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Article

Research on Artificial Intelligence-assisted Design and Dynamic Adaptive Learning Module in Self-study Examination Systems

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Abstract: Under the development trend of diversification of education forms, the self-study examination system faces a series of dilemmas such as imperfect support system and slow updating and iteration speed. As a result, this paper designs and proposes a self-study examination system with the addition of intelligent auxiliary module and dynamic adaptive learning module. It explores the construction of the self-study examination management and service system from three aspects: the architecture technology of the self-study examination management and service system, the tripartite operation topology and the module characteristics. Aiming at the problem that the Teaching-Learning Optimization Algorithm (TLBO) is prone to premature maturity and low precision, an adaptive change factor is introduced to adjust the ability of exploring new solutions in the iterative optimization search process. Simulation experiments of the dynamic adaptive learning algorithm show that when the adaptive scaling factor parameter range in the DSLTLBO algorithm is set to λ_{start} =0.3, λ_{end} =3, the simulation results of the algorithm converge to the optimal value for both unconstrained and constrained functions, and the algorithm has better accuracy and stability. The maximum number of concurrent users that the self-study examination system with intelligent assistant module and dynamic adaptive learning module can successfully respond to is 100000, which is in line with the design expectation.

Keywords: pedagogical optimization algorithm; DSLTLBO algorithm; adaptive change; intelligent assistance module; self-study examination system

1. Introduction

The establishment and implementation of China's self-study examination system is a great invention in the human education system, which flexibly combines individual self-study, state examination, and social assistance, improves the cultural cultivation and aptitude quality of Chinese citizens, enlarges the benefiting surface of education, and cultivates a large number of shortage or excellent talents for China [1-3]. Self-study examination is another special form of higher education and examination system in China besides college education, and it is also the most mainstream examination without walls in the world [4]. Since the implementation of the self-study examination system in the country, every year will be held to two or even more exams, which is not quite the same as the traditional examination is to participate in a wide range of objects. There is no school unified arrangement system, so for the self-study examination many examination-related notification delivery will seem cumbersome [5]. On the other hand, the existing self-study examination system can't update the services such as the recent examination dynamics in a timely manner or the information is lagging behind, etc., which can't meet the requirements of the candidates, and the information management system of self-study examination is relatively closed [6-7]. Therefore, the development of a more intelligent and efficient self-study examination system and its application to the daily work affairs of self-study examination information management can not only meet the urgent needs of all related workers, but also better serve the social candidates, prompting the implementation of China's self-study examination to informationization to a new level.

The self-study examination system is an educational model with Chinese characteristics, which adapts to and develops from the development situation and needs of higher education in China at different times. In the 1990s of the last century, it became an important supplement to higher education, solving the problem of insufficient investment in higher education by the state, and in the present time, the self-study examination takes education for all and lifelong education as the goal and direction of development, in order to satisfy the increasingly diversified educational needs of the general public [8-10]. In terms of examination research and development, literature [11] constructed a set of outcome scoring system for self-study students, which can enable students to understand the key elements of knowledge, ability, skills and personal qualities by assessing the quality of students' self-study and transforming education into a unique and objective measure. Literature [12] proposes a self-learning system that can generate specific learning paths based on the competency structure of the learner's knowledge domain, and it was found that the self-learning system was acceptable to the learners and included more competency nodes, and that there was no significant difference between the ratings of the competency-based links. Literature [13] used a histology laboratory course at the University of Cleveland School of Medicine as a self-study module and found that there was no significant change in performance on the internal exams and a significant increase in the overall practical exam mean score associated with the self-study module, while the content of the acquisition remained the same. This suggests that converting a traditionally taught course into a self-study module is a viable option. Literature [14] builds a simulator-based Intelligent Tutoring System (ITS) for STEM (Science, Technology, Engineering, and Mathematics) self-directed learning, which covers elementary school, middle school, high school, and college as well as extracurricular training, and provides learners with a convenient and low-cost Learning Methods. These ITSs are usually equipped with massive question banks, intelligent paper-making, strict examination processes, good interactivity, and statistical analysis of examination results, completely replacing and surpassing the existing paper-and-pencil-based examination learning methods.

In the context of rapid development of information technology, the Internet, big data, artificial intelligence and other technologies are being widely integrated into the field of education, prompting the self-study examination to develop in the direction of openness, diversification and personalization, and the traditional self-study examination mode is difficult to meet the needs of talent cultivation in the new era, and thus the exploration of intelligent and personalized self-study examination has become a key link in the digital transformation of self-study examination [15-17]. The breakthrough development of artificial intelligence technology, especially the rise of generative big model technology, provides a new paradigm for self-study examination. Literature [18] conducted semi-structured interviews with 20 students who had used AI tools for self-study, and most of them believed that AI technology could enhance the effectiveness of self-study with a certain degree of diversity and representativeness in different subject areas and learning levels. Literature [19] applied AI technology to English independent learning and found that AI technology has a double-edged sword effect, with the benefit that using AI can help learners to improve their knowledge and skills, which in turn will make them become more autonomous and have good learning attributes. Literature [20] describes the development and implementation of two chatbots based on AI technology, with feedback from more than 700 students that the results were able to provide students' self-directed learning with more convenient digital tutoring support. Similar results were obtained by literature [21], who concluded that with the assistance of AI chatbots, they were able to develop students' self-directed learning skills and foster lifelong learning. Literature [22] explored the transformative potential of AI and virtual reality in self-directed learning, and they concluded that these cutting-edge technologies provide a personalized, adaptive, and contextualized learning experience that improves students' self-control and motivation. It can also ensure that diverse groups have access to quality educational opportunities through self-directed learning.

Adaptive learning is a personalized learning paradigm based on real-time data feedback and algorithmic adjustments, the core of which lies in the optimization of learning content, paths, and strategies by means of artificial intelligence technology [23-25]. Literature [26] systematically evaluated the deployment of adaptive learning and its educational implications, and they concluded that AI/machine learning algorithms play a key role in personalized learning, and that these technologies can optimize learning paths, increase engagement, and improve academic performance. Meanwhile, the literature [27] also pointed out the current challenges of adaptive learning, including insufficient knowledge of the technology, bottlenecks in affective domain modeling, separation of education and technology, security of data management, and the risk of privacy breaches, etc., for which they drew on the decentralized management model to proposed a new adaptive learning push model. Literature [28] points out that algorithms in Artificial Intelligence and Machine Learning (ML) are able to optimize an individual's learning process by automatically and dynamically matching the student's behavioral attributes with a specific learning style. Literature [29] explores the application of AI in combination with adaptive recommendation models, especially in online learning, emphasizing the importance of this technological advancement for recommender systems, and personalized learning, where adaptive recommendation models help learners to learn efficiently in personalized learning environments by dynamically adjusting learning paths and content.

This paper analyzes the basic theory of self-study examination management and service system, the main technology of the system architecture, in order to achieve the strong functionality of the system, high security design, the choice of C/S structure and B/S structure combined strategy to optimize the development of the system. Based on the candidates, universities and colleges, the Office of Self-study Examination of the Educational Testing Service draws a topology map of the operation of the self-study examination system. Intelligent teaching aid module and dynamic adaptive learning module are added, dynamic adaptive teaching and learning optimization algorithm is selected for population optimization evolution, and simulation verification is carried out through multiple constraint functions. Combining the intelligent assistant module and dynamic adaptive learning module, the whole self-study examination management and service system is tested for performance.

2. Self-Study Examination System Design and Technical Support

2.1. Theory and Technology of Self-Study Examination Management System

(1) C/S structure and B/S structure combined strategy

In the system development of the self-study examination management information system, consider that C/S and B/S should be combined, each taking its strengths and avoiding weaknesses. Both taking into account the B/S structure of technological advances, but also taking into account the C/S structure in the application process of maturity, the use of C/S and B/S hybrid structure to develop the self-study examination information management system is the best solution.

This kind of mixed mode architecture by C/S and B/S mainly has the following advantages:

a. Strong security, the security of sensitive data can be strongly guaranteed. In particular, for the data in the database control, strengthened the ability to add, modify and delete data records in the database control, such as the establishment of the operation log.

b. Reduced costs. In terms of resources, the computer resources of the LAN were fully utilized. In terms of hardware facilities, the number and configuration of clients were simplified as much as possible.

c. Not only to ensure the ease of use of the system functions, but also to ensure good interactivity.

d. The system is highly maintainable, and the network efficiency can always be in good working condition to ensure the smooth flow of the network.

For the self-study examination management information system, which information browsing, querying, less data entry and other characteristics are more suitable for the use of B / S model, the client can operate the software anywhere at any time as long as the Internet can be. And for some software flexible open functions such as creating reports, and involves the process is too complex function should be used C/S structure mode. Because the C/S model of the client has a strong function, high security features. Through this treatment, not only make full use of the respective advantages of the two modes, while skillfully avoiding the B/S structure in the operation of the response speed, data confidentiality and system security and other aspects of the shortcomings and to overcome the C/S structure can not meet the user query browsing and other aspects of the lack of off-site.

(2) Database technology

For data preservation and query system, the database is very important. Especially for the self-study examination management information system so that the amount of data involved is very large system, database design in the whole development process occupies a very high position, the database design is good or bad directly affects the final user experience and the ease of system management band, therefore, it can be seen that the application of database technology in this system is particularly important.

In the system, the C/S structure model will be used to develop the client with special requirements for data processing, using the database development tool PowerBuilder 10.0. it is suitable for the development of distributed database applications, this development tool has a variety of ways to choose the database connection method such as SQL, MYSQL and so on, and in this paper the ODBC interface is used, through the ODBC interface, the user request to connect with the target database.

Due to the portability of PowerBuilder 10.0, which makes the application program more compatible and easy to port and maintain, it only needs to establish the corresponding data source in different environments to run up. Each client only needs to install the browser Broswer on its own machine can easily and conveniently interact with the target web server, send requests to the web server, the server will return the results to the client's browser.

(3) Other related technologies

In B/S mode, the system uses ASP as the scripting language. The backend database of the system adopts SQL Sever, and the web pages are planned and produced in Dreamweaver environment in combination with ASP. For the animation in the system, Flash tools are utilized, Photoshop technology is used for the beautification of pictures and web pages, and the overall code of the system is written in C# statements.

As the system, there are also user input and output operations, the use of ASP.NET built-in object properties and methods are Response, Request, Server three objects. Through these methods, the interaction between the client and the server is well realized, and the user can control the connection between the web server and the database just through the client's browser, after connecting to the target database. Users through each browser input request transmitted to the database will be transformed into the appropriate database commands to operate on the database, after the end of the operation, the results will be organized, the results of the original way back to the client, presented in the browser for the user to browse.

2.2. Self-Study Examination Management and Service System

The system is oriented to the three parties: candidates, universities and the Self-study Examination Office of the Education Examination Authority, and all parties are required to log into the system to complete various operations in one-stop:

(1) Candidates' end: registration and application, download of pass, personal information maintenance, result inquiry, result review application, pre-application for exemption information, certificate issuance application and appointment, graduation application, degree application.

(2) The work terminal of the examining university is divided into two parts, namely, entry management and query memo: entry management includes the entry of results, management of exemption information, management of disciplinary information, acceptance and registration of result review, and the setting of conditions for degree application, etc. The query memo contains the basic card of the examinee, which can be used for the examination. The query memo contains candidates' basic information card, candidates' results table, self-study file (containing information on the transfer of examination registration, exemption information, graduation application acceptance and registration information, degree application acceptance and review and recognition of automatically extracted information, text memo, document attachments for storage, etc.).

(3) Functions of the Self-study Examination Office of the Educational Examination Authority and the different functions of the examining colleges and universities: management of the examination program of the examining colleges and universities, management of the exemption regulations and final examination and certification of related businesses.

In order to realize the concept of one-stop solution for the candidates, universities and colleges in charge of the examination, this paper conceptualizes that on the basis of calling the relevant data, the candidates can deal with the relevant matters through online pre-application on-site processing. Based on the above working framework and actual working needs, the proposed system server is set up in the Education and Examination Bureau, and the operation topology of the self-study examination system is shown in Figure 1.

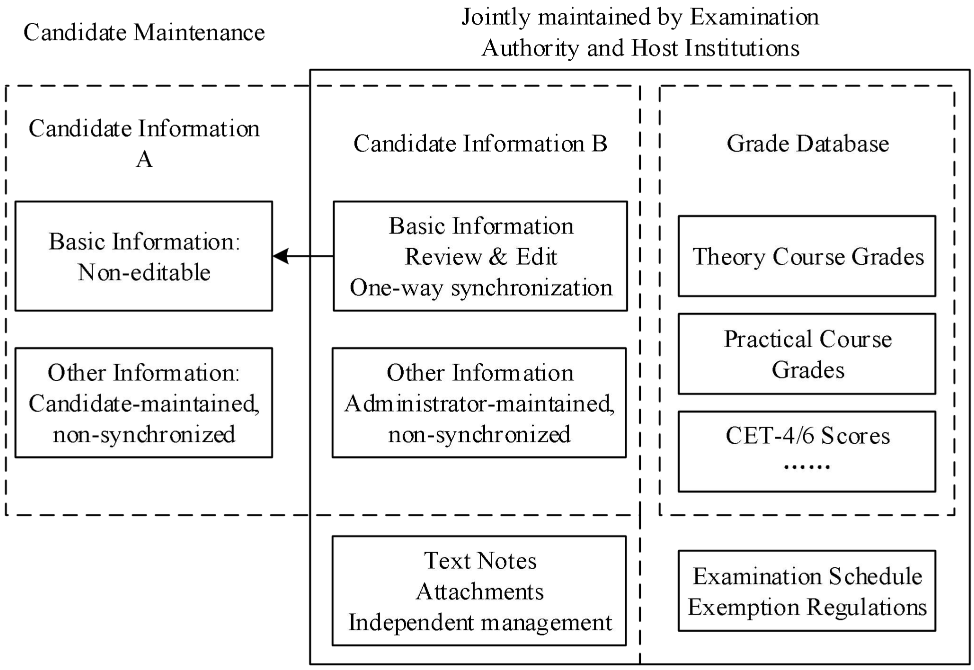

Figure 1. Self-study test system operation topology.

2.3. Intelligent Teaching Aid Module Design

Artificial intelligence brings multiple advantages to online teaching. First, it can realize the personalized recommendation of teaching resources. By analyzing students' learning history, interest preferences and knowledge gaps, we can accurately push appropriate course materials, practice questions and extended reading materials for students. For example, for students who are interested in AI algorithms and have mastered basic programming knowledge, we recommend resources that explain the principles and practical applications of machine learning algorithms in depth. Second, intelligent counseling is provided during the learning process. The AI system can monitor students' learning behavior in real time, for example, in programming exercises, timely detection of students' code errors and give targeted tips and modification suggestions. Further, it helps the accuracy of teaching evaluation. In addition to traditional performance evaluation, it can also analyze students' learning attitudes, learning strategies, knowledge application ability and other multi-dimensional analysis, providing teachers with richer data support so that they can develop more targeted teaching improvement measures.

2.3.1. Operating system design

There are various tasks in the teaching scenario such as real-time data acquisition, intelligent analysis, and transmission of teaching resources. In order to ensure that key tasks are prioritized for execution, the system adopts a priority-based preemptive scheduling algorithm. Each task is assigned a priority level, and the formula for calculating the priority level is as follows:

$$\begin{aligned} &P = W_1 \times U + W_2 \times R + W_3 \times E \\ &W_1 + W_2 + W_3 = 1 \end{aligned} \tag{1}$$

where P denotes the priority of the system task. U denotes the degree of urgency of the task (value range 1-10). R denotes the degree of demand of the task on the system resources (value range 1-10). E indicates how long the task has been waiting. W_1, W_2, W_3 denote the weight coefficients.

In order to utilize the memory efficiently, the system divides the program and data into code segments, data segments and other information segments according to the task logic, and introduces the partner system algorithm. When a memory block is released, the system checks whether its neighboring memory blocks are partner blocks. If both neighboring memory blocks are free partner blocks, they will be merged into one larger memory block. The partner block address relationship satisfies the following conditions:

$$A_{buddy} = A + 2^k \tag{2}$$

where A_{buddy} denotes the memory block address. k denotes the memory block address size. A denotes the partner block address.

In order to enable the operating system to effectively interact with hardware devices such as Bluetooth sensors and data acquisition devices, the system is designed with a unified device driver interface. The device driver is responsible for abstracting the physical operations of hardware devices into function calls recognizable by the operating system. For different types of devices, the driver follows the following generic model:

$$I / O = f(C, D, S) \tag{3}$$

where I / O denotes a device input/output operation. C denotes the control command. D denotes the data buffer. S denotes device status information.

Through this standardized interface, the operating system can conveniently manage all kinds of hardware devices and guarantee the stable operation of the system.

2.3.2. Database management design

Database management design is crucial in smart campus intelligent teaching aid system. It is responsible for efficiently storing, managing and retrieving massive teaching data, providing accurate data support for artificial intelligence, and facilitating teaching decisions and personalized learning.

The system adopts a relational database model to organize data in a normalized way. Taking students, courses, and grades as an example, the following relationships are constructed: the student table includes student number name, age, and class. The course table includes course number, course name, and instructor. The grade table includes student number, course number, and grade. The student number and course number of the grade table are used as primary keys. Then students, courses, grades and the primary key to establish an association, both need to meet the referential integrity constraints, the constraints are as follows:

$$\begin{cases} \forall S_{id} \in \text{Report Card}, \exists S_{id} \in \text{Student Form} \\ \forall C_{id} \in \text{Report Card}, \exists C_{id} \in \text{Student Form} \end{cases} \tag{4}$$

where S_{id} denotes the student number of the grade table. C_{id} denotes the course number of the grade table.

In order to improve the data storage efficiency and query performance, the partition storage strategy is used. The performance data is partitioned according to the time dimension, and the formula for calculating the number of partitions is shown below:

$$N = \left\lceil \frac{T_{end} - T_{start}}{30} \right\rceil \tag{5}$$

where T_{end} , T_{start} denote the start and end of the time range of the achievement data. N denotes the number of partitions.

The system utilizes the statistical analysis function of the database to quickly locate the relevant records through the index of the school number to provide decision-making support for teaching. In order to improve the indexing speed, the system chooses the correlation coefficient r to calculate the indexing time complexity and relevance to reduce the number of indexing times. The correlation coefficient is calculated as follows:

$$r = \frac{\sum_{i=1}^{z} \left(L_{time} - \overline{L_{time}} \right) \left(G_{score} - \overline{G_{score}} \right)}{\sqrt{\sum_{i=1}^{z} \left(L_{time} - \overline{L_{time}} \right)^2 \left(G_{score} - \overline{G_{score}} \right)^2}} \tag{6}$$

where r denotes the correlation coefficient. L_{time} denotes the correlation of the indexed parameters. G_{score} denotes the complexity of the lookup time. Z denotes the number of records to be indexed.

2.4. Dynamic Adaptive Teaching and Learning Optimization Algorithm/DSLTLBO

2.4.1. Teaching Optimization Algorithm

The core idea of TLBO divides the algorithm into a teacher phase and a student phase, where the teacher phase simulates the process of teachers teaching in the classroom and disseminating knowledge to students, and the student phase simulates the process of students discussing and communicating and learning from each other. In TLBO, the class size corresponds to the population size, the number of study subjects is similar to the dimension of the optimization problem, each student represents a solution of the optimization problem, and the student's performance is equivalent to the fitness value of the solution [30-31].

(1) Teacher stage

The highest achiever is selected from the class and set as the teacher, while the others are considered students and learn from the teacher. In this stage, the teacher expects to maximize the average performance of the students through teaching activities, however, due to the inherent variability among students, it is often difficult for students to reach the teacher's level of average performance. Therefore, the process in the teacher stage is as follows: students learn based on the gap between the teacher's position M_{new} and the class average position M_t. Namely:

$$Difference\_Mean_t = rand \times \left(M_{new} - T_F M_t \right) \tag{7}$$

$$X_{new,i} = X_{old,i} + Difference\_Mean_t \tag{8}$$

where t represents the population evolved to the t th generation. $rand$ is a 0-1 random number, and M_{new} is the position of the teacher in the t th generation. T_F is the teaching factor, whose value is typically taken to be 1 or 2, and which determines the degree of change in the mean. M_t is the average position of the class.

The details of M_t are calculated as follows:

$$M_t = \frac{1}{n} \times \left[\sum_{i=1}^{n} x_{i,1}, \sum_{i=1}^{n} x_{i,2}, \cdots, \sum_{i=1}^{n} x_{i,D} \right] \tag{9}$$

where n represents the class size. D represents the subject of study and $x_{i,1}$ represents the position of the first dimension of the i th student. After the teacher phase, if the new solution $X_{new,i}$ is better than the old solution $X_{old,i}$, the new solution is accepted, otherwise the old solution is kept.

(2) Student phase

Students complement each other by learning from each other, and the disadvantaged individuals approach the relatively advantaged individuals to improve their performance. Therefore, the learning process in the student stage is as follows: two students X_i and X_j are randomly selected, where $i \neq j$, $f(X_i)$ and $f(X_j)$ are the students' fitness values. If $f(X_i) < f(X_j)$, it means that student X_i is better than X_j, then $X_{new,i}$ moves closer to X_i, and vice versa, it means that student X_j is better than X_i, then $X_{new,i}$ moves closer to X_j. That is:

$$\begin{cases} X_{new,i} = X_{old,i} + rand \times (X_i - X_j) & f(X_i) < f(X_j) \\ X_{new,i} = X_{old,i} + rand \times (X_j - X_i) & f(X_i) > f(X_j) \end{cases} \tag{10}$$

Similarly, at the end of the student phase, if the new solution $X_{new,i}$ is better than $X_{old,i}$, the new solution is accepted, otherwise the old solution is kept.

2.4.2. Dynamic Adaptive Learning

The idea of the TLBO algorithm originates from the teaching process of the simulated class, so it is a feasible way to improve the algorithm from the phenomena in life. Consider that in the process of teaching" by the teacher, the generation of a new state of the student depends on the sum of the proportion of transformation of his/her own state and the proportion of transformation of the knowledge gained through learning. The standard algorithm in the formula of $rand(0,1)\times(X_t(t)-\beta\times X_m(t))$ part of the knowledge gained from the teacher's learning for the students, while the students' own knowledge of the state of the equation to the new state of the transformation of the state, with the reality does not match. Therefore, the equation is modified to become equation (11), where the student's original state is converted to the new state proportionally. That is:

$$X_i'(t)=\delta\times X_i(t)+rand(0,1)\times(X_t(t)-\beta\times X_m(t)) \tag{11}$$

$\delta=1/(1+\exp(k\times(T-2\times t)/T))\in(0,1)$ is a nonlinear adaptive factor, T is the preset maximum number of iterations, t is the current number of iterations, and k is the rate of change. It is easy to see that in the early stage of the algorithm, the population mainly learns from the teacher individual, and can quickly approach the optimal individual. As the iteration δ gradually increases, the ability of individuals to maintain their own state increases, which slows down the speed of approaching the optimal individual and avoids gathering around the teacher too early. This mechanism is also consistent with the learning behavior of students in life. In the early stage, when students are less capable, they mainly learn from the teacher to improve the average score of the class quickly. Later in life, when students' status improves, students selectively absorb the knowledge imparted by the teacher and their ability to maintain their status increases.

2.4.3. Dynamic random search

DRS realizes a fine search of the space around an individual by dynamically adjusting the step size. In the swarm intelligence algorithm, the optimal individual of the population contains more information that guides the population to converge to the global optimum. If the swarm intelligence algorithm can realize global convergence, the search space formed by the optimal individual must contain the search space formed by the global optimal solution. Therefore, in order to improve the accuracy of the algorithm, teacher individuals are introduced to perform DRS in the later stages of the algorithm (starting after 2/5 of the preset number of iterations).

Algorithm 1: DRS algorithm

Input: individual X, number of iterations n.

Output: individual X.

Step 1: Initialize the step size d.

Step 2: Generate vector $X'\in[-d,d]$.

Step 3: Generate vectors $X_1=X+X'$ and $X_2=X-X'$.

Step 4: Choose the superior of X_1, X_2, X as X.

Step 5: Adjust the step size d.

Step 6: Iteration does not end, go to step 2. otherwise output X and end the algorithm.

2.4.4. Algorithm implementation

Algorithm 2: Dynamic Adaptive Teaching and Learning Optimization Algorithm (DSLTLBO)

Input: population size n, maximum number of iterations M.

Output: optimal individual $X_t(t)$.

Step 1: Initialize the population POP in the solution space.

Step 2: Pick the optimal individual, i.e., the teacher individual, labeled as $X_t(t)$.

Step 3: Perform teaching" based on Eq. (11).

Step 4: Execute the learning" operator.

Step 5: If it is the late stage of the algorithm, the individual teacher executes the DRS algorithm.

Step 6: If the algorithm does not satisfy the termination condition, go to step 2, otherwise output the best individual $X_t(t)$ and terminate the algorithm.

2.4.5. Convergence of the algorithm

DEFINITION: Apply $\{X(t),\forall X(t)\in Y\}_{t=0}^{\infty}$ to denote an absorbing state Markov process in a region with optimal state space $\Omega\subset Y$. Let $\chi(t)=p(X(t)\in Z^*)$ be the probability of reaching the optimal state in a region at moment t. If $\lim_{x\to\infty}\chi(t)=1$, then $\{X(t)\}_{t=0}^{\infty}$ is said to converge.

Lemma 1: The DSLTLBO algorithm corresponds to a stochastic process $\{X(t)\}_{t=0}^{\infty}$, then its variation process is an asymptotic absorbing state Markov chain.

PROOF: According to Algorithm 2, the population change process of DSLTLBO is $\{X(t)\}_{t=0}^{\infty}$, which is a discrete randomized sequence with time independence. From the learning formulas of the two operators, the state $X_i(t)$ of any individual in the population at a certain time is only related to its previous state $X_i(t-1)$, and DSLTLBO uses random initialization to obtain the population, so Eq. (12) must hold:

$$p(X(t)\mid X(t-1),X(t-2),\cdots,X(0))=P(X(t)\mid X(t-1)) \tag{12}$$

Therefore, $\{X(t)\}_{t=0}^{\infty}$ has the Markov property. any individual in the DSLTLBO algorithm performs the two operators of teaching" and learning", and preserves the superiority over the inferiority. Let its optimal space be Ω, we can see that $P(X(t+1)\notin\Omega\mid X(t)\in\Omega)=0$ holds, that is, $\{X(t)\}_{t=0}^{\infty}$ is an asymptotically absorbing Markov process.

Lemma 2: Let the optimal region $\Omega^*\subset\Omega$ in the solution space of DSLTLBO, where Ω is any one region space, corresponds to an absorbing state Markov process $\{X(t)\}_{t=0}^{\infty}$. where:

$$p(X(t)\in\Omega^*\mid X(t-1)\notin\Omega^*)\geq h(t-1)\geq 0 \tag{13}$$

And:

$$\lim_{x\to\infty}\prod_{i=0}^{t}\left[1-h(i)\right]=0 \tag{14}$$

Then:

$$\lim_{x\to\infty}(p(X)\in\Omega^*)=1 \tag{15}$$

Theorem: The DSLTLBO algorithm must converge to the global optimum $X_t(t)$.

Proof: Analyze the search of the individual $X_i(t)$ in DSLTLBO. Early in the algorithm, the teach" operator executes a process where the individual learns mainly from $X_t(t)$, i.e., moves closer to the optimal individual. This ability is suppressed with the gradual increase of δ, and the ability of $X_i(t)$ to maintain its own state is gradually strengthened, which enriches the diversity of the population and alleviates the pressure of premature convergence brought by the teach" operator. In the late stage of the algorithm, $X_t(t)$ starts to execute the DRS algorithm, which enhances the search of the surrounding local space, and balances the global and local searches of the algorithm.The learning" operator in DSLTLBO empowers $X_i(t)$ to jump out of the constraints of the local optimum.

Due to the optimality preserving strategy, if the number of iterations is large enough:

$$X_{gb}=\min\{X_{1b}(t),X_{2b}(t),\cdots,X_{ib}(t)\} \tag{16}$$

Eq. (16) will necessarily converge to the global optimum, i.e., the DSLTLBO algorithm is able to converge to the global optimum with probability 1.

3. System application analysis

3.1. Simulation experiments and analysis of dynamic adaptive learning algorithm

3.1.1. Experiments on unconstrained test functions

Six Benchmark functions are selected to test the performance of the designed algorithms, and examples of the test functions are shown in Table 1, where the optimal value of all the functions is zero.

The solution results of the DSLTLBO algorithm are compared with the corresponding algorithms, including Particle Swarm Optimization (PSO), TLBO, ETLBO, and Improved TLBO (ITLBO), which are all implemented in C language and compiled under VC6 environment.

The population of all the algorithms is set to 30, and the number of iterations of the six functions of

$f_1 \sim f_6$ is set to 2000, the number of iterations of f_7 is 20,000, and the number of iterations of the functions of f_8, f_9 are 5,000. dsltlbo The range of the adaptive scale factor parameter in the algorithm is set to λ_{start} =0.3, λ_{end} =3. The inertia weight of the PSO algorithm is 0.3, $c_1 = c_2 = 3$.

The above algorithms involved in the comparison are run independently for 50 times on each of the six Benchmark functions, and then the algorithms are compared in terms of their final average solution accuracy, solution variance, and so on.

Table 1. Unconstrained benchmark function for testing.

Function	Variable range
$f_1(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]
$f_2(x) = -20exp\left(-0.2\sqrt{\sum_{i=1}^{n} x_i^2/n}\right) - exp\left(\sum_{i=1}^{n} cos\left(2\pi x_i\right)/n\right) + 20 + e$	[-36.125,36.125]
$f_3(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\left(x_i/i\right) + 1$	[-700,700]
$f_4(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + \left(1 - x_i\right)^2\right]$	[-30,30]
$f_5(x) = \sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j^2\right)^2$	[-100,100]
$f_6(x) = \sum_{i=1}^{n}\lvert x_i\rvert + \prod_{i=1}^{n}\lvert x_i\rvert$	[-30,30]

The solution means and standard deviations of the five algorithms on the unconstrained test function are shown in Table 2.

Analyzing the data in the table, the f_1 function is a single-peak function, which is easier to optimize.The DSLTLBO algorithm successfully converges to the optimal value 0 in both 50 and 100 dimensions, which is the best solution among all the algorithms.

Table 2. The average and standard deviation of the five algorithms.

Algorithm		$f_1(x) = \sum_{i=1}^{n} x_i^2$	
		50	100
PSO	Mean value	4.12E-14	1.95E+23
	Variance	1.32E-14	7.81E+3
TLBO	Mean value	9.81E-12	2.45E-10
	Variance	7.41E-15	9.82E-13
ETLBO	Mean value	4.11E-14	1.63E-164
	Variance	2.64E-166	2.39E-162
ITLBO	Mean value	2.23E-215	6.79E-215
	Variance	2.25E-213	5.68E-214
DSLTLBO	Mean value	0	0
	Variance	0	0

On the two single peak functions of f_3, f_5, the solutions of the five algorithms are shown in Table 3.

On the two single-peaked functions of f_3, f_5, the three algorithms, DSLTLBO, ETLBO, and ITLBO, find the optimal values in both 50 and 100 dimensions. While PSO and TLBO do not find the optimal value.

Table 3. The solution of the five algorithms on the single peak function.

Algorithm		$f_3(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}cos\left(x_i/i\right)+1$	
		50	100
PSO	Mean value	1.63E-3	1.55E-12
	Variance	4.01E-3	1.36E-12
TLBO	Mean value	1.53E-15	5.78E-16
	Variance	3.72E-11	4.05E-13
ETLBO	Mean value	0	0
	Variance	0	0
ITLBO	Mean value	0	0
	Variance	0	0
DSLTLBO	Mean value	0	0
	Variance	0	0
Algorithm		$f_5(x)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i}x_j^2\right)^2$	
		50	100
PSO	Mean value	2.61E-28	2.99E-23
	Variance	1.15E-26	1.56E-24
TLBO	Mean value	4.71E-24	8.65E-23
	Variance	5.15E-23	1.94E-24
ETLBO	Mean value	0	0
	Variance	0	0
ITLBO	Mean value	0	0
	Variance	0	0
DSLTLBO	Mean value	0	0
	Variance	0	0

When the functions are selected as f_2, f_4, and f_6, the solutions of the five algorithms are shown in Table 4.

f_2 is a typical multi-peak function, f_4 function has a very smooth surface, f_6 function has a strong jump in the surface, which is easy to make the population fall into the local optimum, and all three functions are very difficult to optimize. None of the algorithms mentioned above can find the optimal value at this time, but the DSLTLBO algorithm performs better.

Both solution accuracy and solution variance are optimal on the three functions, showing that the algorithm has a better balance between global and local search, especially on the f_6 function, which is much better than the other algorithms.

Table 4. The solution of the five algorithms.

Algorithm		$f_2(x)$	
		50	100
PSO	Mean value	2.36E+0	3.12E+0
	Variance	5.91E+0	5.72E+0
TLBO	Mean value	6.65E-7	2.36E-8
	Variance	9.31E-8	1.03E-7
ETLBO	Mean value	6.23E-15	1.89E-15
	Variance	6.25E-14	1.96E-13
ITLBO	Mean value	7.28E-15	6.25E-15
	Variance	8.11E-14	1.35E-14
DSLTLBO	Mean value	5.86E-159	0
	Variance	5.84E-16	0

Algorithm		$f_4(x)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(1-x_i\right)^2\right]$	
		50	100
PSO	Mean value	4.41E+1	2.38E+1
	Variance	4.67E+1	2.69E+1
TLBO	Mean value	5.89E+1	8.01
	Variance	1.72E+1	2.06
ETLBO	Mean value	2.64E+1	2.51E+1
	Variance	2.31E-1	3.13E-1
ITLBO	Mean value	3.15E+1	2.04E-1
	Variance	3.48E+1	2.25E-1
DSLTLBO	Mean value	3.04E+1	9.05E+1
	Variance	1.45E-1	1.83E-1
Algorithm		$f_6(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	
		50	100
PSO	Mean value	7.07E-6	1.46E-6
	Variance	1.75E-5	4.25E-6
TLBO	Mean value	7.54E-8	9.12E-7
	Variance	6.58E-8	2.04E-7
ETLBO	Mean value	1.35E-84()	3.04E-85()
	Variance	2.32E-85	4.25E-85
ITLBO	Mean value	7.15E-89	4.15E-91
	Variance	3.15E-90	4.17E-87
DSLTLBO	Mean value	7.84E-177	6.31E-118
	Variance	8.91E-120	6.75E-112

3.1.2. Test experiments with constraint functions

To further test the performance of the algorithms, five constrained test functions were continued to be selected. The population size of all the algorithms involved in the comparison is 10 and the number of iterations is 3000. The other parameter settings are the same as in the previous section, and the solution results of several algorithms are shown in Table 5.

From the results given in the table, it can be seen that the three algorithms, DSLTLBO, ETLBO, and ITLBO, have found the optimal values in both f_7 and f_9 functions.

Table 5. The solution of the four algorithms.

Function	Global optimal value	Algorithm	Optimal value	Mean value	Variance
$f_7=\sum_{i=1}^{n} max\lvert x_i\rvert$	-5001.623	TLBO	-45263.12	-30544.105	132.94
		ETLBO	-45263.12	-30168.714	0
		ITLBO	-45007.65	-31253.685	0
		DSLTLBO	-45239.07	-32008.146	0
$f_9=10^6 x_1^2\sum_{i=1}^{n} x_i^2$	-5023.112	TLBO	-7025.261	-6953.991	50.50
		ETLBO	-7021.045	-6982.124	0
		ITLBO	-7019.124	-6964.205	0
		DSLTLBO	-6986.098	-6522.540	0

On the other three functions, the DSLTLBO algorithm outperforms ETLBO, ITLBO, and TLBO in terms of optimal value, mean, and variance.The optimal solution results of the algorithms are shown in Table 6.

Table 6. The optimal solution of the algorithm.

Function	Global optimal value	Algorithm	Optimal value	Mean value	Variance
$f_8 = \sum_{i=1}^{n} ix^4 + rand[0,1)$	9012.005	TLBO	8526.694	7661.893	56.91
		ETLBO	7215.336	6012.208	152
		ITLBO	6551.694	7263.251	82.64
		DSLTLBO	5025.001	5001.689	23.98
$f_{10} = \sum_{i=1}^{n} \lvert x_i \rvert^{i+1}$	-23.74	TLBO	-565	-91.251	5.82
		ETLBO	-623	-98.107	1.21
		ITLBO	-712	-101.641	2.04
		DSLTLBO	-401	-35.852	0.65
$f_{11} = \sum_{i=1}^{n} ix_i^2$	45.6069	TLBO	51.261	48.621	0.236
		ETLBO	50.003	49.532	0.248
		ITLBO	49.869	48.004	0.521
		DSLTLBO	45.227	32.068	0.123

3.2. Performance testing of the self-study examination system

System testing is an important part of the system design process, and the time and cost spent in the testing process accounts for a high percentage of system development, thus it should be done properly. Ensure the realization of system goals. The completion of the testing work has a direct impact on the performance of the system, which is the key to ensure the quality of the software, but also the summary and evaluation of the previous stages of work.

This system in the design process, to ensure that the core functions of the relevant system to meet the basis of appropriate system environment for the reasonable deployment, and to simplify the corresponding environment is shown in Table 7.

Table 7. System test environment.

Software environment	Client side	Operating system	Windows 10
		Browser	360 browser
		Database	SQL Server 2020
Hardware environment		CPU: Intel Core i7-3210M 3.2GHz	
		Memory:8.00GB	
		Hard disk: 1T	
	Server	Application server	CPU:E5-2603 3.2GHZ 10M
		Database server	

The LoadRunner table is used when testing the performance and the performance test results are shown in Table 8.

Table 8. Performance test case.

Test title	Operation step	Expected result	Actual result
The resource footprint required by the server	When the user logs in to the system, it opens the resource manager on the server and calculates the situation	The processor's occupancy rate is no higher than 60%, and the same is the memory footprint.	Will meet the requirements of all performance
	Analyze the usage of the processor by connecting the client to the server side		
Concurrent demand	By using concurrent access analog tools, simulate the information of 20 system users.	After the user is in the financial system, the relevant effective information is sent in a short timesend	Meet system development requirements

3.2.1. Throughput

The performance test results of the self-study exam system are shown in Figure 2. The corresponding test operation is carried out by LoadRunner, and the corresponding duration is 80 min. after the system runs for 15 min, the number of bytes processed per second of the self-study examination system reaches the maximum value of 1302496. After the system runs for 55 min, the number of bytes processed per second of the self-study examination system decreases. It can be seen that the performance demand can be satisfied.

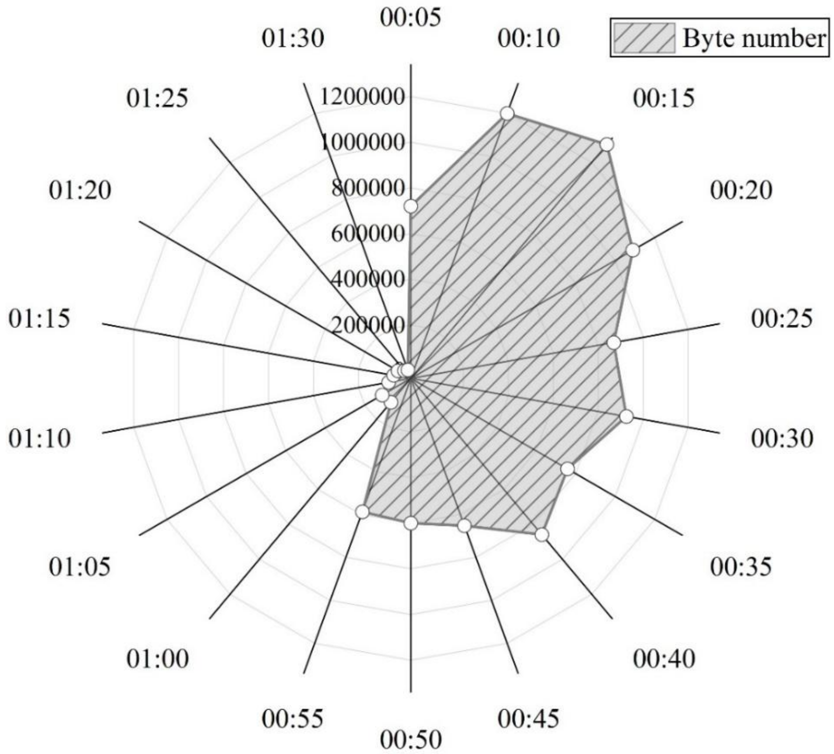

Figure 2. Performance test results of self-taught examination system.

3.2.2. Average transaction response time

Test Objective: To accurately count the maximum value of the throughput of the system and conduct an effective study to determine the performance of the system corresponding to a certain pressure conditions. At the same time, the system's operational bottleneck industry processing capacity is analyzed. Ensure that the relevant requirements are met.

Specific implementation behavior: that is, simulate the performance of the system in the case of N virtual users, statistical analysis of the server's performance indicators, and performance monitoring, to identify the corresponding bottleneck link. In this paper, the design of the self-study examination system running under the evaluation of the transaction response time shown in Figure 3. It can be seen that when the number of virtual users in the same period of time to reach 100,000 people, the self-study examination system in the initial period of operation requires 15.21s to produce a response. And after the system runs for 40 min, the response time is only 0.32 s. The self-study examination system can meet the large-scale user service requirements, and the modules are designed effectively.

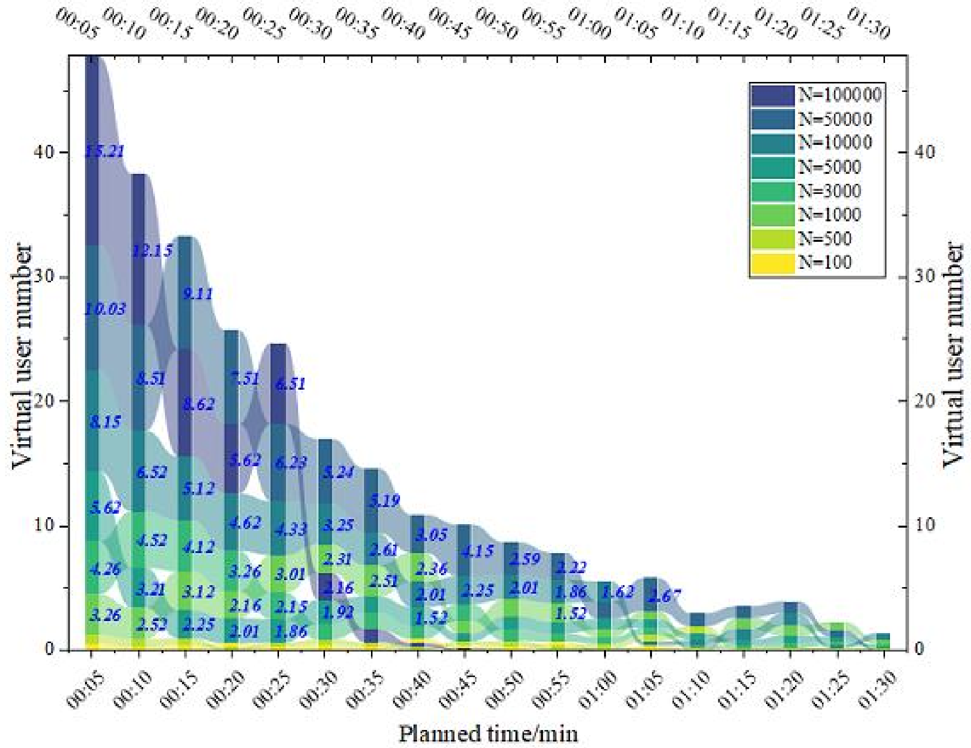

Figure 3. The evaluation of the response time of the self-study test system.

4. Conclusion

This paper designs and constructs a self-study examination management and service system, strengthening the artificial intelligence auxiliary module and dynamic adaptive learning module. The dynamic adaptive teaching and learning optimization algorithm is used to adjust the optimal state of teaching” and learning” and realize the group intelligence evolution in the iterative optimization process.

(1) Multiple test functions are chosen to divide the simulation of the dynamic adaptive teaching and learning optimization algorithm into tests with and without constraint functions.The DSLTLBO algorithm converges to the optimal value with single-peak functions f_1, f_3, f_5 constraints, and the algorithm converges better when the function is a multi-peak function (f_2) The algorithm converges better when the function is multi-peaked (f_2). Experiments with multiple Benchmark functions show that the algorithm has better convergence speed and solution accuracy, and has a greater ability to improve than the standard TLBO, which is suitable for solving higher dimensional optimization problems.

(2) The maximum number of concurrent accesses to the self-study examination management and service system, which combines the artificial intelligence auxiliary module and the dynamic adaptive learning module, can satisfy the maximum number of users that can respond normally is 100,000. the functions of the self-study examination management and service system meet the expected requirements, then the system development goal can be considered to have been realized, and the system can be operated on-line.

According to the test results show that the system's development goals have been achieved, there are also certain defects, specifically expressed as follows:

(1) Problems in the design of the database are mainly manifested in the lack of relevant preparatory work in the pre-development stage, and the lack of proficiency in database operation during the development process.

(2) in the analysis of the user's personalized needs, only basic to meet the user's operational needs, can not meet the user's humane services in various situations, in the user's operating guidelines are not very reasonable, requiring users to be familiar with the computer-related operations to understand.

(3) The design of the intelligent auxiliary module is not perfect.

In this paper, the design of the self-study examination management and service system still has some defects, in the following aspects should be improved:

(1) Supplementing the refined settings for the needs of self-study examination students to meet the self-study needs of different students.

(2) Improve the level of interface design. By designing a high-performance system interface, it can effectively enhance the user's good experience, and also realize the continuous improvement of the system in accordance with the information of the user's needs.

(3) Strengthen the role of intelligent auxiliary module, select intelligent algorithms to optimize system performance. In addition, the fault tolerance and stability of the self-study examination system should be optimized appropriately and tested repeatedly to provide support for the improvement of system performance.

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