Proffering a Brand New Methodology for Resource Discovery and Pricing in Computational Grid Using Learning Automata

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ABSTRACT
Grid Computing is a parallel and distributed system that facilitates the virtualization of distributed computing and enables coordinating and sharing of computing and storage resources. Mechanism based on economic models is an effective approach to solve the problem of grid resources management. The essence of this problem is how to discover resources for achieving the goal of a highly efficient utilization of resources in response to current resource prices. In this paper, we present a method of resource discovery and pricing based on the learning automata, and discuss the process of resource discovery and resource pricing algorithms for discover and pricing resources to grid users in order to maximize the benefit for both grid providers and grid users. We formulate the problem as an environment that learning automata's discover best resource based on its complete time for proffered application. After discover of resource, pricing of it based on its complete time is done. Using computer simulations, it is shown that the proposed methodology have higher performance comparing to the existing ones.

Keywords
resource pricing; learning automata; resource discovery; grid computing

1. INTRODUCTION
Computational Grid [12] is a new paradigm in distributed computing which aims to realize a large-scale high performance computing environment over geographically distributed resources. Computational Grid enables the sharing, selection, and aggregation of highly heterogeneous resources for solving large scale problems in science, engineering and commerce. Grid Computing always is a parallel and distributed system that facilitates the virtualization of distributed computing.

sources Numerous efforts have been exerted focusing on various aspects of grid computing including resource specifications, information services, allocation, and security issues. A crucial issue to meeting the computational requirements on the grid is the resource discovery and pricing. The research in the areas of grid resource pricing so far have been fairly limited.

In [Bapna et al (2006)], a portfolio of solutions to the grid resource allocation and pricing problem was developed. However, pricing of discovered resources for applications in heterogeneous environment remain challenging problems.

Existing method for gird resources pricing have many drawbacks. The main its drawback is not having a correct base for evaluating of price. Resource sellers mainly focus on economic criteria and maximizing of their benefits. In economic grid environment mainly both users and resources owner want maximizing their benefit through selling or buying of resources.

Many method for resource pricing in grid computing environment are represented such as Fixed Price Model‹Posted Price Model‹Bargaining Model‹Tendering/Contract-net Model‹Auction Model‹Cooperative Bartering Model‹Monopoly/Oligopoly [6][19][15][16][14][21].

But almost none of these methods do not focus on pricing of computational resource based on their suitability and capability in executing of applications. In this paper we try solve this problem by representing a new model of computing resource pricing in computational grid using learning automata.

The proposed approach uses learning automata for resource discovery with shortest time in executing of proffered application and then discovered resource pricing based on its total time for executing of proffered application estimate. Proffered methodology illustrated in blew figure.

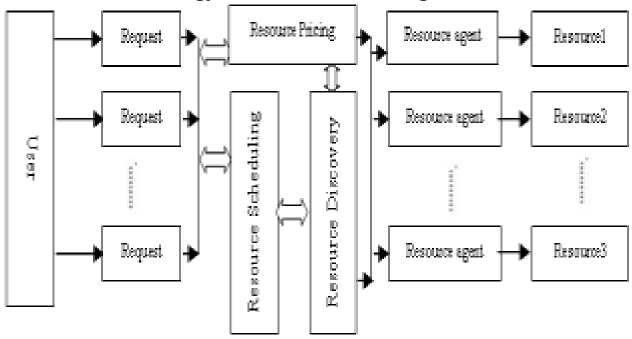

Figure 1. Proffered method for resource discovery and pricing

2. RELATED WORK
There are some published researches on resource management for grid computing based on economics principles, and these economic models can be improved both conceptually and computationally. The distributed pricing method is studied in [4], which is based on the equilibrium theory to realize an optimal allocation of grid resources by the market mechanism, and introduced an iterative algorithm of resource-agent. It is suitable for large-scale distributed systems. In [5], 'G-commerce', which is computational economies for controlling resource allocation in Computational Grid settings, is investigated. This paper defines a hypothetical resource and resource producers, then measure the efficiency of resource

allocation under two different market conditions: commodities markets and auctions. The results indicate that commodities markets are a better choice for controlling Grid resources than previously defined auction strategies. In [8], a commodity market based approach is used to allocate resources, where resources are classified into different classes based on the hardware components, network connectivity, and operating systems. In a commodity market, the prices of the commodities (”resources”) are fixed using individual supply and demand functions. GRACE [20][17][18] (the Grid Architecture for Computational Economy) proposed by Buyya is a distributed computational economy-based resource allocation framework, which provides a mechanism for regulating the Grid resources demand and supply. GRACE offers incentive for resource owners to be part of the Grid and encourages consumers to optimally utilize resources and balance timeframe and access costs. It is built on the existing Grid middleware systems and offers an infrastructure for resource management and trading in the Grid environment. A distributed group-pricing algorithm is presented for determining the price according to the general equilibrium theory in [2]. According to this algorithm, resources in the system are divided into multiple resource groups according to the degree of price correlation of resources. When the demand and supply of resources in the system changes, the price of one resource group will be adjusted simultaneously until the excess demand of all resources becomes zero. However, [2] didn’t analyze how to allocate resources for achieving the goal of most efficient utilization of resources.

3. REQUIREMENTS FOR ECONOMIC-BASED RESOURCE MANAGEMENT

Economic-based resource management systems need to provide mechanisms and tools that allow resource consumers (end users) and providers (resource owners) to express their requirements and facilitate decision-making to further their objectives [3]. That is, they need 1) the means to express their valuations and objectives [value expression], 2) scheduling policies to translate them to resource allocations [value translation], and 3) mechanisms to enforce selection and allocation of differential services, and dynamic adaptation to changes in their availability at runtime [value enforcement].

Similar requirements are raised [7] for market-based systems in a single administrative domain environment such as clusters. However, they are limited to co-operative economic models since they aim for social welfare. Grids need to use competitive economic models as resource providers and resource consumers have varying goals, strategies, and requirements that vary with time. Essentially, resource consumers need a utility model—to allow them to specify resource requirements and constraints. They need brokers that provide strategies for choosing appropriate resources [value translation] and dynamically adapt to changes in resource availability at runtime to meet user requirements [value enforcement]. The resource owners need mechanisms for price generation schemes to increase system utilization and protocols that help them offer competitive services

[value expression]. Grid resources have their schedulers (e.g., OS or queuing system) that allocate resources [value translation]. An economic approach to Grid computing introduces a number of new issues like resource trading and QoS-based scheduling in addition to those such as site autonomy, heterogeneous substrate, policy extensibility, online control already addressed by existing Grid systems. To address these new issues, the economy-based Grid systems need to support the following.

•An information and market directory for publicizing Grid entities.
• Models for establishing the value of resources.
•Resource pricing schemes and publishing mechanisms.
•Economic models and negotiation protocols.
•Mediators to act as a regulatory agency for establishing resource value, currency standards, and crisis handling.
•Accounting, Billing, and Payment Mechanisms.
•Users’ QoS requirements-driven brokering/scheduling systems.

4. LEARNING AUTOMATA

Learning Automata [9] are adaptive decision-making devices operating on unknown random environments. A Learning Automaton has a finite set of actions and each action has a certain probability (unknown to the automaton) of getting rewarded by the environment of the automaton that Equation (1) has been shown desire response. The aim is to learn to choose the optimal action through repeated interaction on the system. If the learning algorithm is chosen properly, then the iterative process of interacting on the environment can be made to result in selection of the optimal action. Figure 1 illustrates how a stochastic automaton works in feedback connection with a random environment. Learning Automata can be classified into two main families: fixed structure learning automata and variable structure learning automata (VSLA) [10]. In the following, the variable structure learning automata which will be used in this paper is described.

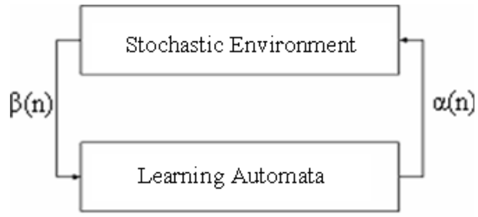

Figure 2. The interaction between learning automata and environment

A VSLA is a quintuple < α, β, p, T(α,β,p) >, where α, β, p are an action set with s actions, an environment response set and the probability set p containing s probabilities, each being the probability of performing every action in the current internal automaton state, respectively. If the response of the environment takes binary values learning automata model is P-model and if it takes finite output set with more than two elements that take values in the interval [0, 1], such a model is referred to as Q-model, and when the output of the environment is a continuous variable in the interval [0, 1], it is refer to as S-model. The function of T is the reinforcement algorithm, which modifies the action probability vector p with respect to the performed action and received response. Assume $\beta \in [0,1]$. A general linear schema for updating action probabilities can be represented as follows. Let action i be performed then:

A) Desire response

$$p_i(n+1) = p_i(n) + a[1 - p_i(n)]$$
$$p_j(n+1) = (1-a)\, p_j(n) \qquad \forall j \quad j \neq i \tag{1}$$

B) Undesired response

$$p_i(n+1) = (1-b)\, p_i(n)$$
$$p_j(n+1) = \frac{b}{r-1} + (1-b)\, p_j(n) \quad \forall j \quad j \neq i \tag{2}$$

Where a and b are reward and penalty parameters. When a=b, the automaton is called L_{RP}. If b=0 the automaton is called L_{RI} and if 0<b<<a<1, the automaton is called $L_{R\varepsilon P}$. For more

Information about learning automata the reader may refer to [9].

5. RESOURCE DISCOVERY

Resource discovery is one of the main functions of resource management for scheduling of application in grid environment. The grid resource discovery problem [1] can be defined as the problem of matching a query for resources, described in terms of required characteristics, to a set of resources that meet the expressed requirements. The problem is complicated by the fact that some resource information (e.g., CPU load or available storage) changes dynamically. Resource discovery techniques maintain the resource attribute and status information in a distributed database and differ in the way they update, organize, or maintain the distributed database. The challenge is to devise highly distributed discovery techniques that are fault tolerant and highly scalable.

Matching the needs of an application with available resources is one of the basic and key aspects of a Grid system. Resource Discovery is systematic process of determining which grid resources are the best candidate to complete an application with following trade-offs.

- In shortest amount of time.
- With most efficient use of resources.
- At minimum cost

The output of this phase of scheduling is set of resource that meets minimum requirement of users and in resource selection phase one of this resources with highest match with users application requirement will be selected. In this paper we used of shortest time parameter for grid computing resource discovery.

6. GRID RESOURCE DISCOVERY AND PRICING BASED ON LEARNING AUTOMATA

We have tried in this method with using a set of learning automata complex operation resource discovery with time optimization criteria be done. In this algorithm for resource discovery, each of the applications is equipped with a Learning Automata. These learning automata have a variable structure and those actions are discovery of best computational resource for executing proffered application. In fact learning automata associate to an application discovers resource that application should be entrusted to it.

When all of application chooses their resource reward or penalty from the environment is taken. Then again all of applications carry out resource discovery for receiving environment response. This operation is repeated until to certain number pending all of application discovers their proper resource. Discovered resource by learning automata in this step execute proffered application in minimum time in comparing with other resource. In fact learning automata task is founding this resource. After specified run time of proffered application with discovered resource by learning automata.

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1- Sorting the received requests in descending order in
terms of the duration the pertinent resource is required.
2- The beginning of the learning procedure in
the learning automata connected to the application
        2-1: Reiterate them 5000 times:
            2-1-1 Deplete the assignment queue of
                  each resource
            2-1-2 Conduct the following stages for
                  each application:
                  2-1-2-1 Opt for the germane
                          resource of each application
                          and set the application in the
                          designation queue of the
                          pertinent resource
            2-1-3 The beginning of the penalty
                  proffering phase:
                  Inflict financial penalty on each
                  application who has opted for a
                  resource that does not fulfill the
                  temporal limitation
            2-1-4 The beginning of the reward
                  proffering phase:
                  if a application is not fined and
                  chooses a resource who is identical
                  or earlier than the previous one,
                  reward it with 0.02 rating.
3. Each application will be registered to the most
appropriate resource subsequent to the convergence of
results and the completion of reiterations.
4. T= Run time of selected resource  //that is lower in
      comparing with other resource
5. R= T*const   //Const is conventional value that specify
      by resource management center
6. C=1/R(cent)  //Cost of resource utilization for per
      second
   7. Total_cost=T*C  //Total cost of resource utilization
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Figure 3. proffered algorithm

7. CRITERIA FOR SELECTING REWARD AND PENALTY BY LEARNING AUTOMATA 5-

Environment response for learning automata associated to application based on ideal conditions in a time optimization criteria will be complete. For this propose environment uses of blew tow point for give reward or penalty to selected action by learning automata.

1- Run time of transferred application to busiest resources shouldn't have many differences run time with other resource.

2- Each work must be assigned to resource that can run it earlier from other resources

Thus the environment by using the first points will give penalty to selected action and with second point give reward to selected action by learning automata.

8. EXPERIMENTS

The goal of this experiment is to compare the performance of the learning automata based resource discovery and pricing algorithm to other conventional resource discovery approach such as p2p model [11], which no pricing is used, and the incoming task queries are matched with the next available resource offer which meets the task’s constraints. We simulate grid environment to evaluate experimentally the learning automata-based resource discovery and pricing algorithm by means of gridsim[13].

The most suitable parameters for evaluation of this algorithm have been propounded with regard to the effectuated securitizations. The error rate parameter expenditure improvement algorithms are regulated with

regard to each selection for instance in failure cases of discovery, or in cases demanding re-discovery. Another parameter is the wait time that defines as duration of times before discovery of resource to a task and total time is complete time of a task. And finally efficiency of proffered algorithm in compared of conventional method will be shown. Reported results, is for average 20 times of simulation. Grid environment including a number of resources and users. Grid resource is high heterogeneous.

We neglect the network topology and the communication costs associated with it. Instead, we assume that each of the users can submit applications to any of the resources. However, it is still adequate for certain situations. This experiment is to study discover and pricing efficiency of learning automata-based resource discovery and pricing algorithm in terms of conventional resource discovery efficiency. In this experiment, we choose respectively 100, 200, 600, and 1000 resource domains to compare resource discovery efficiency of the learning automata-based resource discovery and pricing algorithm to the conventional approach under various the numbers of resource domains. The experiment results are shown in blew for resource discovery efficiency.

From the results in Fig. 3, when the number of resource domains is low, the difference in resource discovery efficiency between the two discovery methods is small, and both can achieve good discovery efficiency, so using conventional approach might be sufficient. When the number of resource domains increases, resource discovery efficiency of both methods will decrease. However, the resource discovery efficiency of approach might be sufficient. When the number of resource domains increases, resource discovery efficiency of both methods will decrease. However, the resource discovery efficiency of learning automata-based resource discovery and pricing algorithm decreases slower than that of the conventional approach. In other words, for a large number of resource domains, the conventional approach will not match the performance of the learning automata-based resource discovery and pricing algorithm. From above performance comparisons, we can see that the resource discovery efficiency of the learning automata-based resource discovery and pricing method is effective improved.

As the Fig. 4 show Completion time of allocated job to the resource‹ discovered by the proffered algorithm is less than to completion time of the same job allocated to other resources. But as shown in Fig. 3 the error rate in applying the proffered algorithm because of repeated learning automata to reach the desired resource is more. Fig. 5 shows the relation between completion time and resource price based on proffered algorithm. As you can see with decrease in completion time resource price will increase.

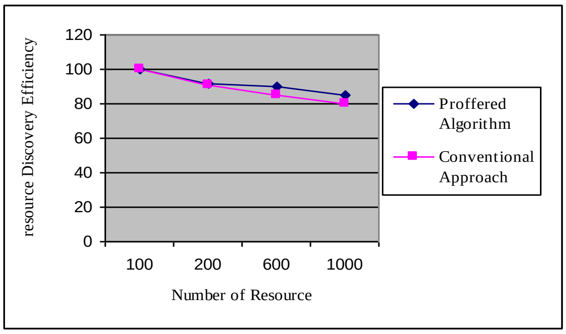

Figure 4. Resource Discovery Efficiency

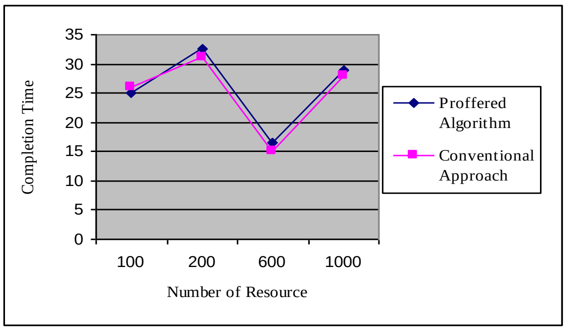

Figure 5. Completion Time

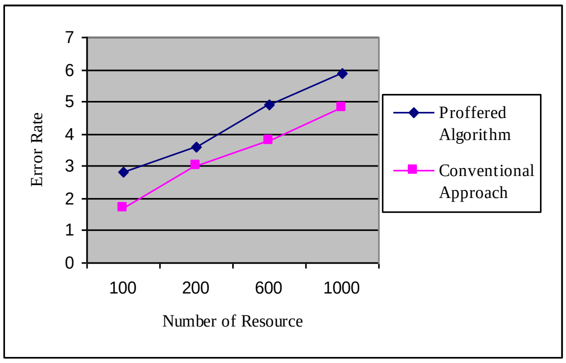

Figure 6. Error Rate

9. CONCLUSIONS

Resource Discovery and pricing based on learning automata is an effective approach to manage resources of economic grid computing environment. In this paper, we analyzed a resource discovery and pricing method based learning automata model in detail, which consists of set of learning automata associated to user's application to select best resource for executing applications and finally based on obtained run time, resource price will be evaluated. Efficiency of proffered algorithm based an Error rate and Completion time parameters were shown.

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