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Energy Optimization Based on Grid Resource Scheduling Algorithm

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Abstract: Grid technology is an emerging technology developed in the mode of computer network computing. This technology has many characteristics such as distribution, sharing, and polymorphism. In the grid environment, due to the high-performance computing of the grid, the task scheduling process becomes efficient, but it also has the problem of complex grid resource management and scheduling strategies, resulting in huge energy consumption. In order to solve the problem of energy consumption, an energy optimization model based on time constraints and energy constraints is proposed in this paper, grid resource scheduling is carried out through heuristic scheduling algorithm, and energy optimization simulation experiments are carried out under the condition of changing the number of resources and tasks. The results show that, The resource execution time corresponding to a single grid task is short, and the energy consumption value is also small. In the simulation experiment of multiple grid tasks, as the number of grid tasks increases, the task execution time increases, and the adjustment factor is 0.5 , that is, when the ratio of the time consumption factor and the energy consumption factor in the resource scheduling optimization cost function is the same, the fluctuation of the energy consumption rate is relatively stable.

1. Introduction

With the wide application of the Internet, grid technology has developed rapidly and can realize efficient distributed computing. However, due to the difficulty of resource management in the grid environment and the consideration of time, load and energy consumption in resource scheduling, grid resource scheduling algorithms have attracted the attention of scholars and research institutions [1].

At present, energy optimization research based on grid resource scheduling algorithm has achieved good results. For example, a scholar compared the optimal task scheduling time of the GA algorithm and the BGA algorithm, and the results proved that with the increase of the population number, the time for the grid resource scheduling system to obtain the optimal solution showed an upward trend, and the smaller the population number, the faster the convergence. This is because the smaller the population, the easier it is to achieve the consistency of the solution, while it is more difficult for a larger population to obtain a convergence criterion. Although the time for a small population to complete the optimization is relatively short, the optimization results are not satisfactory. In addition, the convergence algebra and time for obtaining the optimal solution of BGA are better than GA [2-3]. Based on the operating cost and system reliability, some related researches put forward a scheduling algorithm based on energy constraints based on the traditional DVS scheduling algorithm, considering the energy consumption and time limit constraints in the scheduling process. The scheduling algorithm requires all tasks to be completed within the time limit and minimize energy consumption [4]. Although scholars have achieved good results on energy optimization based on grid resource scheduling algorithms, optimization algorithms can be used to reduce energy consumption during grid resource scheduling.

This paper first proposes an energy optimization model and optimization algorithm, namely the Sufferage Algorithm and the Improved E_sufferage Algorithm, and then uses the GridSim tool to conduct energy optimization experiments for single resource task and multiple resource tasks on Ad Hoc grid resources, and finally compares the two The energy consumption rate under the scheduling algorithm proves that the improved algorithm can achieve optimal energy consumption.

2. Related Models and Algorithms

2.1. Energy Optimization Model

In this paper, an energy optimization model is proposed. From the perspective of grid tasks, the optimization model introduces the time constraints in the traditional grid task scheduling algorithm into the Ad Hoc grid energy optimization. By reducing the task completion time MET, to achieve The purpose of energy optimization [5-6]. Therefore, the scheduling model is based on the traditional energy optimization model by adding the factor of time cost, and comprehensively considering the time factor and energy factor to realize the energy optimization of scheduling [6-7].

$$EC=\sum_{j=0}^{n-1}(EC_j/B_j)/n=\sum_{j=0}^{n-1}((\sum_{i=0}^{k}EC_{ij})/B_j)/n \tag{1}$$

$$MET=Max(C_i) \tag{2}$$

$$Cost(i,j)=h\cdot EC_{ij}+(1-h)\cdot(D_i+ET_{ij}) \tag{3}$$

Among them, Equation (1) represents the energy consumption sub-model, Equation (2) represents the time consumption sub-model, EC is the average energy consumption rate of all grid resources, EC_j is the total energy consumption, and EC_{ij} is the grid task assigned to a certain The total energy consumption value of grid resources, MET is the maximum execution time or optimal span, B_j is the initial energy value of the resource node, C_i is the actual execution time, D_i is the start execution time, and Cost(i, j) is the cost function , h is the adjustment factor of the function, ET_{ij} is the execution time required by the resource node to execute the task [8].

2.2. Energy Optimization Algorithm

The traditional Sufferage algorithm is a heuristic scheduling algorithm with high load balancing ability, but when scheduling grid resources, the task completion time is considered instead of energy consumption. As long as the task time is the shortest, the algorithm is implemented. The ultimate purpose of scheduling [9]. The Sufferage Algorithm is an improved algorithm of the Sufferage Algorithm. The sufferage algorithm is based on the Ad Hoc grid energy optimization algorithm. It adds the energy consumption constraint to the traditional sufferage algorithm. It is a requirement to improve the algorithm to achieve the optimal energy consumption within a certain task execution time [10].

3. GridSim Simulation Tool

GridSim adopts a layered architecture, and the entire architecture from bottom to top is:

The first layer is mainly the Java virtual machine, which is the runtime environment of the Java language, and is available to both single-processor and multi-processor systems.

The second layer is the Simjava basic discrete event package, which contains basic classes for creating and running simulations, and supports logging and statistics.

The third layer is the GridSim tool layer, which contains the key entities of GridSim simulation, such as resource entities, resource allocation, job management, etc. These entities communicate using the interface provided by the Simjava discrete event simulation package to simulate interactive behavior.

The fourth layer is mainly a collection of simulation resources, namely grid resource agents or schedulers [11-12].

GridSim is a very powerful and simple grid simulation tool. The system uses JAVA for coding, which inherits the advantages of JAVA's cross-platform well, and can be used on multiple platforms at the same time, such as Windows, Linux, etc. [13]. GridSim is a simulation tool based on an economic model. It mainly has the following characteristics:

GridSim introduces the economic model widely used in grid resource scheduling, which is closer to reality and can simulate and display grid environment more realistically [14].

GridSim contains a wealth of function libraries, such as action package, datagrid package, filter package, net package, and util package, which can provide users with powerful underlying support for simulation experiments, and provide simple and practical for the simulation of grid resource scheduling solution [15].

GridSim uses the message event method to communicate between entities during simulation. This simple, convenient and general method provides a simple and convenient way to build complex and powerful resource scheduling experiments through the GridSim simulation tool [16].

GridSim can be used in conjunction with the VM graphical user tool to facilitate simulation and result analysis of grid resource allocation.

GridSim provides the library function GridStatistics for statistical analysis, which is convenient for analyzing the results of simulation experiments.

When GridSim conducts simulation experiments, the calculation of resource scheduling time is carried out through mathematical calculation. Using this method can simplify the model of scheduling simulation, reduce the consumption of simulation experiments, and make efforts to provide targeted results [17].

4. Simulation Results

4.1. Simulation of Single Task Energy Consumption

In this simulation experiment, resources are scheduled only from the perspective of energy consumption, and the constraint condition of task completion time is not considered, that is, the adjustment factor h of the cost function is 1. This experiment mainly studies the load balancing problem caused by the algorithm E_sufferage without considering the time constraints. In this simulation experiment, four Ad Hoc grid resources are created, namely Resource A, Resource B, Resource C, and Resource D. Each resource includes a machine, and each machine includes a computing unit. Some basic parameters are the same for each resource. Create a grid user, this user has 5 grid tasks, namely Task 1, Task 2, Task 3, Task 4, Task 5, which are similar to the definition of grid resources, and have little impact on the performance of this algorithm. Task parameters, which are set the same for each task.

According to the description of the algorithm E_sufferage, the time required for each task to run on each resource is known, which is represented by the matrix ETC, and the definition of ETC is shown in Table 1.

Table 1. Grid tasks correspond to each resource completion time (s)

	Resource A	Resource B	Resource C	Resource D
Task 1	7	5.5	4	6
Task 2	4.5	5	3.5	4
Task 3	5	6.5	8	2
Task 4	8	7	6	5.5
Task 5	7.5	6	5	5

According to the grid resources and related information of grid tasks provided in Table 1, the cost value consumed by each grid task corresponding to each grid resource can be calculated. Because the influence of time factor is not considered, in the algorithm The value of w in the cost function is 1, so the energy consumption value of grid resources can be calculated according to formula (3), as shown in Figure 1.

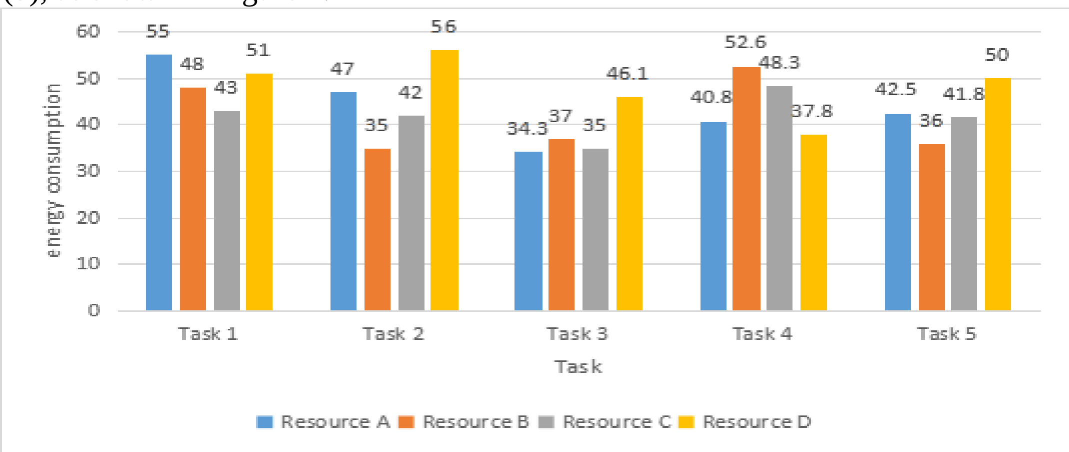

Figure 1. Grid resources consume energy

4.2. Multi-Task and Multi-Resource Energy Optimization Simulation

Only the number of single grid tasks and single grid resources involved in the above simulation experiment has its shortcomings for the analysis of algorithm performance. Next, consider the case of multi-tasking and multi-resources. The basic settings of each grid task in this simulation experiment are similar to the above simulation experiments, and the data transmission amount of the grid task is randomly generated between 10 and 30. Grid resources are divided into high-performance resources and low-performance resources. The value of high-performance resources is randomly generated between 10 and 20, the value of low-performance resources is randomly generated between 1 and 10, and the energy consumption of network transmission is between 1 and 5. The energy reserve value of each grid resource is randomly generated between 100 and 150 [18-19]. In addition, in order to ensure that all grid tasks are completed, grid resources must be sufficient. In the experiment, the number of grid tasks and grid resources are the same. In the experiment, the number of tasks is 5, 10, 15, 20, and 25, respectively, to test the scheduling algorithm, and repeat it 100 times to calculate the mean value of MET, as shown in Table 2.

Table 2. The relationship between the number of grid tasks and MET

	5	10	15	20	25
h=0	9	13	18	22	25
h=0.25	12	21	35	48	56
h=0.5	15	28	41	60	73
h=0.75	16	37	56	92	135
h=1	18	45	73	114	162

It can be seen from Table 2 that with the increase of the number of grid tasks, the MET generally shows an upward trend. However, due to the different values of h, the growth curves are different. When the number of grid tasks is the same, MET decreases as the value of h decreases. When the value of h is 1, the scheduling algorithm only schedules resources from the perspective of energy cost. The load balancing problem caused by mutual waiting for low-energy resources is more prominent. The number of tasks increases from 20 to 25, and the value of MET increases by nearly 50s . In addition, by comparing the MET curves with different h values, it can be seen that the greater the proportion of time factor in the cost function, the smoother the growth of MET.

Next, we analyze the change of energy consumption rate EC when the number of tasks is different. The parameter definitions of grid tasks and grid resources in the simulation experiment are the same as those in the above experiments, and the ECs corresponding to different number of tasks are calculated respectively, as shown in Table 3.

Table 3. The relationship between the number of grid tasks and EC

	5	10	15	20	25
h=0	63	65	66	54	62
h=0.25	60	61	68	51.5	55
h=0.5	58	58	59	61	57.5
h=0.75	55	56.5	56	92	135
h=1	52	49	73	114	162

It can be seen from Table 3 that when the number of grid tasks is equal, the value of EC decreases as the value of w increases. But there are exceptions. When the number of tasks is 15, the energy consumption rate when the h value is 0.25 is higher than that when the value is 0. This is mainly because the energy parameter values in this simulation experiment are randomly generated. If the energy reserve value randomly reaches When the value is relatively small, the increase of the total energy consumption value with the increase of the number of grid tasks is greater than the increase of the total energy reserve value, and the larger the h value is, the larger the EC is, but in this case relatively rare. When the number of grid tasks continues to increase, the energy consumption rate EC fluctuates up and down, and as the value of h becomes smaller and smaller, the fluctuation becomes larger and larger. For example, when the value of h is 0, the number of grid tasks is 20 and 25. , the fluctuation is more obvious. In general, when the h value is set to 0.5, the fluctuation is relatively small, and the energy consumption rate tends to be stable.

Comparing and analyzing Table 2 and Table 3, when the value of h is 0.5, the performance of the scheduling algorithm is the best, the task completion time MET and the energy consumption rate EC tend to be stable, and both can achieve the best results.

4.3. Algorithm Comparison

This experiment mainly studies the performance comparison between E_sufferage and traditional heuristic scheduling algorithm Sufferage in terms of energy optimization and completion time. From the experiments in Table 2 and Table 3, it can be concluded that when the value of h is 0.5, the performance of E_sufferage is the best. Therefore, in this comparative test, the value of h is 0.5. In the experiment, the number of tasks is 5, 10, 15, 20, and 25, respectively, to test the scheduling algorithm, repeat the execution 100 times, and calculate the mean value of EC, as shown in Figure 2.

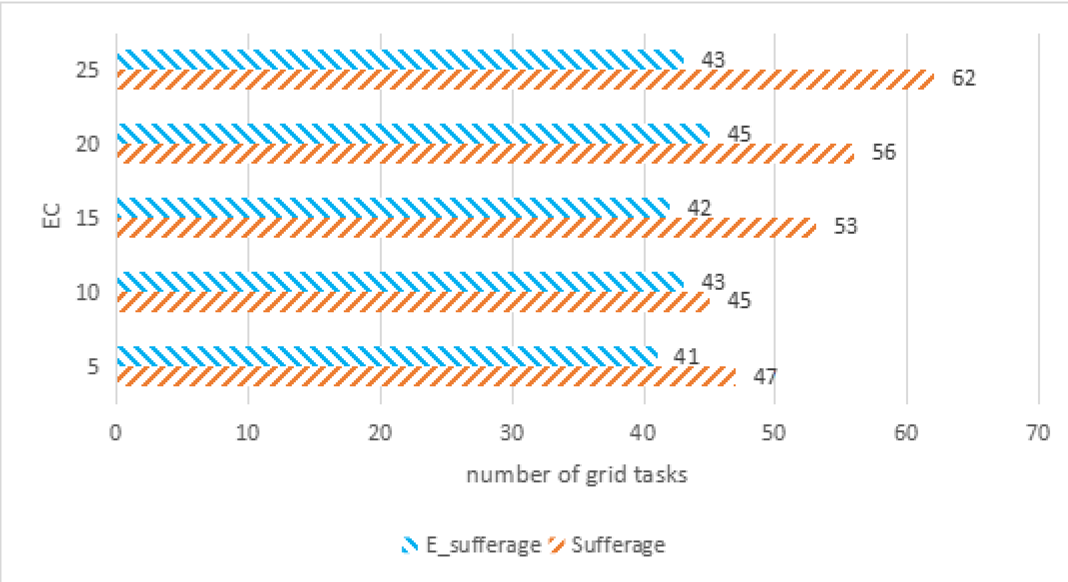

Figure 2. Energy consumption under different algorithms

It can be seen from Figure 2 that, compared with the traditional Sufferage algorithm, the energy consumption rate of the E_sufferage algorithm is relatively low, and with the increase of the number of tasks, the energy consumption rate EC does not fluctuate much, while the traditional Sufferage algorithm fluctuates relatively large. There is a tendency to increase with the increase of grid tasks. It shows that using the E_sufferage algorithm to schedule grid resources can minimize the energy consumption and achieve the optimal energy consumption effect.

5. Conclusion

Considering the energy consumption and time constraints, this paper uses the GridSim tool to conduct simulation experiments to compare the energy optimization effects of the E_sufferage algorithm and the Sufferage algorithm. The simulation experiment proves that with the increase of the number of grid tasks, the energy consumption value under the supplementage algorithm is on the rise as a whole, while the energy consumption under the E_sufferage algorithm is relatively stable, the fluctuation is not large, and the energy consumption is smaller than that of the supplementage algorithm , indicating that the E_sufferage algorithm can optimize the energy of grid resource scheduling.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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