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# A Green Cloud Service Provisioning Method for Mobile Micro-Learning

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***Abstract*—As a fundamental reform of traditional education, mobile micro-learning has developed rapidly in recent years. However, with the frequent access of users to cloud platforms, mobile terminal is facing serious energy consumption pressure, which limits the development of micro-mobile learning. Therefore, we propose a green cloud service provisioning method for mobile micro-learning. Firstly, the category homogenizing method and dynamic TF-IDF (D-TF-IDF) are used to classify user request, which can provide guidance for future service mode selection. Secondly, we search service from the 2-tier cloud architecture module according to the classified accuracy. Finally, Grey Wolf optimization (GWO) algorithm is used to find the server with the lowest energy consumption and finish service provisioning process. The simulation results demonstrate that our method can achieve saving energy goal. In addition, the accuracy of D-TF-IDF algorithm ran up to 83.91%, which is 2.92% higher than that of Nave Bayes algorithm, 3.65% than that of Rocchio algorithm, and 7.64% than that of TF-IDF algorithm.**

***Index Terms*—Green Cloud Service, Service Provisioning method, Mobile Micro-Learning, Grey Wolf optimization**

## I. INTRODUCTION

Mobile micro-learning can be defined as the new learning paradigm that provides service with flexible, and on-demand. It aims to provide all kinds of learning services for the mobile terminal user through the mobile network. In the process of service, the mobile intelligent terminal is regarded as the information access port [1]. As an ideal non-traditional learning mode, its mobility can meet the needs of learners in dynamic environment. The micro characteristic can facilitate learners to learn in fragmented time. The ubiquity and interactivity mean learning happens anytime, anywhere and on demand. Therefore, it can be defined as learning model, in which learners have numerous choices to use various types of device, whenever they want and wherever they are, to get access to various kinds of cloud learning resources by mobile network. Because its operation does not have the limitation of time and geography space, mobile micro-learning has received extensive attention.

Mobile micro-learning delivery and completion require continue support of energy, storage and computing resources, and the capability of cloud platform is limited by cloud data centers in the real world, so insufficient resources maybe cause business interruption or storage overflow during service delivery, which will directly affect application and promotion of mobile micro-learning. Fortunately, high computation and huge storage power are provided by mobile cloud computing (MCC) can overcome obstacles of mobile terminal and ensure the reliability of mobile micro-learning [2].

MCC has started from the three related fields of mobile computing, mobile Internet, and cloud computing [3]. It is a promising system by introducing the powerful cloud computing ability into the mobile computing environment. Hence, users can take full advantages of a huge of storage space, high computing power and reliable security that the cloud can provide [4]-[5]. Recent market research shows that cloud-based mobile applications will grow 88% from 400 million in 2009 to 9.5 billion in 2014 [6]. The similar prediction made by ABI is that global MCC subscribers will grow from 42.8 million in 2008 to over 988 million in 2014 [7]. Massive users frequently access to cloud platform will increase pressure on the cloud platform, which will lead resource consumption and harm service reliability.

With the increase of user requests, energy consumption management is an increasingly important case for mobile micro-learning because cloud platform are not unlimited "sea" resources. An effective way to solve high energy consumption problem is to offload computing and data intensive tasks from private cloud resource scarce private cloud to resource rich public cloud. With the collaboration of private cloud and public cloud, the goal of low energy consumption can be accomplished, but it also faces some problems to a certain extent. We mainly describe those problems in mobile micro-learning process from mobile environment, mobile micro-learning users and service migration. In the wireless mobile communication network environment, private cloud access to public cloud has the disadvantages of bandwidth limitation, long delay time, and poor of stability and predictability, which will bring poly clusters, fluctuations and other non-stationary characteristics to mobile communication network environment. Mobile micro-learning users are advanced biochemistry, and they have a rich sense of thinking, which will make their requests have personalized labels. Therefore, the cost of finding satisfying services from a large pool of resources, and the cost that the users is willing to pay cannot be accurately measured. In the process of service migration, private cloud and public cloud are bound to produce many times information

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exchanges and transmissions. Due to the device status and network environment may change during the execution of the application, which will further increase the instability of wireless traffic, the bandwidth consumption, latency, network congestion, service quality decrease, cloud downtime, and other factors that affect the Quality of Service (QoS).

Based on the current trend of mobile micro-learning requirements, which are dynamic, personalized, and explosive growth, and taking into account the limitations of cloud platform, we find it is particularly important to study how to provide low energy consumption and continuous cloud services to legitimate users in a dynamic environment for promoting the development of mobile micro-learning. The major contributions of this paper can be summarized as follows.

We propose a service provisioning framework for mobile micro-learning, which consists of the user request module, the classification and service selection module, and the optimal module.

We propose category homogenizing method and D-TF-IDF algorithm to improve the classified accuracy of small sample category and find the highest classified accuracy that is relatively fair for large samples and small samples.

We formulate the energy consumption problem base on the framework and the simulation results prove the superiority of method in energy consumption.

The rest of the paper is organized as follows. We review related literature in section II. We propose a green framework of mobile micro-learning based on cloud in section III. We formulate energy consumption base on the framework in section IV. The simulation and numerical results are presented in section V. The conclusion of the paper is provided in section VI.

## II. Related Works

Education professionals try to regard mobile micro-learning as a regular formal teaching approach [8], but the experimental results show that its completion rate is still very low [9]. There are two main reasons for user who spends a lot of time unable to get satisfactory learning effect. Firstly, the arrival of the big data makes it difficult for learners to quickly choose the suitable learning resources. Secondly, learning style, learning preference and learning environment of user make their expectations of learning effect inconsistent. Based on the above reasons, in order to ensure the smooth completion of mobile micro learning, a large number of scholars start a wide range of research in recent years. In view of the above mentioned facts, in order to meet the gap that is the socio-technical mechanisms to enhance teamwork performance are lacking, literature [10] adopt the social computing to affiliate learners’ behaviors and offer them computational choices to build a better collaborative learning context. Sun et al. designs MLaaS, which is a cloud system for mobile micro-learning in massive open online courses (MOOC), it aims to provide adaptive micro-learning contents and institute the learning paths customized for each individual learner [11]. Chen et al. introduces a method based on process mining, which try to organize the learning units that come from a large number of disorganized micro-learning units according to the situation of users [12]. In the current research process of mobile micro-learning, research mainly focuses on data collection of user behavior [13], framework and data analysis [14], learning style [15], time management [16], the energy consumption during mobile micro-learning is not considered.

Mobile cloud computing has a wide market because of its low cost and ease to use, but heavy loads of large-scale user applications executed in the cloud call for efficient cloud resource management strategies to save energy without compromising the performance [17]. Moreno et al. propose a dynamic resource provisioning mechanism, which solve the over allocate capacity of cloud data centers in real-time according to the patterns of customer utilization [18], the main idea is to exploit the resource utilization patterns of each customer to decrease the waste that is produced by resource request over estimations, but it increases the risk of reducing QoS of user. Alahmadi et al. develop a novel approach for a large number of cloud tasks scheduling, sharing and migrating [19], even though the approach can reduce energy consumption while ensuring execution time and higher system throughput, there is no consideration for the additional energy consumption that is introduced by dynamically monitoring the cloud. Liu et al. emphasize the virtual machine placement (VMP) problem is significant in cloud computing [20], it achieves energy saving targets by improving the utilizing of physical resources and reducing the number of physical servers running, but its implementation requires a large number of virtual machines. Farahnakian et al. use the k-nearest neighbor regression algorithm to predict resource usage in each host, and the virtual machine is dynamically integrated to achieve the purpose of reducing energy consumption in the premise of guaranteeing performance [21], but it has some limitations, because it totally dependent on the utilization of the virtual machine regardless of other factors. Knauth et al. design a scheduler, named OptSched, it is a scheduler based on the virtual machine size, batch request and run time. It reduces the execution time and achieves energy saving goals in a certain extent [22]. Zhao et al. adapt the harmonic algorithm to study the online placement problem of virtual machine from service provider benefits, the research results prove the superiority of the algorithm [23], but it does not consider services migration situation. Mashayekhy et al. study pricing strategy of resource based on the current resource utilization ration, this method excessively pursues the biggest benefit and harms QoS of some users [24]. Although all the approaches concentrate on energy consumption problems, they have some limitations. We consider the problem of energy consumption in the process of mobile micro-learning service delivery from classification of user request, service selection and cloud platform cooperation in real-time environment.

In order to solve the needs of users for rich micro-learning resources and personalized service, we consider data processing, service selection and service migration in the process of mobile micro-learning, and borrow research results from previous studies to study the energy consumption in mobile micro-learning. We use D-TF-IDF algorithm to improve the accuracy of classification. Meanwhile, we search service from the 2-tier cloud architecture module according to the classified accuracy. On the basis of guaranteeing QoS, we do our best effort to minimize energy consumption during service delivery.

## III. System Model

### A. Mobile micro-learning system architecture

The system architecture of the mobile micro-learning is shown in Fig.1. As shown above, mobile micro-learning is influenced by mobile terminal, mobile network and the learning resources of cloud platform. Among them, the platform function of the mobile terminal determines whether the mobile micro-learning process can be successfully completed or not. Mobile network state affects the dependability of operation selection. The interactivity and accuracy of learning content determine mobile micro-learning effect. In order to provide users with continuous cloud services and achieve energy saving goal, we will take into account of user mobile terminal, mobile network environment state and cloud service resource in mobile micro-learning.

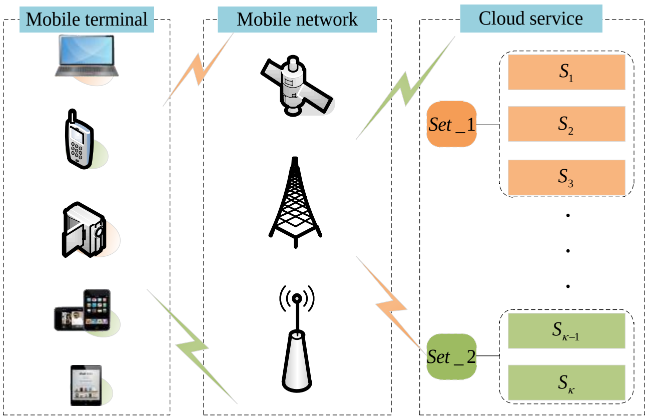


Fig. 1 Mobile micro-learning system architecture

In Fig. 1, $Set\_\tau = \{S_1, S_2, \cdots, S_\kappa\}$ refers to service set, where $S_\kappa$ refers to $\kappa$th service. $\tau$ refers to $\tau$th service set.

### B. Green service providing framework of mobile micro-learning based on cloud

With the deepening research of infrastructure and cloud, a large number of applications and systems have begun to develop based on mobile cloud computing platforms. In this paper, we introduce cloud into the mobile micro-learning environment and build green service providing framework of mobile micro-learning, the framework is shown in Fig.2. As shown in Fig.2, the framework is consisted of three parts which are user request module, classification and service selection module, and optimal module. Next, we will explain the process of the model in detail.

For the user request module, first of all, because of the limited processing capacity of the cloud platform, we gather the micro-learning requests of users and temporarily store requests in the request database. Secondly, we use ICTCLAS2013 (Institute of Computing Technology, Chinese Lexical Analysis System, 2013) [25] and Stop Words table of Harbin Institute of Technology [26] to pretreating requests, the purpose is to remove the meaningless words and find the vocabulary collection that can best represent the characteristics of request. Then, we choose several words that are more frequently used in the request as the feature word of user request to complete the keyword extraction process. Finally, we collect all keywords of training set and form a keyword database, which is main step of D-TF-IDF algorithm in classification and service selection module. For the classification and service selection module, firstly, we extract keywords based on the steps of the user request module. Next, we match keywords that we extract form user request to the keyword database in the user request module and calculate the classified accuracy. Finally, we select service according to the classified accuracy. According to the above ideal, the mobile micro-learning users can find the learning resources they need in the ideal case by collaboration on the 2-tier cloud architecture module. For optimal module, we formulate the energy consumption problem in the mobile micro-learning process and use GWO algorithm to find the lowest energy consumption in mobile micro-learning services.

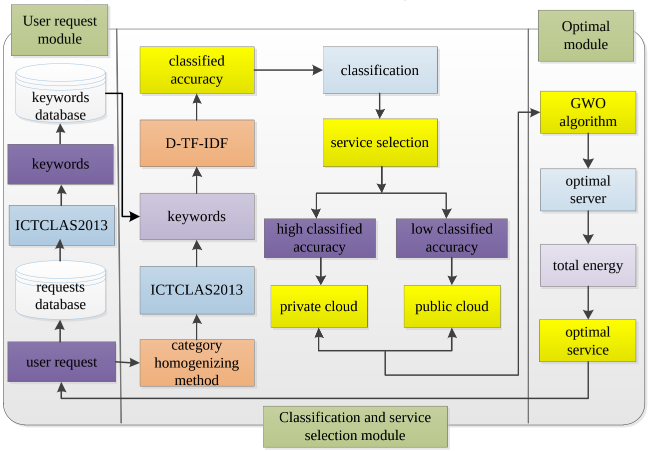


Fig. 2 Green service providing framework of mobile micro-learning based on cloud

## IV. Problem Formulations

In this section, we mainly formulate the energy consumption in mobile micro-learning. Based on the model presented in Fig. 2, this paper is divided into three steps to describe mobile micro-learning, which are classification, optimization and service delivery.

In 1988, Saltond proposed the IF-IDF algorithm, which is one of the more promising and effective keyword automatic extraction technology in recent years [27]. By multiplying the word frequency (IF) [28] and the inverse document frequency (IDF) [29], we obtain the TF-IDF value of a word. The greater the TF-IDF values of a word, the greater its impact on classified accuracy. TF-IDF is shown in Equation (1).

$$tf-idf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \times \log \frac{|V|}{|\{j : w_i \in v_j\}|+1} \quad (1)$$

where $n_{i,j}$ is the number of times a word $w_i$ appears in resource $v_j$, $\sum_k n_{k,j}$ is the sum of all words appear in the resource $v_j$, $|V|$ is the total number of resource in the training set, $|\{j : w_i \in v_j\}|$ is the number of resource that contain the word $w_i$.

In order to obtain the maximum classified accuracy that is fair for both large sample category and small sample category, we dynamically adjust $\varepsilon$ and $\vartheta$ in Equation (2), we call this method D-TF-IDF.

$$d-tf-idf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \times \log \frac{|V|}{|\{j : w_i \in v_j\}| + \varepsilon} + \vartheta \quad (2)$$

where $\varepsilon$ and $\vartheta$ are arbitrarily small positive number.

In summary, we have the average classified accuracy,

$$\varpi = \frac{\sum_{j=1}^{|V|} \sum_{i=1}^{\varsigma} d-tf-idf_{i,j}}{|V| \times \varsigma} \quad (3)$$

where $\varsigma$ is the number of keywords we extract from $v_j$ .

In Fig.2, we search mobile micro-learning resources from the public cloud platform and the private cloud platform according to $\varpi$ that is the classified accuracy of the classification module. Therefore, we need to consider the time and energy consumption when we get service from different platforms.

The time cost when the services are provided by private platform is shown in (4).

$$T_{\text{private}} = \frac{(1 + \frac{S_k}{S_{\text{doc}}}) S_{\text{cdoc}}}{M' * R_{\text{loc}}} + \frac{S_{\text{task}}}{M * R_{\text{loc}}} \quad (4)$$

where $S_{\text{cdoc}}$ is the byte size of the resource, which is requested by the current mobile micro-learning users. $M'$ is the total number of processor that will be open on the private cloud, $M$ is the total number of processors currently open in the private cloud. $R_{\text{loc}}$ is the execution rate when the task is executed by private cloud platform. $S_k$ is the byte size of keywords, which is extracted from the training set, $S_{\text{doc}}$ is the byte size of the training set.

Therefore, energy consumption in ideal case is described as,

$$E_{\text{private}} = P_t^l * T_{\text{private}} \quad (5)$$

where $P_t^l$ is energy consumption that private cloud platform handles one byte and it can be calculated according to the literature [30].

At the same time, we have time cost in non-ideal situation,

$$T_{\text{public}} = T_{\text{th}} + T_{\text{mig}} + \frac{S_{\text{mig}}}{M'' * R_{\text{clo}}} \quad (6)$$

where $T_{\text{th}}$ is the threshold time, it is the maximum time that private cloud platform can tolerate mobile micro-learning execution on it, $S_{\text{mig}}$ is the byte size that are migrated to the public cloud platform, $R_{\text{clo}}$ is the execution rate in the public cloud. $M''$ is the total number of processor that will be open on the public cloud. $T_{\text{mig}}$ is calculated by [31].

When the service is provided by public cloud platform, the energy consumption can be define as,

$$E_{\text{public}} = P_t^c * T_{\text{public}} \quad (7)$$

where $P_t^c$ represents the public cloud energy consumption for handling one byte and it can be calculated according to the literature [30].

Because the total resources are stored in private cloud and public cloud, ideally, the corresponding service can be obtained through private cloud and public cloud collaboration after a certain amount of time, therefore, we get the total energy consumption of mobile micro-learning,

$$E_{\text{total}} = \varpi' * E_{\text{private}} + (1 - \varpi') * E_{\text{public}} \quad (8)$$

## V. Simulation and Numerical Results

In this section, we evaluate the performance of our method by simulation and numerical results. The experimental parameters and experimental results are as follows.

Experiments are coded using C and Python, on PC with Intel Core i3-2130 3.40GHz processor, 4.00GB memory. Classified data set is classified corpus of Fudan University [32]. The corpus divide 19,637 texts into 20 categories, the training set includes 9804 texts and the testing set includes 9833 texts. In the corpus, the largest category contains 1,600 texts, and the smallest category contains 25 texts. This is consistent with the uneven distribution of various types of resources in the actual environment.

Our aim is to find the highest average classified accuracy of 20 categories of samples. Fig.3 reveals the process of the average classified n accuracy with the $\varepsilon$ change. When $\varepsilon < 2.6$, the growth trend of the average classified accuracy is swift, when the $\varepsilon > 2.6$, the downward trend of the average classified accuracy is gentle. Therefore, when $\varepsilon = 2.6$, we can get the highest classified accuracy rate that is 83.91%.

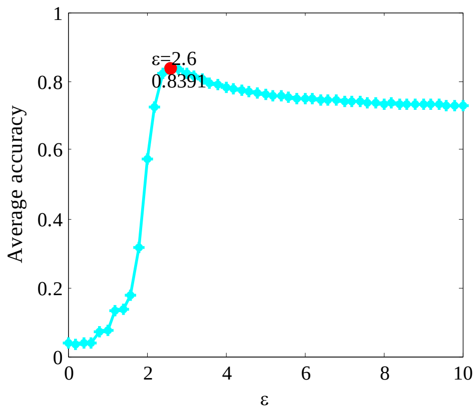


Fig.3 the curve of average classified accuracy with $\varepsilon$

Fig.4 and Fig.5 show the relationship between the average classified accuracy and the sample size when $\varepsilon$=2.6.

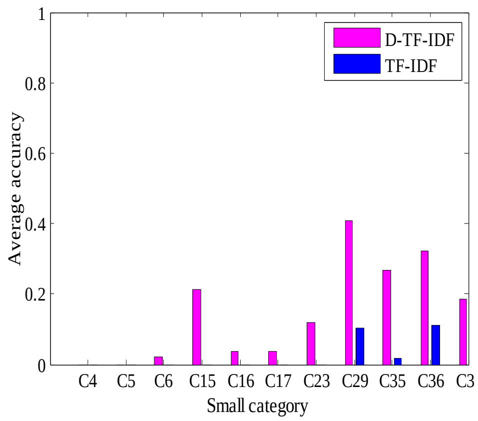


Fig.4 the classified accuracy of small sample category

We can see that the average classified accuracy fluctuates with the number of samples. For the small samples, the minimum classified accuracy is 0, the maximum classified accuracy is 40.7%. For the large samples, the maximum classified accuracy is 94.3%, the minimum classified accuracy is 70.5%. To a certain extent, this proves the assumption that we put forward in the previous section. Small samples may lead to inaccurate keyword extraction, which leads to lower classified accuracy and the method is feasible to place high accuracy samples in the private cloud and place low accuracy samples in the public cloud.

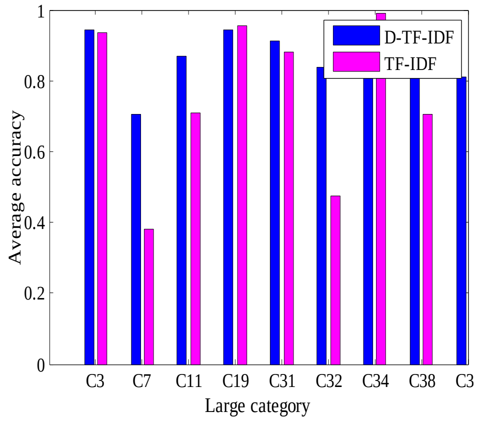


Fig.5 the classified accuracy of large sample category

In order to validate the superiority of D-TF-IDF algorithm, we compare the classified accuracy of this method with the Naive Bayes algorithm, the Rocchio algorithm, and the TF-IDF algorithm. The results are shown in Fig. 6.

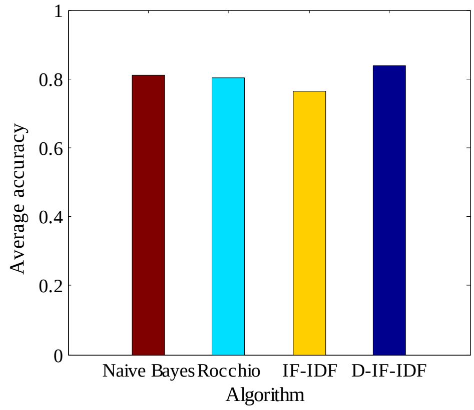


Fig.6 the average accuracy of different algorithm

In Fig. 6, we can see that the D-IF-IDF algorithm has the highest classified accuracy that is 83.91%. The classified accuracy of Naive Bayes algorithm, Rocchio algorithm and TF-IDF algorithm is 80.99%, 80.26%, and 76.27% respectively. This proves that the D-IF-IDF algorithm is more advantageous in terms of classified accuracy. Therefore, we can use D-TF-IDF algorithm to classify user request and provide guidance for future service mode selection.

For the time and energy consumption based on our proposed method, we independent run each instance for 10 and the best result is reported. During simulate process, the number of terminal users is 50 and the maximum number of generations is 1000. The user's location is randomly generated in [-100,100]. We assume that each VM memory is 5000, the number of instrument is 4, the transmission rate is 0.5, the maximum tolerance time is 160s. The other comparison algorithms are PSO (Particle Swarm Optimization), CS (Cuckoo Search), BAT (Bat Algorithm). In addition to the above mentioned parameters, we make further detailed settings. For PSO, the speed is 6, the learning factor is 2, and the inertia weights are 0.9 and 0.2 respectively. For CS, the probability of discovery is 0.25. For BAT, the maximum pulse loudness is 0.5, the maximum pulse frequency is 0.5, the pulse frequency range is [0,2]. The results of the experiment are as follows.

The average time calculated by various algorithms is shown in Fig.7. We can clearly see that the average execution time of the GWO algorithm is the largest, which is much higher than that of PSO, CS and BAT algorithm. Therefore, the experimental results show that the GWO algorithm adopted in this paper does not have some advantages in the average execution time. It is mainly because the GWO algorithm has multiple processes such as encircling, hunting, and attacking, each of them will cause a certain amount of time consumption.

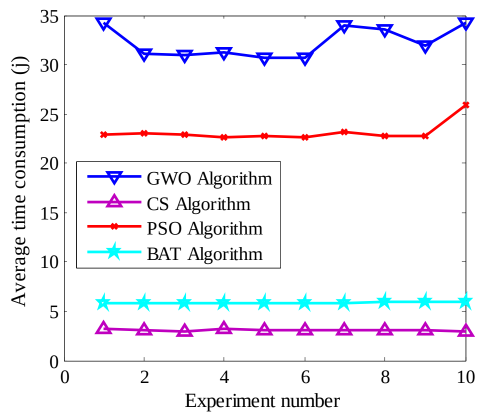


Fig.7 the average time consumption of different algorithm

The min energy consumption of different algorithm is shown in Fig.8. We can see that the energy consumption of BAT algorithm is much higher than the other three methods, which are GWO algorithm, CS algorithm, and PSO algorithm. More importantly, the energy of GWO algorithm, CS algorithm, and PSO algorithm is very small, which prove that those algorithms can find optimal energy consumption and BAT algorithm easily falls into local optimum.

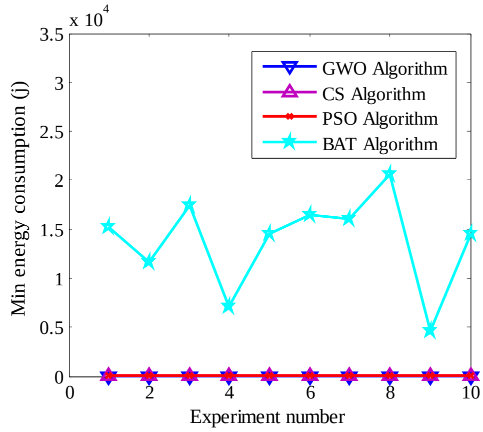


Fig.8 the min energy consumption of different algorithm

In order to further demonstrate the superiority of this method, we adopt average energy consumption as the criteria for evaluating the merits of the algorithm. As shown in Fig.9, we can see that the average energy consumption of GWO algorithm is minimal, which is 355.9625j, that of PSO algorithm is 471.4975j, that of CS is 2465.503j, that of BAT method is 15148.22j. Therefore, we think GWO algorithm is superior to others algorithms.

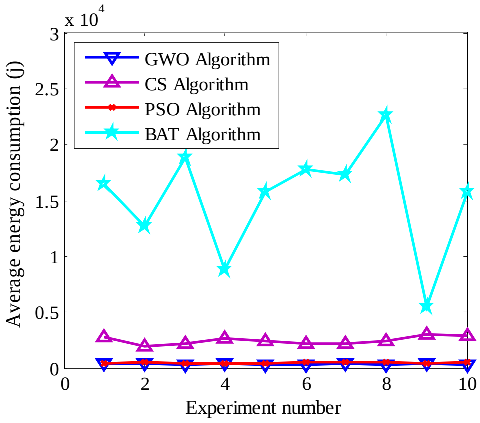


Fig.9 the average energy consumption of different algorithm

## VI. Conclusions

In this paper, we focus on energy consumption of mobile micro-learning. We propose green service providing framework of mobile micro-learning based on cloud. At the same time, the D-TF-IDF method can extract keyword and finish request classification process, the service selection module can provide service by the collaborative between private cloud and public cloud, the GWO algorithm can find the server with the lowest energy consumption and finish service provisioning process. Through the above operation, the user request will be able to get a response. The simulation results show that the method can reduce mobile terminal energy consumption and ensure dependability of mobile micro-learning within the threshold time.

## VII. Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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