From Market-driven Agents to Market-oriented Grids (Position Paper)

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Providing efficient mechanism for allocation and management of resources is essential for realizing a computational grid. Since resource providers and consumers may be independent bodies in a computing grid platform, negotiation among these participants is necessary. This position paper discusses (i) the design considerations of e-negotiation agents for grid commerce, and (ii) the possible application of *Market-driven agents* (*MDAs*) as negotiation mechanisms for managing resources in a computational grid. *MDAs* are negotiation agents designed with the flexibility of (i) making adjustable amounts of concession taking into account factors such as market rivalry, time preferences, and outside options, and (ii) relaxing trade expectation in the face of intense pressure. In addition to having stable strategies, making prudent compromises and optimizing utility, additional desirable properties of *MDAs* that are suitable for a computational grid include: adaptivity to changes in market conditions, and flexibility of reaching faster consensus.

Additional Key Words and Phrases: automated negotiation, Grid-commerce, resource allocation.

1. INTRODUCTION

The rapid development of grid and peer-to-peer computing provides enabling technologies for bolstering virtual enterprises in sharing geographically distributed resources. In a computational grid [1], one envisions 'software applications "plugging" into a "power grid" of computational resources drawing upon the necessary computing resources from the global supply for their executions' [2]. While there are much attention focusing on the software mechanism and software infrastructure for engineering the grid vision, to date, there is little work that addresses the resource control policies of a computational grid. It was noted in [3] that allocation and management of resources is essential for realizing a computational grid, and providing efficient resource allocation mechanism is a complex undertaking [4]. Software agents, in particular e-negotiation agents can play an essential role in realizing the Grid vision [5]. To the best of the author's knowledge, at present, there are only a few (preliminary) efforts on applying e-negotiation agents for resource management in grid computing, (e.g., [4-9]). Additionally, the strategies adopted by these agents do not take the dynamics of the market into consideration. This position paper discusses the motivation for considering market factor as a design consideration of negotiation mechanisms for grid resource allocation (section 2.1). Although still in its infancy, this work rests on the author's previous work on market-driven agents (*MDAs*) [10-15] (section 3). Section 2 discusses the possible transformation of e-negotiation technology for e-commerce into grid-commerce (G-commerce) applications. Sections 4 and 5 discuss the desirable properties of *MDAs* and its suitability in resource negotiations in a computational grid.

2. FROM E-COMMERCE TO G-COMMERCE

As pointed out in [8], both e-commerce systems and market-oriented grids share a common objective because in both systems, business transactions are carried out via a network such as the Internet. While one envisions more specific types of products such as computational power, storage, and associated services to be traded in market-oriented grids, e-commerce systems generally and potentially deal with a wide range of products. In some cases, adapting an e-commerce system for one kind of product to be used in trading another product involves minor or perhaps minimal modifications. Hence, it seems plausible to think that (some) agents developed for e-commerce generally share some (or many) of the design principles for agents in market-oriented grids. For instance, an e-Negotiation agent shares the same objective as a negotiation agent in market-oriented grids because they are both expected to be designed to optimize utilities of buyers (resource consumers) or sellers (resource providers) through some forms of bargaining strategies. While the determination of their utility functions may not necessarily be similar, previously proven and useful negotiation strategies adopted by e-Negotiation agents can also be (potentially) adopted by negotiation agents in market-oriented grids. However, as discussed in section 2.1, there are additional design issues that may need to be addressed.

2.1. Resource Negotiation in a Computational Grid

Negotiation activities in a grid-computing platform are required because participating parties are independent bodies [8] with different policies, objectives and requirements. Through negotiation, players in a grid marketplace, i.e., resource owners (or service providers) and consumers [4], are given the opportunity to maximize their return-on-investment and minimize their cost (the price they pay) respectively. In addition, it is envisioned that negotiation in a market-oriented grid must take into consideration the following:

(i) the dynamics of the computing environment
(ii) the speed at which resources are allocated or de-allocated.

While factor (i) is an essential consideration because resources and services are constantly being added or removed from the grid [8, 16], factor (ii) is important because any delay incurred on waiting for a resource assignment is perceived as an overhead [3]. Both factors (i) and (ii) collectively help to define some of the design considerations of G-commerce negotiation agents listed as follows:

(i) *market factors*: To optimize their returns, G-commerce negotiation agents should consider factors such as opportunity and competitions
(ii) *time constraint*: G-commerce negotiation agents should be sensitive to deadlines
(iii) *tradeoff*: 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. Like time constraint, this consideration relates to the issue of overhead [3].

Although there are many existing e-Negotiation agents (eg, just to name a few: Kasbah [17], Faratin et al. *negotiation decision functions* [18], Fuzzy e-Negotiation Agent (FeNA) [19]), none of these agents was designed to take into consideration all the three design issues mentioned above. In Kasbah [17], relaxation of bids/offers is largely determined by trading conventions, or strategies encoded by users. Although Kasbah considered deadline as a factor when selecting the strategy for making concession before trading commences, such selection cannot take into account the ever-changing external influences such as increasing/decreasing number of producers and consumers. Using negotiation decision functions (*NDFs*) based on time, resource, and the behavior (attitude) of its opponents, Faratin et al. [18] defined a range of tactics for generating (counter-)proposals. While time-*NDFs* consider deadlines, resource-*NDFs* take into consideration diminishing level of resources when determining the amount of concession. Behavior-*NDFs* allow agents in [18] to replicate the attitude of their trading partners. Like Kasbah, Faratin et al.'s *NDFs* do not address design issues (i) and (iii) mentioned above. *FeNAs*[19] adopts fuzzy constraint-based reasoning for bolstering multi-issue negotiations. One of the distinguishing features of *FeNAs* is that preferences, priorities and constraints are defined as fuzzy constraints (e.g. low price, high quality, short delivery time and budget at about $90). *FeNAs's* objectives may also be defined as soft objectives (e.g. an agent prefers to pay $200 but is still happy with paying a little bit more). Although this feature may provide *FeNA* with the flexibility of acquiring available suboptimal resources more quickly, it does not take into account market factors as well as time constraints. In a highly dynamic grid environment, it is essential to take market dynamics into consideration because (i) providers can make resources/services available to and disconnect from a market-oriented grid, and (ii) consumers can enter and withdraw requests, perhaps at machine speed in both cases. On this account, it seems prudent to design negotiation agents in a market-oriented grid by considering market factors (such as opportunity and competition) that can significantly enhance or diminish the successful acquisitions (or provisions) of resources/services with optimum returns.

3. MARKET-DRIVEN AGENT

Sim et al. [10-15] proposed several variants of market-driven strategies for negotiation agents that make concessions taking into account factors such as outside options, market rivalry, and time pressure. A *market-driven agent* (*MDA*) is a negotiation agent that makes adjustable amounts of concession by considering *deadline*, *competition*, and *opportunity*. Due to space limitation, this section only presents a very brief summary of the features of *MDAs*, and detailed designs and previous empirical results evaluating *MDAs* can be found in [10-15]. An *MDA* makes concession by narrowing the difference k_t between its proposal and the counter-proposal of its opponent in a negotiation round t. In determining the appropriate amount of concession, an *MDA* adopts the following three decision functions to determine the difference k_{t+1} in proposal and counter-proposal in the next round t+1:

$$k_{t+1}=f[\boldsymbol{O}(n^B_t,\ v^{B\rightarrow Sj}_t,\ <w^{Sj\rightarrow B}_t>),\boldsymbol{C}(m^B_t,n^B_t),\boldsymbol{T}(t,\tau,\lambda)]k_t$$

The above formulation models the decision functions from a buyer agent's perspective (the formulation for a seller agent is similar). Let B be a buyer agent. The opportunity function $\boldsymbol{O}(n^B_t,\ v^{B\rightarrow Sj}_t,\ <w^{Sj\rightarrow B}_t>)$ of B determines the amount of concession based on (i) n^B_t –which is the number of trading alternatives of B (i.e., the number of sellers) and (ii) differences in utilities ($v^{B\rightarrow Sj}_t$) generated by the proposal of B and the counter-proposal of its trading partner(s) ($<w^{Sj\rightarrow B}_t>$) [11,12]. $v^{B\rightarrow Sj}_t$ is the utility that B will receive if seller S_j accepts B's proposal. $<w^{Sj\rightarrow B}_t>$ is a set of utilities such that each $w^{Sj\rightarrow B}_t$ is the utility that B will receive if B accepts seller S_j's proposal. When determining opportunity, it was shown in [11] that if there is a large number of trading alternatives, the likelihood that some agent proposes a bid/offer that is potentially close to an *MDA*'s offer/bid may be high. However, it would be difficult for the *MDA* to reach a consensus if none of the so many options are viable (i.e., there are large differences between the proposal of the *MDA* and the counter-proposals of all its trading partners). On this account, $\boldsymbol{O}(n^B_t, v^{B\rightarrow Sj}_t, <w^{Sj\rightarrow B}_t>)$ determines the probability of obtaining a utility $v^{B\rightarrow Sj}_t$ with at least one of its n^B_t trading partners by considering the notion of *conflict probability* [20,21]. Due to space limitation the derivation of $\boldsymbol{O}(n^B_t, v^{B\rightarrow Sj}_t, <w^{Sj\rightarrow B}_t>)$ is omitted here but details can be found in [11,12].

In designing *MDAs*, competition is modeled as a decision function $C(m^B_t, n^B_t)$. While n^B_t is the number of sellers, m^B_t is the number of competitors (i.e., the number of sellers). $C(m^B_t, n^B_t)$ 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. Suppose $\boldsymbol{B}$ has m^B_t-1 competitors, and one trading partner, the probability that $\boldsymbol{B}$ is not the most preferred trading partner of other agents is $(m^B_t -1)/ m^B_t$. If $\boldsymbol{B}$ has m^B_t-1 competitors, and n^B_t trading partners, the probability that $\boldsymbol{B}$ is *not* the most preferred partner of *all* its trading partners is $\left[(m^B_t - 1)/m^B_t\right]^{n^B_t}$. Details of deriving $C(m^B_t, n^B_t)$ are given in [11, p. 622, 12, p. 192]. Hence, at round i, the probability that $\boldsymbol{B}$ is considered the most preferred trading partner by at least one agent is:

$$C(m^B_t, n^B_t) = 1 - \left[(m^B_t - 1)/m^B_t\right]^{n^B_t}$$

The probability of being considered the most preferred trading partner by some parties increases with the number of trading partners n^B_t. However, with a larger number of competitors m^B_t, the likelihood of being considered the most preferred trading partner decreases.

The time-dependent function $T(t, \tau, \varepsilon)$, models the intuition that as time passes, an *MDA* relaxes its proposal by making attempt(s) to narrow its difference(s) with other parties given as follows:

$$T(t,\tau,\varepsilon) = 1 - \left(t/\tau\right)^{1/\varepsilon}$$

where t is the current trading time, τ is the deadline, and ε is an agent's eagerness that represents the user's desire to complete the deal. While $\varepsilon\in[0,1]$, both t and τ are measured in terms of the number of trading rounds. $T(t, \tau, \varepsilon)$ enables an *MDA* to adopt various patterns to determine the discount factors when narrowing the differences among proposals with the passage of time. In [14], *MDAs* with different values of eagerness ($0<\varepsilon\leq1$) adopt different strategies in making concession with respect to remaining trading time and are classified as follows:

1) Linear: ε=1 and $T(t, \tau, \varepsilon)=1-(t/\tau)$. An agent makes a *constant* rate of concession.

2) Conservative: When $0<\varepsilon<1$, an agent makes smaller concessions in early rounds and larger concessions in later rounds.

3) Arrogant: ε=0 and $T(t, \tau, \varepsilon)=1-(t/\tau)^{\infty}$. This special case is not considered, because it represents the situation where an agent is totally not interested to negotiate.

4) Conciliatory: In addition, there is also another class of strategies – conciliatory strategies, which were adopted by *MDAs* in [11,12]. *MDAs* adopting conciliatory strategies make larger concessions in the early trading rounds and smaller concessions at the later stage. However, in [14], *MDAs* (with $0<\varepsilon<1$) are *not* designed with conciliatory strategies. Analyses by Sim [12] showed that conciliatory strategies *MDAs* are more likely to achieve *lower utilities* even though they face *lower risk* of losing deals to other competitors. Since *MDAs* in [14] are designed with fuzzy rules to lower their expectation in the face of intense negotiation pressure such as short deadlines, conciliatory strategies were not adopted.

Relaxing Expectation: Sim and Wang [14] have developed *enhanced MDAs* (*EMDAs*) that are programmed to relax their expectation in the face of intense pressure (e.g., when an *EMDA* has urgent need to acquire a resource, or is facing strong competition or fast approaching deadlines). Since notions such as "very slight" difference in their proposals, "strong" competition, "fast" approaching deadline, and "very urgent" are vague, a fuzzy decision controller (*FDC*) was designed in [14] to guide *EMDAs* in making decision when relaxing their aspirations. In designing the *FDC*, *EMDAs* considered factors such as competition and eagerness. These factors put a negotiator under pressure. Since the fuzzy rules are designed to relax a negotiator's trading conditions (e.g., its aspiration value/level), they are only applied when a negotiation agent is under negotiation pressure. For instance, some of the rules are applied when an agent risks losing the deal in the face of competition or when an agent is very eager to complete a deal. Details are given in [14].

Negotiation Process: Negotiation proceeds in a series of rounds as follows. At any round, at most one agent enters the market randomly. Trading begins when there are at least two agents of the opposite type (one buyer and one seller). When trading starts, an agent proposes a deal from their space of possible deals (e.g., the most desirable price, the least desirable (reserved) price, and those prices in between), typically an agent proposes its most preferred deal initially. Adopting Rubinstein's [22, p. 100] *alternating offers protocol*, a pair of buyer and seller agents negotiates by making proposals in alternate rounds. Multiple buyer-seller pairs can negotiate deals concurrently. If no agreement is reached, negotiation proceeds to another round. Negotiation between a pair of agents terminates (i) when an agreement is reached, or (ii) with a conflict when one of the agents' deadline is reached. For an *MDA*, an agreement is reached when its trading partner's offer matches or exceeds what it asked for. An *EMDA* uses the fuzzy rules in the *FDC* to determine if an offer is acceptable.

4. DESIRABLE PROPERTIES

This section discusses some of the desirable properties of *MDAs* and *EMDAs* with respect to their possible applications as negotiation tools in resource allocation of a computational grid. *MDAs* possess many of the desirable properties of negotiation mechanisms prescribed in [23], such as being stable and selecting best-response strategy to maximize utility. These properties were proven in [13] and are discussed below.

Best-response strategy: In [13] it was shown that the conservative strategy is the best-response (optimal) strategy regardless of the strategy adopted by its opponent.

Sequential equilibrium: At every of its decision point, adopting the conservative strategy is the best response for an *MDA*. This satisfies the notion of sequential rationality [24]. Using this notion, it was shown in [13] that the strategies of an *MDA* and its opponent forms a *sequential equilibrium* [24] and neither the *MDA* nor its opponent finds any incentive to deviate from the dominant strategy which is the conservative strategy.

(Detailed proofs can be found in [13]). 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 opponent [25, p. 21] or to speculate about strategies of others [26, p. 8].

Making prudent compromises: An agent receives a utility of 0 if it never trades [27, p. 152] or is unsuccessful in trading (because disagreement is the worst outcome [27, p.33]). Hence, *both* (1) the size of the possible payoffs *and* (2) the probability of achieving these are essential. Although conceding more increases the probability of reaching a deal, it is inefficient because an agent "wastes" some its utility. However, if an agent concedes too little, it runs the risk of losing a deal. In [13], it was shown that *MDAs* make *minimally sufficient concessions*. 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 market situations. This satisfies design consideration (i) in section 2.1.

Sensitive to deadlines: Like Kasbah and Agents in [18], the time decision function of *MDAs* is inherently designed to respond to deadlines. This satisfies design consideration (ii) in section 2.1.

Making Trade off: By augmenting an *MDA* with an *FDC*, an *EMDA* is designed to relax trading expectation to increase its chance of completing a deal. Empirical results in [14] obtained from stochastic simulations in a wide variety of market conditions showed that by relaxing trade expectation, both the success rate and expected utility of *MDAs* are enhanced in many market situations, particularly when they are facing short deadlines. While details can be found in [14], selected empirical results are given in Figs. 1a-1d in the appendix to make this position paper more self-contained. Figs. 1a-1d showed that *EMDAs* achieved higher expected utility and success rate in relatively short deadlines (eg, between 15 to 40 rounds of negotiation), as well as under different constraints when the agents have different eagerness. This feature is desirable for addressing design consideration (iii) in section 2.1.

5. DISCUSSION AND CONCLUSION

This position paper attempts to answer the following questions:

(i) What are the desirable properties of a negotiation agent in resource allocation in a computational Grid?
(ii) Can some of the negotiation tools in e-Commerce be adapted for resource negotiation in a computational Grid?
(iii) Explain how the theoretical results in [13] and empirical results in [14] show the suitability of MDAs and EMDAs for resource negotiation in a computational Grid?

In addition to the desirable properties (such as stability, utility maximizing, best response strategy) in negotiation mechanism design (*NMD*) noted in [25, 28, 23], in section 2.1 this position paper suggests that *NMD* for resource allocation in a computational grid should also consider the market factors as well as making tradeoff to increase the speed of allocation.
While a testbed for simulating the application of *MDAs* and *EMDAs* in a grid computing

environment is still under construction, this position paper envisions that negotiation tools such as *MDAs* previously developed for e-commerce may be adapted for grid resource allocation if design considerations such as speed and market dynamics are taken into account. The testbed that is under development consists of (i) a set of *grid resources* represented by a set of *provider agents*, and (ii) a set of *resource consumers* represented by a set of *consumer agents*, (iii) a *repository of resource information*, (iv) a *library of negotiation strategies*, and (v) a heterogeneous market of *negotiation agents* (that includes *MDAs*, *EMDAs* and others).

Theoretical results in [13] showed that the strategies of *MDAs* are stable and that *MDAs* are utility maximizing and respond to different market conditions by making minimally sufficient concession (based on the assumption that the current proposal of an *MDA* reflects its beliefs about the current market conditions, and any revision of the proposal depends on the random and unpredictable arrival of new information). Empirical results in [14] showed that *EMDAs* generally enhance the expected utility and success rate of *MDAs*. Furthermore, previous empirical results in [10] demonstrated that in general market-driven strategy outperformed fixed strategy. Some selected results as summarized in Fig 2 in the appendix show that *MDAs* (with different levels of eagerness) generally achieved higher utilities than fixed strategy agents. However, an *MDA* that is very anxious (eager) to trade in not so favorable market conditions (e.g. less trading partners), did not outperform agents adopting fixed strategy (see the circled region in Fig.2). This corresponds to the intuition in real-life trading. For instance, if one urgently needs to fly during a busy (high) season, one would be coerced to pay higher airfare.

Building on previous theoretical and empirical results, a future agenda is to demonstrate the suitability of *MDAs* and *EMDAs* as economic models for resource management in a Grid computing platform.

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APPENDIX

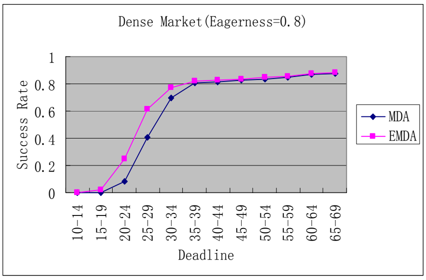

Fig. 1a. *EMDAs*' Success rate [14]

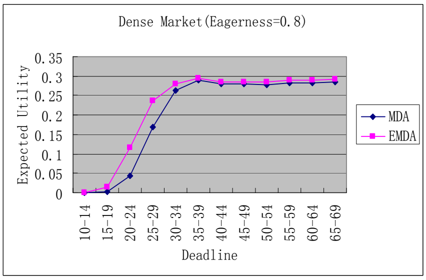

Fig. 1b. *EMDAs*' Expected Utility [14]

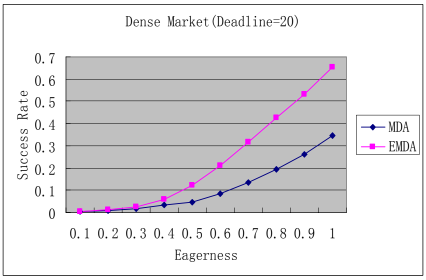

Fig. 1c. *EMDAs*' Success rate [14]

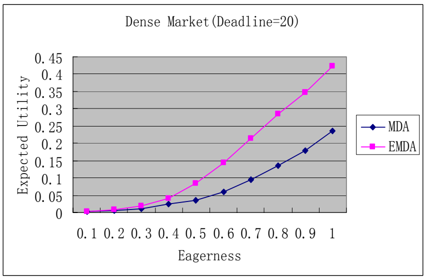

Fig. 1d. *EMDAs*' Expected Utility [14]

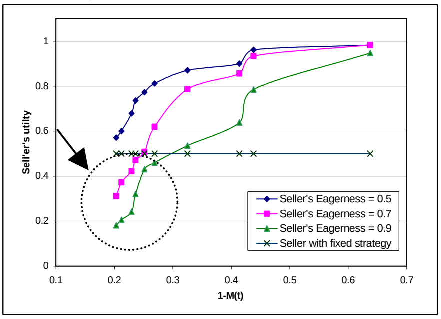

Fig. 2. Market-driven and Fixed Strategies [10]