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Article

Intelligent Collaborative Algorithm Design in the Construction of Teaching Innovation Team Building System for Higher Vocational Teachers in the Information Age

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Abstract: In response to the challenges faced in the construction of teaching innovation teams at higher vocational colleges, including low efficiency and quality in resource integration and the absence of collaborative mechanisms, this paper designs a course resource construction process within the framework of swarm intelligence theory, comprising three stages: the preliminary organizational stage, the mid-term construction stage, and the post-construction refinement stage. To address the optimization needs of various resources and the coordination tasks of different types of workloads, a Markov decision process is introduced to achieve multi-dimensional resource and workload coordination and scheduling. A reinforcement learning framework based on collaborative relationship representation learning is proposed, consisting of three components: an agent value function network, a collaboration graph encoder, and a hybrid network. This framework is used to construct a multi-dimensional resource collaborative optimization algorithm based on reinforcement learning. The educational resource sharing platform established using this method demonstrates superior service performance compared to traditional educational resource sharing platforms, with an average throughput increase of 180.71 b/s and an average response time controlled within 5 seconds.

Keywords: swarm intelligence theory; reinforcement learning; multi-dimensional resource collaboration optimization; educational resource sharing; Markov decision process

1. Introduction

In the information age, the application of intelligent algorithms has achieved some remarkable results [1-2]. Traditional teaching models are typically teacher-centered, with students primarily playing a passive role in receiving knowledge. This model has many limitations and fails to meet the personalized needs of different students or enhance their interest in learning [3-5]. Intelligent algorithms are methods that utilize computers to simulate human intelligent behavior. They not only mimic human thought processes but also process complex problems through learning and self-improvement [6-7]. Intelligent algorithms in educational innovation include deep learning, neural networks, and genetic algorithms [8]. Personalized learning based on intelligent algorithms is a current hot research topic. By collecting and analyzing student data, such as learning styles, knowledge levels, and interests, artificial intelligence algorithms can provide each student with learning content and pathways tailored to their individual characteristics [9-11]. This personalized teaching method can stimulate students' interest in learning and improve learning outcomes. At the same time, teachers can adjust teaching strategies in a timely manner based on students' learning progress and difficulties, providing individualized tutoring and guidance.

Through a current status survey, it was found that teaching innovation methods based on intelligent algorithms are mostly personalized learning path recommendations and learning resource recommendations, achieving personalized teaching innovation. For example, Deng et al. constructed a dynamic model to simulate personalized learning path design and used a dynamic personalized learning path resource recommendation algorithm based on incremental learning to accurately recommend learning resources. The research results proved the potential and application value of the model in teaching innovation [12]. Ma et al. proposed a personalized learning path recommendation model that combines multiple algorithms to providing learners on online learning platforms with learning guidance. This model can offer learners ideal learning paths and learning resources, thereby enhancing their learning quality and effectiveness [13]. Wang et al. integrated multiple algorithms to construct a network-based teaching system, successfully implementing personalized learning, shared open resources, and other virtual learning activities. The results indicated that under this innovative teaching model, students' learning interest and innovative thinking abilities significantly improved [14]. Huang developed a personalized educational resource recommendation model, applying it to the personalized recommendation of ideological and political education course materials. The results showed that the model could better understand students' learning and lifestyle characteristics, providing them with highly diverse ideological and political education course materials and enhancing their interest in such learning [15].

Teaching innovations based on intelligent algorithms are of great significance for improving teaching effectiveness. Huan et al. utilized ant colony algorithms to identify the optimal planning route for artificial intelligence course instruction, establishing a student-centered teaching environment that leveraged students' initiative and enthusiasm, successfully cultivating students' innovative abilities and comprehensive qualities [16]. Dou combined traditional teaching with digital learning methods, using an efficient recurrent neural network (MO-ERNN) model to predict teaching effectiveness. The results showed that the model's prediction accuracy reached 93%, improving teaching effectiveness [17]. Zheng established an LSTM-Attention model in ideological and political education, achieving an 85.2% accuracy rate in annotating ideological and political knowledge points, enhancing students' ability to summarize learned knowledge points and effectively alleviating the imbalance of educational resources [18]. Vazquez-Carretero et al. integrated artificial intelligence into physical education and achieved significant research breakthroughs. The study found that AI-enabled classrooms significantly increased students' classroom participation and promoted interaction between teachers and students, with most students and teachers expressing satisfaction with this teaching innovation [19].

Teaching innovations based on intelligent algorithms can provide teachers with targeted teaching plans and enhance students' enthusiasm and interest in learning. However, this method may not be appropriate for students with poor self-control. This is because the learning model based on intelligent algorithm innovations often relies on multimedia intelligent devices, which may cause students with poor self-control to lose focus on their learning tasks.

This paper explains the concept of collective construction based on the development history of swarm intelligence theory. Combining the construction needs of teacher education course resources, it designs a course resource construction process guided by swarm intelligence theory and forms a theoretical framework for research and analysis. It then elaborates on the basic principles and operational processes of the Markov decision process and uses it to coordinate the scheduling of multi-dimensional resources and loads in course teaching construction. Subsequently, the paper elucidates the conceptual framework for constructing a multi-agent reinforcement learning algorithm based on collaborative relationship representation learning, establishes an overall framework, and focuses on the main architecture and computational process of the collaborative graph encoder within the algorithm. Based on this, a comprehensive multi-dimensional resource coordination optimization algorithm based on reinforcement learning is proposed. This algorithm is used to construct an educational resource sharing platform, and its performance is compared with that of traditional educational resource sharing platforms. Finally, the paper analyzes the impact of the proposed method on students under assisted teaching conditions and evaluates and analyzes the application effectiveness of the proposed method in assisted teaching.

2. Collective Intelligence Theory: A New Approach to Building Teacher Education Course Resources

Collective intelligence, or swarm intelligence, is a form of intelligence proposed based on observations of social animals in nature. It is characterized by the collective wisdom of a group surpassing the wisdom of its individual members. Since decisions made by a group of people are often more accurate than those made by a single individual, collective intelligence was initially viewed as a process of sharing opinions and converting them into decisions. In the 2.0 era, swarm intelligence has primarily been applied in computer science and the internet field, giving rise to theories such as swarm intelligence perception, swarm intelligence collaboration, swarm intelligence management, and swarm intelligence innovation. These theories emphasize the importance of broadly and rapidly collecting information from various users and contributors to make resource development more precise and efficient. Against the backdrop of education entering the “smart” era, swarm intelligence theory also holds significant implications for the development of educational course resources for teachers.

2.1. Group-Based Construction Concept

Swarm intelligence theory posits that each individual within a group can sensitively respond to and alter the environment. Consequently, the collective intelligence emerging from the interactions of these individuals often exhibits self-organizing properties, manifesting as distributed control rather than centralized control. This means that even if one or a few individuals encounter issues, it does not impair the group's decision-making process. The self-organizing nature of collective intelligence means it surpasses not only the intelligence of a single individual but also the simple sum of the intelligence of multiple individuals—this is the "collectivization" emphasized by swarm intelligence theory. Applying the concept of collectivization to the development of teacher education course resources can meet the requirements of "interdisciplinary integration" in the smart era: on one hand, the integration of interdisciplinary knowledge requires scholars and experts from multiple disciplines to participate in course resource development. Additionally, the builders of teacher education course resources are also their users, so teachers, teacher trainees, and even parents and other relevant members of society should also participate in the course resource development process. This can address issues such as low-quality course resources, redundant development, and insufficient attention to niche courses and special-needs courses caused by the "individual effort" course resource development model, enabling teacher education course resources to achieve the goal of "flexible and comprehensive" development.

2.2. Operable Construction Process

The development of teacher education course resources is a large-scale systematic project that requires a scientific, comprehensive, and practical set of methods and procedures. Collective intelligence theory provides such a set of procedures, which are specifically divided into three stages: the preliminary organizational stage, the intermediate development stage, and the final refinement stage. The course resource development process based on collective intelligence theory is shown in Figure 1.

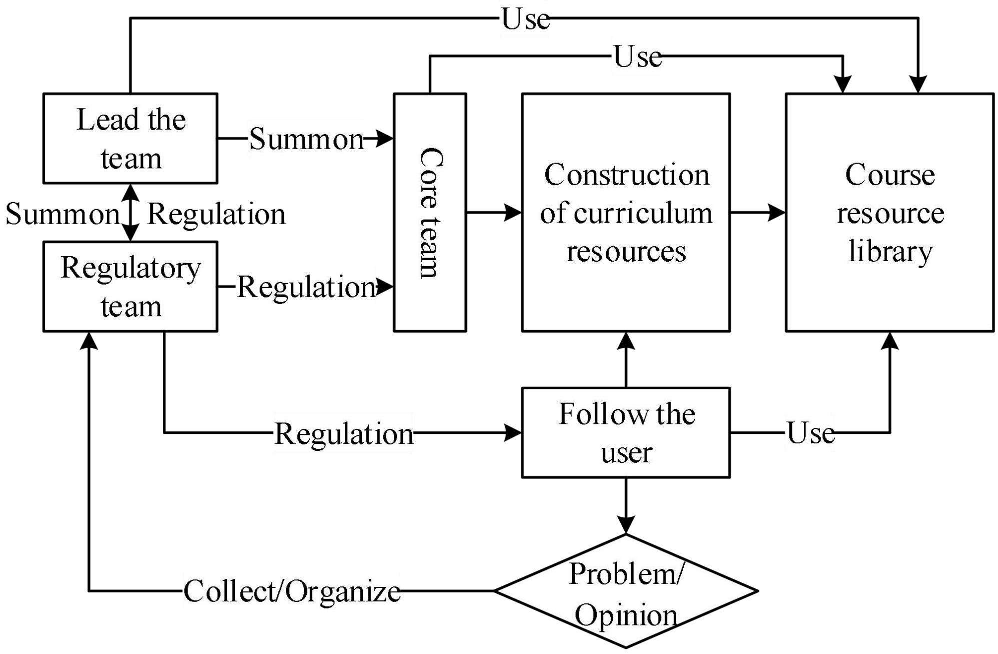

Figure 1. The process of course resource construction.

Initial organizational phase: The core task of this phase is to clearly define the roles and responsibilities of the builders, including the "leadership team," "core team," "user group," and "supervisory team," and to specify their specific rights and responsibilities.

Mid-term Construction Phase: First, the "Leadership Team" (comprising experts from regional education administrative departments or teacher training institutions) establishes the overall framework and core content of the course resources. Then, experienced frontline teachers and education experts are assembled into the "Core Team" to oversee the specific implementation of course resource development. Once the course resources are preliminarily established, the "Follow-up Users" (teacher trainees and other course resource users) provide supplementary, enriching, and refining contributions in a follow-up manner. Finally, an independent "supervisory team" (comprising education administrative departments or third-party institutions) monitors the use of course resources, promptly identifying and resolving any issues that arise during the development process.

Later refinement phase: The "core team" can further optimize course resources based on feedback from "follow-along users" and the "supervisory team," while also expanding the scope of developers to involve more individuals in the development of teacher education course resources.

3. Multi-Dimensional Resource Coordination Optimization Algorithm Based on Reinforcement Learning

3.1. Markov Decision Process

The task scheduling process of AIDC aligns perfectly with the Markov Decision Process (MDP), which is a mathematical problem used to describe decision-making problems involving randomness. It is one of the foundations of reinforcement learning, used to model the interaction between an agent and its environment. The Markov property refers to the fact that the probability distribution of future states is solely dependent on the current state, meaning it has no memory. In each environmental state, the intelligent agent selects an action and executes it, then receives the corresponding reward from the environment and the environment transitions to the next state. MDP is based on the Markov property, which assumes that when the intelligent agent makes decisions, the current state contains all past information, meaning future decisions depend solely on the current state and are unrelated to past decisions or states. At t moment, the agent is in the state S_t, and the agent will select the action A_t according to the scheduling strategy, and the agent has a certain transition probability $p(S_t+1, R_{t+1} \mid S_t, A_t)$ is transferred from S_t to S_{t+1}, and then the environment returns the agent reward R_{t+1}. This process is known as the Markov decision process, in which a sequence such as that in Equation (1) is generated:

$$S_0, A_0, R_1, S_1, A_1, R_2, \cdots, S_{T-1}, A_{T-1}, R_T, S_T \tag{1}$$

A Markov decision process is a stochastic process. In reinforcement learning, problems are typically abstracted into Markov decision processes based on the interactive learning between intelligent agents and the environment in order to make more optimized decisions. The Markov property simplifies the environment model, as shown in Equation (2):

$$p(S_{t+1} \mid S_t) = p(S_1, S_2, \cdots, S_t) \tag{2}$$

The Markov decision process is shown in Figure 2. State S_1 is only related to state S_0, and the real-time reward is R_1. State S_2 is only related to state S_1 and is unrelated to state S_0, with real-time reward R_2, and so on. An MDP is composed of the tuple (S, A, P, R). At time t, all states S_t in the Markov decision process constitute the set of all states in the current environment. The intelligent agent selects and executes an action based on the scheduling strategy, where A_t belongs to the action set A, which contains all possible actions in the current state. P is the state transition probability, which represents the probability of executing the action A_t into the state of $t+1$ time in the state of t time, expressed as $p(S_t \mid A_t, S_{t+1})$. R is the reward, which is expressed as $R(S_t \mid A_t, S_{t+1})$. When the agent selects an action, the environment moves to the next state S_{t+1} (S_{t+1} belongs to the state set S) and is rewarded with R_{t+1}.

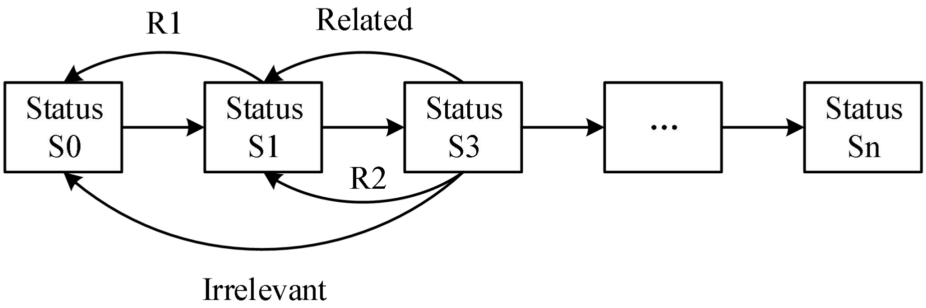

Figure 2. Markov Decision Process.

One scenario of a finite Markov decision process (FMDP) is that the state S_t at time t and the reward R_t given by the environment depend only on the state S_{t-1} at the previous time. This aligns with the description process of FMDP, where the state transition probabilities are used to simulate the single-step interaction between the agent and the environment. For a given state S_{t+1} and reward R_{t+1}, their probabilities of occurrence are expressed as in Equation (3):

$$p(s^{'},r \mid s,a) = P(S_{t+1} = s^{'}, R_{t+1} = r \mid S_t = s, A_t = a) \quad (3)$$

The formula for calculating the expected return of a state-action pair is shown in Equation (4):

$$r(s^{'},a) = E\{R_{t+1} \mid S_t = s, A_t = a\} = \sum_{r \in R} r \sum_{s^{'} \in S} p(s^{'},r \mid s,a) \quad (4)$$

3.2. Multi-Agent Reinforcement Learning Based on Collaborative Relationship Representation Learning

In multi-agent systems, especially large-scale ones, interactions between agents exhibit local characteristics. For a given agent, it is not necessary to collaborate with all other agents, nor is it required to collaborate at all times. However, most current multi-agent reinforcement learning algorithms do not explicitly model this local interaction. Instead, they achieve implicit coordination by maximizing the same reward signal among agents. Some multi-agent reinforcement learning algorithms that use coordination graphs to model agent interactions predefine the coordination graph based on heuristic rules. Such coordination graphs are often static and state-independent, failing to meet the requirements of complex tasks.

Traditional collaboration graphs are typically used to decompose joint value functions into utility functions and payoff functions between pairs of agents, and then infer the joint optimal action through message passing on the edges of the collaboration graph. Such collaboration graphs are generally undirected graphs. This paper extends the collaboration graph by modeling the collaborative relationships between agents using a directed graph $G = (V, E)$. Each vertex $v_i \in V$ in the graph represents agent i, and the directed edge $\{i, j\}$ connecting vertices v_i and v_j represents the collaborative relationship between agent i and agent j. This paper assumes that there is a random variable z_i representing the collaborative relationship of agent i. Unlike traditional methods that learn binary weights on the edges of the collaboration graph, this paper is inspired by DICG and adopts a self-attention mechanism to automatically learn the collaborative relationships among agents. The self-attention weights are used as the weights on the edges of the collaboration graph, and the weight matrix serves as the adjacency matrix of the collaboration graph. Then, a variational graph autoencoder is used to encode the collaboration graph, where both the encoder and decoder employ graph convolutional neural networks. Constrained by the centralized training and distributed execution framework, each agent predicts the collaborative graph from an individual perspective based on the local observation-action history trajectory h_i, and the local predictions of all agents constitute the complete collaborative graph. The overall framework of the algorithm is shown in Figure 3, which consists of three parts: the agent value function network, the collaborative graph encoder, and the hybrid network.

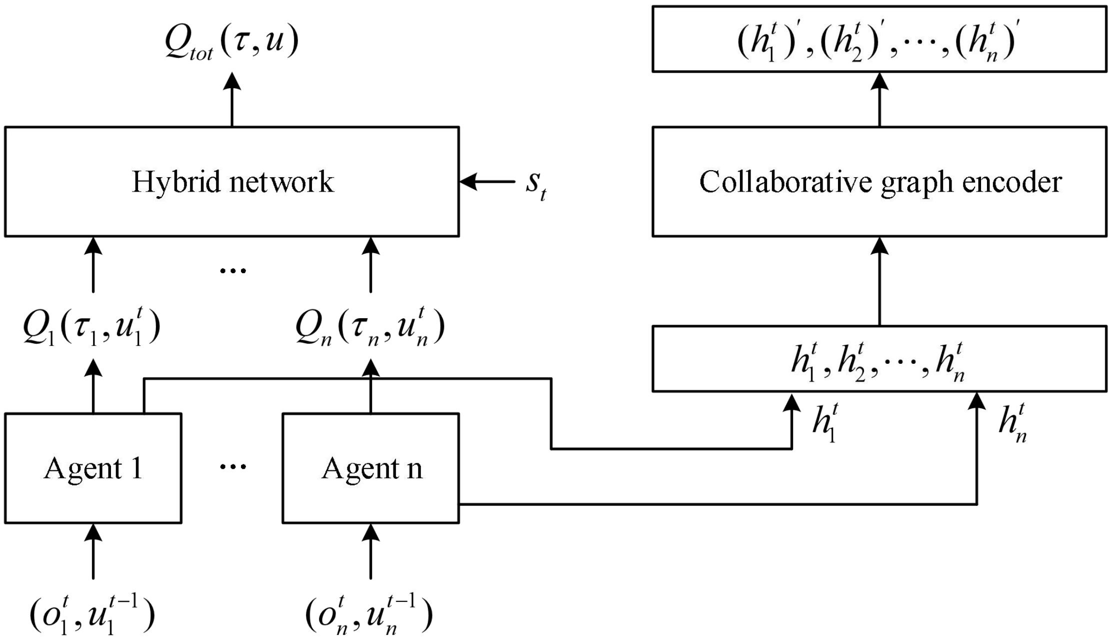

Figure 3. Framework diagram of the MACRL algorithm.

3.3. Collaborative Graph Encoder

The collaborative graph encoder uses a graph variational autoencoder to encode the collaborative relationships between agents. The overall framework is shown in Figure 4.

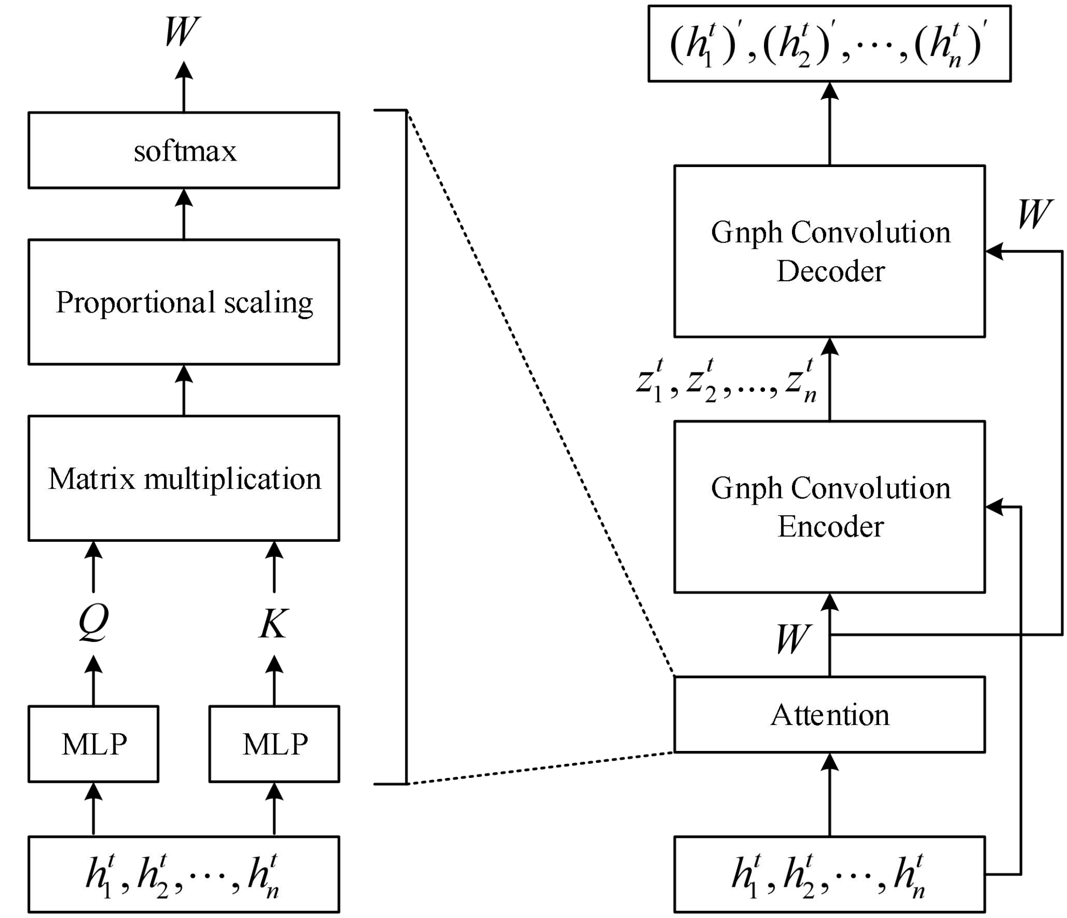

Figure 4. Cooperative Graph Encoder.

The input to the collaborative graph encoder is the local observations $\{o_i\}_{i=1}^n$ of the agent, which are encoded by the agent's value network to obtain n observation-action history trajectory vectors $\{h_i\}_{i=1}^n$, each with dimension d. For the sake of simplicity, this section ignores the time identifier t. First, attention weights are calculated based on these observation action history trajectory vectors using an attention mechanism, as shown in Equation (5).

$$w_{ij} = \frac{\exp(Attention(h_i, h_j, W_q, W_k))}{\sum_{k=1}^{n} \exp(Attention(h_i, h_k, W_q, W_k))} \tag{5}$$

where W_q and W_k are trainable $d \times d$ weight matrices, as shown in equation (6):

$$Attention(h_i, h_j, W_q, W_k) = h_j^T W_q W_k h_i \tag{6}$$

These attention weights form the adjacency matrix M of the collaboration graph, where $M_{ij} = w_{ij}$. Since these attention weights are obtained through softmax, we have equation (7):

$$\sum_{j=1}^{n} w_{ij} = 1 \tag{7}$$

Stack the n observed action history trajectory vectors $\{h_i\}_{i=1}^n$ to form an $n \times d$ feature matrix F, where the i th row of the matrix represents the i th observed action history trajectory vector h_i^T. Based on the feature matrix F and the adjacency matrix M, the collaborative graph is encoded using a graph convolutional network. The computation process of each graph convolutional layer can be expressed as in equation (8).

$$H^{l+1} = \sigma(\tilde{D}^{-\frac{1}{2}} \tilde{M} \tilde{D}^{-\frac{1}{2}} H^l W^l) \tag{8}$$

where H^l denotes the feature matrix of convolution layer l, and $H^0 = F$. $\tilde{M}$ denotes the adjacency matrix of the graph, and $\tilde{M} = M$. σ denotes the ReLU activation function, W^l is the trainable parameter matrix of convolution layer l, and $\tilde{D}$ denotes the degree matrix. Since equation (9) holds:

$$\tilde{D}_{ii} = \sum_{j=1}^{n} \tilde{M}_{ij} = \sum_{j=1}^{n} w_{ij} = 1 \tag{9}$$

Therefore, $\tilde{D}$ is an identity matrix, so the operation process of convolution layer l can be simplified to equation (10):

$$H^{l+1} = \sigma(M H^l W^l) \tag{10}$$

After graph convolution encoding, we obtain n variational distributions $\{N(\mu_i, \sigma_i^2)\}_{i=1}^n$. By sampling from these n variational distributions, we obtain n latent variables $\{z_i\}_{i=1}^n$. The latent variable z_i represents the collaborative relationship of agent i. In order to achieve the backpropagation of gradients, this paper introduces a reparameterization technique to sample ϵ from the standard positive distribution $N(0, I)$, and then calculate the latent variable $z_i = \mu_i + \sigma_i \odot \epsilon$ based on ϵ, where $\odot$ denotes the Hadamard dot product. Like the encoder, the graph convolutional network is used as the decoder, and the eigenvector prediction of n nodes is finally obtained: $\{h_i'\}_{i=1}^n$.

4. Performance Verification and Application Evaluation of Collaborative Optimization Algorithms

4.1. Performance of the Educational Resource Sharing Platform

Based on the algorithms and methods proposed in this paper, an educational resource sharing platform was established. Under the same experimental conditions, a traditional educational resource sharing platform was used as the control group. The performance of the designed platform was evaluated based on the transmission throughput of educational resource sharing at different scales. The test results are shown in Table 1. The average throughput of the traditional platform was 325.98 b/s, while the average throughput of the platform designed using the methods proposed in this paper was 506.69 b/s, an increase of 180.71 b/s compared to the traditional platform. This indicates that the platform designed using the method proposed in this paper has superior service performance compared to the traditional platform when sharing large-scale data analysis course online educational resources.

Table 1. Test results of the online education resource sharing platform.

Total amount of educational resource sharing (b)	Shared Time (s)	
	Textual platform	Traditional platform
1000	2.6	3.7
2000	4.4	6.5
3000	6.1	9.4
4000	7.8	12.2
5000	9.5	15
6000	11.4	17.7
7000	13.1	21.4
8000	14.7	23.3
9000	16.5	26.1
10000	18.3	28.8

The average response time and resource matching performance of the designed platform and the traditional platform under different user numbers and request frequencies are shown in Table 2. The designed platform outperforms the traditional platform in all aspects, not only keeping the average response time within 5 seconds but also maintaining a resource matching rate of 90.00% or higher, ensuring stable and superior operational performance. When the number of users is 55 or fewer and the number of requests is 150 or fewer, resource matching efficiency can reach as high as 99.30% or above. In contrast, the traditional platform can only maintain operation under conditions of fewer users and fewer requests. As the number of users increases, its response speed and resource matching efficiency become less favorable.

Table 2. Average response time and matching degree of shared resources.

Number of users	Request frequency (times)	Average response time (s)		Shared resource matching degree (%)	
		Textual	Traditional	Textual	Traditional
15	35	0.4	0.41	99.6	95.2
55	150	0.42	0.45	99.3	53.55
100	300	0.45	1.15	94.4	43.8
150	450	0.46	2.11	94.1	20

4.2. Analysis of the Impact on Students

A total of 356 second-year students from the Mathematics and Information Science Department of University A were selected as the experimental subjects. During this semester's courses, the main content areas for which the teaching team provided guidance for student learning activities included: (T1) Mathematical Analysis, (T2) Advanced Algebra, (T3) Discrete Mathematics, (T4) Database Principles, and (T5) Operations Research and Optimization. The teacher-student learning guidance relationship was categorized into six levels: 0, 1, 2, 3, 4, and 5, with higher numbers indicating better relationships. The teacher-student learning guidance relationship under the method described in this paper (randomly selecting 10 students and assigning them numbers from 1 to 10) is shown in Figure 5.

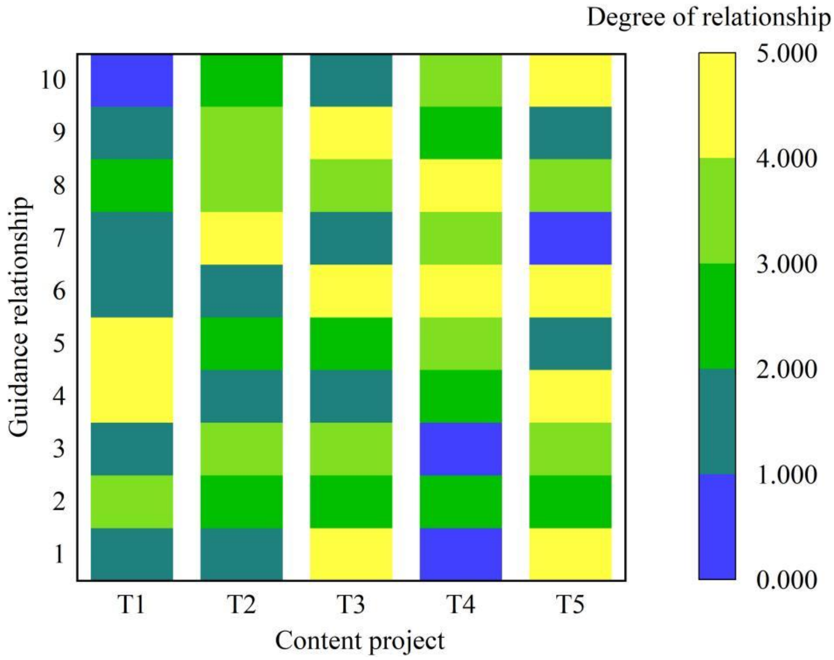

Figure 5. The learning guidance relationship between teachers and students.

4.2.1. Students' Interest in Learning and Attitude Toward Learning

A survey was conducted in the form of a questionnaire to assess students' learning interests and attitudes toward learning. A total of 356 questionnaires were distributed, with 343 valid responses collected, resulting in a response rate of 96.35%. Learning interest was divided into: (B1) the degree of interest in the content of learning activities, and (B2) whether the learning activity methods were enjoyable. Learning attitude was divided into: (C1) opinions on learning methods based on the educational resource sharing platform, and (C2) willingness to continue participating in learning activities supported by this method. Each evaluation was divided into four levels: 1, 2, 3, and 4, with different evaluation degrees corresponding to each level. Specifically, (B1) corresponded to the following evaluation degrees: Very interested, Somewhat interested, Neutral, Not interested; (B2) corresponds to: Very relaxed, Relaxed, Not relaxed, Unclear; (C1) corresponds to: Collaborative learning methods are better, Somewhat interested, Neutral, Not interested; (C2) corresponds to: Very willing, Willing, Unwilling, Indifferent. The survey results on students' learning interest and learning attitude are shown in Figure 6.

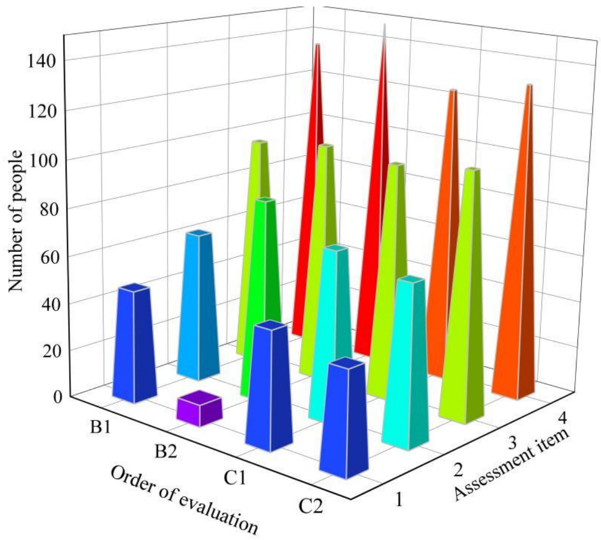

Figure 6. Learning interest and learning attitude.

It can be seen that most students have positive feelings about their learning interests and attitudes. Among them, 67.93% of students are interested in the activity content, 72.87% of students feel that the learning method based on the educational resource sharing platform is relaxed, 65.31% of students believe that this learning method is better/more interesting, and 68.51% of students are willing to continue participating in learning activities supported by this method.

4.2.2. Information Technology Proficiency

This paper briefly categorizes information technology skills into the following five areas: (I1) searching for and accessing online resources related to the subject matter, (I2) using Word/PPT to organize materials and create learning projects, (I3) using Excel to create and edit tables and perform basic data analysis, (I4) using mind mapping tools to organize materials and create learning projects, and (I5) using drawing tools to perform basic image editing. The mastery levels are categorized as follows: (M1) completely unable, (M2) basic mastery, (M3) not very proficient, and (M4) proficient mastery. The mastery levels of 356 students are shown in Figure 7. It can be seen that in terms of searching for and locating online resources and using basic office software such as Word, PowerPoint, and Excel, most students (>250) are at the not very proficient to proficient mastery level. However, over half of the students are at the basic proficiency to not very proficient level in using mind mapping tools, which may be related to students' learning habits and usage preferences. Overall, students' information technology proficiency levels are relatively good, with over 50% of students able to basic proficiency in using multiple software applications.

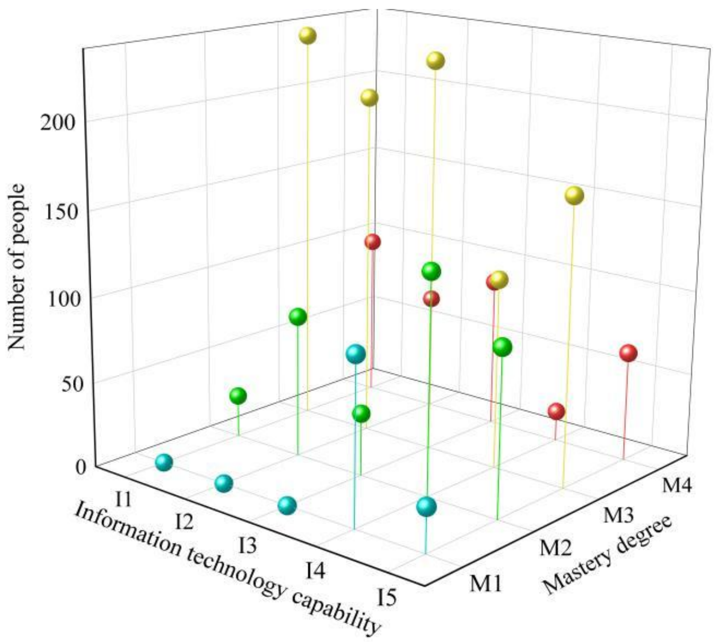

Figure 7. The students' mastery of information technology.

4.3. Application Effect Evaluation and Analysis

4.3.1. Comparative Analysis between the Experimental Group and the Control Group

The 230 students were divided into two groups of equal size: the experimental group (EG) and the control group (CG), with 115 students in each group. The EG used the method described in this paper for teaching and learning, while the CG continued to use traditional teaching and learning methods. Post-test analyses of learning engagement were conducted for both the experimental and control groups across four dimensions: (SS) total learning engagement score, (BE) behavioral engagement, (CE) cognitive engagement, and (EE) emotional engagement. Each dimension was scored out of 25 points. The results of the independent samples t-test are presented in Table 3, and the results of the independent samples t-test for differences are presented in Table 4.

Table 3. Independent sample statistics.

		N	Average value	Standard deviation
SS	EG	115	22.17	1.323
	CG	115	14.68	5.478
BE	EG	115	19.88	2.222
	CG	115	12.95	8.763
CE	EG	115	22.25	1.707
	CG	115	16.91	4.431
EE	EG	115	21.07	1.677
	CG	115	17.11	7.49

Table 4. Independent sample difference test.

	t value	*df*	*P* value (double tail)
SS	5.196	60	0.000
BE	3.422	60	0.025
CE	3.325	60	0.039
EE	5.076	60	0.087

Combining Tables 3 and 4, the experimental group (EG) achieved scores of 15 or higher in all four dimensions under the guidance of the method described in this paper, with minimal overall differences and standard deviations ranging from 0 to 2.5. In contrast, students in the control group (CG), who continued to use traditional teaching and learning methods, scored slightly higher in only two dimensions: (CE) cognitive engagement and (EE) emotional engagement, with scores of 16.91 and 17.11, respectively. Additionally, in the (SS) learning engagement total score dimension, the (EG) experimental group and (CG) control group students exhibited a strong statistically significant difference ($p = 0.000$), and similarly showed significant differences in the other three dimensions ($p < 0.1$).

4.3.2. Nonparametric Tests of Learning Behavior

Since the three variables—(V1) number of times participating in learning activities, (V2) number of times completing learning tasks, and (V3) duration of experimental exercises (hours)—for students in the (EG) experimental group and (CG) control group were subjected to the Shapiro-Wilk (S-W) test, the data did not follow a normal distribution. Therefore, in this section, the non-parametric Mann-Whitney U test was used to compare and analyze the data after the teaching experiment. The test results are shown in Table 5.

Table 5. Mann-whitney U test result.

Variable	EG		CG		Z	P
	Average	Quartile	Average	Quartile		
V1	23	20(18,26)	14	15(9,19)	-2.91	0.000
V2	25	23(20,29)	12	11(8,16)	-2.64	0.023
V3	37.8	30.1(24.9,50.7)	22.3	21(17.6,28.9)	-0.98	0.011

As shown in Table 5, there were significant differences ($p < 0.05$) between the (EG) experimental group and the (CG) control group in terms of the number of times students participated in learning activities (V1), the number of times learning tasks were completed (V2), and the duration of experimental exercises (hours) (V3). In all three learning behaviors, the performance of students in the (EG) experimental group was superior to that of the (CG) control group, further validating the reliability of the method proposed in this study in terms of assisting teaching effectiveness and student learning behaviors.

5. Conclusion

(1) In the construction of an educational course resource sharing platform, the idea of Markov decision processes is used to optimize the scheduling of multi-dimensional resources and loads. A reinforcement learning framework consisting of three main parts—an agent value function network, a collaborative graph encoder, and a hybrid network—is designed. Compared to traditional educational course resource platforms, the established educational course resource sharing platform achieves an average throughput increase of 180.71 b/s. It not only maintains an average response time of less than 5

seconds and a resource matching rate of 90.00% or higher but also achieves a maximum resource matching rate of 99.06%.

(2) When applying the method described in this paper to the learning assistance of 356 second-year students majoring in mathematics and information science at University A, 60.00% or more of the students showed positive evaluations in terms of learning interest and attitude, and 50% or more of the students were able to master the use of multiple software programs. In terms of learning outcomes, students assisted by the method proposed in this paper demonstrated statistically significant differences ($p < 0.05$) compared to students using traditional methods across multiple dimensions.

(3) In terms of educational course resource development pathways, guided by swarm intelligence theory, the course resource development process is divided into three stages: preliminary organization, mid-term development, and post-development refinement. By integrating a multi-dimensional resource coordination optimization algorithm based on reinforcement learning, this approach can provide vocational college teaching innovation teams with abundant and diverse course teaching resources, thereby promoting the overall development and construction of the team system.

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