Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 7563351, 10 pages
https://doi.org/10.1155/2022/7563351

Research Article

Research on the Application of Artificial Intelligence Wireless Network Technology in the Optimization of University Resources

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Received 29 November 2021; Accepted 25 January 2022; Published 16 March 2022

Academic Editor: Narasimhan Venkateswaran

With the increase of teaching resources in universities, allocation for teaching resources has gradually attracted people's attention. How to optimize and reorganize the numerous teaching resources so as to maximize the teaching efficiency and achieve the best teaching effect is a question that the majority of college management workers must think deeply. Due to the development of computer science, artificial neural networks and wireless networks have made considerable progress. This article optimizes the resources of colleges and universities from these two aspects. First, this work proposes an improved artificial neural network to optimize school resources. The algorithm pointed out that the adaptive genetic algorithm itself has problems such as slow evolution speed and poor individual diversity of the population. After that an improved adaptive genetic algorithm is proposed to optimize BP network training process. By introducing individual evolutionary trend adjustment parameters, a new calculation formula for crossover probability as well as mutation probability is constructed. Improved BP algorithm can effectively avoid the shortcomings of local minima. Second, additional momentum and adaptive learning rate strategies are used to optimize BP network to promote the efficiency for network training. Third, the artificial intelligence network is deployed in the wireless network, and the wireless network will complete the work of data collection, processing, and transmission, so as to optimize the resources of colleges and universities.

1. Introduction

Education and educational equity have been put on an important position. Educational equity, as the name implies, refers to the process of regulating and rationally distributing limited educational resources between different levels of education, between different regions, and between different schools in accordance with established principles. The fair allocation of educational resources is the essence and core of the allocation of educational resources. Educational equity is to uphold the principle of equal educational opportunities and to carry out a reasonable allocation of educational resources through established educational policies and educational regulations. Provide educational resources in a reasonable and balanced manner for the education system at all levels of schools in all regions, so that the subject of education can fully enjoy the educational resources and achieve the optimization of educational benefits when the educational resources reach a relatively balanced state of supply and demand. Educational equity is closely linked to social equity, and equity in the allocation of educational resources is the prerequisite and basis for achieving educational equity. Therefore, only through reasonable and balanced implementation of the optimization of the allocation of educational resources can education fairness be realized and social fairness be made possible [1–5].

At present, an important aspect that affects the equity of my country's higher education is the unbalanced allocation of resources, which is specifically manifested in the following aspects. (1) The distribution for resources is unbalanced between regions. (2) The uneven distribution for resources between different universities. (3) The unbalanced distribution for resources within universities. (4) The allocation for educational resources between public universities and private universities is not balanced. (5) The efficiency of resource allocation in higher education is not high. The unbalanced allocation of resources directly leads to the unfairness of the school-running foundation and development platform of different schools, and thus the unfairness of the teaching staff. Ultimately, it affects the balanced training of talents, leads to unfair economic development in different regions, and ultimately restricts social equity. Therefore, the optimal allocation of higher education resources has become a major issue facing my country's higher education [6–10].

Higher education is the cutting-edge part of education. It is an education link that cultivates a large number of in-depth and specialized talents for the society. It not only provides human resources for the society but also the main source of social technical resources. These high-level professionals are the backbone of the development today and are successors, builders, and innovators of socialist modernization. Higher education directly affects the cultural level of the country. The development for higher education is a driving force for the country's economic development and an indicator of the level of social development. It promotes the progress of culture, is the cultural foundation of the country's development, and is a source of strength. Only the healthy and sustainable development for education can strive to maximize effectiveness of higher education, improve continuous advancement for social and economic construction. Therefore, as a necessary condition for the healthy development for higher education, optimal allocation of resources has great research significance [11–19].

Relying on computer technology, this work embeds neural network and wireless network into optimization for college education resources. The contributions are as follows: (1) Design an improved adaptive genetic algorithm, and combine it with the BP network to optimize the resources for universities. (2) Embed the additional momentum method and adaptive learning rate into the training of the BP network to improve network performance. (3) Combine the neural network and wireless network, and deploy the neural network in the remote wireless network to realize the optimization of university resources.

2. Related Work

On the whole, the existing researchers' research on resource allocation in universities mainly focuses on the differences in resource allocation in higher education, existing problems, factors affecting resource allocation, and resource allocation optimization strategies.

Research on the difference in resource allocation of higher education: Mao [20] found that the differences in the per-student construction area and the per-student total value of school fixed assets between provinces, cities, and regions all show a decreasing trend, but the student-teacher ratio has shown an increasing trend. Hayhoe et al. [21] discussed the regional differences in the allocation of resources for higher education in my country. The study found that the number of universities in the eastern, central, and western regions decreased successively. The overall investment in higher education in my country presents a pattern of strong in the east and weak in the west. From the perspective of funding sources, the more we go to the west, the more we rely on national financial support, and the tuition and miscellaneous fee income of colleges and universities and social donations show a trend that the east is higher than that in the west.

Research on the allocation of higher education resources: Zhou [22] pointed out that the resource allocation of higher education in my country has problems such as single-resource supply channels, unreasonable supply methods, and unbalanced supply structure. At the same time, there is still an imbalance in the allocation of educational resources. Liu and Gao [23] show that the subject, object, and allocation method of the allocation of higher education resources in my country are all unbalanced to varying degrees. Liu [24] analyzes the Matthew effect of higher education resource allocation in terms of financial subsidies, personnel mobility, infrastructure, and scientific research projects. The study puts forward that the limitation of educational resources, the relative fairness of education and the influence of the unified evaluation mechanism are the reasons for the Matthew effect. The establishment of a diversified evaluation system and funding input system is the main method to alleviate the Matthew effect. Geng and Zhao [25] analyze the problems existing in the allocation of educational resources in universities in different regions. It is believed that the main problems existing in the allocation of higher education resources in Sichuan and Chongqing are as follows: unbalanced distribution of educational resources, large regional differences, lack of high-quality educational resources, and large gaps in the benefit structure. An effective resource-sharing mechanism has not been formed and the sharing mode needs to be further improved.

Research on the influencing factors of higher education resource allocation: Researchers believe that there are many factors affecting the allocation of higher education resources, some of which come from the macro level and some from the micro level. Researchers have found that socioeconomic factors such as per capita GDP, geographic location, and institutional settings affect the allocation of higher education resources. Tóth [26] uses the DEA-Tobit method to study the factors affecting the efficiency of higher education in 19 European countries. The results found that GDP per capita has a positive influence on higher education. Yao [27] shows that the geographical location, natural conditions, and transportation development of universities will affect the allocation for education resources. This is mainly achieved through the selection of colleges by students, the attraction of talents by universities, introduction of funds, and improvement of the school's software and hardware capabilities. Kempkcs and Pohl [28] show that institutional settings are a key factor affecting the efficiency of college allocation. It also proved that the construction of school hospitals and engineering colleges in universities will significantly affect the efficiency of educational resource allocation. Wu et al. and Feng and Zhang [29, 30] show that regional economic material foundation, economic growth mode, relative insufficient economic aggregate, and differences in economic development, quality and level of difference will lead to insufficient supply of education resources. And there are differences and imbalances between regions.

3. Method

As a cutting-edge technology in artificial intelligence, ANNs have a unique form of calculation in dealing with nonlinear problems. A network is consisted of many nodes, that is, neurons. These simple structural units are connected to each other to form a huge network system to achieve the ability to learn and store knowledge. Therefore, it is often used in pattern recognition, optimization decision-making, data compression, and prediction. As one of many optimization algorithms, the basic principle of genetic algorithm is to follow the biological evolution theory of natural selection as well as survival of the fittest. The genetic algorithm searches from the initial population, not from a single solution. Traditional optimization algorithms are usually easy to be locally optimized. The main reason is that they only start iterative calculations from a single value. Therefore, the initial calculation coverage of genetic algorithms is wide, thereby reducing the risk of falling into a local optimization. Advantage for genetic algorithm is that there are many initial calculation objects, it can process a large number of individuals at the same time, it is easy to realize parallel processing, and it improves the solving speed of the algorithm. Using the characteristics and advantages of genetic algorithm to optimize BP model is also one of key contents of this paper. This work combines neural network and genetic algorithm to optimize the resources of universities.

3.1. BP Network. For the BP network to be able to learn and remember many different nonlinear mapping relationships, it relies on the error back propagation algorithm to alter the weights and thresholds of the neuron connections. There are two basic processes that make up the BP network algorithm: forward propagation of the working signal and back propagation of the error signal. Input signal forward propagation and reverse network error transmission are used to determine the error between network output and actual value. The network parameters are updated according to the allowable range set by the error. When propagating forward, the input signal is processed by each layer of neurons along the network topology and finally reaches the output layer to obtain the network output result. If the output signal is very different from the actual signal, the network enters the reverse transmission process of the error signal. In backpropagation, the network divides the error value into each layer evenly according to the weight and serves as the basis for modifying each unit. After the repeated propagation process of the signal, the algorithm can achieve the purpose of modifying the network weight and neuron threshold until final output result meets the actual expectation.

The BP network model is composed of input layer, hidden layer, and output layer. Only the units of adjacent neural layers are connected, but the neurons of the same layer are not connected to each other. The network structure is shown in Figure 1. There are p nodes in the hidden layer.

The BP modifies threshold value as well as connection weight of neuron according to the following formula:

$$\Delta w = -\eta \frac{\partial E}{\partial w}, \tag{1}$$

$$\Delta b = -\eta \frac{\partial E}{\partial b}, \tag{2}$$

where η is learning rate and E is the loss.

The BP neural network repeatedly propagates signals and errors back and forth and constantly adjusts the thresholds and connection weights of each layer. Until the error between the output and expected value reaches a predetermined range, the network will stop the training process when the network reaches the convergence state. If the number of network training has reached the set upper limit and the output result fails to meet the required output expectations, it indicates that the network has not reached the convergence state, and the algorithm iteration stops.

The BP algorithm is not only mature but also covers a wide application, the network has high level of nonlinear approximation, and its generalization ability and fault tolerance are better than traditional algorithms. (1) Nonlinear mapping: BP is the most widely used method to deal with nonlinear problems. After learning, it can store relationship between input as well as output. (2) Generalization: the network has strong self-learning and self-adaptive capabilities. Through the learning and training of a large number of input samples, the network can obtain the output results corresponding to the input. When new sample data are input, the network can gradually approach the inherent characteristics and laws of the sample data by gradually learning the new data and completing the training. (3) Fault tolerance: A large amount of information learned and trained by BP network is stored in the connection weights in a distributed form. Even if the local is damaged, it will not have much impact on the global output, and it has a certain fault tolerance.

Although the BP neural network algorithm is favored by many different fields, it cannot ignore some of its own shortcomings. (1) The problem of local minima. The traditional BP is a local algorithm and a nonlinear optimization model. It uses the gradient descent method as the learning criterion and trains along the direction of the error function declining continuously. In the training, connection weight is adjusted along the direction of local improvement. If the local minimum is encountered first in the adjustment process, the network will fall into the trap of local extreme worth and miss the global optimum, leading to training failure. BP is more sensitive to initial weights as well as thresholds. If the initial weights are different each time, the network converges to different local minima, and the output will also change accordingly. (2) The learning efficiency is low. Since the BP algorithm uses the gradient descent method, the error function adjusts the network connection weight along the negative gradient direction. And the

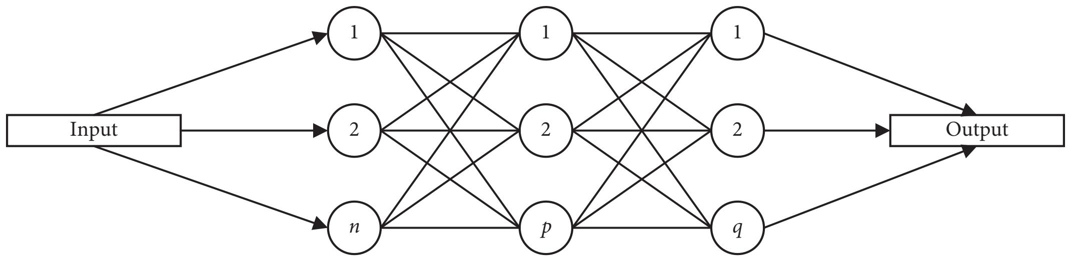

Figure 1: BP network.

optimized objective function is very complex, which will lead to low learning efficiency. If the weight changes very little during the training process, it will also cause the network to stagnate. (3) It is difficult to set the network parameters. The BP neural network has a complex structure and a large amount of parameters. As there is not enough theoretical support, it is difficult to set the parameter values, including hidden layers, neurons, and learning rate can only be set by experience. This also has a certain degree of impact on performance. (4) The choice of network structure. Size of the network structure determines the level of network performance. At present, there is no clear basis for the choice of network structure, and it can only be selected based on experience. In a large number of network structure debugging, it can be known that if the network training has an over-fitting phenomenon, it may be that the structure is set too large. If convergence cannot be achieved during network training, the structure may be set too small. Therefore, a reasonable choice of BP neural network structure is also an important strategy to improve the overall performance.

3.2. Optimizing BP Based on Genetic Algorithm. When the input-output relationship is complex, BP may step into the local minimum trap, network convergence speed is not fast, and even nonconvergence phenomenon may occur. The local optimization ability of BP network is quite superior, but global search will be poor. Global search of genetic algorithm is very prominent, but the local optimization is not ideal. A genetic algorithm is proposed to optimize BP model, so that achieves the effect of complementary advantages, and improves speed and accuracy. This article mainly studies the use for genetic algorithm to optimize initial connection weights and thresholds, so as to avoid phenomenon of BP falling into local optimization as well as convergence stagnation. The initial weights and thresholds are obtained randomly by computer programs, if this set of initial random parameters is not suitable for the target problem solved by the current network, it will cause differences in network convergence results. It will also cause network falls into a local optimization, which reduces the training speed as well as prediction accuracy. Therefore, the use of genetic algorithm to optimize the parameters can help BP algorithm to obtain the most suitable initial weights and thresholds for network learning and effectively overcome the shortcomings.

3.2.1. Algorithm Flow. The initial connection weights and thresholds improved with genetic algorithm are more suitable for network training and avoid network oscillation or even nonconvergence caused by improper selection of initial values. The operation: First determine the structure of network and select a suitable coding method to form the initial population of the algorithm. Then through the operation of selection, crossover as well as mutation operators, new individual is generated to improve overall fitness of the population. Finally, when the conditions for stopping the algorithm are met, the optimal individual obtained is decoded, and the initial weights and thresholds are assigned. Operation of BP algorithm: According to the obtained network parameters, use the sample to train network and calculate error value. If the error value is too large, the error signal will be propagated back, and the network weight and threshold will be corrected at the same time, and the network learning will be terminated until the error reaches the predetermined requirement. Specific process is shown in Figure 2.

Encoding is to transform the parameters of the optimization problem into the form of chromosome gene strings that can be understood by the genetic algorithm. The coding object for this article is initial weight and threshold. To reduce complexity of coding and increase the speed, this paper chooses real number coding. The selection of population size is also a science of genetic algorithm parameter selection. If population size is large, it is difficult to dominate the evolution direction. If population size is small, algorithm search speed is slow, and some local optimal individuals have an adverse effect on the population evolution. The proportion of China has risen. According to relevant experience, the general initial population size is between 30 and 200. Assuming initial population consists of N strings of real numbers, the genetic algorithm searches for optimal solution from this population. The selection operator is operated according to the size of the fitness value, which is not affected by the encoding form and can use the roulette method, the optimal individual preservation method or the tournament method. The processing objects of crossover operator as well as mutation are individual chromosomal gene strings. It is necessary to design corresponding crossover operator as well as mutation form for different encoding methods. This article uses real number coding, the crossover operator can use arithmetic crossover method, and the mutation operator can use uniform mutation or nonuniform mutation. Since the output error of BP is as

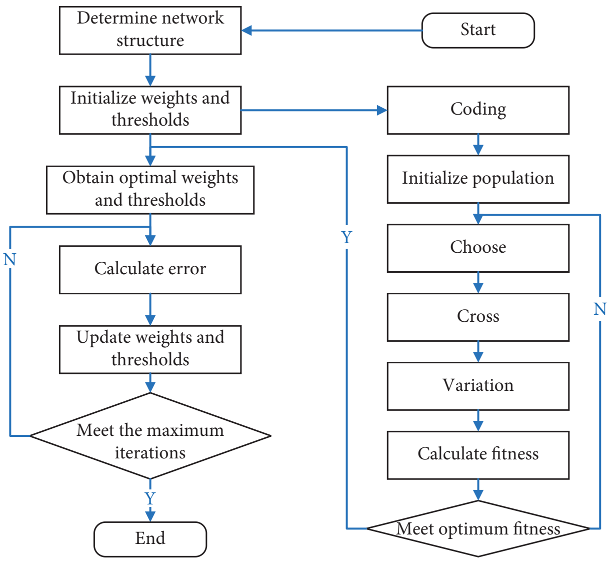

Figure 2: Genetic neural network algorithm flow chart.

small as possible, the optimization goal of the genetic algorithm is to obtain a set of parameter values that minimize the sum of squared errors. Obviously, the smaller the sum for squares corresponding to an individual is, the better the individual is. Therefore, the individual fitness value is inversely proportional to the error sum of squares, and the calculation formula is as follows:

$$F = \frac{1}{1 + \sum_{i=1}^{N} \left(y_i - o_i\right)^2}, \tag{3}$$

where y_i is truth value and o_i is the predicted value.

3.2.2. Adaptive Genetic Algorithm and Improvement. The control settings of both the classical genetic algorithm and the existing modified genetic algorithm remain unchanged. Crossover probability and mutation probability are two invariable constants in the evolution process of genetic algorithm that may not be able to match the needs of the genetic algorithm. When the individual fitness value is lower than the average fitness value, a higher crossover probability must be chosen when designing a genetic algorithm. Only in this way can the algorithm's search area be expanded by speeding up the generation of new individuals. It is conceivable, however, if the crossover probability is too high, to damage the beneficial qualities of the individual, which will further alter how the group evolution process is conducted and reduce algorithmic stability. If the likelihood of a crossover is too low, the algorithm is more likely to reach a local extreme point or to stagnate. The genetic algorithm's mutation operation is another key tool for creating new individuals. This random search algorithm will emerge when the mutation chance is too high for the genetic algorithm to use historical information to lead the search space to a more suitable area. The genetic algorithm can only generate a small number of new individuals when the mutation chance is low, making it difficult to sustain population diversity. Therefore, the optimization performance of genetic algorithm mainly depends on the calculation method of crossover probability and mutation probability.

The basis of adaptive genetic algorithm is in process of population evolution, individuals can automatically adjust crossover probability p_c as well as mutation probability p_m. When individual fitness is poor, p_c and p_m can be appropriately increased. When individual fitness is greater than the average value, set lower p_c and p_m to protect the excellent individual from inheriting to the next generation. Therefore, the adaptive crossover probability as well as mutation probability can always maintain p_c with p_m required for the optimal solution at the current evolutionary moment. The adaptive genetic algorithm is better than basic genetic algorithm in maintaining the diversity, it increases convergence ability of genetic algorithm and improves optimization performance of the genetic algorithm.

The calculation of p_c and p_m are as follows:

$$p_c = \begin{cases} \dfrac{\alpha_1 \left(f_{\max} - f_c\right)}{f_{\max} - f_{\min}}, & f_c \geq f_{\text{avg}}, \\ \alpha_2, & f_c < f_{\text{avg}}, \end{cases} \tag{4}$$

$$p_m = \begin{cases} \dfrac{\beta_1 \left(f_{\max} - f_m\right)}{f_{\max} - f_{\min}}, & f_m \geq f_{\text{avg}}, \\ \beta_2, & f_m < f_{\text{avg}}, \end{cases} \tag{5}$$

where $f_{\max}$ and $f_{\min}$ are maximum and minimum fitness, f_{avg} is the average fitness value, f_c is the maximum fitness of two individuals of parent of crossover operation, and f_m is the individual value of mutation operation.

The calculation methods of adaptive crossover probability and mutation probability cannot globally consider whether population individuals can smoothly enter the next generation of genetics, resulting in slow evolution of the algorithm as a whole. Aiming at the defects of adaptive genetic algorithm, such as slow evolution speed and poor self-adjustment ability, this paper improves the method of solving two control parameters for crossover probability and mutation probability on basis of adaptive genetic algorithm. A strategy to improve adaptive genetic algorithm (IAGA) is proposed. From the above analysis, it can be known that in the early stage of evolution, the best individuals in the population, that is, the individuals with the greatest fitness, will have a greater possibility to participate in the genetic evolution of the next generation. However, the offspring characteristics of these individuals after crossover are not very different from their parents, which cause the evolution of the algorithm to become slow. Therefore, this paper proposes an adjustment parameter μ to evaluate the evolutionary trend of individuals. Its purpose is to enable the genetic algorithm to maintain good search performance and search speed in the early, middle, and late stages of evolution. The specific calculation process is as follows:

Step (1): generate average fitness:

$$F_{\text{avg}} = \sum_{i=1}^{N} \frac{F_i}{N}, \tag{6}$$

where N is the population size and F is the fitness value of chromosome.

Step (2): calculate adjustment parameters:

$$\mu = F_{i\max} - \overline{F_i}, \tag{7}$$

where $F_{i\max}$ is maximum fitness and $\overline{F_i}$ represents an individual fitness greater than average fitness.

F_{avg} not only includes some individuals with higher than average fitness value but also includes individuals with poorer than average fitness value. In order to get a possible solution as soon as possible, genetic algorithm first selects individuals as parents to pass on excellent genes to the next generation. First, by solving $\overline{F_i}$, the individuals whose fitness is greater than the average are counted. This index better avoids the adverse effects of poor individuals in F_{avg}. Then perform the operation of calculating difference between $F_{i\max}$ and $\overline{F_i}$. The purpose of this move is to prevent poor individuals with less than average fitness from entering the adjustment mechanism, thereby destroying the normal iteration of the algorithm.

(1) Improved Adaptive Crossover Probability. When the individual genes in the population are poor, appropriately increase the crossover probability value to improve the individual's adaptability, so that the genes of the offspring are better than the previous generation. The specific calculation formula is as follows:

$$p_c = \begin{cases} \dfrac{\alpha_3}{1+e^{k_c}}, & f_c \geq f_{\text{avg}}, \\ \alpha_4, & f_c < f_{\text{avg}}, \end{cases} \tag{8}$$

where $k_c = f_c - \mu$, α_3, and α_4 are constant.

(2) Improved Adaptive Mutation Probability. When the individual fitness of the population reaches an unprecedentedly consistent height, the individual genetic characteristics of offspring and parents are not much different. When the algorithm is to complete the iteration, in order to increase diversity of group, value of mutation probability will increase appropriately. The specific calculation formula is as follows:

$$p_m = \begin{cases} \dfrac{\beta_3}{1+e^{-k_m}}, & f_m \geq f_{\text{avg}}, \\ \beta_4, & f_m < f_{\text{avg}}, \end{cases} \tag{9}$$

where $k_m = f_m - \mu$, β_3, and β_4 are constant.

According to the improved formula, in the population evolution process, when the parameter μ becomes larger, that is, when the population individual diverges, the crossover probability increases and the mutation probability decreases, so that the population tends to converge. When the parameter μ decreases, that is, when the population individuals converge, the mutation probability increases and the crossover probability decreases, maintaining the diversity of the population.

By designing a genetic algorithm to optimize BP model, this paper makes a deeper improvement to the genetic algorithm, and we design an adaptive genetic algorithm for real-time parameter adjustment. Using the improved algorithm to optimize BP network can make prediction model calculation faster and the prediction accuracy higher. The improved BP (IBP) process is illustrated in Figure 3.

3.3. Adaptive Learning Rate and Additional Momentum Term. The standard BP neural network has a fixed learning step length, or learning rate. Network instability occurs when the learning rate is too high and the network oscillates. The network convergence speed will be slow if the learning rate is too low. As a result, optimizing the overall network topology for problem-specific learning is difficult. It is the goal of adaptive learning to continuously adjust the weights and thresholds between linked layers in order to speed up convergence. This is done by monitoring the network error and adjusting the learning rate accordingly. Assuming given the initial $\eta(0)$, the error calculated by the kth iteration is $E(k)$. The learning rate changes are as follows:

$$\eta(k) = \begin{cases} \lambda_1 \eta(k-1), & E(k) < E(k-1), \\ \lambda_2 \eta(k-1), & E(k) > E(k-1). \\ \eta(k-1), & \text{others}. \end{cases} \tag{10}$$

The convergence speed can be increased by adaptively altering the learning rate throughout the error back propagation phase. It is important to note that only current time t and the gradient direction prior to time t are considered, which will lead to turbulence in training and the model being unstable. This will result in a model that is more likely to fall into a local minimum. It is necessary to insert an additional momentum term in order to alleviate this paradox, which modifies the weight value in order to dampen the error back propagation process:

$$\Delta w(k) = \nu \Delta w(k-1) - \eta \frac{\partial E(n)}{\partial w(n)}, \tag{11}$$

where ν is the momentum term.

3.4. Combination of the Neural Network and Wireless Network. With development of wireless network technology, the combination of wireless network and neural network can solve many problems. This article combines the designed BP network with the wireless network to complete the optimization of university resources. The framework is illustrated in Figure 4.

When training a neural network, first use the wireless network to collect training data. The input parameters of each training data consist of 10 indicators, and the specific

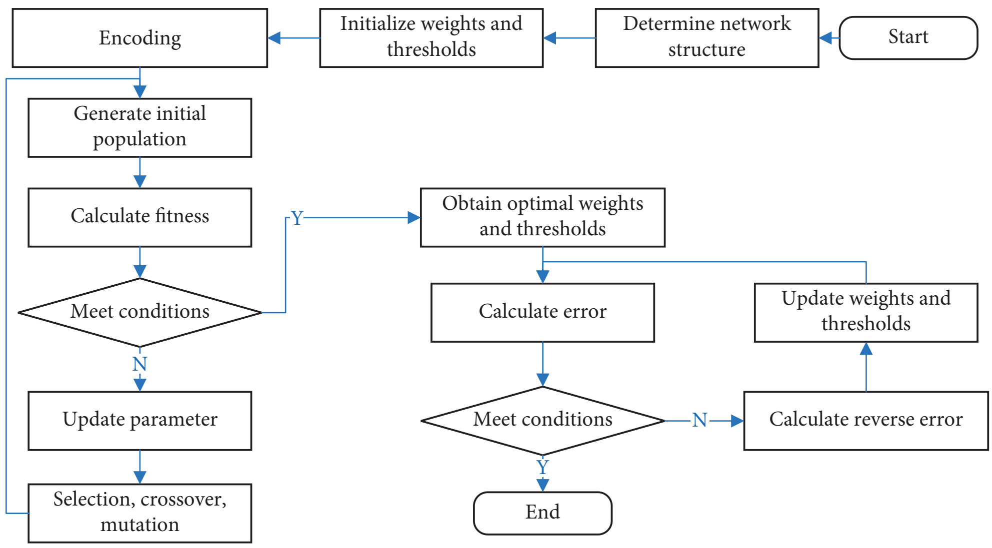

Figure 3: Improved BP algorithm.

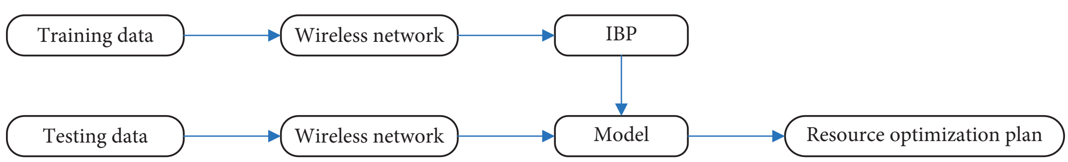

Figure 4: Combination of the neural network and wireless network.

settings are given in Table 1. After that, the neural network is deployed in the wireless network, and the collected data are used to train and optimize the network. Finally, a well-trained complete model is obtained.

When using the network for testing, first use wireless network to collect test data. After that, the trained model is used to perform feature extraction on the test data in the wireless network, and finally the resource optimization plan corresponding to the data is obtained. The optimization plan specifically refers to the input ratio of various resources as illustrated in Table 1.

4. Experiment

4.1. Data Set. This work collects data from universities in two provinces and cities, and self-made two data sets URA and URB. URA contains 1793 pieces of training data and 561 pieces of testing data. URB contains 2416 pieces of training data and 794 pieces of testing data. The evaluation metrics used in this work are precision, recall, and F1 score.

4.2. Evaluation on Training Loss. The convergence of the neural network is a significant indicator for evaluating performance. Only when network reaches the convergence state can it be predicted. Therefore, this article first evaluates the loss of the network on two data sets. The result is illustrated in Figure 5.

Obviously, with the training iterations increases, the loss of the network gradually decreases. When epoch is 60, the loss no longer decreases, which indicates that the network has converged.

Table 1: The input and output indicators of neural network.

Item	Index
Input	Teacher-student ratio
Input	Teaching level
Input	Percentage of teaching expenditure
Input	Teaching infrastructure costs
Input	Classroom utilization
Input	Laboratory utilization
Input	Number of books per student
Input	Number of instruments per student
Input	Student employment rate
Input	Student competence
Input	Faculty research funding
Input	Teacher's research results
Output	Human resources ratio
Output	Financial resources ratio
Output	Material resources ratio

4.3. Comparison with Other Methods. To verify the effectiveness of this method, the designed method is compared with other methods. The selected methods include Logistic regression (LR), decision tree (DT), Adboost, and SVM. The results are illustrated in Table 2.

It is not difficult to find that the improved BP network can obtain the best performance. Compared with best-

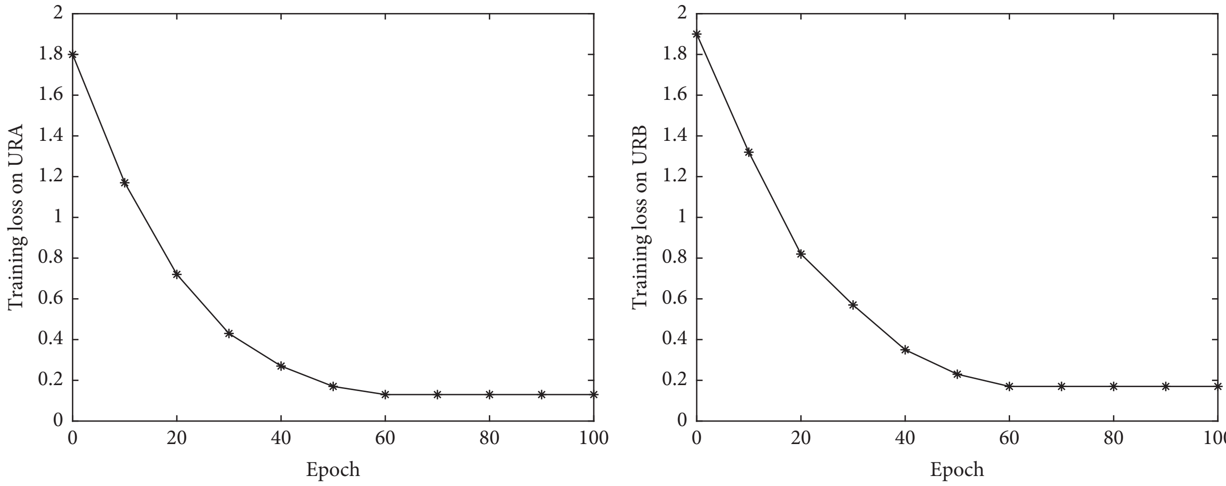

Figure 5: Training loss on URA and URB.

Table 2: Comparison with other methods.

Method	URA			URB		
	Precision	Recall	F1 score	Precision	Recall	F1 score
LR	81.3	78.9	80.5	80.7	77.5	79.3
DT	84.7	81.9	82.3	84.2	80.6	82.1
Adboost	87.9	84.5	86.2	86.9	83.8	84.7
SVM	89.2	86.2	87.8	88.7	85.2	87.1
IBP(Ours)	91.4	87.9	90.6	90.8	87.1	88.8

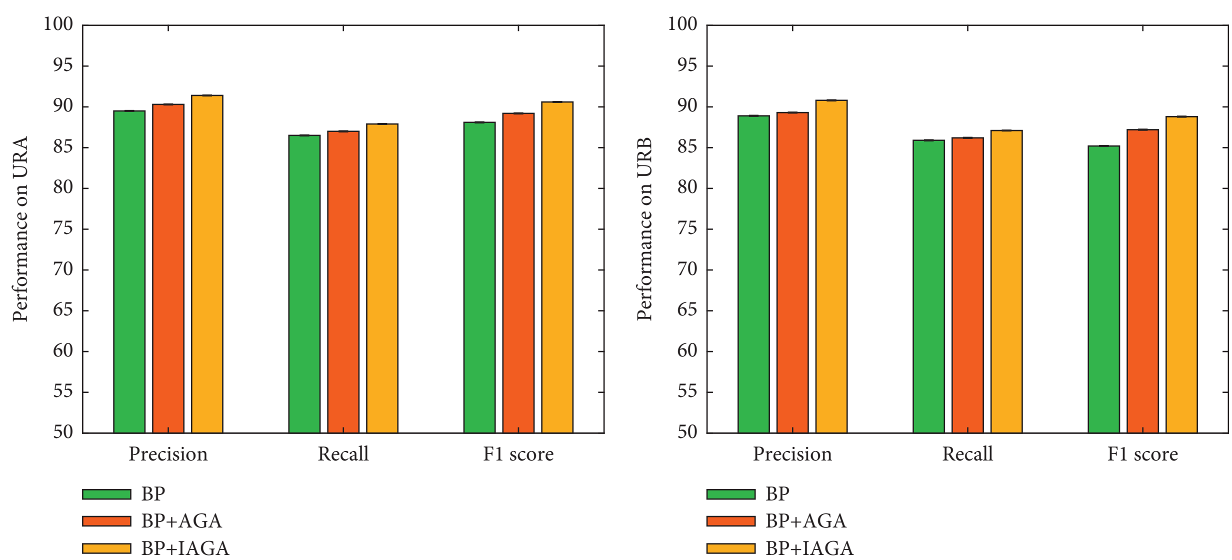

Figure 6: Evaluation on IAGA.

performing SVM method in the table, the performance improvement of 2.2%, 1.7%, and 2.8% gains on precision, recall, and F1 score can be obtained on the URA data set. The performance improvement of 2.1%, 1.9%, and 1.7% gains on precision, recall, and F1 score can be obtained on the URB dataset. This proves the validity and reliability of our method.

4.4. Evaluation on Improved Adaptive Genetic Algorithm. This work proposes an improved adaptive genetic algorithm (IAGA) to optimize BP network. To verify effectiveness for this strategy, this work compares the performance of the traditional AGA optimization algorithm with the performance of the improved IAGA optimization algorithm. The result is illustrated in Figure 6.

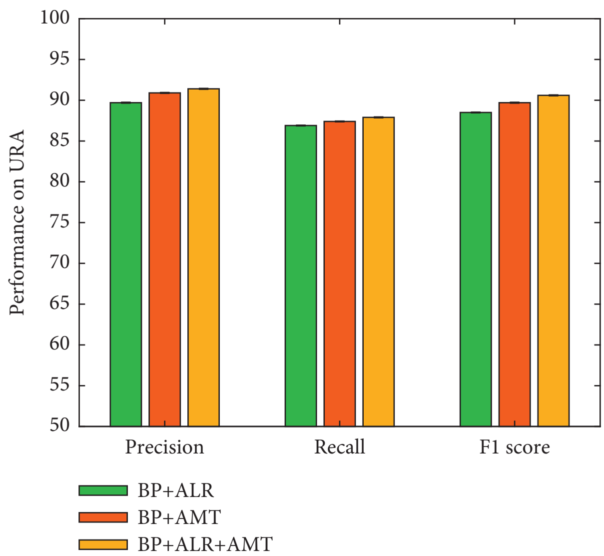

Figure 7: Evaluation on ALR and AMT.

Obviously, the performance corresponding to the traditional BP algorithm is the lowest. When the AGA algorithm is introduced, the performance of the network can be improved to a certain extent, but the room for improvement is relatively limited.

4.5. Evaluation on Adaptive Learning Rate and Additional Momentum Term. This work proposes an adaptive learning rate (ALR) and additional momentum term (AMT) to optimize BP network. To verify the effectiveness of this strategy, this work compares the performance of not using them with the performance of the improved BP algorithm. The result is shown in Figure 7.

Obviously, both ALR and AMT optimization strategies can improve network performance. However, neither of these two methods can achieve the best performance improvement when used alone. Only when the two are combined with each other and then used in the training and optimization of the BP network, the best performance can be obtained. These data also prove the correctness and reliability of the ALR and AMT strategies used in this article.

5. Conclusion

The allocation of university teaching resources has been a topic of discussion as the number of teaching resources grows. In order to increase teaching effectiveness and efficiency, college administrators must consider all of their options for optimizing and reorganizing their many educational resources. Artificial neural networks and wireless networks have made significant progress as a result of the advancements in computer science. This article helps schools and universities maximize their resources in both of these ways. First, this work proposes an improved adaptive genetic algorithm, combined with BP network to optimize teaching resources in colleges and universities. Second, the additional momentum method and adaptive learning rate are embedded in the training of the BP network to improve the network performance. Third, deploy an artificial intelligence network in the wireless network. The wireless network will complete data collection, processing, and transmission, and optimize university resources. This work has carried out a large number of experiments on the designed method, which proves the validity and reliability for our method.

Data Availability

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

Conflicts of Interest

The authors declare no conflicts of interest.

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