluating the allocation of educational resources*

This paper evaluates the allocation of educational resources from three aspects of human resources, financial resources and material resources respectively, and constructs the evaluation index system of educational resource allocation as shown in Figure 1. It contains eight indicators: teacher-student ratio, number of teachers per student higher than the required academic qualifications, number of teachers per student with intermediate or above professional and technical positions, number of computers per student, number of teaching instruments and equipment assets per student, number of books per student, total floor area of school buildings per student, and area of physical education and sports venues per student [20].

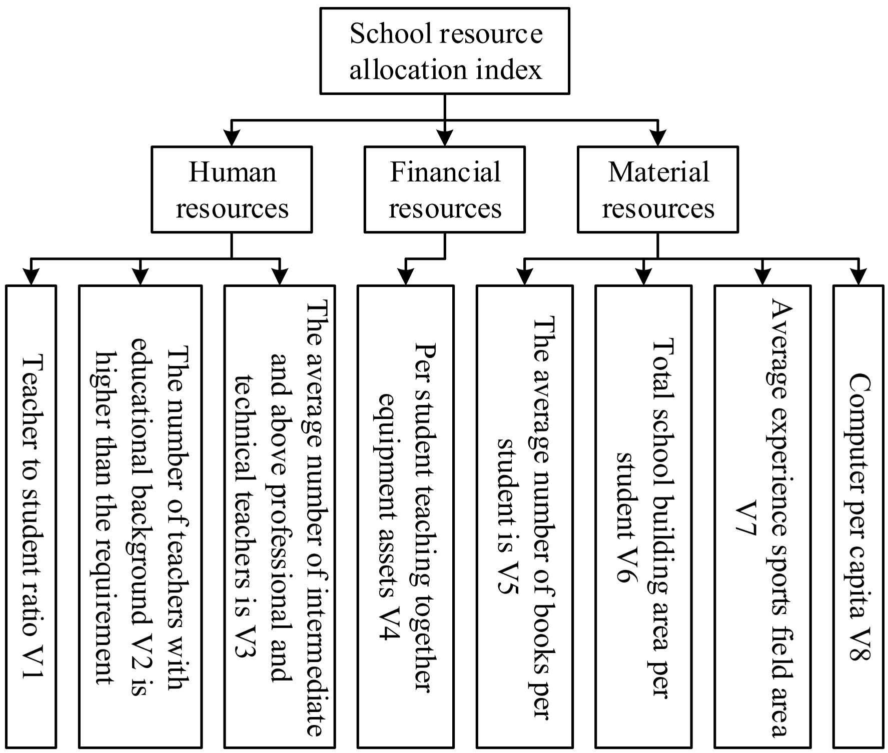

Fig. 1. Education resource allocation evaluation index system

2.2. *BP-based Evaluation System for Educational Resource Allocation*

BP neural network consists of forward propagation of information and reverse propagation of error, it is a multilayer feed-forward type of network and is trained using error back propagation algorithm [21]. The model structure includes input, hidden and output layers. The topology of BP neural network is shown in Fig. 2.

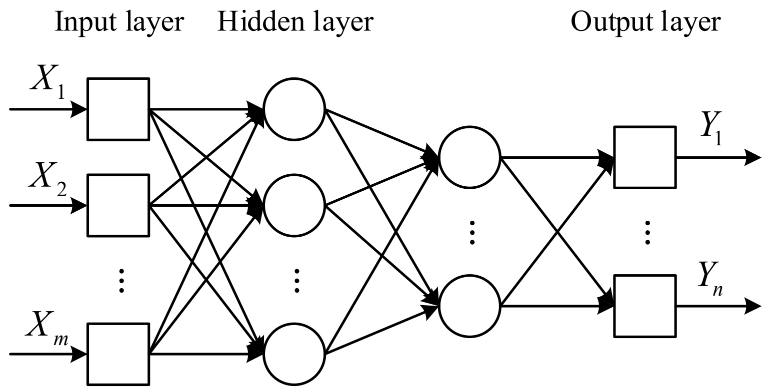

Fig. 2. BP neural network topology

The BP neural network in this study is based on MATLAB R2012a software for model construction. MATLAB, short for Matrix Laboratory, is a high-level programming language for algorithm development, data visualization analysis and computation. Due to its high programming efficiency, intuitive and flexible language, excellent graphical processing, advanced visualization tools and powerful toolbox, MATLAB has become one of the widely used scientific and engineering computing software, with outstanding achievements in many fields such as engineering computation, image processing, neural networks, signal processing and so on.

2.2.1. Analysis and processing of input layer variables:

1) Analysis of input layer variables. BP neural network is the process of reducing the error between the learning sample data and the target sample through continuous and repeated learning, and finally trained into a system model. Therefore, to construct the BP neural network model of the educational resource allocation evaluation system, what needs to be determined is the data of the input layer variables, i.e., the learning samples. The selection of learning samples generally follows two principles: first, the selected samples have a greater impact on the output and are typically representative. The second is that the correlation of the learning sample is small.

Based on the education resource allocation evaluation index system constructed above, a total of eight indicators, including teacher-student ratio, number of teachers with per capita higher than the required academic qualifications, number of teachers with per capita intermediate and above professional and technical positions, number of computer units per capita, assets of per capita teaching instruments and equipments, number of books per capita, total floor area of per capita school building, and area of per capita physical education and sports venues, are identified as the input layer of the model.

2) Input data processing. In MATLAB, the learning samples we collected are input into the model in the form of a matrix, due to the different significance of the physical quantities of the selected indicators in the evaluation system we have identified, the order of magnitude of the vectors is somewhat different, if we directly apply the original data is easy to cause the formation of large fluctuations in the measured value, affecting the training of the neural network, so the data is usually normalized first, and all the data are transformed into [0,1] or between [-1,1]. Through the normalization of the data, to avoid the formation of network learning error is large because of the large differences in the input data, which is conducive to improving the training speed of the network and accelerating the convergence.

There are usually two methods for data normalization:

The first max-min method. The formula is as follows:

$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x_{min} is the smallest number in the data sequence. x_{max} is the maximum number in the data series.

The second method of mean variance. The formula is as follows:

$$x = \frac{(x - x_{mean})}{x_{var}} \tag{2}$$

Where x_{mean} is the mean of the data series. x_{var} is the variance of the data.

In the educational resource allocation evaluation system, we apply the first method to normalize the collected raw data.

2.2.2. Selection of the number of nodes in the implicit layer. The hidden layer is the intermediate layer connecting the input layer and the output layer, which plays a decisive role in the performance of this neural network, therefore, the determination of the number of nodes in the hidden layer is very important.

At present, there is no scientific and general theoretical method for determining the number of nodes in the implied layer, which is often derived through empirical formulas and practical experiments. The following are several common empirical formulas:

$$X = 2m + 1 \tag{3}$$

$$X = \log_2 \max_2 m \tag{4}$$

$$X = \sqrt{m+n} + a \tag{5}$$

$$X = \sqrt{(m * n)} + \frac{N}{2} \tag{6}$$

$$X = \sqrt{0.43mn + 0.12n^2 + 0.77n + 2.54m + 0.35} + 0.51 \tag{7}$$

$$a = \frac{m+n}{2} \le X \le (m+n) + 10 = b \tag{8}$$

where N is the number of training samples, m is the number of neurons in the input layer, n is the number of neurons in the output layer, and a takes any constant between 1 and 10.

To apply this method, firstly, the test point $j_1 = 0.618 \times (b-a) + a$ is taken on interval $[a,b]$ and the result of the first test point is recorded as $E(j_1)$, where $E(j_1)$ denotes the output error when the number of nodes in the hidden layer is j_1. Secondly, the second test point i.e. symmetry point $j_2 = 0.382 \times (b-a) + a$ which is j_1 is determined and the result of the test is recorded as $E(j_2)$. Then, the results of the two tests are compared and the superior one is taken i.e. if $E(j_1) < E(j_2)$, interval $[a, j_2]$ is removed and interval $[j_2, b]$ is retained. Conversely, if $E(j_1) > E(j_2)$, the $[j_2, b]$th interval is removed and the $[a, j_2]$ interval is retained. If $E(j_1) = E(j_2)$, then take the $[j_1, j_2]$ interval. Finally, the above process is repeated several times to obtain the number of implied point knots X, and $E(X) = \min[ZE(a), E(b), E(j_1), E(j_2), \ldots\}$, where $j_1, j_2, \ldots$ bits of the golden section test points on the interval $[a,b]$.

Based on experience, this paper adopts the first empirical formula, and combines the “trial and error method”, that is, first use the formula to derive the number of test nodes, and then gradually increase or decrease the number of test nodes, and then use the same sample for training, compare the degree of fit between the output error of the network and the expected error, and select the best simulation training effect, that is, the network error is the smallest selected The number of hidden layer nodes is used as the final number of nodes adopted.

2.2.3. Output layer design. For this paper on the evaluation of educational resource allocation through the BP neural network will be qualitative into quantitative output a final result, and then comprehensive evaluation of the output results, to make a qualitative evaluation of the level of educational resource allocation. Therefore, the output layer is the evaluation result of educational resource allocation. Here, in order to be able to analyze the evaluation results in a more specific way, we have classified the evaluation results into four levels, and the specific evaluation level classification is shown in Table 1.

Table 1. Evaluate the hierarchical class

Grade	Very good	Good	Acceptability	Bad
Expected output	[1,0,0,0]	[0,1,0,0]	[0,0,1,0]	[0,0,0,1]

According to the evaluation level classification table we can conclude that the number of neurons in the output layer is 4.

3. Optimizing the design of educational resource allocation

This paper takes the optimization of educational resource allocation in 13 districts and counties of Y city as the goal, uses the BP neural network-based educational resource allocation evaluation system to analyze the educational resource situation, and then constructs the educational resource allocation optimization model and solves it with the artificial raindrop algorithm, so as to optimize the allocation of educational resources in Y city.

3.1. Assessment of the current status of education resource allocation

The study conducted statistics on the educational resources of 13 districts and counties in Y city in 2023 according to the evaluation index system of educational resource allocation, and the data obtained for each index are shown in Table 2. Taking district and county 1 as an example, the teacher-student ratio and the number of teachers with per pupil higher than the required academic qualifications are 1:25, the number of teachers with per pupil intermediate and above professional and technical positions accounts for 60%, there is one computer for every 10 students, and the number of books owned by each student is less than 25. The number of teachers with per pupil intermediate and above professional and technical positions in district and county 1 is more ideal, but there is still much room for improvement of other educational resources.

Table 2. Education resource configuration data

Region	V1	V2	V3	V4	V5(yuan)	V6	V7(m^2)	V8(m^2)
1	0.04	0.04	0.6	0.1	304.4	24.8	15.3	3.3
2	0.06	0.03	0.7	0.1	344.3	28.6	12.3	1.7
3	0.04	0.03	0.7	0.1	362	28.7	18.2	6.8
4	0.05	0.06	0.6	0.1	339.9	25	12	4.7
5	0.05	0.06	0.6	0.1	337.8	21.1	15	1
6	0.06	0.03	0.6	0.1	357.8	20.8	17.1	9.8
7	0.07	0.03	0.7	0.1	370.4	23.8	15	7.9
8	0.05	0.05	0.7	0.2	363	27	15.9	9.2
9	0.06	0.04	0.8	0.2	310.7	28.8	14.7	6.9
10	0.06	0.05	0.7	0.1	265.8	27.3	12.3	2.1
11	0.06	0.05	0.5	0.1	214.1	22.2	10.4	7.7
12	0.05	0.03	0.5	0.1	207.4	18.6	11.6	4.9
13	0.04	0.03	0.4	0.1	233.8	15.8	18.3	5.7

The raw data of 13 districts and counties are substituted into the BP neural network-based education resource allocation evaluation system, and the results are shown in Table 3. The number of districts belonging to “very good”, “good”, “acceptable” and “poor” grades are 1, 2, 5 and 5 respectively. The results of the system evaluation show that the current situation of educational resource allocation in Y city is not optimistic and needs to be re-planned urgently.

Table 3. The education resource allocation evaluation results in Y city

Region	Evaluation result	Region	Evaluation result
1	Very good	8	Good
2	Acceptability	9	Acceptability
3	Bad	10	Acceptability
4	Bad	11	Bad
5	Acceptability	12	Bad
6	Bad	13	Good
7	Acceptability		

3.2. Optimization Model Construction of Educational Resource Allocation

In order to optimize the allocation of educational resources in City Y, this chapter designs a multi-objective optimization model to increase the level of educational resource allocation, reduce the differences between counties, and increase the utilization rate of educational resources.

3.2.1. Objective function of the model. For the problem of optimizing the allocation of educational resources among districts and counties, the objective function constructed in this section is shown below.

1) To improve the level of educational resource allocation, the following objective function is constructed:

$$\max F_{lev} = \sum_{i=1}^{m} \sum_{j=1}^{5} \varphi_j lev_{ij} \tag{9}$$

2) Reduce the differences in resource allocation between districts and counties by establishing the following objective function:

$$\min F_{diff} = \frac{1}{\overline{F_{lev}}} \sqrt{\sum_{i=1}^{m} \frac{1}{m} \left(\sum_{j=1}^{5} \varphi_j lev_{ij} - \overline{F_{lev}}\right)^2} \tag{10}$$

In the objective function for reducing the variability of resource allocation between districts and counties, $\overline{F_{lev}}$ represents the average of all districts and counties under the jurisdiction of the city, and m represents the number of districts and counties under the jurisdiction of the city.

(3) To improve the utilization rate of educational resource allocation, establish the following objective function:

$$\max F_{eff} = \sum_{i=1}^{m} \sum_{j=6}^{8} \varphi_j eff_{ij} \tag{11}$$

The eight indicators related to education resources have different factors influencing education, so the corresponding weights of each indicator need to be considered when dealing with the objective function of improving the level of education resource allocation, reducing the variability of resource allocation between districts and counties, and improving the utilization rate of education resource allocation. Therefore, the relevant weights $\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6, \varphi_7, \varphi_8$ are introduced to the above objective function model.

The decision-making options obtained when solving the above single objective function are all relatively one-sided, and secondly, this section of the district and county education resource allocation model aims to realize the rationality, fairness and efficiency of education resource allocation at the same time. Therefore, the objective function for the allocation of district and county education resources in this section considers the above three objectives comprehensively, as shown in equation (12):

$$\begin{cases} \max\left(\sum_{i=1}^{m}\sum_{j=1}^{5}\varphi_j lev_{ij}\right) \\ \min l\left(\frac{1}{F_{lev}}\sqrt{\sum_{i}^{m}\frac{1}{i^2}\left(\sum_{j=1}^{5}\varphi_j lev_{ij}-\overline{F_{lev}}\right)^2}\right) \\ \max\left(\sum_{i=1}^{m}\sum_{j=6}^{8}\varphi_j eff_{ij}\right) \end{cases} \tag{12}$$

In equation (12):

i denotes the number of the districts and counties under the jurisdiction of the city.

j indicates the number of the indicator weights related to educational resources.

m indicates the number of districts and counties under the jurisdiction of the city.

φ indicates the weight of the education resource-related indicator.

$\overline{F_{lev}}$ indicates the average of the educational resource allocation levels of all districts and counties within the city's jurisdiction.

lev_{ij} indicates the performance of the i th district within the city's jurisdiction in terms of capacity for the j th indicator.

eff_{ij} indicates the capacity performance of the i th district within the city's jurisdiction in terms of the utilization rate of educational resource allocation for the j th indicator.

3.2.2. Constraints of the model. Based on the above specific description of the educational resource allocation problem in each district and county, the constraints of the optimization model of educational resource allocation in each district and county are as follows:

1) Ensure that the city's educational resources to be allocated to each district and county are allocated only once:

$$\sum_{h=0}^{m} D_{hi} = \sum_{j=1}^{m+1} D_{ij} = 1(i = 1, 2, \ldots, n) \tag{13}$$

2) The square footage of newly configured instructional and support rooms in each district needs to be less than or equal to the square footage of instructional and support rooms to be configured and optimized:

$$0 \le \sum_{i=1}^{n} newA_i \le L\_A \tag{14}$$

3) The area of newly allocated sports venues in each district and county needs to be less than or equal to the area of sports venues to be allocated and optimized:

$$0 \le \sum_{i=1}^{n} newG_i \le L\_G \tag{15}$$

4) The number of newly allocated books in each district needs to be less than or equal to the number of books to be allocated and optimized:

$$0 \le \sum_{i=1}^{n} newB_i \le L\_B \tag{16}$$

5) The number of newly configured computers in each district needs to be less than or equal to the number of computers to be configured and optimized:

$$0 \le \sum_{i=1}^{n} newC_i \le L\_C \tag{17}$$

6) The asset value of newly configured teaching instruments and equipment in each district and county needs to be less than or equal to the asset value of teaching instruments and equipment to be configured and optimized:

$$0 \le \sum_{i=1}^{n} newE_i \le L\_E \tag{18}$$

7) The number of new full-time teachers in each district needs to be less than the number of full-time teachers to be optimized:

$$0 \le \sum_{i=1}^{n} newT_i \le L\_T \tag{19}$$

8) The number of new teachers in mid-level and above professional and technical positions in each district needs to be less than or equal to the number of full-time teachers to be optimally deployed:

$$0 \le \sum_{i=1}^{n} newM_i \le L\_M \tag{20}$$

9) The number of new teachers with higher than required degrees in each district needs to be less than or equal to the number of teachers with higher than required degrees to be optimized:

$$0 \le \sum_{i=1}^{n} newH_i \le L_H \tag{21}$$

10) The cost of new educational resources allocated to the five indicators is less than or equal to the total price of the highest educational resources to be allocated and greater than or equal to the total price of the lowest educational resources to be allocated, and the total cost of new educational resources allocated to teachers is less than or equal to the total price of the highest educational resources to be allocated and greater than or equal to the total price of the lowest educational resources to be allocated to teachers.

$$\begin{aligned} & sumP\_low \le newA_iP_a + newG_iP_g + newB_iP_b + newC_iP_c + newE_iP_e \\ & \le sumP\_hight \\ & sumW\_low \le newT_iW_i + newM_iW_m + newH_iW_h \le sumW\_hight \end{aligned} \tag{22}$$

3.3. *Model solving based on artificial raindrop algorithm*

This chapter utilizes the Artificial Raindrop Algorithm to implement the computation and search of optimal solutions to provide a decision-making solution for resource allocation.

The Artificial Raindrop Algorithm (ARA) is a heuristic algorithm obtained from the natural rainfall phenomenon. By simulating the natural rainfall process, it is divided into six stages which are: raindrop formation, raindrop descent, raindrop collision, raindrop flow, raindrop pool renewal, and water vapor renewal, and the optimization process is based on the evaluation of the potential energy of raindrops and selecting the raindrops with lower potential energy [22].

The model of this paper is introduced into the ARA, and in order to speed up the operation of the algorithm, the raindrop descent operator of the original ARA is omitted, and the rest of the five optimization stages except the raindrop descent operator are used. The initial population is $N \times D$-dimensional real-valued parameter vectors, each vector represents a water vapor, and all water vapor vectors form a candidate solution set for the problem being optimized. A set of weight loss exercise prescription parameter vectors is treated as a water vapor or a raindrop. The i rd water vapor vector in a G-generation population can be defined as in Eq. (23), where N is the population size and D is the problem dimension:

$$V^G = \left[v_{i,1}^G, v_{i,2}^G, \ldots, v_{i,\mathrm{D}}^G \right], i = 1, 2, \ldots, N \tag{23}$$

Raindrops are formed by the continuous fusion and absorption of water vapor to increase the volume, and the raindrop formation operator can be expressed as shown in Eq. (24):

$$R^G = \left(\frac{1}{N} \sum_{i=1}^{N} v_{i,1}^G, \frac{1}{N} \sum_{i=1}^{N} v_{i,2}^G, \ldots, \frac{1}{N} \sum_{i=1}^{N} v_{i,\mathrm{D}}^G \right) \tag{24}$$

Large raindrops falling to the ground will produce a collision operation, the collision for a number of small raindrops, define the number of small raindrops as the number of populations N, raindrop collision operator can be expressed as shown in Equation (25):

$$smallR_i^G = R^G + sign\left(\alpha - 0.5\right) \cdot \log \beta \cdot \left(R^G - v_k^G \right) \tag{25}$$

where α and β are random numbers between 0 and 1, $sign(\cdot)$ is a sign function, and v_k^G is a randomly selected water vapor in the population.

The small rain drops fall to the ground and flow towards the location with lower potential energy, and the flow direction is controlled using d_1 and d_2 as in Eq. (26):

$$\begin{aligned} d_{1i} &= sign(f(RP_{k1}^G) - f(smallR_i^G)) \cdot (RP_{k1}^G - smallR_i^G) \\ d_{2i} &= sign(f(RP_{k2}^G) - f(smallR_i^G)) \cdot (RP_{k2}^G - smallR_i^G) \\ d_i &= \tau \cdot rand1_i \cdot d_{1i} + \tau \cdot rand2_i \cdot d_{2i} \end{aligned} \tag{26}$$

where RP_{k1}^G and RP_{k2}^G are two raindrops randomly selected from the raindrop pool, τ is the flow factor of the raindrops, and $rand1_i$ and $rand2_i$ are random numbers between 0 and 1. The raindrop flow operator is shown in Equation (27):

$$newSR_i^G = smallR_i^G + d_i, i = 1, 2, \ldots, N \tag{27}$$

The potential energy of the raindrop is calculated using the raindrop after the flow. If the potential energy of the raindrop after the flow is greater than the potential energy before the flow, it means that the flow direction is wrong. If the potential energy is lower than the potential energy before the flow, the flow continues in that direction, and since raindrops do not flow all the time in nature, a maximum number of flows is set to limit the flow.

Finally, the raindrop pool is updated, the raindrops with the lowest calculated potential energy are put into the raindrop pool, due to the limited size of the raindrop pool, after iterating to a certain number of times the raindrop pool is full of raindrops overflowing, then raindrops are deleted from the raindrop pool using a random selection method.

The process of raindrop updating algorithm is as follows: the flowed raindrops $newSR_i^G$ and water vapor V^G are sorted by bubble sorting according to the potential energy, and the N individuals with the lowest potential energy are selected as the new generation of water vapor population V^{G+1}.

At the end of the algorithm, the raindrop with the lowest potential energy is the final result.

In this study, the following solution process is designed for optimizing the allocation of compulsory education resources in Y city:

1) Statistics of compulsory education resource allocation data of compulsory education stage in Y city and county, and data preprocessing.

2) Set $\omega_1 = 0.4$, $\omega_2 = 0.3$ and $\omega_3 = 0.3$ for the coefficients ω_1, ω_2 and ω_3 of the three objective functions proposed in this study.

3) Use the entropy weighting method to solve the value of weight $\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6, \varphi_7, \varphi_8$ corresponding to the eight indicators.

4) Bring the preset values of the three objective functions ω_1, ω_2 and ω_3 and the weights accounted for by the eight indicators into the model, and use the artificial raindrop algorithm to find the optimal solution. The experimental flow is shown in Fig. 3.

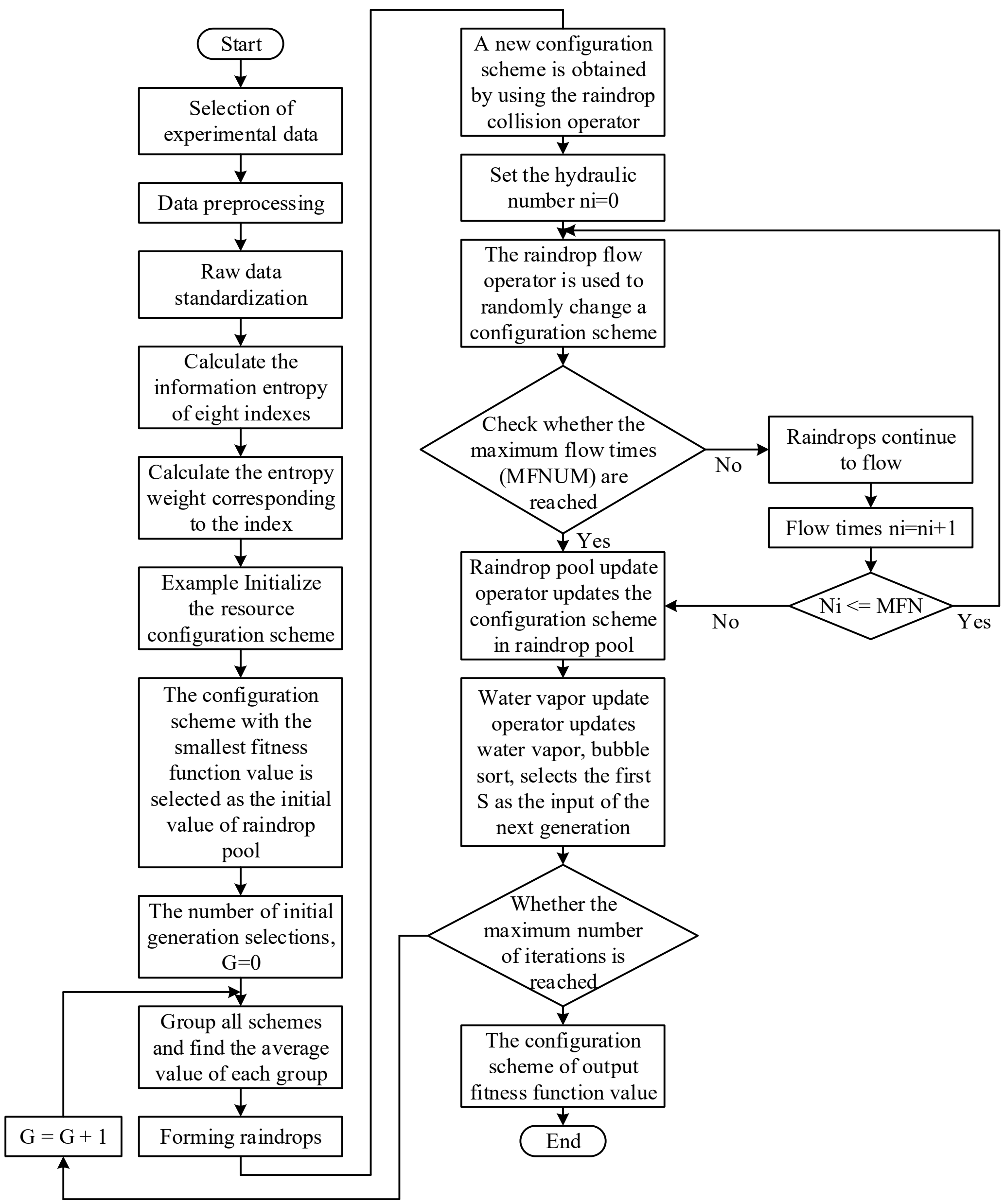

Fig. 3. Model solution process

4. Solving models for optimizing the allocation of educational resources

This chapter uses the artificial raindrop algorithm for experimental testing and applies the artificial raindrop algorithm to solve the optimization model of educational resource allocation proposed in this study.

4.1. Entropy weighting method to solve the weights of indicators

For the district and county education resource allocation model, the eight indicators will have different impacts on the education of the district and county. Entropy weight method is an objective assignment method calculated based on the discrete nature of the data itself [23]. The entropy weight method can assess the change status of indicators in an indicator system. The specific steps are shown below:
1) Data standardization. Assuming a given k indicator $X_1, X_2, \ldots, X_k$ of which $X_i = \{x_1, x_2, \ldots, x_n\}$. According to the formula (28) can be obtained as follows evaluation matrix:

$$Y_{ij} = \frac{x_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} \tag{28}$$

The results of data normalization are shown in Table 4.

Table 4. The standardization results of data

Region	V1	V2	V3	V4	V5	V6	V7	V8
1	0.0575	0.073	0.0791	0.0651	0.0717	0.0707	0.0391	0.0552
2	0.0435	0.0596	0.0643	0.0727	0.0905	0.0435	0.0484	0.0423
3	0.0447	0.0481	0.064	0.0442	0.0709	0.0798	0.0776	0.0829
4	0.0969	0.0468	0.0855	0.0979	0.1088	0.0953	0.0778	0.0911
5	0.0906	0.0727	0.0854	0.0752	0.0897	0.1031	0.099	0.0868
6	0.0899	0.1048	0.0732	0.0819	0.0515	0.0728	0.0909	0.0704
7	0.124	0.1065	0.1059	0.0941	0.0615	0.0931	0.1111	0.0921
8	0.025	0.0385	0.0387	0.0315	0.0394	0.0685	0.0711	0.0431
9	0.0611	0.1014	0.0918	0.0801	0.041	0.0943	0.0953	0.1028
10	0.0641	0.0864	0.0746	0.0731	0.086	0.0705	0.0625	0.0713
11	0.1061	0.0868	0.0948	0.0952	0.1255	0.0773	0.101	0.0884
12	0.0663	0.0847	0.0483	0.0717	0.1248	0.0698	0.0565	0.0807
13	0.0968	0.0929	0.0996	0.0669	0.0448	0.0835	0.0949	0.0743

2) Calculate the information entropy of the indicators in the evaluation system. Assuming that the system contains n evaluation index and m objects. Construct the evaluation matrix as A and its standardized matrix R, both matrices are $m \times n$-dimensional. The calculation of information entropy is shown in equation (29):

$$\begin{aligned} E_j &= -\frac{1}{\ln m} \sum_{i=1}^{m} P_{ij} \ln P_{ij}, j = 1, 2, \ldots, n \\ P_{ij} &= \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}}, i = 1, 2, \ldots, n \end{aligned} \tag{29}$$

When $P_{ij} = 0$, $P_{ij} \ln P_{ij} = 0$, the information entropy of the district and county indicators is derived as shown in Table 5.

Table 5. The information entropy of indices in districts and counties

Evaluation index	Information entropy	Evaluation index	Information entropy
V1	0.9763	V5	0.9966
V2	0.9762	V6	0.9953
V3	0.9801	V7	0.995
V4	0.9793	V8	0.9999

3) Calculate the entropy weight of the indicators in the evaluation system. The entropy weight is calculated as shown in equation (30):

$$w_j = \frac{1-E_j}{n-\sum_{j=1}^{n} E_j}, j = 1, 2, \ldots, n \tag{30}$$

According to the formula for calculating the weights of the indicators, the proportion of the evaluation indicators of education-related resources can be obtained as shown in Table 6.The weights of V1~V8 are 0.2214, 0.1986, 0.0563, 0.0711, 0.1655, 0.0635, 0.1452, and 0.0784, respectively.

Table 6. The wight of region and county indices

Evaluation index	Wight	Evaluation index	Wight
V1	0.2214	V5	0.1655
V2	0.1986	V6	0.0635
V3	0.0563	V7	0.1452
V4	0.0711	V8	0.0784

4.2. Simulation experiments of the model

Based on equation (30), the corresponding weights of the eight indicators are obtained, the weights are brought into the model, and then the artificial rain algorithm is applied for the optimization of educational resource allocation to solve the problem. The experimental results are shown in Table 7. The number of full-time teachers (NT), the number of teachers with higher than required academic qualifications (NM), the number of teachers with intermediate and above professional and technical positions (NS), the number of computer stations (NF), the assets of teaching instruments and equipment (NE), the total number of books (NB), the total area of school buildings (NX) and the total area of sports venues (NY), which are allocated to each district and county, are solved respectively.

Table 7. The results of experiment of counties and districts

Region	NT	NM	NS	NF	NE	NB	NX	NY
1	431	216	590	4399	10158	273869	868370	31827
2	607	214	413	5540	5560	244992	759831	144890
3	355	290	24	4686	7279	322619	650820	101520
4	145	99	1	1751	3537	272	439260	40413
5	1	244	1	663	2396	1	145410	9167
6	141	268	1	2761	6899	74041	152971	1
7	1	352	1	1	5888	80	19	1
8	1220	252	247	9941	15670	398081	1156719	45740
9	1	194	21	2640	10761	235237	372601	1
10	34	223	542	8285	10860	290080	1031920	73227
11	70	147	1	1057	811	46	67348	1
12	620	249	348	9306	1138	379661	1282220	10604
13	43	166	22	2587	8177	223	129310	1

The iterative convergence of the algorithm is shown in Fig. 4, and it can be seen that the experiment stabilizes at about 160 generations, indicating that at this point we get the optimal solution of the model, and the value of the fitness function at this point is 25763.1.

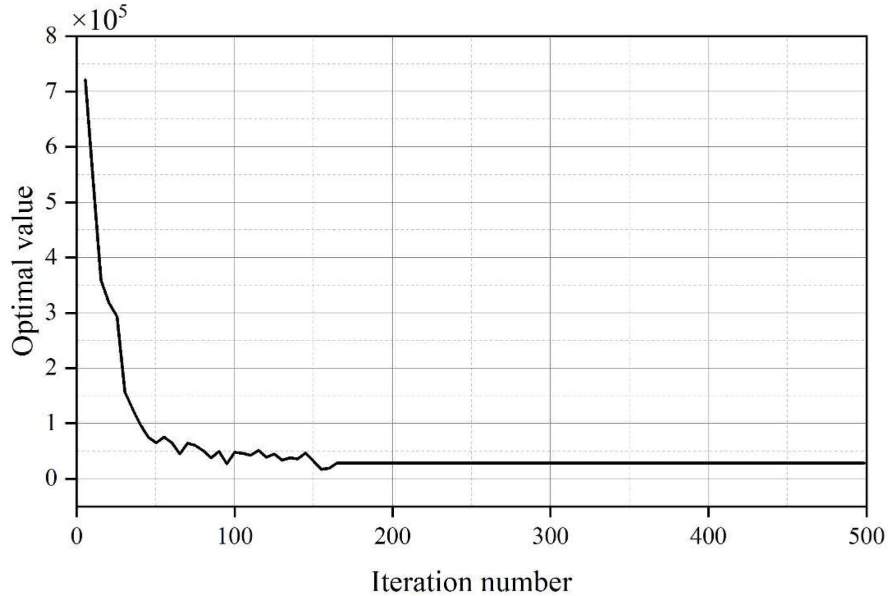

Fig. 4. The iteration graph of algorithm

4.3. Comparative analysis of experimental results

The experiment obtained the results of educational resource allocation in each district and county of Y. The existing resources of each district and county plus the allocated resources are the results of the optimized resource allocation in that district and county. The study was conducted in accordance with the educational resource allocation evaluation index system on the optimized educational resources in Y city, and the data obtained for each index is shown in Table 8. At this time, the allocation of educational resources in district and county 1 is as follows: the teacher-student ratio (1:20), the number of teachers per student higher than the required academic qualifications (1:4), the number of teachers with intermediate and above professional and technical positions per student accounted for 60% of the total number of teachers, every 1 student owns 1 computer, and every student owns 45.5 books, etc., which is a big improvement in the optimized allocation of educational resources.

Table 8. The resource allocation optimization results of counties and districts

Region	V1	V2	V3	V4	V5(yuan)	V6	V7(m^2)	V8(m^2)
1	0.05	0.25	0.6	1	324.6	45.5	24.7	7.9
2	0.06	0.83	0.6	1	364	47.9	23.8	11.7
3	0.05	0.68	0.6	0.9	383.4	49.1	29.2	16.3
4	0.06	0.76	0.7	0.8	360.3	45.1	22.1	14.2
5	0.07	0.7	0.6	1	357	40.8	24.8	15.6
6	0.1	0.69	0.6	1	376.3	41.1	27.9	13.4
7	0.06	0.79	0.6	0.9	391.4	44.9	24.8	17.2
8	0.07	0.13	0.6	1	384	47.1	26.9	11.6
9	0.09	0.16	0.7	0.8	331.2	48.8	23.6	12.3
10	0.06	0.92	0.6	1	283.7	46.7	21.5	9.6
11	0.07	0.11	0.7	1	232	42.5	20.9	13.2
12	0.08	0.88	0.7	0.9	228.5	36.3	21.3	11.6

13	0.1	0.38	0.7	0.8	253.1	35.2	29.7	11.9

The optimized allocation of educational resources was evaluated based on the BP evaluation system, and the evaluation results are shown in Table 9. The 13 districts and counties were 5, 7 and 1 in the "very good", "good" and "acceptable" grades, respectively, and the allocation of educational resources in no districts and counties was in the "poor" level. The results show that the optimized allocation of educational resources can better meet the demand of educational resources in Y city.

Table 9. The education resource optimization distribution evaluation result

Region	Evaluation result	Region	Evaluation result
1	Very good	8	Very good
2	Good	9	Very good
3	Good	10	Very good
4	Acceptability	11	Good
5	Good	12	Good
6	Good	13	Very good
7	Good		

5. Conclusion

The study used the BP neural network-based educational resource allocation evaluation system to analyze the specific data of educational resources in 13 districts and counties of Y City in 2023, and the allocation of educational resources in the urban area and county was quite different, which could be divided into 4 levels, and only 3 districts and counties belonged to the "very good" and "good" levels. Therefore, this paper constructs a multi-objective optimization model to improve the level of educational resource allocation, reduce the difference between counties, and improve the utilization rate of educational resources, and uses the artificial raindrop algorithm to solve the model.

The artificial raindrop algorithm was used to obtain the results of educational resource allocation in each district and county of Y city, and the optimized resource allocation evaluation system based on BP neural network was used to evaluate the optimized resource allocation. At this time, a total of 12 districts and counties were allocated to "very good" and "good" educational resources, and only 1 district and county was "acceptable". The decrease in the classification of grades indicates that the difference in the allocation of educational resources in districts and counties has become smaller, and the level of educational resource allocation has improved in most districts and counties, indicating that the calculated allocation of educational resources has improved the level of educational resource allocation and the utilization rate of educational resources.

The optimization method of educational resource allocation designed in this paper can reasonably plan educational resources and realize the coordinated development of education. The correctness and usability of the model are verified to provide theoretically based decision-making guidelines for the allocation of educational resources.

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