Grid Commerce, Market-Driven G-Negotiation, and Grid Resource Management

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***Abstract*—Although the management of resources is essential for realizing a computational grid, providing an efficient resource allocation mechanism is a complex undertaking. Since Grid providers and consumers may be independent bodies, negotiation among them is necessary. The contribution of this paper is showing that market-driven agents (MDAs) are appropriate tools for Grid resource negotiation. MDAs are e-negotiation agents designed with the flexibility of: 1) making adjustable amounts of concession taking into account market rivalry, outside options, and time preferences and 2) relaxing bargaining terms in the face of intense pressure. A heterogeneous testbed consisting of several types of e-negotiation agents to simulate a Grid computing environment was developed. It compares the performance of MDAs against other e-negotiation agents (e.g., Kasbah) in a Grid-commerce environment. Empirical results show that MDAs generally achieve: 1) higher budget efficiencies in many market situations than other e-negotiation agents in the testbed and 2) higher success rates in acquiring Grid resources under high Grid loadings.**

***Index Terms*—Grid commerce, Grid resource allocation, negotiation, resource management, software agent.**

I. Introduction

GRID COMPUTING is distinguished from conventional distributed computing because it focuses on large-scale resource sharing [1, p. 200]. Hence, a resource management system is central to the operation of a Grid [2, p. 135]. 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 agrees to share their local resources with each other [2, p. 135]. Due to its scale, and because resource owners and consumers may have different goals, preferences, interests, and policies, providing an efficient resource management and coordination mechanism in the Grid is a *complex undertaking*. Hence, automatic scheduling programs are needed to (re)allocate computing resources because of both the complexity of the resource allocation problem and the dynamically changing performance of the Grid resources [3, p. 747]. Agents (or autonomous problem solvers) that can act flexibly in dynamic environments can provide supportive efforts for a computational Grid [4, p. 8]. Sim [5] argued that software agents, in particular e-negotiation agents, can play an essential role in realizing the Grid vision. Adopting a market-driven approach [6], this work attempts to address some of the issues raised in [5] by designing and building negotiation agents that participate in Grid-commerce (G-commerce) [3], [7], [8] in a *market-oriented Grid* [9]–[11].

1) G-commerce and Market-Oriented Grid: In [3], [7], and [8], Wolski coined the term G-commerce to refer to computational economies for controlling the resource allocation in computational Grid environments. The Grid can be viewed as a network of computations [12], and computations can be viewed in economic terms [13, p. 133]. It was noted in [7] and [8] that casting the Grid resource allocation problem in economic terms is both intuitive and advantageous.

First, the utilization of Grid resources is not for free [3]. In a market-oriented Grid, providers can receive royalties for the (computing and storage) resources and services they provide, whereas Grid users can attempt to mold the Grid systems to their needs by exercising their market powers as Grid consumers. In a Grid economy [14, p. 699], resource management systems should provide the tools and mechanisms for both providers and consumers to express their requirements and facilitate the realization of their goals. A Grid economy not only helps regulate the supply and demand for Grid resources, but also provides the incentives for providers to contribute resources and benefit from doing so and offers an efficient mechanism for managing resources [14, p. 699].

Second, there is an enormous literature on economic theories and principles for explicating and understanding the emergent behavior of the Grid and its constituents (participants). It was also noted in [13, p. 134] that using market models as an economic organization for computation is effective in promoting efficient and cooperative interactions among entities with different goals and knowledge.

Third, it was pointed out in [3, p. 748] that many economic systems and some of their assumptions seem to be familiar (e.g., many people can associate price to the supply-and-demand patterns of resources). Moreover, these economic principles also extend to artificial decision-making agents in general [13, p. 134], including software agents and entities.

Finally, it was noted in [14, p. 699] that some of the economic models for resource allocation include: commodity market models, auction models, tendering or contract-net models, and bargaining or negotiation models.

2) Market-Driven G-Negotiation: Whereas [3], [7], and [8] focused on both commodity markets and auction formulations

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of G-commerce, the contribution of this work is designing a testbed of negotiation agents for resource management and allocation in a Grid computing platform. Negotiation activities are necessary in a computational Grid because of the following reasons.

1) It cannot be assumed that a resource provider will unconditionally provide a (computing) capability to a consumer [4, pp. 12–13].
2) Since Grid participants are independent bodies [10], some form of mechanism is needed to resolve their differences.
3) Through negotiation, players in a Grid marketplace, i.e., resource owners (or service providers) and consumers [11], 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 cost of providing the service and the desired level of service. Hence, adopting automated negotiation as a means for establishing contracts and 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. Moreover, it was noted in [15, p. 231] that prices and negotiations can be used to coordinate the activity of objects and software entities.

To the best of the author's knowledge, to date, there are only a few (preliminary) efforts on applying e-negotiation agents to resource management in Grid computing (e.g., [10] and [16]–[18]). Additionally, the strategies adopted by these agents do not take the dynamics of the market into consideration. In a highly dynamic Grid environment, 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.

3) Design Considerations: It is envisioned that negotiation in a market-oriented Grid must take into consideration the following:

1) dynamics of the computing environment;
2) speed at which resources are allocated or deallocated.

The availability of resources and the load continuously vary with time [19, p. 81]. Since resources and services are constantly being added or removed from the Grid [10], [20], factor 1) is an essential consideration. Factor 2) is important because any delay incurred on waiting for a resource assignment is perceived as an overhead [7]. Both factors 1) and 2) collectively help define some of the design considerations of Grid-resource-negotiation (G-negotiation) agents listed as follows.

1) Market factors: To optimize their returns, G-negotiation agents should consider factors such as opportunity and competition in response to the availability and changing loads in the Grid (i.e., the dynamics of the computing environment).
2) Time constraint: G-negotiation agents should be sensitive to deadlines. In addition to the cost of resource set by owners and the price a consumer is willing to pay, it was pointed out in [14, p. 7] that deadline is another important parameter that can influence the way resource scheduling is carried out.
3) Tradeoff: 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 that 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). 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 [7].

Even though there are many existing e-Negotiation agents (e.g., just to name a few: Kasbah [21], and negotiation decision functions (NDFs) [22]), none of these agents was designed to take into consideration all the aforementioned three design issues. For instance, although both Kasbah and NDF model the devaluation of goods with time using time-dependent NDFs, they were primarily designed for bilateral negotiations and did not take into consideration the influence of market factors. While there are some (but very few) works on building Grid-negotiation agents [10], [16], [17], most of these research efforts are preliminary, and both considering market dynamics and making tradeoff decisions are not among their research focuses (see Section V). The goal of this research is to show that market-driven agents (MDAs) (Section II) previously engineered for e-negotiation are appropriate tools for G-negotiation because they possess many desirable properties (see Section II-A) such as being able to negotiate optimally and make tradeoff decisions. Empirical results obtained from stochastic simulations using a testbed (Section III-A) to simulate a Grid computing environment show that MDAs generally achieved relatively high budget efficiencies in many market situations and relatively high success rates in G-negotiation under high Grid loadings.

II. Market-Driven E-Negotiation Agent

An MDA [23]–[28] is a negotiation agent that was originally designed for bolstering negotiation activities in e-commerce. MDAs are e-negotiation agents that incorporate all the design considerations listed in Section I. An MDA is sensitive to deadline and model devaluations of goods over time due to perishing [28]. It takes into consideration the influence of both market rivalry as well as trading options. The novel features of an MDA are its abilities to make: 1) adjustable amounts of concession by reacting to different market conditions and bargaining constraints and 2) tradeoff decisions for reaching a consensus with a higher probability by slightly relaxing its bargaining terms.

1) Reacting to Market Situations: An MDA determines the appropriate amount of concession using three NDFs: *time*, *competition*, and *opportunity*. It makes concession by narrowing the difference k_t between its proposal and the counterproposal of its opponent in a negotiation round t. In determining the amount of concession, an MDA uses the time, competition, and opportunity functions to determine the expected difference k_{t+1} in its proposal and the counterproposal of its opponent in the next round $t+1$

$$k_{t+1} = f\left[\boldsymbol{O}\left(n_t^{\mathrm{B}}, v_t^{B\to Sj}\left\langle w_t^{Sj\to B}\right\rangle\right), \boldsymbol{C}\left(m_t^{\mathrm{B}}, n_t^{\mathrm{B}}\right), \boldsymbol{T}(t,\tau,\lambda)\right] k_t.$$

2) Time Function: In a bilateral negotiation, the decision of an MDA is generally influenced by time. The time-dependent function $T(t,\tau,\lambda)$ models the intuition that as time passes, an MDA relaxes its proposal by attempting to narrow its difference(s) with the counterproposal(s) of 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 [29, p. 67], an MDA has different time preferences (e.g., negotiators with different time preferences may adopt different concession rates with respect to time) [30, pp. 32–33]. In an MDA, the concession rate is determined with respect to $0 < \lambda < \infty$. With infinitely many values of λ, there are infinitely many possible strategies in making concession with respect to the remaining trading time. However, they can be classified 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 $1 < \lambda < \propto$. An MDA makes smaller concessions in early rounds and larger concessions in later rounds.

In all the above strategies, for all Δ_t (including Δ_τ), there is an additional constraint [28, p. 715] requiring that for a buyer agent B (respectively, a seller agent S), $l_t^{\mathrm{B}} + \Delta_t \leq \mathrm{RP}_B$, where RP_B is B's reserve price, and l_t^{B} is B's proposal at round t (respectively, $l_t^{\mathrm{S}} - \Delta_t \geq \mathrm{RP}_S$, where RP_S is S's reserve price, and l_t^{S} is S's proposal at round t). If $l_t^{\mathrm{B}} + \Delta_t > \mathrm{RP}_B$ (respectively, $l_t^{\mathrm{S}} - \Delta_t < \mathrm{RP}_S$), then negotiation terminates with a conflict.

3) Opportunity Function: In a multilateral negotiation, having outside options may give a negotiator more bargaining "power." However, negotiations may still break down if the proposals between two negotiators are too far apart. The opportunity function $O(n_t^{\mathrm{B}}, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle) = (1 - \prod_{j=1}^{n_t^{\mathrm{B}}}(v_t^{B\to Sj} - w_t^{Sj\to B})/(v_t^{B\to Sj} - c^{\mathrm{B}}))$ determines the amount of concession based on: 1) trading alternatives (number of trading partners n_t^{B}) and 2) differences in utilities ($v_t^{B\to Sj}$) generated by the proposal of an MDA and the counterproposal(s) of its trading partner(s) ($\langle w_t^{Sj\to B}\rangle$) [6], [24], [28]. Details of deriving the opportunity function are given in [6], [24], and [28].

4) Competition Function: MDAs are designed for multilateral negotiations, and rivalry in an e-market is inherent. The amount of competition of an MDA is determined by the probability that it is not being considered as the *most* preferred partner. The competition function $C(m_t^{\mathrm{B}}, n_t^{\mathrm{B}})$ determines the probability that an agent $\boldsymbol{B}$ is ranked as the most preferred trading partner by *at least one* other agent at round t [6], [24], [28]. If $\boldsymbol{B}$ has $m_t^{\mathrm{B}} - 1$ competitors, and n_t^{B} trading partners, then, $C(m_t^{\mathrm{B}}, n_t^{\mathrm{B}}) = 1 - [(m_t^{\mathrm{B}} - 1)/m_t^{\mathrm{B}}]^{n_t^{\mathrm{B}}}$. Details of deriving the competition function are given in [6], [24], and [28].

5) Relaxing Bargaining Terms: An MDA uses a set of fuzzy rules to determine when it should relax its bargaining terms in the hope of having a higher chance of reaching a consensus. Augmented with a fuzzy decision controller (FDC) (see [26]), Sim's enhanced MDAs (EMDAs) are programmed to slightly relax their bargaining terms in the face of intense pressure (e.g., urgent need to acquire a resource or facing fast approaching deadlines). Since notions such as "very slight" difference in proposals, "strong" competition, and "fast" approaching deadline are vague, an FDC, together with a set of 16 fuzzy rules, were used in [26] to guide EMDAs in making decision when relaxing their aspirations. In relaxing its bargaining terms, an EMDA is influenced by factors such as competition (c), and its *eagerness* (ε). ε represents how urgent it is for an EMDA to acquire a resource before a deadline [26] and $\varepsilon = 1/\lambda$, because an EMDA that is *more* (respectively, *less*) eager to reach a consensus will adopt a strategy with a *smaller* (respectively, *larger*) value of λ. Both c and ε form the antecedents of the fuzzy rules, while the amount of relaxation η is the consequent. Whereas c and ε are the inputs to the FDC, η represents the amount that an EMDA would relax its bargaining terms in a given situation (the output of the FDC). Conciliatory strategies are not adopted in EMDAs because Sim [6] has proven that, with shorter deadlines, MDAs adopting Conciliatory strategies are more likely to achieve lower utilities even though they face lower risk of losing deals to other competitors. EMDAs are already designed with a set of fuzzy rules to relax their bargaining terms in the face of intense negotiation pressure such as short deadlines. Such a design complements the adoption of only conservative and linear strategies that are more likely to achieve higher utilities, but face higher risks of losing the deal to other agents (perhaps in the face of high competition).

A. Desirable Properties

MDAs possess many desirable properties of negotiation mechanisms prescribed in [31] (e.g., being stable and selecting the best-response strategy to maximize utility). Consequently, MDAs also satisfy many of the criteria of a market model for Grid resource allocation mentioned in [11]. Additionally, MDAs negotiate optimally by responding to changing market conditions and are able to make tradeoff decisions.

1) Negotiating Optimally: An agent receives a utility of zero if it never trades [30, p. 152] or is unsuccessful in trading (because disagreement is the worst outcome [30, p. 33]). Hence, *both*: 1) size of the possible payoffs *and* 2) probability of achieving these payoffs are essential. Although conceding more increases the probability of reaching a deal, it is inefficient because an agent "wastes" some of its utility. However, if an agent concedes too little, it runs the risk of losing a deal. In [25] and [28], Sim has proven that MDAs make *minimally sufficient concessions* (see [28, Lemmas 4.1–4.2 and Proposition 4.1, pp. 718–719]). Hence, they avoid making excessive concessions in favorable markets and inadequate concessions in unfavorable markets. This distinguishing property of MDAs enables them to optimize their returns in different e-market situations. Whereas previous theoretical analyses showed that MDAs can negotiate optimally in different market situations by making minimally sufficient concessions, empirical results in this work (see Section IV) demonstrate that in a simulated Grid computing environment, MDAs can successfully negotiate Grid resources while achieving relatively high utilities in different market situations.

2) Making Tradeoff Decisions: Previous empirical results in [26, pp. 1605–1607] obtained from extensive stochastic simulations in a wide variety of market conditions showed that by slightly relaxing bargaining terms (at the expense of achieving slightly lower average utilities), the success rates of EMDAs are enhanced in many e-market situations. This is essential because successfully acquiring the necessary resource even though at the expense of paying a (slightly) suboptimal price is crucial in ensuring efficient operations in a computational Grid. It may be more beneficial for a Grid resource scheduling system if a G-negotiation agent acquires a resource more rapidly or with more certainty by perhaps paying a slightly higher price provided that more jobs in the system can be accomplished.

3) Stability and Sequential Equilibrium: Mathematical analyses in [25] showed that the conservative strategy (Section II) is an MDA's best-response (optimal) strategy regardless of the strategy adopted by its opponent. It was proven in [25] that S (a seller MDA) achieves the best utility regardless of whether B (a buyer MDA) adopts the conservative, the linear, or the Conciliatory strategy. Furthermore, it was proven in [25] that the conservative strategy is the best response for an MDA at every of its decision points, and, thus satisfies the notion of sequential rationality [32] (see [25, Lemmas 3.1–3.2 and Proposition 3, pp. 36–39]). Hence, an MDA's strategy is optimal whenever it has to move, given its belief and other agents' beliefs. Consequently, the strategies adopted by MDAs are stable. Stability is an essential property because a negotiation agent that is stable requires fewer computational resources to outguess its opponents [33, p. 21] or to speculate about strategies of others [34, p. 8].

III. Market-Driven G-Negotiation Agents

To demonstrate the application of MDAs in G-negotiation, a testbed (Section III-A) to simulate a Grid computing environment has been developed. Since the testbed facilitates the comparison between MDAs and other negotiation agents, the basis for comparing these agents in the same testbed is explicated in Section III-B. This section also discusses the interactions of agents (Section III-C) in the testbed and the negotiation protocol of G-negotiation agents (Section III-D).

A. Grid Simulation Testbed

Implemented using the GridSim toolkit [35], the testbed consists of: 1) a set of Grid resources; 2) a set of resource consumers; 3) provider agents; 4) consumer agents; 5) a repository of resource information; 6) a Grid-resource record agent (GRRA); and 7) an e-market of heterogeneous negotiation agents.

1) Grid Resource Providers/Consumers: A Grid resource provider RP_i may possess a series of resources or computing machines $\{M_{i1}, \ldots, M_{ik}\}$. Each computing machine M_{ik} can be a single processor, shared memory multiprocessors, or a distributed memory cluster of computers. M_{ik} can be formed by one or more processing elements $\{\mathrm{PE}_1, \ldots, \mathrm{PE}_n\}$, and each PE_i can have different speeds measured in terms of MIPS. In GridSim [19, p. 94], both a computing machine and a processing element are represented as Java classes gridsim.Machine and gridsim.PE, respectively. Consequently, with n resource providers registered in the computational Grid, the list of computing machines in the Grid can potentially be $(\{M_{11}, \ldots, M_{1i}\}, \ldots, \{M_{n1}, \ldots, M_{nk}\})$. A provider RP_i is represented by a provider agent PA_i. Each PA_i performs the following functions: 1) registers RP_i's computing resource(s) with the GRRA and generates a seller agent to negotiate the selling price of each of the resources of RP_i, and 2) if a resource is leased to a consumer after successful negotiation, PA_i receives computation task(s) sent by a consumer agent CA_j representing a resource consumer RC_j, sends the task(s) to the leased computing machine(s) for executions, and returns the computation results back to CA_j. Each resource consumer or application can have one or more jobs $\{J_1, \ldots, J_m\}$. Each J_i is represented as a Java class gridsim.Gridlet, and is characterized by a job length measured in MI, length of input and output data, execution start and end times, as well as the originator of the job [19, p. 96].

2) Resource Information: The resource information dictionary is a repository of information about the computing resources registered in the Grid. The GRRA updates the resource information dictionary when a resource joins/leaves the Grid.

3) Heterogeneous e-Market: In the e-market, negotiation agents are either: 1) buyer agents $\{B_1, \ldots, B_m\}$ representing consumers in negotiating and acquiring resources, or 2) seller agents $\{S_1, \ldots, S_n\}$ representing resource providers negotiating optimal returns for their resources. The problem of Grid resource allocation is transformed into a problem of bargaining between and among buyer and seller agents. In a computational Grid, it is intuitive to think that different providers, as well as consumers, are likely to adopt different strategies of negotiation. Although it is acknowledged that there are many extant negotiation strategies and e-negotiation agents, for the purpose of simulation and experimentation, the testbed in its present form only includes negotiation strategies adopted from MDA, EMDA, Kasbah, and NDF (see Table I). The basis for comparing with both Kasbah and NDF is given in Section III-B. In Table I, it can be seen that the strategy set of EMDAs does not include the Conciliatory strategy. Conciliatory is not included in the original design of EMDAs [26] because it was proven in [6] that an agent adopting Conciliatory is more likely to achieve lower utilities even though it faces lower

TABLE I
STRATEGIES OF NEGOTIATION AGENTS

Agent Type	Agent Strategy Set	Legend
MDA	*{MDA_CC, MDA_L, MDA_CS}*	*CC: Conciliatory L: Linear CS: Conservative*
EMDA	*{EMDA_L, EMDA_CS}*	
Kasbah	*{Kasbah_A, Kasbah_C, Kasbah_G}*	*A: Anxious C: Cool-headed G: Greedy*
NDF	*{NDF_C, NDF_L, NDF_B}*	*C: Conceder B: Boulware L: Linear*

risk of losing deals to competitors. Since an EMDA is already designed with fuzzy rules to relax its bargaining terms in the face of intense negotiation pressure (e.g., short deadlines), Conciliatory is not considered in an EMDA's design. Whereas the designs of MDA and EMDA are summarized in Section II and detailed in [24]–[28], the strategies of Kasbah and NDF are summarized in Section III-B.

B. Basis for Comparing With Kasbah and NDF

The rationale for comparing MDAs and EMDAs with Kasbah and NDF is that all these agents take into consideration the issue of time constraint, and it is shown below that NDF and Kasbah have quite similar time-dependent negotiation strategies to MDAs and EMDAs.

1) Comparing With NDF: Although, on the surface, MDA and NDF may appear to have different time-dependent NDFs, it can be shown that, for every strategy in NDF, there is a corresponding strategy in MDA. For every time-dependent negotiation strategy $S(\psi)$ in NDF, there is a corresponding time-dependent negotiation strategy $\Im(\lambda)$ in MDA, where λ and ψ are time preferences of an MDA and an NDF agent, respectively, and $\lambda = 1/\psi$. This can be demonstrated as follows.

Following [22] and [36], the time-dependent negotiation function $f^A(t)$ of an NDF agent is given as $f^A(t) = k^A + (1 - k^A)(\min(t,\tau)/\tau)^{1/\psi}$, where t is a discrete trading (negotiation) time indexed by $\{0, 1, 2, \ldots\}$, τ is the deadline of agent A, $\psi \in \mathbb{R}^+$ (i.e., $\psi \geq 0$) represents A's time preference, and k^A is a constant that when multiplied by the size of the interval $[\mathrm{IP}^A, \mathrm{RP}^A]$ determines the price to be offered in the first proposal of A. (IP^A and RP^A are, respectively, the initial and reserve prices of A). Even though there are infinitely many strategies for NDF agents (since there are infinitely many values of ψ), like MDAs, the strategies of NDF agents can be categorized into three classes as follows.

1) *Boulware:* For $\psi < 1$, the initial offer is maintained until the deadline is almost reached, when A concedes up to its reserve price.
2) *Conceder:* For $\psi > 1$, A rapidly concedes to its reserve price.
3) *Linear:* For $\psi = 1$, A's price increment is linear.

In NDF, the offer $p(t)$ made at t is defined as follows:

$$p(t) = \begin{cases} \mathrm{IP}^\mathrm{B} + f^\mathrm{B}(t)(\mathrm{RP}^\mathrm{B} - \mathrm{IP}^\mathrm{B}) & \text{for buyer} \\ \mathrm{RP}^\mathrm{S} + \left(1 - f^\mathrm{S}(t)\right)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}) & \text{for seller} \end{cases}$$

where IP^B, RP^B, IP^S, and RP^S are the initial and reserve prices of a buyer agent (B) and a seller agent (S), respectively. In NDF, $0 \leq f^A(t) \leq 1$ [22], [36], where $f^A(0) = k^A$ and $f^A(\tau) = 1$. For instance, B's initial offer is $p(0) = \mathrm{IP}^\mathrm{B} + k^A(\mathrm{RP}^\mathrm{B} - \mathrm{IP}^\mathrm{B})$. In this testbed, all types of negotiation agents (including both MDAs and NDF) are designed to follow the negotiation protocol described in Section III-D, in which all agents typically start negotiation with their most preferred deals (i.e., its initial prices). For NDF agents, this is achieved by substituting $k^A = 0$, so that for $0 \leq t \leq \tau$, $f^A(t) = 0 + (1-0)(\min(t,\tau)/\tau)^{1/\psi} = (\min(t,\tau)/\tau)^{1/\psi}$, such that

$$f^A(t) = \begin{cases} 0, & t = 0 \\ \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}, & 0 < t < \tau \\ 1, & t = \tau. \end{cases}$$

Hence, for a buyer NDF agent

$$p(t) = \begin{cases} \mathrm{IP}^\mathrm{B} + 0(\mathrm{RP}^\mathrm{B} - \mathrm{IP}^\mathrm{B}) = \mathrm{IP}^\mathrm{B}, & t = 0 \\ \mathrm{IP}^\mathrm{B} + \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}(\mathrm{RP}^\mathrm{B} - \mathrm{IP}^\mathrm{B}), & 0 < t < \tau \\ \mathrm{IP}^\mathrm{B} + 1(\mathrm{RP}^\mathrm{B} - \mathrm{IP}^\mathrm{B}) = \mathrm{RP}^\mathrm{B}, & t = \tau \end{cases}$$

and for a seller NDF agent

$$p(t) = \begin{cases} \mathrm{RP}^\mathrm{S} + (1-0)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}) = \mathrm{IP}^\mathrm{S}, & t = 0 \\ \mathrm{RP}^\mathrm{S} + \left(1 - \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}\right)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}), & 0 < t < \tau \\ \mathrm{RP}^\mathrm{S} + (1-1)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}) = \mathrm{RP}^\mathrm{S}, & t = \tau. \end{cases}$$

Since

$$\mathrm{RP}^\mathrm{S} + \left(1 - \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}\right)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}) = \mathrm{IP}^\mathrm{S} - (\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S})\left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}$$

for a seller NDF agent, $p(t)$ can be rewritten as follows:

$$p(t) = \begin{cases} \mathrm{RP}^\mathrm{S} + (1-0)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}) = \mathrm{IP}^\mathrm{S}, & t = 0 \\ \mathrm{IP}^\mathrm{S} - \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}), & 0 < t < \tau \\ \mathrm{RP}^\mathrm{S} + (1-1)(\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S}) = \mathrm{RP}^\mathrm{S}, & t = \tau. \end{cases}$$

Hence, the offer $p(t)$ of a buyer (respectively, seller) NDF agent at t can be rewritten as follows:

$$p(t) = \begin{cases} \mathrm{IP}^\mathrm{B} + (\mathrm{RP}^\mathrm{B} - \mathrm{IP}^\mathrm{B})\left(\frac{t}{\tau}\right)^{\frac{1}{\psi}} & \text{for buyer} \\ \mathrm{IP}^\mathrm{S} - (\mathrm{IP}^\mathrm{S} - \mathrm{RP}^\mathrm{S})\left(\frac{t}{\tau}\right)^{\frac{1}{\psi}} & \text{for seller.} \end{cases} \quad (1)$$

For an MDA, if one only considers the time negotiation decision function, then, the expected difference in the next round k_{t+1} between the proposal of an agent and its trading partner is

$$k_{t+1} = k_t T(t, \tau, \lambda) = k_t\left(1 - \left(\frac{t}{\tau}\right)^\lambda\right)$$

and the amount of concession at t is

$$\Delta_t = k_t - k_{t+1} = k_t - k_t\left(1 - \left(\frac{t}{\tau}\right)^\lambda\right) = k_t\left(\frac{t}{\tau}\right)^\lambda.$$

For $0 \leq t \leq \tau$, it follows that

$$\Delta_t = \begin{cases} 0, & t = 0 \\ k_t \left(\frac{t}{\tau}\right)^{\lambda}, & 0 < t < \tau \\ 1, & t = \tau. \end{cases}$$

In MDA, the offer l_{t+1} made at time $t+1$ is given as follows:

$$l_{t+1} = \begin{cases} l_t + \Delta_t \leq \mathrm{RP}_B & \text{for buyer} \\ l_t - \Delta_t \geq \mathrm{RP}_S & \text{for seller.} \end{cases}$$

Hence, it follows that

$$l_{t+1} = \begin{cases} l_t + k_t \left(\frac{t}{\tau}\right)^{\lambda} \leq \mathrm{RP}_B & \text{for buyer} \\ l_t - k_t \left(\frac{t}{\tau}\right)^{\lambda} \geq \mathrm{RP}_S & \text{for seller.} \end{cases} \quad (2)$$

By comparing (1) and (2), even though there are differences between MDAs and NDF in the ways they compute the offers, the patterns of concessions are based on very identical functions:

$$k_t \left(\frac{t}{\tau}\right)^{\lambda} \quad \text{and} \quad (\mathrm{RP^B} - \mathrm{IP^B}) \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}$$
$$\left(\text{and } - k_t \left(\frac{t}{\tau}\right)^{\lambda}, \text{ respectively, } -(\mathrm{IP^S} - \mathrm{RP^S}) \left(\frac{t}{\tau}\right)^{\frac{1}{\psi}}\right).$$

Hence, it can be seen that the Boulware ($\psi < 1$), Conceder ($\psi > 1$), and Linear ($\psi = 1$) strategies in NDF correspond, respectively, to the Conservative ($\lambda > 1$), Conciliatory ($\lambda < 1$), and Linear ($\lambda = 1$) strategies in MDAs with $\lambda = 1/\psi$.

2) Comparing With Kasbah: A seller (respectively, buyer) Kasbah agent lowers (respectively, raises) its price over a given time frame following a "decay" function [21]. For a seller (respectively, buyer) agent, the curve of the "anxious," "cool-headed," and "greedy" strategies follows a linear curve, an inverse-quadratic (respectively, quadratic) curve, and an inverse-cubic (respectively, cubic) curve, respectively. Kasbah's linear, quadratic, and cubic time decay functions correspond, respectively, to time-dependent negotiation functions in MDAs with $\lambda = \{1, 2, 3\}$ and in NDF with $\psi = \{1, 1/2, 1/3\}$, respectively. Hence, it can be seen that the "anxious," "cool-headed," and "greedy" strategies of Kasbah agents correspond to the linear strategy in MDAs and to the conservative strategy with $\lambda = 2$ and $\lambda = 3$, respectively.

Consequently, even though the agents in the testbed for the simulation can adopt different strategies, the empirical results reported in Section IV are tabulated so that the performance of MDAs adopting conservative strategies with $\lambda = 2$ and $\lambda = 3$ is compared to that of NDF agents adopting Boulware strategies with $\psi = 1/2$ and $\psi = 1/3$, and Kasbah agents adopting the "cool-headed" and "greedy" strategies, respectively. The performance of MDAs adopting $\lambda = 1$ is compared to NDF agents adopting $\psi = 1$ and Kasbah agents adopting the "anxious" strategy. Additionally, the performance of MDAs adopting a Conciliatory strategy with $\lambda = 1/3$ is compared to the NDF agents adopting the Conceder strategy with $\psi = 3$.

C. Interaction Model

Following [19, p. 87], the interaction protocol among the agents and entities in the testbed is implemented using events and is given in Fig. 1. Agents/entities use events for both service requests and service deliveries.

1) Events: Events are classified into *internal* events originating from the same entity, and *external* events originating from external entities. Furthermore, an event is a *synchronous* event if the event source entity/agent waits until the event destination entity/agent performs all actions associated with the event. For instance, in Fig. 1, the provider agent initiates two synchronous events: "register resource" and "register seller agent," both of which must be completed before the resource can be leased out. An event is *asynchronous* if the event source entity initiates an event and continues with other activities without having to wait for its completion. Except "register resource," "register seller agent," "get resource list," "get resource characteristics," and "register buyer agent," all other events in Fig. 1 are asynchronous. The stages of interaction among entities are given as follows.

2) Registering Resources and Consumers: At the start of the simulation, resource provider entities register their resources through provider agents that send "register resource" events to the GRRA entity. To facilitate resource trading, provider agent entities register seller agents with the e-market entity by sending synchronous events. Depending on users' requests, consumer entities query the GRRA entity through consumer agents, which send synchronous events to: 1) GRRA entity to obtain the contact details of the resource owners and their list of registered resources and 2) provider agents to obtain the characteristics of these resources. The resource characteristics include the architecture of a computing resource (e.g., HP alpha server, Sun Fire V480, etc.), operating system (e.g., AIX, Unix, etc.), list of computing machines (e.g., $\{M_{11}, \ldots, M_{1i}\}$), and expected and reserve prices of leasing a computing machine. Additionally, to acquire the necessary computing resource, consumer-agent entities register buyer agents with the e-market entity by sending synchronous events.

3) G-Negotiation: In the e-market, concurrent negotiation among multiple pairs of buyer and seller agents is carried out following the G-negotiation protocol described in Section III-D.

4) Task Execution: If negotiation is successful, the e-market entity sends the results (e.g., the price for leasing the resource and the period of utilization) to the consumer agent entity by raising an asynchronous event. The consumer agent entity submits the consumer's task(s) to the provider agent entity, which in turn submits the task(s) to the provider entity, which services the task(s). Task executions by providers are represented by internal events (task(s) processing events), as shown in Fig. 1. On completion of servicing the task(s), the provider agent entity sends the results back to the consumer agents by raising one or more external events.

If negotiation is unsuccessful, the e-market entity sends an asynchronous event to the provider agent to indicate that its resource has been released, and, perhaps, the provider may utilize its resource to service its own task(s).

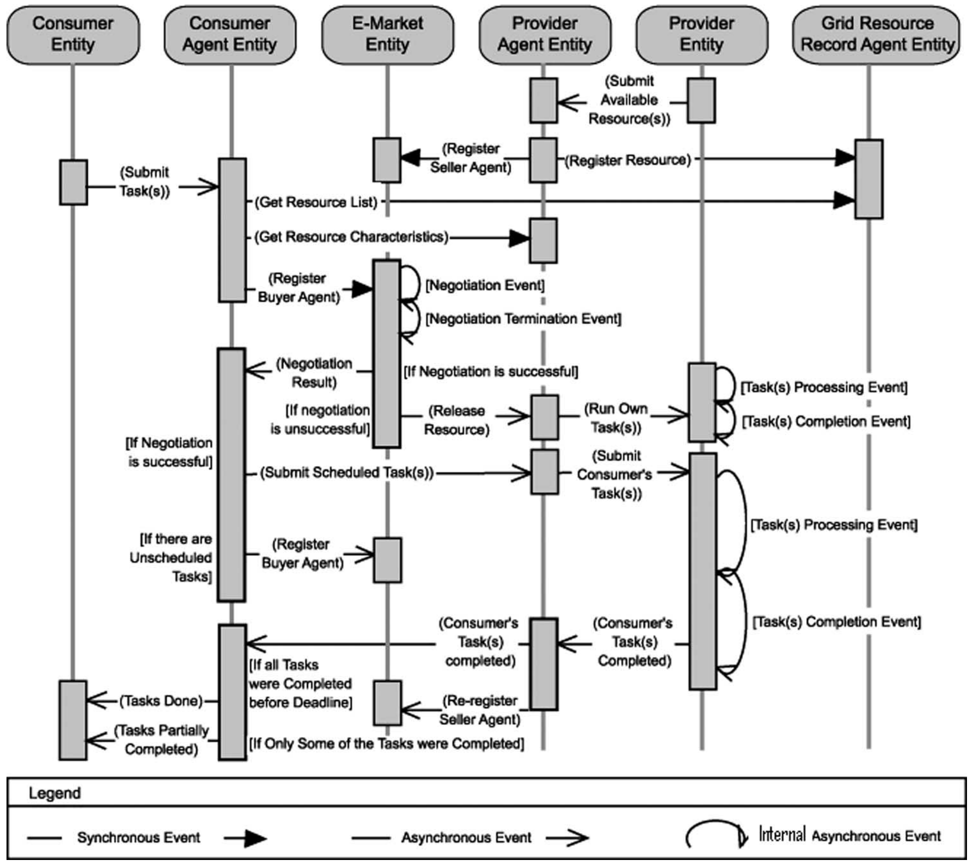

Fig. 1. Event diagram for interactions among agents and entities.

D. G-Negotiation Protocol

Negotiation proceeds in a series of rounds as follows. At round $t = 0$, the e-market opens. At any round, a buyer (respectively, seller) agent enters the e-market when a consumer agent places a request for a resource (respectively, a provider agent registers a resource for lease). Trading begins when there are at least two agents of the opposite type (i.e., one buyer and one seller). On the first round of trading, an agent proposes a deal from their space of possible deals (e.g., the most desirable price, the least desirable (reserve) price, and those prices in between). Typically, an agent proposes its most preferred deal initially. This work adopts Rubinstein's alternating offers protocol [37, p. 100], so that a pair of buyer and seller agents negotiates by making proposals in alternate rounds. Multiple buyer–seller pairs can negotiate deals simultaneously. If no agreement is reached, negotiation proceeds to the next round. Negotiation between two agents terminates: 1) when an agreement is reached or 2) with a conflict when one of the two agents' deadline is reached. An agent (either buyer or seller) can be an MDA, EMDA, Kasbah agent (KA), or an NDF agent (NDFA). Additionally, an agent can adopt any of the strategies listed in Table I. In the G-Negotiation protocol in this paper, the rules for reaching a consensus are as follows.

R1) An agreement is reached if an agent B_1 and its trading partner S_1 propose deals b_1 and o_1, respectively, such that either: 1) $b_1 \geq o_1$ or 2) $o_1 \geq b_1$, where b_1 and o_1 represent the buying and selling prices of resources.

R2) An agreement is reached if either: 1) $\eta = o_1 - b_1$, such that $\eta \to 0$, or 2) $\eta = b_1 - o_1$, such that $\eta \to 0$, where η is the amount of relaxation determined using an FDC described in Section II (details can be found in [26]).

All the four types of agents (i.e. MDA, EMDA, KA, and NDFA) follow R1, and an agreement is reached when an agent's trading partner's offer matches or exceeds what the agent asked for. However, only EMDAs follow R2. An EMDA (guided by a set of fuzzy rules) may also reach a consensus with other agents if the offer is sufficiently close (albeit, it does not totally match the EMDA's bargaining terms)—this is a novel feature of the negotiation protocol of this work, which distinguishes it from the protocols in other e-negotiation and G-negotiation agents. The difference between the negotiation protocol in [26] and this work is that the G-negotiation protocol in this work is embedded as part of an interaction protocol (see Section III-C).

IV. Simulations and Empirical Results

A series of experiments was carried out using the testbed described in Section III-A. Two major sets of experiments for evaluating MDAs and EMDAs in G-negotiation were carried out through stochastic simulations.

1) Objectives and Motivations: The first set of the experiments is designed to explore the influence of market dynamics on the performance of MDAs, EMDAs, Kasbah, and NDF agents. The rationale for comparing MDAs and EMDAs with

TABLE II
INPUT DATA SOURCE

Input Data	**Possible Values**		
Grid Load (*GL*)	*GL = R_p/ C_c where 0≤GL≤1*		
Characteristic:	*low*	*high*	
Resource Utilization level:	*0←GL*	*GL→1.0*	
R_p: the expected amount of processing requested per time interval			
C_c: the total computing capacity of the Grid			
e-Market Type	*Favorable*	*Balanced*	*Unfavorable*
Characteristic: *-Buyer-seller ratio*	{1:2 1:5,1:10}	{1:1}	{10:1,5:1,2:1}
Job Deadline (Time Unit)	{100, 600, 1100, 1600, 2100, 2600, 3100, 3600}		

Kasbah and NDF agents is that all these agents take into consideration the issue of time constraint, and it was shown in Section III-B that they all have similar time-dependent negotiation strategies. The difference is that whereas MDAs and EMDAs also take into consideration market factors, such as opportunity and competition, both Kasbah and NDF agents do not. By comparing these agents, one can explore and investigate the influence of market factors on the negotiation outcomes in an e-market. The second set of the experiments is designed to study the performance of MDAs, EMDAs, Kasbah, and NDF agents under different Grid loadings. What distinguishes EMDAs from the other negotiation agents is that they are designed to slightly relax their bargaining criteria in the face of intense pressure. By comparing EMDAs with MDAs, Kasbah, and NDF, one can study the possible benefits of designing negotiation agents that slightly relax their bargaining criteria, especially when the Grid loading is very high.

2) Experimental Settings: As shown in Table II, there are three input parameters to the testbed: 1) the Grid load; 2) the e-market type; and 3) deadlines for consumers to complete their set of tasks.

The Grid load $(0 \leq \mathrm{GL} \leq 1)$ represents and simulates different levels of utilization of the computing resources in the Grid. GL is defined here as the ratio of: 1) R_{p}—the expected amount of processing requested per time interval and 2) C_{c}—the total computing capacity of the Grid. Both R_{p} and C_{c} are measured in millions of instructions (MI). R_{p} depends on both the requests (tasks) from the consumers and the average size of each task. It is assumed that the arrival rate of tasks follows a Poisson distribution, and the average task size approximates to 10 000 MI with 0% to 10% random variations (for simulation purpose, such task size is also used in [35, p. 1207]). Different levels of system utilization (different GL) are simulated by varying the time interval between the possible arrivals of two tasks. As GL $\rightarrow 1$ (respectively, GL $\rightarrow 0$), fewer (respectively, more) computing resources in the Grid are available for lease.

The e-market type simulates the intuition of supply and demand and the degree of competition in a Grid computing environment. There are three types of e-markets: *favorable*, *balanced*, and *unfavorable*, and they are characterized by the ratio of buyer agents to seller agents. From a buyer agent's perspective, in a favorable (respectively, unfavorable) e-market, there is a little (respectively, stiff) competition among buyer agents as there are more (respectively, fewer) resource providers. For the purpose of simulation, different buyer-to-seller ratios are simulated by fixing the number of resource providers but varying the number of consumers that simultaneously place their requests at the beginning of the simulation. The buyer–seller ratios selected (see Table I) are representative of the three types of e-market. In an (almost) balanced market, the ratio is simply $1:1$ since there are (almost) equal number of buyers and sellers. For unfavorable markets (respectively, favorable markets), ratios such as $100:1$, $50:1$, and $20:1$ (respectively, $1:20$, $1:50$, and $1:100$) representing extremely unfavorable (respectively, favorable) trading environments were not selected. This is because based on the previous experimental tuning in [26], it was observed that for extremely unfavorable (respectively, favorable) markets with buyer–seller ratios such as $100:1$ (respectively, $1:100$), the success rates of both MDAs and EMDAs were generally close to zero. From a buyer's perspective, in very unfavorable trading environments, since only at most one pair of buyer and seller can complete the deal, the probability that a buyer agent successfully completes a deal is inherently very low. For instance, for a $100:1$ buyer–seller ratio, there is only a probability of 1/100 that a buyer can complete a deal, if there is at least one seller agent in the market. Similarly, for a $1:100$ buyer–seller ratio, there is only a probability that a seller can complete a deal.

For simulation purpose, a consumer's deadline for completing a task is measured in time units. A consumer's deadline is randomly generated from the set between 100 and 3600 time units in steps of 500 (this setting was also used in [35, p. 1207]).

3) Performance Measure: Whereas success rate and utility are two performance measures used in evaluating MDAs and EMDAs in e-negotiation, in G-negotiation, it is more prudent to measure the following:

1) the percentage (P_A) of a consumer's set of tasks that is accomplished by successfully negotiating and leasing Grid resources;
2) how efficiently is the available budget spent (B_{eff}).

$P_A = N_{\mathrm{suc}}/N_{\mathrm{tot}}$, where N_{tot} is the total number of tasks requested by a consumer, and N_{suc} is the number of tasks that are successfully scheduled and executed.

Since consumers may be allocated different amounts of budgets and may have different numbers of tasks, it seems more plausible to normalize B_{eff} as follows:

$$B_{\mathrm{eff}} = \frac{N_{\mathrm{suc}}/B_{\mathrm{spt}}}{N_{\mathrm{tot}}/B_{\mathrm{bgt}}}$$

where B_{bgt} is the initial budget allocated to a consumer, and B_{spt} is the amount of budget spent in leasing computing resource(s) for processing tasks that are successfully scheduled and executed (see Table III). Whereas $N_{\mathrm{suc}}/B_{\mathrm{spt}}$ represents the actual number of tasks processed per currency unit measured in "Grid dollars" or "G$" [3], $N_{\mathrm{tot}}/B_{\mathrm{bgt}}$ represents the expected number of tasks processed per currency unit before they are successfully scheduled (and executed).

4) Simulations: The first set of simulations examines the performance of agents adopting different strategies subject to different job deadlines and degree of competition. In the

TABLE III
PERFORMANCE MEASURE

% of Tasks Completed	N_{suc}/N_{tot}
Budget efficiency	$B_{eff} = (N_{suc}/B_{spt})/(N_{tot}/B_{bgt})$
N_{tot}	Total number of tasks requested by consumer
N_{suc}	Number of tasks completed
B_{bgt}	Consumer's initial budget in G$
B_{spt}	Amount of G$ a consumer spent for completing the tasks

TABLE IV
COMBINATIONS OF SETTINGS

deadline		
100	1600	3100
λ=1/3, ψ=3	λ=1/3, ψ=3	λ=1/3, ψ=3
λ=1, ψ=1, *A*	λ=1, ψ=1, *A*	λ=1, ψ=1, *A*
λ=2, ψ=1/2, *C*	λ=2, ψ=1/2, *C*	λ=2, ψ=1/2, *C*
λ=3, ψ=1/3, *G*	λ=3, ψ=1/3, *G*	λ=3, ψ=1/3, *G*
λ=20, ψ=1/20	λ=20, ψ=1/20	λ=20, ψ=1/20

second set of simulations, agents adopting different strategies are subject to different job deadlines as well as different GL.

5) Results: Empirical results were obtained for all representative combinations of the input data (i.e., deadline $= \{100, 1600, 3100\}$, buyer−seller ratio $= \{10:1, 5:1, 2:1, 1:1, 1:2, 1:5, 1:10\}$, and GL $= \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}$, and EMDAs (MDAs) adopting $\lambda = \{1/3, 1, 2, 3, 20\}$ corresponding to NDF agents adopting $\psi = \{3, 1, 1/2, 1/3, 1/20\}$ together with Kasbah's strategies {A(Anxious), C(Cool headed), G(Greedy)} corresponding to $\lambda = \{1, 2, 3\}$).

In Table IV, 15 combinations of grouping of the simulation results were plotted for the seven buyer–seller ratios and ten values of GL. However, due to space limitation, only some of the graphs are shown in Figs. 2 and 3. For $\lambda = 1/3$ and $\psi = 3$, there is no corresponding strategy in Kasbah, and EMDAs are not designed with Conciliatory strategies. Hence, the graphs in Fig. 2(a) and (b) only show the performance of MDAs and NDF agents. Similarly, for $\lambda = 20$ and $\psi = 1/20$, there is no corresponding strategy in Kasbah, and Fig. 2(i) and (j) only show the performance of MDAs, EMDAs, and NDF agents. For all other combinations, the performance of all the four agent types is plotted.

6) Observations: The following observations are made.

1) The budget efficiency for all types of agents increased as the buyer-to-seller (consumer-to-provider) ratios decreased.
2) MDAs and EMDAs generally achieved higher budget efficiency than other negotiation agents, except for unfavorable markets. However, the difference in budget efficiency between MDAs (as well as EMDAs) and NDF (as well as Kasbah) diminishes for higher values of λ (respectively, lower values of ψ).
3) Under high Grid loadings, EMDAs are generally more successful in acquiring the resources for executing tasks.

Observation 1) coincides with the common intuition of supply and demand. When there were many (respectively, few) consumers and few (respectively, many) providers, buyer agents had to spend more (respectively, less) for the same resource.

For observation 2), the amount of improvement in the budget efficiency for MDAs and EMDAs over the other types of agents is significantly more for both favorable markets [i.e., with buyer−seller ratio $= \{1:2, 1:5, 1:10\}$) and balanced market (buyer−seller ratio $= \{1:1\}$)] than unfavorable markets (buyer−seller ratio $= \{10:1, 5:1, 2:1\}$). Even though in unfavorable markets, the points of all the curves appear to coincide, the recordings of budget efficiency for MDAs and EMDAs are still slightly higher, albeit not very visible. For instance, in Fig. 2(d), for a consumer-to-provider ratio of 2 : 1, the budget efficiency for MDAs and EMDAs was 1.16, while that of NDF and Kasbah agents was 1.13. This is because in an unfavorable market, there are fewer available resources and more competing consumers, and all buyer agents that complete a bargaining deal with such a weak bargaining position are likely to acquire a computing resource at a high price. Whereas MDAs and EMDAs are likely to concede more in unfavorable markets to avoid making inadequate concessions, all agents (including NDF and Kasbah) that succeeded in trading had to make a great deal of concessions before reaching a consensus.

Although space limitation prevents the graphs on success rates of negotiation for favorable markets from being included in this paper, all types of agents are generally (100%) successful in acquiring resources to complete their tasks, since there are more available resources and fewer competitors. Since MDAs and EMDAs are designed to avoid making excessive concessions in favorable market situations (see Section II-A, and [25, pp. 717–719]), they are more likely to make comparatively smaller concessions than Kasbah and NDF agents in favorable markets. Hence, it can be seen from Fig. 2 that in favorable markets, the budget efficiency of MDAs and EMDAs is visibly higher than Kasbah and NDF. Nevertheless, the difference between the budget efficiencies of MDAs (as well as EMDAs) and NDF (as well as Kasbah) decreased as MDAs adopt strategies with higher λ or correspondingly smaller ψ in NDF agents (these agents are considered to be more *patient* players in [36, p. 2]). The results show that agents adopting a more "patient" strategy seem to confer more bargaining power and appear to be less influenced by market dynamics. This seems to align with an insight mentioned in [38, p. 41] that "it seems intuitive that for players to have some incentive to reach agreement, they should find it costly to haggle." However, being relatively more patient confers a greater bargaining power [38, p. 51]. Additionally, it was proven by Sim [6] that with longer deadlines, MDAs adopting conservative ("patient") strategies achieve higher utilities than those adopting ("impatient") Conciliatory strategies (see [6, Proposition 5, p. 627]). In Fig. 2, for deadline = 3100 and a consumer-to-provider ratio of 1 : 10, the budget efficiency increased from close to two [Fig. 2(b)] with $\lambda = 1/3$, to approximately 2.4, 2.6,

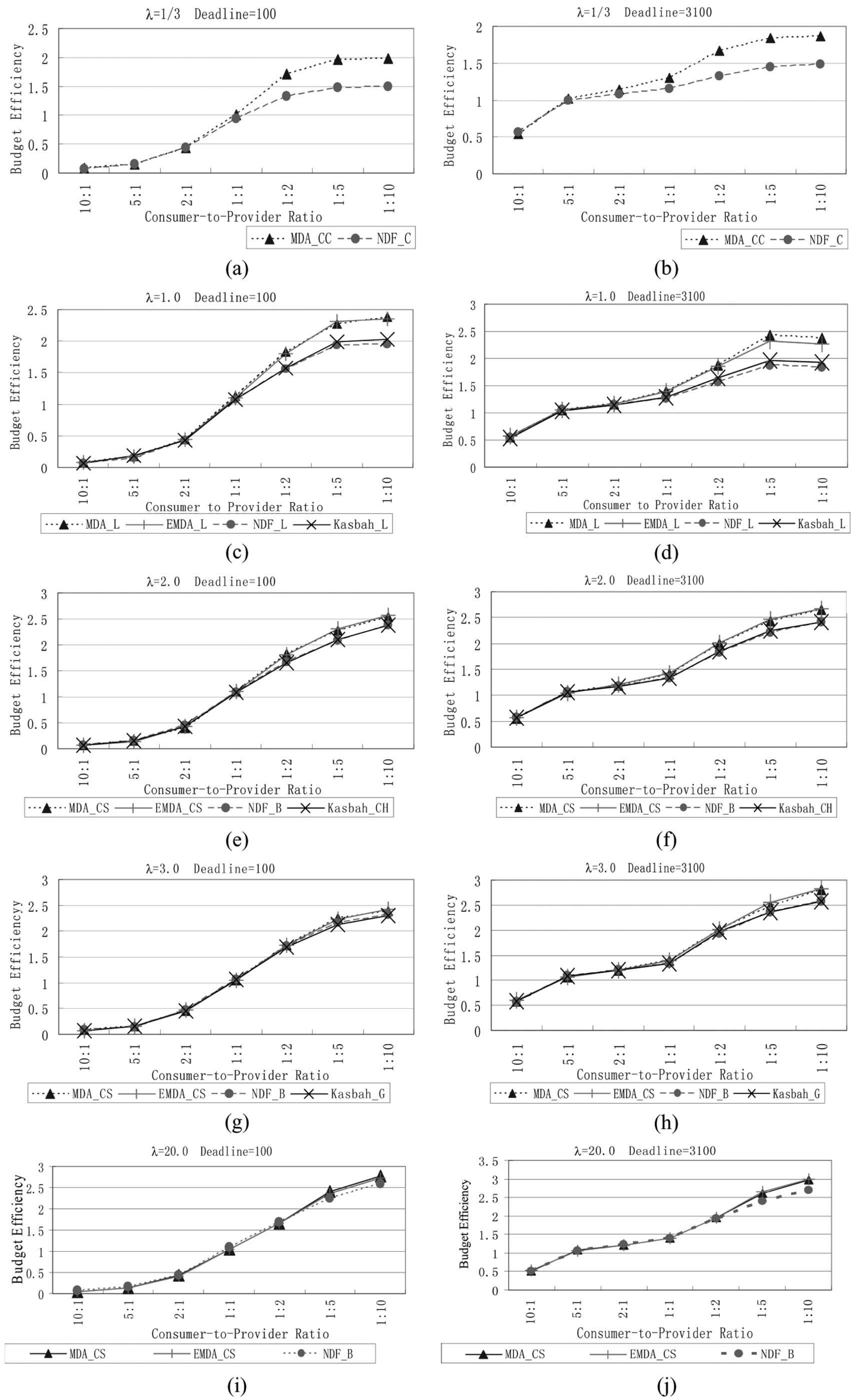

Fig. 2. Performance under different market situations. (Color version available online at http://ieeexplore.ieee.org.)

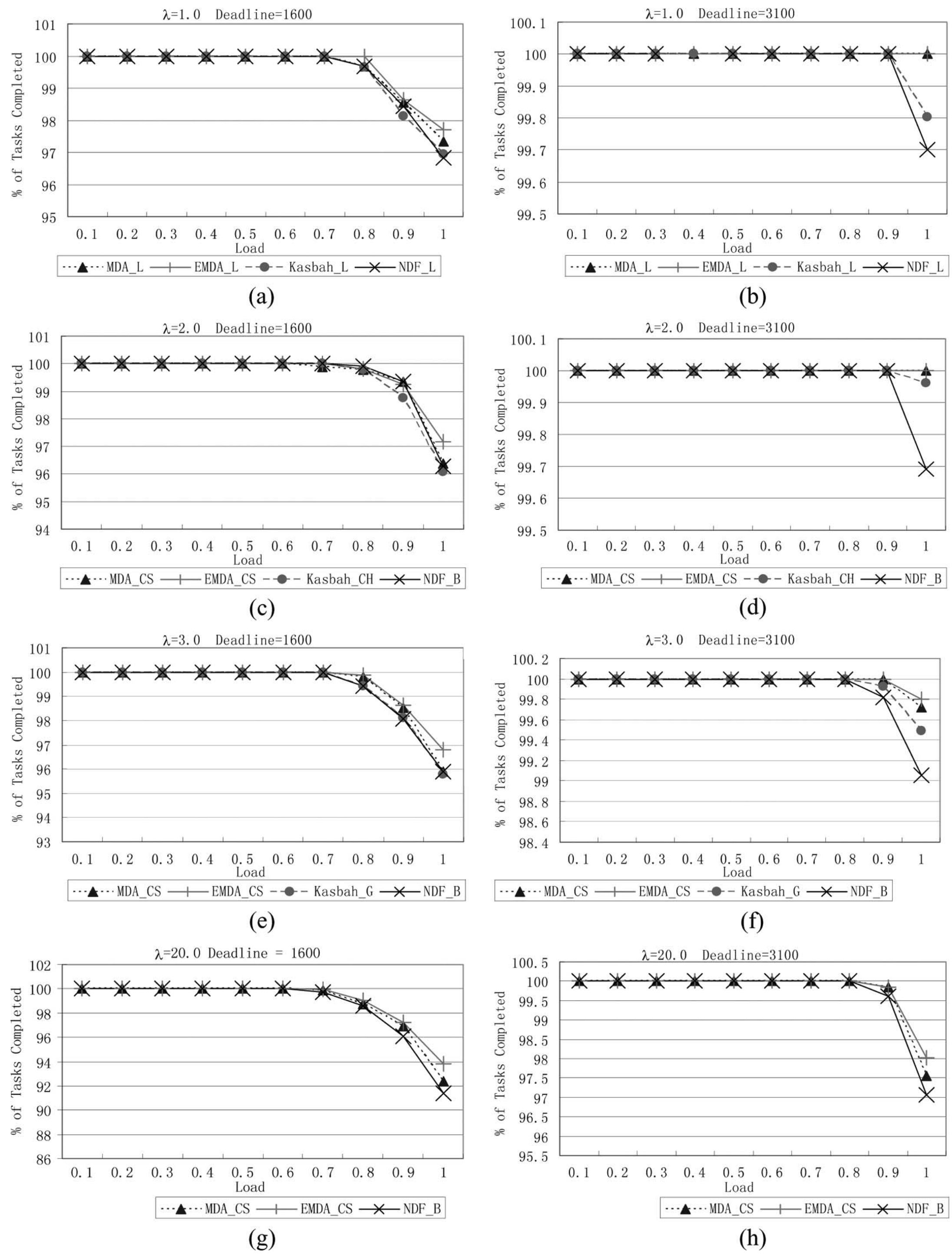

Fig. 3. Performance under different Grid loadings. (Color version available online at http://ieeexplore.ieee.org.)

2.75 [with $\lambda = 1, 2, 3$, respectively, in Fig. 2(d), (f), and (h)] to three [Fig. 2(j) with $\lambda = 20$]. A similar trend of increment can also be observed for NDF with decreasing values of ψ. However, while adopting more "patient" strategies may confer more bargaining power, by doing so, agents (with shorter deadlines) have higher risks of losing deals to other competing agents, especially in multilateral negotiations (see [6, Proposition 5, p. 627]). Whereas the influence of market dynamics may diminish as agents adopt more "patient" strategies, considering market dynamics is still essential in multilateral negotiations.

It can be seen from Fig. 3 that observation 3) generally holds for moderate and long deadlines and different agent strategies. For long deadlines, all types of agents achieved a 100% success rate in acquiring resources to complete the tasks for GL ≤ 0.8 (since more resources are available). However, at extremely high loadings, with GL $= \{0.9, 1.0\}$, both EMDAs and MDAs were more successful than the other negotiation agents in acquiring resources to complete the tasks. With extremely high loadings, all agents competed very strongly for very few available resources. Since MDAs and EMDAs are more likely to concede more when there is more competition, they are more likely to be successful in acquiring resources in high Grid loading than NDF and Kasbah agents. Furthermore, EMDAs were generally even more successful than MDAs in acquiring resources at extremely high Grid loadings. Under extremely high Grid loadings, EMDAs are more likely than MDAs to reach agreements with their trading partners since they are more likely to slightly relax their bargaining criteria under intense negotiation pressure such as very stiff competition. The results generally show that by slightly relaxing their bargaining criteria, EMDAs only outperformed the other agents in successfully acquiring resource only when the Grid loading is extremely high. This seems to be a desirable property since it is plausible to think that negotiation agents should be designed not to relax their bargaining terms when there is a reasonably good supply of resources (i.e., "why pay slightly more, when one has an option to spend slightly less").

V. Related Work

Since this work explores the issue of applying negotiation agents for e-commerce to resource negotiation in a computational Grid, the areas that relate to this research include: 1) e-negotiation agents; 2) G-commerce; and 3) preliminary initiatives on building agents for G-negotiation.

1) e-Negotiation Agents: The literature in automated negotiation [33] and negotiation agents [39], [40] forms a very huge collection, and space limitation precludes all existing negotiation agents from being introduced here. Since more complete surveys of negotiation agents for e-commerce can be found in [39] and [40], this section only discusses Kasbah [21] and NDF [22].

2) Kasbah: Kasbah agents increase/relax their bids/offers at different rates by adopting the three strategies mentioned in Section III-A. Although they are not restricted by trading policies, these strategies have fixed rate adjustments of bids/offers and do not react to the changing market conditions. Even though human traders can use deadline as a criterion for deciding the pattern of concession in Kasbah before trading commences, such selection did not and could not take into consideration the ever-changing external influences such as the increasing number of buyers and sellers at a given time.

3) Negotiation Decision Function (NDF): Faratin *et al.* [22] presented a negotiation model that defines a range of strategies based on time-dependent, resource-dependent, and behavior-dependent NDFs. Whereas time-dependent NDFs were compared with the strategies in MDAs in Section III-A, resource-dependent NDFs generate proposals based on how a particular resource (e.g., remaining bandwidth) is being consumed. Agents become more Conciliatory as the quantity of the resource diminishes. Resource-dependent functions are similar to time-dependent functions, except that resource-dependent functions depend on the resource quantity available instead of the remaining time. There are three categories of resource-dependent NDFs: *Impatient*, *Steady*, and *Patient*, representing the patterns of usage of resources. In behavior-dependent NDFs, an agent generates its proposal by replicating (a portion of) the previous attitude of its opponent. Nevertheless, since the model of Faratin *et al.* only considered bilateral negotiation, there is no notion of competition and opportunity. Furthermore, there is no corresponding feature of agents relaxing bargaining terms in the face of negotiation pressure.

4) G-Commerce: In [3], [7], and [8], two broad resource-allocation schemes under different market conditions: 1) commodity markets and 2) auctions were examined. In a commodity market, a consumer purchases a resource from a pool of available equivalent resources without being able to specify exactly the required resource. In auction markets, consumers bid for and purchase specific resources from resource providers. Using a set of simulated Grids consisting of resource providers and applications (consumers), Wolski *et al.* investigated the effectiveness of both these schemes [3], [7], [8]. However, both auction and commodity markets rely on a trusted third party to mediate transactions. As pointed out in [3, 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. In contrast, MDAs and EMDAs negotiate without third-party mediation.

5) Negotiation Agents for Grid Resource Allocation: In addition to economic models in [3], [7], and [8], there are also research initiatives (albeit, very few and very new) adopting negotiation models for Grid resource allocations [10], [16], [17] (see [41] for a survey). Preliminary work in this area aims to either integrate methods of negotiation [10] or adapt the negotiation mechanism by selecting from a range of methods [16].

In [10], Chao *et al.* proposed a two-stage negotiation mechanism for the allocation of Grid resources, which combines the coevolutionary method with the game theory approach. In the first stage, the mechanism explores the search space of possible deals to find effective negotiation strategies. In the second stage, it attempts to find an equilibrium solution using the payoff matrix of the strategies generated through coevolution in stage one. Whereas this mechanism combines the strengths of game theory approach and the coevolutionary method, one of its weaknesses as pointed out in [10] is that deals cannot be made during the coevolutionary process.

In [16], Shen *et al.* proposed a negotiation framework for Grid resource allocation with a focus on balancing the loads of computing resources. It was suggested that the negotiation framework should allow negotiation agents to adapt to specific computation needs, available resources, and computing loads by selecting an appropriate negotiation approach from a list of trading models such as: auction, contract-net, and game theory based models. Whereas this seems to be an ambitious project, no empirical or theoretical evaluation was provided because, like the two-stage negotiation mechanism in [10], (to the best of the author's knowledge) Shen *et al.*'s project is still in its infancy as this paper is being written.

Additionally, Lawley *et al.* [17] investigated the use of negotiation agents for identifying the mutually acceptable terms among information publishers (providers) and consumers of message notification services in a Grid computing environment.

Adopting NDFs in [22], the agents in [17] negotiate on terms such as frequency, format, and accuracy of information being delivered by the notification service. Empirical results in [17] seem to suggest that through negotiation, an information publisher can balance between the utility (satisfaction) of the consumers and its workload. Although 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) allows a publisher to benefit from serving more consumers.

Finally, it is noted that some of the very preliminary ideas of this work are presented in [42]. This work has significantly and considerably augmented and detailed the preliminary initiative in [42] as follows.

1) While Sim [42] *only* presents (very briefly) the general components of the testbed, this paper provides detailed descriptions of the testbed, interaction model (Fig. 1), as well as the negotiation protocol.
2) In [42], *only* a very small set of results was obtained for simulations when agents were only subject to different job deadlines. This work significantly augments and generalizes the results in [42] by conducting considerably more experiments with different loadings of the simulated Grid and different market situations.

VI. Conclusion

The novelty and significance of this work are that (to the best of the author's knowledge) it is one of the earliest works that applies a market-driven bargaining model to a G-commerce environment.

The contribution of this work is showing that MDAs and EMDAs are appropriate tools for Grid resource negotiation, and is detailed in the following.

1) In contrast to other related work [3], [7], [8], [10], [16], [17], this paper not only argues for the need of having negotiation activities, but also provides justifications for considering market dynamics in a computational Grid (see Section I).
2) A testbed (Section III-A) to simulate a Grid computing environment was developed. Whereas previous testbeds of MDAs and EMDAs in [24], [26], and [27] consist of e-markets with only MDAs and EMDAs in a generic e-commerce environment, the testbed in this work includes a heterogeneous e-market consisting of MDAs, EMDAs, NDF, as well as Kasbah agents. The differences between the author's previous testbeds in [24], [26], and [27], and this paper are as follows. The testbed in [24] consists of only MDAs, and it examined the impact of deadline, buyer-seller ratio, and spread [6], [24] (difference between negotiation agents' proposals) on the negotiation outcomes of MDAs. The testbeds in [26] and [27] consist of both MDAs and EMDAs, and they compared the performance of MDAs and EMDAs in terms of their success rates in negotiation. The testbed in this paper compares the performance of MDAs and EMDAs with NDF and Kasbah agents in a G-commerce environment.
3) The rationale for comparing MDAs and EMDAs with Kasbah and NDF is given in Section III-B by showing that they have quite similar time-dependent strategies.
4) Empirical results (Section IV) show that: 1) in many different market situations, both MDAs and EMDAs generally achieve higher budget efficiencies than Kasbah and NDF-like agents and 2) when there is an extremely high utilization level of Grid resources, EMDAs are generally more successful in acquiring resources than MDAs, Kasbah, and NDF-like agents. These results provide evidence to support the design considerations 1) and 3) in Section I.

In summary, favorable empirical results suggest that by taking the market dynamics of the Grid into consideration and slightly relaxing the bargaining terms under intense negotiation pressure, EMDAs and MDAs are appropriate mechanisms for Grid resource allocation. To this end, this work provides an evidence for showing that negotiation tools for e-commerce can be adapted for resource negotiation in a computational Grid—an issue raised in Sim's position paper [5].

While there is much attention focusing on the software mechanisms and infrastructures for realizing the Grid vision, to date, there is little work (e.g., [3], [7], [8], [10], [16], and [17]) that addresses the resource control policies of a computational Grid. On this account, this paper addresses an essential and comparatively less explored issue for realizing a computational Grid. Furthermore, providing an efficient resource allocation mechanism is a complex undertaking [11], and finding an appropriate economic model for managing Grid resources largely remains an open problem.

Since considering market dynamics and making tradeoff decisions are generally not among the current focuses of the very few (preliminary) initiatives on developing G-negotiation agents [10], [16], [17], this research does not compete with the existing related literature, but, rather, it supplements and complements the very small number of preliminary works in this novel and emerging area.

Whereas previous theoretical [6], [25], [28] and empirical results [24], [26], [27] show desirable properties of MDAs and EMDAs such as stability, negotiating optimally, reacting to changing market situations, and making tradeoff decisions, this paper demonstrates an application of MDAs and EMDAs.

Future agenda of this work include: 1) augmenting the heterogeneous testbed with other types of e-negotiation agents with learning capabilities (e.g., [43] and [44]) and 2) considering G-negotiation agents that negotiate not only for the cost of providing the service but also the desired level of service.

Finally, it is hoped that this paper will shed new light and inspire others in finding an appropriate economic model for Grid resource allocation.

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REFERENCES

[1] I. Foster, C. Kesselman, and S. Tuecke, "The anatomy of the Grid: Enabling scalable virtual organizations," *Int. J. Supercomput. Appl.*, vol. 15, no. 3, pp. 200–222, 2001.

[2] K. Krauter, R. Buyya, and M. Maheswaran, "A taxonomy and survey of Grid resource management systems," *Int. J. Softw., Pract. Exp.*, vol. 32, no. 2, pp. 135–164, 2002.

[3] R. Wolski *et al.*, "Grid resource allocation and control using computational economies," in *Grid Computing—Making the Global Infrastructure a Reality*, F. Berman, A. Hey, and G. Fox, Eds. New York: Wiley, 2003, pp. 747–771.

[4] I. Foster, N. Jennings, and C. Kesselman, "Brain meets brawn: Why Grid and agents need each other," in *Proc. 3rd Int. Conf. Auton. Agents and Multi-Agent Syst.*, New York, 2004, pp. 8–15.

[5] K. M. Sim, "From market-driven agents to market-oriented Grids," *ACM SIGECOM: E-Commerce Exchange*, vol. 5, no. 2, pp. 45–53, Nov. 2004.

[6] ——, "A market-driven model for designing negotiation agents," *Comput. Intell.*, vol. 18, no. 4, pp. 618–637, 2002.

[7] R. Wolski *et al.* (2001). *G-Commerce: Building Computational Marketplaces for the Computational Grid*. [Online]. Available: http://www.cs.ucsb.edu/~rich/publications/

[8] ——. *Analyzing Market-Based Resource Allocation Strategies for the Computational Grid*. [Online]. Available: http://www.cs.utk.edu/~rich/publications/CS-00 453.ps.gz

[9] R. Buyya and S. Vazhkudai, "Compute power market: Towards a market-oriented Grid," in *Proc. 1st IEEE/ACM Int. Sym. Cluster Comput. Grid*, Australia: Brisbane, May 15–18, 2001, pp. 574–581

[10] K. Chao, R. Anane, J.-H. Chen, and R. Gatward, "Negotiating agents in a market-oriented Grid," in *Proc. 2nd IEEE/ACM Int. Sym. CCGRID*, 2002, pp. 436–437.

[11] R. Buyya *et al.*, "Economic models for resource management and scheduling in Grid computing," *Concurrency Comput.: Pract. Exp.*, vol. 14, no. 13–15, pp. 1507–1542, 2002.

[12] Grid computing: Conceptual flyover for developers, IBM. [Online]. Available: http://www-128.ibm.com/developerworks/grid/library/gr-fly.html?ca=dgr-lnxw01-obg-GridFlyover

[13] M. Miller and K. Drexler, "Markets and computation: Agoric open systems," in *The Ecology of Computation*, B. Huberman, Ed. North Holland, The Netherlands: Elsevier, 1988, pp. 133–176.

[14] R. Buyya, D. Abramson, and S. Venugopal, "The Grid economy," *Proc. IEEE*, vol. 93, no. 3, pp. 698–714, Mar. 2005.

[15] K. Drexler and M. Miller, "Incentive engineering for computational resource management," in *The Ecology of Computation*, B. Huberman, Ed. North Holland, The Netherlands: Elsevier, 1988, pp. 231–266.

[16] W. Shen *et al.*, "Adaptive negotiation for agent-based Grid computing," in *Proc. AAMAS2002 Workshop Agentcities: Challenges Open Agent Environ.*, Bologna, Italy, 2002, pp. 32–36.

[17] R. Lawley *et al.*, "Automated negotiation between publishers and consumers of Grid notifications," *Parallel Process. Lett.*, vol. 13, no. 4, pp. 537–548, Dec. 2003.

[18] Z. Juhasz and P. Paul, "Scalability analysis of the contract net protocol," in *Proc. 2nd IEEE/ACM Int. Sym. CCGRID*, 2002, p. 346.

[19] R. Buyya, "Economic-based distributed resource management and scheduling for grid computing," Ph.D. dissertation, Monash Univ., Melbourne, Australia, Apr. 12, 2002.

[20] J. Cao *et al.*, "Performance evaluation of an agent-based resource management infrastructure for Grid computing," in *Proc. 1st IEEE/ACM Int. Sym. CCGRID*, Brisbane, Australia, 2001, pp. 311–318.

[21] A. Chavez and P. Maes, "Kasbah: An agent marketplace for buying and selling goods," in *Proc. 1st Int. Conf. Practical Appl. Intell. Agents and Multi-Agent Tech.*, London, U.K., 1996, pp. 159–178.

[22] P. Faratin *et al.*, "Negotiation decision functions for autonomous agents," *Int. J. Robot. Auton. Syst.*, vol. 24, no. 3, pp. 159–182, Sep. 1998.

[23] K. M. Sim and E. Wong, "Towards market driven agents for E-auction," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 31, no. 6, pp. 274–284, Nov. 2001.

[24] K. M. Sim and C. Y. Choi, "Agents that react to changing market situations," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 33, no. 2, pp. 188–201, Apr. 2003.

[25] K. M. Sim, "Equilibrium analysis of market-driven agents," *ACM SIGECOM: E-Commerce Exchange*, vol. 4, no. 2, pp. 32–40, Oct. 2003.

[26] K. M. Sim and S. Y. Wang, "Flexible negotiation agent with relaxed decision rules," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 3, pp. 1602–1608, Jun. 2004.

[27] K. M. Sim, "Negotiation agents that make prudent compromises and are slightly flexible in reaching consensus," *Comput. Intell.*, vol. 20, no. 4, pp. 643–662, Nov. 2004.

[28] ——, "Equilibria, prudent compromises, and the 'Waiting' game," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 35, no. 4, pp. 712–724, Aug. 2005.

[29] G. Kennedy, *Field Guide to Negotiation*. Cambridge, MA: Harvard Business School Press, 1994.

[30] M. J. Osborne and A. Rubinstein, *Bargaining and Markets*. New York: Academic, 1990.

[31] R. Dash and N. Jennings, "Computational mechanism design: A call to arms," *IEEE Intell. Syst.*, vol. 18, no. 6, pp. 40–47, Nov./Dec. 2003.

[32] D. Kreps and R. Wilson, "Sequential equilibria," *Econometrica*, vol. 50, no. 4, pp. 863–894, Jul. 1982.

[33] J. Rosenschein and G. Zlotkin, *Rules of Encounter: Designing Conventions for Automated Negotiation Among Computers*. Cambridge, MA: MIT Press, 1994.

[34] T. Sandholm and N. Vulkan, "Bargaining with deadlines," in *Proc. Nat. Conf. AAAI*, Orlando, FL, 1999, pp. 44–51.

[35] R. Buyya and M. Murshed, "GridSim: A toolkit for the modeling and simulation of distributed resource management and scheduling for Grid computing," *Concurrency Comput.: Pract. Exper.*, vol. 14, no. 13–15, pp. 1175–1220, 2002.

[36] S. Fatima *et al.*, "Bargaining with incomplete information," *Ann. Math. Artif. Intell.*, vol. 44, no. 3, pp. 207–232, 2005.

[37] A. Rubinstein, "Perfect equilibrium in a bargaining model," *Econometrica*, vol. 50, no. 1, pp. 97–109, Jan. 1982.

[38] A. Muthoo, *Bargaining Theory With Applications*. Cambridge, U.K.: Cambridge Univ. Press, 1999.

[39] A. Lomuscio *et al.*, "A classification scheme for negotiation in electronic commerce," *Int. J. Group Decis. Negot.*, vol. 12, no. 1, pp. 31–56, 2003.

[40] N. R. Jennings *et al.*, "Automated negotiation: Prospects, methods and challenges," *Int. J. Group Decis. Negot.*, vol. 10, no. 2, pp. 199–215, 2001.

[41] K. M. Sim, "A survey of bargaining models for Grid resource allocation," *ACM SIGECOM: E-Commerce Exchange*, vol. 5, no. 5, pp. 22–32, Jan. 2006.

[42] ——, "From market-driven e-negotiation agents to market-driven G-negotiation agents," in *Proc. IEEE Int. Conf. e-Technology, e-Commerce and e-Services*, Hong Kong, 2005, pp. 408–413.

[43] Y. Ishihara, R. Huang, and K. M. Sim, "Learning opponent's eagerness with Bayesian updating rule in a market-driven negotiation model," in *Proc. Int. Conf. Adv. Inf. Netw. and Appl.*, Taipei, Taiwan, 2005, pp. 903–908.

[44] D. Zeng and K. Sycara, "Bayesian learning in negotiation," *Int. J. Human-Comput. Stud.*, vol. 48, no. 1, pp. 125–141, Jan. 1998.

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