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Dynamic scheduling model of computing resource based on MAS cooperation mechanism

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Allocation of grid resources aims at improving resource utility and grid application performance. Currently, the algorithms proposed for this purpose do not fit well the autonomic, dynamic, distributive and heterogeneous features of the grid environment. According to MAS (multi-agent system) cooperation mechanism and market bidding game rules, a model of allocating allocation of grid resources based on market economy is introduced to reveal the relationship between supply and demand. This model can make good use of the studying and negotiating ability of consumers' agent and takes full consideration of the consumer's behavior, thus rendering the application and allocation of resource of the consumers rational and valid. In the meantime, the utility function of consumer is given; the existence and the uniqueness of Nash equilibrium point in the resource allocation game and the Nash equilibrium solution are discussed. A dynamic game algorithm of allocating grid resources is designed. Experimental results demonstrate that this algorithm diminishes effectively the unnecessary latency, improves significantly the smoothness of response time, the ratio of throughput and resource utility, thus rendering the supply and demand of the whole grid resource reasonable and the overall grid load balanceable.

multi-agent system (MAS), resource scheduling model, evolutionary game, cooperation mechanism, utility function

1 Introduction

With the rapid development of Internet, the grid computation that makes use of a large quantity of resources on Internet will become the only way to solve large-scale and complicated problems. To realize high-effective grid computation, many complicated problems must be dealt with, among which the problem of how to allocate resources is crucial for both the research and application of grid. High-effective resource allocation schemes and algorithms can fully utilize the treatment ability of grid system to improve the performance application and to make good use of grid resources. A grid resource is composed of computing and storing resources which are geographically distributed, affiliated to different organizations, dynamic and heterogeneous. The target of allocating grid resources is to harmonize the share of resources, that

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is, to allocate resources rationally between every individual of grid resource group and its job targets, so that individuals can use the resources more rationally and furthermore attain individual target and/or group target at a high level[1]. Therefore one of the basic missions of grid is to distribute different calculations in a rational way to the corresponding resource node and complete them by using parameters such as state of resource node and network communication performance. Since under the grid environment, resources are heterogeneous, autonomous and dynamic, allocation of resources under the grid environment is much more complicated than under the traditional environment. With the development of grid technology, and with the resources functioning as server, there appears the grid standard based on service[2], which in a way unifies the way of presentation of sources and simplifies the interface of the mission allocation, but resources under grid environment remain autonomous and dynamic. Because the agreements on which the grid depends are multilayered, the responding time of grid mission is not decreased but increased instead[3]. As a result, how to allocate and improve the ratio of throughput of the grid poses a difficult problem under the long delay, high dynamic and high automatic grid environment. What is more, a large portion of resources are not free in reality. Therefore, in order to attract the owners of sources to participate in the grid, their benefit should be guaranteed. When dealing with the changing resource relationship between supply and demand, the price of grid resources also becomes more and more important. Therefore, the problem as to how to support the share and cooperation of dynamic resources has become a burning problem demanding prompt solution under a heterogeneous, dynamic, autonomous and distributive computing environment.

Conventional research and evaluation of the performance of resource allocation started with such aspects of engineering technologies as utility ratio of resources, equity of consumers and so on, laying emphasis on improving one or several performance indexes, but without considering the non-cooperative consumers' behaviors that exist objectively[3−5]. Because there are dynamic and complicated consumer behaviors under grid environment, fundamentally speaking, these resource-allocating technologies have high technological indexes and fail to give reasonable explanation of the behaviors of the consumers. In a grid free of restriction, nobody will observe agreements actively because no consumers are willing to be restrained and they may try to rush out of chains. And most nodes are willing to consume more resources of others, and are unwilling to share local resources. While every rational consumer pursues the maximization of its own interests, the efficiency of cooperative wholeness will be seriously affected. For example, due to overload of CPU, online contribution of international conference theses of the OSDI (operating systems design and implementation) in 2004 witnessed the "tragedy of the commons" of grid resources. Therefore, when studying the technologies of design and optimization of grid, it is necessary to explore and introduce new approaches and theories.

Market economy method is one of the effective methods for allocating resources, as well as a simple yet effective method to resolve resource allocation problem among selfish individuals, and to gain optimal solution or hypo-optimal solution to the problem. The introduction of multi-agent technologies enables us to realize a global catalogue service and dynamic loaded balance of resources. The mechanism of computing economy adjusts the supply and demand of grid resources, stimulates the owner of resources to take part in the grid, and urges consumers to use resources in an optimum way. Market game theory lays a solid mathematics basis for researching the problem of how to allocate grid resources.

2 Related work on resource allocation problem

Resource-allocating in distributed system is to distribute certain resources to every calculation mission submitted to the system, to assign the starting and ending time during which the resources are occupied and to accomplish all given missions as soon as possible. Resource-allocating is a process of using different algorithms to map a mission on corresponding resource to be implemented according to the property of the mission and resource. Many researches on resource allocation in the grid have already been done at home and abroad, and various allocation algorithms have been successively put forward. According to the resource-allocating strategy, these algorithms can be divided into two categories: dynamic allocation algorithms and static allocation algorithms. Dynamic allocation starts to map a mission as soon as it arrives. Static allocation collects missions and maps all of them when mapping affairs arrive. Generally speaking, the latter depends on statistic model in estimating and predicting requirements to resources (it is conservative to sudden flux). It is hard to be realized in the real-time or interactive applications where the parameters such as peak value or velocity of application flux should be known a priori. As grid resource is dynamic, heterogeneous and autonomous, in the process of allocating resources, the following two targets should be considered: 1) justice among consumers (such as resources distributed, and QoS produced by allocating resource); 2) utility ratio of resources. Comparatively speaking, dynamic allocation algorithms can easily adapt to environment; it has good performance and is flexible and usable under many different environments. Therefore, they are more suitable for grid environment.

The main allocation criterions of the grid are time, economy and other indexes such as equality, stability, and robustness. There are also allocation methods that combine allocation criterions together such as QoS (quality of service).

From the economics angle, it is good to allocate computing resources of grid in which the supply and demand is always dynamic. The distributive resource-allocating methods based on microeconomics theory are suitable to solve the problem of resource management of grid[4]. They can also accomplish optimization of such targets as QoS, Pareto optimum, justice, and at last get fine results[5−7]. Firstly, market in economic activities is a mechanism to allocate resources based on distributive self-determination; that is, every participant in the market makes decision according to market price and his own preference. Resource allocation under the grid environment also needs to realize the distributed self-determination. Secondly, market mechanism reflects the dynamic change in supply and demand of resources by floating price and optimizes allocation through balancing supply and demand. Thirdly, the economics theories about market mechanisms give an accurate depiction of the efficiency of grid resource allocation.

At present, the ways of applying economic principle to grid resource allocation are mainly divided into two kinds. One kind is to manage the grid resources based on the general equilibrium: Every consumer is assumed to be reasonable (the individual tries to maximize his efficacy); the resource heterogeneity and the state of supply and demand are reflected by price and floating price. Each participator adjusts himself by price so that the entire grid system works in cooperation. This kind of methods can realize the effective allocation by balancing the supply and demand. The other kind is to manage the grid resources based on the Nash equilibrium, putting particular emphasis on the analysis of the effect and interaction produced by the behaviors of many reasonable beneficial principles. During the analysis, personal optimum choice is the function chosen by others, resource allocation is viewed as a game problem, and the optimization scheme of resource allocation is achieved by finding the solution of Nash equilibrium. Some representative learning viewpoints and methods are as follows. Refs. [2, 3] adopted centralized price adjustment method. But it is hard to ensure that it is the optimum distributed decision of resource allocation because resource price is designated in advance according to resource significance in resource-allocating experiment based on economic principles[4]. Ref. [5] put forward the distributed price adjustment WALRAS algorithm and discussed the conditions under which the algorithm works. Ref. [6] made a comparison between the performance of centralized price adjustment algorithm and the performance of distributed price adjustment WALRAS algorithm. Ref. [7] advanced the distributed-centralized price adjustment algorithm by combining the advantages of centralized price adjustment algorithm and the strongpoint of distributed price adjustment WALRAS algorithm. Bunya, Abramson et al.[8−12] discussed various representative grid resource management principles based on economy, such as auction model, multi-merchandise exchange model, contract model, negotiated price model; developed the service-centered and extensible grid system structure GRACE (grid architecture for computational economy) based on economic theories, presented methods for realizing existing grid technologies, introduced merchandise exchange model and auction model of resource allocation, and addressed the applications of merchandise economic model for resource management and allocation in the computing grid and the data grid. Ref. [13] brought forward a pricing algorithm of grid resource based on commodity market by using micro-economics theories. The algorithm can make the curve of supply and demand converge rapidly and reach price equilibrium very quickly. Ref. [14] brought forward a resource allocation method based on market mechanism with general equilibrium theory as the basis, which is a distributive method for adjusting the price of resources. Wolski[15] studied the efficiency of resource allocation of the commodity market model and the auction model from the angle of computing economy. Chun et al.[16] adopted auction-biding model to sell or/and buy resources in the market competition of resource exchanges, to match resources demanded and resources available, and to maximize the efficacy of resource aggregation. Feldman et al.[17] adopted the best-response algorithm to gain high efficacies on the supposition that consumers describe their preference to resource in advance. Nash[18] assumed an agent of grid resources who uses economic model to flexibly choose resources. Unfortunately, these methods are idealized under many situations because only the relationship between resources and consumers is considered, while the interactions among the consumers are ignored. Even though the equilibrium price of resource decided in this way can reach the Pareto optimum, the price can hardly satisfy the need of the practical grid environment. Kwok[19] put forward a game model of grid with layers, which takes into account the effect of selfish behavior of resources on the implementation performance of the whole grid, but ignores the selfish behaviors of consumers. Bredin[20] studied the game problem where many grid consumers with serial mission compete for the same resources, and put forward a resource-allocating strategy. His strategy optimizes implementation time of task with budget as limit. Refs. [21, 22] put forward another resource-allocating strategy under the assumption that the auction based on the Nash equilibrium may divide the cost of optimizing consumer. However, their strategy is based on the past loads information of CPU, without considering the future change of the resource loads, and therefore can neither find the rational resource price, nor optimize the resource allocation effectively. Ref. [23] put forward a multi-agent system, Spawn, to support the implementation of parallel mission, in which the agent must accomplish the computing mission in the given budget. The key of Spawn is how to distribute funds to different sub-missions, namely the control of parallel computing. Ref. [24] proposed a D'Agent system, whose key is to reach internal stability of system and realize the balance of resource allocation among consumers by limiting the requirements of greedy consumers.

The aforementioned researches mainly studied such problems as frame structure of grid resources, pricing strategy, business algorithm using economic principles, but they fail to analyze the characteristics of grid resources and the relevant market models, especially failed to give due consideration to the situation where consumers passively gain the resources (this allocation is usually implemented by concentrating computation). When competing for the limited grid resources, the unreasonable deviating behaviors of consumers make the process of allocation resources more complicated. The above problems can be solved by enabling the reasonable participators not to deviate from their own interests according to market economy theories[25]. At the same time, game method can decentralize resource allocation, which is a concentrative process of finding the solution. The optimization process of avaricious consumers obeys identical optimum resource allocation; that is, the optimal fair resource allocation can be realized using the distributive algorithm, and distributing solution of resource cooperation can be found using MAS (multi-agents system)[26]. The aim of this paper is to normalize the avaricious behaviors of consumers in resource allocation by the MAS market game mechanism; and to set up an optimal distributed resource allocation mechanism on the basis of Nash equilibrium theory. The mechanism can not only fully utilize consumers' computing ability but also sufficiently consider the behaviors of consumers. Under this mechanism, application and allocation of resources of consumers will be made more rational and valid.

3 The optimization model of resource allocation based on MAS cooperation

A grid system is composed of many distributed automatic resource regions. Every resource region is generally within the local area network (LAN) of the same organization, and is linked together by the wide area network (WAN). Every resource region contains some kinds of resources, such as computing resource, and storing resource. In a resource region, there are also a few grid applications that need corresponding resources. Therefore, during a certain period of time, some special resource regions can provide unnecessary resources to the outer by the grid, or request some resources from the outer by the grid. Every resource region is autonomous; that is, the use of resources in the current situation is determined by its need. From the angle of the entire system, the system is distributive and self-deciding.

According to economy computing theory, the pricing scheme of resources based on the supply and demand can produce different levels of service. When the resources are overburdened, only those consumers who can afford higher price can use them, and the charge for consumers' use will encourage consumers to acquire resources in a more reasonable way[27]. We are in need of a dynamic pricing mechanism of resources, under which the price of grid resources can dynamically reflect the working condition of grid and consumer's urgency degree (preference) of needing grid resources, thereby avoiding idleness or overburden of resource effectively.

The computing economy mechanism provides methods of describing system state and balancing loads. Through adjusting economic lever to appraise resources, these methods can accomplish the purpose of allocating resources impartially and effectively and at the same time optimize the targets of both resources and consumers, thereby matching resource supply with demand. Driven by the QoS of consumers, these methods can manage and meet the requirements of providers and consumers of the grid service well. The competitive economic model provides the share/allocation of resource in grid with algorithms and strategies.

3.1 MAS resource allocation strategy

In the open and dynamic environment of computing grid, a rational agent maximizes its own interests through representing consumer's will. Resource allocation is also an important problem in multi-agent system (MAS). In recent years, competitive bidding, as a rapid and effective method of resource allocation, becomes the highlight in MAS research[7,11,18,23−28]. In a self-adjustable resource allocation model, the agent that has the ability of economy reasoning and evolution study, can gradually amend its strategy using enlightening, adaptable and consulting strategy, and through machine study (such as the Windrows-Hoff "delta" studying algorithm) to stabilize the price in the entire system. Just owing to its advantage in computing and memory, agent most fits to replace man in making prices[28].

The supply and use of grid resources are realized by the way of market mechanism. The market participators are divided into two kinds: the mission agent (the resource buyer) and resource agent (the resource seller). Both try to maximize their own interests. Hence, in the frame of the computing grid, two kinds of agent are structured. One is resource provider agent (resource agent) who is responsible for the management of grid resource, and by which the occupants of grid resources make prices and allocate resources. The other is consumer agent (mission agent) who is responsible for the computing missions of consumers, and by which the consumers of grid resources distribute the missions to be completed to suitable resources. And the two kinds of agents negotiate about resource prices and corresponding resource amounts and adjust price according to the supply and demand in the resource market so that the balance of supply and demand of resources is reached. This allocation is accomplished through satisfying consumers' QoS, aiming to maximize the efficacy sum (satisfaction) of the entire consumers, and to keep balance of global loads.

Resource-allocating frame based on agents is divided into three layers: resource layer, MAS layer (computing resource market) and consumer layer from the bottom to the top. Resource layer consists of a lot of computing resources that construct an autonomous computing system. In MAS layer, every autonomous computing system corresponds to a resource agent, which is responsible for allocating and managing all computing resources in the autonomous computing system. According to different application fields, the characteristics of application loads and consumers' needs, the applications of computing grid can be divided into several categories. Every application category corresponds with one or more application agents. Every application agent buys computing resources from a special group of resource agents according to the features of application and the market price of resources, uses the computing resources under certain regulations of task allocation, and thereby provides computing serves guaranteed by QoS for the category application.

Both the provider and the consumer of service expect the maximization in grid. Free market economy can manage and satisfy the conflicting requests of several million agents, so it can be looked upon as the distributive autonomous principle. Game theory in micro-economics is introduced into grid resource administration. The mechanism of computing economy is used to adjust the supply and demand of grid resources, to stimulate the owner of resource to participate in the grid, to gain maximal profit, and to urge the consumers to use resources more reasonably especially when resources are scarce. The definition of game covers the price negotiation of resource allocation. During the exchange of grid resources, the bidding mechanism in the game will optimize the target explored by the participator.

Bidding method in a game is very easy; it can distribute resources reasonably within a short time and gain the optimal solution or hypo-optimal solution in the system. There are many standards for estimating the function of bidding method. The following several aspects will be emphatically considered[29,30].

(1) Efficacy. The efficacy is the primary problem in bidding. With respect to the bidding result, the buyer efficacy is the result of his evaluation value minus the transaction price (if the deal fails, the efficacy is zero); the seller efficacy is the result of the transaction price minus goods cost. Every agent tries to realize its efficacy maximization. However, the entire system expects the maximization of efficacy sum of all agents. Therefore, from the angle of efficacy, an ideal bidding method should ensure that the sum of the efficacies is maximal.

(2) Strategy. Strategy is the second primary problem in bidding. The complication degree of agents' strategy in bidding decides the rational degree of agents and the computation spent in bidding. In bidding, every participator takes income maximum as its target (if the participators are unable to benefit from bidding, they will refuse to take part in bidding). The major indexes for judging agents' strategy in bidding are as follows: (a) The existence of optimal strategy, that is, there should be an optimal strategy no matter how other agents behave. If not, there should be the Bayes optimal strategy, i.e. there should be an optimal strategy in the sense of probability. (b) The complication degree of time of strategy. (c) Satisfaction of the stimulation compatibility, i.e. the optimal tactic of agent is to call out its true price. In bidding, there exists a simple optimal tactic satisfying the stimulation compatibility. The bidding makes the least rational demands on agent. (d) Independent rationality, i.e. the efficacy of every

rational agent can be ensured to be not negative. From the strategy angle, an ideal bidding method should have the least requirements on the agent's rationality and computing ability and can satisfy stimulation compatibility best.

(3) Efficiency. Bidding efficiency decides whether the resource can be allocated rapidly. Bidding efficiency can be weighed by indexes, such as complication degree of time and times of bidding in entire bidding.

3.2 The model of cooperation and allocation by MAS

In a grid there are N non-cooperated consumers using grid resource by bidding and willing to buy grid resources to finish assignment (a list of various kinds of tasks). The implementation time of assignment is the sum of implementation time of all tasks.

Definition 1. The non-coordinated game model of resource allocation is built up as a three-member group $G = (N, S_i, S_i)$, where

1) N is the non-coordinated consumer (mission agent) set. $N = \{J_1, J_2, \ldots, J_n\}$. Consumer (mission agent) J_i contains JN_i submission (list). The jth submission of mission agent J_i is $O_{i,j}$. $J_i = \{O_{i,1}, O_{i,2}, \ldots, O_{i,JN_i}\}$.

2) S_i is the resource set of consumers (mission agents) J_i. Suppose that the set of all resources facing mission agent set N is M. Then $M = \{f_1, f_2, \ldots, f_m\}$. There are m resources such that $S_i \subset M$. Thereby $M = S = S_1 \times S_2 \times \ldots \times S_n$.

3) The income function of agent J_i is U_i. There are the following suppositions: (a) $pt_{i,j}(f_k)$ is the time taken by submission $O_{i,j}$ of agent J_i to use resource f_k, where $f_k \in S_n$. (b) $tt_{i,j}(f_k, f_{k-1})$ is the transmission time of the mission agent J_i in two resources. (c) $st_{i,j}(f_k)$ is the beginning time when submission $O_{i,j}$ of mission agent J_i occupies resource f_k.

According to the above definitions, the income function U_i of agent J_i can be expressed as

$$U_i(s) = \frac{1}{st_{i,JN_i}(f_k) + pt_{i,JN_i}(f_k)}, \tag{1}$$

where $s = (s_1, \ldots, s_i, \ldots, s_n)$, $s_k \in S_n$, limited by

$$st_{i,j}(f_k) - tt_{i,j}(f_k, f_{k-1})$$
$$\geqslant st_{i,j-1}(f_{k-1}) + pt_{i,j-1}(f_{k-1}), \tag{2}$$
$$st_{i,j}(f_k) \geqslant st_{x,y}(f_k), \tag{3}$$

with $i, x = 1, \ldots, n$; $j = 1, \ldots, JN_i$; $y = 1, \ldots, JN_x$.

According to the above-mentioned non-coordinated game model, the resource-allocating problem is transformed into the problem of how to find the solution of Nash equilibrium point based on corresponding limitation, namely the following formula should be satisfied:

$$U_i(s_i^*, s_{-i}^*) \geqslant U_i(s_i, s_{-i}^*), \tag{4}$$

where $i = 1, \ldots, n$.

Definition 2. The bidding price set of a consumer is $S = \{s_i | s_i = (p_i, q_l), i = 1, \ldots, N|\}$, where p_i is the price the consumers i are willing to provide for their expected resources, q_1 is the quantity of resources to be used by consumer i. Furthermore the consumer's bidding satisfies $p_1 \geqslant p_2 \geqslant \ldots \geqslant p_N$. The quantity of grid resources applied in the bidding set satisfies

$$\sum_{j=1}^{r} q_j \leqslant Q < \sum_{j=1}^{r+1} q_j. \tag{5}$$

Then we define the price p_y of consumers y as the price of grid resource.

In Definition 2, there are two other cases of the number of resources applied: (a) $\sum_{j=1}^{N} q_j \leqslant Q$; that is, the present grid situation can satisfy all requirements for resources. The price of resources is $p_y = 0$. (b) $q_1 > Q$; that is, the resource request of the consumer who gives the highest bidding price cannot be satisfied. In this case, we can make prices by starting with $\sum_{j=2}^{r} q_j \leqslant Q < \sum_{j=2}^{r+1} q_j$. If $q_2 > Q$, then, by analogy, the resources are allocated to the consumer who satisfies Definition 2.

Definition 3. In the model of Definition 1, there are N grid consumers competing limited computing resources. There are K kinds of resources, and every consumer can only accomplish a mission on a special kind of resources. The following parameters are defined:

$\{q_k^i\}_{k=1}^{K}$: Mission list of grid consumer. The mission must be carried out in the sequence (that is, there is data dependence between the mission). q_k^i is the size of the kth type mission of the ith grid consumer.

c_k^i : The ability of the ith grid consumer to choose resources to accomplish the type k mission.

b_k^i : The bidding price per second of the type k resources used by the ith grid consumer.

A_k : Grid consumer set.

B_k : The bidding price sum of consumers for the type k resources received from A_k.

B_k^{-i} : The set of bidding prices of all grid consumers except the ith grid consumer for the kth type grid resource, $B_k^{-i} = \sum_{j\in A_k, j\neq i} b_k^i$.

Because the ratio of the resources allocated to the ith grid consumer to the whole resources is equal to the ratio of bidding prices of the grid consumer i to the bidding price sum of all consumers, the quantity of the resources allocated to the ith grid consumer are counted by

$$r_k^i = c_k^i\left(\frac{b_k^i}{B_k^i}\right) = c_k^i\left(\frac{b_k^i}{b_k^i + B_k^{-i}}\right). \qquad (6)$$

Suppose that the grid consumer has consummate information on various resource prices; that is, B_k^{-i} is known. Since b_k^i does not depend on B_k^{-i} , and $(B_k^{-i} + b_k^i)$ can replace B_k, the time the ith grid consumer takes to accomplish the type k mission is

$$t_k^i = \frac{q_k^i}{r_k^i} = \frac{q_k^i(b_k^i + B_k^{-i})}{c_k^i b_k^i}. \qquad (7)$$

And, the cost is

$$e_k^i = t_k^i \cdot b_k^i = \frac{q_k^i(b_k^i + B_k^{-i})}{c_k^i}. \qquad (8)$$

Figure 1 gives the system frame of transaction model of grid resources based on MAS. The transaction of resources proceeds as follows:

(a) Resource agent and mission agent are registered in the market.

(b) Mission agent deposits grid currency in grid bank.

(c) Resource agent announces resource price information to the market; mission agent can observe the price information.

(d) Mission agent signs a contract with the resource agent; the contract overseer verifies and manages their bank deposits.

(e) If a transaction is successful, the bank deposits of mission agent are allocated to the account of resource agent.

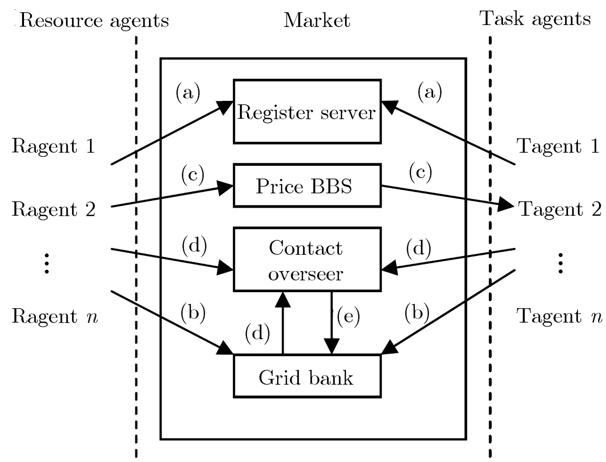

Figure 1 System frame of transaction model of grid resources based on MAS.

3.3 The analysis and solution of model

The algorithm based on microeconomics can allocate grid resources and grid mission agent. Grid resource agent provides consumers with some resources during a certain time and charges for it. Consumers of computing grid pay for the use of resources to an entity that "abstractly owns" the entire grid, and set up a deposit account for every request agent of resources. Suppositional currency flows at a fixed rate into the deposit accounts. Request agent of resources sets up a consumption account for every mission agent, and then the consumers can continually adjust the speed rate of suppositional currency flowing from the deposit account of request agent of resources into the consumption accounts of each mission according to the number of current missions and characteristics of each grid mission (such as implementation time and urgency degree). Grid resource agent chooses the mission agent whose bidding price is the highest to carry out it, and collects fees for that period of time from the consumption account of corresponding mission agent.

When the completion of the mission is submitted, grid mission agent is in a wait state at the beginning which indicates that grid resources have not been distributed to a grid mission agent. When the grid mission agent acquires resources requested and uses them to carry out the mission, the agent becomes active. At any moment before the completion state, it is possible for a grid mission agent to stop carrying out the mission and then to fall into the failure state. A failure may be caused by diversified causes, such as stops caused by people, the mistake of request form, problems of management system of bottom resources, and refusal to resource visit. When all calculations in the grid mission agent are normally finished, all resources will be released, and then grid mission agent is in the completion state.

These grid mission agents may transfer states at any moment. Every resource node must be auctioned for one time after a period of time in order to decide which grid mission agent can use computing resources and how long it uses them in the next period of time. Every grid mission agent who bids will choose a proper period of time and the charge for it. According to regulations on top sealed auction, the grid mission agent who pays the highest price will bid successfully. And the ultimate price has to be shown on the announcement board after bidding. Grid mission agent can work out various bidding strategies at its own preferences, such as low cost strategy, the minimum responding time strategy, maximal price strategy[31,32]. In this way, the heterogeneous needs of grid consumers can be satisfied by economics method.

By the pricing mechanism above-mentioned, resource application of grid can be satisfied, and the consumers can gain the right to use resources by bidding. To make use of the resources, the consumer must have the ability to pay m_i and the minimum quantity demand q_i. Then maximal resource price charged by consumers is $p_{i\_\max} = m_{i\_\max}/q_i$, and consumers cannot afford the price higher than this.

The price of resources is not decided by a single consumer, but by many consumers (game decision). Thus game models of resource-allocating should be studied by addressing the following problems: Firstly, the price should be priced impartially according to game theory; secondly, the resource price cannot be raised too high or too low by hostile competition; thirdly, the resource price can properly reflect the rational needs of a majority of consumers participating in bidding.

In the game of allocating resources, consumers bid for their maximal efficacy. Furthermore, the potential effect of consumers' resource occupancy on other consumers' efficacy must be taken into consideration. For instance, when a consumer transfers data, the other consumers' data transfer is affected, and then "the outside efficacy" comes into being. Therefore, bidding standard of maximal consumer efficacy is studied in the following section. When allocating resources, consumes' efficacy function is composed of two parts: (a) the income gained by consumers who use the resources. This part is mainly related to the quantity of resources gained by consumers and the resources left; (b) the necessary payout from consumers who use resources. This part is mainly related to the price and number of the resources applied by consumers.

Definition 4. In the game of allocation resources, CES efficacy function is transformed into the efficacy function of the consumer i.

$$U_i(\boldsymbol{s}) \triangleq U_i(\boldsymbol{s}_i, \boldsymbol{s}_{-i}) = (1 - r_i) \cdot q_i(Q - q_i), \tag{9}$$

where $\boldsymbol{s}$ is the vector of bidding strategy of the entire system, $\boldsymbol{s}_i$ is the bidding vector of system i, $\boldsymbol{s}_{-i}$ is the vector of other consumers except system i, $i \in N$, $U_i(\cdot)$ is the efficacy of the consumer i using the resources, r_i is the risk coefficient of consumer i, and q_i is the resources needed by consumer i.

We analyze the consumer efficacy function below: $q_i(Q - q_i)$ is the efficacy of system using q_i (quantity) resources, $(1 - r_i)$ is the probability of bidding to get resource, r_i is the risk coefficient of bidding without getting resources. If the bidding price is smaller than p_y (the resource price after the bidding), customers cannot afford to use the resources, nor gain the resources. Now the consumer efficacy now is 0. In order to enable the consumers to weigh the risk of getting no resources because of the bidding price, $y_i = \mathrm{e}^{-p/p_y}$ is used to calculate the probability of consumers gaining no resource (The consumer bids at the price p_i). As a result, $(1-r_i)$ represents the probability of consumer bidding to get the right to use resources at the price p_i. The efficacy function of the consumer i is

$$U_i(\boldsymbol{s}) \triangleq U_i(\boldsymbol{s}_i, \boldsymbol{s}_{-i}) = (1 - \mathrm{e}^{-p/p_y})q_i(Q - q_i). \tag{10}$$

The following is easy to understand: $U_i(\boldsymbol{s})$ is a continuous monotone increasing function whose value region is $[0, \infty]$, and is doubly continuous differentiable. $U_i(\cdot) = 0$. At the same time, $U_i'(\cdot) > 0$; that is, $U_i(\boldsymbol{s})$ is a continuous monotone increasing function.

Then, the definition, existence and uniqueness of Nash equilibrium point in the game of allocating resources are discussed using the efficacy functions in eq. (10).

Definition 5. In the non-coordinated game of resource allocation, $U_i(\boldsymbol{s}_i, \boldsymbol{s}_{-i})$ is the efficacy function of the consumer i. If and only if $\forall i \in N, \forall \boldsymbol{s}_i \in \boldsymbol{s}_i$, $U_i(\boldsymbol{s}_i^*, \boldsymbol{s}_{-i}^*) \leqslant U_i(\boldsymbol{s}_i, \boldsymbol{s}_{-i}^*)$, $(\boldsymbol{s}_1^*, \ldots, \boldsymbol{s}_i^*, \ldots, s_N^*)$ constitutes a Nash equilibrium point, where S_i is the space of all bidding price vectors of the consumer i.

The system reaches Nash equilibrium point accordingly. The efficacy of any bidding price vector $\boldsymbol{s}'$ deviating from Nash equilibrium point will not be larger than $\boldsymbol{s}^*(\boldsymbol{s}_1^*, \ldots, \boldsymbol{s}_N^*)$. The sufficient and necessary conditions of Nash Equilibrium point indicate that bidding price according to the vector $\boldsymbol{s}_i^*$ of resource allocation is the optimal tactic of the consumer i, and the method of finding the Nash Equilibrium point in the game of resource allocation is choosing s_i whose efficacy is maximal, namely $\max_{\boldsymbol{s}_I \in \boldsymbol{s}_I} U_i(\boldsymbol{s}_i^*, \boldsymbol{s}_{-i}^*)$.

Because the bidding targets of consumers is $\max_{\boldsymbol{s}_I \in \boldsymbol{s}_I} U_i(\boldsymbol{s}_i^*, \boldsymbol{s}_{-i}^*)$, two aspects of bidding must be considered by the consumer i: the price of resources p_i and the quantity of resources q_i. Because the maximum purchasing ability $m_{i\_\max}$ of the consumer i is fixed and $p_i q_i \leqslant m_{i\_\max}$, the price and quantity are mutually contradictory parameters in bidding.

Theorem 1. In the game problem of resource allocation, N consumers gain resources by bidding. If the efficacy function of the consumer i is defined by eq. (10), then the Nash equilibrium point of entire game system exists and is unique.

Proof. Under the condition given by Theorem 1, game strategy worked out by the consumer i can be expressed by the following optimization problems:

$$\max_{\boldsymbol{s}_i \in \boldsymbol{S}_i} U_i(\boldsymbol{s}_i^*, \boldsymbol{s}_{-i}^*), \quad \text{s.t} \quad \sum_{i \in N} p_i \cdot q_i \leqslant m_{i\_\max}. \tag{11}$$

For the above-mentioned nonlinearity optimization problem, Lagrange function can be structured as follows:

$$L_i(\boldsymbol{s}, w) = U_i(\boldsymbol{s}_i, \boldsymbol{s}_{-i}) - w\left(\sum_{i \in N} p_i \cdot q_i - m_{i\_\max}\right). \tag{12}$$

K-T condition in eq. (12) is

$$\begin{aligned} &\partial L_i(\cdot)/\partial p_i = \partial U_i(\cdot)/\partial p_i - w q_i = 0, \\ &\partial L_i(\cdot)/\partial q_i = \partial U_i(\cdot)/\partial q_i - w p_i = 0, \\ &w\left(\sum_{i \in N} p_i \cdot q_i - m_{i\_\max}\right) = 0, \quad w \leqslant 0. \end{aligned} \tag{13}$$

Set $\nabla_i(S) = \partial U_i(\cdot)/\partial p_i$, and combine it with eq. (11). Then K-T condition (eq. (13)) is written as

If $\sum_{i \in N} p_i q_i \leqslant m_{i\_\max}$, then $w = \nabla_i(S)/q_i$.

If $\sum_{i \in N} p_i q_i \leqslant m_{i\_\max}$, then $w = 0$.

Besides, because $\partial^2 U_i(\cdot)/\partial p_i^2 > 0$, $\partial^2 U_i(\cdot)/\partial p_i^2 < 0$ the Hessian matrix of efficacy function $U_i(\cdot)$ at $s_i = (p_i q_i)$ is expressed as

$$\nabla U_i^2(\cdot) = \begin{bmatrix} \dfrac{\partial^2 U_i(\cdot)}{\partial p_i^2} & \dfrac{\partial^2 U_i(\cdot)}{\partial p_i \partial p_i} \\ \dfrac{\partial^2 U_i(\cdot)}{\partial q_i \partial p_i} & \dfrac{\partial^2 U_i(\cdot)}{\partial q_i^2} \end{bmatrix}. \tag{14}$$

Evidently, $|\nabla U_i^2(\cdot)| < 0$; that is , $\nabla U_i^2(\cdot)$ is a negative definite matrix. Therefore efficacy function $U_i(\cdot)$ is a concave function. The optimization problems of Formula (11) have a unique extremely large value; that is, the Nash equilibrium point in the game exists and is unique.

Here consumers' bidding strategy will be discussed by studying the bidding price at the point of Nash equilibrium.

Theorem 2. At the Nash equilibrium point in the above-mentioned resource-allocating game, the bidding price of the consumer i can be obtained when $p_i q_i = m_{i\_\max}$.

Proof. Suppose that in the optimization problem of Formula (11), $U_i(\cdot)$ gets the maximum value and $w = 0$ when $p_i q_i \leqslant m_{i\_\max}$. Substitute w into eq. (13). Then

(a) if $\partial U_i(\cdot)/\partial p_i = 0$, then $p_i = 0$ or $Q - q_i = 0$;

(b) if $\partial U_i(\cdot)/\partial q_i = 0$, then $p_i = 0$ or $Q - 2q_i = 0$.

Substitute $p_i = 0$ into eq. (10). Then $U_i(\cdot) = 0$, $p_i \neq 0$; and, condition $Q - q_i = 0$ contradicts with $Q - 2q_i = 0$, so $p_i q_i < m_{i\_\max}$ is unable to get the maximum value.

Therefore, only if $p_i q_i = m_{i\_\max}$, does $U_i(\cdot)$ get maximum value. With it and together with eq. (13), it is not difficult to get the maximum value point (p_i^*, q_i^*), that is, the equilibrium point.

From the above discussion, it can be concluded that the bidding price of consumers reflects the urgency degree of resource needs, and the game makes the price of resources better reflect consumers' needs and current grid situation.

3.4 Resource allocation algorithm

Designing objectives of resource allocation algorithm are: 1) every consumer bids and applies for resources for his maximum efficiency; 2) by implementing resource-allocating algorithm, resources are able to gain a rational pricing, and the resource allocation of consumers is able to converge at the resource allocation result of Nash Equilibrium point.

Resource-allocating algorithm is a game of bidding. The algorithm frame is shown in Figure 1. What the consumers should do is to calculate the bidding price, make grid analysis and collect information. The module of calculating bidding price calculates the bidding price according to the present resource information, and then submits the bidding price to the resource provider according to resource-allocating algorithm. The module of grid analysis extracts and analyzes the collected information, judges the resource usage and the demand of other consumers according to the price of resources, and then resolves and preserves the resource price. The module of collecting information collects resource information (such as resource price, and allocation instruction) and information of other consumers (such as bidding information and the request resource amount).

The resource providers mainly include the module of resource pricing and the module of resource allocation. The module of resource pricing calculates the resource price according to Definition 2, and announces the resource price. The module of allocating resources judges who can gain the resources and allocates some resources. Furthermore the module of allocating resource takes resources back periodically, sends out allocation instruction, and begins a new round of bidding process.

3.4.1 Change of consumer state. Figure 2 shows three states of consumer agent: S (stable state), B (bidding state) and A (analysis state of grid). At the beginning, consumer's state is S. Consumer agent will act with some initial strategy, and simultaneously publish periodically bidding information of the system to other consumer agents in grid (even if the strategy are not adjusted, decision information of the system should be regularly published to enable new consumers to know other consumers' present state in time). When the information of grid state and other consumer agent state is collected, the consumer will judge the performance state of the grid according to the information, and enter into state A. After the analysis, if there is no jam, consumer agent will record the information for bidding and come back to state S at the same time. When the moment (which happens regularly or when the grid jam is examined) comes, the consumer will bid dynamically according to the collected information of other consumers (other consumers' bidding information) and grid situation, and then the consumer enters into state B. After a new bidding price comes into being, the state of consumer agent will return to S, and the consumer will work with newly-born action[33].

3.4.2 Algorithm. In resource-allocating algorithm based on market game mechanism, the core module of consumers is the module of computing bidding. By Theorem 2, consumers' bidding price at the Nash equilibrium point can be calculated. Substituting $q_i = m_{i\_\max}/p_i$ into eq. (10), we have

$$\begin{aligned}\frac{\partial U_i(\cdot)}{\partial p_i} &= \frac{1}{p_y}\mathrm{e}^{-p/p_y-1}\left(m_{i\_\max}Q - \frac{m_{i\_\max}}{p_i}\right) \\ &\quad + (1-\mathrm{e}^{-p/p_y})\left(\frac{2m_{i\_\max}^2}{p_i^3} - \frac{m_{i\_\max}}{p_i}Q\right) \\ &= 0, \end{aligned} \tag{15}$$

where p_y is the resource price. The resource price after last bidding can be used to guide this bidding of consumers. Evidently, by Formula (5), analytical solution of p_i is difficult to be sought out, but the approximate solutions of p_i in $[m_{i\_\max}/Q, m_{i\_\max}/q_i]$ can be obtainable. And then, by calculating the approximate solution of the quantity of resources q_i applied by consumers

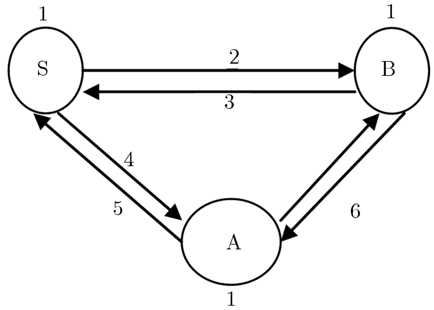

Figure 2 Change of consumer state.

whose bidding price is p_i, we get the bidding of the consumer i in this time at last.

Suppose that the resources applied by the consumer c from the provider p are R_C basic units, the budget cost is B_C. Suppose that the currently available number of resources of the provider p are P_R basic units. When allocating resource, the provider first compares resources currently available with the presupposed threshold Δ. If $P_R \geqslant \Delta$, then resources currently available are thought to be abundant, and the game pattern is adopted to allocate the resources. Otherwise, the resources current available are regarded as being insufficient, and the bidding pattern is adopted. Δ is determined by provider according to the record of the history of the resource usage.

Algorithm 1. Consumer bidding algorithm.

Input: the base price given by the resource provider, consume's maximal ability to pay, required resource amount.

Output: final transaction price.

1) The provider publishes the base price B_p of resources to consumers.

2) If $R_c \cdot B_p \leqslant B_c$, the provider is informed that "consumers are willing to accept the price", otherwise the provider is informed that "consumers refuse the price".

3) After the provider receives all consumers' responses, the number of consumers N_A who are willing to accept the current price is calculated. If $N_A > 0$, the selling price $B_p = B_p + \varepsilon$ (ε is the step length of raising the price) should be raised, and the up-to-date price of resource should be published to consumers, go to step 2). Otherwise go to step 4).

4) The provider arranges all selling prices $B_{p1}, B_{p2}, \cdots$ which the consumers willingly accept from high to low in the order $B_p^1, B_p^2, \cdots$.

5) Set $i = 1$.

6) Allocate R_c^i (R_c^i is the number of resources that the consumer applies for) basic units of resource to the consumer who accepts the price B_p^i.

7) Go to step 6) if the provider still has resources available and consumers who have accepted the sales price and are waiting for the allocation of resources, then $i = i + 1, \ldots$

8) If the consumers' demands cannot be satisfied, the provider must consult with them. If the consultation fails, the consumers quit from the bidding.

9) The practical charge of consumers is calculated according to the quantity of consumers' resources used and their highest selling price accepted. End.

The above model of bidding cooperation is defined as

$$M = \langle Ag, A, \Theta, Te, S, \mathrm{Pr\,otocol}\rangle, \qquad (16)$$

where Ag is the consulting participator agent i, j, referring to either the producer or the consumer in consultation; A is the feasible combination of actions of both sides; Θ is the combination of consulting types of object; Te is the deadline of both sides; S is the consulting strategy; Protocol is the consulting regulation abided by the participators.

The process of consultation is that any agent i bids at the moment t before the deadline. If the agent $j(i \neq j)$ does not accept the bidding price, it will give a counteroffer according to its strategy at the moment $t+1$. Then, the agent t decides whether the agent j's counteroffer is acceptable; and the agent j decides in turn. Bidding is alternately decided in this way. If the agent j accepts the bidding price of the agent i, then accept and the consultation is ended. If the agent j chooses to quit from the cooperation, then quit and consultation is over.

The resource allocation algorithm involves the realization in consumers and resource providers. The resource-allocating algorithm on consumers proceeds as follows:

Algorithm 2. The Kth implementation of the resource-allocating algorithm on the consumer i

Input: Maximal payment ability m_i of the consumer i and the minimal bandwidth demand q_i, the resource amount Q and the resource price $p^{(k-1)}$ after $(K-1)$th bidding;

Output: The bidding price $s_i = (p_i, q_i)$ of the consumer i at the Kth bidding;

```
Customer (){
    fetch (Q,p0) // Gain current resource amount and last price of resource
    calc flow (p,q) // Calculate the bidding price by Formula (15)
    submit (dstRSC,s) // Submit the bidding price to the resource provider
    }
```

The resource-allocating algorithm on resource providers goes as follows:

Algorithm 3. The Kth implementation of the resource allocation algorithm on the resource provider i.

Input: the resource amount Q and every consumer's bidding price $s = \{s_i\}_{i \in N}$.

Output: the result of resource allocation and the resource price after the Kth bidding.

```
Provider {
    Collect(s)              // collect the bidding price of every consumer
    Calc_rsrc_price(Q,P)    // calculate the resource price according to Definition 2
    Broadcast (P)           // announce the current price
    For i - 1 to N
      If p[i] > P then allocation (p[i],q[i])
                            // allocate resources to the consumers whose bidding price is higher than P.
    }
```

In the above-mentioned pattern, the process of allocating resource is in fact a bidding game process between consumers and providers, which aims at deciding the proper occupancy amounts of resources for the consumers and the proper selling price for resource providers to make Pareto optimum under Nash Equilibrium, thus realizing win-win.

4 Performance analysis

(1) Model rationality. Whether a model is rational is mainly reflected by two aspects: (a) The model assumes that different provider agents of the same resources bid the same price in the market. The main aim of the study is to prevent intentional cheating behavior possibly existing in resource transactions under the grid environment. The simplest way of cheating is that providers with low reliable resources always bid the same price as that bidden by the providers with high reliable resources so as to make consumer agents unable to make differentiation. Otherwise, consumer agent can distinguish the reliability of resource provided according to the price of resource provider agent. Therefore, the price bidden by all resource provider agents to the same resource is assumed to be identical although the resource provided by different resource provider agents is differently reliable. (b) The model abstracts two sides of resource transaction. The participators in the market are abstracted into two kinds of people or two peoples: the consumer agent and resource provider agent. All agent strategies of mission are the same. All agent strategies of resources are the same, too. Under the market environment, competition among mission agencies is likely to lead to a similar behavior of all mission agents and the competition among resource agents is likely to lead to a similar strategy of all resource agents. Therefore, the premise that model should be of some rationality conforms to the characteristics of buyers and sellers in the market economy with free competition.

(2) Full resource allocation. In resource allocation, although we desire to maximize the utility ratio of resources, potential troubles to the entire systematic operation might occur when all resources are exhausted. For instance, the complete allocation of network bandwidth resources may possibly bring about congestion or even paralysis of the network; the complete use of computing resources such as processors may possibly bring about overload or even breakdown of the whole system. As a result, the resource provider cannot respond to newly-arriving resource requirements in time. Therefore Definition 2 should be rewritten as

$$\sum_{j=2}^{r} q_j \leqslant Q' < \sum_{j=2}^{r+1} q_j, \tag{17}$$

where $Q^1 = Q - \varepsilon$, $\varepsilon > 0$ or $Q^1 = a \cdot Q$, $0 < a < 1$.

The refusal of consumers' application for resources is shown in the following two aspects: A consumer who bids at a price lower than resource price cannot gain resources; the resource application of newly-arriving consumers, owning to the missing of this resource bidding, has to wait for the next bidding. Both aspects will reduce admitting rate of the entire system. Therefore, formula (17) can be invoked to reserve part of resources to the traditional resource service style (such as FIFS style). Then consumers who are refused by the bidding and the newly-arriving consumers who miss this resource bidding can use non-guaranteed resource service whose quantity is $(1 - a)Q$.

(3) Bidding period (time of resource occupancy). After bidding, how long will the successful bidding consumer can own resource? In other words, how long is the period between two biddings? This is a crucial problem in the game of resource allocation. If the bidding period is too long, the consumers who get resources successfully will own resources for a long time, the newly arriving consumers cannot participate in bidding immediately, and consumers who did not gain resources cannot adjust bidding strategy in time. If the period of bidding is too short, the consumers who get resources successfully cannot fully utilize resources before releasing resource and cannot participate in a new round of bidding. What is more, the quantities of resources gained are probably different, and the resources allocated to the consumer may be "jolty". So the time range of resource allocation is very important. Generally, this time range can be worked out using a leading resource management scheme.

(4) Consumers' buying ability. In the above research, consumers' maximal buying ability is $m_{i\_\max} = p_i, q_i$, but this is not a strict definition because it ignores the time-of-use. Denote by p_i the resource price, by q_i the resource quantity; and by

$m_{i\_\max}$ the price of the resource quantity q_i. Then as far as the bidding period is concerned, the maximal buying ability of consumers is expressed as

$$m_{i\_\max} = \int_0^T p_i(t) \cdot q_i dt, \tag{18}$$

where T is a bidding period, and $p_i(t)$ is the resource price at the moment t. The resource price is unchanged after bidding; therefore $p_i(t) = p_i$ and then $m_{i\_\max} = p_i q_i \int_0^T dt = p_i q_i T$. At last, we have

$$p_i q_i = m_{i\_\max}/T. \tag{19}$$

If the bidding period and consumers' buying ability are known in a game system, bidding can be worked out using eq. (19).

(5) Algorithm convergence. When there is change in supply and demand, convergence velocity adjusting price to the equilibrium price is an important measure in appraising bidding algorithm, i.e. the number of bidding cycles in one process of bidding. In order to conveniently compare convergence velocities between the algorithm in this paper and WALRAS algorithm, we suppose that the bidding price process of them are synchronous; that is, resource provider and consumer are synchronous in WALRAS algorithm. But resource agents of the algorithm in this paper synchronously calculate extra needs function and submit it to the corresponding consumer agent who calculates the new equilibrium price to form the systematic price vector. This process is repeated until the change of price vector is smaller than appointed threshold. In WALRAS algorithm, a nonlinear equation must be solved when every bidding calculates the equilibrium price every time in WALRAS, while in the algorithm in this paper, the system of n_k-order nonlinear equations must be solved by consumer agent. But, in the topological structure of grid shown in Figure 1, the expense on the network transmission within Wide Area Network is a major part of the expense in a bidding process.

Therefore, performance indexes of convergence velocity of algorithm are: 1) the number of cycles of price adjustment before balance is reached, namely the times resource providers and consumers regularly carry out corresponding algorithm in one price adjustment; 2) square root of the sum of squares of extra need of entire resources, which directly reflects the convergence velocity in pricing.

5 Experimental analysis

To verify the validity of the method in the paper, the above dynamic computing model of resource allocation is realized by using NS2 Simulation System. The simulation topology is shown as Figure 1. In the experiment environment (Figure 1), the quantity of resources is set at $Q = 3.0$ (in the experiment the quantity of resources is considered to have no difference; that is, the ID and the unit of resource are ignored), the number of consumers is 7. The distribution of the consumers' lowest resource needs (such as bandwidth) q_{0-6} is tabulated in Table 1, and the distribution of consumer's buying ability $m_{i\_\max}$ is tabulated in Table 2, where the initial price of resources is set at 1.2.

Table 1 The distribution of minimal bandwidth needs of the consumer

	q_0	q_1	q_2	q_3	q_4	q_5	q_6
Bandwidth	0.105	0.075	0.067	0.035	0.187	0.267	0.207

Table 2 The distribution of payment ability of the consumer

	$m_{\_\max}$	$m_{1\_\max}$	$M_{2\_\max}$	$M_{3\_\max}$	$M_{4\_\max}$	$M_{5\_\max}$	$M_{6\_\max}$
Pay	0.135	0.118	0.1264	0.127	0.132	0.112	0.122

The simulation result shown in Figure 3 demonstrates the relationship between the bidding price and actual resource price. It can be seen that consumer's bidding price fluctuates around the resource price, and when the resource price is settled, the resources used by the consumers are also determined by their maximal payment ability. Therefore, the consumers can charge a price near the actual one, thus avoiding effectively vicious bidding behaviors of the consumers, and moreover, the quantity of resources gained by the consumers is higher than their minimum QoS needs[27].

Figure 4 depicts the situation where the supply-demand relation has impact on the selling price of resources when the supply-demand factor is set at $\delta = 0.6$ in the game pattern. When $\delta < 0.6$, the selling price of resources changes a little, otherwise it changes sharply. Therefore the effect of supply-demand relations on the selling price of resource is very sensitive in the game pattern.

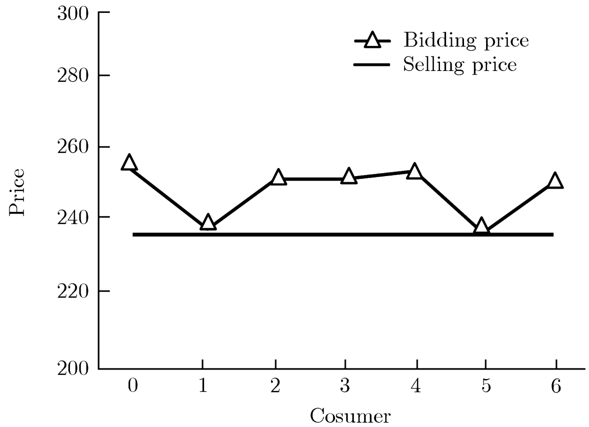

Figure 3 The bidding price of the consumer.

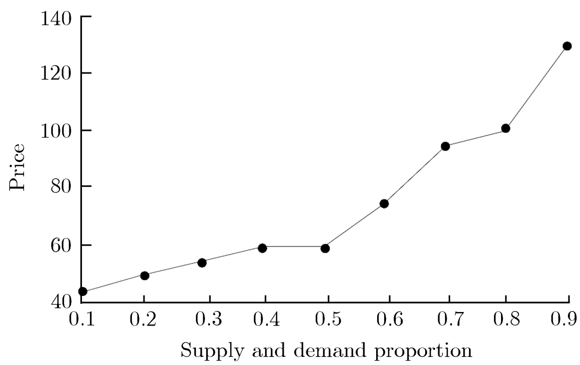

Figure 4 The supply-demand relation and the selling price.

Figure 5 illustrates the effect of supply-demand relations on the provider and the consumer efficacy. Though the selling price of resources tends to rise as δ rises, the efficacy of the consumers and providers has no sharp changes. Therefore, in the game pattern, the good efficacy of both sides can be achieved, and the goal of win-win is achieved.

We compare load balance between our bidding algorithm and the algorithm of cost preference of commodity market model in ref. [8]. The experimental results tabulated in Table 3 indicate that the bidding algorithm outperforms the pricing algorithm in loads balance. The reason is that both cooperation sides adjust the cooperation strategy after each cooperation completion of task in our bidding algorithm. While resources are insufficiently used, the resource provider adjusts strategy (e.g. reducing the transaction price) in the subsequent cooperation to win resources. In this way of competition, resource loads in the system are balanced. In the pricing algorithm, the resource price is stable within a period of time, and resource agents all choose the cheapest resources to carry out resource tasks; thus, the load of a few resources are too heavy to be used.

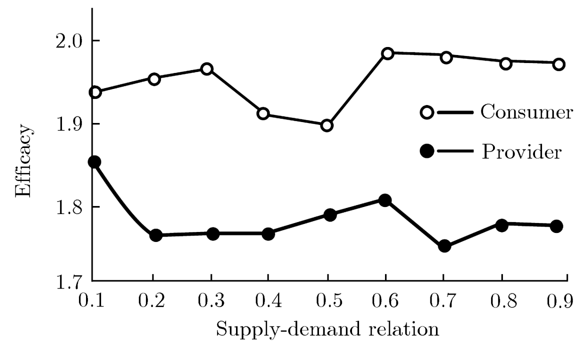

Figure 5 The supply-demand relation and the efficacy of the consumer/provider.

Table 3 Comparison of loads balance between the bidding algorithms and the pricing algorithm

Resource number	1	2	3	4	5	6	7	8	9	10
Bidding	2	2	0	2	3	2	3	1	4	1
Pricing	0	0	4	0	5	0	5	1	5	0

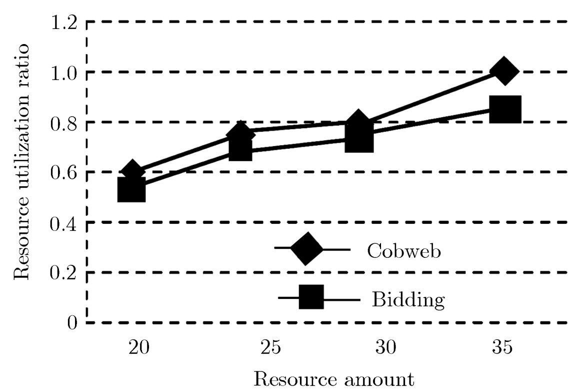

Figure 6 Quantity contrast of resource utility ratio.

The bidding algorithm and the cobweb model are finally simulated in PC[28]. Every resource provider may serve many consumers, and every consumer has different needs. The total number of resources required by consumers is 32 standard missions. Resource utility ratio of the bidding algorithms and the cobweb algorithm are compared in Figure 6. If the number of resource providers is less than 32 (e.g. the demand exceeds the supply), the resource providers satisfy the needs of part of consumers, and the resource utility ratio of bidding model is higher than that of the cobweb model. If the supply exceeds the demand, the cobweb model iterates to reach the equilibrium point, and satisfies the needs of part consumers. Now the bidding model can satisfy the needs of all consumers. Therefore, the resource utility ratio of the bidding model is higher than that of the cobweb model.

Figure 7 shows the iteration times the cobweb model and the bidding model iterate to reach the equilibrium price. The equilibrium price of the bidding price model is 6, while the number of the total resource supply is 35. The initial bidding of resources can be changed in cobweb model. The further the initial bidding is away from the equilibrium price, the more the iteration times will be. The bidding price model adjusts every iteration according to the differences between the supply and the demand: The greater the difference between the supply and the demand is, the wider the range of price adjustment is, and the more quickly the balance state is reached.

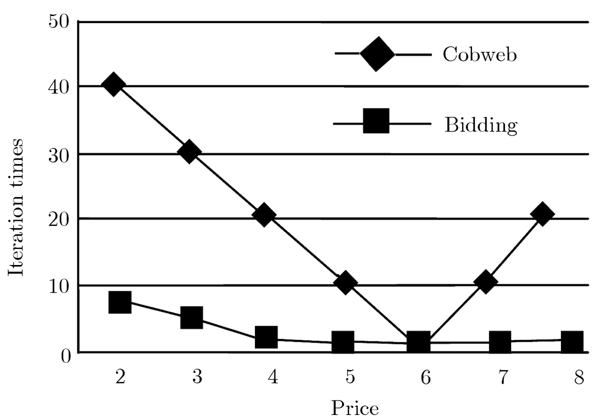

Figure 7 The iteration times.

6 Conclusions and outlook

At present, under the major grid environment, the allocation of resources is accomplished by traditional methods; that is, according to the cost function established, the place where the mission is carried out is decided by the allocation components (e.g. Clobus, Legion, and Condor). These cost functions get centralized on the system, but are not driven by the service quality QoS of the consumers. The use of the economic model to allocate resource has a lot of special advantages. For instances, dynamic allocation of resources improves the systematic self-adaptability, and the adoption of economy principle can encourage the resource occupants to contribute their disengaged resources and to profit out of them, which is helpful for building large-scale grid systems and so on.

A computing grid resource allocation method based on the market mechanism and the multi-agents cooperation strategy is put forward in this paper. The method depicts the heterogeneous needs of consumers by efficacy functions, and allocates resources according to the market mechanism and the general equilibrium theory. The main contributions of the paper are as follows: a computing grid resource-allocating frame based on multi-agents is built; a market game model and a performance model for dynamically allocating resources are founded; it is proved that the resource allocation is optimum under the equilibrium state; an iteration algorithm of resource-allocating grid is designed to solve the cooperation allocation problem of the grid resources. Simulation experiment indicates that the algorithm can regulate effectively the bidding of grid resource (applied by consumers), avoiding ill-intentional bidding behavior; the simulation experiment can realize resource rational allocation, dynamic loads balance and effective share; the simulated experiment can improve system resource efficiency rates, and maximize the benefit of producers and consumers.

The method of allocating resources in this paper has advantages over such resource-allocating technologies as Globus, Legion, WebFlow, WALRAS and the cobweb model. 1) The distributed implementation of resource allocation reduces its cost, and thereby improves systematic extensible performance. 2) Based on the general equilibrium theory in economics, using the technology, the equilibrium state is proven to be the optimum state of resource allocation, raising the efficiency and realizing fairness. The distributed bidding algorithm can make actual allocation of resources near the equilibrium state. 3) Through the price fluctuation in the resource market, resource allocation can automatically adapt to the change in the resource supply and demand of resources, balance the resource loads in the sense of benefit, and finally realize the cooperative multi-resource allocation.

In our subsequent work, we plan to improve the system structure of the game model by applying it in various complicated environments, and to explore cooperative allocation strategy to make it adapt to the manifold QoS needs of different consumers (e.g. deadlines, priority, security and request). It is our hope that our allocation algorithm should be able to harmonize various requests.

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