A Survey of Bargaining Models for Grid Resource Allocation

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Whereas it is noted that various types of auctions, commodity market models, and contract-net (tendering) model are more widely used for managing Grid resources, this paper focuses on discussing bargaining (negotiation) models for Grid resource management. To this end, this survey supplements and complements existing surveys by reviewing, comparing, and highlighting the very few extant research initiatives on applying bargaining as a mechanism for managing Grid resources. The contributions of this paper are (i) discussing the motivations for considering bargaining models for Grid resource management, (ii) discussing the issues in building bargaining mechanisms for Grid resource management, (iii) comparing the strategies and protocols of state-of-the-art bargaining models for Grid resources, and (iv) discussing possible new directions.

Additional Key Words and Phrases: Automated negotiation, bargaining, Grid resource allocation, Grid resource management, computational economy.

1. INTRODUCTION

Since a computational Grid focuses on large-scale resource sharing, a resource management system is central to its operations [1, p.135]. However, providing efficient resource allocation mechanisms in the Grid is a complex undertaking due to its scale and that resource owners and consumers may have different goals, preferences, and policies. In a position paper by Sim [2], it was argued that software agents (or automatic scheduling programs), in particular negotiation agents, can play an essential role in realizing the Grid vision. Numerous economic models for Grid resource management such as commodity market models, auction, contract-net/tendering models, bargaining models, posted price models, bid-based proportional resource sharing models, cooperative bartering models, and monopoly and oligopoly had been proposed in the literature and were summarized in [3-4]. While some of the more commonly-referenced work (e.g.,[5-8]) focused on commodity markets, auction and contract-net/tendering models for Grid resource management, this paper focuses on discussing bargaining (negotiation) models for Grid resource management. The intention of this paper is to supplement and complement the existing survey papers on Grid resource management [1,3-4] by reviewing and highlighting the very few extant research initiatives on applying automated negotiation as a mechanism for managing Grid resources. The contributions of this paper are listed as follows. Section 2 discusses the motivations for considering automated negotiation as a model for allocating Grid resources. Section 3 discusses the challenges of the bargaining problem in Grid resource management and identifies some issues for consideration when building negotiation mechanisms for Grid resource management. Section 4 reviews the state-of-the-art bargaining models for Grid resource management, of which there are not many. Section 5 concludes this paper by comparing the bargaining models in section 4, and discusses new directions and open problems.

2. GRID RESOURCE NEGOTIATION

Negotiation activities are necessary in a computational Grid because: (i) it cannot be assumed that a resource provider will unconditionally provide a particular (computing) capability to a consumer, (ii) since Grid participants are independent bodies, some mechanism is needed to resolve their differences, and (iii) through negotiation, players in a Grid marketplace (providers and consumers) are given the opportunity to maximize their return-on-investment and minimize their cost (the price they pay) respectively.

Even if a resource provider is willing to provide a service or to lease a computing resource, one would still be faced with the question of determining the desired level of service, as well as the cost of providing the service. In [9], it was noted that one of the problems in distributed applications is mapping computation or data transfer activities to (a set of) resources that meet the requirements (such as cost, performance, security and other service metrics) of applications. The fundamental problem is the difficulty of successfully negotiating for access to resources from a different administrative domain. Whereas consumers require assurance on the level, type, and quality of service being provided by the resources, resource owners are concerned about maintaining local control on how resources are being utilized (the usage policy). Hence, adopting automated negotiation as a means for establishing contracts and for resolving the differences in the goals, objectives, preferences, access policies, and supply-and-demand patterns of both providers and consumers is a topic of considerable interest. Furthermore, it was noted in [10, p. 231] that prices and negotiations can be used to coordinate the activity of objects and software entities.

Additionally, it is noted that unlike other economic models such as auction and commodity markets, bargaining generally does not rely on a trusted third party to mediate transactions. Many of the bargaining models (e.g., [11-21]) do not involve a third party (e.g., a facilitator or mediator) for enforcing special rules of interaction. As pointed out in [5, p.751], in a commodity market, the third party (often termed the market) sets a price for a resource, and queries providers and consumers for their willingness to transact at that price. In an auction model, the third party (termed the auctioneer) gathers bids and resources, and determines the transaction of an individual resource (or resource bundle) based on the bids. However, it is noted that auction and commodity market models are based on well-founded economic models and it serves the emphasis to mention that it is *not* the intention of this paper to debate the advantages or disadvantages of bargaining versus auction and commodity market models. Rather, the intention of such comparison is to highlight some of the differences between bargaining, and auction and commodity market models.

3. ISSUES IN DESIGNING GRID NEGOTIATION MECHANISMS

The bargaining problem in Grid resource management is difficult because while attempting to optimize utility, negotiation agents need to: (i) negotiate for simultaneous access to multiple resources, (ii) consider the (market) dynamics of a computational Grid, and (iii) be highly successful in acquiring resources to reduce delay overhead in waiting for resources.

Optimizing utility: Through bargaining, Grid resource providers can strive to maximize their return-on-investment, and consumers can strive to minimize the price they pay for utilizing Grid resources or services. Both resource providers and consumers can initiate resource trading and participate in the trading process depending on their requirements and objectives. Whereas consumers select resource providers that offer the lowest service costs and also meet their deadline and budget requirements, resource providers offer services to the resource consumer with the highest bid as long as the consumer's objectives can be met. Both resource providers and consumers have their own utility functions that must be satisfied and maximized [p. 1514, 4]. In a bargaining model, this may involve devising a competitive negotiation strategy for optimizing the utility of self-interested agents in a *distributive negotiation* environment [22], and/or strategies for agents to search for joint gains in an *integrative negotiation* environment [22].

Acquiring multiple resources: Unlike bargaining in generic e-commerce applications in which one buyer typically negotiates with a seller on a single product/service at one time, Grid applications involving large-scale simulations may require access to multiple large computational resources simultaneously [9, p.1]. However, given that each of these resources may belong to different administrative domains (i.e., owned and operated by different resource providers), establishing a single service level agreement across all the desired resources can be very difficult.

Considering market dynamics: Since resources and services are constantly being added or removed from the Grid [23-24], it is essential to take market dynamics into consideration because providers can make resources/services available to and disconnect from a Grid, and consumers can enter and withdraw requests, perhaps at machine speed in both cases. However, responding to market dynamics is a difficult issue, and it was noted in [25] that the Grid resource allocation problem is aggravated by the dynamic and volatile nature of demand and supply. Both the node connectivity and service demands change frequently and new (as well as different) services are constantly being created and composed [26, p.1]. Load balancing of resources and supply in Grids can vary considerably over time, and there may also be unpredictable dynamic needs for Grid services that must be served on short notice [12, p.1].

Relaxing bargaining terms: The speed at which Grid resources are allocated and de-allocated is an essential consideration because any delay incurred on waiting for a resource assignment is perceived as an overhead [7]. To acquire resources more rapidly, bargaining agents should be designed to slightly relax their bargaining terms or bargaining criteria (e.g., accepting a slightly lower price) by considering using a suboptimal (or slightly more expensive) resource that can be allocated more quickly rather than the best (least expensive) resource which may be more difficult to acquire [2].

In addition to the set of criteria (such as stability, and individual rationality) used for evaluating negotiation mechanisms prescribed in [27] and reiterated in [4] in the context of economic models for Grid resource management, the issues of optimizing utility, acquiring multiple resources, considering market dynamics, and relaxing bargaining terms form *some* of the design considerations of the state-of-the-art research (section 4) in devising the strategies (decision making models of agents) and protocols (rules governing the interactions of agents) of negotiation mechanisms for Grid resource management.

4. NEGOTIATION MODELS FOR GRID RESOURCE MANAGEMENT

This section reviews negotiation mechanisms for managing Grid resources based on their strategies and protocols. Table I (see below) provides a summary for comparing the work reviewed in this section.

Lang [12] proposed a multiple-attribute negotiation mechanism for managing the resource usage in a computational Grid using a *Grid carrier agent* (GCA) to implement the intermediary function of matching suppliers' service capabilities and resource consumers' demand profiles. (Note that in [12] the *GCA* is utilized to support the connection of services and demands rather than to enforce the rules of negotiation or interaction). The goal is to design agents that autonomously negotiate multiple-attribute Grid service contracts. In [12] the negotiation protocol consists of (i) a *distributive negotiation phase*, in which (self-interested) agents adopt heuristic strategies to iteratively exchange bids (make proposals and counter proposals) among themselves, and (ii) an *integrative negotiation phase*, in which agents attempt to find joint gains while trying to maintain the utility distribution outcomes from the distributive negotiation phase.

In the distributive negotiation phase, agents attempt to maximize utilities by adopting a heuristic strategy that takes into account knowledge of the user's goal (e.g., attribute weight), and knowledge about the market (supply/demand ratio). In [12], an agent determines the amount of concession by considering both time-dependent and market factors. With respect to time, agents in [12] adopt three concession making strategies: *aggressive*, *neutral*, and *defensive* corresponding respectively to the *Bouleware*, *Linear*, and *Conceder* negotiation decision functions in [13]. Whereas an agent adopting a Bouleware strategy maintains its bid/offer until almost toward its deadline, an agent adopting a Conceder strategy rapidly concedes to its reservation value (e.g., its reserved price). Additionally, a service agent determines its "market power" by taking into account the ratio of (i) the number of supply advertisements for the same competing service and (ii) the total number of advertisements published in the entire system. In this phase, agents negotiate by alternately exchanging proposals and counter-proposals following the *alternating offers protocol* [28, p.100]. Moreover, it was noted in [12] that the distributive phase may generate service allocations that are below *Pareto efficiency* since self-interested agents (representing the interests of different individuals/organizations may not share common goals) negotiate with incomplete information (e.g., agents lack information about specific parameters of their opponents which are private such as their preferences over the possible outcomes, and reserve price [29]). An outcome is Pareto efficient if there is no other outcome that improves the outcome for one agent without making another agent worse off [30]. When an agent does not know the preference of the other agent, it does not know which of the possible joint outcomes is Pareto-optimal, and this may lead to a negotiation outcome that may not necessarily be best for all agents.

Whereas the distributive phase allows an agent to strive to optimize its individual outcome, the integrative phase allows agents to make minor adjustments to the preliminary agreement in the distributive phase with the hope of improving the joint outcomes of all agents. In the integrative negotiation phase, agents attempt to search for mutual improvements by exchanging proposals to slightly modify the preliminary agreement (contract) made in the distributive negotiation phase. Agents achieved this by randomly modifying the preliminary contracts using a Gaussian distribution such that the probability for making minor (respectively, major) modification is high (respectively, low) for each of the attributes. The objective is to find a solution that is more pareto-efficient than the preliminary contract in the previous phase while still preserving the utility gain of each individual agent as much as possible. Modifications of the preliminary contract follow a Gaussian (or normal) distribution because this will preserve as much as possible the utility gain of each individual agent obtained in the distributive negotiation phase. The probability function of a Gaussian distribution follows a normal curve (or "bell-shaped" curve) with the property that there is a higher probability of making minor changes (i.e., higher chance of having smaller deviations from the preliminary contract) and a lower probability of making more major changes (i.e., lower chance of having larger deviations from the preliminary contract). Similar to the distributive phase, agents in the integrative negotiation phase adopt the alternating offers protocol to modify their contracts (based on their current preliminary contracts) until no further improvement is found.

PANDA (Policy-driven Automated Negotiation Decision-making Approach) [11] is a negotiation mechanism that utilizes a rule-based framework for decision making of automated negotiation in service contracts. In *PANDA*, the basic building block of a strategy is a single condition-action rule, and a strategy is implemented using a set of rules. The rules reason on an *object pool*, consisting of negotiation history (previous messages exchanged among the agents), current offer, and *estimation programs*. Estimation programs derive parameters such as the desirability of a new contract, the feasibility (the costs of resources) for a service provider to support a contract, and a probabilistic measure of risk. These parameters provide guidelines for the decision criteria on issues such as how far a counter-proposal should deviate from the opponent's current proposal, and hence, how much concession an agent should make. An agent in *PANDA* computes the difference in utilities between its proposal and the proposal of its opponent based on attributes such as price, delay, response time, and availability, and determines a counter-proposal using the parameters derived by the estimation programs.

An example of a rule set in *PANDA*'s agents is given as follows: (i) if LEVEL_OF_DISSENT < 0.05 then ACCEPT, (ii) if LEVEL_OF_DISSENT < 0.05 and NEW_CUSTOMER then ACCEPT, and (iii) if LEVEL_OF_DISSENT > 0.2 then FIND_TRADE_OFF_OFFER. The "LEVEL_OF_DISSENT" refers to the utility difference between an agent's proposal and the counter-proposal of its opponent. An interesting feature of *PANDA* is that the rule set expresses the policies for negotiation and other aspects such as business reputation and customer satisfaction rather than just profitability and maximizing utilities. For instance, rule (ii) expresses the policy of giving preference to new customers. The protocol adopted by *PANDA* is simply a bilateral exchange of messages. While either agent can start a bilateral negotiation, neither of the two agents is required to alternate with sending messages. Whereas this deviates from many of the negotiation mechanisms which adopt the alternating offers protocol, it provides more flexibility in allowing multiple messages from both provider agents and consumer agents to be exchanged.

The work of Lawley et al. [14] investigated the use of negotiation agents for identifying mutually acceptable terms among information publishers (providers) and consumers of message notification services in a Grid computing environment. Adopting negotiation decision functions (*NDFs*) [13] for a bilateral negotiation model, Lawley et al's agents negotiate on terms such as frequency, format and accuracy of information being delivered by the notification service. Whereas agents in Faratin et al. [13] adopt a range of strategies based on time-dependent, resource-dependent and behavior-dependent *NDFs*, the strategies in Lawley et al. [14] are determined using only a combination of time-dependent and resource-dependent *NDFs*. Time-dependent *NDFs* consist of the *Boulware*, *Linear*, and *Conceder* tactics [13] (see above) that determine the amount of concession based on the fraction of remaining time. Using a resource function to determine the amount of resource consumption, resource-dependent *NDFs* consisting of *Patient, Steady,* and *Impatient* tactics generate proposals based on how a particular resource (e.g., remaining bandwidth) is being consumed. Agents become more conciliatory as the quantity of resource diminishes. By placing different weightings for the time-dependent and resource-dependent *NDFs* different strategies can be composed. For example, at the beginning of a negotiation process, agents adopt a strategy that places more weighting on resource-dependent *NDFs* and modifying the weighting towards the deadline by exerting more influence on time. Additionally, Lawley et al.'s agents negotiate with one another following the alternating offers protocol.

Based on a previous work on *market-driven agents* [16-20], Sim [15] presents a market-driven negotiation mechanism for Grid resource management. The distinguishing features of the negotiation mechanism in [15] include (i) a *market-driven strategy* and (ii) a *relaxed-criteria negotiation protocol*. Using a market-driven strategy, agents in [15] make adjustable amounts of concession by considering factors such as outside option, market rivalry, and time. A market-driven agent (*MDA*) determines the appropriate amount of concession using a combination of three negotiation functions: opportunity (***O***) function, competition (***C***) function and time (***T***) function.

The ***O*** function determines the amount of concession based on (i) trading alternatives (i.e., outside options or number of trading partners) and (ii) differences in utilities generated by the proposal of an *MDA* and the counter-proposal(s) of its trading partner(s). When determining opportunity, it was shown in [16-17] that if there is a large number of trading alternatives, the likelihood that an agent proposes a bid/offer that is potentially close to an *MDA*'s offer/bid may be high. However, it would be difficult for the *MDA* to reach a consensus if none of the so many options are viable (i.e., there are large differences between the proposal of the *MDA* and the counter-proposals of all its trading partners). On this account, the ***O*** function determines the probability of reaching a consensus at its own term by determining its bargaining position based on trading alternatives, differences between its proposal and others, and considering the notion of *conflict probability* [31].

The ***C*** function determines the amount of competition of an *MDA* by determining the probability that it is not being considered as the most preferred partner. Since *MDAs* are utility maximizing agents, an *MDA* is more likely to reach a consensus if its proposal is ranked the *highest* by some other agent. Suppose an agent ***B*** has m-1 competitors $\{B_2,\ldots, B_m\}$ and n trading partners $\{S_1,\ldots, S_n\}$. The probability that ***B*** is *not* the most preferred trading partner of *any* S_j (where $S_j \in \{S_1,\ldots, S_n\}$) is $(m\text{-}1)/m$. In this model, a uniform distribution [18, p.714] is assumed. Furthermore, it is also assumed that agents do not form coalitions [18, p. 723]. Hence, the probability that ***B*** is *not* the most preferred partner of *all* $S_j \in \{S_1,\ldots, S_n\}$ is $\left[(m-1)/m\right]^n$. In general, the probability that ***B*** is considered the *most preferred* trading partner by at *least one* of $S_j \in \{S_1,\ldots, S_n\}$ is: $C(m^B{}_t, n^B{}_t) = 1 - \left[(m^B{}_t - 1)/m^B{}_t\right]^{n^B{}_t}$ where $m^B{}_t$ and $n^B{}_t$ are respectively, the numbers of buyer agents (including ***B***) and seller agents at round t.

The ***T*** function models the intuition that as time passes, an *MDA* relaxes its proposal by making attempt(s) to narrow its difference(s) with other parties using: $T(t, \tau, \lambda) = 1 - (t/\tau)^{\lambda}$ where t is the current trading time, τ is the deadline, and λ is an *MDA*'s time preference. Whereas deadline puts negotiators under pressure, they have different time preferences (e.g., negotiators with different time preferences may have different concession rates with respect to time). With infinitely many values of λ, there are infinitely many possible strategies in making concession with respect to remaining trading time but they are classified into *Conservative, Linear* and *Conciliatory strategies* corresponding to making (i) larger concessions in the early trading rounds and smaller concessions at the later stage, (ii) a *constant* rate of concession, and (iii) smaller concessions in early rounds and larger concessions in later rounds. Additionally, it was proven in [18] that *MDAs* negotiate optimally by making minimally sufficient concession.

The relaxed-criteria negotiation protocol enhances the alternating offers protocol by slightly relaxing the criteria for agents to reach a consensus. In the alternating offers protocol and also in most negotiation models (e.g., [12-14], only to name a few because of space limitation), a pair of negotiation agents reaches an agreement when one agent proposes a deal that matches (or exceeds) what another agent asks for. This criterion was relaxed in [19-20] where an *MDA* accepts a (counter-)proposal even though it deviates slightly from (i.e., is slightly less favorable than) its own proposal. In [15], *MDAs* are programmed to slightly relax their bargaining terms in the face of intense pressure (e.g., when it has an urgent need to acquire a resource, or is facing strong competition or fast approaching deadlines). Since notions such as "very slight" difference in their proposals, "strong" competition, "fast" approaching deadline, and "very urgent" are vague, a fuzzy decision controller (*FDC*) together with a set of fuzzy rules were designed in [19-20] to guide *MDAs* in making decisions when relaxing their aspirations. By slightly relaxing its bargaining terms, empirical studies in [19-20] show that *MDAs* are more likely to achieve higher success rates in negotiation in the face of relatively shorter deadlines. In Grid resource allocation, a computational Grid is more likely to achieve a higher throughput if the negotiation agents are more successful in negotiating and acquiring resources. In summary, whereas the market-driven strategy attempts to optimize an *MDA*'s utility, the relaxed criteria protocol is designed to enhance their success rate in acquiring Grid resources.

Ghosh et al. [21] considered the issue of load balancing in a mobile computational Grid by proposing a fair pricing strategy and an optimal static job allocation scheme. In their model, a mobile Grid computing system consists of mobile devices which are sellers of resources, and WAP (wireless access point) servers which bargain with mobile devices to purchase resources for providing services to a community of Grid resource consumers. The bargaining between a WAP server and a mobile device is modeled as a 2-player non-cooperative bargaining game of incomplete information. If there are n mobile devices under a single WAP server, the WAP server will compose a price per unit resource vector $(p_1,\ldots,p_n)$ by playing n such games with all n corresponding mobile devices. The pricing strategy adopted in [21], considers factors such as resource constraints, time discount factor, "market price", the expected counter-proposal of an agent's opponent, and the perceived probabilities that an agent's opponent will (i) accept its proposal, (ii) reject its proposal but negotiation will continue as the opponent will make a counter-proposal, and (iii) reject its proposal and negotiation breaks down (i.e., terminate without an agreement). Intuitively, resource constraints prescribe that negotiation should break down if a mobile device does not have sufficient resources to offer. Time discount factor models the devaluation of a resource with the passage of time. In [21], "market price" refers to the "market value" of a resource determined based on the history of recent bargaining games that a WAP server and a mobile device have participated in. An agent attempts to predict the expected counter-proposal of its opponent by making "intelligent guesses" of its opponent reserved valuation. Although not identical, the perceived probability that an agent's opponent will accept its proposal is reminiscent of the *opportunity* ***O*** function in *MDA* described above, and the probability that an agent's opponent will reject its proposal corresponds to the conflict probability in *MDA*. Like many extant bargaining models, bargaining between a pair of a WAP server and a mobile device is carried out following the alternating offers protocol.

In addition to the bargaining and pricing strategies for Grid resource and service management described above, there are also negotiation protocols that are used for match-making and reservations that do not specifically consider the economics of resource management. For example, *SNAP* (Service Negotiation and Acquisition

Protocol) [9] has been proposed for advanced resource reservation and is utilized in a Grid computing platform. In *SNAP*, Grid participants negotiate a *service-level agreement* (*SLA*) in which a resource provider establishes a contract with a client or consumer to provide some measurable capabilities or to perform a task. Given that establishing a single *SLA* across a set of (simultaneously required) resources that may be owned and operated by different providers is very difficult, *SNAP* defines a resource management model in which (i) consumers or clients can submit tasks to be performed, and (ii) get promises of capability (commitment from the providers or servers), and bind (i) and (ii). In *SNAP*, *SLAs* are classified into: *Resource SLAs* (*RSLAs*), *Task SLAs* (*TSLAs*), and *Binding SLAs* (*BSLAs*). In a *RSLA*, clients negotiate with resource providers for the rights to consume a resource without specifying how the resource will be utilized. For example, an advanced resource reservation takes the form of an *RSLA*, and it characterizes a resource in terms of its abstract service capabilities. In a *TSLA*, clients negotiate with resource providers for the performance of an activity or a task. For example, a *TSLA* is created by submitting a job description to a queuing system and it characterizes a task in terms of its service steps and resource requirements. In a *BSLA*, clients negotiate with resource providers for the application of a resource to a task. A *BSLA* associates a task defined by a *TSLA* to a *RSLA*.

In the *SNAP* protocol, there are four states in resource planning: S_0, S_1, S_2, and S_3. In S_0, *SLAs* have not been created or have been resolved by termination or cancellation of the *SLAs*. In S_1, both *RSLAs* and *TSLAs* have been agreed upon, but they are not matched with each other. A movement from S_0 to S_1 indicates that a client has successfully negotiated with resource providers to establish both *RSLAs* and *TSLAs*. A movement from S_1 to S_2 indicates that a client has successfully negotiated with resource providers for the application of resources to tasks (i.e., successfully establishing *BSLAs*). In S_2, the *TSLA* is matched with the *RSLA*, and this binding represents a dependent *BSLA* to resolve the task. A movement from S_2 to S_3 represents the scheduling of resources by a resource provider to satisfy a *TSLA* (only a provider can move the control from S_2 to S_3). In S_3, although resources are actively being utilized to support a task, they can still be controlled and changed (e.g., moving back to S_2 from S_3).

Table I. A Summary of Bargaining Models for Grid Resource Allocation

Work	Strategy		Protocol	
	Optimize utility	Consider market dynamics	Relax bargaining terms	Acquiring multiple resources
Lang [12]	√	√	×	×
Gimpel [11]	√	×	√	×
Lawley [14]	√	×	×	×
Sim [15]	√	√	√	×
Ghosh[21]	√	√	×	×
Czajkowski [9]	×	×	×	√

5. DISCUSSION AND CONCLUSION

In summary, the six negotiation mechanisms discussed in section 4 address only some of the issues mentioned in section 3.

While *SNAP* [9] finds the solutions for satisfying the resource requirements of Grid consumers, [11-12, 14-15, 21] (as well the other economic models surveyed in [3-4]) focus on optimizing the return on investment and purchasing price of Grid participants. Whereas the *SNAP* protocol focuses on negotiating for multiple (simultaneous) access of resources through advanced resource reservation, establishment of service level agreements, and *RSLAs* and *TSLAs* bindings, [12, 14-15, 21] follows the alternating offers protocol or its variant (e.g., with relaxed criteria for reaching a consensus [15]). Even though the alternating offers protocol has been widely adopted in many bargaining mechanisms for generic e-commerce applications in which a buyer typically negotiates with a seller on a single product/service at one time, it may not be adequate for specifying the procedures that a negotiation agent in Grid resource management will follow when it has to negotiate for multiple resources simultaneously with several other agents. However, unlike *SNAP*, [12, 14-15, 21] considered strategies for optimizing utilities of Grid participants.

The bargaining strategy in [12] not only focuses on optimizing the utility of an individual agent, but also attempts to increase the mutual gains of all agents. Whereas [12] adopted variants of the time-dependent *NDFs* [13] as the concession making strategies, the concession making strategies in [14] used a combination of time-dependent and resource-dependent *NDFs*. Additionally, it is noted that time discount factor was also considered in [12, 14-15, 21]. However, while [14] and [11] considered bilateral bargaining models for services management, bargaining models in [12, 15, 21] take into consideration the influence of market factors. In [12], a service agent's "market power" (which is the ratio of (i) the number of supply advertisements for the same competing service and (ii) the total number of advertisements published in the entire system) generally corresponds to the ***C*** function in *MDA*. However, the notion of opportunity was not modeled in [12]. Even though market dynamics were not explicitly modeled in [21], the "market value" of a resource is determined using the history of recent bargaining. Whereas the notion of the probability that the opponent will accept an agent's offer bears some resemblance to an *MDA*'s ***O*** function, there is no explicit modeling of market rivalry and outside options. However, even though *MDAs* react to current market situations by considering the ***O*** and ***C*** functions, in their present stage, *MDAs* do not have any mechanism for predicting market dynamics (e.g., future outside options).

Moreover, it is noted that the rule sets in *PANDA* express policies that consider customer satisfaction and business reputation rather than just profitability and maximizing utilities. For instance, *PANDA* can express a policy such as "if the customer's offer is close to an agent's proposal, and if the customer is new, then accept the offer" using a (hard-coded) rule such as "if LEVEL_OF_DISSENT < 0.05 and NEW_CUSTOMER then ACCEPT". In [15], while the market-driven strategy attempts to optimize utilities, the relaxed criteria protocol uses a set of fuzzy rules to guide *MDAs* in making decision to slightly relax their bargaining terms. Whereas *MDAs* use fuzzy rules to determine the amount of relaxation based on the intensity of competition and the need to acquire a resource, *PANDA* slightly relaxes its bargain terms based on business policy such as giving preferences to new customers. By slightly relaxing bargaining terms the negotiation success rate of an agent can be enhanced [19-20], even though in some situations this may be done at the expense of achieving slightly lower utility (i.e., utilizing a slightly more expensive resource). However, in a Grid computing environment, being (more) successful in negotiating for access of computing resources is essential for avoiding any possible delay overhead incurred on waiting for a resource assignment. Whereas relaxing bargaining terms slightly (at the expense of achieving slightly lower utility) may be desirable to enhance the success rate of acquiring computing resources, the problem of determining the appropriate amount of relaxation to achieve both optimal utility and optimal success rate under different market conditions and constraints remains open. This problem is currently being investigated by the author and his students in an on-going project [32].

Finally, this paper suggests that both (i) satisfying requirements of Grid consumers to access multiple resources simultaneously, and (ii) considering the economics of resource allocation mechanisms, are essential. The selection of a server/provider for a task is not only a question of mapping job description to resource availability, but should also take into consideration the conditions about price, performance, and quality of service of the server. To the best of the author's knowledge, there is no bargaining mechanism that (i) adopts a negotiation protocol that is similar to *SNAP*, (ii) adopts a negotiation strategy that optimize the utility, as well as (iii) considers the issues of Grid market dynamics and relaxing bargaining terms. It is envisioned that future work on the bargaining models for Grid resource management will consider issues (i), (ii) and (iii) mentioned above as well as others. Whereas it was proven in [18] that bargaining agents adopting the market-driven strategy [16-20] negotiate optimally by making minimally sufficient concessions in different market conditions, more work needs to be done to (i) determine the appropriate amount of relaxation to achieve both optimal utility and optimal success rate given deadline constraints, market rivalries, and outside options, and (ii) devise a negotiation protocol for acquiring multiple resources that also takes into consideration market dynamics and relaxation of bargaining terms.

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