

Research Article

Mobile Edge Computing Application in English Teaching Classroom Evaluation System Based on BPSO Algorithm

Junling Yu 

College of Foreign Languages, University of Shanghai for Science and Technology, Shanghai 200093, China

Correspondence should be addressed to Junling Yu; wendysunwater@usst.edu.cn

Received 24 June 2022; Revised 21 July 2022; Accepted 30 July 2022; Published 17 August 2022

Academic Editor: Shadi Aljawarneh

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This paper proposes a multi-user and multi-MEC scenario based on mobile edge computing to maximize the overall revenue to complete the task and proposes business guarantee and resource constraints as conditions to form the optimal task offloading resource allocation problem based on the Lyapunov mobile edge computing theory. Because this problem is NP-hard problem, decoupling is proposed as a solution to the channel resource allocation problem, which is solved by the KKT task allocation condition and the 0-1 integer programming problem. Aiming at the high-speed mobile terminal scene, a high-speed unloading algorithm is proposed, which explains the task unloading system model in the high-speed mobile terminal scene. The task offloading algorithm first allocates several subtasks according to the number of MEC servers and the remaining available resources of the MEC servers. At the same time, taking campus as an example, the English teaching classroom evaluation application uses the big data evaluation scale to complete the evaluation and uses statistical software to test the reliability of the evaluation results. Based on the analysis results, it summarizes and reflects on the education evaluation index system and puts forward suggestions for improving the evaluation system and implementing the English education guarantee mechanism. This paper uses the research of mobile edge computing resources to allocate big data and applies it to the application of English teaching classroom evaluation, thereby promoting the rapid development of classroom teaching.

1. Introduction

With the advent of the big data era, many computationally intensive and latency-sensitive applications need to achieve low latency and low power consumption. However, the allocation of mobile edge computing resources of mobile devices is limited, which makes computing data have the disadvantages of high latency and high-power consumption of the device. Mobile edge computing is proposed to meet users' high-quality service requirements for the network. It uses servers located at the edge of the network to provide users with computing resources, resource allocation, and IT services, which will greatly improve the quality of service. At present, the problems of computing offloading and resource allocation are still unresolved, which has great research value. In order to minimize task execution delay and energy consumption, this paper mainly studies the cooperative mobile edge computing and resource allocation strategies in the MEC system [1]. Since the

release of the experimental draft of the curriculum standards, the demand for art education in English teaching has continued to increase, and the pursuit of English teaching by front-line teachers, professionals, and scholars has kept pace with the times [2]. In recent years, with the continuous improvement of the application of English teaching classroom evaluation and educational practice, English culture education has also developed [3]. However, on the other hand, although English cultural education has attracted the attention of many scholars and teachers, it also has its drawbacks. In other words, the evaluation research of English art education has not kept up with the development of art education [4]. The big data questionnaire survey has enabled art education to be widely disseminated [5]. When I checked the literature, I found that the meaning, methods, and content of English art education have been deeply explored, and satisfactory results have been obtained. However, there are few studies on English classroom assessment [6]. There is a serious lack of art education

evaluation theory, and there is no operable index system for art education evaluation, which will affect the overall development of English art education [7]. From the perspective of English classroom teaching, this article has carried out an extended exploration of the application of current English teaching classroom evaluation, aiming to provide reference materials for the development and improvement of cultural education evaluation theory [8]. After determining the subject of constructing constructive and meaningful English teaching evaluation application system, this research focuses on relevant literature and big data, as well as the relationship between culture and language [9]. Based on the analysis of cultural education, we have carried out cultural education surveys and evaluations [10]. On the basis of research and analysis, this research conducted a preliminary assessment of art education and tried to analyze examples.

2. Related Work

The literature introduces the theory of multi-user and multi-MEC scenarios based on Lyapunov and proposes a collaborative optimization algorithm for task offloading resource scheduling [11]. Computing and channel resources are allocated according to factors such as user task load, MEC server processing capacity, mobile device processing capacity, and channel resource usage, so as to maximize the benefits of completing tasks for all users [12]. The literature introduces the research of Q learning on end-side cloud collaborative task offloading and resource allocation management. A computing offloading framework for end-to-side cloud collaboration is proposed, the two factors of time delay and energy consumption are considered to define the terminal benefit reflecting QoS guarantee, and the optimization goal is to maximize the terminal benefit [13]. Then, the problem is further formulated as a semi-Markov in the decision-making process, and Q learning is used to optimize the optimization target to obtain the best task offloading decision and resource allocation strategy [14, 15]. The literature introduces a distributed and cooperative joint computing offloading and resource allocation strategy. If there are frequent requests for computing tasks, the local MEC server with limited resources cannot meet the needs of users. Therefore, the calculation task is forwarded to the nearby MEC server to complete the calculation, and additional calculation is provided for the task in the local area that cannot meet the requirements, so that the load of the local MEC server is effectively reduced [16]. The literature introduces collaborative computing offloading and resource allocation strategies. This article first created a network model, a communication model, and a task calculation model [17]. The task execution cost was defined as the weighted sum of execution delay and energy consumption, and the task execution cost was minimized under the constraints of communication resources and computing resources [18]. The literature introduces the mathematical modeling of delay and energy cost in the process of task offloading and formulates an objective function to minimize task execution cost [19]. Then, the optimization problem is split, the resource allocation sub-problem is solved by the Lagrangian multiplier method, the computational unloading

sub-problem is solved by the proposed computational unloading algorithm based on the greedy algorithm, and finally the experimental simulation and performance evaluation are carried out.

3. Mobile Edge Computing Resource Allocation and Big Data Evaluation System

3.1. System Model and Problem Description. In this section, we first introduce the multi-user multi-cell MEC network scenario, then formulate the system communication model and calculation model, and finally describe the established optimization problem.

Figure 1 shows a multi-user multi-cell MEC network scenario. In this network scenario, the MEC server is deployed in the macro base station (MacroBS, referred to as MBS) of each cell, and the calculation task is sent to other execution modules through the task offloading strategy, including the local device CPU, the local area MEC server, and the nearby area MEC server. Each user accesses the MEC server through a wireless channel in the mobile network, and the MBS of two adjacent cells is connected to each other through a high-speed backhaul link (backhaul). This chapter mainly optimizes the computing tasks of users in cell 1 and does not consider the optimization of computing tasks in other cells for the time being. When the computing resources of the MEC server in the local area cannot meet the offloading requirements of internal users, and the MEC server in nearby cell 2 still has remaining computing resources, the local computing task can be transferred to the nearby MEC server. At this time, the MEC server in cell 2 acts as an auxiliary calculation function.

Due to the variability of the number of users, the MEC server in cell 1 may be overloaded. In order to solve this problem, three execution methods for users to complete their computing tasks are considered:

- (1) Local device execution: when the local and nearby MEC servers are overloaded, computing tasks can only be executed on the local device CPU.
- (2) Offload to the local MEC server: the computing resources of the local MEC server can meet the task offloading requirements, and the user offloads the task to the local MEC server through the wireless uplink.
- (3) Offload to nearby MEC server: when the local MEC server is overloaded and cannot meet the user task offloading requirements in the area, the computing task will be forwarded by the local MBS to the nearby MBS MEC server through the backhaul link.

Therefore, the binary variable of the uninstallation decision on the mobile device side is defined as x_i , namely,

$$x_i = \begin{cases} 0, & \text{Task } i, \\ 1, & \text{Task } i \text{ MEC server.} \end{cases} \quad (1)$$

The local MEC server needs to make further uninstall decisions based on its own computing resources. Whether the task is to be uninstalled on the local

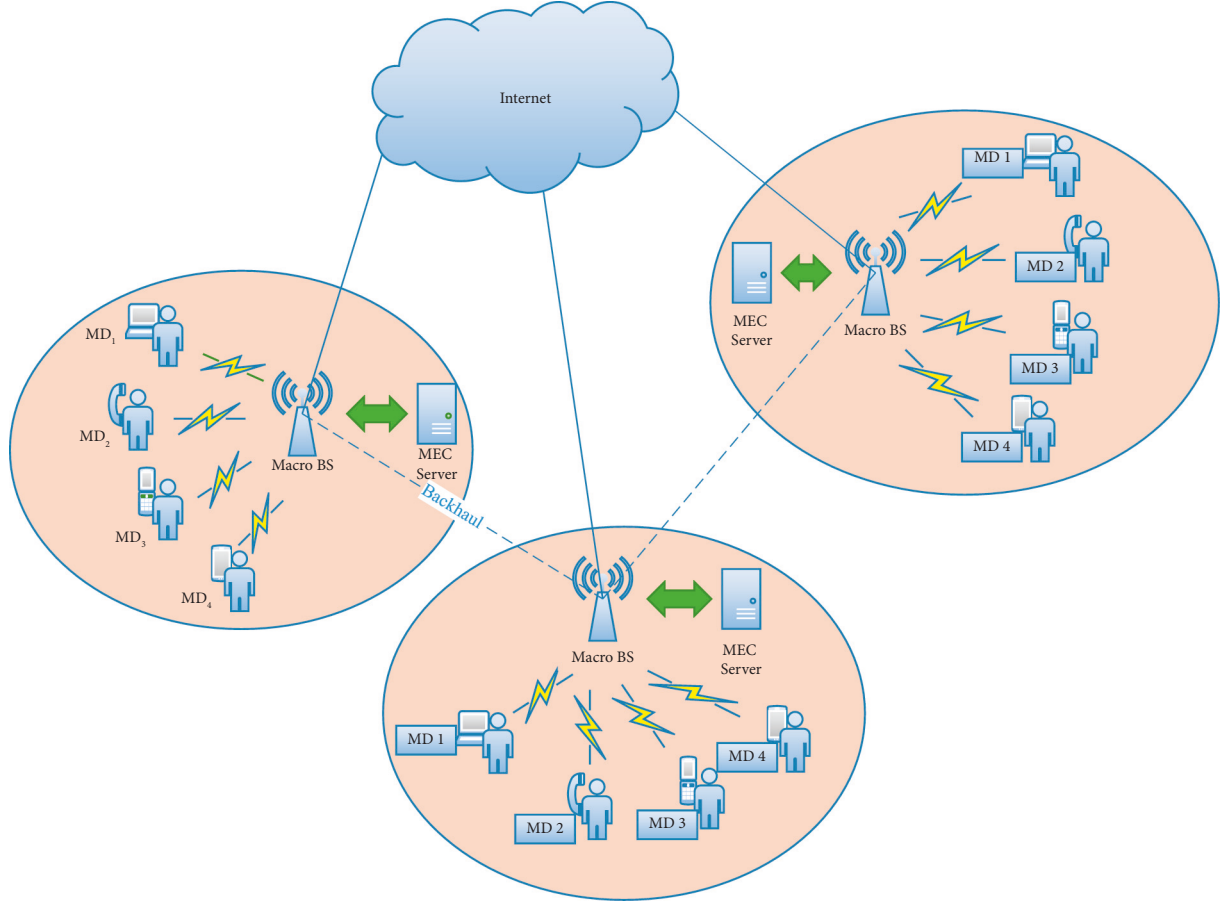


FIGURE 1: Multi-user and multi-cell MEC network scenario.

MEC server or the nearby MEC server, the server-side uninstall decision binary variable is defined as y_i , namely,

$$y_i = \begin{cases} 0, & \text{Task } i, \\ 1, & \text{Task } i \text{ Never MAC.} \end{cases} \quad (2)$$

If $y_i = 1$, the task i is first uploaded to the local MEC server via the wireless uplink and then forwarded between base stations via the backhaul link, and finally the task calculation results in the nearby MEC server are returned via the backhaul link again, and then via the wireless downlink road down to the user equipment.

This section introduces the communication model in the network scenario, including communication between users in a cell and base stations, and communication between base stations between cells. Since the result data volume of the computing task processed by the MEC server is very small and much smaller than the upload data volume, the delay and energy consumption of the task return phase (the task is transmitted to the user equipment via the downlink) are compared to the task upload and the execution stage is very small and generally ignored. The communication model in this chapter only considers the upload phase and does not consider the return phase for the time being.

In this cell, users upload tasks to the MEC server through the wireless uplink transmission channel. The user channel bandwidth is defined as w_i , and then the uplink transmission rate is

$$r_i = w_i \log_2 \left(1 + \frac{p_i g_i}{\sigma^2} \right). \quad (3)$$

The time delay required for user equipment to transmit via the uplink is

$$T_i^t = \frac{B_i}{r_i}. \quad (4)$$

The data forwarding between the local area MEC server and the nearby area MEC server is transmitted through the high-speed backhaul link between the two base stations. In fact, the backhaul link is bidirectional transmission, but this article only considers the task forwarding from the local area MEC server to nearby regional MEC server. Assuming that the transmission rate between the two base stations is v , the delay required for forwarding calculation tasks between the base stations through the backhaul link is

$$T_i^r = \frac{B_i}{v}. \quad (5)$$

The CPU computing power of the mobile device is defined as f_i^l , and then the delay required for the execution of the computing task on the local device is

$$T_i^l = \frac{C_i}{f_i^l}. \quad (6)$$

Correspondingly, the energy consumption required for the execution of the computing task on the local device is

$$E_i^l = \varepsilon_i C_i = k(f_i^l)^r C_i. \quad (7)$$

Considering the cost of delay and energy consumption required for computing task execution, define γ as the preference parameter for task execution delay and δ as the preference parameter for task execution energy consumption, and satisfy $\gamma + \delta = 1$, specific preference parameter settings. It can be adjusted according to the task type or user needs. Define the calculation task execution cost as the weighted sum of delay and energy consumption, and then the total cost of task execution on the local device can be calculated as

$$C_i^l = \gamma T_i^l + \delta E_i^l. \quad (8)$$

Offload to the MEC server in the local area in this network scenario, the user first offloads the task to the MEC server deployed in the macro base station of the local cell, and the MEC server processes the task and then transmits the task result back to the mobile device. Define the computing resources of the local MEC server allocated to the task as s_i^c , and the sum of the computing resources allocated to all tasks must meet the condition $\sum s_i^c = S_{\max}^c$, where S_{\max}^c is the maximum amount of computing resources available for the local MEC server. The time delay required to process the task is

$$T_i^{c,exe} = \frac{C_i}{s_i^c}. \quad (9)$$

The total delay of task offloading to the MEC server in the local area is the sum of upload delay, processing delay, and download delay. The download delay is too small to be ignored. Therefore, according to formula (4), the total delay required for task offloading is

$$T_i^c = T_i^t + T_i^{c,exe}. \quad (10)$$

When the task is offloaded, the energy consumption of the device in the idle state is very small, and it is ignored for simple calculations. The energy consumption during task offloading mainly considers the energy consumption of tasks uploaded from the device to the local MEC server. Therefore, the energy consumption required for task offloading is

$$E_i^c = p_i T_i^t = p_i \frac{B_i}{r_i}. \quad (11)$$

The total cost of offloading tasks to the MEC server in the local area is

$$C_i^c = \gamma T_i^c + \delta E_i^c. \quad (12)$$

According to formulas (8) and (12), it can be evaluated whether offloading tasks to the local MEC server can improve task offloading performance. If the system cost of offloading the task to the local MEC server is less than the cost of completing the calculation task in the local device, the decision to offload the task to the local MEC server to

complete the calculation task is beneficial. Due to the limited resources of the local MEC server, if too many users simultaneously offload tasks to the local server to obtain computing resources, the computing resources of the MEC server in the area will be exhausted. Therefore, when the number of offloading tasks exceeds the maximum load of the MEC server in the local area, you can choose to forward the computing tasks to the MEC server in the nearby area to make full use of the remaining computing resources in the server.

Then, the delay required by the MEC server in the nearby area to process the task is

$$T_i^{n,exe} = \frac{C_i}{s_i^n}. \quad (13)$$

If the user decides to offload the computing task to a nearby MEC server, the task data transmission between the two base stations will cause additional delay. At this time, the total delay of task offloading to the nearby MEC server is the sum of upload delay, transmission delay, and processing delay. Therefore, according to formulas (4), (5), and (13), the total delay required for task offloading is

$$T_i^n = T_i^t + T_i^r + T_i^{n,exe}. \quad (14)$$

Similarly, the energy consumption required for task uninstillation is still the task upload energy consumption, that is, $E_i^n = E_i^c$. Therefore, the total cost of offloading tasks to nearby MEC servers is

$$C_i^n = \gamma T_i^n + \delta E_i^n. \quad (15)$$

Time delay and energy consumption are important indicators to measure system performance. We consider defining the total execution cost of the system as the weighted sum of the execution delay and energy consumption of all tasks in the unit, and jointly allocate unloading decisions, bandwidth allocation, and computing resources. The optimization problem is modeled as follows:

$$\begin{aligned} & \min_{x, Y, W, S^c, S^n} \sum_{i=1}^N C_i^l (1 - x_i) + C_i^c x_i (1 - y_i) + C_i^n x_i y_i, \\ & \text{s.t. C1: } \sum_{i=1}^N s_i^c \leq S_{\max}^c, \\ & \text{C2: } 0 \leq s_i^c \leq S_{\max}^c, \\ & \text{C3: } \sum_{i=1}^N s_i^n \leq S_{\max}^n, \\ & \text{C4: } 0 \leq s_i^n \leq S_{\max}^n, \\ & \text{C5: } \sum_{i=1}^N w_i \leq W_{\max}, \\ & \text{C6: } 0 \leq w_i \leq W_{\max}, \\ & \text{C7: } x_i, y_i \in \{0, 1\}, \\ & \forall i \in N. \end{aligned} \quad (16)$$

3.2. *Problem Solving and Algorithm Design.* Uninstall to nearby area MEC server user set satisfies $N_0 + N_1 + N_2 = N$. The optimization problem can be transformed into

$$\begin{aligned}
& \min_{W, S^c, S^n} \sum_{i \in N_0} C_i^l + \sum_{i \in N_1} \left[\gamma \left(\frac{B_i}{w_i \log_2(1 + (p_i g_i / \sigma^2))} + \frac{C_i}{s_i^c} \right) + \delta \frac{p_i B_i}{w_i \log_2(1 + p_i g_i / \sigma^2)} \right] \\
& + \sum_{i \in N_2} \left[\gamma \left(\frac{B_i}{w_i \log_2(1 + p_i g_i / \sigma^2)} + T_i^r + \frac{C_i}{s_i^n} \right) + \delta \frac{p_i B_i}{w_i \log_2(1 + p_i g_i / \sigma^2)} \right], \\
& \text{s.t. } \sum_{i \in N_1} s_i^c \leq S_{\max}^c, \forall i \in N_1, \\
& \sum_{i \in N_2} s_i^n \leq S_{\max}^n, \forall i \in N_2, \\
& \sum_{i \in N_1 \cup N_2} w_i \leq W_{\max}, \forall i \in N_1 \cup N_2.
\end{aligned} \tag{17}$$

The optimization problem is further transformed into

$$\begin{aligned}
& \min_{W, S^c, S^n} \sum_{i \in N_0} C_i^l + \sum_{i \in N_2} \frac{1}{\xi_i} \leq 1, \forall i \in N_2 \\
& \sum_{i \in N_1} \left[\gamma \left(\frac{\lambda_i \vartheta_i}{W_{\max}} + \frac{C_i}{S_{\max}^c} \mu_i \right) + \delta \frac{p_i \lambda_i \vartheta_i}{W_{\max}} \right] \\
& + \sum_{i \in N_2} \left[\gamma \left(\frac{\lambda_i \vartheta_i}{W_{\max}} + T_i^r + \frac{C_i}{S_{\max}^n} \xi_i \right) + \delta \frac{p_i \lambda_i \vartheta_i}{W_{\max}} \right], \tag{18} \\
& \text{s.t. } \sum_{i \in N_1} \frac{1}{\mu_i} \leq 1, \forall i \in N_1, \\
& \sum_{i \in N_1 \cup N_2} \frac{1}{\lambda_i} \leq 1, \forall i \in N_1 \cup N_2.
\end{aligned}$$

Due to the large scale of calculation of this problem, the CVX toolkit is needed to solve it. Due to the discreteness of the unloading decision variables X, Y , this chapter designs a heuristic algorithm based on binary particle swarm to solve the optimization problem to obtain the unloading decision variables X, Y . Combined with the optimization problem, the fitness function is defined as

$$\text{Fitness} = \sum_{i=1}^N C_i^l (1 - x_i) + C_i^c x_i (1 - y_i) + C_i^n x_i y_i. \tag{19}$$

The fitness function can be used to measure the total cost of delay and energy consumption caused by the unloading scheme. The larger the fitness function, the higher the computational cost, indicating that the program has poor performance and is not suitable for execution. On the contrary, the smaller the fitness function, the more suitable the scheme as shown in Figure 2.

Create a N -dimensional particle search space, map $\{X, Y\}$ to the particle position according to the unloading decision variables X, Y , and define $Z = \{X, Y\}$ as the unloading decision set of all tasks. In the search space, consider a particle swarm containing K particles, and define the position vector of the ($\forall k \in K$) particle as

$$X_k = (x_{k1}, x_{k2}, \dots, x_{kN}). \tag{20}$$

The velocity vector is

$$V_k = (v_{k1}, v_{k2}, \dots, v_{kN}). \tag{21}$$

The optimal position of individual particles is

$$p_{\text{best}} = (p_{k1}, p_{k2}, \dots, p_{kN}). \tag{22}$$

The optimal position of the particle swarm is

$$g_{\text{best}} = (g_1, g_2, \dots, g_N). \tag{23}$$

The particle velocity update formula is

$$v_{kl}^{t+1} = \omega \cdot v_{kl}^t + c_1 \cdot r_1 \cdot (p_{kl}^t - x_{kl}^t) + c_2 \cdot r_2 \cdot (p_{gl}^t - x_{kl}^t). \tag{24}$$

In the traditional BPSO algorithm, the particle position value is limited to 0 or 1, and the velocity v_{kl} represents the probability of the position x_{kl} taking 1. Therefore, by defining a logistic regression activation function (v_{kl}^t) to achieve the particle position update, the position update formula is as follows:

$$\text{Sig}(v_{kl}^{t+1}) = \frac{1}{1 + \exp(-v_{kl}^{t+1})}, \tag{25}$$

$$x_{kl}^{t+1} = \begin{cases} 1, & R_{kl} < \text{Sig}(v_{kl}^{t+1}), \\ 0, & \text{other.} \end{cases} \tag{26}$$

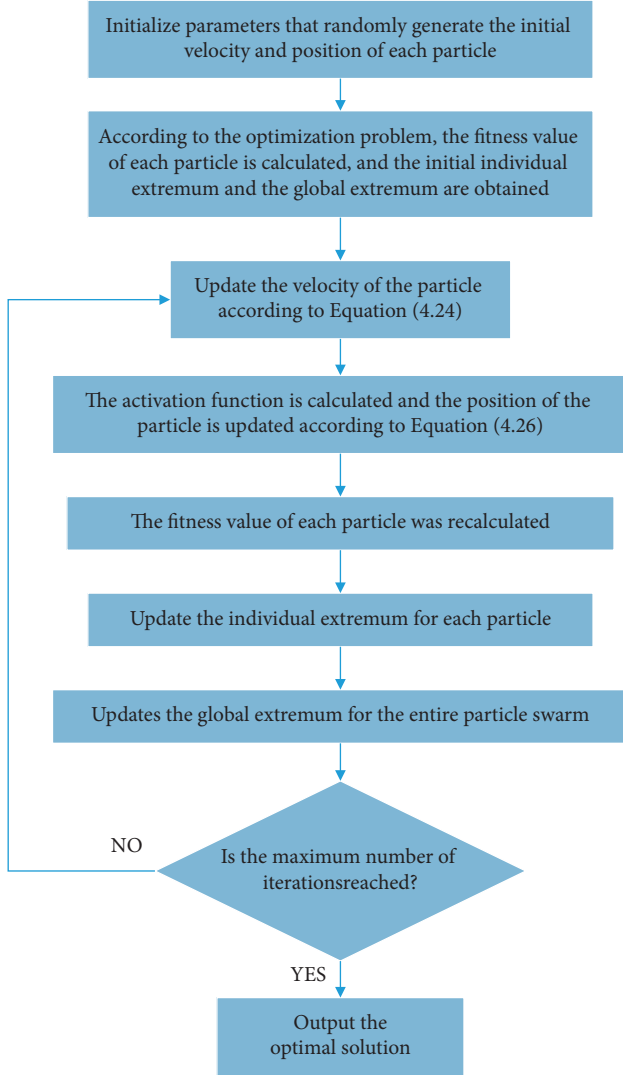


FIGURE 2: Flowchart.

Among them, R_{kl} is randomly generated from a 0-1 uniform distribution. In order to prevent the particles from prematurely converging in the search process and falling into the local optimal state, a new transfer function is used to replace formula (25) to update the particle position, and the formula is as follows:

$$\text{Sig}(v_{kl}^{t+1}) = |\tanh(v_{kl}^{t+1})|. \quad (27)$$

3.3. Experimental Simulation and Performance Evaluation. In the simulation scenario of a multi-user and multi-cell MEC system, the macro base station is located in the center of cell 1, the MEC server is deployed, and the coverage radius of the macro base station is 1000 m. The macro base stations in the two regions are connected through the backhaul link, and the data forwarding rate on the backhaul link is 10 MB/s. We set the number of mobile devices randomly distributed in the cell to 20~100, and the system communication bandwidth to 40 MHz. The experimental simulation parameters in this chapter are summarized as shown in Table 1.

TABLE 1: Simulation parameter table.

Parameter	Value
Number of mobile devices N	20, 40, 60, 80, 100
System communication bandwidth W_{\max}	40 MHz
Mobile device transmission power p_i	0.5 W
Wireless channel gain g_i	$127 + 30 \times \log_{10} d$
Gaussian channel noise σ^2	2×10^{-13} W
Maximum calculation of local area MEC server Resources S_{\max}^c	20 GHz
Maximum calculation of MEC server in nearby area Resources S_{\max}^c	100 GHz
Resources S_{\max}^c	~U(500, 100) kB
Mobile device computing power f_{li}	~U(1000, 100) megacycles
Task data size B_i	0.5
Task computing resources C_i	10 MB/s

First, the convergence of the algorithm proposed in this chapter is evaluated. Figure 3 shows a graph of the system cost varying with the number of iterations. The number of mobile devices is set to 40, 60, and 80, respectively. It can be seen from the figure that the system cost of the algorithm proposed in this chapter gradually decreases in the iterative process, and after a finite number of iterations, it can converge to a stable solution. At the beginning of the iteration of the algorithm, the fitness curve will appear flat. That is because the algorithm falls into the local optimum, but the algorithm can continue to generate new feasible solutions and jump out of the local optimum, which can further reduce the system cost. In addition, the convergence of the proposed algorithm is approximately linear with the number of devices.

Figure 4 shows the impact of the number of mobile devices on the system cost. It can be seen from the figure that the algorithm proposed in this chapter can achieve the lowest system cost compared with other schemes in the case of a small number of mobile devices (low cell load) and a large number of mobile devices (high cell load). For the random unloading algorithm, due to the randomness of unloading decision, the system cost also has great randomness. While only the local MEC server offloading algorithm is close to the cost of the algorithm mentioned in this chapter when the number of mobile devices is low, but as the number of mobile devices increases, the local MEC server will be overloaded, so the cost gradually increases.

Figure 5 shows the number of offloading tasks of different offloading algorithms in the local device, the MEC server in the local area, and the MEC server in the nearby area. The number of mobile devices in the system is set to 60. In the random offloading scheme, the number of tasks offloaded to the MEC server is random, so the delay and energy consumption costs are also random. In the local MEC server-only offloading solution, more computing tasks are executed on the local device, and the local MEC server has a relatively large load, which will cause a large delay and energy consumption. However, the algorithm proposed in this chapter offloads more computing tasks to nearby MEC

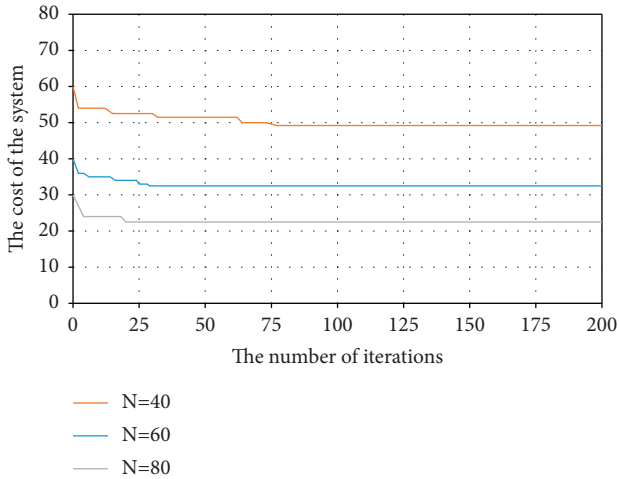


FIGURE 3: System cost under different iteration times.

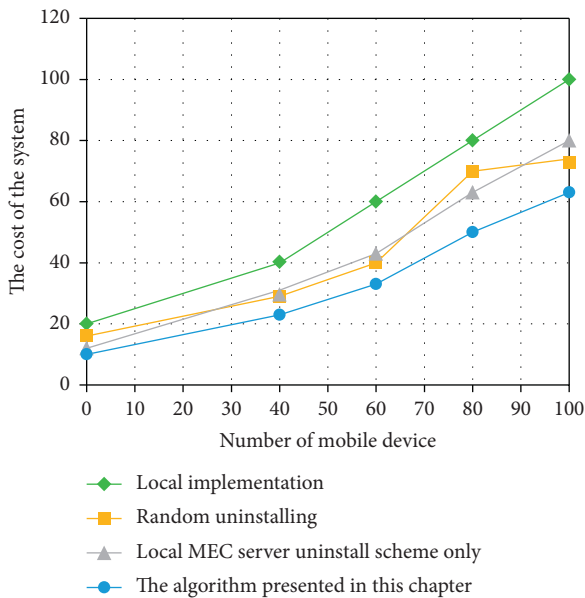


FIGURE 4: The impact of the number of mobile devices on the system cost.

servers, thereby reducing latency and saving energy consumption. Therefore, the distributed cooperative MEC system in this chapter can achieve better offloading performance than the single-server MEC system.

In order to evaluate the resource allocation strategy, the system costs when using average resource allocation and optimal resource allocation in different offloading algorithms were compared. In the average resource allocation, the user communication bandwidth is equal to the system communication bandwidth divided by the number of offloading tasks, and the computing resources allocated to each offloading task are equal to the maximum computing resources of the MEC server divided by the number of offloading tasks on the server. In the optimal resource allocation, the CVX toolkit is used to solve the problem and obtain the optimal communication bandwidth and computing resource allocation result.

Figure 6 evaluates the system cost under the average and optimal resource allocation, and compares the random offloading, only the local MEC server offloading scheme, and the algorithm proposed in this chapter. From the perspective of the three sub-graphs, the average resource allocation is relatively close to the system cost under the optimal resource allocation, but the system cost of the average resource allocation is slightly higher. This is because the task calculation scales in this experiment simulation are similar, resulting in the same amount of resource allocation. The system cost is relatively close. Therefore, in cells with little difference in calculation amount, the use of average resource allocation can simplify the algorithm and reduce the computational complexity.

There are three execution methods for the user’s computing tasks. The calculation models are established for these three execution methods, respectively, and the optimization problem is designed with the goal of minimizing the system delay and the total cost of energy consumption. This section proposes a heuristic algorithm based on binary particle swarm to obtain the best offloading decision, bandwidth allocation, and computing resource allocation. Finally, experiments show that the algorithm can achieve convergence in a few times and can effectively reduce the overall execution cost of the system to ensure user QoE.

4. Application of Classroom Evaluation in English Teaching

4.1. Construction of the First-Level Index Evaluation System. From the perspective of cultural education, this research uses theoretical analysis to construct a school education evaluation index system with cultural and educational characteristics, and seeks expert opinions to continuously adjust and optimize the constructed index system. The theoretical analysis method is based on the theoretical analysis of the evaluation problem, dividing the measurement objects of the evaluation index system into several different components or different aspects, collectively called subsystems. Each part is described by specific statistical indicators and gradually decomposed into subsystems and functional modules at all levels until it is realized. Based on the analysis of the basic elements of the formation of English classroom culture, the evaluation indicators for students in grades 1–3 are formed, and finally an evaluation indicator system for the formation of English classroom culture is formed.

Like any other educational process, the education in English classroom includes three stages: the preparation stage of classroom education, the process stage of classroom education, and the stage of classroom education effect. In order to make the evaluation indicators formed by English teaching culture more reasonable, this paper makes a rational analysis of various educational evaluation works, referring to a large number of documents and master and doctoral dissertations, combined with expert suggestions. On the basis of research, the differences in cultural and educational stages have been determined, and a series of indicators for the first level have been formulated.

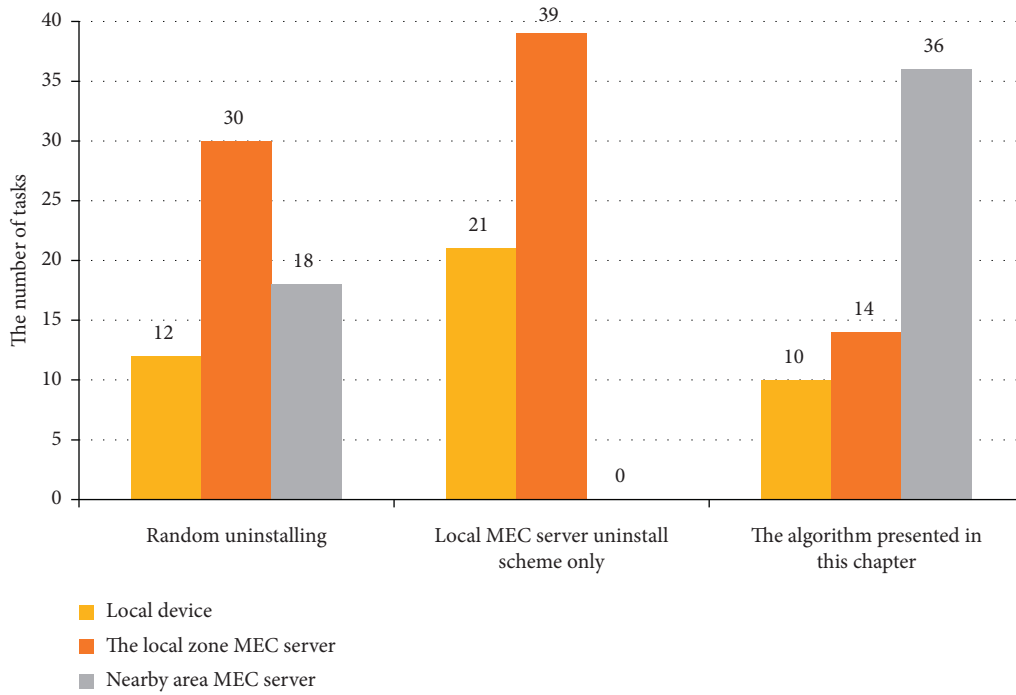


FIGURE 5: The number of tasks uninstalled by different algorithms in each execution mode.

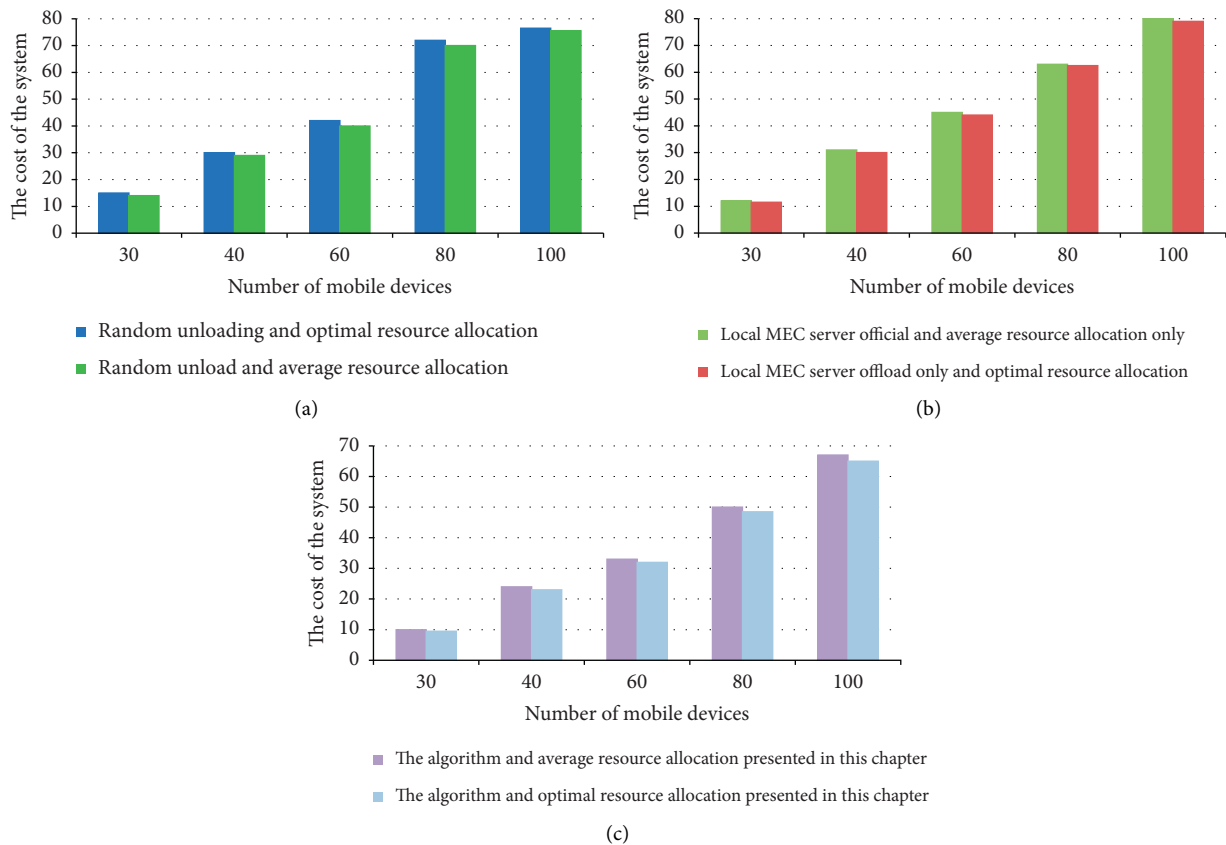


FIGURE 6: Comparison of system cost under average and optimal resource allocation. (a) System costs for random offloading. (b) System costs for local MEC server offloading. (c) The system cost of the algorithm presented in this chapter.

The main function of the classroom art education grading system constructed in this article is not to provide its tool value, but to provide an accurate reference for English art education grading.

In the following article, we will compile secondary and tertiary art education indicators for English teaching from three perspectives: classroom education preparation, classroom education process, and classroom education effect.

4.2. Construction of Secondary Index Evaluation System. For the construction of the secondary rating index system, this study mainly adopted methods such as theoretical analysis and expert advice. The theoretical analysis method has been explained before, so I will not elaborate too much here. The expert consultation method is a method by which auditors describe several evaluation indicators in a questionnaire based on the characteristics of evaluation objectives. Experts are required to make decisions based on their own knowledge and experience. The investigators finally summarize their opinions and then analyze and process the results of the consultation, and fed it back to the experts. If the experts reach a unified opinion after several consultations, a specific rating indicator system will be established in the final consultation. Although the methods of expert consultation are subjective, these indicators reflect the knowledge and experience accumulated by experts over the years. By absorbing the opinions of most experts, subjectivity can be transformed into objectivity to a certain extent. In the method suggested by experts, anonymous suggestions are usually adopted, and the reliability risk of the evaluation index system is eliminated through the mutual influence of experts.

Based on the evaluation indexes of the first stage, the evaluation indexes of the second stage shown in Table 2 are established through literature search, consulting faculty, experts, etc. Then, the applicability of each indicator is investigated through a questionnaire. A total of 60 questionnaires were distributed this time, including 30 English teachers of all grades in high school, 30 English majors, and 57 effective public opinion surveys. We use software to analyze the results and use the applicability of the inspection index as the secondary evaluation index. The results are as shown in Table 2.

According to the KMO indicator, it is found that it is less than 0.5 that the correlation is very weak, and it is not a qualified secondary indicator. From the statistical results in the above table, it can be seen that the relevant evaluation factors in the table, including teaching background, process, style, management, and attitude, have not passed the correlation test, and the abovementioned scoring factors cannot be included in the scoring system of English class art education.

The nine evaluation indicators determined by this research are shown in Table 3.

The main purpose of materiality testing is to eliminate nonessential indicators and retain indicators that may reflect key information. The importance test mainly uses the Delphi method, which is a statistical method

developed by the American RAND Corporation. The process of using this method to determine indicators is as follows: by issuing questionnaires and talking to appropriate experts; after the first survey, immediately after statistical processing, report to the experts the overall response such as the average value and the frequency of each weight range; and then based on the feedback, the expert decides whether to change his mind and gives a second answer. Here, you can weigh and choose the indicators widely until the final result is consistent. The specific steps are as follows. First, you need to create a "Weight Distribution Consultation Form." Importance is usually divided into five levels: unimportant, general, important, very important, or extremely important, represented by 1, 2, 3, 4, and 5, respectively. The table format is shown in Table 4.

Later, a "Weight Allocation Consultation Form" was issued to valuation experts. In the first round, the weights of each index were independently allocated to experts, and the reasons were required to be fully explained. To recover the consultation form, the data need to be statistically sorted, and the average value and deviation value of each index are calculated.

4.3. Standards and Evaluation Points of the Secondary Rating Index System. The evaluation standard is the standard by which individuals make value judgments when performing evaluation activities. Therefore, the formulation and application of evaluation standards directly affect the quality and effect of evaluation. At present, there is no unified requirement for the formulation of evaluation standards. Generally speaking, standards should follow certain specifications and strive to ensure that the standards are simple, clear, and easy to use in order to achieve the goals of evaluation. In this study, the definition of the secondary evaluation index evaluation standard mainly includes two steps. The first is to subdivide each sub-indicator, and the scoring points are determined according to the main content and characteristics of each sub-indicator; the second is to determine the degree of satisfaction of each secondary index according to the degree of completion of each evaluation point. At present, there is no unified rule for determining the rating level, which can be determined according to needs. The higher the number of levels, the more accurate the classification.

The evaluation of teachers' classroom education preparation stage is mainly to prepare teachers for the next classroom education. The secondary evaluation indicators include teachers' classroom education philosophy, classroom education goals, and classroom education design.

The concept of classroom education is an important factor affecting the implementation of classroom skills education. The concept of classroom education involves two main aspects: on the one hand, whether teachers fully understand the necessity of classroom education, and on the other hand, whether teachers correctly understand the relationship between language education and classroom education inner relationship.

TABLE 2: Correlation analysis of secondary indicators.

Factor	Factor1	Factor2	Factor3	Factor4	Factor5
Cultural teaching philosophy	0.669	—	—	—	—
Cultural teaching goals	0.874	—	—	—	—
Cultural teaching background	0.423	—	—	—	—
Cultural teaching design	0.614	—	—	—	—
Cultural teaching content	—	0.725	—	—	—
Cultural teaching process	—	0.373	—	—	—
Cultural teaching style	—	0.336	—	—	—
Cultural teaching management	—	0.427	—	—	—
Cultural teaching attitude	—	0.314	—	—	—
Cultural teaching methods	—	0.778	—	—	—
Cultural teaching atmosphere	—	0.664	—	—	—
Class response	—	—	0.642	—	—
Teaching feedback	—	—	0.619	—	—
Teaching reflection	—	—	0.342	—	—
Compliance status	—	—	0.672	—	—

TABLE 3: Cultural teaching evaluation index system.

Teaching stage	First-level indicator	Secondary indicators
Teaching preparation stage	(A) Cultural teaching preparation	(A-1) Cultural teaching philosophy (A-2) Cultural teaching objectives (A-3) Cultural teaching design
Teaching process stage	(B) Cultural teaching process	(B-1) Cultural teaching content (B-2) Cultural teaching methods (B-3) Cultural teaching atmosphere
Teaching effect stage	(C) Cultural teaching effect	(C-1) Teaching feedback (C-2) Class response (C-3) Compliance status

TABLE 4: Consultation form for weight configuration.

Index number	A	B	C	D	...
Weights	—	—	—	—	...

The goal of classroom education is the expected result that students hope to achieve through classroom education activities of teachers in cultural learning. The goal of classroom education is not the one-sided goal of teachers and students. This includes not only the cultural teaching goals of teachers, but also the cultural learning goals of students. From the perspective of classroom education, the evaluation of classroom education goals should take into account the following two points. First, the description of art education goals should be clear and concrete, reflecting the integration of three-dimensional goals; second is whether the goals of classroom education focus on student culture and the development of awareness and understanding.

The classroom education process is the center of classroom education, so classroom education process evaluation is also the center of overall classroom education evaluation. The classroom education process refers to the classroom education activities organized and implemented by teachers in order to achieve the goal of English classroom education and guide students to develop cultural cognition. The first indicator of this stage is the process of cultural education.

The second indicator mainly includes the content of teacher's classroom education, the methods of classroom education, and the cultural atmosphere of the classroom.

The classroom education content of high school English class is mainly textbooks and related classroom teaching materials. For the English teaching of high school English teachers, the assessment points of classroom teaching content mainly include two aspects. The first is the teacher's perception of cultural content. This is the requirement for English teachers to provide classroom education. If they do not have a comprehensive understanding of cultural content, there is no classroom education; the second is the teacher's exploration of cultural content, the cultural content that the teacher chooses, what kind of cultural content the teacher chooses to teach, and what kind of cultural content the teacher does not teach, which affect the quality of classroom education; the third is how teachers arrange cultural content, which cultural content is transmitted first, and which is transmitted later, which has a great influence on the effect of cultural education.

4.4. Determination of Index Evaluation System.

Traditional educational effect evaluation usually uses testing methods. Educational effect evaluation methods commonly used in schools include formative evaluation, comprehensive evaluation, and diagnostic evaluation. These evaluation

methods have specific usage scenarios and advantages. However, in terms of classroom education, due to cultural complexity and abstract curriculum education, we believe that it is appropriate to adopt and shape the evaluation of the effectiveness of English classroom education, as well as evaluation and diagnostic evaluation or a combination of three evaluation methods. The main points of classroom education effect evaluation are as follows: firstly, in terms of students' classroom response and evaluation, whether the teacher's classroom education philosophy has stimulated students' interest in cultural learning, whether students actively participate in cultural learning, and whether the teacher's culture is in harmony with education.

Secondly, feedback is given. Classroom education should not ignore every student. It needs to be good at listening to every student's idea and suggestion and responding positively. There is no end to cultural education, and reflection on classroom education is essential to further improve the effectiveness of classroom education. Therefore, when evaluating the effectiveness of classroom education, we must also consider students' feedback on cultural teaching and teachers' thinking about classroom education. Third is the degree of achievement of cultural education goals, including the achievement of students' cultural learning, knowledge, skills, and emotional attitudes.

5. Conclusion

In this article, we will split and solve the optimization problem. First, the solution of the resource allocation sub-problem is obtained based on the Lagrangian multiplier method, and then a computational offloading algorithm based on the greedy algorithm is proposed to solve the computational offloading sub-problem. Finally, the final solution of the problem is obtained through the joint algorithm, and the computational complexity is lower than the optimization algorithm and the traditional branch algorithm that proves the algorithm at the same time. Simulation experiments show that the proposed algorithm can achieve lower system cost compared with the benchmark scheme with local execution, complete offloading, and DPH offloading. We provide a platform to understand cultural education through evaluation. It can not only examine the cultural knowledge of students, but also consider the preparation and process of cultural education, and also consider the evaluation of education and the effect of cultural education, so as to evaluate the daily teaching of teachers. Through this construction and practice, it can provide reference for the further development of cultural evaluation theory.

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 conflicts of interest.

Acknowledgments

This paper was supported by fund from Shanghai Municipal Education Commission: English taught Model Course Practical Business for International Students in Shanghai University, 2018–2020 International Exchange Office 301-31.

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