A Method for Digital Resource Allocation in Mobile Online Education Based on Ant Colony Algorithm

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Abstract. In response to the problems of low accuracy and long time consumption in traditional methods for mobile online education digital resource allocation, a mobile online education digital resource allocation method based on ant colony algorithm is proposed. Firstly, the characteristics of mobile online education digital resources were extracted and the key nodes for resource allocation were determined. Based on this, we can accurately grasp the core issues of resource allocation and improve the accuracy and efficiency of resource allocation. On this basis, the Ant colony optimization algorithms is used as the basis of resource allocation. By initializing the mobile online education digital resource allocation Pheromone, and according to the resource allocation path selection rules, the dynamic Pheromone update is carried out. By simulating the behavior of ant colonies in searching for food, the allocation of digital resources for mobile online education is achieved. The resource allocation method based on Ant colony optimization algorithms has better global search ability and adaptability, can better guide the process of resource allocation, and improve the accuracy and efficiency of resource allocation. The experimental results show that this method has a shorter extraction time for educational digital resource information, better integration and output of educational digital resources, better accuracy in resource allocation, and higher allocation efficiency. The experimental results show that the method in this paper takes less time to extract the information of educational digital resources, the integration and output of educational digital resources are better, the accuracy of resource allocation is better, and the allocative efficiency is better.

Keywords: Ant Colony Algorithm · Mobile Online Education · Characteristics of Teaching Resources · Digital Resource Allocation

1 Introduction

Mobile online education is a rapidly emerging form of education with the rapid development of the mobile internet. It advocates autonomy, interactivity, and diversity, allowing learners to access personalized learning services anytime and anywhere without time and

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spatial distance constraints. It has become a new direction and trend in current educational development. At the same time, mobile online education has also brought a large amount of digital resources, such as video, audio, graphic and other forms of course materials, which require efficient allocation and management to meet the rapidly growing needs of learners. In this trend, the allocation of digital resources for mobile online education is becoming increasingly important [1]. The problems of digital resource allocation include resource waste, unfairness, and low efficiency, which pose challenges to the development of mobile online education. How to effectively allocate digital resources, fully utilize the benefits of resources, and improve user experience has become an urgent problem to be solved. The allocation of digital resources involves various factors, such as network bandwidth, user scenario requirements, resource types, number of users, and so on. Currently, statistical methods are mainly used for the allocation of digital resources, but their shortcomings lie in their inability to address the differentiated needs of learners. With the continuous development of internet technology and artificial intelligence technology, researchers have begun to consider how to apply internet technology and artificial intelligence technology to achieve accurate and efficient allocation of digital resources for mobile online education, and continuously optimize and adjust configuration methods to improve the quality and effectiveness of resource allocation [2].

Reference [3] proposed an online ideological and political education resource allocation method based on the decision tree algorithm. It uses the mutual information method to extract the characteristics of online ideological and political education resources, uses the decision tree algorithm to build a decision tree classifier, and inputs the extracted characteristics of ideological and political education resources into the classifier to complete resource allocation. This method has a high accuracy of educational digital resource allocation, but poor allocative efficiency. Reference [4] proposes a classification method for college English teaching resources based on density clustering algorithm. Firstly, fully consider the correlation between resources between adjacent grids and construct a weighted grid for each resource partition; Secondly, the corresponding weights are set based on resource correlation. After calculating the density parameters of the grid cells, the COMCORE-MR algorithm is used to determine the range of Key value parameter values; Finally, when the Key value parameter value is within the given density threshold parameter range of the grid unit, the corresponding educational resources and the central target grid object are divided into similar resources. This method has higher allocative efficiency of educational digital resources, but poor accuracy.

In response to the problems of the above methods, this article proposes a mobile online education digital resource allocation method based on ant colony algorithm. The Ant colony optimization algorithms is used as the basis of resource allocation, and the allocation of digital resources for mobile online education is realized by simulating the behavior of ant colony in the process of searching for food. The dynamic update mechanism can adjust the weight of Pheromone according to the search results of Ant colony optimization algorithms and the changes of the objective function, so as to better guide the process of resource allocation and improve the accuracy and efficiency of resource allocation. The resource allocation method based on Ant colony optimization algorithms has better global search ability and adaptability, and can effectively solve the problems of low precision and long time consumption in traditional methods.

2 Mobile Online Education Digital Resource Preprocessing

In mobile online education, the preprocessing of digital resources plays an important role in improving the availability and effectiveness of resources, providing better support and assistance for the teaching process.

For digital resource preprocessing, multiple aspects need to be considered. Firstly, it is necessary to process educational resources, including cleaning, integrating, optimizing, etc., to ensure the quality and availability of resources, and to improve the access and browsing speed of resources. Secondly, it is necessary to consider the characteristics and limitations of mobile devices and adapt or tailor resources to ensure smooth playback and display effects on mobile devices. In addition, it is also necessary to consider the combination with teaching scenarios to better serve teaching and enable it to be better integrated into the teaching process.

Digital resource preprocessing is an indispensable part of mobile online education, which can improve the quality and effectiveness of digital resources and provide better learning support and assistance for students. At the same time, digital resource preprocessing is also a continuous process of updating and optimizing, requiring continuous exploration and experimentation with new technologies and strategies to meet the constantly changing educational and student needs.

2.1 Feature Extraction of Digital Resources in Mobile Online Education

In mobile online education, feature extraction of digital resources is an important link in achieving efficient allocation and management of digital resources. By extracting features from digital resources, they can be transformed into numerical data that machine learning algorithms can process for better analysis and application. The features of digital resources also include but are not limited to various types such as visual features, speech features, text features, etc. These features can provide a foundation and basis for the classification, recommendation, and search of digital resources. In the application process of mobile online education digital resources, with the increase of teaching course hours, resource data shows an incremental development trend. In the process of extracting the features of mobile online education digital resources, both new and historical data should be considered, and feature extraction should be implemented based on a global perspective to avoid ignoring the hidden information contained in the resources [5].

The adaptive sliding window mutual information method is used to process the historical data and incremental data of mobile online education digital resources, and realize the feature extraction of mobile online education digital resources.

Use matrix $X_1=[x_1, x_2, \cdots, x_m]$ to represent the original window data, and matrix $X_2=\left[x_{m+1}, x_{m+2}, \cdots, x_{m+r}\right]$ to represent the incremental window data; All data contained in mobile online education digital resources is represented by $X = [X_1, X_2]$; Z_1 and Z_2 represent the mutual information matrix of original window data and new window data of mobile online education digital resources respectively; Z represents the mutual information matrix of all mobile online education digital resource samples.

According to the definition of mutual information, the expression of mutual information matrix can be obtained as follows:

$$Z = \frac{1}{m + r}(Z_1 + Z_2) \tag{1}$$

The eigen decomposition formula of diagonalization using identity matrix to represent Z_1 is as follows:

$$I = G_1^T Z_1 G_1 \tag{2}$$

Using the space formed by G_1 to receive the projection of Z_2, the formula can be obtained as follows:

$$\overline{Z_2} = G_1^T Z_2 G_1 \tag{3}$$

Summing formula (1) and formula (2) yields:

$$G_1^T (Z_1 + Z_2) G_1 = I + \overline{Z} \tag{4}$$

The formula for feature decomposition $\overline{Z_2}$ is as follows:

$$\overline{Z_2} = P_2 \Lambda_2 P_2^T \tag{5}$$

Substitute formula (5) into formula (4) to obtain the following expression:

$$P_2^T G_1^T (Z_1 + Z_2) G_1 P_2 = I + \Lambda_2 \tag{6}$$

Through the above process, the feature decomposition results of all mobile online education digital resources can be obtained.

According to formula (2):

$$G_1 = B_1 \Lambda_1^{-\frac{1}{2}} \tag{7}$$

In formula (7), $\Lambda_1 \in R^{m \times k}$ and $B_1 \in R^{n \times k}$ respectively represent the matrix composed of the first k eigenvalues and the principal component decision matrix of the original mobile online education digital resources.

The eigenvalue Λ_2 and eigenvector P_2 of the mutual information matrix of the newly added window data, and $\Lambda_2 = [\mu_1, \mu_2, \cdots, \mu_n]$ and $P_2 = [\beta_1, \beta_2, \cdots, \beta_n]$, are obtained through the above process.

The formula for obtaining the eigenvalues of all mobile online education digital resources based on feature vectors and eigenvalues is as follows:

$$\Lambda = \frac{1}{m + r}(I + \mu_i) \tag{8}$$

In formula (8), m represents historical mobile online education digital resource data; r represents the addition of mobile online education digital resource data.

The feature vector formula for mobile online education digital resources is as follows:

$$P = G_1 \beta_i \tag{9}$$

Using the obtained feature vectors to establish a principal component decision matrix, mapping mobile online education digital resources to the established principal component decision matrix can achieve data dimensionality reduction [6]. Repeat the above process in the subsequent window to achieve feature extraction of all mobile online education digital resource samples.

2.2 Determine Key Nodes for Digital Resource Allocation in Mobile Online Education

Before allocating complex mobile online education digital resources, determine the key nodes in the allocation process. In the current mobile online education digital resources, with continuous reform and practice, there are more and more applied education digital resources. Mobile online education digital resources no longer only refer to theoretical knowledge that may be used in teaching classrooms, but also include many practical content. In this case, this article divides mobile online education digital resources into theoretical education digital resources and applied practical education digital resources, and organically combines and allocates them [7–9]. This article uses genetic method theory to determine the allocation nodes. According to genetic methods, the classification of digital resource types for mobile online education is completed through multiple iterations. Subdivide mobile online education digital resources into N resource category area, and set the dispersion set of education digital resources as F, with the expression:

$$F = \{f_1, f_2, \cdots f_N\}_{N+1} \tag{10}$$

In the formula, $f_1, f_2, \cdots f_N$ represents the dispersion of educational digital resources in the 1, 2, ..., n region. Calculate the demand for educational digital resource allocation channels, set the coverage of allocation nodes as D, and the calculation matrix is:

$$D = \{d_1, d_2, \cdots d_N\}_{N+1} \tag{11}$$

In the formula, $d_1, d_2, \cdots d_N$ represents the coverage of educational digital resource allocation nodes in the 1, 2, ..., n region. Set interference constraints based on the calculation results of coverage, calculate the minimum value of non interference between different allocation nodes, and the maximum distance between allocation nodes in different regions. Set the distance of the allocation node to D. The calculation formula is:

$$\begin{cases} C_{\max} = (d_N + f_N)_{m \times n} \\ C_{\min} = (d_N - f_N)_{m \times n} \end{cases} \tag{12}$$

In the formula, m represents the allocation frequency of educational digital resource allocation nodes, and n represents the distance that generates allocation interference. If the key node of educational digital resource allocation is A, its calculation formula is:

$$A = \{d_N | d_N \in \{0, 1\}\}_{m \times n} \tag{13}$$

According to the above formula, calculate the key nodes for the allocation of digital resources in mobile online education, complete the division of theoretical education digital resources and application practical education digital resource allocation channels in mobile online education, and achieve the preprocessing of mobile online education digital resources.

By pre processing mobile online education digital resources, educational resources can be processed, including cleaning, optimization, and integration, to ensure the quality and availability of resources, improve resource access and browsing speed, and thereby improve the effectiveness and availability of digital resources. It can also better serve teaching and integrate resources into the teaching process, becoming an important auxiliary tool for teaching.

3 Educational Digital Resource Allocation Based on Ant Colony Algorithm

Educational digital resource allocation based on ant colony algorithm is a method that solves the problem of educational digital resource allocation by simulating the behavior of ant colonies. In this algorithm, educational digital resources are seen as a resource, establishing a weight relationship between learners and educational resources. Educational digital resources also include multiple resources, each with different characteristics in terms of availability, quality, and other aspects. The ant colony algorithm simulates the behavior of the ant colony. When searching for resource allocation schemes, the ant colony's search ability and route selection are taken as the basic methods, and the priority of each resource is determined through pheromone, distance and other factors, so as to finally provide learners with the best resource allocation scheme.

The advantage of ant colony algorithm lies in its ability to effectively handle multi-objective, complexity, and change issues in the allocation of educational digital resources. It simulates the behavior of ants in the process of searching for resources, taking into account the priority, availability, and other characteristics of resources, and can better meet the needs and requirements of learners in the learning process.

Based on the above construction and allocation model, the dynamic optimization of mobile online education digital resources using ant colony algorithm is carried out. The specific optimization process is described as follows:

(1) Assign pheromone initialization

Release all resource information in the current construction model with equal amount of pheromone, and complete initialization of all pheromone according to the following formula.

$$\tau_{ij}(0) = T0 \tag{14}$$

where, $\tau_{ij}(t)$ represents the total amount of pheromone of mobile online education digital resources remaining on the corresponding resource allocation path at t time points, and c represents the vector coefficient.

(2) Resource allocation path selection rules

In order to ensure the integrity of the resource allocation network, when an ant individual in the ant colony is assigned a corresponding resource, its state transition rule is set to the next moving position as the state point, thereby ensuring that the entire ant colony can simultaneously receive adjacent allocation resource information [10–12]. $allow_k$ represents the allocation status point that Ant k has not passed through. The probability of ant k transferring from position i to position j at time point $\tau_{ij}(t)$ represents t is:

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\mu_{ij}(t)]^{\beta}}{\sum_{j \in allow_k} [\tau_{ij}(t)]^{\alpha} \cdot [\mu_{ij}(t)]^{\beta}} & j \in allow_k \\ 0 & other \end{cases} \tag{15}$$

In the formula, $\mu_{ij}(t)$ represents the activation function, and represents the information concentration of the allocated resources transferred from status point i to status point j, generally $\mu_{ij}(t) = 1/d_{ij}$; $\mu_{ij}(t)$ represents the residual pheromone concentration on the corresponding distribution path at t time points; α represents the pheromone activation factor, and represents the importance of the resource allocation track. The larger the coefficient value, the greater the decisive role of the pheromone accumulated in the process of ant movement; β represents the activation factor, representing the range of influence of assigned visibility. The larger the coefficient value, the higher the weighting of the activation information of ants on the selection of assigned paths during their movement [13–15].

(3) Dynamic allocation pheromone update

Considering that in the process of dynamic allocation, the information parameters have the attribute of short-term change, and the pheromone on the corresponding allocation resource information track will speed up the volatilization speed, which is not conducive to the ant information search at the next state point [16, 17]. In order to better extend the residual time of the dynamic allocation resource information, and stimulate the pheromone concentration propagation ability, the correlation between the pheromone concentration and the time variable is conducted for all ants who have completed a cycle, Keep its pheromone update frequency consistent with the time variable of resource allocation [18–20], and obtain the dynamic allocation and update rules of mobile online education digital resources based on ant colony algorithm as follows:

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}, 0 < \rho < 1 \tag{16}$$

$$\Delta\tau_{ij} = \sum_{k=1} \Delta\tau_{ij}^{k}, 0 < \rho < 1 \tag{17}$$

In the equation, parameter ρ represents the volatility coefficient of the information concentration element; $1-\rho$ represents the concentration of residual pheromone of ants at the previous time point; $\Delta\tau_{ij}$ represents the total concentration of pheromone released at status point i and status point j in the current resource allocation cycle; $\Delta\tau_{ij}^{k}$ represents the total concentration of pheromone released by the seventh ant at status point i and status point j, and the relationship function is $\Delta\tau_{ij}^{k} = W/L_k$, where W represents the residual concentration of pheromone, and L_k represents the iteration cost after ant k completes a dynamic allocation of pheromone updates.

4 Experimental Analysis

The experiment takes a school in a certain region as the experimental object, and randomly selects one class with a population of 30 people. The selected mobile online education digital resources are C language education digital resources, consisting of pre class, in class, and post class teaching activity information. The original information and newly added C language teaching information before, during, and after class are shown in Table 1.

Table 1. C Information set of Language Education Digital Resources

C Language Education Digital Resources Information set Name	Original information quantity/GB	New information volume/GB
Pre class C language teaching information	30.6	5.2
C language teaching information in class	25.4	8.8
C language teaching information after class	40.5	3.6

Using the raw information of C language educational digital resources before, during, and after class in Table 1 as the experimental object, the effect of different window sizes on the feature extraction of educational digital resources before, during, and after class was tested. The experimental setting was an adaptive sliding window with a width of 50–300 bytes. The time for extracting C language teaching features was observed, and the average value was calculated as the experimental result. The experimental results are shown in Fig. 1.

As shown in Fig. 1, the time for extracting information from educational digital resources before, during, and after class decreases with the increase of window width. When the window width is greater than 200 bytes, the time for extracting information from educational digital resources gradually increases. This is because when the window width is small, information is often extracted from the buffer, which takes up more time. When the window width is too large, the time for decomposing information features of educational digital resources increases, The temporal trend of feature extraction of educational digital resources is consistent under different information quantities. The experimental results show that when the window width is 200 bytes, the time for feature extraction of educational digital resource information before, during, and after class is the shortest, and the speed of feature extraction is the fastest.

In order to test the performance of this method in the information integration of C language education digital resources, the experiment takes the information of three kinds of education digital resources in Table 1 of the C language education digital resources Information set as the test sample, and uses this method to integrate the historical information and new information of the C language teaching world before, during and after

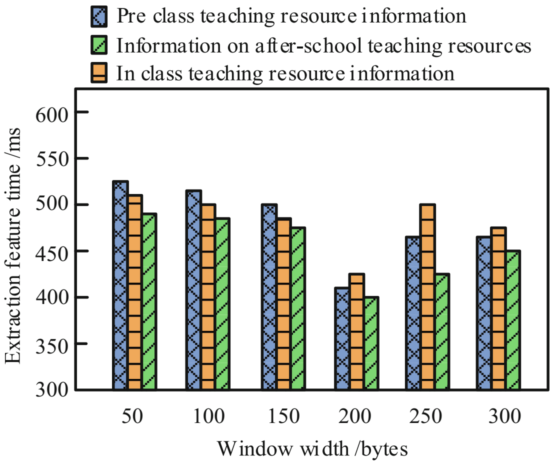

Fig. 1. Information extraction results of digital resources for pre class, in class, and post class education

class. Blue represents the historical information before, during and after class of C language teaching, The red color indicates the pre class, in class, and post class information of the newly added C language teaching history. Integrate the method of this article into pre class, in class, and post class educational digital resource information, and output it in the educational digital resource information space. The output results are shown in Fig. 2.

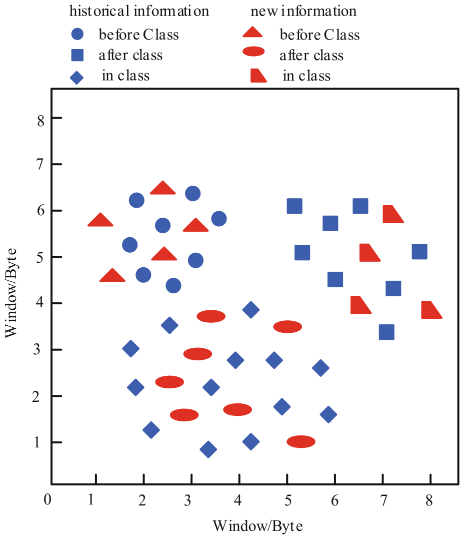

Fig. 2. Integrated Output of Digital Resources for Pre class, In class, and Post class Education

As shown in Fig. 2, it can be seen from the integration of historical and newly added information of educational digital resources before, during, and after class that after the integration of the method in this article, the historical and newly added educational digital resource information of C language teaching before, during, and after class is evenly distributed in the educational digital resource information space, with no irregular distribution of educational digital resource information. The method in this article has a good balance in the integration of C language educational digital resource information, And the integration effect is stable, and the balance of integration is consistent across different educational digital resource information. The experimental results indicate that the method proposed in this paper has a high balance in integrating C language resource information, and the integration effect of C language education digital resource information is better.

On this basis, the methods of Reference [3] and Reference [4] were used as experimental comparison methods. Analyzed and compared the accuracy of digital resource allocation for mobile online education corresponding to different methods, and its calculation method can be expressed as:

$$P_r = \frac{x_r}{X} * 100\% \tag{18}$$

In the formula, P_r represents the accuracy of the corresponding method, x_r represents the total amount of correctly allocated educational resources, and X represents the total amount of educational resources.

According to the above calculation method, the accuracy of allocation results for different methods is shown in Fig. 3.

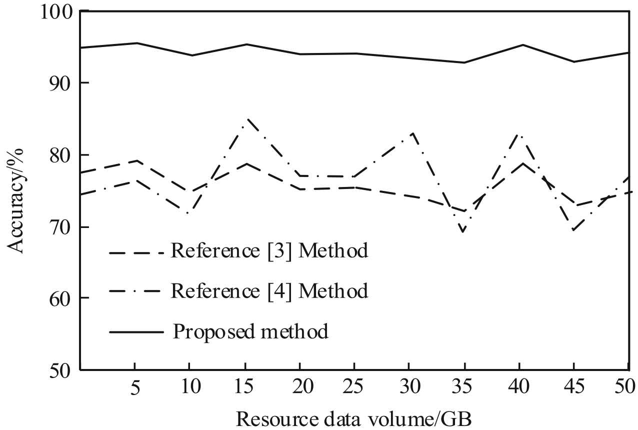

Fig. 3. Comparison of accuracy of allocation results using different methods

By analyzing the data information in Fig. 3, it can be seen that among the three methods, the accuracy of allocation of educational resources shows a certain degree of fluctuation, but there are significant differences in the specific allocation results. Among them, the allocation results of the method in Reference [3] showed relatively high stability overall, with an accuracy rate of 72% −80% for the allocation of educational resources. In the test results of the method in Reference [4], there is a significant fluctuation in the accuracy of allocation of educational resources, with an accuracy rate ranging from 68% to 85%. In the test results of this method, the accuracy of allocation of educational resources is relatively stable, ranging from 92% to 96%. The test results indicate that this method can achieve accurate allocation of digital resources for mobile school education.

When calculating the allocative efficiency of the three methods for mobile online education digital resources with different window sizes, the comparison results are shown in Fig. 4.

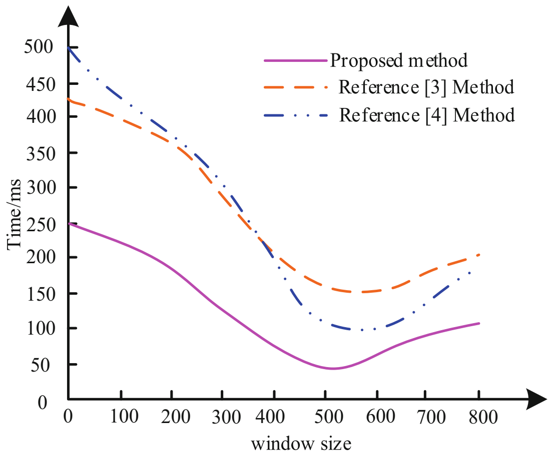

Fig. 4. Impact of window size on allocative efficiency

Figure 4 shows that the running time of allocating mobile online education digital resources using different methods decreases with the increase of window size. Compared with the other two methods, the allocative efficiency of this method is the highest in different window sizes, which indicates that the allocation efficiency of this method is higher than that of the other two methods.

To sum up, the mobile online education digital resource allocation method based on ant colony algorithm proposed in this paper first extracts features from the mobile online education digital resources to determine the key nodes, then uses the ant colony algorithm to initialize the pheromone of resource allocation, and determines the path selection rules. Finally, by dynamically updating the pheromone, the mobile online education digital resource allocation is realized. This method can extract information from digital resources quickly, and has a high degree of balance in the integration of educational digital resources. The integration effect of digital resources is better, and the distribution accuracy and allocative efficiency of educational digital resources are better.

On this basis, the time consumption of three methods for allocating digital resources in mobile online education was tested, and the experimental comparison results are shown in Fig. 5.

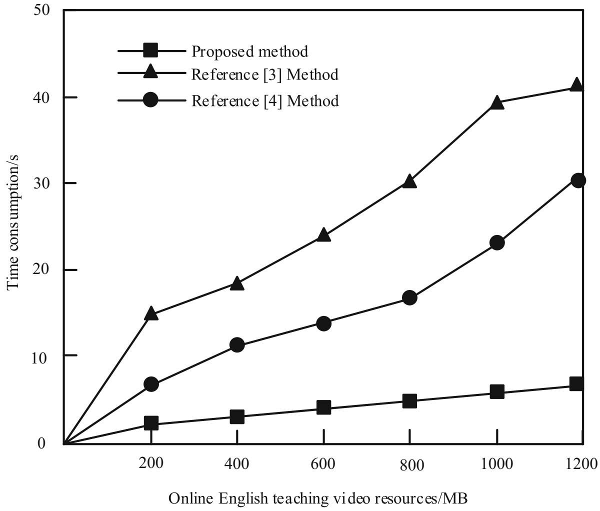

Fig. 5. Efficiency of digital resource allocation in mobile online education

Analyzing Fig. 5, it can be seen that the allocation time of mobile online education digital resources in the method of reference [3] is 30 s, the allocation time of mobile online education digital resources in the method of reference [4] is 42 s, and the recommended allocation time of mobile online education digital resources in the method of reference [3] is 7 s. The mobile online education digital resource allocation method proposed in this article has a short time consumption and good efficiency in the allocation algorithm.

5 Conclusion

This article proposes a mobile online education digital resource allocation method based on ant colony algorithm. The experimental results show that the method in this paper has the advantages of short time consumption, excellent output effect, high allocation accuracy and high allocative efficiency. The ant colony algorithm based digital resource allocation method for mobile online education has great application prospects and practical value. According to the needs of learners and the characteristics of resources, the algorithm simulates the behavior of ants, determines the priority of each resource through pheromone and distance, and provides the best resource allocation scheme for learners. This algorithm can handle multi-objective, complexity, and variability issues in educational digital resource allocation, and can better meet the needs and requirements of learners in the learning process.

In summary, this method will effectively improve the resource usage and user experience of mobile online education platforms, and have a positive promoting effect on research and development in the field of mobile online education. In future research, we can further optimize the application of Ant colony optimization algorithms in mobile online education digital resource allocation. Multiple objectives in the allocation of digital resources for mobile online education can be considered, such as learners' personalized needs, resource quality, and learning effectiveness. By designing suitable multi-objective optimization models and algorithms, more comprehensive and balanced resource allocation results can be achieved.

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