Research Article

An Optimization Method for Integrating Educational Information Resources Based on Edge Computing

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Received 8 June 2022; Revised 27 June 2022; Accepted 2 July 2022; Published 19 July 2022

Academic Editor: Gengxin Sun

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This paper adopts an edge computing approach to conduct in-depth research and analysis on the optimization of educational information resource integration and constructs an integrated teaching resource design model concerning the integrated teaching model, human-centered mobile learning resource design, and the interdisciplinary concept of physics subject teaching method. The learning field constituted by the model is divided into two parts, the explicit field and the potential field and then designs a five-stage teaching resource based on the model. Based on the cloud service center model, we propose a hierarchical mechanism for sharing educational information resources and analyze how each hierarchical entity constructs and shares resources and the rights and responsibilities of each hierarchical entity; we explain the meaning and functions of the personalized educational resource integrated development environment provided by the cloud service center for users. The dynamic evaluation model of the value of educational information resources is summarized and proposed for the resource exchange behavior in the sharing of educational information resources, and the significance of the calculation method of resource value, parameter values, and resource value difference for resource sharing is introduced. Firstly, the mechanism for coconstruction of educational information resources at different levels is proposed, and the construction tasks of subjects at different levels in the process of coconstruction and sharing of resources are elaborated. The sharing mechanism of educational information resources covering the regularization system, evaluation mechanism, incentive mechanism, problem handling mechanism, and supporting service mechanism is proposed, and a dynamic evaluation model of the value of educational information resources is designed to improve the enthusiasm of the coconstruction and sharing subjects.

1. Introduction

In mobile edge computing, the data collected by sensors can be analyzed and processed in situ without uploading to the cloud [1]. On the one hand, it frees up a large amount of backhaul link bandwidth resources to reduce network congestion and improve network throughput. On the other hand, the local processing of data can also ensure data security and user privacy [2]. The mobile edge computing system can pinpoint the specific location of end devices by obtaining the signaling information of the wireless network. MEC servers deployed in different locations of the wireless network can quickly capture real-time network context information, such as wireless network environment, network load, and resource utilization. Specific applications can use real-time network data to establish connections between users and focal events or incidents [3]. By analyzing the problem structure, the authors demonstrate that the optimal policy will balance the current transmission cost and the average future transmission cost and obtain the mutual constraints between storage and bandwidth resources.

In this era of product intelligence, to better promote the importance of innovation, this project is aimed at promoting the development of the creative movement by designing and developing a creative education resource-sharing platform to make more aware of the ideas of creators and their industrial structure. The platform provides a platform for creators to highlight their creativity, enabling the release of creators' works and the implementation of creators' education to rely on the online platform, as well as crowdfunding and product
promotion for their works. At the same time, it allows more people to learn about the creative movement through the creators’ works displayed on the platform and the related creators’ learning videos shared on the platform, which will lead to the construction of an innovative society. For the collaborative computation between the computing user and each of its assisting users, the total available computation time is a given value depending on the intensity of the computation task [4]. This computation period is divided into three time slots for task offloading from the computation user to the assisting user, for the assisting user to perform the computation and for the return of the computation results from the assisting user to the computation user. Based on the above work, the model is extended to the more general scenario of multiple energy transfer machines and multiple computation users with multiple assistance users.

The above work designs a typical single-computing user model and elucidates the limits of the user system computation under this model. The edge layer is the core of the three-tier architecture of edge computing and is used to receive, process, and forward data streams from the field layer, providing time-sensitive services such as intelligent sensing, security and privacy protection, data analysis, and intelligent computing, process optimization, and real-time control. Traditional SOA wants to solve the dependencies between services through ESB, microservices wants to have no dependencies between services and let the upper layer or front-end business integrate these backend services. This can only reduce the depth and breadth of dependencies, and Spring boot’s microservice development framework gives a good start. Never have a ring of dependencies; extremely strong coupling can lead to complex and difficult service deployments and can lead to endless recursive failures and problems that you might not expect. The next work reveals the impact of each variable on the system computation in a complex environment variable, to find more generalized optimization algorithms to improve the system performance. In this scenario, in addition to the energy, channel state, and user computational capacity constraints in the above work, the pairing between computational users and assisting users (assisting users to select a computational user to assist them in their computations), the collaborative energy transfer waveform design among multiple energy transfer machines, and the coupling of multiple computational users to allocate fixed bandwidth resources and time resources all make the problem more complex. The proposed system computation maximization problem is thus a class of nonconvex optimization problems with high solution complexity.

2. Related Jobs

The authors propose an optimal binary computation migration policy scheme based on a one-dimensional search algorithm with the optimization goal of reducing the computation task latency. In this scheme, the computation migration decision process involves three states: the waiting state of the computation task in the queue buffer, the state of the local computation of the computation task, and the state of the wireless link-based transmission of the computation task [5]. Whether to execute computation migration is decided by the end-users computation migration decision module. Simulation results show that the optimal computation migration strategy can significantly reduce the task execution delay compared to the strategy of local execution of computation tasks [6, 7]. However, in this scheme, the communication delay between the end-user and the MEC server is too large because the end-user needs to make the migration decision based on the feedback from the MEC server [8]. The authors propose a binary dynamic computational migration algorithm based on Lyapunov optimization, which aims to optimize the completion latency of computational tasks. The authors mainly consider that the user can optimize the energy overhead of the local computation and the energy overhead of the task transfer process by dynamically adjusting the voltage frequency and performing power control, respectively. In each iteration, the proposed strategy allocates both CPU clock cycles for computational tasks processed locally and transmission power for tasks migrated to the MEC side [9]. The simulation results show that the proposed binary computation migration strategy can reduce the latency by 64%. Moreover, the proposed strategy can reduce the probability of packet loss during migration.

Second, the authors consider the partial computation migration problem with competition for computational resources among multiuser scenarios and design a set of heuristic dynamic resource allocation algorithms for dynamic computation migration decisions [10]. In the literature, the authors first consider both local computation and computation migration and propose the problem of maximizing computation utility based on energy consumption [11]. Second, an efficient partial computation migration algorithm is designed based on the gradient descent method, which can effectively balance the weights between local computation and computation migration to maximize the computation utility [12]. Simulation results show that when the required computational resources of a computational task are small, a high local computation weight gives better performance. Conversely, when the required computational resources of the computational task are large, a high computational migration weight gives better performance.

Teaching resources mainly refer to the conditions that provide support for effective teaching and learning, including books, teaching examples, explanatory videos, display pictures, multimedia courseware, and recorded audio that need to be used in the teaching process and include teachers and various equipment. In a broad sense, teaching resources refer to all elements used in the teaching process, including all things that support teaching and serve teaching conditions, such as the support of teaching policies. In a narrow sense, teaching resources mainly include teaching and learning-related materials, environmental conditions for teaching and learning, and supporting material equipment systems. When the system process view was used to study the media about other elements in the teaching and learning process, a new idea of teaching and learning was developed, which relies on resources for effective teaching and learning. Instructional resources refer to all the necessary elements
used by the instructor in carrying out the teaching and learning process, not only the learning content and learning materials but also the people, media, strategies, methods, and environmental conditions that have a significant relationship with the learners. Conspicuous education refers to tangible education through organized, planned, direct, and visible educational activities, which make the participants consciously affected by the education. The most important characteristic of explicit education is that it has a clear purpose.

3. Optimization Analysis of Educational Information Resources Integration by Edge Computing

3.1. Edge Computing Design. Edge computing refers to the use of an open platform that integrates network, computing, storage, and application core capabilities on the side close to the source of objects or data to provide the most recent services nearby. Its applications are initiated on the edge side to generate faster network service responses and meet the basic needs of the industry in real-time business, application intelligence, and security and privacy protection. Edge computing sits between, or on top of, physical entities and industrial connections. With cloud computing, historical data from edge computing can still be accessed [13]. As shown in Figure 1, edge computing is mainly composed of four layers of functional structures: core infrastructure, edge computing center, edge network, and edge devices.

The edge layer collects industrial data generated by the end layer and performs protocol analysis and edge processing for industrial data from different sources. It is compatible with various industrial communication protocols such as OPC/OPC UA and Mod-Bus, converts and unifies the format of the collected data, and then, transmits the relevant data in wired or wireless ways (such as 5G and NB-IoT) remote transmission to the Industrial Internet platform. Edge computing technology is an important part of the edge layer. It is based on advanced technologies or tools such as high-performance computing chips, real-time high-speed processing methods, and high-precision computing systems [14]. It performs data preprocessing and preprocessing on the data source side of industrial equipment and smart terminals to improve system response speed and data. The transmission speed solves the delay problem of data transmission and communication.

\[
y = \frac{g_{an}(t^2)}{\sigma^2} - \sum_{i} p_{u,n}(t^2)g_{u,n}(t^2).
\]  

(1)

Edge resources are scattered and distributed in the edge network. It is a waste of resources if the resource scheduling does not utilize the dispersed resources efficiently. For example, smart vehicles have powerful communication and computing capabilities and have free time to perform computational work. They can be aggregated by an effective resource scheduling strategy to create a pool of available and cost-effective computing resources. Moreover, both users and service providers try to benefit from it.

\[
k(p_{an}) = 2\gamma p_{an} + g(P_{an}).
\]

(2)

From an architectural perspective, compute offloading is the transfer of computing tasks between different layers to achieve lower latency, reduced energy consumption, and improved resource utilization and system efficiency. From the offloading direction, computational offloading includes user-to-edge offloading, edge-to-edge offloading, and cloud-to-edge offloading, where most research focuses on user-to-edge offloading. In terms of offloading granularity, computation offloading is divided into full offloading and partial offloading. Full offload indicates that all computational tasks are offloaded to the edge, while partial offload indicates that only some computational tasks are offloaded to the edge. From the offloading technology point of view, current offloading methods are mainly divided into centralized and distributed algorithms.

\[
S_u = \{ p_{umin} = p_{1}, p_{2}, \ldots, p_{n} = p_{max}. \}
\]

(3)

The learning field constituted by the teaching resource model is divided into two parts: the explicit field and the potential field. The explicit field mainly refers to the physical space composed of elements of concrete things, centered on the teaching context, including four parts: video, platform, technology, and tools, which form the sum of actual or potential resources for learners. The potential field is the meaning space formed in the process of dynamic change of the explicit field, centered on the problem, including the experience, innovation, application, and meaning construction of the learners [15]. The explicit field and the potential field interact with each other to evolve and change, and the learning field constructed with teaching resources forms a dynamic field of continuous collaboration and competition with students at the center.

\[
H_{ij} = G_{ij}F_{ij}^2.
\]

(4)

According to the requirement description of the Statistics Management module, this module is used for statistics and analysis of various data in the system, and the objects of the statistics are the information corresponding to various other objects. According to the requirement description of the Order Management module, it uses the order details. The order information mainly includes the customer's information, the name of the corresponding work, the name of the creator who published the work, the name of the person who wrote the lesson plan for the work, the name of the person who taught the lesson according to the lesson plan, the status of the order, the progress of the order, and the note information.

\[
R_{ij} = \frac{W_{ij} \cdot \ln \left(1 - \gamma_{ij}^2 \right)}{\sum_{i=1}^{N} \gamma_{ij}^2}.
\]

(5)
Due to the basic unrelatedness between service interfaces, the system can use multiple server-sides to accomplish the response of different interfaces, i.e., each server-side is configured with a different interface. This allows each service to respond to business requests individually, making it run in distributed parallel so that high-performance NIO communication can be maintained between the client and the server. In the case of high concurrency, the Dubbo framework uses the corresponding random algorithm to reasonably allocate each business request to each server, thus achieving load balancing and speeding up the platform’s response to the requested business.

First, users transferring a large amount of data to the cloud is bound to bring network congestion, which may affect the network state and cause network latency; in addition, when users are in an unstable network environment, it takes a long process when they go through a series of access networks, transmission networks, and even core networks for processing. Through computational migration, some tasks are migrated to the edge server, which can directly process and correspond to users and reduce network load and latency. Resource sharing refers to the access of scarce resources to the required resources by means of a common or shared use. At its source, resources are the basic material for social, economic, and scientific development, so sharing is a right of actors in social development. Many disciplines have carried out research on resource sharing, and resource sharing is a very important part of resource allocation research, mainly from the perspective of public service construction to analyse the efficiency of sharing and the feasibility of sharing.

There are two types of enterprises involved in the construction and sharing of resources: one is involved in building a cloud service center for the construction and sharing of educational information resources, responsible for building cloud-based infrastructure construction, providing platforms and services for the construction, sharing of educational information resources, and assisting in the construction and sharing of resources; the other type of enterprises compete with schools to build curriculum educational information resources [16]. The relationship between schools and enterprises is one of both competition and cooperation. Competition for the application of cloud service center construction and project construction, the government in the selection of resource builders, considers the comprehensive strength of enterprises and schools, examines the ability to build resources, pays attention to the availability, applicability, and reusability of resources, and chooses a more suitable resource builder to build curriculum resources. After the successful construction of resources, enterprises and schools cooperate in resource sharing and share various services provided by the cloud service center. In the sharing process, the government should also play a macroregulatory role and set strict sharing standards; if other enterprises and schools want to participate in resource sharing, they need to exchange or purchase resources according to the resource sharing standards, so that resources can be shared more fairly and equitably in a larger scale, as shown in Figure 2.

Aiming at the problem of edge computing resource allocation and task scheduling, it can be seen from the above overview of task offloading decision-making, task allocation under resource constraints, and DAG scheduling and allocation: some modeling works are relatively systematic, and accurate methods are proposed on the basis of analyzing system characteristics. However, the algorithm has high complexity and occupies a lot of computing resources, so it is not suitable for large-scale problems; most of the work adopts heuristic strategies to allocate resources and schedule tasks, although in the face of large-scale tasks and heterogeneous resources, such methods are convenient to design.
It is easy to implement and does not take up too many computing resources, but it is difficult to achieve a good overall optimization effect; intelligent algorithms are suitable for complex problems with strong constraints and multiobjectives and have strong scalability, but are difficult to apply to real-time distributed online problems and other real-time problems, sexually demanding scenes.

3.2. Optimized Design of Educational Information Resource Integration. The integrated teaching resource “Happy Electric City” consists of ten functional areas that form an overall physical space, divided into four components and accessories used in the teaching and learning process, and the overall model is shown in Figure 3. When applying the resources for teaching, teachers, students, and the resource model form an open learning field, and teachers and students can choose to enter the overall model or enter one of the areas or a specific module. The teacher can teach the corresponding knowledge content based on the built-in circuits of each module, and students can participate in different activities to form a mutual teacher-student-student communication in the field, with the teacher providing scaffolding support and teaching guidance for students and students collaborating in learning to obtain resources and promote knowledge internalization while forming competition. The “Happy Electric City” can be seen as the integration of several open

Figure 2: Workflow of CEC framework.
sublearning fields, where the capital advantage of students facilitates the operation of the field and constantly generates new resources to optimize and expand the original learning field. The learning field is student-centered and transforms the physical space of resources into a meaningful learning space in the learning activities.

First, users should select the role they belong to in the platform and then enter their account information and personal information in the corresponding text box [18]. After filling out the form and clicking the confirmation button, the platform backend system will check whether the content entered in the text box is legal or not; if it is legal, the registration will be displayed on the interface successfully. If the application is approved, the user will be able to log in to the platform.

The initial interface shows only part of the user’s information, and the administrator can click the View button to get the details of the corresponding user. Only users with approved status can log in to the platform. The administrator can also change the user’s information by clicking the Edit button and can also change the user’s status to restrict illegal users from logging in. At the top of the user information list, the administrator can quickly search for the corresponding user based on two query criteria: account name and user status.

And change a user’s access rights to a file by clicking the Deny or Agree with the button on the right. The administrator can then also query the file access request information by the status of the approval request and the user’s name that initiated the request to get the desired information quickly.

After the regional cloud service center undertakes the construction task, it should also analyze the construction task, determine the resource construction plan of the region according to the resource construction plan of the cross-regional cloud service center, and deploy the resource construction force according to the plan. In this way, the government leads the construction of resources of each cloud service center to form a cascading mechanism for the common construction of educational information resources, so that educational resources can truly realize cross-regional and large-scale sharing [19]. Each level in the hierarchical mechanism of educational information resources is interdependent and requires joint efforts to complete the construction of resources, and the problems and difficulties in the process of resource construction can be solved promptly. Therefore, the hierarchical resource construction mechanism has certain practical significance for solving the problems in resource construction.

Authoritative evaluation is comprehensive and accurate in evaluating the value of resources, but the evaluation period is long; user evaluation and user self-evaluation can evaluate resources in real-time, but the evaluation process is subjective, and it is difficult to accurately assess the value of resources. Therefore, to determine the value of resources more accurately in the cloud computing environment, the evaluation method should combine the above three resource evaluation methods and use user evaluation and user self-evaluation to evaluate resources within the period of authoritative evaluation; once the authoritative evaluation is obtained, the authoritative evaluation can be combined with user evaluation and user self-evaluation to determine the value of resources. Mobile edge computing leverages the wireless access network to deliver the services and cloud computing capabilities required by telecoms users nearby, creating a carrier-grade service environment with high performance, low latency, and high bandwidth, accelerating the rapid download of content, services, and applications over the network and enabling consumers to enjoy an uninterrupted, high-quality network experience. The advantage of using this evaluation mechanism is that it considers the interests of resource builders and resource users and combines objective and authoritative third-party evaluations to obtain a more accurate evaluation. The resource evaluation mechanism is shown in Figure 4.

We should deeply explore the internal inducements of resource construction and resource sharing and establish effective incentive policies, such as material incentives, spiritual incentives, and team incentives, based on the principle of mutual benefit, to motivate resource construction subjects to share resources actively. Cloud computing grasps the whole, focusing on big data analysis of non-real-time, long-period data, and can play a special role in periodic maintenance and business decision support; edge computing focuses on local, real-time, short-period data analysis and

![Figure 3: Framework of integrated teaching resources.](image-url)
can better support the real-time intelligent processing and execution of local business. Therefore, edge computing and cloud computing are synergistic with each other, and there is a close interaction and synergy between the two.

Before resource sharing, it should be clear that the identities of resource builders and resource users are convertible, that is, some users are both resource builders and resource users, and users have the dual identities of resource builders and resource users. For such users, the rights and obligations of resource sharing should be interlinked [20]. The more resources a user shares, the more rights he or she enjoys, and the wider the range of resources he or she can access should be, to ensure that users continue to engage in resource-sharing behavior. Therefore, compensation measures should be used to motivate more users to participate in resource sharing.

In the cloud computing environment, it has become easier and easier for users to access resources. Some resource users, after acquiring resources, upload the acquired resources to the network for other users to download and use out of the motivation of resource sharing, and some even gain benefits in this way. From this, disputes and problems are likely to arise in the process of resource sharing, even if a regulatory mechanism exists. Therefore, effective dispute handling and resolution mechanisms should be established among resource builders, among resource users, and between resource builders and users, which is a necessary means to guarantee the rights and obligations of resource builders and is also the key to realizing that education information resource sharing can be developed sustainably. Multisensor data fusion is an emerging field of research on data processing for the specific problem of using multiple sensors in one system. Multisensor data fusion is a practical and applied technology developed in recent years, and is a new multidisciplinary intersection involving signal processing, probability statistics, information theory, pattern recognition, artificial intelligence, fuzzy mathematics, and other theories.

In the supporting service mechanism, the business model refers to the commercial operation process of promoting educational information resources to be shared on a larger scale [21]. Any company or school that designs and produces a product needs a third-party research organization to evaluate the value of the product, such as the teaching effectiveness of the software and the authority of the resources. These evaluation results also provide feedback on the company’s product, making it clear the strengths and weaknesses of the product, so that the company can

![Figure 4: Evaluation mechanism for sharing educational information resources.](image-url)
improve the product in a targeted manner, while the research results of third-party organizations can also provide a reference for users to select products. Social media can also participate in publicizing the construction, advantages, and characteristics of educational information resources and evaluation results to promote the sharing of resources. Through a perfect resource-sharing service system, a virtuous cycle of resource construction and sharing can be promoted.

4. Analysis of Results

4.1. Mobile Edge Computing Performance Analysis. As shown in Figure 5, the system utility of the BFS algorithm is high; its time overhead is too large to meet the actual delay requirements. From Figure 5, we can see that the system utility of the proposed algorithm is close to that of the BFS algorithm and significantly better than that of SO and CO. As the number of vehicles increases, the gap between the system utility of the proposed algorithm and the system utilities of SO and CO becomes larger and larger. This is because the proposed algorithm optimizes both the edge server selection decision and the computational resource and migration ratio decisions, while SO and CO only consider the edge server selection decision and the computational resource and migration ratio decisions, respectively. Further analysis shows that compared to the proposed algorithm, the performance of SO is severely affected by the initial value of computational resources because computational resource optimization is not considered.

CO always allows all vehicles to migrate their computational tasks to the nearest edge server, which leads to severe overloading of individual edge servers when the number of vehicles becomes large. The proposed algorithm greatly improves the system utility because it optimizes all three variables simultaneously and optimizes the computational resources and migration ratio while balancing the load on each edge server.

Therefore, it is not practical in practical scenarios. Second, compared to the CO algorithm, the system utility of the proposed JSCO algorithm is relatively stable as the computational resources increase, and its system utility can still maintain relatively high values at lower values of computational resources. This is because the proposed algorithm can fully utilize the computational resources of all the edge servers distributed on the roadside units, instead of utilizing only the resources of the edge servers of the nearest roadside units. Therefore, the performance of CO is poor when the computational resources of the nearest edge server are small and cannot satisfy the migration task requests of all vehicles. In contrast, the proposed algorithm can maintain relatively high and stable system utility because it can transfer the load from the nearest edge server to other edge servers. Teaching resources are the materials and other conditions that can be used for the effective development of teaching, usually including teaching materials, cases, films, pictures, and courseware. They also include teacher resources, teaching aids, and infrastructure. In a broad sense, they should also involve education policies and other contents. In a broad sense, teaching resources can refer to all elements that are used by the pedagogue in the teaching process, including people, money, materials, and information that support and serve teaching and learning. In a narrow sense, teaching resources mainly include teaching materials, a teaching environment, and a teaching backup system.

Since each processor core accesses the memory in an RPP node faster than other nodes, the virtual machine can theoretically obtain the best performance when the virtual machine memory size is less than or equal to the memory size of the RPP node. As shown in Figure 6, when allocating virtual machines on this physical server, it did not allocate more than 8 GB of memory to each virtual machine. If more memory is allocated to a virtual machine, the virtual machine must access some memory outside its RPP node, so it will affect its performance more or less. If the application is RPA-aware, even better. vSphere uses RPCT to create a RPA-aware virtual machine. The virtual machine will be split into virtual RPP nodes, and each RPP node will be placed on a different physical RPP node. Although the virtual machine is still spread across two RPP nodes, the operating system and applications within the virtual machine are RPC-aware, and resource usage will be optimized.

Algorithms for constrained optimization can basically be divided into two categories: direct methods and indirect methods. The indirect method is to convert the constrained optimization problem into an unconstrained optimization problem to solve, while the direct method does not need to convert the problem into an unconstrained problem and generally includes feasible methods and coordinate rotation methods. As shown in Figure 6, the penalty function discussed in this homework is more critical to find a good penalty function. In the composite shape method, the initial composite shape needs to be given, and the initial composite shape must be in the feasible region. The initial composite shape can be given manually or can be generated by random method, which is determined according to the degree of difficulty, but in order to meet the feasible region condition, we must check whether each vertex is in the feasible region, which is a critical step.

This indicates that the increase in the number of RSUs improves the level of collaboration among RSUs, which effectively reduces the average total latency of the task. In addition, the CA-DTS algorithm has the smallest latency and has a significant advantage over the other four algorithms. This indicates that the proposed CA-DTS algorithm is highly scalable and can cope with network scenarios of different sizes. In addition, the performance of the IA-AC algorithm is slightly lower than that of the CA-DTS algorithm, but its scalability performance is good. The other three algorithms are less scalable, and the average total delay fluctuates with the number of RSUs. The S-AC algorithm is the least scalable, and Figure 6 shows that the S-AC algorithm has the lowest average task success rate and offload rate. This is because as the RSU size increases, the state size of the centralized algorithm increases dramatically making it more difficult to learn the optimal decision for the intelligence. As a centralized algorithm, the performance of the
Figure 5: Changes in the system utility.

Figure 6: Average response time of four applications under three resource allocation algorithms.
SA-AC algorithm is relatively good, indicating that the ASN idea can improve the decision-learning ability of the intelligence.

4.2. Analysis of Optimization Results of Educational Information Resource Integration. Before the lecture, the teacher analyzes the objectives and knowledge skills of the course and sets up the teaching context with the teaching resource model, incorporating interdisciplinary and cross-topic knowledge learning content. The instructor explains the knowledge points and asks questions to guide students’ inquiry and learning. In the laboratory class, teachers can use the integrated teaching resource model to design relevant experiments that need to be investigated in the textbook, and students can simulate the experiments and compare them with the ideal experimental situation to analyze the phenomena. Students can make open and innovative designs in the integrated teaching resource model scenarios based on the knowledge they learn, introduce more works to the model, and form new resources. Students can integrate knowledge from other disciplines or learn to design works through a web search. The geographical dispersion and heterogeneity of edge computing resources as well as the demand for performance, energy consumption, cost, and stability increase the complexity of optimal scheduling. By introducing the system model of edge computing in collaboration with IoT and cloud computing, giving the optimization metrics, scheduling models, and their solution algorithms, including exact algorithms, heuristics, and intelligent optimization methods, summarizing typical application cases, and pointing out the contents and directions for further research, it helps to promote the development of edge computing.

The test is divided into two main types, objective questions and subjective questions. The objective questions mainly examine students’ proficiency in relevant definitions or concepts, understanding of laws and calculations, etc. The subjective questions mainly examine the students’ skills in using the method, etc. The study compared the mean values of the subjective and objective questions and the total score pretest of the experimental and control groups, respectively, and analyzed whether there were significant differences in each score between them, as shown in Figure 7.

Figure 7 presents the data related to the independent samples t-test. STEM education has situational characteristics. It does not teach students isolated and abstract subject knowledge but emphasizes restoring knowledge to a rich life, combining interesting and challenging problems in life, and completing teaching through students’ problem-solving. STEM education emphasizes enabling students to acquire the ability to apply knowledge in context and at the same time to understand and identify the performance of knowledge in different contexts, that is, to be able to identify the nature of the problem and flexibly solve the problem according to the background information where the knowledge is located. STEM education emphasizes that knowledge is the product of learners’ interactive construction through the learning environment, rather than from external indoctrination. Context is an important and meaningful part of STEM education. Learning is affected by specific contexts, and learning is different in different contexts. Meaningful learning occurs only when learning is embedded in the context in which that knowledge is applied. When teachers design STEM education projects, the questions of the project should be based...
on real-life situations on the one hand, and the structured knowledge to be taught on the other hand. In this way, in the process of solving problems, students can not only acquire knowledge but also acquire the social, situational, and transfer ability of knowledge. Solving situational problems allows students to experience real-life and gain social growth.

The problem of maximizing the number of computable tasks for users within this collaborative computing system is investigated by jointly optimizing the energy beams of multiple wireless energy transmitters and calculating the pairing scheme of users and assisting users, the transmission computation time between them, bandwidth, and other resource allocations. Since this maximization problem is highly nonconvex and complex, firstly, we fix the pairing state of the computational user and the assisting user and in this case apply iterative optimization techniques and convex optimization techniques to optimize the allocation of resources such as energy, communication, and computation. Secondly, the greedy algorithm combined with the efficient pairing scheme is designed, and other control schemes are given. Numerical results show that the joint optimization design proposed in this paper makes full use of the communication and computational resources in the system and significantly improves the computational power of the users in the system compared with the traditional scheme, as shown in Figure 8.

When the model is first to run, it classifies all the existing works on the platform once and saves the keywords corresponding to each classification. When a new work is published on the platform, the platform first obtains its keywords by dividing the description of the work into words, then introduces the value of each keyword through the TF-IDF value calculation interface, and finally, calculates the similarity between the work and each prime work, selects the highest one as the cluster set of the file, and updates the cluster set again according to the method in the previous section.

5. Conclusion

To effectively support integrated teaching, this study builds an integrated teaching resource design model based on learning field theory, constructivism theory, experiential learning theory, and information processing theory, from the perspective of the concept of integrated STEM education and designs an integrated teaching resource development path based on the model interpretation. By using data compression algorithms to optimize the performance of the platform for transmitting data and text clustering algorithms to achieve the automatic classification of works, the platform is made more perfect and smoother. The problem of long task queuing delays still exists in the edge-enhanced cloud wireless access network. To reduce the user network access delay, this paper designs a load-shifting algorithm with a 2-stage threshold; firstly, the RRU obtains the user terminal’s profile, gets the user resource request quantity and the user queuing delay requirement, and then, judges whether the remaining resource quantity on the corresponding RRU is sufficient. Based on the cloud service center model, we propose a hierarchical mechanism for sharing educational information resources and analyze how each hierarchical entity constructs and shares resources and the rights and responsibilities of each hierarchical entity; we explain the meaning and functions of the personalized educational resource integrated development environment provided by the cloud service center for users. The dynamic evaluation model of the value of educational information resources is summarized and proposed for the resource exchange behavior in the sharing of educational information resources, and the significance of the calculation method of resource value, parameter values, and resource value difference for resource sharing is introduced.

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 there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Department of Control Technology Wuxi Institute of Technology.

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