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Knowledge-Based Scheduling Resource into Grid System by Second-Price Auctions with Best Response Dynamics

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Abstract: In recent years, grid computing systems have become popular for the resolution of large-scale complex problems in science, engineering and industry. In order that grid computing focus on scalability of high system and also on large-scale resource sharing, an effcient resource management system is crucial for the efficacy of the system. However, providing effective scheduling and resource allocation mechanisms in grid is a complex undertaking due to their scale and the fact that resource owners and consumers may have different goals, preferences and policies. This paper proposed a knowledge-based scheduler that unifies the advantages of the systems for benefiting both consumers and owners. The scheduler is able to infer for defining resource behavior and managing them in an autonomic manner using management policies and Best Response Dynamics approach. The inference ability helps to make decision about happened status accurately and maps jobs to suitable distributed resources using Second-Price Sealed Auction with common valuations. Here we present inference model for our scheduler. The approach outperforms other scheduling schemes in optimizing incentives for both consumers and providers, leading to highly successful job execution and fair profit allocation.

Key words: Inference · Utility · Grid Computing · Second-Price Sealed Auction · Best Response Dynamics · Bayesian

INTRODUCTION

With the rapid development of networking technology, grid computing [1], which enables large scale resource sharing and collaboration, has emerged as a promising distributed computing paradigm. In a grid environment, resources are dynamic, autonomous, heterogeneous and wide area distributed. Due to these unique characteristics, resource scheduling in grid systems is significantly complicated and particularly challenging.

A considerable amount of work has been devoted to tackling the problem of scheduling for grid computing. Unfortunately, the majority of the previous work [2-9] has focused on optimization with respect to systemcentric or applicationcentric performance metrics. In grid systems, resources belong to respective administrative domains and every domain has full control over usage of their own resources.

Recently a few research projects [2, 7] have taken profit into account and applied economic methods in grid resource scheduling. As viewed from economics, there are two parties in grid systems: resource provider and resource consumer. It is individual economic behavior of all the participants that accomplishes the resource scheduling. Most related research projects share the common problem that their scheduling only considers the performance objectives for resource consumers, such as shorter response time or less payment, but neglects the performance objectives for the other important party in the market. Actually, resource providers also have their expectation of benefits. Once their expectation fails to be realized, they may quit the market. To build a practical grid, it is important to guarantee every participant with enough incentive to stay and play in it.

Since Matching demand to supply is one of the key features of smart grid infrastructure, researchers have been investigating the usefulness of game theory in

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solving the task and resource allocation problems in grid computing. Using game theoretic models enables including more requirements and features into the computational optimization model for the problem. Meta heuristics can then be used for solving the game to more effectively tackle the resolution of the resulting computationally hard problem of finding equilibrium points of the resulting games.

In this paper, we propose knowledge based scheduling, with the goals of building smart grid as a knowledge system that every participant has enough incentive to stay and play in it. The scheduler isdesigned to tackle the difficulty of automatic rescheduling, self-protection, incentives, heterogeneous resource sharing, reservation and SLA in Grid computing. In order to provide the system, we need to represent mechanisms and tools that allow resource consumers and providers to express their requirements and facilitate decision-making to further their objectives. That is, they need 1) the means to express their valuations and objectives, 2) scheduling policies to translate them to resource allocations and 3) mechanisms to enforce selection and allocation of differential services and dynamic adaptation to changes in their availability at runtime.

The rest of this paper is organized as following. In section 2, we discuss related work. Section 3 describes the proposed scheduling model in detail. Section 4 gives the concluding remarks.

Related Work: Grid computing is becoming a popular way of providing high performance computing for many process intensive, scientific and business applications. Grid computing consists of large sets of diverse, geographically distributed resources that are collected into a virtual computer for high performance computation [13, 24].

In recent years, there have been efforts in developing a resource management system for scheduling computations on resources distributed across the world with varying quality of service [7]. In [28], the proposed algorithm is an analytic hierarchy process based Resource Allocation (ARA) method that estimates a value for the preference of each resource and then selects the appropriate resource based on the allocated values. The paper [24] proposes grid architecture as a collection of clusters with multiple worker nodes in each cluster. They propose a new scheduling algorithm Novel Adaptive Decentralized Job Scheduling Algorithm that applies both Divisible Load Theory and Least Cost Method and also considers the user demands. The paper [9] proposes a semantic based service discovery framework. It presents an example of the Grid Job Submission Service that written in DAML-S in order to show how service ontologies are implemented. Fatos Xhafaa and Ajith Abraham [10] propose heuristic and metaheuristic methods for scheduling in grid and also revealed the complexity of scheduling problem in Computational Grids when compared to scheduling in classical parallel and distributed systems and shows the usefulness of heuristic and metaheuristic approaches for the design of efficient Grid schedulers.

G. Sumathi *et al*. [12] propose performance factor based local scheduling algorithm for heterogeneous grid environment. The paper explains that prioritizing the subtasks in this way can improve the performance of grid resources that in turn improve the overall efficiency of the computational grid. In paper [26], a new task scheduling algorithm called RASA, considering the distribution and scalability characteristics of grid resources, is proposed. The paper [27] propose a fault tolerant technique for improving reliability in mobile grid environment considering the node mobility. The result analyze the node and link failures on parameters such as delivery ratio, throughput and delay against the rate of success.

At present, grid resources management and dynamic scheduling based on game theory is becoming a focus of researches. R. Buyya, *et al*., propose computational economy as a metaphor for effective management of resources and application scheduling and identifies challenges in managing resources in a Grid computing environment. This paper also presents the use of commodity economy model for resource management and application scheduling in both computational and data grids [2]. The paper [11] presents the use of economy model for resource management by Grid Association. Authors in [14] present Game Theoretic Modeling and derive the Nash equilibrium and optimal strategies for the general case. The paper [15] proposes a mechanism for Grids. The mechanism is embedded in state of the art Grid middleware Sun N1 Grid Engine 6.

Luis Rodero Merino *et al*. [16] introduce and analyze an economic mechanism to set resource prices and resolve when to scale resources depending on the consumers' demand. The paper [17] depicts and evaluates broker selection strategies for job reservation and bidding. It analyzes two different types of existing algorithms simple and categorized aggregation algorithm.

Our work is quite different from other marketbased systems as the auction mechanism is invisible to both the consumers and the resources. We propose a knowledge based scheduler that infers using obtained knowledge from grid environment and past experience. In order to minimize utility cost and maximize customer social welfare, we allocate resources to jobs by using secondprice sealed auction. In follow, we explain our model completely.

Knowledgebased Scheduling in Grid Computing: The change in the meaning of knowledge that began 250 years ago has transformed society and economy. Knowledge is the only meaningful resource today. Knowledge systems are systems that solve a real life problem using knowledge about the application domain and the application task [19]. They are used to aid in human problemsolving like scheduling, planning, aiding medical diagnosis [9]. As the resources in the Grid are heterogeneous and geographically distributed with varying availability and variety of usage and cost policies for diverse consumers at different times, priorities as well as goals of both consumers and owners vary over time. The management of resources and services in such a large distributed environment is a complex task. In scheduling, the sequences of jobs need to be allocated to resources during a certain time interval. In this paper, we propose knowledge based scheduling into grid computing that use information and knowledge involved in a knowledge intensive problem domainin order to construct a program that can perform difficult tasks of scheduling adequately. In our model, there are roles to gather and store existence knowledge in system. The knowledge helps scheduler to find best solution for allocating resource to jobs. But the knowledge is not useful unless there is an inference engine. The scheduler uses obtained knowledge which is located in knowledge base by experts and also the information supplied by the providers and the consumers to match jobs to the appropriate resources byusing auction. The scheduler aims to allocate resources such that consumers and providers satisfy about cost. Figure 1 shows the elements of the scheduler, which can be divided into five parts: (1) Selector: collects all requests and looks for providers which can provide request's need.

Then it sendsrequests and providers' information to Auctioneer., (2) Auctioneer:after receiving providers' information and requests from Selector, it interacts with Inference engine for making best decision for allocating resource to jobs., (3) Inference Engine: this part decides by knowledge and rules in KB which request and resource do not continue probably and also survey previous status of requests, resources and results of scheduling to make best decision to allocate resources to jobs., (4) Allocator: it is responsible to contract with consumer and provider and also allocate resources to jobs.

Then it stores the status of providers and jobs in KB during job executing and (5) System Analyst: throughoutthe time, status of system will be monitored by system analyst and if it sees changes in system, it would savethem in the KB.

It should be mentioned that concepts, relations and rules which are gathered by experts and analysts save in knowledge base. The roles who exist in grid system would explain in section 3.2.

Scheduling Scenario: Let U = $\{U_1,...,U_n\}$ be a set of n consumer. We consider the problem of scheduling a set of jobs J = $\{J_1,...,J_n\}$. Each job $J_i \in J$ has to be done by the consumer $U_i \in U$, i=1,...,n,and each job $J_i \in J$ consists of a set of interdependent tasks. Some tasks are executed with specialized equipment. We consider such equipment as common resources to be used by the consumers in order to accomplish their jobs.

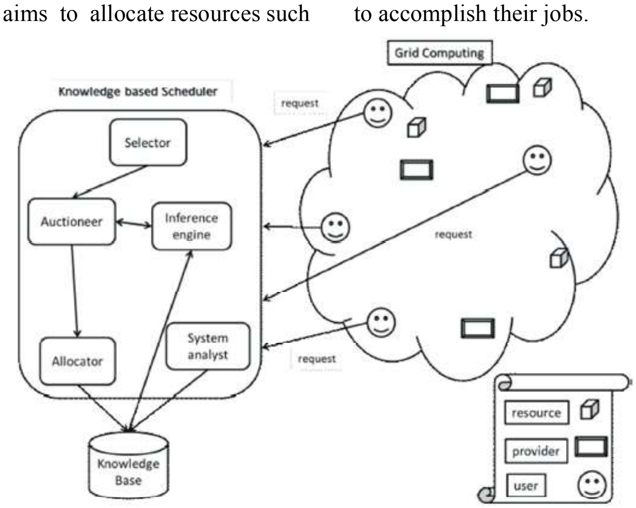

Fig. 1: The proposed model

Let T = $\{t_1,...,t_e\}$ be the set of difierent tasks to be carried out so that each consumeraccomplishes his job. Let R = $\{R_1,...,R_k\}$ be the set of common resources to be used in the grid system in order to execute the tasks. In scheduling, the sequences of jobs need to be allocated to resources during a certain time interval.Resources are managed at different sites by Service Providers who have to cater to the consumer's needs at their site. In this model, consumers submit their jobs to the knowledge based schedulerforexecution within information related to the required resources in the computing grid.

The resource information (job profile) consists of information which will be need to match the consumers' jobs to appropriate resources likeresource name, QOS of resources, priority, deadline and budget that they wish to pay to the auctioneer without specifying a total price or a unit price. The deadline is estimated by a consumer on the basis of expected execution time of the job and his/her urgency. However, the jobs will besubmitted to selector part. Selector looks for the providers which match with the consumer's need. It sends information of providers to auctioneer for surveying requests and providers and starts an auction with players (consumers and providers).

It is possible that a provider does not often work properly, so it is not good to send a job with high priority to the provider. In order this, we use another part called inference engine to investigate provider and consumer status and infer by the knowledge which be obtained later and save in the KB. On the other hand, inference engine negotiates with auctioneer to select optimal strategy for players during the time. In fact, the two parts collaborate together to make best decision for players. In next part, we will describe inference engine and auctioneer operationin detail properly. After finishing the auction, Auctioneer sends the results of game to Allocator. Finally, Allocator saves the results into KB and allocates the resource(s) to consumers.

The Roles of Knowledge-Based Scheduling in Grid Computing: Complex information and knowledge is difficult to observe, so it is required to have experts for producing special knowledge of system. In proposed model, there are roles as knowledge provider, knowledge manager and knowledge developer. These roles aid to gather, monitor, manage and develop existence knowledge into system. Relationship between these roles is depicted in Figure 2. We explain tasks of each role in follow.

- *Knowledge providers* are persons with extensive experience in an application domain and can provide also plan for domain familiarization.
- *Knowledge analyst* is a person that analyzes system and elicits and delivers the knowledge to knowledge provider for validating and producing knowledge.
- *Knowledge developer* is a person that implements a knowledge system on a particular target platform and needs to have general design/implementation expertise and understand knowledge analysis.
- *Knowledge manager* defines knowledge strategies and facilitates knowledge distribution. He also monitors organizational purpose of system developed in a project and knowledge assets developed/refine.

The Knowledge Management Cycle: We present a framework for knowledge management that is shown in Figure 3. The following activities with respect to knowledge and its management are distinguished:

Define: This part specifies the internal and external knowledge which exist in system.

Acquire/ Develop: The knowledge that is required for inferring will be acquired by this part. And also it is possible to develop it.

Inference: Uses the acquired knowledge from system to make best decision about current state. This part surveys the feasibility of scheduling.

Schedule: It schedules and allocates the resource to the consumers based on the decision that inference engine makes.

Maintain: All of system statuses, inference decisions and results of decision will be maintained by this part.

One definition of knowledge management is 'a framework and tool set for improving the organization's knowledge infrastructure, aimed at getting the right knowledge to the right people in the right form at the right time.

Inference Engine: While studying the effciency of auction is central to game theoretic design, another important aspect is to develop inference engine that enable consumers and providers to reach a certain desired game outcome. The inference engineuses a set of predefined rules to generate the new knowledge that are called inference rules. An example of such a rule would be: "if P then Q", applied to a knowledge base containing the expression P, it would infer that Q is the case. There are a number of other issues related to the representation

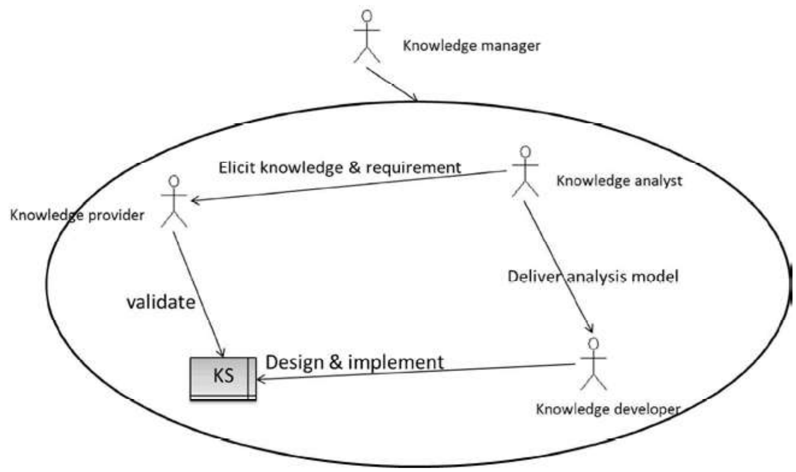

Fig. 2: Relationship between roles in knowledge system

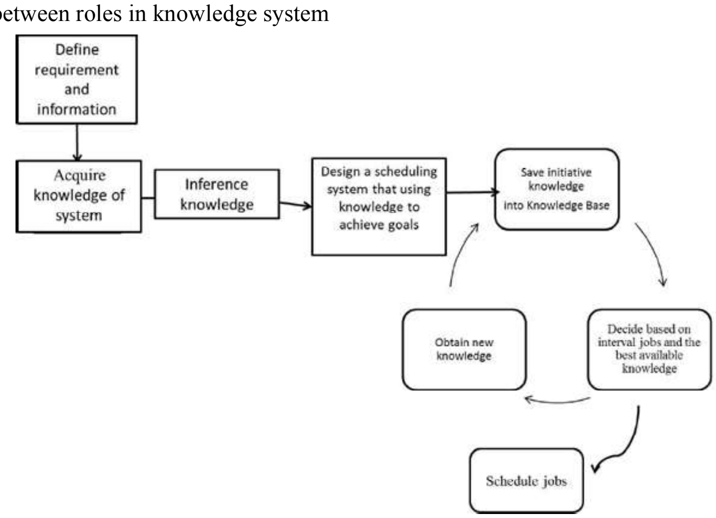

Fig. 3: Activities in knowledge management and the associated knowledge value chain

language and the knowledge representation model used. Inference engine need to inference knowledge to act on resources to define their behavior and manage them in an autonomic manner using management policies. In the inference knowledge, it will be described how these static structures can be used to carry out a reasoning process. The main ingredients of the inference knowledge are the inferences, the knowledge roles and the transfer functions [19]. An inference carries out a primitive reasoning step. Typically, an inference uses knowledge contained in some knowledge base to derive new information from its dynamic input. The engine comprises a feasibility study on ways to improve knowledge management and knowledge-systems support for the scheduling jobs in grid computing.

Why do we give primitive functions such a special status? A major reason is that inferences are indirectly related to the domain knowledge. This feature is realized through the notion of a knowledge role. Knowledge roles enable us to construct catalogs of recurring reasoning patterns. In fact, inference I/O is described as functional roles: abstract names of data objects that indicate their role in the reasoning process.

In order to achieve soundness and completeness even when knowledge is distributed among self-interested consumers, we require a new paradigm that marries logic and game theory in a new way.

In this model, we distinguish two types of knowledge roles, *dynamicroles* and *staticroles*. Dynamic roles are the run time inputs and outputs of inferences.

```
INFERENCE schedule;
   ROLES:
         INPUT: bids;
         OUTPUT: solutions;
         STATIC: casual-model;
   SPECIFICATION:
         *Each time the inference is invoked, it generates a candidate solution that could have caused the
bids. The output should be an initial state in the state-dependency network which causally 'schedule' the
input bids.
END INFERENCE schedule;
KNOWLEDGE-ROLE bids;
         TYPE: DYNAMIC;
         DOMAIN-MAPPING: visible-state;
END KNOWLEDGE-ROLE bids;
KNOWLEDGE-ROLE solutions;
         TYPE: DYNAMIC;
         DOMAIN-MAPPING: invisible-state;
END KNOWLEDGE-ROLE solutions;
KNOWLEDGE-ROLE casual-model;
         TYPE: STATIC;
         DOMAIN-MAPPING: state-dependency FROM grid-network;
END KNOWLEDGE-ROLE casual-model;
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Fig. 4: A sample textual specification of the schedule inference and its dynamic and static roles

Each invocation of the inference typically has different instantiations of the dynamic roles. We assume an*inference schedule* that uses the behavior of the grid system. Such an inference would have two dynamic knowledge roles: (1) an input role *bids*, denoting a domain object representing bids about the behavior of the consumers and providers and 2) an output role *solutions*, representing candidate solution. On the other hand, static roles are more or less stable over time. Static roles specify the collection of domain knowledge that is used to make the inference [19]. Here, the inference *schedule* could use the state-dependency network to find candidate solutions.

We display a sample textual specification of the *schedule* inference and its dynamic and static roles in Figure 4. The first part shows how the knowledge roles are bound to the domain. Objects of domain type *visible-state* can play the role of bids and the role *solutions* can be played by all *invisible-states*. The static role *casual-model* maps to the state dependencies in the knowledge base.

How might be a steady state reached if assumes that consumers and providers start with an unexplained "prior" belief about the other players' actions and changes these beliefs? How may inference engine make a decision with best profit for both provider and consumer? For answering the questions, we suppose that inference engine uses best response dynamics approach to make decision. We use concept of "learning" for inference engine. It means that the inference engine can learn from observing the fortunes of consumers and providers, from discussing the game with such players, or from its own experience playing the game.We suppose that inference engine is as a player in this time and plays game itself.It trends to improve its' decision and finally consumers' and providers' utility. In fact in this model, two games are played. One of them is played between consumers and providers and another one between inference engine and itself. The inference checks whether the results of the evaluation lead to a decision. Sometimes, the truth value of one norm is sufficient to arrive at a decision. Norms encode desirable behaviors for the population of natural or artificial societies. For example, a norm might specify that users are expected to stop if so signaled by an authority.

In general, they are commonly understood as a specification of what is expected to follow (obligations, goals, contingency plans, advices, actions and …) from a specific state of requests. The inferences described are shown graphically in the inference structure of Figure 5.

Second-Price Sealed Auctions with Common Valuations: In attempting to reason about interactions between multiple agents, the artificial intelligence community has recently developed an interest in game theory, a tool from economics. Game theory aims to help us understand situations in which decisionmakers interact [18, 20].

Grid is a power network composed of intelligent nodes that can operate, communicate and interact, autonomously, in order to effciently deliver resources to their consumers. This heterogeneous nature of the grid motivates the adoption of advanced techniques for overcoming the various technical challenges at different levels such as design, scheduling, control and implementation. In this respect, game theory is expected to constitute a key analytical tool in the design of the future grid especially scheduling. It is a formal analytical as well as conceptual framework with a set of mathematical tools enabling the study of complex interactions among independent rational players. So, we consider to scheduling problem and aim to solve it with game theory.

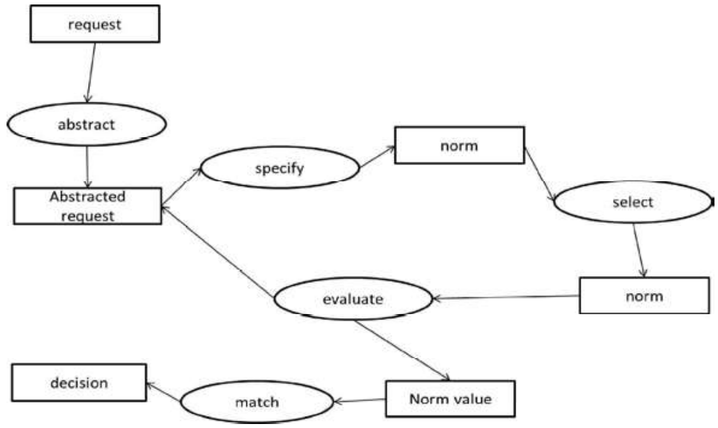

Fig. 5: Inference structure for scheduling requests

Consumers and providers bid with together to maximize their profit. Since, it is possible that every bidder (consumer and provider) does not know every other bidder's valuation of the object for sale. So, we use Bayesian game to analyze auctions.

In Bayesian game, the bidders' valuations are private. If each bidder's signal is simply her valuation of the object, we say that the bidders' valuations are private. If a bidder is uncertain of her valuation, which is related to that of other bidders, then in an open ascending auction she may obtain information about her valuation from other participants' bids, information not available in a sealed bid auction. Each bidder knows that all other bidders' valuations are at least $\underline{v}$ where $\underline{v} \geq 0$ and at most $\bar{v}$. She believes that the probability that any given bidder's valuation is at most v is F(v), independent of all other bidders' valuations, where F is a continuous increasing function.

In an auction with common valuations, each player's valuation depends on the other players' signals. We assume that the players' signals are independent. We denote the function that gives player i's valuation by g_i and assume that it is increasing in all the signals. Given the appropriate specific action of the function P that determines the price P(b) paid by the winner as a function of the profile b of bids [18]. We model the following Bayesian game by second price auctions with common valuation.

Players The set of bidders, say {1,…, n}.
States The set of all profiles $(t_1,...,t_n)$ of signals that the players may receive.
Actions Each player's set of actions are the set of possible bids (non-negative numbers).
Signals The signal function τi of each player i is given by $\tau i\ (t_1,...,t_n) = t_i$ (each player observes her own signal).
Beliefs Each type of each player believes that the signal of every type of every other player is independent of all the other players' signals.
Payoff functions Player i's Bernoulli payoff in state $(t_1,...,t_n)$ is 0 if her bid b_i is not the highest bid and $(g_i(t_1,...,t_n) - P(b))/m$ if no bid is higher than b_i and m bids (including b_i) are equal to b_i [18]:

$$u_i(b,(t_1,...,t_n)) = \begin{cases} (g_i(t_1,...,t_n) - P(b))/m & \text{if } b_j \leq b_i \text{ for all } j \neq i \text{ and} \\ & b_j = b_i \text{ for } m \text{ player} \\ 0 & \text{if } b_j > b_i \text{ for some } j \neq i \end{cases}$$

Nash Equilibrium in a Second-Price Sealed Auctions: The main ideas in the analysis of sealed bid common value auctions are illustrated by an example in which there are two bidders, each bidder's signal is uniformly distributed from 0 to 1 and the valuation of each bidder *i* is given by $v_i = \propto t_i + \gamma t_j$, where *j* is the other player and $\propto \geq \gamma \geq 0$. The case in which $\propto = 1$ and $\gamma = 0$, the bidders' valuations are private. If $\propto = \gamma$ then for any given signals, each bidder's valuation is the same-a case of "pure common valuation". If, for example, the signal t_i is the number of CPUrequests in attract, then the expected valuation of a bidder i who knows the signals t_i and t_j is.

$$p \times \frac{1}{2}(t_i + t_j)$$

p is the monetary worth of a CPU request. Our assumption, of course, is that a bidder does not know any other player's signal. However, a key point in the analysis of common value auctions is that the other players' bids contain some information about the other players' signalsinformation that may profitably be used. A second price sealed-bid auction has a Nash equilibrium in which each type t_i of each player i bids $(\propto + \gamma)t_i$.

To verify this claim, suppose that each type of player 2 bids in this way and type t_1 of player 1 bids b_1. To determine the expected payoff of type t_1 of player 1, we need to find the probability with which she wins and both the expected price she pays and the expected value of player 2's signal if she wins.Probability that player 1 wins: Given that player 2's bidding function is $(\propto + \gamma)t_2$, player 1's bid of b_1 wins only if $b_1 \geq (\propto + \gamma)t_2$or if $t_2 \leq b_1/(\propto + \gamma)$. Now, t_2 is distributed uniformly from 0 to 1, so the probability that it is at most $b_1/(\propto + \gamma)$ is $b_1/(\propto + \gamma)$. Thus a bid of b_1 by player 1 wins with probability $b_1/(\propto + \gamma)$.

Expected price player 1 pays if she wins: the price she pays is equal to player1's bid, which, conditional on its being less than b_1, is distributed uniformly from 0 to b_1. Thus the expected value of player2's bid, given that it is less than b_1, is $\frac{1}{2}b_1$.

Expected value of player2's signal if player1 wins: player2's bid, given her signal t_2, is $(\propto + \gamma)t_2$, so that the expected value of signals that yield a bid of less than b_1 is $\frac{1}{2}b_1/(\propto+\gamma)$ (because of the uniformity of the distribution of t_2).

Now, player1's expected payoff if she bids b_1 is the difference between her expected valuation, given her signal t_1 and the fact that she wins and the expected price she pays, multiplied by her probability of winning. Combining the calculations above, player1's expected payoff if she bids b_1 is thus:

$$(\propto t_1 + \frac{\frac{1}{2}\gamma b_1}{\gamma + a} - \frac{1}{2}b_1)b_1/(a+\gamma) = \frac{\propto}{2(\propto+\gamma)^2}.(2(\propto+\gamma)t_1 - b_1)b_1$$

This function is maximized at $b_1 = (\propto + \gamma)t_1$. If each type t_2 of player2 bids $(\propto + \gamma)t_2$, any type t_1 of player1 optimally bids $(\propto + \gamma)t_1$. Symmetrically, if each type t_1 of player1 bids $(\propto + \gamma)t_1$, any type t_2 of player2 optimally bids $(\propto + \gamma)t_2$. Hence, as claimed, the game has a Nash equilibrium in which each type t_i of each player i bids $(\propto + \gamma)t_i$ [18].

CONCLUSIONS

In this paper, we propose knowledge based scheduling that uses a second price sealed auction for allocating resources to users. The two principal objectives that we consider are: cost minimization and customer social welfare maximization.We consider the knowledge proves itself in actions and infer best solution for allocating resources such that benefit users and providers based on knowledge.It is worthwhile to note that the proposed model is much more applicable than some basic auction models. However, the network delay, fraud user, reliability of resources problems are not considered in this paper. Thus, how to make the model realistic, fulfill the QoS requirements of users and improve the resource scheduling algorithms form the next step of our work.

REFERENCES

1. Buyya, R., D. Abramson and S. Venugopal, 2005. The Grid Economy. In the Proceedings of the IEEE, pp: 698-714.
2. Murugesan, G. and C. Chellappan, 2010. An Economic-based Resource Management and Scheduling for Grid Computing Applications. International Journal of Computer Science Issues, 7(5).
3. Birjea, M.N. and S.S. Manvi, 2012. Agent Based Economic Scheme for Seamless Job Scheduling in Bandwidth Constrained Wireless Grids. International Journal of Grid and Distributed Computing, 5(1).
4. Bsoul, M.A.R., I.W. Phillips and C.J. Hinde, 2006. A framework for economic scheduling in Grid computing using tender/Contract-net mode, PG Net.
5. Sherwani, J., A. Nosheen, L. Nausheen, Z. Hayat and Rajkumar Buyya, 2004. Libra: a computational economy-based job scheduling system for clusters. Journal of Software, Practice and Experience, 34: 573-590.
6. Abramson, D., R. Buyya and J. Giddy, 2002. A computational economy for grid computing and its implementation in the Nimrod-G resource broker.Journal of Future Generation Computer Systems, 18: 1061-1074.
7. Subrata, R. And B. Landfeldt, 2008. A Cooperative Game Framework for QoS Guided Job Allocation Schemes in Grids. Journal of IEEE Transactionson Computers, 57(10): 1413-1422.
8. Schrieber, G., H. Akkermans, A. Anjewierden, R.D. Hoog, N. Shadbolt, W.V. Velde and B. Wielinga, 2000. Knowledge engineering and management. The MIT Press.
9. Ludwig, S.A. and S.M.S. Reyhani, 2005. Introduction of semantic matchmaking to Grid computing.Journal of Parallel Distributed Computing, 65: 1533-1541.

10. Xhafa, F. and A. Abraham, 2010. Computational models and heuristic methods for Grid scheduling problems. Journal of Future Generation Computer Systems, 26: 608-621.
11. Manavalasundaram, V.K. and K. Duraiswamy, 2012. Association Based Grid Resource Allocation Algorithm. European Journal of Scientific Research, 78(2): 248-258.
12. Sumathi, G., S. Sathyanarayanan and R. Santhosh Kumar, 2012. Performance Factor based Local Scheduling for Heterogeneous Grid Environments. International Journal of Computer Applications, 44(22): 45-49.
13./ Morales, B.B., 2010. Survey: Grid Computing and Semantic Web. Journal of Computer Science Issues, 7(5).
14. Kwok, Y.K. and S. Song, 2007. Selfish Grids: Game-Theoretic Modeling and NAS/PSA Benchmark Evaluation.Journal of IEEE Transactions on Parallel and Distributed Systems, 18(5): 621-636.
15. Bodenbenner, P., J. Stößer and D. Neumann, 2007. A Pay-as-Bid Mechanism for Pricing Utility Computing. 20th Bled eConferencee Mergence: Merging and Emerging Technologies, Processes and Institutions, pp: 699-712.
16. Merino, L.R., E. Carona, A. Muresana, F. Desprez, 2011. Using clouds to scalegridre sources: Aneconomic model. Journal of Future Generation Computer Systems, pp: 1-14.
47. Ramyachitra, D. and S. Poongodi, 2011. Grid Meta Broker Selection Strategiesfor Job Reservation and Bidding. Journal of Grid Computing and Applications, 2(3): 13-25.
18. Osborne, M.J., 2000. An Introduction to Game Theory. Oxford University Press.
19. Rahwan, I. and K. Larson, 2011. Logical mechanism design. Journal of the Knowledge Engineering Review, 26(1): 61-69.
20. Haitof, H., 2011. A Framework for Autonomic Service-based Resource Management Using a Semantic Approach. PhD Thesis.
21. Basar, T. and G.J. Olsder, 1999. Dynamic Non-cooperative Game Theory. Philadelphia, PA, USA: SIAM Series in Classics in Applied Mathematics.
22. Han, Z., D. Niyato, W. Saad, T. Bas¸ar and A. Hjørungnes, 2011. Game Theory in Wireless and Communication Networks: Theory, Models and Applications. Cambridge, UK: Cambridge University Press.
23. Blum, B., 2006. A Continuation Method for Nash Equilibria in Structured Games, Journal of Artificial Intelligence Research, 25: 457-502.
24. Murugesan, G. and C. Chellappan, 2012. Fuzzy Based Optimal Allocation of Resources for Grid Scheduling. Journal of Applied Sciences, 7: 119-125.
25. Kamalam, G.K. and V.M. Bhaskaran, 2012. Novel adaptive job scheduling algorithm on heterogeneous grid resources. Am. J. Appl. Sci., 9: 1294-1299.
26. Parsa, S. and R. Entezari-Maleki, 2009. RASA: A New Task Scheduling Algorithm in Grid Environment. World Applied Sciences Journal, 7: 152-160.
27. Thenmozhi, S., A. Tamilarasi and P.T. Vanathi, 2012. A Fault Tolerant Resource Allocation Architecture for Mobile Grid, Journal of Computer Science, 8(6): 978-982.
28. Golmohammadi, R. and H.S.H. Shahhoseini, 0000. Load Balancing in Local Computational Grids within Resource Allocation Process. Journal of Applied Sciences, Engineering and Technol., 4(21): 4546-4551.