Grid Resource Negotiation: Survey and New Directions

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***Abstract*—Since Grid computing systems involve large-scale resource sharing, resource management is central to their operations. Whereas there are more Grid resource management systems adopting auction, commodity market, and contract-net (tendering) models, this survey supplements and complements existing surveys by reviewing, comparing, and highlighting existing research initiatives on applying bargaining (negotiation) as a mechanism to Grid resource management. The contributions of this paper are: 1) discussing the motivations for considering bargaining models for Grid resource allocation; 2) discussing essential design considerations such as modeling devaluation of Grid resources, considering market dynamics, relaxing bargaining terms, and co-allocation of resources when building Grid negotiation mechanisms; 3) reviewing the strategies and protocols of state-of-the-art Grid negotiation mechanisms; 4) providing detailed comparisons and analyses on how state-of-the-art Grid negotiation mechanisms address the design considerations mentioned in 3); and 5) suggesting possible new directions.**

***Index Terms*—Automated negotiation, bargaining, computational economy, G-commerce, Grid economics, Grid resource allocation, Grid resource management, negotiation agent.**

I. Introduction

Since a computational Grid [1], [2] focuses on large-scale resource sharing, resource management is central to its operations [3, p. 135]. However, providing efficient resource allocation mechanisms in the Grid is a complex undertaking due to its scale and the fact that resource owners and consumers may have different goals, policies, and preferences. A Grid is a very large-scale network computing system that can potentially scale to Internet size, and the network computing system can be viewed as a virtual computer consisting of a networked set of heterogeneous machines (owned by multiple organizations) that agree to share their local resources with each other [3, p. 135]. Computing resources required by an application to execute tasks may be owned by other organizations, and resource owners and consumers often have different objectives, preferences, and policies. To this end, Grid applications generally do not have complete control over the resources that they need to execute their tasks. With resource owners and consumers having different management policies, access models and cost models, it may be difficult to implement the mechanisms and policies needed for effective use of shared resources.

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In a position paper by Sim [4], 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 [5] and [6]. Whereas some of the more commonly referenced work (e.g., see [7]–[10]) focused on commodity markets, auction, and contract-net/tendering models for Grid resource management, this paper focuses on reviewing and comparing 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 [3], [5], [6] by reviewing and highlighting existing research initiatives on applying automated negotiation as a mechanism to Grid resource management. The contributions of this paper are listed as follows. Whereas Section II provides the motivations for considering automated negotiation as a model for allocating Grid resources, Section III 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 IV reviews some state-of-the-art bargaining models for Grid resource management. Section V provides detailed comparisons and analyses of the strategies and protocols of the bargaining mechanisms discussed in Section IV. Sections VI and VII summarize and conclude this paper by discussing new directions and open problems.

II. Grid Resource Negotiation

Whereas the arrival of e-commerce blurred the difference between negotiations and auctions, Kersten *et al.* [11] and Bichler *et al.* [12] outlined some of their major differences. Negotiation is a form of decision making with two or more actively involved agents who cannot make decisions independently (or achieve their goals unilaterally), and therefore must *make concessions to achieve a compromise* [13]. On the other hand, an auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market agents [14]. It was noted in [11, p. 10] that while auction-like protocols play a major role when determination of value is the primary concern, negotiation-like protocols may be more appropriate when participants are not only concerned with determining value, but *also* other factors, e.g., inter-business relationships (see Section IV-B) and success rates (see Section IV-D). In situations involving inter-business relationships, an *integrative*

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negotiation mechanism (which finds solutions to reconcile the interests of all agents) may be more appropriate than auctions, because "auctions focus on determining the value of objects of unknown value while negotiations are about cooperating to create value" [11, p. 6]. Section IV-A describes an example of a G-negotiation mechanism that has an integrative negotiation phase for improving the joint outcome of all agents. Moreover, in a Grid computing environment, being more successful in acquiring computing resources is essential (see Section III). To this end, it seems more prudent to adopt negotiation mechanisms for successfully reconciling the differences between resource providers and consumers rather than using auctions for purely determining the value of resources. Section IV-D describes a G-negotiation mechanism that not only strives to optimize agents' utilities, but also their negotiation success rates. However, it is *not* the intention of this paper to debate the differences/similarities and advantages/disadvantages between negotiations and auctions. These issues are already debated quite considerably in [11]. Rather, this section discusses some motivations for considering Grid resource negotiation mechanisms as follows. In [15, p. 231], it was noted that prices and negotiations can be used to coordinate the activities of objects and software entities. In a Grid setting, negotiation among Grid applications and Grid resource providers is necessary because:

1) there is a need to obtain contracts and commitments for provisioning resources/services;
2) there is a need to resolve differences between Grid applications and resource providers;
3) through negotiation, resource providers are given the opportunity to maximize their return-on-investment and consumers to minimize the price they pay for utilizing Grid resources.

1) Obtaining Contracts/Commitments: To execute a task, a Grid application may need resources that are owned by other organization(s), possibly spanning multiple administrative domains [16, p. 632]. This is because: 1) computationally (or data) intensive applications may require more resource(s) than a single computing machine (e.g., a workstation, a supercomputer, or a cluster of computers) can provide in one administrative domain [5, p. 1]; or 2) an application may require a type or several types of computing capability (that it does not have) from resource owner(s) in other administrative domain(s). Consequently, it cannot be assumed that a resource provider will unconditionally provide a (computing) capability to a consumer [17, pp. 12–13]. Hence, it is necessary for an application to obtain commitments or contracts from a resource owner to provide a service/resource [17, pp. 12–13]. To ensure that the necessary capabilities will be available when required, it is essential for automatic scheduling programs (or software agents) of a Grid application to have the ability to negotiate an agreement for a specific time [16, p. 633].

2) Resolving Differences: Since Grid participants are independent bodies, with different access policies, objectives, requirements, and supply-and-demand patterns, negotiation is needed to resolve their differences. For instance, even if a resource owner (perhaps, from a different administrative domain) is willing to provide a service or to lease a computing resource to a Grid application, one would still be faced with the question of determining the desired level of service and the cost of providing the service because resource owners set their own policies and cost [18, p. 2]. Hence, a Grid resource management system should support negotiation between consumers and providers. Whereas consumers require assurance on the level, type, and quality of service (e.g., timeliness [19, p. 104]) being provided by the resources, resource owners are concerned about maintaining local control on how resources are being utilized (the usage policy).

3) Optimizing Utility: Through bargaining, 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 [6, p. 1514]. 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 [20], and/or strategies for agents to search for joint gains in an integrative negotiation environment [20].

III. 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: 1) model devaluation of Grid resources with time; 2) consider the (market) dynamics of a computational Grid; 3) be highly successful in acquiring resources to reduce delay overhead in waiting for resources; and 4) negotiate for simultaneous access to multiple resources (sometimes spanning different administrative domains).

1) Modeling Devaluation of Resources: Grid resources are perishable in the sense that "computing capacities not used now is worthless in the next moment" [21, p. 3]. Time discounting is the standard way for modeling devaluation of goods over time due to perishing [22, p. 715]. As noted by Binmore and Basgupta (see [23, p. 14]): "*The passage of time has a cost in terms of both dollars and the sacrifice of utility which stems from the postponement of consumption, and it will be precisely this cost which motivates the whole bargaining process. If it did not matter when the parties agreed, it would not matter whether they agreed at all*." For Grid resources, time discounting is also essential for modeling losing utility (e.g., decreasing value of a resource) with time as a result of a resource not being leased out and utilized. Hence, Grid resource management systems should model the devaluation of Grid resources with time.

2) Considering Market Dynamics: Like conventional resources (e.g., electricity and gasoline), computing resources in a Grid also have dynamic values. The value of Grid resources is derived from a combination of need and scarcity [21, p. 2]. Grid consumers' demand for resources does not remain constant but changes with time. For instance, during a project life cycle, users may have varying workloads and number of tasks in different project stages. Intuitively, when computing resources are scarce, variation in consumers' demand affects the value of resources. Furthermore, resources and services are constantly being added or removed from the Grid [24], [25]. Hence, it is essential to take market dynamics into consideration because: 1) the value of resources varies with changing consumers' demand, and consumers can enter/withdraw requests, perhaps at machine speed; and 2) resource capacities vary as providers can make resources/services available to and disconnect from a Grid.

The use of market mechanisms helps regulate supply and demand of resources [5, p. 2]. The use of currency offers incentives for resource providers to contribute resources and Grid applications should be more prudent when using resources given that budget is limited and resources are scarce. Hence, using a market mechanism may reduce the likelihood that applications become wasteful in using limited computing resources [26, p. 8]. Additionally, a resource management system needs to continuously adapt to changes in: 1) the availability of computing resources (e.g., due to providers leaving the Grid or more consumers joining the Grid); and 2) requirements of applications (e.g., due to more job requests from consumers) [5, p. 2].

3) Relaxing Bargaining Criteria: A resource management system should consider resource availability and application QoS requirements (e.g., timeliness [19, p. 104]). G-negotiation agents should be designed to consider the tradeoff between the benefit of using a suboptimal (or slightly more expensive) resource that can be located and allocated more quickly and the benefit of using the best (or least expensive) resource, which may be more difficult to acquire. For instance, to acquire resources more rapidly, they should be designed to slightly relax their bargaining criteria (such as accepting a slightly higher price), especially when the Grid loading is very high (i.e., many computing resources are occupied). It was noted in [27, p. 113] that when the QoS requirements of an application cannot be fully met, one of the options is using an alternative implementation. Like time constraint, this consideration relates to the issue of the speed at which resources can be allocated, which, in turn, relates to the issue of overhead [9]. Furthermore, it was noted in [26] that resource management systems should take both economic and computational factors into consideration. Echoing [26], this work takes the stance that the desire for more resources (or to acquire less expensive resources) should be balanced by an attention to more traditional system metrics (e.g., computational efficiency).

4) Resource Co-Allocation: A Grid resource management system should bolster co-allocation of computing (or data) resources [18, p. 2]. In Grid computing, the problem of resource co-allocation is allocating to an application multiple resources belonging to different administrative domains. To coordinate the utilization of multiple resources owned by different administrative domains, advance reservation of resources that specifies the time and duration of a resource capacity is essential [16, p. 3]. Unlike generic e-commerce negotiations where a buyer-seller pair negotiates for a product or a service, perhaps in a single negotiation phase, a Grid application may need to engage in a multiphase negotiation process with resource owners, to reserve, acquire, coordinate, schedule, and potentially renegotiate resource access. Whereas common bargaining protocols such as the *alternating offers protocol* [28, p. 100] will suffice for most generic e-commerce negotiations, dealing with negotiation of resource co-allocation and advance resource reservations requires more sophisticated negotiation protocols. One such protocol is Service Negotiation and Acquisition Protocol (*SNAP*)—see Section IV-F.

IV. G-Negotiation Models

This section reviews and discusses state-of-the-art approaches of Grid resource negotiation mechanisms in terms of their strategies and protocols. These include works that:

1) adopt a two-phase bargaining protocol for G-negotiation (see Section IV-A);
2) use rule sets to express policies for G-negotiation (see Section IV-B);
3) employ time-dependent and resource-dependent negotiation decision functions (*NDFs*) for negotiating Grid information notification services (see Section IV-C);
4) design market-driven strategies and relaxed-criteria protocol for G-commerce (see Section IV-D);
5) use a bargaining game to model G-negotiation in mobile Grids (see Section IV-E);
6) devise negotiation protocols for resource co-allocation and advance reservation (see Section IV-F).

A. Two-Phase Protocol for G-Negotiation

Lang [29] 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 [29], 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 [29], the negotiation protocol consists of: 1) a *distributive negotiation phase*, in which (self-interested) agents adopt heuristic strategies to iteratively exchange bids (make proposals and counterproposals) among themselves; and 2) 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 [29], an agent determines the amount of concession by considering both time-dependent and market factors. With respect to time, agents in [29] adopt three concession making strategies: *aggressive*, *neutral*, and *defensive* corresponding, respectively, to the *Boulware*, *Linear*, and *Conceder NDFs* in [30] and [31]. Whereas an agent adopting a Boulware 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 reserve price). Additionally, a service agent determines its "market power" by taking into account the ratio of: 1) the number of supply advertisements for the same competing service; and 2) the total number of advertisements published in the entire system. In this phase, agents negotiate by alternately exchanging proposals and counterproposals following the alternating offers protocol. Moreover, it was noted in [29] 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 prices [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 [32]. 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 in 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 achieve 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.

B. Policy-Driven G-Negotiation

Policy-driven Automated Negotiation Decision-making Approach (*PANDA*) by Gimpel *et al.* [33] adopts a rule-based framework for negotiation in service contracts. In *PANDA*, rule sets express policies that consider customer satisfaction and business reputation rather than just maximizing utilities. The basic building block of a *PANDA* strategy is a single condition-action rule, and a strategy is implemented using a set of rules. For instance, *PANDA* has rules such as "if the customer's offer is close to an agent's proposal, and if the customer is new, then accept the offer" to express the policy for giving preference to new customers. The rules reason on an *object pool*, comprising of negotiation history (previous messages exchanged among the agents), current offer, and *estimation programs*. The estimation programs are used to derive parameters such as: 1) desirability of a new contract; 2) feasibility for a service provider to support a contract; and 3) probabilistic risk measure. These parameters provide guidelines for the decision criteria on issues such as how far a counterproposal 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 counterproposal using the parameters derived by the estimation programs.

An example of a rule set in *PANDA*'s agents is given as follows:

1) "if LEVEL_OF_DISSENT < 0.05 then ACCEPT;
2) if LEVEL_OF_DISSENT < 0.2 and NEW_CUSTOMER then ACCEPT;
3) if LEVEL_OF_DISSENT > 0.2 then FIND_TRADE_OFF_OFFER."

Here, "LEVEL_OF_DISSENT" refers to the utility difference between an agent's proposal and the counterproposal 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, whereas rule 2) expresses the policy of giving preference to new customers, rule 3) performs an optimization task by using a tradeoff heuristic for computing an adequate counter offer. 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.

C. G-Negotiation Agents for Information Notification Service

Lawley *et al*. [34] 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. Through negotiation, an information publisher can balance between the utility (satisfaction) of the consumers and its workload. Even though in some cases, consumers' utility may be lowered (e.g., receiving less frequent message updates), lowering its workload (e.g., sending message updates less frequently to a consumer) allows a publisher to benefit from serving more consumers.

Adopting *NDFs* [30] [31] 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*. [30] adopt a range of strategies based on time-dependent, resource-dependent, and behavior-dependent *NDFs*, the strategies in Lawley *et al.* [34] are determined using only a combination of both time-dependent and resource-dependent *NDFs*. Time-dependent *NDFs* consist of the *Boulware*, *Linear*, and *Conceder* tactics [30] [31] (details are given in Section V-A) that determine the amount of concession based on the fraction of remaining time (these will be compared to the other negotiation mechanisms in Section V-A).

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 on the time-dependent and resource-dependent *NDFs*, different strategies can be composed. For instance, at the beginning of a negotiation process, an agent may adopt a strategy that places more weighting on resource-dependent *NDFs* but it can modify the weighting as it reaches towards the deadline to exert more influence on time. Additionally, Lawley et al.'s agents negotiate with one another following the alternating offers protocol.

D. Market-Driven and Relaxed-Criteria G-Negotiation

Based on a previous work on *market-driven agents* (*MDAs*) [22], [35]–[40], Sim [41]–[44] presents a market-driven negotiation mechanism for Grid resource management. The distinguishing features of the negotiation mechanism in [38]–[41] include: 1) a *market-driven strategy* and 2) a *relaxed-criteria negotiation protocol*.

1) Market-Driven Strategy: Using a market-driven strategy [35]–[40], agents in [41]–[44] make adjustable amounts of concession by considering factors such as outside options, market rivalry, and time. An *MDA* determines the appropriate amount of concession using a combination of three negotiation functions: time (***T***) function, opportunity (***O***) function, and competition (***C***) function. In an abstract *MDA* model [22], a linear combination of all three functions is used to determine the overall concession. For the purpose of experimentation, *MDAs* in [36], [41], [43], and [44], respectively, used the product and the average of the sum of the three functions for determining the overall concession.

The ***T*** function models the intuition that as time passes, an *MDA* relaxes its proposal by making attempt(s) to narrow the difference k_t between its proposal and the counterproposal of its opponent in the current trading time t using $T(t, \tau, \lambda) = 1 - (t/\tau)^{\lambda}$ where 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 concessions with respect to remaining trading time. However, they are classified in [22] and [36] as follows.

1) *Linear*: $\lambda = 1$ and $k_{t+1} = [T(t,\tau,\lambda)]k_t = [1-(t/\tau)]k_t$. At any round t, an *MDA* makes a *constant* rate of concession, $\Delta_t = k_t - k_{t+1}$. At the deadline $t = \tau$, $k_\tau = [1-(\tau-1/\tau)]k_{\tau-1}$ and $k_{\tau+1} = [1-(\tau/\tau)]k_\tau = 0$. Hence, $\Delta_\tau = k_\tau - k_{\tau+1} = k_\tau$ (an *MDA* expects and attempts to narrow the difference completely at the deadline).
2) *Conciliatory*: $k_{t+1} = [1-(t/\tau)^{\lambda}]k_t$, where $0 < \lambda < 1$. An *MDA* makes larger concessions in the early trading rounds and smaller concessions at the later stage.
3) *Conservative*: $k_{t+1} = [1-(t/\tau)^{\lambda}]k_t$, where $1 < \lambda < \infty$. An *MDA* makes smaller concessions in early rounds and larger concessions in later rounds.

In all the previous strategies, for all Δ_t (including Δ_τ), there is an additional constraint [22, p. 715] requiring that for a buyer agent *B* (respectively, a seller agent *S*), $l_t^B + \Delta_t \leq RP_B$, where RP_B is *B*'s reserve price and l_t^B is *B*'s proposal at round t (respectively, $l_t^S - \Delta_t \geq RP_S$, where RP_S is *S*'s reserve price and l_t^S is *S*'s proposal at round t). If $l_t^B + \Delta_t > RP_B$ (respectively, $l_t^S - \Delta_t < RP_S$), then negotiation terminates with a conflict.

The ***O*** function determines the amount of concession based on: 1) trading alternatives (i.e., outside options or number of trading parties) and 2) differences in utilities generated by the proposal of an *MDA* and the counterproposal(s) of its trading party (parties). When determining opportunity, it was shown in [35] and [36] 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 counterproposals of all its trading parties). On this account, the ***O*** function determines the probability of reaching a consensus on its own terms by determining its bargaining position based on: 1) trading alternatives; 2) differences between its proposal and others; and 3) considering the probability of obtaining the worst possible utility [45].

In a bilateral negotiation, the probability p of reaching consensus on an agent's own terms can be derived as follows. Suppose agent *B* engages S_1 in round t. *B*'s last proposal generates a payoff of $v_t^{B\rightarrow S_1}$ for itself, and S_1's last counterproposal generates a payoff of $w_t^{S_1\rightarrow B}$ for *B*, with $v_t^{B\rightarrow S_1} > w_t^{S_1\rightarrow B}$ (i.e., $v_t^{B\rightarrow S_1}$ is more favorable for *B*). If *B* accepts S_1's counterproposal, it will obtain $w_t^{S_1\rightarrow B}$ with certainty. If *B* insists on its last proposal, and 1) if S_1 accepts it, *B* will obtain $v_t^{B\rightarrow S_1}$ and 2) if S_1 does not accept it, *B* may be subjected to a conflict utility c^B. c^B is the worst possible utility for *B*, and $w_t^{S_1\rightarrow B} > c^B$. If S_1 does not accept *B*'s last proposal, *B* may ultimately have to settle with lower utilities (the lowest possible being c^B), if there are changes in the market situations in subsequent cycles. For instance, *B* may face more competition in subsequent cycles, and may have to ultimately accept a utility that is lower than $w_t^{S_1\rightarrow B}$ (possibly as low as c^B if the negotiation ends in disagreement). Let the subjective probability of *B* obtaining c^B be p_c (*conflict probability*) and the probability that *B* achieves $v_t^{B\rightarrow S_1}$ is $1-p_c$, then, based on Zeuthen's analysis [46], if *B* insists on holding its last proposal, *B* will obtain an expected payoff of $(1 - p_c) \times v_t^{B\rightarrow S_1} + p_c \times c^B$. Hence, *B* will find that it is advantageous to insist on its last proposal only if $[(1 - p_c) \times v_t^{B\rightarrow S_1} + p_c \times c^B] \geq w_t^{S_1\rightarrow B}$. Thus, $p_c \leq (v_t^{B\rightarrow S_1} - w_t^{S_1\rightarrow B})/(v_t^{B\rightarrow S_1} - c^B)$. Consequently, the maximum value of p_c is the *highest probability of a conflict* that *B* may encounter at round *t* [22], [35], [36]:

$$p_c = \frac{v_t^{B \to S_1} - w_t^{S_1 \to B}}{v_t^{B \to S_1} - c^B} \tag{1}$$

where p_c is a ratio of difference between two utilities. While $v_t^{B \to S_1} - w_t^{S_1 \to B}$ measures the cost of *accepting the trading agent's last offer* (the spread *k* or difference between the (counter-)proposals of *B* and S_1), $v_t^{B \to S_1} - c^B$ measures the cost of *provoking a conflict*.

In a multilateral negotiation, if *B* has *n* trading parties, the aggregated conflict probability of *B* with all *n* parties is:

$$P_c = \prod_{j=1}^{n} \frac{v_t^{B \to S_j} - w_t^{S_j \to B}}{(v_t^{B \to S_j} - c^B)}. \tag{2}$$

Consequently, the probability that *B* will obtain a utility $v_t^{B \to S_j}$ with at least one of its *n* trading parties is

$$O\Big(n, v_t^{B \to S_j}, \Big\langle w_t^{S_j \to B} \Big\rangle\Big) = 1 - \prod_{j=1}^{n} \frac{v_t^{B \to S_j} - w_t^{S_j \to B}}{(v_t^{B \to S_j} - c^B)}. \tag{3}$$

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 trading party. 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 parties $\{S_1, \ldots, S_n\}$. The probability that *B* is *not* the most preferred trading party of *any* S_j (where $S_j \in \{S_1, \ldots, S_n\}$) is (*m*–1)/*m*. In this model, a uniform distribution [22, p. 714] is assumed. Furthermore, it is also assumed that agents do not form coalitions [22, p. 723]. Hence, the probability that *B* is *not* the most preferred party of *all* $S_j \in \{S_1, \ldots, S_n\}$ is $[(m-1)/m]^n$. In general, the probability that *B* is considered the *most preferred* trading party by at *least one* of $S_j \in \{S_1, \ldots, S_n\}$ is: $C(m,n) = 1 - [(m-1)/m]^n$, where *m* and *n* are, respectively, the numbers of buyer agents (including *B*) and seller agents at round *t*.

Additionally, Sim [22] has proven that *MDAs* negotiate optimally by making minimally sufficient concessions with respect to opportunity and competition (see [22, Lemmas 4.1 and 4.2, pp. 718–719]).

2) Relaxed-Criteria Protocol: The G-negotiation protocol used in [41]–[44] enhances the alternating offers protocol by slightly relaxing the criteria for agents to reach a consensus using the following rules:

R1: An agreement is reached if two agents B_1 and S_1 propose deals b_1 and o_1, respectively, such that either 1) $U(b_1) \geq U(o_1)$ or 2) $U(o_1) \geq U(b_1)$, where *U* is a utility function mapping b_1 and o_1 to [0,1].

R2: An agreement is reached if either 1) $\eta = U(o_1) - U(b_1)$, such that $\eta \to 0$ or 2) $\eta = U(b_1) - U(o_1)$, such that $\eta \to 0$, where η is the amount of relaxation determined using a fuzzy decision controller (*FDC*).

In the alternating offers protocol and also in most negotiation models (e.g., [28], [34], [47], only to name a few because of space limitation), a pair of negotiation agents (B_1, S_1) reaches an agreement when one agent proposes a deal that matches (or exceeds) what another agent asks for (see *R1*). *R1* was relaxed in [41]–[44] where a G-negotiation agent *also* accepts another agent's (counter-)proposal if it is *sufficiently close* to its own proposal following *R2*.

In Sim's relaxed-criteria bargaining protocol [43], [44], G-negotiation agents representing resource providers and consumers are programmed to *slightly* relax their bargaining criteria under intense pressure (e.g., when a consumer has a higher demand for resources) in the hope of enhancing their chance of successfully acquiring resources. A consumer agent and a provider agent are both designed with an *FDC*: *FDC-C* and *FDC-P*, respectively. Two sets of relaxation criteria (for consumers and providers, respectively) that are specific to Grid resource management are used as inputs to *FDC-C* and *FDC-P*, respectively.

a) Consumers' relaxation criteria: Two criteria that can influence a consumer agent's decision in the amount of relaxation of bargaining terms are: 1) recent statistics in failing/succeeding in acquiring resources called *failure to success ratio* (fs_t), and 2) demand for computing resources called *demand factor* (df_t). If a consumer agent is *less* successful in acquiring resources recently to execute its set of tasks, it will be under more pressure to slightly relax its bargaining criteria in the hope of completing a deal. Furthermore, if it has a *greater* demand for computing resources it is more likely to be under more pressure to slightly relax its bargaining criteria. Both fs_t and df_t are inputs to *FDC-C*, which a consumer agent uses to determine η (its amount of relaxation) [43], [44].

b) Providers' relaxation criteria: Two criteria that can influence a provider agent's decision are: 1) the amount of the provider's resource(s) being utilized [i.e., the *utilization level* (ul_t)], and 2) recent requests from consumers for resources [i.e., called the *request factor* (rf_t)]. If more of its resources are currently being used to execute its own tasks or are already leased to other consumers, then a provider is less likely to slightly relax its bargaining terms. If there are fewer recent demands from consumers to lease its resources, a provider is more likely to slightly relax its bargaining criteria since it is under more pressure to trade its idle resources. Both ul_t and rf_t are inputs to *FDC-P*, which a provider agent uses to determine η [43], [44].

Empirical results obtained in [41], [43], and [44] show that by slightly relaxing their bargaining terms under intense negotiation pressure, both consumer and provider agents generally achieved higher success rates in negotiation (without sacrificing much of their average utilities).

E. G-Negotiation Agents for Mobile Grid

Ghosh *et al.* [47], [48] 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 that are sellers of resources, and wireless access point (*WAP*) servers

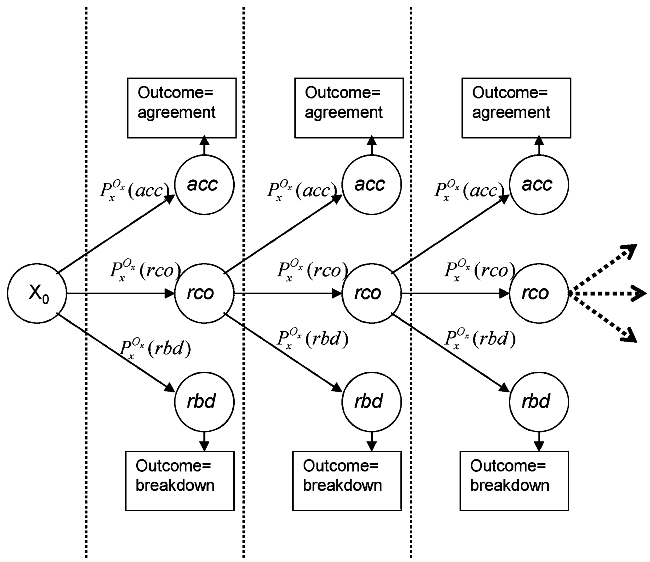

Fig. 1. Bargaining game of alternating offers.

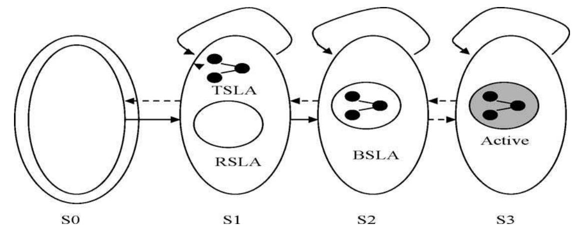

Fig. 2. State transitions of the *SNAP* protocol [49].

that 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 two-player noncooperative 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,. . .,p_n) by playing *n* such games with all *n* corresponding mobile devices. The pricing strategy adopted in [47], [48], considers factors such as resource constraints, time discount factor, "market price," the expected counterproposal of an agent's opponent, and the perceived probabilities that an agent's opponent will: 1) accept its proposal; 2) reject its proposal but negotiation will continue as the opponent will make a counterproposal; and 3) reject its proposal and negotiation breaks down (i.e., terminates without an agreement). Let O_x be the price proposed by a bargainer *x*. Let $P_x^{O_x}(acc)$, $P_x^{O_x}(rco)$, and $P_x^{O_x}(rbd)$ be the perceived probabilities that *x*'s opponent will: 1) accept its offer (*acc*); 2) reject its offer and make a counteroffer (*rco*); and 3) reject its offer and bargaining breaks down (*rbd*). Ghosh *et al.* model a bargaining game of alternating offers as shown in Fig. 1. At each node in Fig. 1, there are three possible outcomes and each is associated with one of the three perceived probabilities listed above.

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 [47] and [48], "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 counterproposal of its opponent by making "intelligent guesses" of its opponent's reserve valuation. Like many existing bargaining models, bargaining between a pair of a *WAP* server and a mobile device is carried out following the alternating offers protocol.

F. Service Negotiation and Acquisition 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* has been proposed by Czajkowski *et al.* [16], [49], [50] for advance 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: 1) consumers or clients can submit tasks to be performed, and 2) get promises of capability (commitment from the providers or servers), and bind 1) and 2). In *SNAP*, *SLAs* are classified into: *Resource SLAs* (*RSLAs*), *Task SLAs* (*TSLAs*), and *Binding SLAs* (*BSLAs*). In an *RSLA*, clients negotiate with resource providers for the rights to consume a resource without specifying how the resource will be utilized. For example, an advance 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 an *RSLA*.

In the *SNAP* protocol, there are four states in resource planning: S_0, S_1, S_2, and S_3 (see Fig. 2). Note that in Fig. 2, a solid arrow represents a request (or action) by a client, and a dashed arrow represents an action or internal behavior of a resource provider. 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. The solid arrow from S_0 to S_1 (see Fig. 2) represents the transition of a client that has successfully negotiated with resource providers to establish both *RSLAs* and *TSLAs*. There are three possible movements from S_1: 1) S_1 to S_0 (dashed arrow); 2) S_1 to S_1 (solid curly arrow); and 3) S_1 to S_2 (solid arrow). S_1 to S_0 represents the transition in which *SLAs* have been either cancelled by a resource provider or a client, or expired. S_1 to S_1 represents the transition in which a client is waiting to establish the *BSLAs* (even though it has

TABLE I
SUMMARY AND COMPARISON

References:	2-Phase negotiation[29]	Policy-driven negotiation[33]	Service Negotiation [34]	MDA [41,43-44]	Mobile Grid negotiation[47-48]	SNAP [16,49-50]
Negotiation Protocol						
Alternating Offers	√		√		√	
Bilateral exchange, not necessarily alternating		√				
Relaxed-criteria				√		
Negotiation Strategies						
Time-dependent	√		√	√	√	
Market-driven	√			√	√	
Resource-dependent			√			
Behavior-dependent			√			
Rule-based		√				
Coordination						
Acquiring multiple resources						√

already established both *RSLAs* and *TSLAs*). S_1 to S_2 represents the transition of a client that 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. There are three possible movements from S_2: 1) S_2 to S_1 (dashed arrow); 2) S_2 to S_2 (solid curly arrow); and 3) S_2 to S_3 (dashed arrow). S_2 to S_1 represents the transition in which a resource provider moves the control back to the prior state because some fault has occurred and the task cannot be scheduled. S_2 to S_2 represents the transition that even though a *BSLA* has been established, a client is waiting for the task to be scheduled. S_2 to S_3 represents the scheduling of resources by a resource provider to satisfy a *TSLA*. 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). Whereas the movement from S_3 to S_3 represents the transition of task execution (a client's task is being executed and it is waiting for the task to complete execution), S_3 to S_2 represents either task completion or faults in the execution so that the resource provider moves the control back to the prior state.

V. COMPARISONS

This section provides comparisons of G-negotiation mechanisms reviewed in Section IV in terms of the approaches adopted for: 1) modeling devaluation of resources with passing time (see Section V-A); 2) considering market factors in the concession making strategies (see Section V-B); 3) relaxing bargaining terms and exploring mutual gains (see Section V-C); and 4) resource co-allocation (see Section V-D). Table I summarizes and compares the main features of the works reviewed in Section IV in terms of their negotiation protocol, negotiation strategies, and coordination. It can be seen in Table I that only *SNAP* [16], [49], [50] considered the issue of coordinating resource utilization by finding solutions to satisfy multiple resource requirements. However, Czajkowski *et al*. [16], [49], [50] did not consider the issues of specifying the negotiation protocols and strategies to enable agents to search for more flexible or perhaps near optimal allocation. On the other hand, coordination of resources was not considered in [34], [41], [43], [44], [47], and [48]. The negotiation models in [34], [41], [43], [44], [47], and [48] can only be adopted for allocation of a single Grid resource.

A. Modeling Time Discounting

Lang [29], Lawley *et al.* [34], Sim [41], Sim and Ng [43], [44], and Ghosh *et al*. [47], [48] incorporated a time discount factor in their concession making strategies to model devaluation of resources with passing time. Whereas Lang [29] adopted variants of the time-dependent *NDFs* ([30], [31]), Lawley *et al.* [34] used a combination of time-dependent and resource-dependent *NDFs*. The time function in [47] and [48] is different from [29], [34], [41], [43], and [44]; however, this section only focuses on comparing the time functions in [29], [34], [41], [43], and [44]. Table II compares the time-dependent functions in [29], [34], [41], [43], and [44] in terms of three major classes of concession making strategies. It serves to highlight the common features of the three different time functions in [29], [34], [41], [43], and [44]. By showing the similarities of these time functions, Table II provides designers with some guidelines on the common properties of the mathematical functions for modeling devaluation of resources. For instance, all functions in [29], [34], [41], [43], and [44] can be used to model 1) concessions made with respect to time, and 2) different attitudes of agents toward time [e.g., a patient (respectively, an impatient) agent can adopt either the *Boulware* or the *conservative* or the *aggressive* strategy (respectively, the Conceder or the conciliatory or the *defensive* strategy)].

B. Modeling Market Dynamics

To model market dynamics in their concession making strategies, Lang [29], Sim [41], [42], and Sim and Ng [43], [44] and Ghosh *et al*. [47], [48] take into consideration factors such as opportunity, probability of an opponent accepting a bargainer's offer, competition, and "market power." Table III compares the opportunity and competition functions of [29], [41]–[44], [47], [48] in terms of making less (respectively, more) concessions in favorable (respectively, unfavorable) market conditions. It serves to show the similar concession making properties of the opportunity functions in [41], [43], [44], [47], and [48] and the competition functions in [41], [43], [44], and [29]. By showing

TABLE II
TIME-DEPENDENT FUNCTIONS

References	**Time function**	Slow decreasing	Constant decreasing	Fast decreasing
[41] [43] [44]	$T(t,\tau,\lambda) = 1 - (t/\tau)^{\lambda}$	*Conservative* (λ>1)	*Linear* (λ=1)	*Conciliatory* (λ<1)
	t is the current trading time, τ is the deadline, and λ is an agent's time preference			
[34]	$f^{A}(t) = k^{A} + (1-k^{A})\left(\dfrac{\min(t,\tau)}{\tau}\right)^{\frac{1}{\psi}}$	*Boulware* (ψ<1)	*Linear* (ψ=1)	*Conceder* (ψ>1)
	t is a discrete negotiation time indexed by {0,1,2,…}, τ is the deadline of agent A, and ψ is A's time preference			
[29]	$\Delta_i(\pi) = \left(\dfrac{t - t_0}{t_{crit}(\pi)}\right)^{\beta_i(\pi)}$	*aggressive* ($\beta_i(\pi)$>1)	*Neutral* $\beta_i(\pi)$=1	*defensive* $\beta_i(\pi)$<1
	π is an agent's belief about the current state about the real world, t = {0, 1, 2,… }, t_0 refers to the time index when t=0, $t_{crit}(\pi)$ is an agent's negotiation deadline, and $\beta_i(\pi)$ is an agent's time preference			

TABLE III
MARKET-DRIVEN FUNCTIONS

References	**Opportunity Function**	Favorable Market (Makes less concession)	Unfavorable Market (Makes more concession)
[41] [43] [44]	$\boldsymbol{O}(n,v_t^{B\to Sj},<w_t^{Sj\to B}>)$	$\boldsymbol{O}(n,v_t^{B\to Sj},<w_t^{Sj\to B}>) \to 1$	$\boldsymbol{O}(n,v_t^{B\to Sj},<w_t^{Sj\to B}>) \to 0$
	$\boldsymbol{O}(n,v_t^{B\to Sj},<w_t^{Sj\to B}>)$ is the probability of reaching a consensus at an agent's own terms. $\boldsymbol{O}(n,v_t^{B\to Sj},<w_t^{Sj\to B}>)$ depends on: 1) n - number of trading alternatives, and 2) differences in utilities between agent B's proposal and each trading partner S_j's proposal.		
[47] [48]	$P_x^{O_x}(acc)$	$P_x^{O_x}(acc) \to 1$	$P_x^{O_x}(acc) \to 0$
	$P_x^{O_x}(acc)$ is the perceived probability that agent x's opponent will accept its proposal O_x. $P_x^{O_x}(acc)$ depends on the number of opponents with proposed prices higher than the "market price".		

References	**Competition Function**	Favorable Market (Makes less concession)	Unfavorable Market (Makes more concession)
[41] [43] [44]	$C(m,n) = 1 - [(m-1)/m]^{n}$	*Little* competition $C(m,n) \to 1$	*stiff* competition $C(m,n) \to 0$
[29]	$\pi_{power_j} = \begin{cases} 1 - 2 \times \pi_{GCA.ratio_j}, & for\ \ provider \\ 2 \times \pi_{GCA.ratio_j} - 1, & for\ \ consumer \end{cases}$	*high* "market power" $\pi_{power_j} \to 1$	*low* "market power" $\pi_{power_j} \to -1$
	$\pi_{GCA.ratio_j} = \dfrac{N_{pro}^{j}}{N_{pro}^{j} + N_{con}^{j}}$, $\pi_{power_j} \in [-1,1]$ N_{pro}^{j} is the number of supply advertisements for the same competing service, and $N_{pro}^{j} + N_{con}^{j}$ is the total number of advertisements published in the entire system.		

the similarities of these opportunity and competition functions, this section provides designers with some guidelines on their common properties for modeling market conditions.

C. Relaxing Bargaining Terms and Mutual Gains

While Sections V-A and V-B analyze various G-negotiation mechanisms in terms of their concession making strategies, this section compares the protocol of G-negotiation mechanisms based on issues such as: 1) exploring joint gains in utility, and 2) relaxing bargaining terms to enhance success rates.

The bargaining protocol in [29] not only focuses on optimizing the utility of an individual agent, but also attempts to increase the mutual gains of all agents. In the integrative phase of its two-phase protocol, agents make small adjustments to their preliminary agreement in the distributive phase in the hope of improving joint gains. On this account, in addition to optimizing individual utility, the protocol of [29] also considers other factors such as finding a Pareto-efficient solution.

The rule sets in *PANDA* [33] 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 rule such as "if LEVEL_OF_DISSENT < 0.05 and NEW_CUSTOMER then ACCEPT." In [41]–[44], while the market-driven strategy attempts to optimize utilities, the relaxed-criteria protocol uses a set of fuzzy rules to guide *MDAs* in making decisions to slightly relax their bargaining terms. Whereas *MDAs* use fuzzy rules to determine the amount of relaxation based on statistics of recent resource demands and recent success-failure rates (for consumer), and amount of resource being utilized and statistics of requests (for provider), *PANDA* slightly relaxes its bargaining terms based on business policies such as giving preferences to new customers. By slightly relaxing bargaining terms, the negotiation success rate of an agent can be enhanced [43], [44], 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 to computing resources is essential for avoiding any possible delay overhead incurred on waiting for a resource assignment.

In summary, agents in [29], [33], and [41]–[44] are designed to make small modifications to their bargaining proposals in the hope of finding a more Pareto-efficient outcome in the case of [29], enhancing bargaining success rates in the case of [41]–[44], and improving customer satisfaction/relation in the case of [33]. The negotiation models in [29],[33] and [41]–[44] are examples of (Grid-)negotiation mechanisms that not only focus on determining the value (price) of Grid resources, but also consider social factors (e.g., inter-business relationships), successful negotiation outcomes, and Pareto-efficiency.

D. Co-Allocation, Concurrent Negotiations, and Coordination

Supporting Grid resource co-allocation involves: 1) bolstering multiple concurrent pairs of negotiations simultaneously, and 2) coordinating the concurrent negotiations. 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. Among the G-negotiation mechanisms discussed in Section IV, either the alternating offers protocol or its variant (e.g., with relaxed criteria for reaching a consensus [43], [44] or a two-phase (distributive and integrative) negotiation protocol [29]) is adopted in [29], [34], [41]–[44], [47], and [48] . However, very often Grid applications running intensive applications may require several (types of) resources simultaneously, and these resources may be owned by different resource owners. Even though it may be possible for a consumer to adopt a concurrent bilateral (or multilateral) negotiation model (with several agents negotiating concurrently with multiple resource providers for several (types of) resources simultaneously) following the alternating offers protocol, the G-negotiation mechanisms in [29], [34], [41]–[44], [47], [48] were not specifically designed to support coordination among different resource providers. Hence, even if a consumer can successfully acquire all required resources through negotiation, the issue of coordinating the utilization of these resources that are owned by different owners still needs to be resolved. The *SNAP* protocol focuses on negotiating for multiple (simultaneous) access of resources through advance resource reservation, establishment of service level agreements, and *RSLAs* and *TSLAs* bindings (see Section IV-F). Using the *SNAP* protocol, a consumer may achieve advance resource reservation and coordinate simultaneous access to multiple resources following the four states in resource planning shown in Fig. 2 (see description in Section IV-F). However, unlike [29], [34], [41]–[44], [47], and [48], where strategies for optimizing utilities of Grid participants were considered, *SNAP* [16], [49], [50] only searches for the solutions for satisfying the resource requirements of Grid consumers, and does not focus on optimizing the return on investment and purchasing price of Grid participants.

VI. Summary of Contributions

Whereas a preliminary short survey of bargaining models for Grid resource allocation by Sim [51] was published as a short newsletter, this paper has significantly and considerably extended and expanded [51] by providing a more detailed review (see Section IV) and very detailed comparisons of the various state-of-the-art G-negotiation models (see Section V). Additionally, considerably much more detailed discussions are provided in Sections II and III describing both the motivations for considering bargaining as a mechanism for Grid resource allocation and the essential considerations for designing G-negotiation mechanisms.

Complementing Existing Surveys: Whereas [3] provided a classification of Grid resource management systems, [5], [6] surveyed economic models (in general) for Grid resource management, focusing mainly on auction, commodity market and contract net models. To this end, this survey that focuses on Grid bargaining mechanisms does not compete with related surveys on Grid resource management, but rather it complements and supplements existing surveys on economic models for Grid resource management. The contributions of this survey are: 1) identifying and describing the essential design issues for building negotiation mechanisms; 2) providing agent designers with a repertoire of time-dependent and market-driven functions for formulating negotiation strategies; and 3) suggesting new research directions in G-negotiations.

Identifying Issues in G-negotiation: While [52] provided guiding principles and described desirable properties of generic automated negotiation systems, and [53] surveyed state-of-the-art negotiation agents for e-commerce, this work identifies and describes the essential design issues for building negotiation mechanisms specific to Grid resource management. In general, negotiation mechanisms can be evaluated according to many types of criteria, and the choice of protocol will depend on the properties the designer wants the overall system to have [54]. Some of the desirable properties of negotiation mechanisms prescribed in [32], [52], [54] include: guaranteed success (ensuring that agreements are reached), searching Pareto-efficient outcomes (see Section IV-A), and being stable. A negotiation mechanism is stable if it provides all agents with an incentive to behave in a desired manner (e.g., they have no incentive to deviate from their chosen strategies [52, p. 21]). In some situations, it is possible to design negotiation mechanisms with dominant strategies [54], i.e., an agent has the best-response strategy no matter what strategies other agents adopt. Among the works reviewed in Section IV, the market-driven negotiation mechanism in [41] and [42] is stable because it was proven in [22] and [40] that conservative strategies (see Section IV-D) are dominant strategies for *MDAs* in [41] and [42]. The negotiation mechanisms in [29] and [34] (which adopt the negotiation model in [30]) are also stable because it was proven in [31] that Boulware strategies (see Sections IV-A and IV-C) are dominant strategies for the negotiation model in [30]. In Section IV-A, it was noted that the work in [29] has an integrative negotiation phase for agents to improve their joint outcome by making minor adjustments to the preliminary agreement in the distributive negotiation phase which may be below Pareto efficiency. The negotiation mechanism in [41] and [44] enhances the negotiation success rates of *MDAs* by adopting a relaxed-criteria G-negotiation protocol.

Guidelines for Designers: Another contribution of this survey is identifying some common properties of the negotiation decision functions used in different G-negotiation mechanisms. By explicitly highlighting some of the similar characteristics (i.e., slow (respectively, constant, and fast) decreasing concession patterns, and making less (respectively, more) concessions in favorable (respectively, unfavorable) markets) of the different negotiation decision functions used in the works surveyed in this paper, Tables II and III in this survey aim at providing agent designers with a repertoire of time-dependent and market-driven functions for formulating negotiation strategies of agents.

Deployment to Grids: It is noted that a resource broker adopting the *SNAP* protocol [16], [49], [50] was deployed and tested in the *White Rose Grid* [57]. The time and opportunity functions in [41], [43], and [44] were adopted in the negotiation strategies in [58] for Grid scheduling using workload traces from the Cornell Theory Center that had 512 *CPU* nodes.

VII. Conclusion and New Directions

The G-negotiation mechanisms discussed in Section IV address only some of the issues mentioned in Section III (see Table I). This section suggests possible new directions by addressing some of the partially addressed or unaddressed issues described as follows.

Predicting market dynamics: Whereas [33] and [34] considered bilateral bargaining models for services management, bargaining models in [29], [41]–[44], [47], and [48] take into consideration the influence of market factors. As detailed in Section V-B, an agent's "market power" in [29] generally corresponds to the ***C*** function in *MDAs*. However, [29] did not model the notion of opportunity. Even though market dynamics were not explicitly modeled in [47] and [48], 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. Nevertheless, in its present form, *MDAs* only react to current market situations by considering the ***O*** and ***C*** functions, they do not have any mechanisms for predicting market dynamics (e.g., future outside options). Given that Grid nodes may join and leave the Grid at any time, modeling future uncertainties of possible outside options (e.g., predicting changing number of resource alternatives) in a Grid market may be a topic for future research.

Optimal relaxation: Whereas relaxing bargaining terms slightly (at the expense of achieving slightly lower utility) may be desirable to enhance the success rates of acquiring computing resources, the problem of determining the appropriate amount of relaxation to achieve both optimal utilities and optimal success rates under different market conditions (e.g., given different resource alternatives and demands) and constraints (e.g., given different deadlines) remains open. This problem may involve devising learning techniques for tuning the set of fuzzy rules for optimal relaxation.

Mechanism for coordination and negotiation: Finally, as mentioned in Section IV-F, whereas *SNAP* finds solutions to satisfy multiple resource requirements of consumers, it does not consider the issue of optimizing utility as given in [29], [34], [41]–[44], [47], and [48], but the protocols given in [29], [34], [41]–[44], [47], and [48] do not address the issue of coordinating resource utilization. This paper suggests that both: 1) satisfying requirements of Grid consumers to access multiple resources simultaneously, and 2) 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, to date, there is no bargaining mechanism that: 1) adopts a negotiation protocol that is similar to *SNAP*; 2) adopts a negotiation strategy that optimizes utilities; and 3) considers the issues of Grid market dynamics and relaxing bargaining terms. It is envisioned that future work on bargaining models for Grid resource management will consider issues 1)–3) as well as others. One of the possible approaches for constructing a negotiation mechanism for Grid resource co-allocation is to incorporate the detailed specifications of the negotiation activities between consumers and providers into a *SNAP*-like coordination protocol by taking into consideration the issues of enhancing negotiation success rates by relaxing bargaining criteria, optimizing utility, and modeling market dynamics. Details of such a mechanism are presented in [55].

Third-party mediation: In addition to the works reviewed in Section IV, it is noted that [56] also considered a G-negotiation mechanism by adopting genetic algorithm (GA) for evolving agents' strategies by exploring the possible agreement space and employed a trusted third party protocol (TTP) to find an optimized point in the agreement space. By employing a negotiation protocol that combines GA and TTP, a mutually beneficial agreement point can be reached. Since the negotiation mechanism in [56] was designed for bilateral negotiations using a trusted third party, the issue of market dynamics was not considered. Even though the pricing mechanism considered factors such as peak periods, normal periods, discount periods, and waiting time, the devaluation of resources with time was not explicitly modeled. Additionally, the issues of relaxing bargaining terms and resource co-allocation were not considered. In particular, [56] differs significantly from the negotiation mechanisms discussed in Section IV because it involves mediations from a trusted third party, which is outside the scope of the issues considered in this paper. Hence, inclusion of a detailed comparison between [56] and the negotiation mechanisms in Section IV is not appropriate.

Concluding remark: Most the works surveyed in this paper [29], [33], [34], [41], [43], [44], [47], [48] address the issues of modeling devaluation of resources and market dynamics, and the issue of relaxing bargaining terms is addressed in [33], [41], [43], and [44]. However, these works only considered negotiation for a single Grid resource and did not address the issue of coordinating multiple Grid resources. This paper suggests that a negotiation mechanism for supporting the allocation of multiple Grid resources will likely be constructed by incorporating some of the negotiation strategies and protocols in [29], [33], [34], [41], [43], [44], [47], and [48] into *SNAP*'s coordination protocol. It is hoped that this survey will not only provide the foundation for understanding Grid bargaining mechanisms, but will also inspire other researchers to take up the challenge to investigate some of the issues raised here as well as other problems relating to Grid resource negotiation.

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