Research Article

Information Analysis of Advanced Mathematics Education-Adaptive Algorithm Based on Big Data

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With the rapid development of artificial intelligence (AI) concept technology, it promotes the innovation of educational concept. Mostly for the education information analysis in the class of mathematics in the university, it should be based on a big data-driven system to promote the quality of teaching in the classroom. In the method of teaching math in university, teachers should take full advantage of the benefits of a big data-driven system powered by AI, grow a good teaching model for students, promote education through big data, progressively teach students according to their aptitude, develop in a tailored direction, increase teaching quality and effectiveness, and finally create more great talents for our country. For the sake of improving the resource sharing and the management level of the curriculum which teaches advanced knowledge about mathematics teaching, based on a particle swarm optimization algorithm, an advanced math teaching system is proposed in this paper. The fusion model that can be used in the teaching process of math in university is constructed, the adaptive scheduling of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources is realized by an optimization algorithm used for fusion particle swarm, the autocorrelation feature of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources is extracted, and the adaptive optimization of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resource fusion is realized by fuzzy correlation feature matching and statistical analysis. In the process of particle swarm optimization, the combination of statistical features is studied and managed, the resource scheduling and information fusion are realized, and the management capability of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching is promoted, and the experimental results demonstrate that the designed system has a high integration of teaching information resources and strong information scheduling ability and improved the management level of the curriculum which teaches advanced knowledge about mathematics complementary teaching.

1. Introduction

Optimization is a very widely used term in real life. It reflects a very common phenomenon in human practical activities. It can be summarized as follows: optimization is how to give full play to the maximum utility of these resources on the premise of established human, material, and financial resources. Optimization is an optimization technology based on mathematics. People have been exploring the optimization method for a long time. As early as the 17th century, Newton of England and Leibnitz of Germany invented calculus containing optimization content. In 1847, Cauchy, a French mathematician (FM), first used the steepest gradient descent method to solve unconstrained optimization problems, in 1938, the former Soviet mathematician kahtopoh (Kantorovich) published mathematical methods in production organization and planning in this paper, and the solution multiplier method for solving the linear programming problem of production planning optimization decision is proposed for the first time. The theoretical discussion of optimization problems is developing with the needs of reality. However, due to the limitations of various objective factors, optimization theory has not formed an independent discipline until the 1930s. Since the birth of the world’s first computer in 1946, with the continuous development of production activities, the research on optimization problems has become an urgent need. Meanwhile, under the great advantage of the repaid advance achieved by
the computer technology (CT), we will have effective tools to solve some super large-scale problems, which can transform the theory into practical application, and make the optimization theory widely used in engineering, economic management, and so on.

Big data is a new concept in the information age. It mainly refers to massive data, which is based on computer information technology and has the characteristics of high digitization. Combining big data with the curriculum which teaches advanced knowledge about mathematics education can innovate teaching ideas as a whole, optimize existing educational ideas, explore a teaching system that meets the requirements of contemporary education, cultivate comprehensive quality talents, and realize teaching reform. At this stage, AI technology helps the education industry achieve a great advance [1–3], which has changed the traditional educational ideas and ideas, created a high-quality environment of study for students, realized the reform of education, and laid a good foundation for the innovation and development of China’s education field. In particular, the application of the big data-driven system supported by AI can make learning more interesting, guide students to study actively, and improve their academic performance [4]. Specifically, the impact of the system on education can be verified in many different aspects, some of which is as follows: first, it has changed the traditional teaching concept and carried out in-depth teaching innovation. For example, based on the big data-driven system, teachers can reasonably collect data, use computers for data editing, create a high-quality learning environment for students, provide students with learning content according to their actual learning situation (LS), realize targeted teaching, and improve the overall teaching quality. At the same time, the big data-driven system can also sort out students’ homework and test papers, strengthen the connection between after-school homework and classroom teaching, compile homework into computer recognizable programming, efficiently analyze data information, clarify students’ actual LS, design the most reasonable teaching strategies, and improve teaching quality. For example, flexible uses of computer AI are for “thinking” and “decision-making,” reasonable AI processing, and assisted teaching through robots [5]. Second, if we can apply the AI technology in our daily educational life, it can help us promote the modularization of excellent experience and make the existing teaching methods get a great progress. For example, the flexible application of the big data-driven system can realize intelligent approval and intelligent correction of students’ test papers, homework, and even Chinese and English compositions. Turn a large number of teaching activities into intelligent models, realize computer operation, reduce the traditional complex workload, and improve teaching efficiency and quality. In the future, the big data-driven system will be applied in more course teaching to help cultivate comprehensive quality talents. Through AI to realize computer vision processing, natural language processing, and automatic reasoning, innovate the existing development direction and realize intelligent processing. Finally, drive personalized teaching resources to achieve innovation. In the teaching process, based on big data drive, provide teachers with good teaching assistance, optimize existing teaching ideas, innovate existing teaching models, help students learn efficiently, and deepen their understanding of knowledge. For example, at this stage, robot learning assistance technology helps students sort out notes and record wrong questions through robots, realizes AI data analysis, gives full play to the value of big data, finds problems in learning, records students’ actual situation, and designs targeted teaching for students through data analysis to promote students’ all-round development [6].

In recent decades, information processing and management technology has made great progress, and also the construction of the curriculum which teaches advanced knowledge about the mathematics teaching management information system, the design method of big data information management, and the intelligent scheduling platform is adopted to realize the optimal design of mathematics in the university auxiliary teaching system and improve the intelligent management ability of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system through parameter optimal allocation and resource scheduling. Therefore, if we can design some new method of auxiliary teaching for the math education in university, it will be of great significance to make the information development and construction of higher education to get a great progress [1]. The designed system is constructed upon the integration of college’s math class’s auxiliary teaching resources and the design of the database model, studies the big data mining model of the curriculum which teaches advanced knowledge about the mathematics assist teaching framework, and realizes the design of the curriculum which teaches advanced knowledge about the mathematics assist teaching system combined with resource management methods. The designed method of resource optimal management of the curriculum which teaches advanced knowledge about the mathematics supplemental teaching system is mainly used to realize the optimal management of the math course assist teaching system resources by analyzing the correlation characteristics of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching system data and combining the fusion clustering method [2]. Among the traditional methods, the resource optimal scheduling models for developing the assistant teaching system in university’s math class, which mainly includes the resource optimal scheduling method of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system based on semantic ontology feature analysis, the resource scheduling method of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system based on data mining, fuzziness detection method, and association rule feature analysis method [3–5]. The parameter fusion model for making a supplementary to the mathematic course is established, in which the fuzzy information recognition and feature cluster analysis technologies are used to implement the system. However, the output stability of traditional methods for the design of the assistant system used to the curriculum which teaches advanced knowledge about mathematics is not high, and the
2.1. Big Data Analysis Technology.

In recent years, the Internet of things (IOT) technology has already achieved a much rapid progress by taking the advantage of the computer communication and Internet technology, so we can collect lots of data very easily and low cost. Unmarked data account for the vast majority of massive data. It takes a lot of human time, material, and energy to manually annotate the data, but some human resources are scarce, especially in some special fields, such as medicine, experienced doctors need to make accurate judgment on the patient’s case data, so the cost of manually marking the data is undoubtedly huge. However, the supervised learning-based method generally needs a large number of labeled data to obtain the necessary accuracy. Whether it is necessary to mark all unlabeled data indiscriminately and how to use unlabeled data have become the research direction of many scholars [10].

On other occasions, since we only have a little of high-quality data which are labeled by the domain export and they have the same distribution with the task field, it is bound to affect the generalization performance of the classifier in the target domain [11]. Fortunately, the training data with different distribution from the source area are easy to collect. How to use these training samples to improve the classifier’s generalization ability in the target domain has gradually attracted the researchers’ attention in recent years.

In many application requirements, such as face recognition and detection, remote sensing image ground object classification, and radar target recognition, we can just improve the classifier’s performance in a limited range [12–15]. If we can combine many different classifiers together, we may get a complicated but high accuracy classifier, this way has increasingly become a research hotspot in recent years. The following question is whether the individual classifiers are beneficial to reduce the generalization error of the integrated system. Balancing the differences between individual classifiers and the accuracy of individual classifiers is not only the starting point but also the difficulty of various ensemble learning algorithms.

As we all know, the low rank matrix filling and recovery problem is a typical practical problem to learn its internal structure and information from known data. In recent years, this problem has been well solved in the data pool environment by minimizing the trace norm of the matrix or other variants of singular value decomposition [16]. In this environment, the scale of massive data, the size of samples, and the number of video frames are obtained in advance. Therefore, the previous problems can be solved by decompose the sparse data matrix with the singular value decomposition algorithm in each iteration, but the time complexity is very high, so this kind of method is not suitable for real-time environment.

In addition to learning its inherent subspace information from known data, it can also be further extended to learning the Riemannian quotient manifold structure behind the full rank matrix decomposition of known data, so we can deal with the low rank constraint through the way of the full rank matrix decomposition.

2.2. Adaptive Particle Swarm Optimization Algorithm.

The particle swarm optimization (PSO) algorithm is a swarm intelligence optimization algorithm in the field of Computational Intelligence in addition to ant colony algorithm and fish swarm algorithm [17]. It originates from the research of human predation behavior of birds. The APSO algorithm is an improvement of the PSO algorithm in the process of particle updating, which affects the convergence due to the lack of diversity of weights [18, 19].
determines the selection of particle learning samples. Different neighbor topologies derive different PSO algorithms. When Kennedy first proposed the particle swarm optimization algorithm, he adopted the global version topology. The neighbors of each particle are all particles in the population except himself. However, after a large number of simulations and practical applications, it is found that this topology cannot get the solution with the lowest value of the objective function in the corresponding flexible domain. Therefore, Kennedy proposed the local version of the PSO algorithm in 1999. The algorithm adopts the ring topology, that is, the neighbor of each particle is only composed of two particles closest to itself. For the sake of further study, the influence of population topology on the algorithm, Mendes studied the information flow between particles from the concept of "small worlds" in sociology, conducted in-depth research on the population topology, and proposed four cluster, pyramid, and square topology. The above five topologies derived five PSO algorithms.

In the PSO algorithm, there are three different properties for every particle, they are position, velocity, and fitness value. For the position, it may be a candidate solution of the function. The speed determines the direction and distance of the particle movement and dynamically adjusts with the movement experience of itself and other particles, so as to make the particle move in the optimal direction. Each particle corresponds to a fitness value determined by the fitness function. The fitness function value is usually understood as the error between the optimal solution and the current solution. In order to simplify the model, first compute a "population" randomly, and the position vector of each particle in the population after the 1th iteration is expressed as

\[ x_i(t) = [x_{i1}(t), x_{i2}(t), \ldots, x_{iD}(t)], \]

where \( D \) is the dimension of the search space and \( i = 1, 2, \ldots, s \) is the number of particles in the population; the velocity vector of each particle after time \( t \) iterations is expressed as

\[ v_i(t) = [v_{i1}(t), v_{i2}(t), \ldots, v_{iD}(t)]. \]

The best position of each particle \( P \) at the current \( t \) can be expressed as \( p_i(t) = [p_{i1}(t), p_{i2}(t), \ldots, p_{iD}(t)] \), the best particle position of the whole population is \( g(t) = [p_1(t), p_2(t), \ldots, p_D(t)] \), according to the individual extremum \( p_i(t) \) and the global extremum \( g(t) \), the particle velocity update formula is

\[ v_i(t + 1) = \omega v_i(t) + c_1 r_1 (p_i(t) - x_i(t)) + c_2 r_2 (g(t) - x_i(t)), \]

where \( \omega \) is the inertia weight; \( c_1 \) and \( c_2 \), called acceleration factors, are nonnegative constants; and \( r_1 \) and \( r_2 \) are random numbers distributed in \([0, 1]\).

The updated position vector of the \( i \)th particle is expressed as

\[ x_i(t + 1) = x_i(t) + v_i(t + 1). \]

After updating the speed and position of each particle, it is necessary to reselect the individual extreme value and the population extreme value for its fitness value, and the update is as follows:

\[ p_i(t + 1) = \begin{cases} p_i(t), & \text{if } f(x_i(t + 1)) \geq f(p_i(t)), \\ x_i(t + 1), & \text{otherwise,} \end{cases} \]

where \( f() \) is a fitness function. In this paper, RMSE is selected as the fitness function to represent the gap between the current position of the particle and the extreme value of the population. The update formula of the extreme value of the population is

\[ g(t + 1) = \text{argmin}_{p_i} (f(p_i(t + 1))). \]

When we are trying to find an optimal solution of the problem, we can initialize each particle’s location randomly. After continuous iteration, it will gradually converge to the optimal position. Specifically, the inertia weight represents the influence proportion of the particle’s speed after the last iteration on the current speed. If its value is large, the particle position update span is large, so that we can find the global optimal solution through the algorithm. On the contrary, if the value of \( \omega \) is small, we can find the local optimal solution with the algorithm [20].

2.3. APSO Algorithm. Due to the contradiction between the global optimal solution and the local optimal solution, and the local optimal solution, we proposed a new method called linear decreasing inertia weight (LDIW) to trade-off these two problems, that is, the inertia weight decreases from large to small from the beginning of the iteration, but this linear decline cannot be dynamically adjusted according to the situation of the particle itself. Since the simple linear process used to model the flight of the particles will make the model lack of diversity, resulting in the rapid convergence to the point close to the extreme value in the early stage of the iteration, and the slow convergence in the later stage. Therefore, in the PSO algorithm, particle diversity plays an important role in improving evolutionary efficiency. In order to increase the diversity, the inertia weight should be dynamically adjusted according to the particle’s own situation. Reference proposed a particle swarm optimization algorithm with adaptive inertia weight, namely, APSO algorithm. When we need to update the inertia weight of the method, we apply a strategy, which can implement the nonlinear property, and define the particle diversity function,

\[ S(t) = \frac{f_{\min}(x(t))}{f_{\max}(x(t))}, \]

where

\[ \begin{align*} f_{\min}(x(t)) &= \min(f(x_i(t))), \\ f_{\max}(x(t)) &= \max(f(x_i(t))), \end{align*} \]

where \( f(x_i(t)) \) is the fitness value of the \( i \)th particle after the \( t \)th iteration. \( f_{\min}(x(t)) \) and \( f_{\max}(x(t)) \) are the minimum
and maximum fitness of the population after the $t$th iteration. The diversity function $S(t)$ represents the motion attribute of particles. According to the diversity function, the nonlinear function is defined as

$$y(t) = (L - S(t))^{-2},$$

where $L$ is a constant we defined previously, and we also set $L \geq 2$.

In addition, in order to characterize the change rate between the current particle and the optimal particle, the change rate function is given as

$$A_i(t) = \frac{f(g(t))}{f(x_i(t))},$$

where $f(g(t))$ is the optimal fitness value of the population.

Through the above analysis, the adaptive inertia weight is defined as

$$\omega_i(t) = \gamma(t)(A_i(t) + c),$$

where $\omega_i(t)$ is the inertia weight of the $i$th particle in the $t$th iteration and $c$ is a nonnegative number, which is used to improve the global search ability of particles.

By constantly modifying the inertia weight of particles, the APSO algorithm can increase particle variety and effectively avoid the problem of nonconvergence in the later stages of iteration. Figure 1 illustrates the optimization effect of the method [21].

As shown in Figure 1, the convergence ability curves of both PSO and APSO algorithms show a rapid downward trend. Although the fitness decline rate of the PSO algorithm is slightly faster than that of the APSO algorithm in the previous generations, it only reached the global optimization after 65 generations of evolution, whereas the APSO algorithm has reached the global optimization after about 10 iterations. Therefore, the convergence rate of the APSO algorithm is much faster than that of the PSO algorithm, and it can find the global optimal value quickly, reduce the time cost, and avoid the problem of slow convergence of the PSO algorithm in the later stage.

3. RBF Neural Network Based on APSO (APSO-RBF)

A radial basis function (RBF) network is a type of artificial neural network (ANN) for functions of supervised learning. RBF is used to solve the approximate learning problem. RBF is a traditional neural network algorithm and a feedforward network with global convergence ability. Through the nonlinear transfer of neurons in the middle layer (hidden layer), any nonlinear mapping from input space to output space can be realized, and any nonlinear functional relationship can be approximated. The model called the RBF neural network is the process which determines the important relationship between input and output. The parameters that specify the network's structure, such as the number of neurons in the hidden layer, and the center and variance of RBF, will be selected during training with samples.

3.1. RBF Neural Network. The architecture of the RBF network is divided into three layers: the first layer is the input layer, which is composed of input signal source nodes and it can transmit the signals between different neurons. The links that connected the neuron in the input layer with the neurons in the hidden layer can be represented as the weight matrix 1. The second layer is the hidden layer. The activation function of neurons in this layer is RBF. In most cases, a nonnegative nonlinear local response function with radial symmetry and attenuation at the central axis is chosen. The closer the input is to the center of RBF, the greater the output value is. The third layer is the output layer, which makes a simple linear transformation of the output of the hidden layer. Hence, we can compute the output of an RBF network by the following formula:

$$y_j = \sum_{i=1}^{p} w_{ij}a_i(x), \quad j = 1, 2, \ldots, p,$$

where $y_j$ is the output of the $j$th neuron in the output layer and $p$ is the number of neurons in the output layer. $w_{ij}$ represents the connection weight between the $i$th neuron of the hidden layer and the $j$th neuron of the output layer and $a_i(x)$ is the activation function of the $i$th neuron in the hidden layer. We usually use the Gaussian function as the activation function for the RBF neural network’s neurons in the hidden layer, and the formulation of that function is defined as

$$a_i(x) = \exp \left( -\frac{x_c - c_i^2}{2\sigma_i^2} \right),$$

where $x_c = (x_1^c, x_2^c, \ldots, x_n^c)^T$ is the input matrix, $c_i$ is the center vector of the $i$th hidden layer neuron, $\sigma_i$ is the variance of the second hidden layer neuron, and $\|x_p - C_i\|$ is the Euclidean distance between the input matrix and the radial basis center.
3.2. APSO-RBF Neural Network. The expansion speed of the RBF neural network is a very important parameter value. If the value of this parameter is too large, radial basis function neurons will respond to the interval covered by the input vector and the prediction curve will be smooth. This not only takes a long time but also cannot achieve the optimal effect. Generally speaking, it is sufficient that some radial basis function neurons can respond to the interval covered by the input vector. The selection of spread parameters directly affects the training time and prediction effect of the model. Therefore, set the spread parameters as the particle position \( x_i(t) \) in the APSO algorithm, that is, the feasible solution of the pedal, and optimize the RBF neural network through the algorithm shown in Table 1.

3.3. Channel Modeling Based on APSO-RBF. The research of channel is the basis of 5 g millimeter (mm) wave communication system design, simulation, and technical evaluation. In order to accurately describe the important role of channel parameters in channel modeling, in the following analysis, the above two channel parameters are predicted by using the RBF neural network optimized by APSO, and the prediction results are used to compare the effectiveness and accuracy of the ML method.

The steps of establishing the RBF model based on APSO optimization are as follows:

1. Preparing training data. From the original measurement data, the coordinates and PL and DS values of each test point are calculated according to the formula.
2. Determine input and output variables. Take the coordinates of Rx and Tx as input variables. Take the large-scale channel parameters (LSCP) such as PL and DS as the output variables.
3. Use the RMSE function as our objective function and apply the APSO algorithm to determine the optimal RBF network spread parameters.
4. Use the optimal spread parameters determined by the APSO algorithm to establish the RBF neural network prediction model.
5. Replace the data in the test set into the APSO-RBF model to obtain the corresponding test output, compared with the traditional RBF neural network, the prediction performance of the model is judged.

In the test scenario described in Section 1 of this paper, for PL, Los path and NLOS path, all test samples on the whole path length are selected, which are 1990 groups. For DS, the Los path and NLOS path intercept any length of 9 m, which are 6550 groups of data for modeling and simulation verification. All channel measurement data are split into two different sets, they are training set and test set. In this paper, they are divided in the proportion of 7:3, and the method of equal interval uniform selection is adopted, taking 70% of the total data as a training set and 30% as a test set. In addition, in this paper, a three-layer RBF network is selected, in which the input-output dimension is determined by the number of training set samples, and the number of hidden layer nodes is equal to the number of input samples.

4. Resource Scheduling of the Curriculum Which Teaches Advanced Knowledge about the Mathematics Auxiliary Teaching System

Through the methods of fuzzy association feature matching and statistical analysis, the adaptive optimization of the fusion of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources is realized, combined with the methods of statistical feature analysis control and association rule mapping the fuzzy iterative expression of the fusion of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources is

\[
W = \frac{Ce^{f(t)+K/2}}{\rho(t)}
\]  

(14)

Using the method of semantic abstract expression, this paper constructs the increment fusion of the curriculum, which teaches advanced knowledge about mathematics auxiliary teaching, and obtains the evaluation optimization iterative function of the curriculum which teaches advanced

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Table 1: APSO-RBF algorithm.

Step 1: initialize the parameters \( c_1, c_2, v_{\text{max}} \), particle number \( s \), position of particle \( x_i(1) \), iteration number \( t_{\text{max}} \);
Step 2: \( p_i(1) = x_i(1), g(1) = \min(p_i(1)), i = 1, \ldots, s \);
Step 3: resolve the current delivery times \( t, t = 1, i < t_{\text{max}} \);
Step 4: resolve the current particle \( i, i = 1: s \);
Step 5: assessing particle diversity \( S(t) \);
Step 6: calculate nonlinear regression function \( y(t) \);
Step 7: calculate the rate of change of particle velocity \( A_i(t) \);
Step 8: calculate inertia weight \( \omega(t) \);
Step 9: update particle speed \( v_i(t + 1) \);
Step 10: update particle position \( x_i(t + 1) \);
Step 11: if \( i < s \), then \( i = i + 1 \), go to step 4, repeat step 5~step 9; if \( i = s \), then go to step 11;
Step 12: calculate particle fitness values \( f(x_i(t + 1)) \);
Step 13: update individual optimal value \( p_i(t + 1) \);
Step 14: update global optimum \( g(t + 1) \);
Step 15: if \( t < t_{\text{max}} \), then \( t = t + 1 \) and go to step 3; otherwise go to step 15;
Step 16: end the algorithm.
knowledge about mathematics auxiliary teaching resources. Under the framework of in-depth learning, the correlation degree information of the curriculum which teaches advanced knowledge about mathematics assisted instruction resource scheduling is extracted and the reliability evaluation function of the curriculum which teaches advanced knowledge about mathematics assisted instruction information fusion is obtained.

Establish the underlying database of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system, realize it in the process of fusion particle swarm optimization, schedule the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources, and obtain the mathematical description of the fuzzy approximate index distribution problem as follows:

\[ G(x) = Q(f_i(x) - g_i(x)) + h_i(x), \]  

(15)

where \( f_i(x) \) is the scheduling level of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources, \( g_i(x) \) is the conditional cost function of the decline degree of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources, and \( h_i(x) \) is the correlation statistical constraint. Integrating the scaling mapping parameters, the quantitative index system of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching is obtained, which is expressed as

\[ x_n = a_0 \sum_{i=1}^{n} x_{n-i} + G(x). \]  

(16)

Among them, \( a_0 \) is the information distribution amplitude of big data for advanced mathematics assisted teaching; \( x_{n-i} \) is the scalar time series of the distribution of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources. The big data decision tree model is used for online scheduling of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources \( \omega \), the optimal solution distribution is

\[ A = \frac{1}{2} \omega + \sum_{n=1}^{N} x_n. \]  

(17)

Using the method of joint density analysis, the conditional probability density parameters for the integration of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources are constructed as follows:

\[ L = \frac{(1 + A)}{((v_i - 1) \sum_i^n s(t))}. \]  

(18)

According to the joint parameter distribution set of the curriculum which teaches advanced knowledge about mathematics aided teaching resource scheduling, the probability density function is

\[ \alpha = Lx_n - f(x_{n-1}). \]  

(19)

In the process of fusion particle swarm optimization, the scheduling and information fusion of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources are realized, and the optimized control function is

\[ R = \frac{1}{2} \alpha^2 + C \sum_{i=1}^{n} (f_i(x)). \]  

(20)

Thus, the adaptive control model of the curriculum which teaches advanced knowledge about mathematics assisted teaching resource scheduling is obtained, and the system design flow is shown in Figure 2.

5. Experiment and Result

Since we need to verify the application performance of the proposed method in the curriculum which teaches advanced knowledge about mathematics assisted teaching and resource scheduling, simulation test and analysis are carried out. Taking a university in Anhui Province as an example, 300 students from the Department of mathematics were selected as the experimental objects and divided into three groups. The students were allowed to use the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system based on fusion particle swarm optimization and the system designed in the literature [3, 4] for one month. The distribution scale of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources was 16GBIT, and the data sampling length was 1024. The training set size of teaching resources is 200, the residual coefficient of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources fusion is 0.74, the number of particle swarm iteration steps is 400, and the particle swarm size is 500. According to the above parameter settings, the distribution of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources is obtained, as shown in Figure 3.

After one month’s auxiliary learning experiment, statistics and comparison of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resource scheduling of different methods are made, and the results are shown in Figure 4. As shown in Figure 4, the linear tracking ability of this method for the curriculum which teaches advanced knowledge about mathematics assisted teaching resource scheduling is good, and the information fusion level of teaching resource scheduling is high. Test the convergence curves of the three methods, as shown in Figure 5.

By analyzing Figure 5, we can see that the convergence of resource scheduling is relatively stable, and the average convergence value is 110, which is significantly higher than the literature comparison method, indicating that the convergence of resource scheduling is better and the operation stability of the teaching system is stronger.
6. Conclusion

This paper constructs the information system of the curriculum which teaches advanced knowledge about mathematics teaching management, realizes the optimal design of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system through the methods of parameter optimal allocation and resource scheduling, and puts forward the design method of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system based on the particle swarm optimization algorithm. Using the method of constructing knowledge rule base, the log base and simulation base of the curriculum which teaches advanced knowledge
about the mathematics auxiliary teaching system are established. In the fuzzy information clustering center, the fusion particle swarm optimization algorithm is used to realize the database access and fusion processing of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system. Through the methods of fuzzy correlation feature matching and statistical analysis, realize the adaptive optimization of the integration of the curriculum which teaches advanced knowledge about mathematics auxiliary teaching resources and realize the optimal design of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system. The research shows that the resource integration and convergence of this method in the design of the curriculum which teaches advanced knowledge about the mathematics auxiliary teaching system are good.

To sum up, in the current era, in the process of the curriculum which teaches advanced knowledge about mathematics teaching, teachers should give full play to the advantages of the big data-driven system supported by AI, innovate existing teaching ideas, build a good teaching model for students, promote the gradual development of education in the direction of personalization through big data, teach students according to their aptitude, improve teaching quality and effect, and then train more excellent talents for our country.

**Data Availability**

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

**Conflicts of Interest**

The author declares that he has no conflicts of interest.

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