Available online at www.ijpe-online.com

International Journal of Performability Engineering

vol. 14, no. 4, April 2018, pp. 673-680
DOI: 10.23940/ijpe.18.04.p10.673680

A Cost Constrained Scheduling Model based on MapReduce

Xuelong Zhang*

Changsha Normal University, Changsha, 4101000, China

Abstract

For the various sizes of random tasks, the possible cost is constrained in the process of cloud resources scheduling. The electricity price of the worldwide dynamic time zones is proposed based on the different electricity price of the world time zone characteristics, the network bandwidth and load levels. The optimization model of energy consumption of such system with execution cost as constraint condition is proposed, which optimizes the energy consumption of cloud system through the load level, electricity price and other factors in the resource scheduling process. In this model, the task hierarchical strategy is designed to realize the hierarchical task energy consumption. Thus, the scheduling algorithm of energy optimization with cost constraint is proposed. The results of experiments show that the algorithm can both optimize the energy consumption and reduce the service cost.

Keywords: cloud computing model; resource dependency; cost constraints; MapReduce

(Submitted on December 25, 2017; Revised on February 2, 2018; Accepted on March 16, 2018)

1. Introduction

Until today, cloud computing energy optimization research has been focusing on how to reduce the total energy consumption of cloud computing system or not impairing the quality of user service while reducing total energy consumption of the cloud computing system. However, the work on energy consumption optimization of cloud computing system does not certainly save execution cost of service providers [5,11]. The service cost of the aforesaid system is not only related to total consumption of energy and also closely bound up with electricity price difference and overall task load in different areas. While considering the optimization of energy consumption, what we do to reduce the cost of cloud computing service providers will have more significance [2,8,9]. But research findings are seldom revealed on the relationship between cost and energy consumption. So far, a majority of cloud providers adjust the relationship between cost and energy consuming by flexible price changes to acquire the highest level of revenue. To be specific, when cloud service is less availed, Amazon increased the cost of revenue by reducing price to realize the benefit maximization. By adjusting cloud service level with the use of time difference and different electricity price in different regions, the revenue is maximized. Cloud computing enterprises its own abundant large-scale data center in different geographic locations, leading to big gaps of revenue. For different regions, the disparity of electricity price may result in certain gap of revenue. At different time points, cloud computing data center may receive different user requirements such as at day and night time. In this case, if user's random tasks can be transferred to other data center with lower demand quantity or electricity price, in addition to improving the efficiency of cloud computing system, it may save energy and increase revenues [3,6].

However, the data center of cloud computing is constituted of plenty of cheap servers; such center can easily malfunction as well as be difficult in execution during service due to factors like heterogeneity: virtual machine task immigration may require some time, declining the quality of service for users; since difference exists between data center, random tasks may produce unequal energy consumption in different data center when executed in cloud computing system; cost is resource cost furnished by the cloud service provider; interest is the ultimate purpose of the service provider, which considers the minimization of cost while optimizing energy consumption[7,10]. If a random task being scheduled for execution in the cloud computing system is limited by factors like cost constraint, there are lots of issues to be solved as for the optimization of energy consumption [4].

* Corresponding author.
E-mail address: xuelongzhangxlz@sina.com

To satisfy the interest of cloud service providers, it needs to optimize energy consumption and also constrain the cost of utilization. The author conducts in-depth studies from perspective of resource utilization of cloud computing multiple data center, current energy consumption status and regional energy consumption ratio. Based on cost limits, he designs the optimization algorithm for energy consumption during scheduling by the cloud computing task hierarchical algorithm; furthermore, he proposes basing on the world regional pricing mechanism to investigate the scheduling problem of cloud computing service. Experimental results indicate that the new resource scheduling energy consumption optimization algorithm based on cloud computing cost constraint decreases energy consumption of cloud data center and meets the requirement for reducing costs. It also improves the parallel property of task execution, and is able to satisfy cost limit in the meantime of optimizing energy consumption.

2. Design of the resource scheduling energy consumption optimization model based on cost constraint

2.1. Research on the cost of cloud data center

In the cloud computing model, the task of computing, data transmission and storage, network bandwidth, transmission distance, and all resources are in the form of services. Here are some definitions of resource usage models.

Definition 1 Random task and cloud system model

When a scientific research worker submits random task to cloud computing system, the worker itself defines a price bottom line, of which the value we set p . Also, we suppose the bottom line conforms to a continuously differentiable probability function F . But providers of cloud computing enterprises define a fixed price according to existing electricity pricing mechanism and service condition, which is J . While cloud computing system is executing random task, the average execution delay T_l would often occur because of waiting. We define the delay cost of user unit time as o , then the cost price out of delay is calculated as $o \times T_l$. We define the quantity of tasks reaching the cloud computing data center in certain time period as σ_j ; with reference to research worker's expectant price and task delay cost, we can deduce Equation (1).

$$\sigma_j = \varphi P(p \geq (J + o \times T_l)) = \varphi(1 - F(J + o \times T_l)) \tag{1}$$

The Equation (1) represents the number of random tasks that the actual execution of the data center is equal to the total number of random tasks to be reached and the actual arrival of the tasks and the probability of the execution. We derive the actual number σ_j of tasks that arrive at the price j for this period of time as shown in Equation (2).

$$\varepsilon(p) = -\frac{\partial \sigma_j(J)}{\partial J} \times \frac{J}{\sigma_j(J)} \tag{2}$$

Assuming that the workers themselves are the price of the bottom line as a function of what we define as F, the number of tasks $i = 1, 2, ...n$. Based on the previous analysis, we can introduce the actual random tasks that might arrive at the cloud system, it is shown in Equation (3).

$$\varphi_i = \varphi(1 - F_i(J + o \times T_l)) \tag{3}$$

In the Equation (3), the actual random task that may arrive at the cloud system is represented, then the function F can be defined as the Equation (4).

$$F = \frac{\sum_{i=1}^{n} \varphi_i F_i}{\sum_{i=1}^{n} \varphi_i} \tag{4}$$

2.2. Resource scheduling model based on cost constraint

The size of the cloud data center to ensure the quality of service needs of users. In order to minimize the energy consumption under the condition of cost constraints, we should consider the constraints such as the upper limit of service capability, the task delay and the price interval.

Definition 2 task energy consumption hierarchy

$T_1T_2,...T_m$ is task energy consumption hierarchy calculated by task energy consumption hierarchical algorithm; T_1's work amount is smaller than T_2; when cost constraint is not satisfied, schedule in sequential order from the first layer task and carry out.

Assume that electricity prices in different regions are defined as A_j. Because of the price of electricity in different parts of the world is different, the value of A_j is different; but because of the time efficiency and other factors, the energy consumption is different.

In this paper, we study the hypothesis of 6 world time zone's (Asia Pacific time zone, European time zone, North and South American time zone, Oceania and New Zealand time zone and Africa time zone) price and energy consumption. Each time zone assumes 5 data centers. Due to the difference in the time zone, the workload of each data center and the state of the network and the cost of electricity are different.

Network transmit distance is L_{ij}; transmit power is P_3; energy consumption is E; in it, f is frequency of cloud node executing the computation; u is utilization rate by node. The cloud computing resource scheduling energy optimization based on cost constraint means in the completion of cloud computing task, doing scheduling computation with the goal of energy consumption minimization in the execution of cost constraint. It is shown in Equation (5).

$$\min Z=\sum_{i=1}^{n}\left[\frac{e_i}{e}\times W(p_i)\right]\times\sum_{i=1}^{n}\left[\frac{e_i}{e}\times W(T_i)\right]$$
$$\begin{cases}\sum_{j=1}^{d}E_jA_jm_jC_j=Y\\ \sum_{j=1}^{d}(\sum_{i=1}^{n}\sigma_{ij}-E_jA_jm_jC_j)>0\\ a\le\varphi^{-1}\left(\frac{\sigma_i}{J}\right)\le b\\ \varphi(J)=\sum_{j=1}^{d}\sigma_j\\ T_j-T_i\ge\sum_{k=1}^{n}t_{ik}X_{ik}\end{cases}\tag{5}$$

3. Design of resource scheduling energy consumption optimization algorithm based on cost constraint

3.1. Dispatching energy consumption analysis

As known to us from Equation (1), to decline the energy consumption during resource scheduling by the cloud computing system, we can choose to achieve the goal by bringing down p_j^1 of the cloud node C_j during scheduling. The approach can be applied for task scheduling when cloud node is lowly utilized, which helps such node and all cloud nodes are effectively utilized, as to reduce the time for lower utilization of cloud node in the system. We can complete the resource scheduling algorithm by enlarging the value of parameter β in p_{ij} calculation Equation. It is shown in Equation (6).

$$\varepsilon=\frac{\sum_{i=1}^{n}T_{size,i}\times C_i}{(t_k\times Q_k)\int_t Capacity(t)}\tag{6}$$

3.2. Hierarchical algorithm design

Hierarchical algorithm computes tasks according to given workload demand quantity and divides the computed results into M layers based on the exponential distribution of workload; each layer's tasks are closely associated. Hierarchical algorithm task incrementation is formally expressed as below. It is shown in Equation (7), Equation (8) and Equation (9).

$$m = \frac{\sum_{i=1}^{n} \int_{0}^{t} f_i(t) u_i(t) dt}{\log_2 \sum_{i=1}^{n} \int_{0}^{t} f_i(t) u_i(t) dt} \tag{7}$$

$$\Delta w = \frac{\int_{tn-1}^{tn} f_n(t) u_n(t) dt - \int_{t1}^{t2} f_1(t) u_1(t) dt}{m} \tag{8}$$

$$T_i = T_{i-1} + \Delta w \tag{9}$$

In the above Equation, M is the task layer, Δw is an incremental computation for each task level. In order to reduce the total energy consumption of cloud scheduling algorithm for target system, the first layer is scheduled to be executed on a data center with a lower resource utilization rate. When the scheduling demand comes again, the next task is scheduled to execute to the relevant data center. The hierarchical algorithm reduces the completion time and the idle probability of the system by increasing the performance of the parallel execution of tasks.

3.3. Energy optimal scheduling algorithm with cost constraints

The energy consumption resource scheduling algorithm based on cost constraint gives the initial cost and energy consumption of one task. When the initial cost is smaller than constrained cost, the algorithm terminates; otherwise, it will do hierarchical scheduling in accordance to workload demand for task at different levels.

The cloud data center performs hierarchical sampling computation, and compares $O_j \times \delta$ between time zone energy consumption cost and load ratio product, preferentially scheduled to cloud data center where the $O_j \times \delta$ is lower. Lower-level free server schedules the task execution of the first task level T_1. The cloud computing resource scheduling energy consumption optimizing algorithm based on cost constraint is described as follows.

Algorithm Energy optimal scheduling algorithm with cost constraints

Input: y , Y

Output: $T_1 \rightarrow D_j$

for every datecenters D_i
build O_j and ideal_download_sum=N
  if y $\leq$ Y goto 18
  else if y >Y
{
  for(int j=1; j<d+1; j++)
for(int k=j+1; j<d+1; j++)
{ if $Q_j \times \delta > Q_k \times \delta$
{ $Q = Q_j, Q_j = Q_k$ }}
  scheduling T_i from D_j to D_{j-1}
Compute $O_j = \frac{\sum_{i=1}^{n} P_{ij}}{(P_{ij})_2}$ for every cloud node
  i++; j++;
compute y
}

3.4. Complexity analysis

The complexity of cost constrained energy optimization algorithm depends on the difference between the initial cost and the minimum cost constraint, because it determines the number of iterations of the algorithm. Since each iteration of the algorithm is getting closer to the lowest cost, the algorithm is convergent. The complexity of the algorithm is determined by the comparison of the price between the service nodes. The more the cloud service node is, the more complex the search is. When the initial cost is close to the lowest cost, the task is iterative, so the algorithm complexity is *XN*. *X* is an optional cloud server node, *N* is the total number of tasks.

4. Experimental results and performance evaluation

4.1. Experimental setup

To test the performance and operating efficiency of the energy consumption optimization algorithm based on cost constraint in different circumstances, the scale of the task and the number of data center nodes are selected in the experimental. Low utilization time series, and time slot size 4 parameters are used. The scale of computing nodes were 16, 32, 64,128 nodes, random tasks in the experiment mainly adopt the CPU intensive tasks, I/O intensive tasks, and interactive computing tasks.

In order to compare the performance of the Energy optimal scheduling algorithm with cost constraints, we abbreviate the designed algorithm as EOSA algorithm. Compared with HAE algorithm [1], HAE algorithm employs the requirement of Game Theory to manage a cloud computing infrastructure intelligent energy hub and puts newly generated tasks to proper data center at the operational stage. Cloud service providers' prices simulate Asia Pacific time zone, European time zone, South and North America time zone, Oceania and New Zealand time zone and African time zone. The simulation on electricity price and service ability of data center is presented in Table 1.

The experiment chose four parameters: task size, data center node number, node area and cost constraint. The size of calculating node is 16, 32, 64 and 128 task quantity as 20 and 40,…,120, which simulates the electricity price and real-time loading in six different regional nodes; constraint cost interval RMB [500,800]. Testing results are the mean value of 500 different scales, algorithm selecting average cost, system's average execution power and average total energy consumption of execution. With those four measuring indicators, we compare the relationship between two kinds of algorithm.

Table 1. Data center electricity price list

place	A($)	u_j	w_j / kw
Asia-Pacific	10.58	12	0.15
Europe	8.64	9	0.11
Latin America	7.58	10	0.10
Oceania	9.56	9	0.13
New Zealand	10.78	10	0.11
Africa	14.89	8	0.15

4.2. Experimental model analysis

In order to prove the advantage of simulative algorithm, the simulation validation is experimented in two parts. To begin, we use Lingo11 to get the model solution as to verify the model. As for the designed energy consumption optimizing model based on cost constraint, we validate the relationship of data center reaching strength σ and system's total revenue I. When data center scale and task quantity are both fixed, observe the relationship between constraint cost, system energy consumption and the amount of data movement.

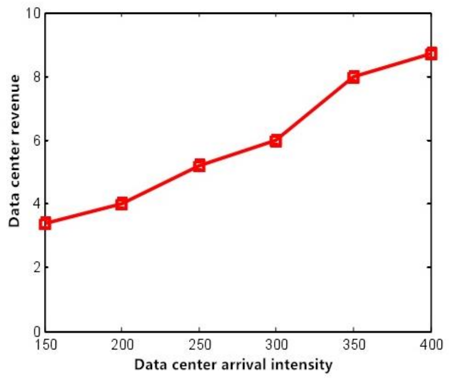

Figure 1. Relationship between arrival intensity and data center revenue

Figure 1 shows the ability to scale a fixed data center, the relationship between the total arrival rate and the total return. With the increase in the intensity of the arrival of the task, the data center revenue will increase. The graph is a wave shape, which can be speculated that the model is correct. Figure 2 and Figure 3 respectively show that the constraint cost and system total can be used in the process of stochastic task scheduling system data movement. The selected data center is 128 and the number of tasks is about 100. As seen from Figure 2 and Figure 3, in the process of random task scheduling, with the gradual increase in the cost of constraints, the average total energy consumption and the amount of mobile data in the cloud system are decreasing, which indicates that the task scheduling process is gradually reduced.

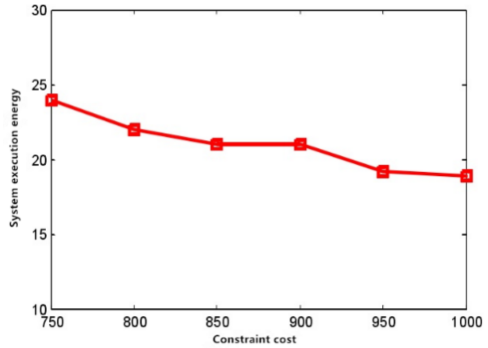

Figure 2. Relationship between cost constraints and energy consumption

4.3. Analysis of experimental results

4.3.1. The effect of random task size change on the results

Figure 4 compares the average energy consumption of system execution for different task sizes. From the results, we can see that EOSA algorithm reduced the average energy consumption more than HAE algorithm for different sizes of task. With the growing scale of tasks, the gap between EOSA and HAE becomes smaller. This is because during energy consumption optimizing, at the initial stage, EOSA algorithm selected computing nodes with smaller $Q_j \times \delta$ to perform calculation of tasks, which saves cost, but slightly increases the transmission expenses due to transmission distance. With task scale becoming bigger, all data centers' size are more highly utilized for the scheduling on a large scale by task hierarchical algorithm; also, since task's degree of parallelism becomes higher thanks to the execution by energy consumption optimized scheduling algorithm, the average energy consumption is smaller than HAE algorithm.

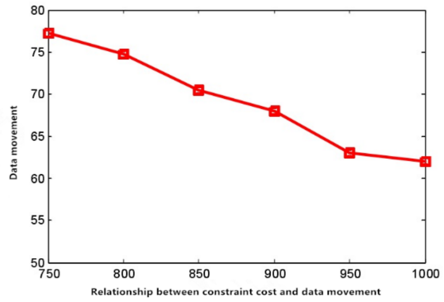

Figure 3. Relationship between cost constraints and data movement amount

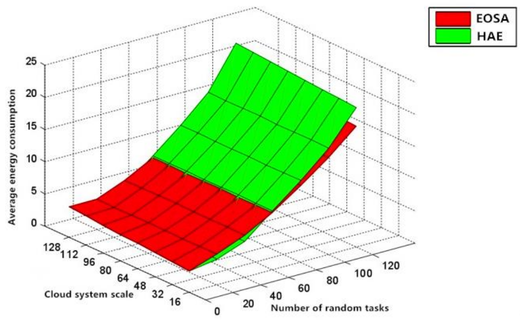

Figure 4. Relationship between task scale and energy consumption

Figure 5 compares the average cost of system execution for different scales of task. Two algorithms have the same initial cost, which tend to grow differently with increasing size of the task. HAE algorithm increases linearly in a zigzag form; EOSA algorithm increases like a horizontal parabola because EOSA algorithm set regional cost constraint and tasks were scheduled to cloud data center with smaller $Q_j \times \delta$ and carried out, avoiding fast growth of the cost and tending to a steady growing linear number. With increasing scale of tasks, the cost optimization by HAE algorithm was not remarkable as EOSA algorithm because its cost optimization is merely correlation scheduling without regional difference. Through computations, EOSA algorithm decreased the average cost by around ten percent for different scales of task, which was supposed to keep growing along with bigger scale of the task.

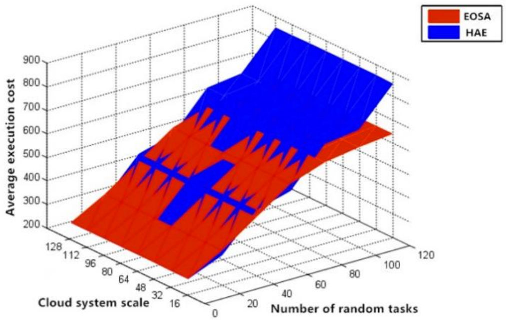

Figure 5. Relationship between task scale and service costs

4.3.2. The effect of constraint cost change on energy consumption

Figure 6 is the effect of the change of constraint cost on the average execution energy consumption of the two algorithms when the task scale is 80 and the data center is 64. As seen from the Figure 6, the HAE algorithm is affected by the cost of about 1.5KJ. With the increase of constraint cost, the average energy consumption of the EOSA algorithm will be gradually lower than the energy consumption of the HAE algorithm. This is mainly due to the fact that when the constraint cost is low, the tasks that are performed need to be scheduled more frequently, and the increase of energy consumption of the system is greater than that of the data transmission in parallel execution of the task. When the constraint cost increases gradually, the number of tasks is reduced. This part of energy consumption is gradually reduced, and the energy consumption is gradually reduced. It tends to be stable at a certain scale.

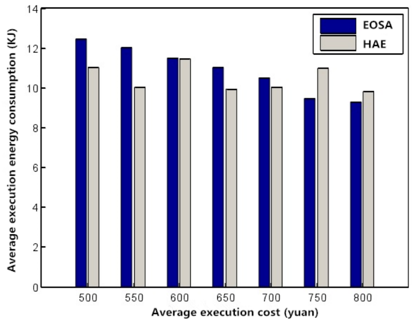

Figure 6. Relationship between cost and energy consumption

4.3.3. The impact of data center scale changes on results.

Figure 7 and Figure 8 show the comparison between the average response time and load balancing of the two algorithms respectively. With the increase of data center scale, the average response time and system load balance of the EOSA algorithm are lower than that of the HAE algorithm. This is mainly in the process of task execution. The EOSA algorithm saves a lot of expenses during task scheduling due to the relative balance between load rate and price adjustment. Make full use of the resources of the system in the implementation process, increase the parallel characteristic of task execution, reduce the overhead of idle computing nodes and reduce the average response time of tasks. This makes the EOSA algorithm of system load balancing rate lower than HAE algorithm's.

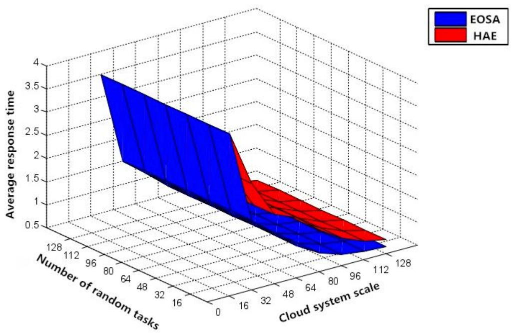

Figure 7.Relationship between nodes scale and response time

Overall, it can be seen from the results of the experiment that when the energy consumption of resource scheduling optimization algorithm is based on cost constraints in cloud data, due to differences in regional electricity prices and service ability, the process of random task scheduling can be used based on the prices to the cost of setting constraints. The precondition of the reasonable scheduling algorithm is used to optimize the energy consumption of cloud computing.

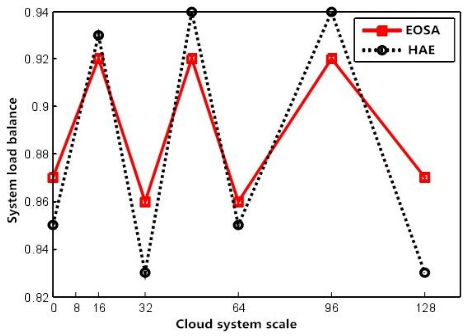

Figure 8. Comparison of Load Balancing

5. Conclusions

With incisive investigations on resource utilization of cloud data center, network transmission energy consumption and system efficiency, the paper presented cloud computing resource scheduling energy consumption optimized algorithm based on cost constraint. By defining the electricity price in the world, the author validated experimentally the proposed method with the use of factors like network load. Findings revealed that with increasing number of computing tasks, the proposed method overcomes system's instant rapid increase of energy consumption during the increasing of the average execution power owing to cost constraint. When task load is small, by raising little transmission energy consumption, it can save lots of service cost; when task load is big, by using task hierarchical algorithm for task scheduling, it can improve the parallel characteristics of task and decline computing nodes' idle probability of data center. Compared with previous methods, our designed algorithm reduces energy consumption of data transmission between data center and also system's response time and load rate. While saving energy consumption, it saves cost and improves the performance of system, offering a better option to cloud computing service providers.

Acknowledgements

This work was supported by design and implementation of teaching call center system based on CTI integration technology (XJK013CXX016), the National Natural Science Foundation of China (61571188) and the excellent youth research project of The Education Department of Hunan Province (No.15B125)

References

1. S. Aras, R. Mohammad, "A Cloud Computing Framework on Demand Side Management Game in Smart Energy Hubs", *Electrical Power and Energy Systems*, pp. 1007-016, 2014
2. Chuang. Lin, "Optimization and Control of Quality of Service in Virtual Data Center in Cloud Computing", *Science and Technology Innovation Herald*, 2016, (2): 172-173.
3. Zhiyong. Li, Shaomiao. Chen, "Task Scheduling Method for Multi Objective Memetic Optimization in Heterogeneous Cloud Environments", *Acta Sinica*, vol.4, pp. 377-390,2016
4. Yan. Ma, "Research on Resource Management and Scheduling Strategy Based on Energy Consumption and Cost", *Shandong University*, 2012
5. Yao. Shen, Xiaolin. Qin, "An Efficient Multi Objective Scheduling Method for Data Streams in Cloud Environment", *Journal of Software*, 2017:579-597
6. Dewen. Wang, Xiaomeng. Liu, "Resource Scheduling Strategy for Power Simulation Cloud Computing Platform Based on Virtual Machine Dynamic Migration", *Automation of Electric Power Systems*, vol.8, pp. 97-105, 2015
7. Bo. Xu, Chao. Zhao, Yanjun. Zhu, "Multi Objective Optimization of Virtual Machine Resource Scheduling in Cloud Computing", *Journal of System Simulation*, vol.1, pp. 592-595,2014
8. Hai, Zhu, Hongfeng. Wang, Xiuwu. Liao, "Task Scheduling Model and Virtual Machine Deployment Algorithm Under Cloud Environment", *System Engineering Theory and Practice*, vol.3, pp.768-778,2016
9. Suqin. Zhang, "Efficient Scheduling Algorithm for Cloud Computing Task Resources", *Computer Simulation*, vol. 11, pp. 410-413, 2016
10. Xiaorou. Zhang, JianHong. Zhai, "Research on Scheduling Strategies Such Calculation of Dynamic Genetic Algorithm Based on Cloud" , *Intelligent Computer and Application*, vol.3, pp. 37-39, 2015
11. Yang. Zhou, Chang. Gong, "Workflow Scheduling Algorithm Based on Dynamic Target Genetic Algorithm", *Journal of Natural Science of Xiangtan University*, vol.6, pp. 123-126, 2017

Xuelong Zhang received his M.S degree from Hunan Normal University. He is an associate professor in Changsha Normal University. His research interests include Circuits and systems.