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Research on Cloud Manufacturing Resource Allocation in Distributed Computing Environment

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Abstract

With the rapid development of network information technology, manufacturing presents a development trend of networking, virtualization, intelligence and servitization. Cloud manufacturing (CMg) with a new type of service-oriented manufacturing model is put forward and excellently satisfies the development requirements of modern manufacturing enterprises. With considering the complex characteristics of cloud manufacturing, firstly, we construct Cloud manufacturing resource scheduling system architecture to schedule service task and allocate manufacturing resource, which includes user requirements, task plan, global task scheduling, service collaboration allocation, virtualization and cloud manufacturing resource. Secondly, we propose a comprehensive resource allocation model based on auctions theory to satisfy different users' request, and then the greedy method is used to search the optimal bid in the bid set. Finally, we implement some simulation experiments, and simulation results show that the solution algorithm of CARA's winner determination problem gets the same solution as the M-HEU algorithm with less time complexity, and it is more applicable, efficient and effective for online multi-resource allocation.

Keywords: *WSNs, non-equilibrium statistical mechanics method, performance evaluation*

1. Introduction

In the 21st century, with the rapid development of network information technology, manufacturing presents a development trend of networking, virtualization, intelligence and servitization [1]. In order to meet the requirement of development trend, a new manufacturing model called distributed manufacturing is emerged as the times require. Distributed manufacturing is adhered to concept that manufacturing is the service. And with the aid of distributed computing, the internet of things and other kinds of related high and new information technology, problem in integration and sharing of manufacturing resource under the network environment is solved, and also search and intelligent matching in service resources and tasks are realized[2-3]. Large quantity and small size are two basic characteristics of small and medium-sized manufacturing enterprises in China. The problems, such as backward manufacturing technology, insufficient information resources, deficiency of developing capacity and corresponding researcher, greatly restrict the development of manufacturing enterprise, which makes it unable to adapt to the trend of modern manufacturing informatization. Then with optimal operation in service resources, an optimal combination in services is formed so as to achieve optimal configuration in service resources. Therefore, sharing and optimal configuration in

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service resources have an important significance and practical value [4-5]. Aiming at the shortcomings of manufacturing enterprises, Cloud manufacturing (CMg) with a new type of service-oriented manufacturing model is put forward and excellently satisfies the development requirements of modern manufacturing enterprises. Meanwhile, Cloud manufacturing is a computing and service-oriented manufacturing model developed from existing advanced manufacturing models (e.g. ASP, AM,NM, MGrid) and enterprise information technologies under the support of cloud computing, IoT, virtualization and service-oriented technologies, and advanced computing technologies[6-9]. It aims to realize the full sharing and circulation, high utilization, and on-demand use of various manufacturing resources and capabilities by providing safe and reliable, high quality, cheap and on-demand used manufacturing services for the whole lifecycle of manufacturing.

With the coming forth of the Cloud manufacturing, it provides a new way for manufacturing industry to transform from production-oriented to service-oriented [10]. Lots of research works have been conducted on various aspects of CMg including system architecture, network topology, application prospects, task scheduling and resource allocation etc. [11-13]. However, CMg is a new research field still in its infancy, and either the theoretical research or the application is not mature enough. At present, there is no longer a unified standard and system theory framework, according to the different applications. Guo put forward the optimization model of manufacturing resources based on genetic algorithm, and validated the feasibility and effectiveness of the optimization model [14]. Laili Y presented the resource allocation method in networked manufacturing environment, genetic algorithm is used to solve the collaborative optimization problem[15]; Cheng Y constructed the optimal allocation model of outsourcing production resources in multi task, and introduced the configuration model and genetic algorithm[16]. However, recent research on resource allocation model is studied from the prospect of logistics optimization, ignores the application of economic theory [17-18]. Teymouri S investigated the allocation of manufacturing resources through auctions. Recently, researchers investigated various market-based models for resource allocation in computational grids [19]. Lin W Y *et. al.*, compared commodities markets and auctions in grids in terms of price stability and market equilibrium [20]. Chandak *et. al.*, studied different economic and system implications of pricing resources in clouds [21]. Sun W *et. al.*, proposed a marketplace for resources where the allocation and pricing are determined using an exchange market of computing resources [22]. In this exchange, the service providers and the users both express bid prices and matching pairs are granted the allocation. Thorat *et. al.*, proposed a test bed for cloud services designed for testing different mechanisms [23]. In order to In order to better allocate cloud manufacturing in a rational way, we need to introduce a new theory and expand the research perspective, a new framework and scheduling method to determine the allocation of different manufacturing resources.

In summary, current research of cloud manufacturing resource allocation is in its infancy, there is considerable problem space to explore and solve [24]. Therefore, with considering the complex characters of cloud manufacturing in different applications, firstly, we construct Cloud manufacturing resource scheduling system architecture to schedule service task and allocate manufacturing resource, which includes user requirements, task plan, global task scheduling, service collaboration allocation, virtualization and cloud manufacturing resource. Secondly, we propose a more comprehensive t manufacturing resource model based on auctions theory to satisfy different users' request, and then the greedy method is used to search the optimal bid in the bid set. Finally, we implement some simulation experiments, and simulation results show that the solution algorithm of CARA's winner determination problem gets the same solution as the M-HEU algorithm with less time complexity, and hence it is more efficient and effective for online multi-resource allocation.

2. Cloud Manufacturing Resource Scheduling System Architecture

In a CMfg system, various manufacturing resources and abilities can be intelligently sensed and connected into the wider internet, and automatically managed and controlled using IoT technologies. Then the manufacturing resources and abilities are virtualized and encapsulated into different manufacturing cloud services (MCSs) that can be accessed, invoked, deployed, and on-demand used based on knowledge by using virtualization technologies, service-oriented technologies, and cloud computing technologies [25]. The MCSs are classified and aggregated according to specific rules and algorithms, and different kinds of manufacturing clouds are constructed. Different users can search and invoke the qualified MCSs from a related manufacturing cloud according to their needs, and assemble them to be a virtual manufacturing environment or solution to complete their manufacturing task involved in the whole lifecycle of manufacturing processes under the support of cloud computing, service-oriented technologies, and advanced computing technologies. Because service task scheduling and manufacturing resources allocation is very important in distributed cloud environment, we propose a system architecture of Cloud manufacturing resource scheduling which is a hierarchical structure as illustrated in Figure 1.

Figure 1. Collaborative Computing System Architecture

The system architecture of Cloud manufacturing resource scheduling includes five layers; Figure 1 shows the key elements of the framework:

(1) Manufacturing resource layer : provides different kinds of manufacturing resource and ability involved in the whole lifecycle of manufacturing, which can be encapsulated into a service that can be invoked by user.

(2) Virtualization and service layer: is responsible for the virtualization of resources and abilities, and encapsulating them into the cloud service， using related technology.

(3) Service and resource allocation: includes Service monitoring, list of available resource and collaboration reserve processor to allocate manufacturing service.

(4) Global Task scheduling Application: optimize the manufacturing tasks scheduling.

(5) User requirements and task access: Get users' needs, decomposition and task planning.

To this end, allocation mechanisms should know the status of each element/resource in the distributed CMfg environment and, based on them, intelligently apply algorithms to better allocate manufacturing resources to applications according to their pre-established requirements. This way, we may consider that cloud manufacturing resources, resource modelling, application requirements, and provider requirements constitute the input used by a resource allocation mechanism. These resources are located in a distributed pool and shared by multiple users. Each provider is free to model its resources according to its business model.

3. Cloud Manufacturing Resource Allocation Model

3.1. Problem Formulation

Figure 1 is a collaborative manufacturing resource allocation example, when the system platform receives n task requests *TR*. Each task can be finished by lots of candidate computing resources, each circular node represents a task unit, which has its task type; each rectangular node represents a resource or service. Each task is completed by a number of manufacturing resource, manufacturing resources are divided into shared and Exclusive type. Manufacturing resource requirements of tasks has the related constraints, such as QoS. There are n tasks and m resources in online Cloud manufacturing system, the number of resource requested by task i is m_i, the upper bound for the k resource is R_k, configuration option of resource i is l_i, in which resource allocation vector of option j, $1 < j < l_i$ is $q_{ij} = (q_{ij1}, \cdots, q_{ijk}, \cdots, q_{ijm_i})$. The utility function u_i of task i in option j is as following:

$$u_{ij} = u_i(q_{ij}) \quad (1)$$

In which Q_i is the set of resources for task i, needing m_i resources, the set of shared resources is S_i, exclusive resource set is E_i, $S_i \cup E_i = Q_i$ and $a + b = m_i$

3.2. Multi Resource Allocation Mechanism (CARA)

The entities in our Cloud manufacturing environment are users and resource owners. Users have one or more independent computational-intensive jobs for execution and are willing to pay for it. Also resource owners have computational resources and are willing to rent them for profit. We use resource consumer agents that work on behalf of the users and resource provider agents that work on behalf of resource owners [26]. The consumer agents and provider agents are two intelligent entities having their own specific objectives. They interact with each other in the form of a double auction protocol for obtaining their objectives.

When the bidding starts, task i submits *XOR* sets $s_i = \{s_{i1}, \cdots, s_{ij}, \cdots, s_{il_i}\}$ to the resource auction division. In bid $s_{ij} = (q_{ij}, p_{ij})$, q_{ij} is the resource R_k demand of configuration options j, p_{ij} is the bid price. q_{i1} is the minimum resource requirements of i, if not be met, the quit it $p_i = \varnothing$, $l_i = 0$. By the formula (1), i will obtain the utility u_{ij} when to get resources q_{ij}. In bidding stage, its bid price is as following $p_{ij} = u_{ij} + f_i$, f_i is the funds assigned to i. When optimal resource allocation is complete, i gets $q_i^* = \arg\max \sum_i p_i$ resource, the bid price p_i. The payment value is $t_i(q_i^*) = W_{-i}(q_i^*) - W(q_{-i}^*)$, and $W_{-i}(q_{-i}^*) = \arg\max \sum_{b \neq i}^{N-1} u_b(q_{-i})$ is the optimal utility when i quits the bid, $W(q_{-i}^*) = \arg\max \sum_{b \neq i}^{N-1} u_b(q_{-i}^*)$ is the optimal utility when i takes part in the bid. The maximum return of i is $v(q_i^*) = p_i - t_i(q_i^*)$.

3.2.1. Objective Functions and Optimization Model

After the application bidding is completed, CARA resource auctioneer collects the bids, and solving the resource allocation scheme, namely the combination auction winner determination problem (Winner Determination Problem, WDP). The auctioneer's goal is to maximize all application bids:

$$V = \max \sum_{i=1}^{n} \sum_{j=1}^{l_j} x_{ij} p_{ij} \tag{2}$$

$$s.t. \quad \sum_{i=1}^{n} \sum_{j=1}^{l_j} x_{ij} q_{ijk} < R_k \ , \ k = 1, \ldots\ldots m_i \tag{3}$$

where x_{ij} indicates whether i options j, $\sum_{j=1}^{l_j} x_{ij} = 1$, $x_{ij} \in \{0,1\}$, $i = 1, \ldots\ldots n$; $j = 1, \ldots\ldots l_j$. By formula (2) (3) we can get:

$$V = \max \sum_{i=1}^{n} \sum_{j=1}^{l_j} x_{ij} (\mathrm{u}_{ij} + \mathrm{f}_i) = \max \sum_{i=1}^{n} \left[(\sum_{j=1}^{l_j} x_{ij} \mathrm{u}_{ij}) + \mathrm{f}_i \right] = \max \sum_{i=1}^{n} \sum_{j=1}^{l_j} x_{ij} \mathrm{u}_{ij} + \sum_{i=1}^{n} \mathrm{f}_i$$

(4)

In formula (4), the second term $\sum_{i=1}^{n} f_i$ is constant, so the formula (3) can be replaced with $\max \sum_{i=1}^{n} \sum_{j=1}^{l_j} x_{ij} \mathrm{u}_{ij}$, Therefore, CARA-WDP can be seen as a MMKP, which belongs to the NP hard problem. According to the distribution of resources under suboptimal solution scheme, incentive compatibility will be lost. At the same time the lie behavior from buyers can be seen as an amendment to the mechanism of non-optimal allocation. When there is no possible correction, the dominant strategy is the real declared utility. Therefore, the closer the suboptimal solution to the optimal solution, the less the incentive compatibility of losses is.

3.2.2. Derivation of CARA-WDP Algorithm

i upgrades from the minimum value, the increasing of K consumption is $\Delta q_{ijk} = q_{ip[i]k} - q_{ijk}$. And the Aggregate consumption increasing will be: $\Delta a_{ij} = \sum_{j=1}^{l_j} [\Delta q_{ijk} C_k / |C|]$, q_{ijk} represents the demand of resource K while I locates in option J, the option J will increase to $\rho[i]$. C is the total resource consumption in the last iteration, $C = (\mathrm{C}_1, \ldots \mathrm{C}_k, \ldots . \mathrm{C}_{m_i})$, and the utility increment is $\Delta p_{ij} = p_{ip[i]} - p_{ij}$, $\frac{\Delta p_{ij}}{\Delta a_{ij}}$ is the greedy factor.

Define discontinuity set of options are as follows: exclusive resource values are discrete values, the option value will jump. Assume J_{ik} is the set of options while the exclusive resources K of i jumps, $J_{ik} \subseteq \{1,...,j,...,l_i\}$. When k matches $r_k \in E_i$, and assume union of all the set J_{ik} is I_i, so called I_i as a discontinuous option set of i . In this example, $r_1 \in E_i$, $r_2 \in E_i$, $r_3 \in E_i$, $r_4 \in E_i$. Make $l_i = 10$, and each option of r_1 is $q_{i1} = \{0.25, 0.25, 0.5, 0.5, 0.75, 1, 1, 1, 1\}$, and each option of r_2 is $q_{i2} = \{0.5, 0.5, 0.5, 0.5, 1, 1, 1, 1, 1\}$, then $J_{i1} = \{3, 5, 7\}$, $J_{i2} = \{5\}$, $I_i = \{3, 5, 7\}$.

Assume j' is the first discontinuity option bigger than j in I_i , j_0 is the first discontinuity option smaller than j . Bids are all the discrete points of function u_i , when $r_k \in E_i$, $\frac{\partial^2 u_i}{\partial r_k^2} < 0$. If $\sum_{k, r_k \in E_i} \Delta q_{ijk} = 0$, namely $\sum_k \Delta q_{ijk} = \sum_{k, r_k \in S_i} \Delta q_{ijk}$, $r_k \in S_i$, $\forall j+1 < \rho[i] \le j' \le l_i$, then when $\rho[i] = j+1$, $\frac{\Delta p_{ij}}{\Delta q_{ijk}}$ turns into its maximum. And $\frac{\Delta p_{ij}}{\Delta a_{ij}} = \frac{\Delta p_{ij}}{\sum_k [\Delta q_{ijk} C_k / |C|]} = \frac{1}{\sum_{k, r_k \in E_i} [(\Delta q_{ijk} / \Delta p_{ij} . C_k) / |C|]}$, at the same time $\frac{\Delta p_{ij}}{\Delta a'_{ij}}$ has its maximum. So we can know that when $\rho[i] = j-1$, $\frac{\Delta a''_{ij}}{\Delta p_{ij}}$ gets its maximum when $r_k \in S_i$, $\forall 1 \le j_0 \le \rho[i] < j-1 \le l_i$ .When $j_0 \ge \rho[i]$ and $\rho[i] \ge j'$, As the function u_i in the interval $[j, \rho[i]]$ or $[\rho[i], j]$ is non concave, the greedy factor is variable. To sum up, the optimization procedure is as follows:

3.2.3. The Progress of CARA-WDP Algorithm

Because abandon part of non-optimal options, the complexity of CARA-WDP algorithm is lower than M-HEU, but the optimal results are the same as in M-HEU. The process of algorithm is as follows:

(1) Pre-treatment. Calculate the element number d_i of I_i . When $l_i - d_i \ge 1$, activate the optimizing process.

(2) WDP algorithm.① find the initial value: calculate the total resource consumption of the lowest bid. If it doesn't satisfy the restrictions, then allocate resources by the descending order of p_{i1} , then turn into step (3). ② The available scheme of upgrade: if $\Delta a_{ij} \le 0$, select the smallest option from Δa_{ij} to upgrade; if $\Delta a_{ij} > 0$, $j' - j \ge 2$, then select the option with the biggest $\frac{\Delta p_{ij}}{\Delta a_{ij}}$ from $\rho[i] \ge j'$ and $\rho[i] = j+1$ to upgrade; repeat ② until there is no option to be upgraded. Assume the total utility now is U, enter into ③. ③the adjustment of allocation: if $j' - j \ge 2$, then select the option with the biggest $\frac{\Delta p_{ij}}{\Delta a'_{ij}}$ from $\rho[i] \ge j'$ and $\rho[i] = j+1$ to upgrade, and the total utility U' after upgrading should bigger than the old U ; if $j - j_0 \ge 2$, select the option with the biggest $\frac{\Delta a''_{ij}}{\Delta p_{ij}}$ from $\rho[i] \le j_0$ and $\rho[i] = j-1$ to downgrade until the total utility $U'' \le U$, then turn into ② to continue the upgrading process. If the adjustment of allocation is not working then shut down the resource allocation, and turn into step (3).

(3) Calculate payment. ① For each i , calculate $W_{-i}(q_i^*)$ by step (1) and (2) in CARA; ② to each i , calculate $W(q_{-i}^*)$; ③calculate the payment of i : $t_i(q_i^*) = W_{-i}(q_i^*) - W(q_{-i}^*)$

4. A Numerical Example Analysis

In order to obtain a large number of accurate real-time data, in this paper, we construct a cloud manufacturing simulation environment by using the network simulator. The simulation is performed in the laboratory including common software and hardware environment, namely CPU Intel core 4.0GHz, memory for the DDRII4G, operating system is Windows7.0 professional edition. We compute the execution time of our algorithm, using the MATLAB tic/toc command. Characteristics set of cloud manufacturing task are randomly generated, taking the average gap option number $d=3, m=5, l=10$. We assume that the ratio between the application number of exclusive resource and the total number of cloud manufacturing task is α. If all the tasks do not utilize exclusive resource, the WDP problem in CARA is degenerated into a convex programming problem, and then the efficiency of our optimizing algorithm is the highest.

4.1. Sample Data

In order to better explain the actual situation, we assume that the cloud manufacturing system gets 5 manufacturing service requests; it means that there are 5 tasks to meet, and there are 10 kinds of resource to meet all tasks, in which there 5 kinds of shared resource. The complete time, cost, quality of each cloud manufacturing resources can be randomly generated by using simulation platform, and then we can collect related available data in Table 1.

Table 1. Statistical Data of Computing Resources

Task number	Resource name	Time	Cost	Quality
1	R_1 （shared resource）	50	30	9
	R_2	45	25	8
2	R_3	…	…	…
	R_4（shared resource）	36	75	7
3	R_5	55	26	4
	R_6（shared resource）	33	54	6
4	R_7	…	…	…
	R_8（shared resource）	56	42	6
5	R_9	33	74	8
	R_{10}（shared resource）	51	42	6

4.2. Comprehensive Evaluation and Analysis of the Results

Figure 2 shows us that the execution time of CARA-WDP algorithm and M-HEU algorithm time grows with the increasing of α value. The smaller theα value is, the more calculation time the algorithm can save. When α=0.5, n=10, the computation time of our algorithm is about 50ms, around 60% of M-HEU. Different α value has no effect on the computing time of M-HEU.

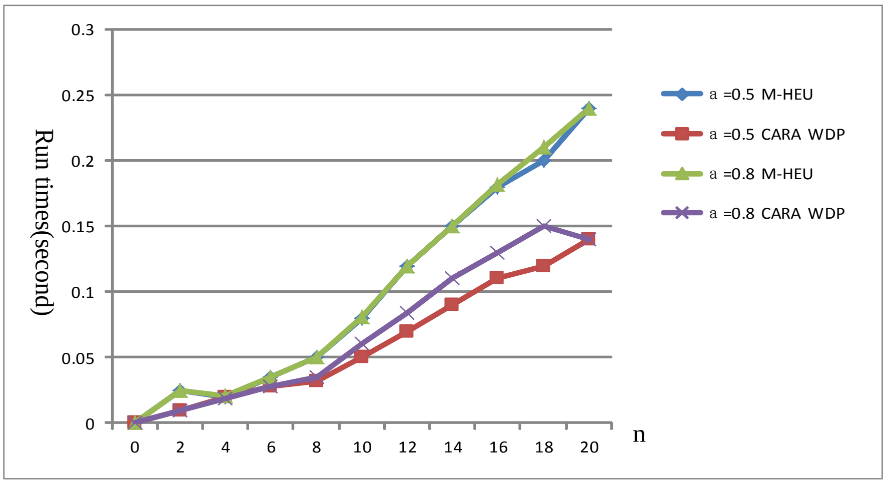

Figure 2. The Influence of a Value on the Computing Time

Figure 3 shows us that the execution time of CARA-WDP algorithm and M-HEU algorithm time is different with the change of *d* value at different time, when α value is all equal to 0.5. Some meaningful results are obtained by simulation experiment, when the d value increases, the search space of the optimal resources range is reduced. Therefore, the computation time of the proposed algorithm relatively increases, but it is always not higher than the computation time of M-HEU.

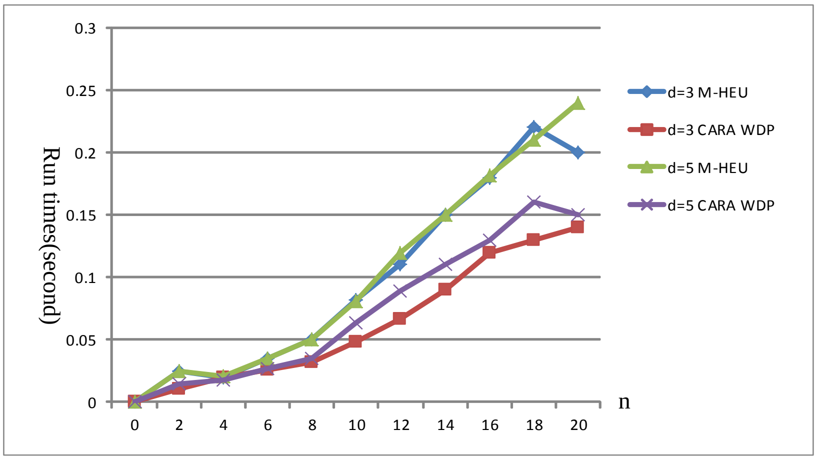

Figure 3. The Influence of D Value on the Computing Time

Figure 3 shows us that the execution time of CARA-WDP algorithm varies with the number of cloud manufacturing task *n*, when α value is always equal to 0.5 and *d* value is equal to 3. We can get many valuable results by simulation experiment, as the trend of the computing time curve is visible, the execution time complexity of CARA mechanism is $O(n^3)$ level, consistent with the calculated results of $O(mn^3(l-1)^2)$. In this paper, we simulate the cloud manufacturing service process on the experimental platform, when $\alpha = 0.5$, d=3, n=10, the resource allocation time is about 400ms in CARA mechanism.

The simulation experiments show us that the time complexity of CARA resource allocation for each time is a polynomial complexity, the time complexity of CARA algorithm is lower 40% than that of M-HEU. Hence, it is more suitable for cloud manufacturing resources online distribution in cloud manufacturing.

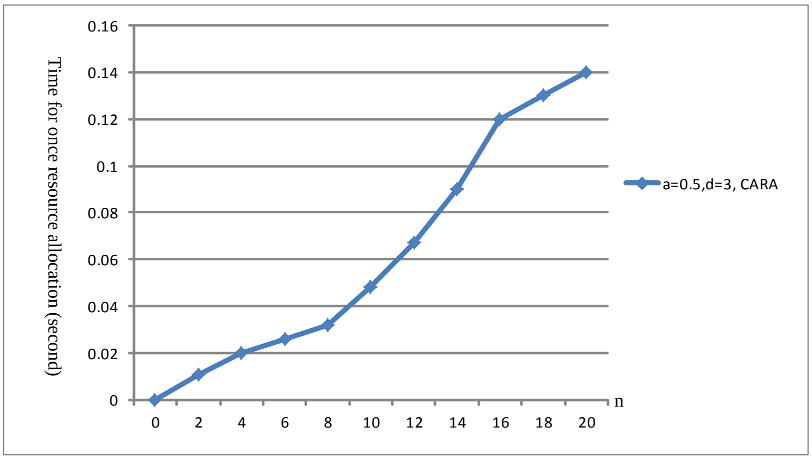

Figure 4. The Time Complexity of CARA Mechanism

5. Conclusion

With the rapid development of network information technology, manufacturing presents a development trend of networking, virtualization, intelligence and servitization. In order to meet the requirement of development trend, a new manufacturing model called Cloud manufacturing is emerged as the times require. Cloud manufacturing is a computing and service-oriented manufacturing model developed from existing advanced manufacturing models and enterprise information technologies under the support of cloud computing, IoT, virtualization and service-oriented technologies, and advanced computing technologies. It aims to realize the full sharing and circulation, high utilization, and on-demand use of various manufacturing resources and capabilities by providing safe and reliable, high quality, cheap and on-demand used manufacturing services for the whole lifecycle of manufacturing. With considering the complex characters of cloud manufacturing, we construct Cloud manufacturing resource scheduling system architecture to schedule service task and allocate manufacturing resource, which includes user requirements, task plan, global task scheduling, service collaboration allocation, virtualization and cloud manufacturing resource. Then, we propose a more comprehensive t manufacturing resource model based on auctions theory to satisfy different users' request, and then the greedy method is used to search the optimal bid in the bid set.

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