International Journal of Grid Distribution Computing
Vol.8, No.1 (2015), pp.55-66
http://dx.doi.org/10.14257/ijgdc.2015.8.1.06

A Cloud Manufacturing Resource Allocation Model Based on Ant Colony Optimization Algorithm

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Abstract

Resources should be allocated efficiently in a cloud manufacturing environment, given specific cloud manufacturing task. We study on the optimal resource allocation after the qualitative analysis of the match between the tasks and the resources in this work. Along this line, many factors should be significant, including time, cost and quality of services. Moreover, the workload of equipments should also be considered, in order to achieve load balance and improve the efficiency of manufacturing and the productivity. Therefore, in this paper, based on a four-dimensional objective function, that is, time, cost, quality of services and the load balance, we adapt the Ant Colony Optimization (ACO) algorithm to find the optimal solution. We also present a case study to evaluate our model.

Keywords: *Cloud Manufacturing, Resource Allocation Model, Ant Colony Optimization*

1. Introduction

In a cloud manufacturing environment, all the manufacturing resources are unified as virtual service resources [1-2]. The cloud manufacturing platform helps to achieve the diversity of manufacturing resources and also the multi-grained resource sharing. The resource is provided by not longer a single real apartment, but a resource service from a virtual manufacturing unit or underlying processing equipment.

However, the construction of manufacturing resources is usually a dynamic process, given the characteristics of manufacturing resources, such as the diversity, multi-granularity and geographical distribution. By dynamic we mean that given a required task submitted to the cloud platform, where the task is split into several subtasks, multiple resource service providers are called for each specific subtask for real time scheduling, which is generated dynamically according to the manufacturing resources in different geographical locations. In this study, we focus on the problem of resource allocation in a cloud manufacturing environment in order to achieve the optimal dynamic resource service provision.

Typically, the whole process of cloud manufacturing resource allocation can be divided into three steps. First, define the scope of candidate manufacturing resources. That is, when a requirement of manufacturing task is proposed, the cloud platform decomposes it into several subtasks, and then search for relative resources according to the characteristics of the manufacturing resources, and finally gets the set of available resources. Second, subjective primary selection. In this step, an indicator system is constructed based on users ratings on resources in terms of time, cost, quality, service, credit and reliability. Then weights for each indicator are learned, and top qualified

ISSN: 2005-4262 IJGDC

resources are selected for each subtask. Last, further optimal resource allocation of cloud manufacturing resources. The objective of the second step is to find a best match between the task requirement and the single local resource, while in this step, the whole set of resources are considered in order to achieve an optimal service portfolio. Figure 1 illustrates the above process. In this paper, we assume the primary selection process is already implemented, and focus on the optimal resource allocation step.

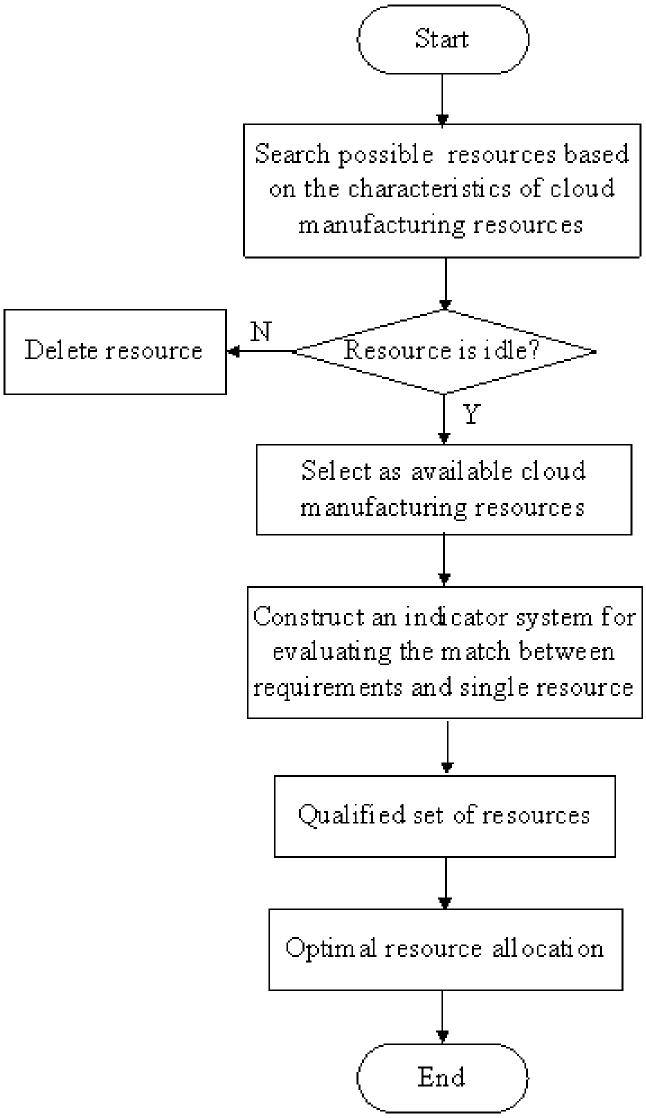

Figure1. The Process o Cloud Manufacturing Resource Allocation

The optimal resource allocation process is essentially a quantitative analysis of cloud manufacturing resources given a set of qualified resources after qualitative analysis in the primary selection step. The objective of manufacturing might be related to cost, time of delivery, quality, service, credit and reliability. Therefore, the process of resource allocation of manufacturing resources is a multi-object optimization problem. Indeed, the resource allocation process can be described as the dynamic match between the requirement of process manufacturing tasks and the capability of manufacturing resources, and the objective is to complete the manufacturing tasks within specific time with the rational use of limited manufacturing resources.

However, during practical manufacturing process, the biased selection of processing equipments leads to the unbalanced usage of equipments. That is, the decision is typically made upon the characteristics of the resources and the technical requirements of the tasks, without consideration of the status of the equipments. As a result, resources that are frequently occupied could be the bottleneck of the whole manufacturing process, while some equipment remains idle because of lack of usage. The unbalanced allocation of resources could contribute to low productivity, and the manufacturing tasks might be hard to complete within the required time.

To this end, in this study, we propose a cloud manufacturing resource allocation method with the consideration of resource load balancing. Specifically, we define the optimization objective as time, cost, quality and load balance, and build evaluation functions to optimize them. Then, we employ Ant Colony Optimization (ACO) algorithm [3] to model the resource allocation problem. Intrinsic properties of ACO such as parallelism, robustness and flexibility determine its feasibility of being applied to solve the cloud services portfolio selection problem.

The remains of this paper are organized as follows. Section 2 discusses the related work, and Section 3 describes the problem statement of cloud manufacturing resource allocation. In Section 4, the proposed resources allocation algorithm based on ACO is presented, and in Section 5 we review a case study for evaluation. Finally, the paper is concluded in Section 6.

2. Related Work

Cloud manufacturing unifies various resources scattered in different geographical locations and provides convenient and timely services for cloud manufacturing tasks. In 2010, the European Union launched a project called Manu Cloud to research on the configurable manufacturing capacity services through a stack of software. Li Bohu et al. [4] first proposed the concept of cloud manufacturing, and provided the definition and architecture of cloud manufacturing. Wang Shilong et al. [5] analyzed the application model and solutions of cloud manufacturing, as well as the cloud security strategies. Fan Wenhui et al. [6] proposed an integrated architecture and the supporting environment of cloud manufacturing. Zhang Lin et al. [7-8] investigated the relationship between cloud manufacturing and other forms of manufacturing, and then discussed the key techniques in building a cloud manufacturing system. Yin Chao et al. [9] studied on the Small and Medium-sized Enterprises (SME) oriented cloud manufacturing platform. Shen Bin et al. [10] proposed a service-oriented architecture to construct a collaborative service platform. Ren Lei et al. [11] built a virtualized framework for cloud manufacturing.

There are also many efforts on resource allocation problem in the fields of virtual manufacturing [12], agile manufacturing [13], application service providers [14-15] and manufacturing grid [16]. Tao Fei et al. [17] designed a cloud manufacturing management system to address the cloud services requirements. Liu Weining et al. [18] investigated the service portfolio problem of multi-task cloud manufacturing, and construct a Genetic Algorithm (GA) based model to find the best solution with the objective to maximize the quality of services. Li Haibo et al. [19] proposed a workflow based multi-grain method for resource allocation. Yin Chao et al. [20] built a multi-objective resource selection model using grey relational analysis. Zhou Ke et al. [21] designed a modified GA based method to find the optimal solution of cloud manufacturing resource allocation with the consideration of cost, time, quality, service and environment. Yu Jianfeng et al. [22] proposed an adaptive ACO based model to optimize time, cost and quality to find the optimal resource allocation.

3. Problem Statement and Objective Functions

As mentioned earlier, we study on the problem of optimal cloud manufacturing resource allocation. In this section, we give the formal problem statement.

As shown in Figure 2, the original cloud manufacturing task requirement is split into n subtasks, termed as CMT (Cloud Manufacturing Task), and each is notated as $CMT_i, i \in [1, n]$. CMT is transparent to physical location, and leverages various kinds of resources from enterprises. The entity that provides cloud resource services is called CRSN (Cloud Resource Service Node), and the manufacturing resources that are dynamically allocated are noted as CMR (Cloud Manufacturing Resource). Each $CMR_i, i \in [1, n]$ is driven by a specific $CMT_i, i \in [1, n]$, and then a set of $CRSN_{ij}, i \in [1, n], j \in [1, m_i]$ are prepared for each CMR_i, where m_i is the number of qualified resources for each CMT_i.

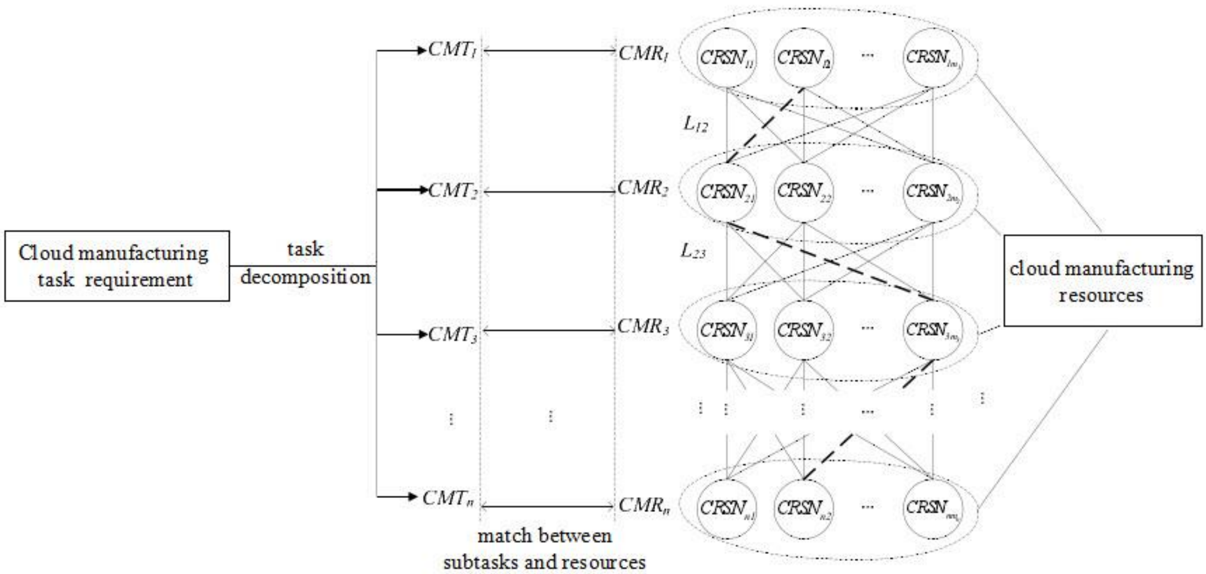

Figure 2. The Service Delivery Process of Cloud Manufacturing Resources

Let $L_{ij,(i+1)k}$ denote the links between $CSRN_{ij}$ and $CSRN_{(i+1)k}$. Accordingly, the time cost of the resource allocation can be represented as the summary of time spent on all links, including transportation and inventory time, and the cost can be described as the cost of link construction, including the cost of transportation and inventory. That is, let $t_{ij,(i+1)k}, c_{ij,(i+1)k}$ be the time and cost of link $L_{ij,(i+1)k}$ respectively.

In this paper, we consider a four-dimensional objective, that is, time, cost, quality and load balance, and formulate the optimal resource allocation as a multi-objective optimization problem. Our objective function can be defined as:

$$F = \min\{w_1 C + w_2 T + w_3 Q + w_4 B\}, \tag{1}$$

where w_i denotes the weight of each dimension, and $\sum w_i = 1$. T is the time function of cloud manufacturing resource allocation, C is the cost function, Q is the quality function which describes the quality of resource allocation, and B is the function to quantify the load balance situation. Please note that we revise each function as negative indicator function so that the objective can be unified as the minimum objective function.

Specifically, the time function T is defined as follows:

$$T = \sum_{i=1}^{x}\sum_{j=1}^{m_i}\sum_{k=j+1}^{m_i} t_{ij,(i+1)k} + \sum_{i=1}^{y}\max_t\{t_{i1,(i+1)2}, t_{i1,(i+1)3}, \ldots, t_{ij,(i+1)k}, \ldots\}, \tag{2}$$

where n is the number of CMR, and m_i is the number of CRSN for each CMR. Suppose there exist x sequential tasks, and the first part of Equation (2) means the time cost of sequential execution. Suppose there are y parallel tasks, and $\max_t\{t_{i1,(i+1)2}, t_{i1,(i+1)3}, \ldots, t_{ij,(i+1)k}, \ldots\}$ denotes the time cost of the longest CMR in one parallel group, and therefore the second part of Equation (2) is the time cost of parallel execution. The less time it takes, the better the allocation solution is.

The cost function C is represented as:

$$C = \sum_{i=1}^{x} C_i + \sum_{i=1}^{y}\left(\sum C_p\right) + \sum C_a, \tag{3}$$

where C_i is the cost of each sequential task, $\sum C_b$ is the cost of each parallel task, and therefore $\sum_{i=1}^{x} C_i$ is the total cost of sequential execution, and $\sum_{i=1}^{y}\left(\sum C_p\right)$ is the total cost of parallel execution. $\sum C_a$ is the cost of publishing cloud manufacturing tasks and advertising.

The quality function Q is defined as:

$$Q = \sum_{i=1}^{n}\sum_{j=1}^{m_i}(1 - q_{ij}), \tag{4}$$

where q_{ij} is the quality conformity rate of resource j to process task i.

Now we consider the function to quantify the load balance requirement. Let θ_j denote the load factor of each resource (or equipment), calculated as:

$$\theta_j = \frac{Load_j}{Ca_j} \times 100\%, \tag{5}$$

where $Load_j$ is the load of resource j, and Ca_j is the available hours of j. Indeed, θ_j represents the usage status of each CRSN. We use the variance of θ_j to describe the load balance status of the whole production line equipments:

$$S(\theta) = \frac{1}{m-1} \sum_{j=1}^{m} (\theta_j - \bar{\theta})^2, \tag{6}$$

where m is the number of resources, and $\bar{\theta}$ is the average of resource utilization, calculated as $\bar{\theta} = 1/n \sum \theta_j$. The smaller $S(\theta)$ is, the less difference in the utilization between the devices, the more balance the resources are. Therefore, the objective function of load balance is defined as:

$$Q = S(\theta). \tag{7}$$

4. Cloud Manufacturing Resource Allocation Model

In this section, we adapt ACO algorithm to optimize the earlier objective functions presented in Section 3 for cloud manufacturing resource allocation.

Ant colony optimization (ACO), first proposed by Marco Dorigo [23], is a swarm intelligence method that can be used to find approximate solutions to difficult optimization problems. The basic idea is to leverage the collaboration of ants to find the shortest path to the destination through the pheromone released on each trail. It is established that ACO is widely used in combinatorial optimization problems [24-27]. Table 1 lists the notations in this section.

Table1. List of Notations

Symbol	Description
m	The number of manufacturing resources in the cloud service pool
K	The number of ants
t	The iteration of search
$\eta_{ij,pq}(t)$	The heuristic factor from $CRSN_{ij}$ to $CRSN_{pq}$ at the t-th iteration

$\tau_{ij,pq}^{h}(t)$	The amount of pheromones on path (ij, pq) at the t-th iteration of ant h
P	The total amount of pheromones released by ants
L_h	The total length of ant h's tour, measured by T, C, Q, B

Initialize all the ants at the starting point, and the initial values of pheromones are $\tau_{ij,pq}^{h}(0) = c$, where c is a constant. Notate the probability of ant h transferring from $CRSN_{ij}$ to $CRSN_{pq}$ at time t as $p_{ij,pq}^{h}(t)$, which is calculated as:

$$p_{ij,pq}^{h}(t) = \begin{cases} \dfrac{\tau_{ij,pq}(t)^{\alpha}\left(\eta_{ij,pq}(t)\right)^{\beta}}{\sum_{s \in allowed_h} \tau_{is,pq}(t)^{\alpha}\left(\left(\eta_{is,pq}(t)\right)\right)^{\beta}}, & \text{if } j \in allowed_h; \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

where $allowed$ denotes the available CRSNs for the next step, α is the heuristic factor indicating the importance of path with remaining pheromones, and β is the heuristic factor denoting the affect of heuristic information between steps.

At iteration $t+1$, the phenomenon at path (ij, pq) is updated as follows:

$$\tau_{ij,pq}(t+1) = (1-\rho)\tau_{ij,pq}(t) + \Delta\tau_{ij,pq}(t), \quad (9)$$

$$\Delta\tau_{ij,pq}(t) = \sum_{h=1}^{K} \Delta\tau_{ij,pq}^{h}(t), \quad (10)$$

$$\Delta\tau_{ij,pq}^{h}(t) = \begin{cases} P / L_h, & \text{if ant } h \text{ passes through} (ij,pq) \text{ at iteration } t; \\ 0, & \text{otherwise.} \end{cases} \quad (11)$$

Where $1-\rho$ is the residual coefficient of pheromones, $\rho \subset [0,1)$, $\Delta\tau_{ij,pq}^{h}(t)$ denotes the increased amount of pheromones of ant h at path (ij, pq) at iteration t, and $\Delta\tau_{ij,pq}(t)$ denotes the increased amount of pheromones at path (ij, pq) in that iteration.

Now we consider the specific restrictions in cloud manufacturing resource allocation problem. First, the timing of CMRs is significant. That is, some CMRs have to wait until the prerequisite tasks are finishes. Second, resources of the same kind are mutual, i.e., given the same CMR, only one resource should be selected among all similar resources.

Last, the status of resources is dynamically changing. For example, if the workload of CRSN is too large, it would be no longer available.

Therefore, we modify the ACO to meet above requirements as follows:

(1) Add a control variable into the tabu list to describe the timing and mutual characteristics, notated as CK_i. If a resource for CMR_i is selected, other resources of the same kind is moved to the tabu list, and CK_i is updated to CK_{i+1};

(2) Add a feedback variable to record the current status of resources, notated as FB_j. If $CRSN_j$ is not available because of excessive workload, for example, FB_j is set to 0; otherwise, FB_j is set to 1.

Besides, to avoid the local optimal solution and low convergence speed, we adjust ρ if there is no improvement of the local solutions within N iterations:

$$\rho(t+1)=\begin{cases}0.95\rho(t), & \text{if } 0.95\rho(t)\geq\rho_{\min};\\ \rho_{\min}, & \text{otherwise.}\end{cases} \tag{12}$$

where $\rho_{\min}$ is the minimum value of ρ.

The whole process of optimal cloud manufacturing resource allocation based on ACO can be summarized as following steps:

Step 1: Initialize the parameters, constraints, and the termination condition of the algorithm;

Step 2: Generate K ants, and randomly put them on CRSN nodes;

Step 3: For each ant h, calculate the transfer probability $p_{ij,pq}^{h}(t)$ to find the next node. During the selection process, firstly check the value of FB_j to specify valid resource nodes. Then, if a CRSN node is valid, continue; otherwise, go back to the last node and search for other nodes. Once one of the candidate resources is selected, others of the same kind are added into the tabu list;

Step 4: After all candidate nodes are searched, calculate the best value of the objective function, and record as F_t^*;

Step 5: If F_t^* is not better than the best solution of earlier N iterations, adjust ρ

as Equation (14). Otherwise, go to Step 6;

Step 6: Update $\Delta\tau_{ij}, \tau_{ij}$, and then set $\Delta\tau_{ij} = 0$, and clear the tabu list;

Step 7: If the number of iterations is smaller than the maximum iteration, go to Step 2. Otherwise, output the best service portfolio, along with the minimum value of objective function.

5. Experiment

In this section, we conduct a case study on a forging enterprise, which needs collaboration from others because of business requirements or the limitation of its processing capability.

Suppose there are two forging material 4130, and each one weights 398 kg. The required hardness of the forgings should be between 175 to 238 HBW, and the surface roughness should be less than 6.3 μm. Besides, the processing section should be perpendicular to the inner hole of the forgings, and the outer diameter should be concentric with the inner hole. The perpendicularity should be less than 0.1 mm, and the concentricity should be no more than 0.1 mm. The maximum cost of forgings is 15 rmb/kg, and the acceptable forging time is 14 days.

The forging task is split into several subtasks $\{CMT_1, CMT_2, CMT_3, CMT_4, CMT_5\}$. Then, prepare candidate resources based on the task requirement and the characteristics of the resources. Figure 3 illustrates the example model of the whole process, where the arrow denotes the sequence of the usage of each resources. Besides, Table 2 shows the cost, time, quality and workload of each CRSN.

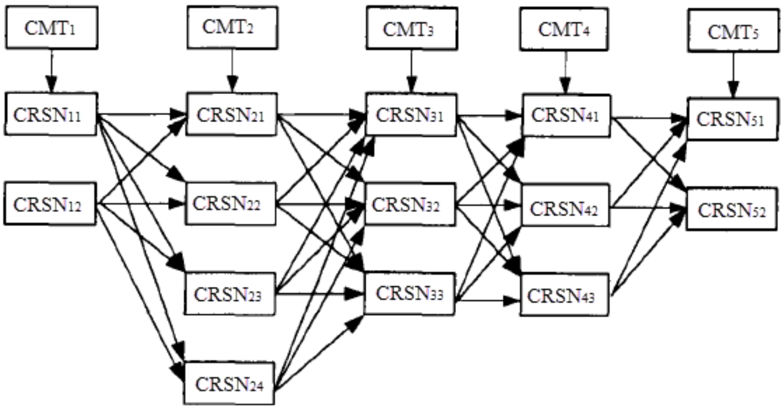

Figure 3. The Example Model

Table2. The Cost, Time, Quality and Workload of each CRSN for Corresponding CMT

	CMT_1		CMT_2				CMT_3			CMT_4			CMT_5	
CRSN	$CRSN_{11}$	$CRSN_{12}$	$CRSN_{21}$	$CRSN_{22}$	$CRSN_{23}$	$CRSN_{24}$	$CRSN_{31}$	$CRSN_{32}$	$CRSN_{33}$	$CRSN_{41}$	$CRSN_{42}$	$CRSN_{43}$	$CRSN_{51}$	$CRSN_{52}$
C	1000	1000	1500	1400	1500	1500	1200	1000	1200	1200	900	1000	800	1000
T	5	4	3	3	3	2	3	3	4	3	2	3	4	3
Q	0.9	0.8	0.8	0.7	0.8	0.9	0.9	0.8	0.7	0.6	0.6	0.8	0.9	0.9
B	0.9	0.9	0.6	0.8	0.9	0.6	0.7	0.8	0.9	0.4	0.6	0.8	0.7	0.9

Now we consider the optimal resource allocation based on ACO algorithm. We simulate the process using MATLAB software. We set the number of ants $K = 50$, $\alpha = 1, \beta = 5, \rho = 0.6, P = 20$. The results are shown in Table 3. Moreover, Figure 4 shows that our model which takes load balance factor into the optimal objective achieves better performance of load balance. In this way, we could increase the utilization rate of equipments and improve the efficiency and productivity.

Table 3. The Results of Resource Allocation

Optimal resource selection	Average number of iteration
$CRSN_{11} \rightarrow CRSN_{23} \rightarrow CRSN_{32} \rightarrow CRSN_{43} \rightarrow CRSN_{52}$	80

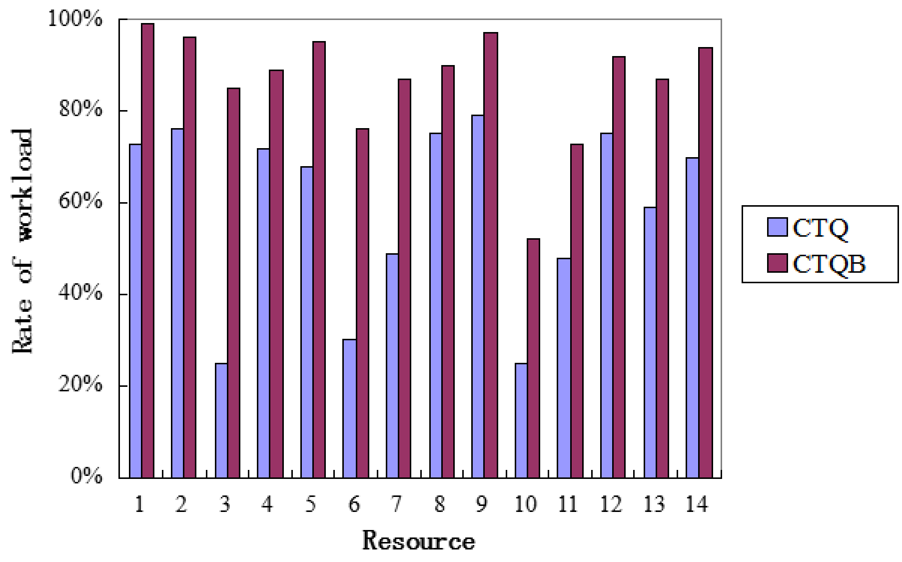

Figure 4. The Workload Comparison between with and without Consideration of Including Load Balance in the Objective Function

6. Conclusion

In this paper, we studied on the optimal resource allocation of cloud manufacturing resources, with the objective to optimize the time, cost, quality of services and load balance of the equipments. We employ a modified ACO algorithm as the solution. However, in this work, we assume necessary preparation is done, such as the match between the task requirements and the characteristics of the resources, and the primary subjective selection of qualified candidate resources. In future, we will try to find a more intelligent way to minimize preparation and assumptions.

Acknowledgement

This work is supported by Shandong Provincial Key Laboratory for Novel Distributed Computer Software Technology Open Program from 2014 to 2015. All authors thank the reviewers for their helpful suggestions.

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