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Multi Workflow Fair Scheduling Scheme Research Based on Reinforcement Learning

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Abstract

In this study, aiming to optimize the multi-workflow scheduling order, in which tasks submitted at different time require different service quality, we present a fair multi-workflow scheduling scheme based on reinforcement learning. Firstly we design a dynamic priority-driven algorithm, in order to set the initial state of the task priority according to the type of cloud workflow and service quality on the one hand, and on the other hand, to adjust the tasks priority dynamically while scheduling so as to avoid violating the Service Level Agreement by delaying the workflow provisioning. Secondly, we design a fine-grained cloud computing model and apply the reinforcement-learning based scheduling algorithm to balance the cluster loads. Finally the experimental results prove the effectiveness of this scheme.

Keywords: cloud workflow, virtual resources, reinforce Learning, fair scheduling

1. Introduction

The cloud computing is a paying model in accordance with the usage amount and this model can provide the available, convenient and on-demand network access to enter the configurable computing resource shared pool (the resources include the network, the servers, the storage, the application software and the services). These resources

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can be quickly provided through inputting a few management work or interacting with the service providers[1]. The existing cloud computing mainly includes the following services: Infrastructure-as-a-Service(IaaS), Platform-as-a-Service (PaaS) and Software-as-a-Service(SaaS). IaaS: the cloud users obtain the complete computer infrastructure service through Internet, such as the rent of hardware service. PaaS: PaaS refers that the platform of software development is considered as a service to provide for cloud users, such as the personalized customization and the development of software. SaaS: it is a model that provides the software through Internet and the users do not need to buy the software, but to rent the software based on Web from the providers to manage the business activities of enterprises.

The cloud workflow (the scientific workflow, the multi-layer Web service workflow, the MapReduce workflow and the Dryad workflow, etc) is a new application model of workflow in the cloud computing environment[2]. The scheduling problem under the sharing heterogeneous distributed resources (the public cloud, the private cloud or the hybrid cloud, etc) has attracted wide attention from researchers in recent years. Chen et al [3] have designed the dynamic task rearrangement and the scheduling algorithm under the prior constraint in view of the task fairness allocation problem of the multi workflow. Fard et al have designed a multi-objective optimization algorithm in view of the heterogeneous cloud computing environment. The algorithm has divided the global task allocation problem into several sub assignment problems and each sub problem is solved by the meta heuristic algorithm[4]. Jing Weipeng et al [5] have proposed a dynamic multi layered DAG scheduling algorithm[6] that considers the link communication competition between virtual machines in view of the reliable scheduling problem of multiple cloud scientific workflow in the cloud computing environment, which has effectively solved the fair scheduling problem when the weights of the tasks in several DAG are greatly different. Tian Guozhong et al have firstly proposed the "relatively strict" index that measures the DAG deadline emergency level, which can properly handle the emergency level relationship of the scheduling between multiple DAG so as to reach the maximum scheduling target of DAG throughput[7]. In this paper, the research group has conducted the deep researches on the cloud workflow scheduling. Zuo Liyun et al have designed a multi-objective optimization task scheduling algorithm through analyzing the operation process of the workflow tasks in the cloud platform[8]. According to the multi workflow scheduling problem of the different QoS demands submitted at different times, a hybrid task fairness scheduling algorithm based on the reinforcement learning and the DAG critical path has been designed[9].This algorithm employs the state clustering to greatly reduce the dimension of state space and improve the convergence speed of algorithm. For the computation intensive and data intensive hybrid tasks, it is required to comprehensively employ the multi agent parallel learning, knowledge reuse and migration to accelerate the search of the optimal strategy[10].

However, in the current cloud workflow scheduling researches, there generally exist the following problems: (1) most of the work is the expansion of the grid workflow task allocation strategy in the "pay-on-demand" feature of computing resources and the fundamental feature of the elasticity resource supply of the cloud computing environment has been ignored. Therefore, the lack of the novelty and the versatility is not suitable to the true cloud computing application scenarios. (2) Generally speaking, the modeling is the single/multi-objective optimization problem under multi constrained conditions. When the task scale becomes large, the optimization problem will become very complex and it will be often unable to get the optimal task allocation strategy and also easy to fall into the local optimum. In this paper, in view of the fair scheduling problem of the multi cloud workflow tasks , a multi workflow task fair scheduling algorithm based on the reinforcement learning has been designed. Firstly, the algorithm has avoided to violate the SLA agreement through the prior dynamic scheduling. Secondly, the load balancing between the various virtual machines has been achieved through the reinforcement learning algorithm. The experimental results have shown the validity of the algorithm in this paper.

2. System Model

In this research, the virtual machine cluster is taken as the granularity to study the multi workflow task fair scheduling mechanisms. The cloud platform model employed in this paper is shown in Figure 1. This model is composed of the interconnected and collaborative-work multiple sub modules (including the task scheduling module, the task execution module and the task transmission module) and it is a cloud model of fine granularity. This model can not only accurately describe the cloud computing environment with dynamic changes, but also instantly reflect the performance indexes in cloud environment, such as the dependent constraint relationship among the achieving rate of tasks, the service rate, the number of virtual machine resources and the queuing length, etc.

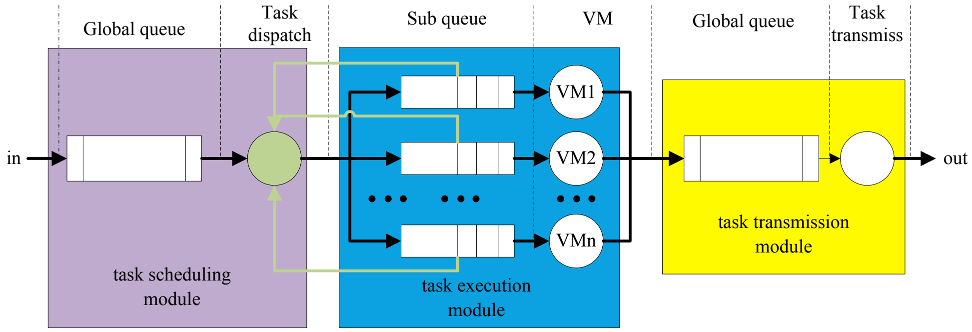


Figure 1 Sketch map of the cloud platform model

3. Priority Partition and Dynamic Adjustment

Juve et al have studied the structural characteristics of five true workflow applications (Montage, CyberShake, Epigenomics, LIGO, SIPHT) and established the corresponding workflow structure. DAX format has been used for description. The workflow structures of Mongtage and LIGO are shown in Figure 2.

3.1 Priority initial setting

The dependent constraint relationship between the workflow tasks is usually described by the directed acyclic graph (DAG). According to the DAG and the demands of service quality of workflow, each scheduling time should be conducted the process decomposition and the priority initial setting. Inspired by the HEFT algorithm, assuming that the tasks v_i and v_j have the dependent relationship and the operation of task v_j directly depends on the operation results of task v_i, the initial priority of the task of the communication consumption can be represented as[6]:

$$rank(v_i) = \overline{w(v_i)} + \max_{j \in succ(v_i)} \{\overline{c(e_{ij})} + rank(v_j)\} \tag{1}$$

In formula (1), $\overline{w(v_i)}$ represents the average execution cost of task v_i in all available virtual machine resources in the current cluster; $\overline{c(e_{ij})}$ represents the average communication cost of task v_i and v_j; the priority of task v_i is the maximum value of the sum of the direct succeeding task priority and the corresponding communication cost plus its computing cost. As the priorities of all tasks are from the export task to traverse the task graph, the priority of the export task can be represented as:

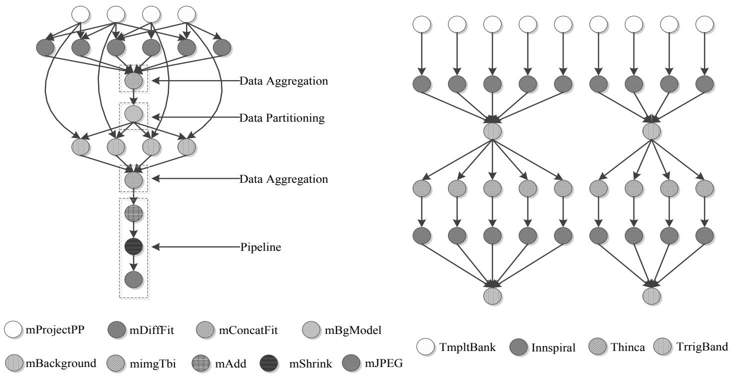
$$rank(v_{exit}) = w(v_{exit}) \tag{2}$$

3.2 Dynamic adjustment of priority

In the cache queuing process of task, the service level agreement may be violated due to the changes of the external environmental factors such as the user demands, the submittal of new workflow and the increase or the decrease of resources in virtual machine cluster. Therefore, in the task execution process of cloud workflow, it is required to conduct the dynamic adjustment for the priority of the initial setting, the formula is shown as follows:

$$rank(v_i)' = \overline{w(v_i)'} + \max_{j \in succ(v_i)} \{\overline{c(e_{ij})'} + rank(v_j)'\} + v_i^{SLA} \tag{3}$$

In formula (3), v_i^{SLA} is the emergency factor that represents the urgency degree of violating the service level agreement of the current task v_i due to the changes of external environmental factors. This emergency factor can effectively avoid the increase of time span without scheduling of the previous DAG due to the remaining tasks.



(a) Montage workflow (b) LIGO workflow

Figure 2 Examples of cloud workflow

4. Multi Workflow Task Fair Allocation Strategy Based on the Reinforcement Learning

According to the cloud platform model and the classical queuing theory in Figure 1, the transfer of the system state at each scheduling time meets the Markov property. The related concepts of the task allocation strategy based on the reinforcement learning can be described as:

The state space: the five tuples $S = (WR, RA, AW, IM, PJ)$ is used to represent the state space, in which *WR* represents the workload of tasks to be scheduled; *RA* represents the available time of resources; *AW* represents the total workload in the waiting queue; *IM* represents the resource number of idle virtual machines; *PJ* represents the ratio of submitting the tasks of users in queue.

The action space: the three tuples $J = (TJ, WS, ET)$ is used to represent the action space, in which *TJ* represents the task type; *WS* represents the user identifier; ET represents the execution time of task.

The reward function: in this paper, it is intended to use the formula (4) as the reward function of multi workflow fair allocation:

$$R_s = \lambda_s W + (1 - \lambda_s) F \tag{4}$$

In formula (4), $\lambda_s \in [0,1]$ is the control factor; W is the response rate of workflow task; *F* is the fair index.

$$W_{v_i} = \frac{execution\ time_{v_i}}{execution\ time_{v_i} + waiting\ time_{v_i}} \tag{5}$$

The fair index F_{v_i} of task v_i is defined as:

$$F_{v_i} = 1 - \frac{\max_k (W_k - S_{kv_i})}{M_{v_i}} \tag{6}$$

In this formula, S_{kv_i} represents the resources demanded by the task v_i submitted by the user *K*; $M = \max_k(W_k)$.

The reward function designed in formula (4) can meet the requirements of the multi workflow task fair allocation which should not only ensure the unit load balancing of each virtual machine in the virtual machine cluster, but also avoid the workflow with different service quality needs to violate the service level agreement and improve the resource utilization rate of the whole virtual machine cluster. The Q-learning reinforcement learning pseudo code employed in this paper is shown in Algorithm 1.

Algorithm 1 Q-value Learning Algorithm	
1:	Initialize *Q* table
2:	Initialize state s_t
3:	error = 0
4:	repeat
5:	for each state *s* do
6:	$a_t = get\_action(s_t)$ using $\varepsilon - greedy$ policy
7:	for (step=1; step<LIMIT; step++) do
8:	Take action a_t observe *r* and S_{t+1}
9:	$Q_t = Q_t + \alpha * (r + \gamma * Q_{t+1} - Q_t)$
10:	$error = MAX(error \mid Q_t - Q_{previous-t})$
11:	$s_t = s_{t+1}, a_{t+1} = get\_action(s_t), a_t = a_{t+1}$
12:	end for
13:	end for
14:	until $error < \theta$

5. Experimental Results

The cloud computing simulation software Cloudsim[11] jointly designed by the Grid Laboratory of Melbourne University in Australia and Gridbus project is selected as the test platform and the experimental parameters are shown in Table 1.

Table 1. Setting of experimental parameters

Parameter	Values
Total number of VMs	3
VM frequency	1,000-5,000 million instructions per second
VM memory (RAM)	1024-2048 mega byte
VM bandwidth	1,000-10,000 mega byte per second
Number of VM buffer	100-200
Number of PEs requirements	5
Number of datacenters	1
Number of hosts	5

In order to compare the performance of this algorithm, the random scheduling algorithm (Ran-sch), the equal job scheduling algorithm (Equ-sch) and the mixed job scheduling algorithm (Mix-sch) are compared. Under the same experimental conditions, the resource utilization rate and the load conditions of each virtual machine are respectively shown in Figure 3 and Figure 4.

From the experimental results in Figure 3 and Figure 4, it is found that the algorithm in this paper can better achieve the balance of the resource utilization rate of each virtual machine rather than the balance of completing the number of job for each virtual machine. It is proved that the algorithm in this paper can conduct the fair scheduling according to the different demands of different users for the virtual resources. At the same time, the dynamic adjustment of the priority can effectively avoid to violate SLA agreement.

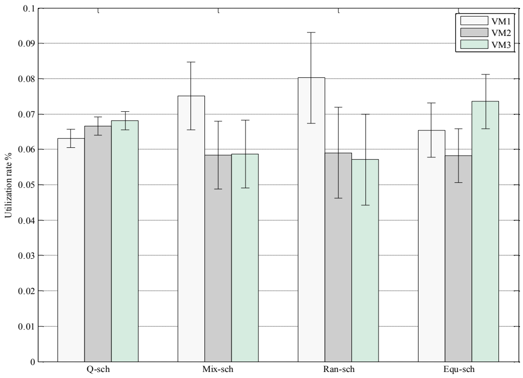


Figure 3 Comparison of the resource utilization rate of each virtual machine

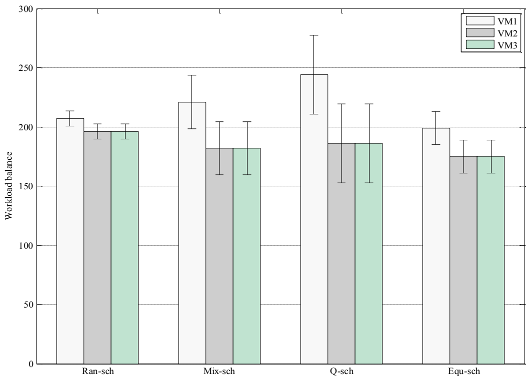


Figure 4 Comparison of the load of each virtual machine

6. Conclusion

In view of the fair scheduling problem of multi workflow under the cloud environment, the cloud scheduling strategy based on the reinforcement learning has been designed in this paper. Through the dynamic adjustment of the priority and the fairness index, the load balance of the virtual machine has been realized. The further analysis on the operation characteristics of the cloud workflow and the design of the more reasonable and effective scheduling algorithm are the research focus in the next step.

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