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Market_based grid resource allocation using new negotiation model

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A B S T R A C T

This paper presents a new negotiation model for designing Market- and Behavior-driven Negotiation Agents (MBDNAs) that address computational grid resource allocation problem. To determine the amount of concession for each trading cycle, the MBDNAs are guided by six factors: (1) *number of negotiator's trading partners*, (2) *number of negotiator's competitors*, (3) *negotiator's time preference*, (4) *flexibility in negotiator's trading partner's proposal*, (5) *negotiator's proposal deviation from the average of its trading partners' proposals*, and (6) *previous concession behavior of negotiator's trading partner*. In our experiments, we compare grid resource consumer (GRC) of type MBDNAs (respectively grid resource owner (GRO) of type MBDNAs) with MDAs (Market Driven Agents) in terms of the following metrics: total tasks complementation and average utility (respectively resource utilization level and average utility). The results show that by taking the proposed factors into account, MBDNAs of both types make a more efficient concession amount than MDAs and are, therefore, considered an appropriate mechanism for grid resource allocation in different grid workloads and market types.

1. Introduction

COMPUTATIONAL GRIDS have been emerging as a new paradigm for solving large-scale problem in science, engineering and commerce
Q4 (Buyya et al., 2001). The popularity of grids has been growing very rapidly, driven by the promise that they will enable knowledge and computing resources to be delivered to and used by citizens and organizations as traditional utilities or in novel forms. They enable the creation of *virtual enterprises* (VEs) for *sharing* and *aggregation* of millions of resources, geographically distributed across organizations and administrative domains (Buyya et al., 2002, p. 1508). As the computational grid focuses on large-scale resource sharing, and because grid resource owners (GROs) and grid resource consumers (GRCs) may have different goals, preferences and policies, which are characterized and specified through a *utility model* (or *utility function*), an efficient resource management, is central to its operations. The term resource management refers to the operations used to control how capabilities provided by grid resources and services are made available to other entities, whether users, applications, or services (Foster and Kesselman, 2004).

Utilization of grid resource is not for free (Xing et al., 2009), which means that the GROs charge GRCs according to the amount of resource they consume, so adapting some of the successful ideas of economical models to resource allocation in large-scale computing systems is essential for realizing the vision of grid computing environments (Bai et al., 2008). In recent years, usage of market based methods (i.e., A market method is the overall algorithmic structure within which a market mechanism or principle is embedded (Tucker and Berman, 1996)) for grid resource management is one of solutions which has received much attention (Izakian et al., 2010).

Numerous economic models (Buyya et al., 2002), including microeconomic and macroeconomic principles for resource management, are proposed in literature (Buyya et al., 2000; Huhns and Stephens, 2000; Buyya, 2002; Lai et al., 2005; Chunlin et al., 2009; Chunlin, 2011; Aminul et al., in press). Negotiation-like protocols may be more appropriate than other commonly referenced works (e.g., see (Wolski et al., 2003; G-Commerce, 2001; Buyya and Vazhkudai, 2001; Wolski et al., 2001)) when the participants cooperate to create value (Kersten et al., 2000, p. 6) and are not only concerned with determining value, but *also* other factors, e.g., inter-business relationships and success rates. Sim (2010) pointed out some issues that should be considered in building the negotiation mechanism for grid resource management: (1) modeling devaluation of resources (2) considering market dynamics (3) relaxing bargaining criteria and (4) resource co-allocation. To complete the issues of (Sim, 2010) we present another issue that should be considered in building the efficient negotiation mechanism for grid resource management: modeling the decision criteria that are used by negotiators of real-life trading market for selecting the pattern of concession during negotiation process. The importance of such improved and extended negotiation model is when the designers of negotiation agents have to face with two opposite concepts: time of acquiring grid resources (respectively, leasing grid resources) and price of acquiring grid

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resources (respectively, price of leasing grid resources). It means that, GRCs (respectively, GROs) should achieve lower utilities to avoid the risk of losing deals to other competitors (and vice versa).To address these issues, a new *Multiagent-based Strategic Negotiation Model* is proposed here for resource allocation and for regulation of supply (grid resources, which are provided by resource owners) and demand (grid resource consumers' requirements) in grid computing environments. Such a new *Multiagent-based Strategic Negotiation Model* proposes grid system objective optimization resource allocation that provides a joint optimization of objectives for both the GROs and GRCs. GRCs (respectively, GROs) use the improved and extended multi_factor negotiation strategies to maximize their number of completed tasks while minimizing the spending cost (respectively, to maximize their utility level while maximizing the received revenue). Like most of the commonly previous works in the grid environment (e.g., see (Chunlin, 2011; Srinivas and Varadhan, 2011; Chunlin and Layuan, 2003; Foster et al., 2005; Pastore, 2008)) this approach provides mechanism for optimizing GROs' and GRCs' profit through providing software components (*Agent*). Optimization refers to the techniques used to allocate resources effectively to meet GROs' and GRCs' requirements. It applies to both GROs (supply-side) and GRCs (demand-side) who must be satisfied and maximized. The software agents that are designed to realize suitable grid resource allocation model by considering market-driven and behavior-driven factors are called **MBDNA**s (Market- and Behavior-driven Negotiation Agents).

The new features of this work are as follows:

(a) Designing a *new* multiagent-based strategic negotiation model for both bilateral and multilateral negotiations. This is so important that not only bilateral negotiation (where resources are provided by one agent and thus an agent is negotiating with one trading partner) but also multilateral negotiation (where resources are provided by multiple agents and thus an agent is negotiating with multiple trading partners) is considered in designing negotiation model. Multilateral negotiation is more realistic in resource allocation process of computational grids where there are more than one seller that sell special type of resource.
(b) Modeling concession behavior of negotiator's trading partner which is inspired from real-life trading market. In real-life trading market the behavior of one negotiator serves as a stimulus for the other negotiator who then screens it, selects its key elements and tries to interpret them (Smolinski, 2006). Negotiators should view their trading partners' behavior to select suitable tactics and strategies (Smolinski, 2006). There are few existing negotiation agents that consider behavior dependent function to determine the amount of concession during negotiation process (e.g., Mok and Sundarraj, 2005; Ren and Zhang, 2008; Montes et al., 2011). Whereas these negotiation agents using complex techniques (like artificial intelligence) that need more computational cost for modeling the behavior function, our work proposes a simple and applicable approach to model the concession behavior of negotiator's trading partner. The importance of such an approach is when the negotiation agents have short deadline and cannot tolerate extra computational cost to make near optimal concession amount. In addition we present two new criteria to classify the behavior of negotiator's opponents: *royalty* and *hasty* which are defined based on the number of successful negotiations between a negotiator and its trading partner in all the GRNMs (grid resource negotiation markets) they both participated and the average negotiation time between a negotiator and its trading partner in all GRNMs which both participate, respectively.
(c) Modeling market driven factors from *new* perspective to handle possible changes on the negotiation environment. Even though some of the previous works (e.g., Lang, 2005; Ghosh et al., 2004, 2005; Sim 2005a, 2005b, 2006) considered the number of trading partners and competitors in modeling negotiators' bargaining power, there still exist some limitations which may restrict its application in the real world. In fact the current negotiator agents cannot handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain. In an open and dynamic environment, agents may enter into and leave of a negotiation freely, and so the uncertainly of the negotiation may increase. The key idea to face with these limitations is that opportunity and competition factors are modeled by considering three criteria: (1) change in number of negotiator's competitors, (2) change in number of negotiator's trading partners and (3) change in ratio of negotiator's competitors to negotiator's trading partners. By doing this, the negotiation agent can make reasonable responses not only to changes in each negotiation market side but also change the balance of one market side's participants to other market side's participants and update its negotiation strategies according to these changes.
(d) Determining the specific amount of concession to each negotiator's trading partner separately, instead of the same amount to all. Although there are many agent-based systems for negotiation in e-commerce (e.g., just to name a few: NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (Guttman and Maes, 1998), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007), Zhao and Li (2009), An (2011), SNAP (Czajkowski et al., 1999, 2002, 2005)), the strategies of most of them make the same concession amount for all negotiators' trading partners. In contrast, our work considers different concession amount for different negotiator's trading partners (by applying muti-criteria decision function) which provides more flexibility in keeping the chance of making deal (by computing rational and sufficiently minimum price) with at least one trading partner.
(e) Formulating a *new* market- and behavior-driven negotiation strategy. In comparison to existing negotiation agents (e.g., just to name a few: NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (Guttman and Maes, 1998), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007; Zhao and Li (2009); An, 2011), SNAP (Czajkowski et al., 1999, 2002, 2005) more negotiation factors which are inspired from real-life trading market are considered to determine minimally sufficient concession amount.
(f) Providing negotiation agents of both types (i.e., GRO_MBDNAs and GRC_MBDNAs) and equipped them with the new proposed negotiation model to improve the profits of both e_market sides (i.e., GRC e_market side and GRO e_market side). By considering this issue we show that MBDNAs are appropriate tools for both sides of negotiation.

The remainder of the paper is structured as follows. In Section 2, some state-of-the-art negotiation models are reviewed for resource management. In Section 3, the negotiation model is presented and the negotiation strategies explained. The simulation configuration and experimental results are analyzed in Section 4. Conclusions and information on future works are given in Section 5.

2. Related works

In this section we review and compare the existing state-of-the-art negotiation agents from the issues for making negotiation model in Sim (2010) and our extra proposed issue for making appropriate negotiation model points of view.

Whereas the agents in NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (extended Kasbah, which focuses on multiple-issue negotiation rather than single-issue negotiation) (Guttman and Maes, 1998), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007), Zhao and Li, 2009, An, 2011) and our work considered the issue of time constraint, the agents in SNAP (Czajkowski et al., 1999, 2002, 2005) and policy-driven negotiation (Gimpel et al., 2003) did not consider this issue in designing the agents.

2-phase negotiation (Lang, 2005), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007; An, 2011) modeled market dynamics in their concession making strategies, but NDF (Faratin et al., 1998), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (Guttman and Maes, 1998), SNAP (Czajkowski et al., 1999, 2002, 2005), policy-driven negotiation (Gimpel et al., 2003; Zhao and Li, 2009) did not consider the market factors in making concession amount. Also, our work modeled market dynamics from new perspective to handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain.

Among the reviewed negotiation models, no model, other than the service negotiation model (Lawley et al., 2003), considered the influence of behavior-dependent functions on the negotiation results in the grid resource allocation process. Our work modeled concession behavior of negotiator's trading partner based on (1) number of successful negotiations between a negotiator and its trading partner in all the GRNMs they both participated and (2) the average negotiation time between a negotiator and its trading partner in all GRNMs which both participate.

Whereas SNAP (Czajkowski et al., 1999, 2002, 2005) addresses the influence of grid resource co-allocation factor on the negotiation results in the grid resource allocation process, no other reviewed protocol consider this issue in designing the agents.

While the protocol adopted by Gimpel et al. (2003), Venugopal et al. (2008), Dang Minh and Jorn (2008) is simply a bilateral exchange of messages the protocol adopted by NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), MDAs (Sim 2005a, 2005b, 2006) and our work is alternating offers and the protocol adopted by EMDAs (Sim and Ng, 2006, 2007) is relaxed criteria. Also An (2011) provided an enhancement of the alternating offers protocol to handle concurrent negotiations in which each agent has multiple trading opportunities and faces market competition. In comparison to alternating offers protocol and relaxed criteria protocol bilateral exchange of messages protocol provides less flexibility in not allowing multiple messages from both GROs and GRCs to be exchanged. In addition *Zhao* and *Li* (Zhao and Li, 2009) did not consider relaxing bargaining criteria.

Finally in comparison to other reviewed works, our work considers more effective factors (and from new perspective) for designing the pattern of making concession amount: flexibility in negotiator's trading partner's proposal and negotiator's proposal deviation from the average of its trading partners' proposals.

3. Proposed four-phase scenario for resource allocation in computational grid

Computational grids are introduced as a new paradigm for solving large-scale problems in science, engineering and commerce. They enable the creation of *Virtual Organizations* (VOs) for *sharing* and *aggregation* of millions of resources geographically distributed across organizations and administrative domains.

This work considers grid environment as a collection of virtual organizations (VOs), which is a group of GRCs and GROs collaborating to facilitate usage of high-end computational resources. VO is formed dynamically while the members (e.g., GRCs|GROs) of grid domain join/leave it. As both GROs and GRCs want to maximize their profit (i.e., the GROs wish to increase their revenue and the GRCs to solve their problems within a minimum possible cost), an economy-aware grid needs to support this challenge. To realize this, a *Multiagent -based Strategic Negotiation Model* for resource allocation and for regulation of supply and demand in grid computing environments is proposed. The proposed *Multiagent -based Strategic Negotiation Model* is the heart of four-phase scenario for grid resource allocation.

The scenario of resource allocation in the economy-aware grid environment includes the following four major phases:

1. *Registering GRCs and GROs*
2. *Creating MBDNAs and providing the required information (that is, information needed for starting negotiation)*
3. *Starting negotiation, based on the proposed strategic negotiation model*
4. *Terminating negotiation process and executing task (if negotiation is successful)*

The proposed scenario is based on synchronous and asynchronous message exchange systems. In synchronous message exchange system, the sender entity/agent and receiver entity/agent wait for each other to transfer the message. That is, the sender entity/agent will not continue until the receiver entity/agent has received the message. On the other hand, in asynchronous message exchange system, the sender entity/agent delivers a message to receiver entity/agent, without waiting for the receiver entity/agent to be ready. A general overview of the event diagram is shown in Fig. 1.

3.1. Registering GRCs and GROs

Each GRC that is represented by a GRC agent (e.g., *GRCA*) can have one or more jobs $\{job_1,\ldots,job_p\}$. Jobs submitted by GRCs into a cluster have varying requirements depending on GRC-specific needs and expectations. The GRC_i's p'th job characteristics (e.g., ($GRC\_job\_prof^i_p$)) include the following: unique identifier, job length measured in MI (millions of instructions), length of input and output data, earliest start time (i.e., the job cannot start before its earliest start time), the period of resource usage, job's negotiation deadline (i.e., the latest start time of the job. Obviously, a job's finish time $\in$ [*earliest start time* + *period of resource usage*, *negotiation deadline* + *period of resource usage*]), initial price, reservation price, and the originator of the job (Sim, 2006).

Also, it is assumed that each GRO, which is represented by a GRO agent (e.g., *GROA*), may possess k computing machines (which is denoted by $\{M_{j1},\ldots,M_{jk}\}$) for the grid environment. As noted in (Sim, 2006, p. 1384), "*Each computing machine M_{jk} can be a single processor, a shared memory multiprocessor, or a distributed memory cluster of computers. M_{jk} can be formed by one or more processing elements $\{PE_1,\ldots, PE_l\}$, and eachPE_i can have different speeds measured in terms of MIPS (millions of instructions per second).*" The GRO_j's rth resource characteristics (e.g., $GRO\_resource\_prof^j_r$) include unique identifier, the architecture of computing resource (e.g., HPalpha server), list of computing machines (e.g., $\{M_{j1},\ldots,M_{jk}\}$), required bandwidth length, required memory capacity, and expected and reserve prices of leasing a computing machine.

The $GRCA_i$ (respectively, $GROA_j$) should register each of its $GRC\_job\_prof^i_p$(s) (respectively, $GRO\_resource\_proof^j_r$[s]) in *GRNM_jobrequester_directory* (respectively, *GRNM_jobrequester_directory*.

3.2. Creating MBDNAs and providing their required information

It was noted in Sim (2010, p. 245) that "*software agents, in particular, negotiation agents, can play an essential role in realizing*

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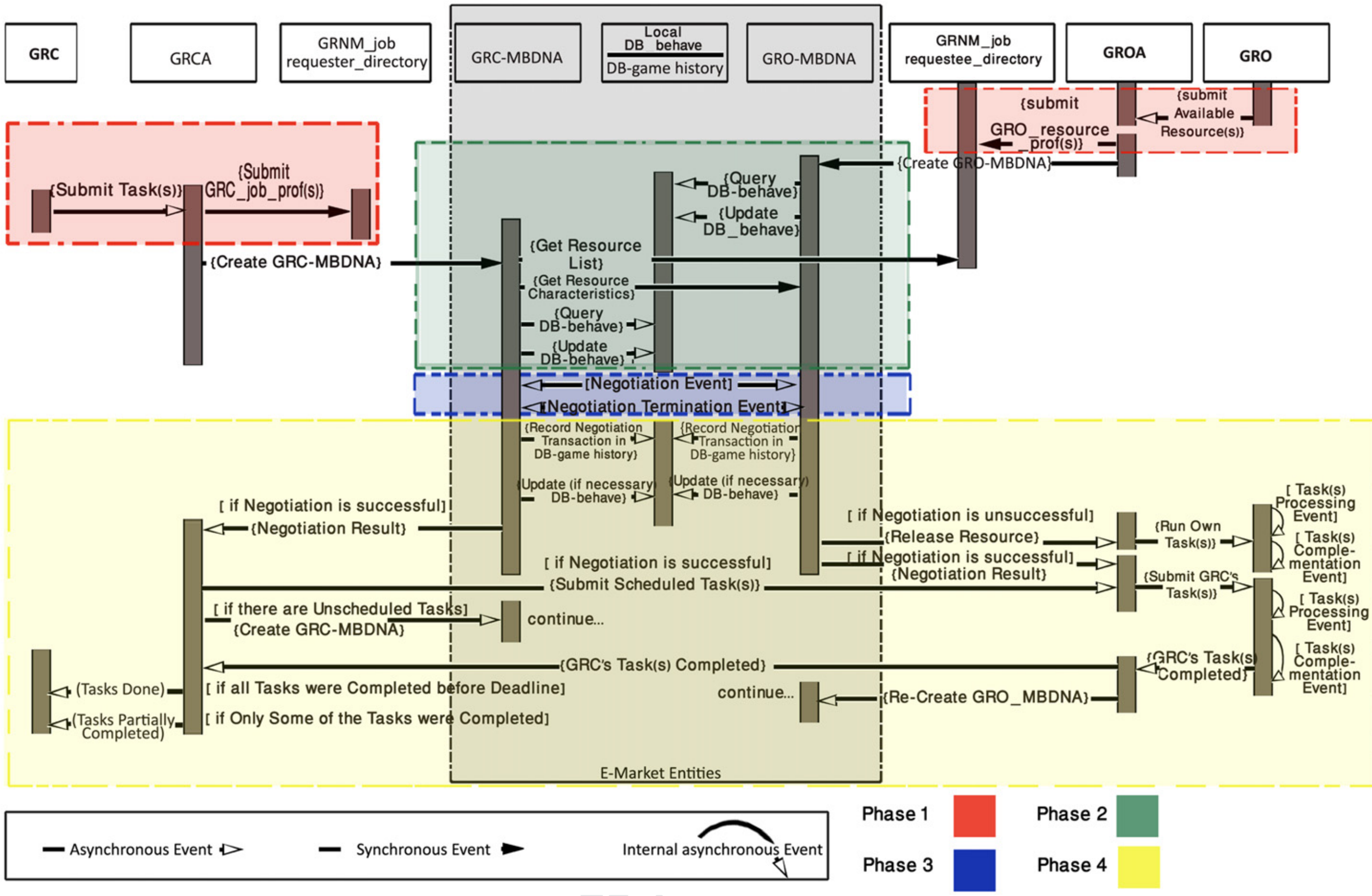

Fig. 1. Event diagram showing message-flow in the proposed four-phase scenario (for grid resource allocation).

the grid vision". Software Agent is a component with the capability of accomplishing its tasks on behalf of its owner (Wooldridge, 2002). In this work, MBDNAs (which are categorized into *GRC_MBDNA* and *GRO_MBDNA* entities) are expected to realize the grid vision. A GRC_MBDNA_i (respectively, GRO_MBDNA_j) is generated according to $GRCA_i$ (respectively, $GROA_j$), which is registered in GRNM to perform the negotiation process.

In the following sections, each *GRC_MBDNA* (respectively, *GRO_MBDNA*) is represented by δ symbol for ease of reading. Also let assume that kth trading partner of negotiator δ_i is denoted by $\delta'_{k,i}$.

Following are the functions performed by δ_i (which its type is *GRC_MBDNA*) in the second phase of resource allocation scenario:

1. Start the process of resource discovery (e.g., discovering appropriate *GRO_MBDNA*(*s*) that match with the δ_i's requirements).
2. Query *DB_behave* database (which is considered to store the previous concession behavior of negotiators' trading partners who participated in GRNM previously) to retrieve all records (if exist) which the value of their $\delta'_{k,i}\_id$ field is equal to the identifier of one of δ_i's trading partners. The retrieved records are used to calculate the previous concession behavior of negotiators' trading partners (details are provided in Section 3.3.3 – MBDNAs part f).
3. Increase the $\#GRNM_{\delta'_{k,i}-\delta_i}$ field of retrieved records by one.

And the functions that are performed by δ_j (which its type is *GRO_MBDNA*) in the second phase of resource allocation scenario are as same as the second and third functions performed by δ_i which its type is *GRO_MBDNA*.

3.3. Starting negotiation based on the proposed negotiation model

The negotiation model has three parts (Kraus, 2001): (1) the negotiation protocol, (2) the used utility models or preference relationships for the negotiating parties and (3) the negotiation strategy applied during the negotiation process. The following three sub-sections address these three parts in MDAs and proposed MBDNAs.

3.3.1. Negotiation protocol

Type of Negotiation Protocol specifies the mechanism and the specific negotiation rules it uses for a particular negotiation. In designing both MDAs and MBDNAs, *Rubinstein's sequential alternating offer protocol* (Rubinstein, 1982) in grids is adopted. The negotiation procedure of this protocol is as follows: The players (negotiators) can take actions only at certain times in the (infinite) set $T=\{1;\ 2;\ 3;\ \ldots t\}$. In each period $t\in T$, one of the players, say *i*, proposes an agreement, and the other player *j* either accepts it or rejects it. If the offer is accepted, then the negotiation ends, and the agreement is implemented. If the offer is rejected, then the process passes to period $t+1$; in this period, player *j* proposes an agreement, which player *i* may accept or reject. The negotiation process will go on in this way.

In setting the stage for specifying negotiation protocol and negotiation strategy in MBDNAs, the following assumptions and rules apply:

1. Time is discrete and is indexed by {0,1,2,…}—it is a logical and believable assumption, which is made in other models also (Sim, 2005, p. 713) and (Osborne and Rubinstein, 1990, p. 152).
2. Grid resource negotiation progresses in a series of rounds.

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3. Multiple pairs of negotiators can negotiate deals simultaneously.
4. Negotiators do not form coalitions; the assumption is logical, because the type of game is non-cooperative (negotiators make decisions independently) with an arbitrary, finite number of negotiators.
5. Negotiation focuses on a single-issue (e.g., price-only).
6. Typically, a negotiator proposes its most preferred deal initially (Sim, 2006).
7. Whenever it is the δ'_is turn to move (e.g. determine the amount of concession), it proposes a deal from its possible negotiation set (e.g., $[IP_{\delta_i}, RP_{\delta_i}]$, where IP_{δ_i} and RP_{δ_i} are, respectively the initial and reserve prices of δ_i).
8. If no agreement is reached, grid resource negotiation proceeds to the next round. At every round, the negotiator offers appropriate concession using the proposed multi factors function (see Section 3.3.3).
9. Negotiation between two negotiators terminates (i) when an agreement is reached, or (ii) with a conflict when one of the negotiators' deadline is reached (Sim, 2006).
10. When the negotiation ends, the history of negotiation is stored. This may be a good augmentation of database for future work (see Section 5).
11. Negotiation begins with negotiators having private information (e.g. deadline, reserve price, time preferences, strategies and payoffs according to them). So, no negotiator knows the private information of the opponent.
12. For strategic reasons, negotiators have information of only the index of the time period, and the then existing number of competitors and trading partners in GRNM (Sim, 2005).
13. If the initial price of δ_i of type *GRC_MBDNA* is not equal to or greater than the reservation price of δ_j of type *GRO_MBDNA*, the negotiation process terminates with conflict.
14. Negotiation process in GRNM begins if only there are at least two negotiators of the opposite type (i.e., one negotiator of type *GRC_MBDNA* and the other of typ e*GRO_MBDNA*).

Also Sim (2005a, 2006) described a negotiation protocol for specifying the negotiation activities among GRCAs and GROAs in MDAs.

3.3.2. *Negotiation utility model*

Any kind of behavior of each negotiator can be modeled with a suitable payoff or "*utility function*". Each negotiator evaluates the resulting outcome through a payoff or "*utility function*" representing her objectives.

Market Driven Agents (MDAs) (Sim, 2006, 2005a, 2005b): The utility model of MDAs can be found in Sim and Ng (2007, p. 111).

Market- and Behavior-driven Negotiation Agents (MBDNAs): The grid computational resource allocation mechanism in this paper is under budget constraint which means that a GRC_MBDNA_i (respectively, GRO_MBDNA_j) makes computational resource acquiring (respectively, assigning) decisions within the budget constraints. The negotiation objective is the expected price that will be obtained via negotiation process. The negotiator δ_i of type *GRC_MBDNA* tries to purchase as much computational resource as possible with the objective of spending the least possible amount of money (minimizing their payment). Also, the negotiator δ_j of type *GRO_MBDNA* tries to sell as much computational resources as possible with the objective of maximizing its revenue.

let $U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}]$ (respectively, $U_t^{\delta_j}[P_t^{\delta_j} \to \delta'_{k,j}]$) and $U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i]$ (respectively, $U_t^{\delta_j}[P_t^{\delta'_{k,j}} \to \delta_j]$) be the utilities of δ_i (respectively, δ_j) if $\delta'_{k,i}$ (respectively, $\delta'_{k,j}$) accepts δ_i's (respectively, δ_j's) proposal and the utility generated for δ_i (respectively, δ_j) if δ_i (respectively, δ_j) accepts the counter proposal of $\delta'_{k,i}$ (respectively, $\delta'_{k,j}$).

For ease of analysis, the utility function of negotiator $\delta_i \in \{\delta_1, \delta_2, \ldots, \delta_{N_t}\}$ of type*GRC_MBDNA* at negotiation round t can be expressed as (one needs to recall here that N_t is the number of negotiators of type *GRC_MBDNA* at round t, δ_i of type *GRC_MBDNA* makes the concession first and at the beginning of GRNM the negotiation round is set to zero):

$$U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] = (RP_{\delta_i} - P_t^{\delta_i})/(RP_{\delta_i} - IP_{\delta_i})$$

and

$$U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i] = (RP_{\delta_i} - P_t^{\delta'_{k,i}})/(RP_{\delta_i} - IP_{\delta_i}) \quad (1)$$

where RP_{δ_i} is δ_i's reserve price, IP_{δ_i} is δ_i's initial price, $P_t^{\delta_i}$ is δ_i's proposal at negotiation round t and $P_t^{\delta'_{k,i}}$ is $\delta'_{k,i}$'s proposal at negotiation round t. For example a *GRC_MBDNA* considers 100$ to buy a special type of resource (i.e., $RP_{\delta_i} = 100\$$) and starts the negotiation process with 20$ (i.e., $IP_{\delta_i} = 20\$$). From *GRC_MBDNA*'s perspective 20$ is the best price that can be paid to buy that type of resource (as 20$ generates the highest utility for *GRC_MBDNA*, $[(100\$ - 20\$)/(100\$ - 20\$)] = 1$) and saves 80$ for him. Also from *GRC_MBDNA*'s perspective 100$ is the worst price that can be paid to buy that type of resource (as 100$ generates the lowest utility for *GRC_MBDNA*, $[(100\$ - 100\$)/(100\$ - 20\$)] = 0$) and saves nothing for him. Furthermore, let assume that the proposed price from $\delta'_{k,i}$ at negotiation round $t-1$ is 62$. At negotiation round t the negotiator δ_i makes its potential concession amount by considering current market situation. Let assume that the potential concession amount of δ_i that can be proposed to $\delta'_{k,i}$ is equal to 50$. Now δ_i should decide to accept 62$ or continue the negotiation process by proposing 50$. This decision is made by computing the utilities generated from 62$ and 50$ as follows: $U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i] = [(100\$ - 62\$)/(100\$ - 20\$)]$ and $U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] = [(100\$ - 50\$)/(100\$ - 20\$)]$. By comparing the generated utilities of 50$ and 62$, δ_i decides to continue the negotiation process instead of accept the counter offer. Rationally, from *GRC_MBDNA*'s perspective the price that saves more money is considered as more appropriate price.

Also the utility function of negotiator $\delta_j \in \{\delta_1, \delta_2, \ldots, \delta_{M_t}\}$ of type *GRO_MBDNA* at game round t can be expressed thus (where M_t is the number of negotiators of type GRO_MBDNA at round t):

$$U_t^{\delta_j}[P_t^{\delta_j} \to \delta'_{k,j}] = (P_t^{\delta_j} - RP_{\delta_j})/(IP_{\delta_j} - RP_{\delta_j})$$

and

$$U_t^{\delta_j}[P_t^{\delta'_{k,j}} \to \delta_j] = (P_t^{\delta'_{k,j}} - RP_{\delta_j})/(IP_{\delta_j} - RP_{\delta_j}) \quad (2)$$

where RP_{δ_j} is δ_j's reserve price, IP_{δ_j} is δ_j's initial price, $P_t^{\delta_j}$ is δ_j's proposal at negotiation round t and $P_t^{\delta'_{k,j}}$ is $\delta'_{k,j}$'s proposal at negotiation round t. For example a *GRO_MBDNA* cannot sell its resource less than 20$ (i.e., $RP_{\delta_j} = 20\$$) and starts the negotiation process with 100$ (i.e., $IP_{\delta_j} = 100\$$). From *GRO_MBDNA*'s perspective 100$ is the best price that can be achieved in trading process (as 100$ generates the highest utility for *GRO_MBDNA*, $[(100\$ - 20\$)/(100\$ - 20\$)] = 1$) and makes maximum revenue (i.e., 80$) for him. Also from *GRO_MBDNA*'s perspective 20$ is the worst price that can be achieved in trading process (as 20$ generates the lowest utility for *GRO_MBDNA*, $[(20\$ - 20\$)/(100\$ - 20\$)] = 0$) and makes no profit for him. Furthermore, let assume that the proposed price from $\delta'_{k,j}$ at negotiation round $t-1$ is 50$. At negotiation round t the negotiator δ_j makes its potential concession amount by considering current market situation. Let assume that the potential concession amount of δ_j that can be proposed to $\delta'_{k,j}$ is equal to 62$. Now δ_j should decide to accept 50$ or continue the negotiation process by proposing 62$. This decision is made by computing the utilities generated from 50$ and 62$ as follows: $U_t^{\delta_j}[P_t^{\delta'_{k,j}} \to \delta_j] = [(50\$ - 20\$)/(100\$ - 20\$)]$ and $U_t^{\delta_j}[P_t^{\delta_j} \to \delta'_{k,j}] = [(62\$ - 20\$)/(100\$ - 20\$)]$. By comparing the generated utilities of 50$ and 62$, δ_j decides to continue the negotiation process instead of accept the counter offer. Rationally, from

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GRO_MBDNA's perspective the price that makes more profit is considered as more appropriate price.

If the proposed deal from δ_i of type *GRC_MBDNA* at round t (e.g., $P_t^{\delta_i}$) is not greater than the one at round $t+2$ (e.g., $P_{t+2}^{\delta_i}$), then $U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] > U_{t+2}^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}]$. Also, If the proposed deal from δ_j of type *GRO_MBDNA* at round t (e.g., $P_t^{\delta_j}$) is greater than the one at round $t+2$ (e.g., $P_{t+2}^{\delta_j}$), then $U_t^{\delta_j}[P_t^{\delta_j} \to \delta'_{k,j}] > U_{t+2}^{\delta_j}[P_t^{\delta_j} \to \delta'_{k,j}]$. Recall that by using *Rubinstein's sequential alternating offer protocol* (Rubinstein, 1982), negotiators in make alternate offers rather than moving simultaneously.

If the negotiation ends in disagreement, both negotiation sides (e.g., δ_i of type *GRC_MBDNA* and δ_j of type *GRO_MBDNA*) receive the worst possible utility (e.g., zero).

3.3.3. Negotiation strategy

In each round of the negotiation, δ_i's choice is called a *strategy*. As MDAs and MBDNAs focus on single-issue (e.g., price only) negotiation, the amount of concession determination, at negotiation round t, is a chosen strategy by δ_i. Following the concession functions of MDAs and proposed MBDNAs are described.

Market Driven Agents (MDAs) (Sim, 2005a, 2005b, 2006): Sim (2002, 2003) investigated the way to assess the probability of successfully reaching a consensus in different market situations by considering the difference between the payoffs generated by the proposal of negotiator and the proposal of its trading partners at each round t. Coming to details, let assume that the proposal of δ_i to its trading partner $\delta'_{k,i}$ at round t is $P_t^{\delta_i} \to \delta'_{k,i}$ and the proposal of $\delta'_{k,i}$ to δ_i at round t is $P_t^{\delta'_{k,i}} \to \delta_i$. Also, let $U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}]$ and $U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i]$ be the utilities of δ_i if $\delta'_{k,i}$ accepts δ_i's proposal and the best utility generated for δ_i if δ_i accepts the counter proposal of $\delta'_{k,i} \in \{\delta'_{1,i}, \delta'_{2,i}, \ldots, \delta'_{no.trading\_partner_t^{\delta_i},\, i}\}$ at t respectively. The (best) spread in the current cycle t is

$$k_t = U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] - U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i] \tag{3}$$

Negotiation is described as a process where the parties attempt to narrow the spread in (counter-) proposals between (or among) negotiators through concession; therefore, for making a suitable concession the *expected utility* of each negotiator's next proposal is determined by itself as follows:

$$U_{t+1}^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] = k_{t+1} + U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i] \tag{4}$$

Finally, the amount of concession at round t (e.g., con_t) is

$$con_t = k_t - k_{t+1} \tag{5}$$

In designing MDAs, the appropriate value of the expected difference k_{t+1} between the proposal of an agent and its trading partner is determined by assessing the current market situation, taking into account factors such as *opportunity* ($O_t^{\delta_i}$), *competition* ($CC_t^{\delta_i}$) and *deadline* (TP^{δ_i}) (Sim, 2005):

$$\begin{aligned} k_{t+1} = {} & [O_t^{\delta_i}(no.trading\_partner_t^{\delta_i},\ U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}], U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i]) CC_t^{\delta_i} \\ & \times (no.competitor_t^{\delta_t},\ no.trading\_partner_t^{\delta_i}) \times TP^{\delta_i}(t, t_{deadline}^{\delta_i}, \lambda)] k_t \end{aligned} \tag{6}$$

Following the factors that are included in (6) are described in details.

(a) *Opportunity function* ($O_t^{\delta_i}$)
In a multilateral negotiation, having outside options may give a negotiator more bargaining power. However, negotiators may still break down if the proposals between two negotiators are too far apart. The δ_i's opportunity function determines the amount of concession based on (1) trading alternatives (number of trading partners $no.trading\_partner_t^{\delta_i}$) and (2) differences in utilities ($U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}]$) generated by the proposal of δ_i and the counter proposal(s) of its trading partner(s) ($\langle U_t^{\delta_i}[P_t^{\delta_{k,i}} \to \delta_i] \rangle$) and is calculated thus

$$\begin{aligned} & O_t^{\delta_i}(no.trading\_partner_t^{\delta_i},\ U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}],\ \langle U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i] \rangle) \\ & \quad = 1 - \prod_{j=1}^{no.trading\_partner_t^{\delta_i}} \frac{U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] - U_t^{\delta_i}[P_t^{\delta'_{k,i}} \to \delta_i]}{(U_t^{\delta_i}[P_t^{\delta_i} \to \delta'_{k,i}] - c^{\delta_i})} \end{aligned} \tag{7}$$

where c^{δ_i} is the worst possible utility for δ_i (e.g., if the negotiation ends in disagreement).

(b) *Competition function* ($CC_t^{\delta_i}$)
As mentioned in Sim (2005, p. 714), since market-driven agents are utility maximizing agents, an agent δ_i is more likely to reach a consensus if its proposal is ranked the highest by some other agent $\delta'_{k,i}$. Let an agent δ_i has $no.competitor_t^{\delta_i}$ competitors and $no.trading\_partner_t^{\delta_i}$ trading partners at round t. If the proposal of δ_i's competitor agent (e.g., $\delta C_{l,i} \in \{\delta C_{1,i}, \delta C_{2,i}, \ldots, \delta C_{no.competitor_t^{\delta_i},\, i}\}$) generates a utility $U_t^{\delta'_{k,i}}[P_t^{\delta C_{l,i}} \to \delta'_{k,i}]$ for $\delta'_{k,i}$ and the proposal of δ_i generates a utility $U_t^{\delta'_{k,i}}[P_t^{\delta_i} \to \delta'_{k,i}]$ for $\delta'_{k,i}$, by considering the mentioned concept, the proposal of δ_i is ranked the highest by $\delta'_{k,i}$ if $U_t^{\delta'_{k,i}}[P_t^{\delta_i} \to \delta'_{k,i}] > \forall U_t^{\delta'_{k,i}}[P_t^{\delta C_{l,i}} \to \delta'_{k,i}] \in \{U_t^{\delta'_{k,i}}[P_t^{\delta C_{1,i}} \to \delta'_{k,i}], U_t^{\delta'_{k,i}}[P_t^{\delta C_{2,i}} \to \delta'_{k,i}], \ldots, U_t^{\delta'_{k,i}}[P_t^{\delta C_{no.competitor_t^{\delta_i},i}} \to \delta'_{k,i}]$. So, the probability of δ_i being considered the most preferred trading partner by at least one of $\delta'_{k,i} \in \{\delta'_{1,i}, \delta'_{2,i}, \ldots, \delta'_{no.trading\_partner_t^{\delta_i},\, i}\}$ is calculated thus,

$$\begin{aligned} & CC_t^{\delta_i}(no.competitor_t^{\delta_i},\ no.trading\_partner_t^{\delta_i}) \\ & \quad = 1 - [(no.competitor_t^{\delta_i}) / no.competitor_t^{\delta_i} + 1]^{no.trading\_partner_t^{\delta_i}} \end{aligned} \tag{8}$$

(c) *Time function* (TP^{δ_i})
As noted by Binmore and Dasgupta (see Binmore and Dasgupta, 1987, p. 14), the passage of time has a cost in terms of both dollars and the sacrifice of utility which stems from the postponement of consumption, and it will be precisely this cost which motivates the whole bargaining process. If it did not matter when the parties agreed, it would not matter whether they agreed at all. Lang, (2005), Lawley et al. (2003), Sim (2005a, 2005b, 2006), and Sim and Ng (2006) take into consideration the mentioned concept by introducing time discount factor in their proposed concession making strategies.
So, the effect of time discount factor in negotiator's bargaining power can be modeled via time-dependent function. Some state-of-the-art time-dependent functions are reviewed by Sim (2010), p. 253). MDAs' time function is calculated as Sim (2005).

$$TP^{\delta_i}(t, t_{deadline}^{\delta_i}, \lambda) = 1 - \left(\frac{t}{t_{deadline}^{\delta_i}} \right)^{\lambda} \tag{9}$$

where δ_i's time preference is denoted by λ (e.g., concession rate with respect to time. For instance, an agent may prefer to concede less rapidly in the early rounds of negotiation and more rapidly as its deadline approaches), δ_i's deadline (e.g., a time frame by which δ_i needs negotiation result) by $t_{deadline}^{\delta_i}$, and current negotiation round by t. λ and $t_{deadline}^{\delta_i}$ are considered private information. Following are the three major classes of concession-making strategies with respect to the remaining trading time (details are discussed by Sim, 2005):

i. *Conservative (or Boulware or aggressive*: $1 < \lambda < \infty$)—δ_i makes smaller concession in early rounds and larger concession in later rounds.
ii. *Linear* (or *Neutral*: $\lambda = 1$)—δ_i makes a constant rate of concession.

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iii. *Conciliatory (or Conceder or Defensive*: $0<\lambda<1$)—δ_i makes larger concession in the early trading rounds and smaller concessions in the later rounds.

Market- and Behavior-driven Negotiation Agents (MBDNAs): The way to assess the probability of successfully reaching a consensus in different market situations is as same as the way in MDAs. MBDNAs determine the amount of concession (e.g., con_t) through (5) where, the appropriate value of k_{t+1} is defined by considering market driven factors, negotiator δ_i's trading partner's concession behavior, closeness of negotiator δ_i's proposal to average of its trading partners' proposals, bargaining power of negotiator δ_i's trading partner and negotiator δ_i's time preference:

$$k_{t+1} = FST_t^{\delta_i}\times k_t \tag{10}$$

where $FST_t^{\delta_i}$ is a price-oriented strategy that is taken by δ_i to determine the amount of concession at round t and is defined through (11):

$$FST_t^{\delta_i} = \kappa[IST_t^{\delta_i}+(PreBehave\_Depend_t^{\delta'_{k,i}}\times IST_t^{\delta_i})] \tag{11}$$

where $\kappa=1/2$ if $[IST_t^{\delta_i}+(PreBehave\_Depend_t^{\delta'_{k,i}}\times IST_t^{\delta_i})]$ is greater than one, else $\kappa=1$. Also $PreBehave\_Depend_t^{\delta'_{k,i}}$ is *previous concession behavior of negotiator δ_i's trading partner* factor which is considered as penalty amount for *misbehaved* trading partners and $IST_t^{\delta_i}$ is denoted by (12):

$$IST_t^{\delta_i} = NC_t^{\delta_i}\times NTP_t^{\delta_i}\times FTP_t^{\delta_i}\times DTPAP_t^{\delta_i}\times TP^{\delta_i} \tag{12}$$

where $NC_t^{\delta_i}$, $NTP_t^{\delta_i}$, $FTP_t^{\delta_i}$, $DTPAP_t^{\delta_i}$ and TP^{δ_i} are *number of competitors*, *number of trading partners*, *flexibility in negotiator's trading partner's proposal*, *negotiator's proposal deviation of the average of its trading partners' proposals* and *negotiator's time preference* factors respectively.

Following the factors that are included in a price-oriented strategy $FST_t^{\delta_i}$ are described in details:

a. *Number of competitors* ($NC_t^{\delta_i}$)

As described in Sim (2010), Lang (2005), and Sim (2005a, 2005b, 2006), competition is one of the factors that contributes to power of negotiation. Even though the MDAs have shown good performance, there still exist some limitations which may restrict its application in the real world. In fact the current MDAs cannot handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain. To face with these limitations, we extend the concession factor of trading competition. There are two cases that need to be considered, namely: (1) change in the number of negotiator's competitors and (2) change in the ratio of the total number of negotiator's competitors to the total number of negotiator's trading partners. In other word the deference between the ratio of number of current competitors to the total number of current GRNM's participants (i.e., $no.competitor_t^{\delta_i}/no.trading\_partner_t^{\delta_i}+no.competitor_t^{\delta_i}$) and the ratio of number of competitors in previous negotiation round $t-1$ to the total number of GRNM's participants in previous negotiation round $t-1$ (i.e., $no.competitor_{t-1}^{\delta_i}/no.trading\_partner_{t-1}^{\delta_i}+no.competitor_{t-1}^{\delta_i}$) is considered. The new perspective of concession factor of trading competition is determined as

IF it is a first δ_i's negotiation round OR ($no.competitor_t^{\delta_i} == 0$) *THEN*

$$NC_t^{\delta_i} = 1-\frac{no.competitor_t^{\delta_i}}{no.trading\_partner_t^{\delta_i}+no.competitor_t^{\delta_i}}$$

Else

IF ($no.competitor_{t-1}^{\delta_i} > no.competitor_t^{\delta_i}$) *THEN*

$$NC_t^{\delta_i} = 1-\left[NC_{t-1}^{\delta_i}\times\left(1+\left|\frac{no.competitor_t^{\delta_i}}{no.trading\_partner_t^{\delta_i}+no.competitor_t^{\delta_i}}-\frac{no.competitor_{t-1}^{\delta_i}}{no.trading\_partner_{t-1}^{\delta_i}+no.competitor_{t-1}^{\delta_i}}\right|/2\right)\right.$$

IF ($no.competitor_{t-1}^{\delta_i} < no.competitor_t^{\delta_i}$) *THEN*

$$NC_t^{\delta_i} = NC_{t-1}^{\delta_i}\times\left(1-\left|\frac{no.competitor_t^{\delta_i}}{no.trading\_partner_t^{\delta_i}+no.competitor_t^{\delta_i}}-\frac{no.competitor_{t-1}^{\delta_i}}{no.trading\_partner_{t-1}^{\delta_i}+no.competitor_{t-1}^{\delta_i}}\right|\right)$$

IF ($no.competitor_t^{\delta_i} == no.competitor_{t-1}^{\delta_i}$) *THEN*

$$NC_t^{\delta_i} = NC_{t-1}^{\delta_i} \tag{13}$$

where $no.competitor_{t-1}^{\delta_i}$ is the number of δ_i's competitors at round $t-1$, $no.competitor_t^{\delta_i}$ is the number of δ_i's competitors at round t, $no.trading\_partner_{t-1}^{\delta_i}$ is the number of δ_i's trading partners at round $t-1$ and $no.trading\_partner_t^{\delta_i}$ is the number of δ_i's trading partners at round t.

If the type of δ_i is *GRO_MBDNA*, then $no.competitor_{t-1}^{\delta_i} = M_{t-1}-1$, $no.competitor_t^{\delta_i} = M_t-1$, $no.trading\_partner_{t-1}^{\delta_i} = N_{t-1}-1$ and $no.\ trading\_partner_t^{\delta_i} = N_t-1$. Also, if the type of δ_i is *GRC_MBDNA*, then $no.competitor_{t-1}^{\delta_i} = N_{t-1}-1$, $no.competitor_t^{\delta_i} = N_t-1$, $no.trading\_partner_{i-1}^{\delta_i} = M_{t-1}-1$ and $no.trading\_partner_t^{\delta_i} = M_t-1$, where M_{t-1} represents the number of negotiators of type *GRO_MBDNA* at round $t-1$, M_t the number of negotiators of type *GRO_MBDNA* at round t, N_{t-1} the number of negotiators of type *GRC_MBDNA* at round $t-1$ and N_t the number of negotiators of type *GRC_MBDNA* at round t. As market-driven negotiators are utility maximizing negotiators (Sim, 2005a, p. 714), a δ_i is more likely to reach an agreement if its number of competitors tends to become **zero**. In fact, the negotiator δ_i's chance of reaching a consensus on its own terms increases as $NC_t^{\delta_i}$ tends to become **one.**

(b) *Number of trading partners*($NTP_t^{\delta_i}$)

Sim (2005a, 2005b, 2006), Ghosh et al. (2004, 2005) considered the number of trading partners in the amount of concession determination by proposing various functions. As noted by Sim (see Sim, 2010, p. 249), "if there is a large number of trading alternatives, the likelihood that a negotiator proposes a bid/offer that is potentially close to a trading partners' offer/bid may be high". Hence, negotiators' bargaining power should be modeled by considering the number of trading partners. Even though the MDAs have shown good performance, there still exist some limitations which may restrict its application in the real world. In fact the current MDAs cannot handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain. To face with these limitations, we extend the concession factor of trading opportunity. There are two cases that need to be considered, namely: (1) change in the number of negotiator's trading partners and (2) change in the ratio of the total number of negotiator's competitors to the total number of negotiator's trading partners. In other word the deference between the ratio of number of current trading partners to the total number of current GRNM's participants (i.e., $no.trading\_partner_t^{\delta_i}/no.trading\_partner_t^{\delta_i}+no.competitor_t^{\delta_i}$) and the ratio of number of trading partners in previous negotiation round $t-1$ to the total number of GRNM's participants in previous negotiation round t–1 (i.e., $no.trading\_partner_{t-1}^{\delta_i}/no.trading\_$

$partner^{\delta_i}_{t-1} + no.competitor^{\delta_i}_{t-1}$) is considered. The new perspective of concession factor of trading opportunity is determined as

$$
\begin{aligned}
&IF\ it\ is\ a\ first\ \delta_i\text{'s}\ negotiation\ round\ THEN\\
&NTP^{\delta_i}_t = \frac{no.trading\_partner^{\delta_i}_t}{no.trading\_partner^{\delta_i}_t + no.competitor^{\delta_i}_t}\\
&Else\\
&IF\ (no.trading\_partner^{\delta_i}_t > no.trading\_partner^{\delta_i}_{t-1})\ THEN\\
&NTP^{\delta_i}_t = 1 - \left[NTP^{\delta_i}_{t-1} \times \left(\left(1 + \left|\frac{no.trading\_partner^{\delta_i}_t}{no.trading\_partner^{\delta_i}_t + no.competitor^{\delta_i}_t} - \frac{no.trading\_partner^{\delta_i}_{t-1}}{no.trading\_partner^{\delta_i}_{t-1} + no.competitor^{\delta_i}_{t-1}}\right| /2\right)\right]\\
&IF\ ((no.trading\_partner^{\delta_i}_t < no.trading\_partner^{\delta_i}_{t-1})\ THEN\\
&NTP^{\delta_i}_t NTP^{\delta_i}_{t-1} \times \left(1 - \left|\frac{no.trading\_partner^{\delta_i}_t}{no.trading\_partner^{\delta_i}_t + no.competitor^{\delta_i}_t} - \frac{no.trading\_partner^{\delta_i}_{t-1}}{no.trading\_partner^{\delta_i}_{t-1} + no.competitor^{\delta_i}_{t-1}}\right|\right)\\
&IF\ (no.trading^{\delta_i}_{partner\,t} = no.trading\_partner^{\delta_i}_{t-1})\ THEN\\
&NTP^{\delta_i}_t = NTP^{\delta_i}_{t-1}
\end{aligned}
\tag{14}
$$

The definitions of the parameters used in (14) are the same as those of the parameters in (13). As mentioned before, market-driven negotiators are utility maximizing negotiators (Sim, 2005, p. 714); so, a negotiator δ_i's chance of reaching a consensus on its own terms increases as $NTP^{\delta_i}_t$ tends to become **one.**

(c) *Flexibility in negotiator's trading partner's proposal($FTP^{\delta_i}_t$)*
From an negotiator agent δ_i's point of view, the difference between its trading partner's two proposals which are made in two consecutive negotiation rounds which that trading partner turn to move (e.g., determine the amount of concession) can be defined as that trading partner's bargaining power amount. The bargaining power amount of δ_i's trading partner increase as the difference between δ_i's trading partner's two proposals which are made in two consecutive negotiation rounds that its turn to move tends to become **zero**. The trading partner's bargaining power amount may not be fixed (means in suitable market conditions an agent δ_i's trading partner's bargaining power amount will be high and vice verse) and is reflected by flexibility concept.
It is assumed that the last two proposals of δ_i's trading partner($e.g.,\delta'_{k,i}$) are $P^{\delta'_{k,i}}_{t-3}$ and $P^{\delta'_{k,i}}_{t-1}$ (recall that Rubinstein's sequential alternating offer protocol is used in our work). In negotiation round t which it is an agent δ_i turn to make concession amount (i.e., $P^{\delta_i}_t$), it reacts to $\delta'_{k,i}$'s bargaining power amount (i.e., $|P^{\delta'_{k,i}}_{t-3} - P^{\delta'_{k,i}}_{t-1}|$) by considering a factor in name flexibility in δ_i's trading partner's proposal in the hope of reaching consensus with $\delta'_{k,i}$. When the next negotiation round which it is an agent δ_i turn to move (i.e., $t+2$) is reached, since δ_i has reacted to the changes of its $\delta'_{k,i}$'s bargaining power amount up to previous negotiation time which it was an agent δ_i turn to move (i.e., t), it is rational that δ_i just reacts to the last bargaining power amount of trading partner from that time.
A proposed factor in name flexibility in δ_i's trading partner's proposal is defined as the ratio of difference between $P^{\delta'_{k,i}}_{t-3}$ and $P^{\delta'_{k,i}}_{t-1}$ (i.e., the last two proposals of $\delta'_{k,i}$) to the difference between $P^{\delta'_{k,i}}_{t-3}$ and $P^{\delta_i}_{t-2}$ (i.e., the last proposal of δ_i):

$$
FTP^{\delta_i}_t = \begin{cases} \left|\dfrac{P^{\delta'_{k,i}}_{t-3} - P^{\delta'_{k,i}}_{t-1}}{P^{\delta'_{k,i}}_{t-3} - P^{\delta_i}_{t-2}}\right| & \text{for } t > 2 \\ 1 & \text{for } 0 \le t \le 2 \end{cases}
\tag{15}
$$

In fact, the bargaining power of δ_i's trading partner decrease as $FTP^{\delta_i}_t$ tends to become **one.** Consequently, with respect to $FTP^{\delta_i}_t$, a negotiator δ_i can make a smaller concession as $FTP^{\delta_i}_t$ tends to become **one**.

(d) *Negotiator's proposal deviation of the average of its trading partners' proposals($DTPAP^{\delta_i}_t$: closeness factor)*
Another criterion for making the pattern of concession is the relative distance between the proposal of a negotiator agent and all the proposals of its trading parties. The general idea is that if the last proposal of a negotiator agent is too far from the average of its trading partners' last proposals, then it seems prudent that a negotiator agent should make larger concession amount to avoid risk of losing a deal. Let $\sum_{k=1}^{no.trading\_partner^{\delta_i}_{t-1}} P^{\delta'_{k,i}}_{t-1} / no.trading\_partner^{\delta_i}_{t-1}$ denote the average of δ_i's trading partners' proposals at round $t-1$. $RD^{\delta_i}_t$ (see (16)) is the ratio of difference between δ_i's last proposal (e.g., $P^{\delta_i}_{t-2}$) and $\sum_{k=1}^{no.trading\_partner^{\delta_i}_{t-1}} P^{\delta'_{k,i}}_{t-1} / no.trading\_partner^{\delta_i}_{t-1}$ to the average of δ_i's trading partners' proposals at round $t-1$. In (16) we just consider the situation that is not suitable for negotiator δ_i, so if $P^{\delta_i}_{t-2}$ is equal to or greater than $\sum_{k=1}^{no.trading\_partner^{\delta_i}_{t-1}} P^{\delta'_{k,i}}_{t-1} / no.trading\_partner^{\delta_i}_{t-1}$, the $RD^{\delta_i}_t$ is considered to be zero:

$$
RD^{\delta_i}_t = \frac{\left(\left(\sum_{k=1}^{no.trading\_partner^{\delta_i}_{t-1}} P^{\delta'_{k,i}}_{t-1}\right) / no.trading\_partner^{\delta_i}_{t-1}\right) - P^{\delta_i}_{t-2}}{\left(\sum_{k=1}^{no.trading\_partner^{\delta_i}_{t-1}} P^{\delta'_{k,i}}_{t-1}\right) / (no.trading\_partner^{\delta_i}_{t-1})}
\tag{16}
$$

A new factor in name negotiator's proposal deviation of the average of its trading partners' proposals is defined by (17) thus,

$$
DTPAP^{\delta_i}_t = \begin{cases} 1 - RD^{\delta_i}_t & \text{for } t \ge 2 \\ 1 & \text{for } 0 \le t < 2 \end{cases}
\tag{17}
$$

Intuitively, a negotiator should make a more attractive concession (to reach a consensus) if its proposal is not sufficiently close to the average of its trading partners' proposals. Hence, the concession rate that is made by δ_i should be increased as $RD^{\delta_i}_t$ tends to become **one** (e.g., $DTPAP^{\delta_i}_t$ tends to become **zero**).

(e) *Negotiator's time preference (TP^{δ_i})*
The present work focuses on time-dependent function that is given in Sim (2005a, 2005b, 2006) (see (9)). The effect of time discount factor in negotiator's bargaining power can be outlined thus:"By passing negotiation round, a negotiator δ_i has a lower chance of reaching a consensus". Hence, the concession rate that is made by δ_i should be increased as TP^{δ_i} tends to become **zero** (e.g., negotiator's deadline is reached).

(f) Previous concession behavior of negotiator's trading partner (*$PreBehave\_Depend^{\delta'_{k,i}}_t$*)
In real-life trading market the behavior of one negotiator serves as a stimulus for the other negotiator who then screens it, selects its key elements and tries to interpret them (Smolinski, 2006). Negotiators should view their trading partners' behavior to select suitable tactics and strategies (Smolinski, 2006). By considering this concept we model the concession behavior of negotiator's trading partners to determine the pattern of concession in grid resource allocation problem. Behavior is meaningful when a pair of grid's resource allocators of the opposite type met each other previously in numbers of GRNMs, so first of all we analyze work load traces from http://www.cs.huji.ac.il/labs/parallel/workload/logs.html to investigate this. By analyzing work load

traces from http://www.cs.huji.ac.il/labs/parallel/workload/logs.html, which are stored in Standard Work load Format (SWF), one can observe that GROs and GRCs repeat their supplies and demands respectively to the grid environment and in most instances, based on their supplies and demands, GROs (respectively GRCs) can find a number of their previous trading partners as the new trading partners in the current GRNM. To prove this claim, it is assumed that (based on the existing SWF archives (http://www.cs.huji.ac.il/labs/parallel/workload/logs.html)) *grid.name* represents the name of observed grid and also the maximum number of potential, unique users of a grid in *grid.name* which is called $max\_pot\_user_{grid.name}$ corresponds to the total number of requested jobs found in *grid.name*'s SWF archive. Further, the set of observed unique users in that *grid.name*'s SWF archive are called $unique\_user\_set_{grid.name}$ and the number of $unique\_user\_set_{grid.name}$'s members is called $unique\_user\_set\_mem_{grid.name}$. The percentage of *grid.name* 's users that are observed previously in $unique\_user\_set_{grid.name}$ is denoted by $repeated\_user_{grid.name}$ and defined as (18). Hence, the variety of *grid.name*'s users increased as $repeated\_user_{grid.name}$ tends to become **0%**:

$$repeated\_user_{grid.name} = \left(1 - \frac{unique\_user\_set\_mem_{grid.name}}{max\_pot\_user_{grid.name}}\right) \times 100 \tag{18}$$

The results of SWF archives' observations (http://www.cs.huji.ac.il/labs/parallel/workload/logs.html) from $repeated\_user_{grid.name}$ perspective are illustrated in Fig. 2.

Also, from GRO's perspective, our claim is rational by considering the number of GROs participated in real grids (presented in http://www.cs.huji.ac.il/labs/parallel/workload/logs.html).

To model the behavior of *k*th trading partner of negotiator δ_i (i.e.,$\delta'_{k,i}$) in grid resource allocation process we proposed a new factor $Prebehave\_Depend_t^{\delta'_{k,i}}$ based on the number of successful

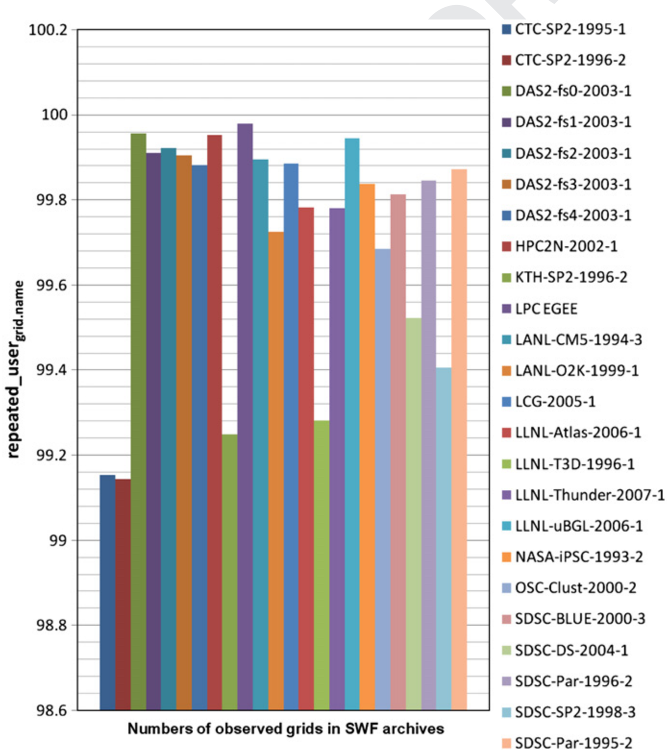

Fig. 2. $repeated\_user_{grid.name}$ in observed grids (based on work load traces from http://www.cs.huji.ac.il/labs/parallel/workload/logs.html.

negotiations between δ_i and $\delta'_{k,i}$ in all the GRNMs they both participated (e.g., $\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$) and the extent of departure from the average of negotiation time between δ_i and $\delta'_{k,i}$ in $\#GRNM_{\delta'_{k,i}-\delta_i}$ (e.g., $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$) from the sum of $\delta'_{k,i}$ $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$ (e.g., $\sum_{k=1}^{no.trading\_partner_t^{\delta_i}} Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$). This means that the $\delta'_{k,i}$, whose ratio of $\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$ is the lowest and its $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$ is too far from zero (makes a longer negotiation) is a *misbehaved* trading partner and deserves to receive more penalty:

$$PreBehave\_Depend_t^{\delta'_{k,i}} = \frac{1}{\eta}[(1-\mu) \times \rho] \tag{19}$$

- ***IF*** $((\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i})=1)$ ***AND*** $(Ave.neg.time_{\delta_i}^{\delta'_{k,i}} <> 0)$ ***THEN*** $(\mu=0$ ***AND*** $\rho=Ave.neg.time_{\delta_i}^{\delta'_{k,i}} / \sum_{k=1}^{no.trading\_partner_t^{\delta_i}} Ave.neg.time_{\delta_i}^{\delta'_{k,i}})$
- ***IF*** $((\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}) <> 1)$ ***AND*** $(Ave.neg.time_{\delta_i}^{\delta'_{k,i}} = 0)$ ***THEN*** $(\mu=\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$ ***AND*** $\rho=1)$
- ***IF*** $((\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}) <> 1)$ ***AND*** $(Ave.neg.time_{\delta_i}^{\delta'_{k,i}} <> 0)$ ***THEN*** $(\mu=\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$ ***AND*** $\rho=Ave.neg.time_{\delta_i}^{\delta'_{k,i}} / \sum_{k=1}^{no.trading\_partner_t^{\delta_i}} Ave.neg.time_{\delta_i}^{\delta'_{k,i}})$
- ***IF*** $((\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i})=1)$ ***AND*** $(Ave.neg.time_{\delta_i}^{\delta'_{k,i}} = 0)$ ***THEN*** $(\mu=1$ ***AND*** $\rho=0)$

If the type of δ_i is *GRO_MBDNA*, then $no.trading\_partner_t^{\delta_i} = N_t - 1$, where N_t represents the number of negotiators of type *GRC_MBDNA* at round *t*. Also, if the type of δ_i is *GRC_MBDNA*, then $no.trading\_partner_t^{\delta_i} = M_t - 1$, where M_t represents the number of negotiators of type *GRO_MBDNA* at round *t*. Also, experiment was made with $\eta=4$ (by experiment, it is believed to be an appropriate value for tuning the amount of concession).

As mentioned before the $PreBehave\_Depend_t^{\delta'_{k,i}}$ factor is modeled based on two parameters: $\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$ and $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$. The best value of $PreBehave\_Depend_t^{\delta'_{k,i}}$ factor (i.e., zero) is achieved in case of $(\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i})=1$ and $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}=0$. So, when the $\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$ is equal to one the effectiveness of the first parameter in $PreBehave\_Depend_t^{\delta'_{k,i}}$ factor is ignored (i.e., $\mu=0$) also when the $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$ is equal to zero the effectiveness of the second parameter in $PreBehave\_Depend_t^{\delta'_{k,i}}$ factor is ignored (i.e., $\rho=1$). Similarly, when the $\#Suc.neg_{\delta'_{k,i}-\delta_i}/\#GRNM_{\delta'_{k,i}-\delta_i}$ is equal to one and the $Ave.neg.time_{\delta_i}^{\delta'_{k,i}}$ is equal to zero the effectiveness of both parameters in $PreBehave\_Depend_t^{\delta'_{k,i}}$ factor are ignored (i.e., $\mu=1$ and $\rho=0$). A local database in name *DB_behave* is considered to store the previous concession behavior of negotiator δ_i's trading partners who participated in GRNM previously. The data fields of a *DB_behave* database's record, together with their brief description, are shown in Table 1.

3.4. *Terminating negotiation process and executing task (if negotiation is successful)*

When the negotiation process between δ_i (which its type is *GRC_MBDNA*) and δ_j (which its type is *GRO_MBDNA*) of each pair

Table 1
The data fields of an agent δ_i's local *DB_behave* database's record and their brief description.

Field Name	Description
$\delta'_{k,i}$_*id*	The identifier of $\delta'_{k,i}$ (e.g., *k*th trading partner of δ_i)
$\#GRNM_{\delta'_{k,i}-\delta_i}$	Total number of GRNMs in which both $\delta'_{k,i}$ and δ_i participate
$\#Suc.neg_{\delta'_{k,i}-\delta_i}$	Total number of successful negotiations between δ_i and $\delta'_{k,i}$, in all GRNMs which both participate
$Ave.neg.time^{\delta'_{k,i}}_{\delta_i}$	The average negotiation time between δ_i and $\delta'_{k,i}$ in all GRNMs which both participate

reaches an agreement, δ_i (respectively, δ_j) performs the following tasks:

(a) *If* δ_i (respectively, δ_j) is the negotiator agent who firstly accepts its trading partner's proposal, *Then* store the information of negotiation's transactions between itself and its opponents in *DB_game history* database. This may be a good augmentation of database for future work.

(b) *******If* a record which its δ_i_*id* (respectively, δ_j_*id*) and $\delta'_{k,i}$_*id* (respectively $\delta'_{k,j}$_*id*) fields are correspond to δ_i (respectively δ_j) and $\delta'_{k,i}$ (respectively, $\delta'_{k,j}$) respectively is exist (among retrieved records), *Then* effect the following changes in the retrieved records from *DB_behave* database:

  (1) Update the $Ave.neg.time^{\delta'_{k,i}}_{\delta_i}$(respectively, $Ave.neg.\ time^{\delta'_{k,j}}_{\delta_j}$) field value using $\frac{\text{previous value} + \text{new negotiation time}}{2}$.

  (2) Increase the $\#Suc.neg_{\delta'_{k,i}-\delta_i}$ (respectively, $\#Suc.neg_{\delta'_{k,j}-\delta_j}$) field value by one.
  Otherwise:

  (3) Create a new record based on the template described in Table 1 and insert it into the *DB_behave* Database.

(c) Send negotiation results (e.g., the price for leasing the resource and the period of utilization) to corresponding $GRCA_i$ (respectively, $GROA_j$)

Also $GROA_j$ and $GRCA_i$ commence executing the task of completing the resource allocation process. The $GRCA_i$ entity submits the consumer's task(s) to $GROA_j$, which in turn submits the task(s) to GRO_j, which services the task(s). The sequence of messages involved in task execution is shown in Fig. 1. The $GROA_j$, on completing the execution of task(s), sends the result back to the $GRCA_i$(s). Finally, the results are announced to GRC_i.

When the negotiation process between δ_i (which its type is *GRC_MBDNA*) and δ_j (which its type is *GRO_MBDNA*) of each pair does not reach an agreement, δ_i (respectively, δ_j) performs the following task:

(a) *If* δ_i(respectively, δ_j) is the negotiator agent who firstly terminates the negotiation process, *Then* store the information of negotiation's transactions between itself and its opponents in *DB_game history* database. This may be a good augmentation of database for future work.

(b) *If* a record which its δ_i_*id* (respectively, δ_j_*id*) and $\delta'_{k,i}$_*id* (respectively $\delta'_{k,j}$_*id*) fields are correspond to δ_i (respectively, δ_j) and $\delta'_{k,i}$ (respectively, $\delta'_{k,j}$) respectively is exist (among retrieved records), *Then* update the $Ave.neg.time^{\delta'_{k,i}}_{\delta_i}$(respectively,$Ave.neg.time^{\delta'_{k,j}}_{\delta_j}$) field value using $\frac{\text{previous value} + \text{new negotiation time}}{2}$.

Otherwise create a new record based on the template described in Table 1 and insert it into the *DB_behave* database.

4. Simulation and experimental results

Simulation is used extensively for modeling and evaluation of real world systems. Consequently, modeling-and-simulation has emerged as an important discipline around which many standard and application-specific tools and technologies have been built.

GridSim (Buyya et al., 2002) is an open-source software platform in Java that provides features for application composition, information services for resource discovery, and java classes for realizing most of microeconomic and macroeconomic principles of resource management and interfaces in assigning applications to resources. GridSim has also the ability to model heterogeneous computational resources of various configurations. For realizing the proposed four-phase scenario (described in Section 3), three Java classes of GridSim were applied: gridsim.Machine, gridsim.PE and gridsim.Gridlet. While the first and the second are used to represent a GROA's computing machine and a processing element respectively the third is used to represent a GRCA's job.

4.1. Objectives and motivations

The main goal of this work is to investigate the impact of the new proposed (or new perspective of the old) factors which are inspired from real-life trading market in designing more applicable and appropriate negotiators for computational grid environment. By considering a common assumption in microeconomics, namely *ceteris paribus* (Salvatore, 1997*)* that says: "the effect of a particular factor can be analyzed by holding all other (or most of) factors constant", it is prudent that the negotiation agents that their negotiation strategy is made by more similar factors to our factors are selected for comparison. This can be leads to have more stable environment to evaluate the effectiveness of our new proposed (or new perspective of the old) factors.

According to Sim (2010), few numbers of the current negotiation agents model market dynamic (which makes two of the most important factors of our proposed negotiation strategy) to determine the pattern of concession. MDAs (Sim, 2005a, 2005b, 2006) are the most reputable negotiator agent that not only take into account market dynamic factors in making concession amount but also their time-dependent function is as same as the one that is used in constructing our negotiation strategy. Furthermore, large number of commonly and valuable previous researches in the field of negotiation based grid resource allocation reviewed, referenced or enhanced the idea of MDA s besides compared their achieved results with them (e.g., see Aminul et al., in press; Sim, 2010; An, 2011; Montano et al., 2008; Chacin et al., 2008; Ren, 2010; Shen et al., 2011). Also according to Yoo and Sim (2010) and Sim (2010) MDAs can be modified to support negotiation activities in cloud computing environment.

We should mention that EMDAs (Sim and Ng, 2006, 2007) (i.e., enhanced MDAs) are another appropriate tools for comparison. As the authors of the paper are working on building intelligent agents (i.e., extended MBDNAs) that make concession strategies, based on combined tactics (e.g., time-dependent, resource-dependent, behavior-dependent, etc.), besides considering to relax bargaining terms to achieve both suitable utilities and suitable success rate under different market conditions (e.g., given different supplies and demands) for both GROs and GRCs, they do not propose here to address comparison of the current research to EMDAs (Sim and Ng, 2006, 2007), and instead leave it for future research. So the authors believe that the reputable negotiation agents in name MDAs (Sim, 2005a, 2005b, 2006) are the most appropriate tools (especially by using market driven factors and same time-dependent strategy) for comparison.

By comparing MBDNAs against MDAs one can understand that MDAs do not employ any mechanism for classifying the negotiator's opponents from their behavior point of view and make penalties for *misbehaved* opponents to put them under pressure to refine their behavior and make reward for *well-behaved* opponents to encourage them in continuing their good behavior. Also the definitions of opportunity and competition factors in MDAs and MBDNAs are not the same which means that in modeling competition and opportunity factors we consider not only the changes in the number of negotiator's competitors and trading partners respectively (as what *Sim* did in designing MDAs (Sim, 2005a, 2005b, 2006)) but also change in the ratio of the total number of negotiator's competitors to the total number of negotiator's trading partners. This is because, even though the MDAs have shown good performance, there still exist some limitations which may restrict their application in the real world. In fact the current MDAs cannot handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain. It other word, MDAs do not employ any mechanism to make reasonable responses to both changes in each negotiation market side and change the balance of one market side's participants to other market side's participants. Finally, while MDAs model three factors in making concession amount our proposed MBDNAs model six factors by studying the activities of negotiators of real-life trading market. The idea behind the proposed factors is to bring more rational decision criteria in making minimally sufficient amount of concession.

The similarity between MBDNAs and MDAs is that they both have similar time-dependent negotiation strategies. Intuitively, for every time-dependent negotiation strategy in MDA there is a corresponding strategy in MBDNA, so MDA is a good choice for comparing MBDNA against it.

For the benefit of readers, Table 2 summarizes and compares the main features of the proposed negotiation model against the MDAs in terms of their negotiation protocol and negotiation strategies.

Table 2
Summary and comparison.

References	MDAs	MBDNAs
Negotiation protocol		
Bilateral negotiation model	Yes	Yes
Multilateral negotiation model	Yes	Yes
Determine the specific amount of concession to each negotiator's trading partner instead of the same amount to all	No	Yes
Negotiation strategies		
Flexibility in negotiator's trading partner's proposal_dependent	No	Yes
Behavior of the negotiator's trading partner_dependent	No	Yes
Change in the ratio of the total number of negotiator's competitors to the total number of negotiator's trading partners_dependent	No	Yes
Change in the number of negotiator's competitors_dependent	Yes	Yes
Change in the number of negotiator's trading partners_dependent	Yes	Yes
Remaining time to deadline_dependent	Yes	Yes
Closeness of negotiator's proposal to its trading partners' proposals_dependent	Yes	Yes

4.2. Experimental settings

All the following input parameters are required for setting grid simulation testbed: (a) the grid load (which is represented by Grid_ load symbol), (b) the e_market type, (c) job size (measured in (MI)), (d) deadline for agents to complete their negotiation process, (e) the total resource capacity of a GROA (measured in (MIPS)), (f) market density, (g) multiagent -based strategic negotiation model (described in Section 3) and (h) time-dependent factor. The values of the most mentioned parameters that are used to conduct simulation are derived from Sim (2005a, 2005b, 2006). The input parameters and their possible values are presented in Table 3. The following eight sub-sections address these eight parameters.

Q3 **Table 3**
Input parameters for setting grid simulation testbed and their possible values.

Input	*Possible values*		
E-market type	**GRC-favorable**	$P_{GRC} < 0.5$	*GRC_to_GRO*={1:2,1:5}
	GRO-favorable	$P_{GRC} > 0.5$	*GRC_to_GRO*={2:1,5:1}
	Balanced	$PGRC = 0.5$	*GRC_to_GRO*={1:1}
P_{GRC}: *probability an agent being a GRC*			
Market density	**Sparse**	**Moderate**	**Dense**
P_{gen}	0.25	0. 5	1
P_{gen}: *Probability of generating an agent per round*			
Grid_load	$0 < \text{Grid\_load} \le 1$ {0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1}		
	Low: 0 ←*Grid_load*	*High*: *Grid_load*⟶1	
Deadline (No. of rounds)	**Short**	**Moderate**	**Long**
	100	1600	3100
Job size(MI)	10–100		
Resource capacity(MIPS)	200–3000		
Negotiation model	MBDNAs' negotiation model is described in Section 3	MDAs' negotiation model is inspired by Sim (2005a, 2005b, 2006)	
Amount of time-preference, type of strategy: abbreviation			
MBDNA time-preferences		***MDA time-preferences***	
(λ=1/3, *Conciliatory*: *CC*)		(λ=1/3, *Conciliatory*: *CC*)	
(λ=1, *Linear*: *L*)		(λ=1, *Linear*: *L*)	
(λ=2, *Conservative*: *CS*)		(λ=2, *Conservative*: *CS*)	
(λ=3, *Conservative*: *CS*)		(λ=3, *Conservative*: *CS*)	

4.2.1. Grid load

Grid load refers to the utilization status of computing resources. As the load varies continuously with time, the simulation should be carried out by considering various grid loads. Sim (2006) proposes two parameters R_p and C_c to represent grid load, where R_p is defined as the expected amount of processing requested per time interval (which is measured in MI) and C_c as the total computing capacity of the grid (which is measured in MI). It was noted in Sim (2006) that "*R_p depends on both the requests (tasks) from the GRCs which depend on P_m (i.e., the probability of a GRC generating a task that needs computing resources at each negotiation round. This parameter is used to simulate the arrival of a task to the grid at each negotiation round) 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 between 10 and 100 MIs. Different levels of system utilization (different grid loads) are simulated by varying the time interval between the possible arrivals of two tasks*". As grid load tends to become one (respectively, to zero), fewer (respectively, more) computing resources in the grid are available for lease:

$$Grid\_load = \frac{R_p}{C_c} \quad \text{where } 0 < Grid\_load \leq 1 \tag{20}$$

4.2.2. E_market types

As the availability of grid resources varies continuously with time, the simulation should be carried out by considering different GRC-to-GRO ratios. These ratios characterize three types of e-market:*GRC-favorable*, *GRO-favorable* and *balanced*. The *GRC-favorable* e-market addresses more GRO agents and consequently more opportunity for acquiring resources; the *GRO- favorable* market addresses more GRC agents and consequently more opportunity for leasing out resources; the *balanced* market addresses normal competition among GRO agents and GRC agents. GRC_to_GRO ratio is controlled by the probability P_{GRC} of an agent being GRC agent (or GRO agent). P_{GRC} follows a uniform distribution.

4.2.3. Job size

The GRC agent's job size is measured in millions of instructions (MI).

4.2.4. GRCA's deadline

As described before, agent's deadline constraint plays a major role in choosing the appropriate strategy. According to Sim (2006), three categories can be descibed for the agent's deadline constraint: Short, Moderate and Long. Space limitation precludes all possible values of GRCA's deadline from being included in depicting figures, and Table 3 only contains GRCA's job deadline values equal to 100, 1600 and 3100 which represent short, moderate and long deadline respectively.

4.2.5. GROA's total resource capacity

The GRO agent's total resource capacity is measured in millions of instructions per second (MIPS).

4.2.6. Market density

Market density depends on the number of GRC agents and GRO agents participating in the GRNM. Market density is controlled by the probability P_{gen} that an agent will enter the GRNM in each round of negotiation. P_{gen} follows a uniform distribution. Market density can be catagorized into three categories: Dense, Moderate and Sparce.

4.2.7. Strategic negotiation model

The proposed *Multiagent-based Strategic Negotiation Model* as the heart of four-phase scenario for grid resource allocation is described in Section 3. Also the MDAs' strategic negotiation model is inspired by Sim (2005a, 2005b, 2006).

4.2.8. Time-dependent factor

As mentioned before the rationale for comparing MBDNAs with MDAs is that both of these agents take into consideration the issue of time constraint, and their time-dependent strategies have similar to each other. The time-dependent negotiation strategies adopted from MBDNAs and MDA are shown in Table 3.

4.3. Performance metrics

Because grids are dynamic in their nature, it is difficult to benchmark and evaluate them (specially, market-oriented resource allocation algorithms are very difficult to analyze analytically (Izakian et al., 2010)). Moreover, there is no general consensus on which metrics to use (Nemeth et al., 2004; Nemeth, 2003). As GRC satisfaction function takes into account both the utility provided to the GRC (i.e., number of tasks that is accomplished successfully) and the price paid for the resources and GRO satisfaction function takes into account both the utility provided to the GRO (i.e., the amount of idle resources being leased out) and the revenue achieved for leasing out its resources, the GRC's metrics to be studied are *task complementation* and *average utility*, and also the GRO's metrics to be studied are *resource utilization level* and *average utility.*

4.3.1. GRC's performance metrics

- *Task complementation* (Sim, 2006): Task complementation is defined as the percentage (P_{tc}) of a GRC's set of tasks that is accomplished by successfully negotiating and leasing grid resources; let N_{tot} denote the total number of tasks requested by a GRC and N_{suc} the number of tasks that are successfully scheduled and executed. $_{Ptc}$ is given as

$$P_{tc} = \frac{N_{suc}}{N_{tot}} \tag{21}$$

- *Average utility*: Average utility defines how efficiently the available budget was spent. Let assume that P_c be the price that a consensus is reached by both parties. The *average utility* metric is calculated based on (1).

4.3.2. GRO's performance metrics

- *Resource utilization level* (Sim and Ng, 2007): Resource utilization level is defined as the ratio of the amount of GRO's idle resources being leased out and utilized (N_{ur}) to the total amount of GRO's idle resources (N_{ir}):

$$U_{rl} = \frac{N_{ur}}{N_{ir}} \tag{22}$$

We assume that the more grid resources are leased out to the GRC's, the higher the *resource utilization level* is:

- *Average utility*: Average utility defines how efficiently the revenue was received. Let assume that P_c be the price that a consensus is reached by both parties. The *average utility* metric is calculated based on (2).

4.4. Evaluation and discussion

A series of experiments was carried out to evaluate the performance of MBDNAs (e.g., *GRC_MBDNAs* and *GRO_MBDNAs*) considering proposed factors: *number of negotiator's trading partners, number of negotiator's competitors, negotiator's time*

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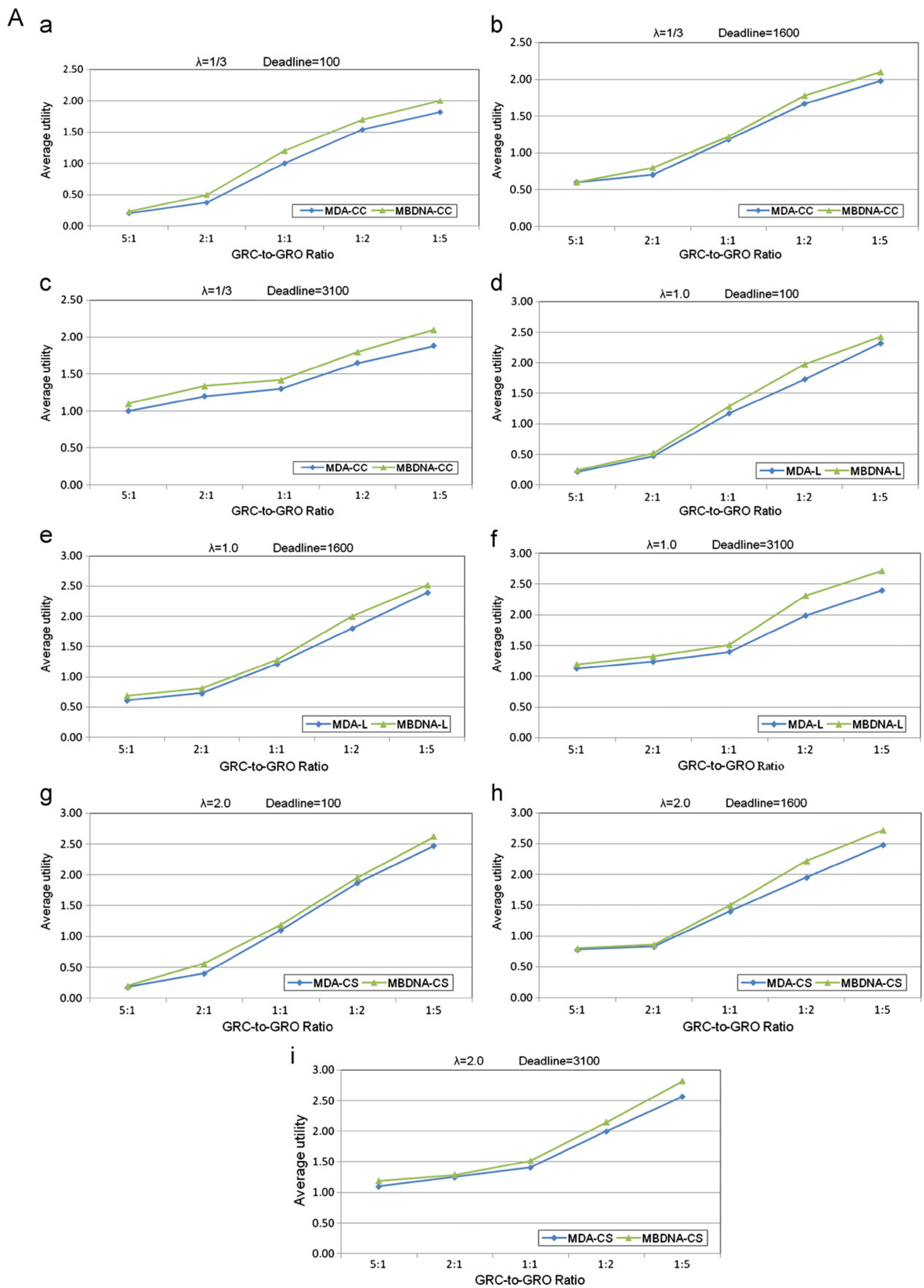

Fig. 3. Performance under different market types. (A) $\lambda=1/3$ Deadline$=100$. (B) $\lambda=1/3$ Deadline$=1600$, (C) $\lambda=1/3$ Deadline$=3100$, (D) $\lambda=1.0$ Deadline$=100$, (E) $\lambda=1.0$ Deadline$=1600$, (F) $\lambda=1.0$ Deadline$=3100$. (G) $\lambda=2.0$ Deadline$=100$, (H) $\lambda=2.0$ Deadline$=1600$ and (I) $\lambda=2.0$ Deadline$=3100$.

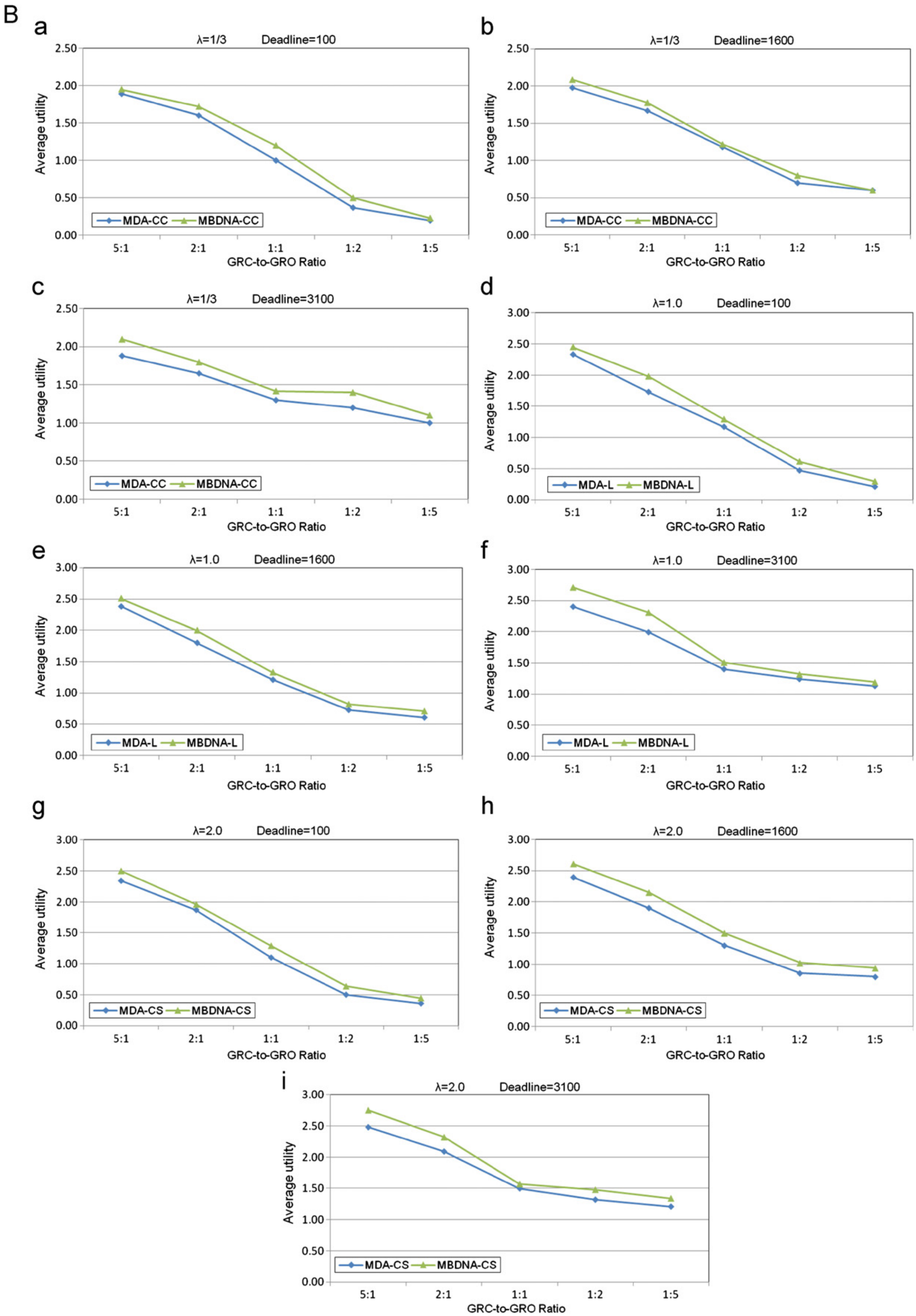

Fig. 3. (*continued*)

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preference, flexibility in negotiator's trading partner's proposal, negotiator's proposal deviation of the average of its trading partners' proposals and previous concession behavior of negotiator's trading partner against MDAs.

Below are presented the results of the impact of the proposed factors on the GRC's and GRO's metrics. The proposed factors injected step-by-step to make final price-oriented strategy (e.g., $FST_t^{\delta_i}$) and evaluate the impact of each factor on performance metrics separately. Some of the proposed factors have greater impact on the GRC's metric (respectively, GRO's metric) of improving tasks complementation (respectively, improving resource utilization level) and the others on the GRC's metric (respectively, GRO's metric) of minimizing budget spent (respectively, maximizing received revenue). Following are the most important observations from the results:

Observation 1: It can be observed from Fig. 3-GRC's perspective that, given the same GRC_to_GRO ratio MBDNAs always get higher utilities by using new negotiation strategy. This is because MBDNAs not only employ mechanisms to make penalties for *misbehaved* opponents to put them under pressure to refine their behavior and handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain but also consider more effective factors which are inspired from real-life trading market to make minimally sufficient concession amount.

In addition, when the type of market tends to be *GRO-favorable* (e.g., the ratio of participants of GRC's e_market side to participants of GRO's e_market side increase), the average utilities of the both types of agents are close especially in the *short* deadline case since under very extreme competition conditions (i.e., *GRO-favorable* market type where GRC_to_GRO ratio = {2:1, 5:1}), the bargaining power of GRCs decreases and it may be extremely difficult for both types of negotiators (i.e., MBDNAs and MDAs) to reach any consensus so they have to concede more to avoid the risk of losing grid resources (which leads to lower average utility) and also with *short* deadline (in comparison to *moderate* and *long*) due to have no plenty

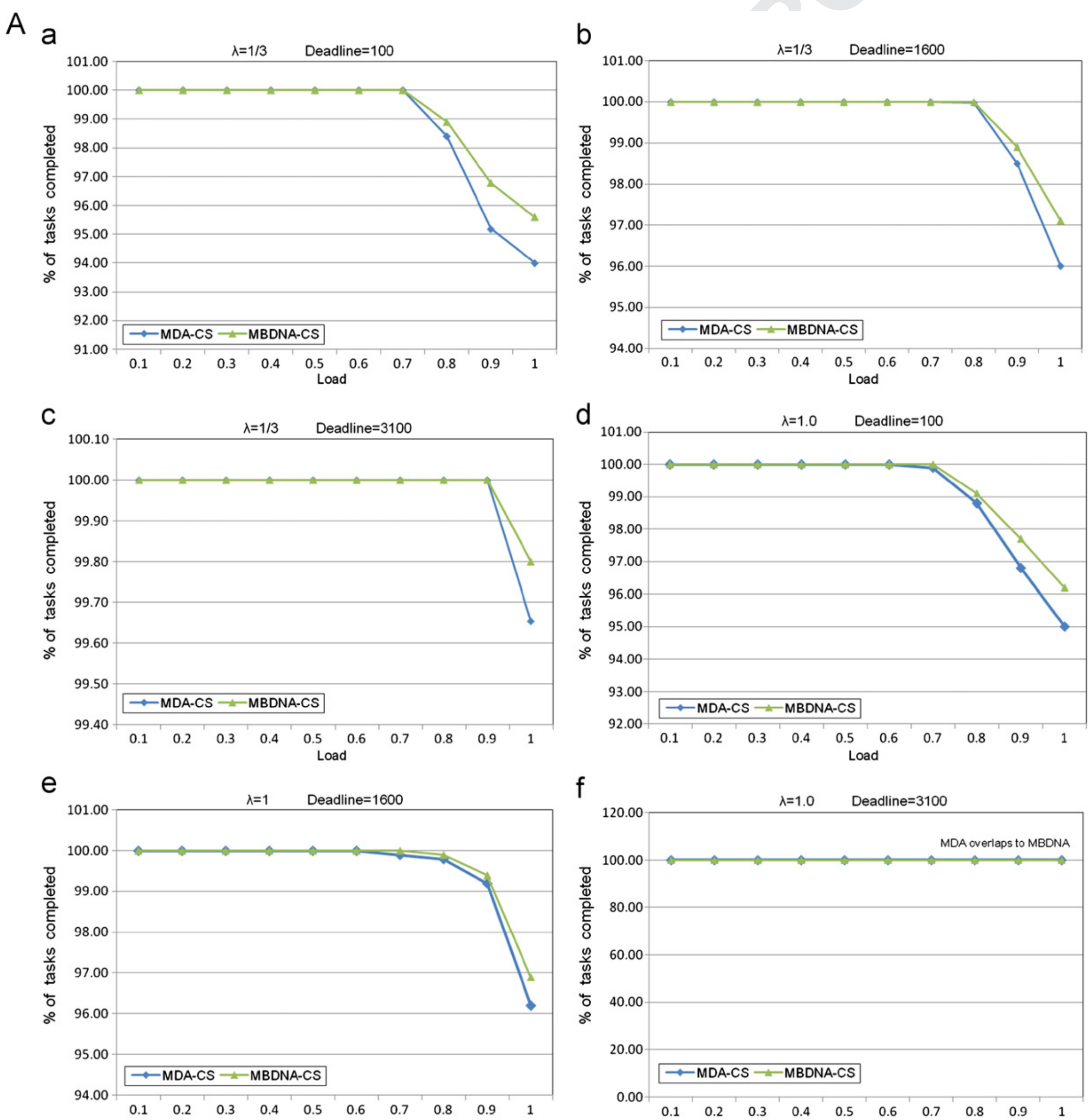

Fig. 4. Performance under different grid work loadings. (A) $\lambda = 1/3$ Deadline = 100. (B) $\lambda = 1/3$ Deadline = 3100, (C) $\lambda = 2.0$ Deadline = 100, (D) $\lambda = 2.0$ Deadline = 3100, (E) $\lambda = 1.0$ Deadline = 100 and (F) $\lambda = 1.0$ Deadline = 1600.

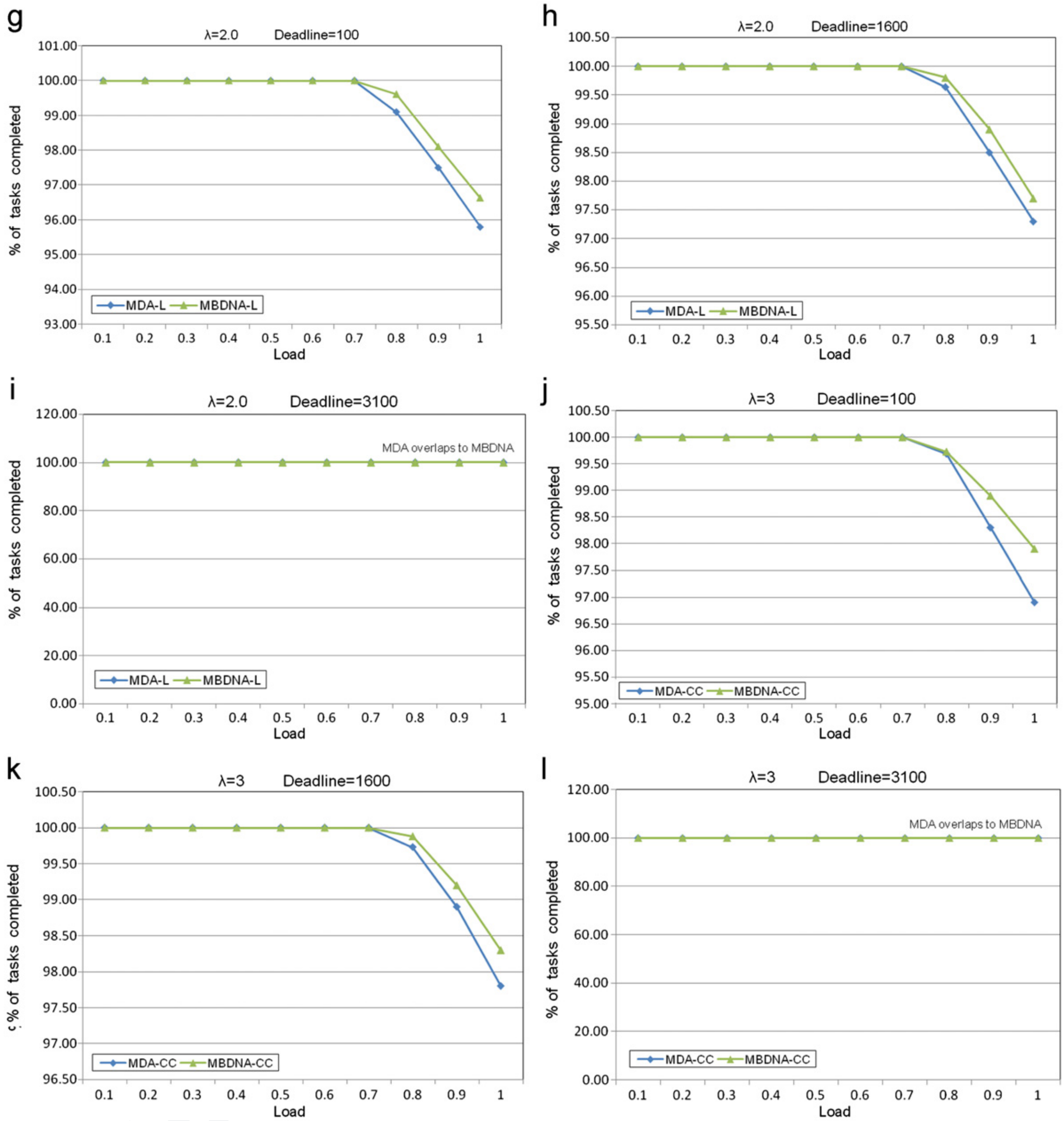

Fig. 4. (*continued*)

of time to complete a deal the bargaining positions of both MBDNAs and MDAs are weaker and if final agreement is reached, both of them are likely to make relatively more concessions (which leads to lower average utility). To show the weaker bargaining power of negotiators having *short* deadline in comparison to negotiators having *moderate* or *long* deadline an example is provided: in Fig. 3-GRC's perspective (g)–(i), for GRC_to_GRO=1:5 and $\lambda=2.0$, the average utility of GRC_MBDNAs increased from 2.51 with deadline=100 (i.e., *short* deadline) to 2.66 and 2.82 with deadline=1600 (i.e., *moderate* deadline) and deadline=3100 (i.e., *long* deadline) respectively.

Furthermore given the same deadline and GRC-to-GRO ratio, GRCs of both types achieved higher utilities by adopting conservative strategies (i.e., $\lambda>1$). As an example, in Fig. 3-GRC's perspective (c), (f) and (i), for GRC_to_GRO=1:5 and deadline=3100 (i.e., *long* deadline), the average utility of GRC_MBDNAs increased from 2.10 with $\lambda=1/3$ (i.e., *conciliatory* strategy) to 2.60 and 2.82 with $\lambda=1.0$ (i.e., *linear* strategy) and $\lambda=2.0$ (i.e., *conservative* strategy) respectively. The proof is provided in *Sim* (Sim, 2005).

Observation 2: Similarly to *observation 1*, it can be observed from Fig. 3-GRO's perspective that, given the same GRC_to_GRO ratio MBDNAs always get higher utilities by using new negotiation strategy. This is because MBDNAs not only employ mechanisms to make penalties for *misbehaved* opponents to put them under pressure to refine their behavior and handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain but also consider more effective factors which are inspired from real-life trading market to make minimally sufficient concession amount.

Additionally, when the type of market tends to be *GRC-favorable* (e.g., the ratio of participants of GRO's e_market side to participants of GRC's e_market side increase), the average utilities of the both types of agents are close especially in the *short* deadline case since under very extreme competition conditions (i.e., *GRC-favorable* market type where GRC-to GRO ratio={1:2, 1:5}), the bargaining power of GROs decreases and it may be extremely difficult for both types of negotiators (i.e., MBDNAs and MDAs) to reach any consensus so they have to concede more to

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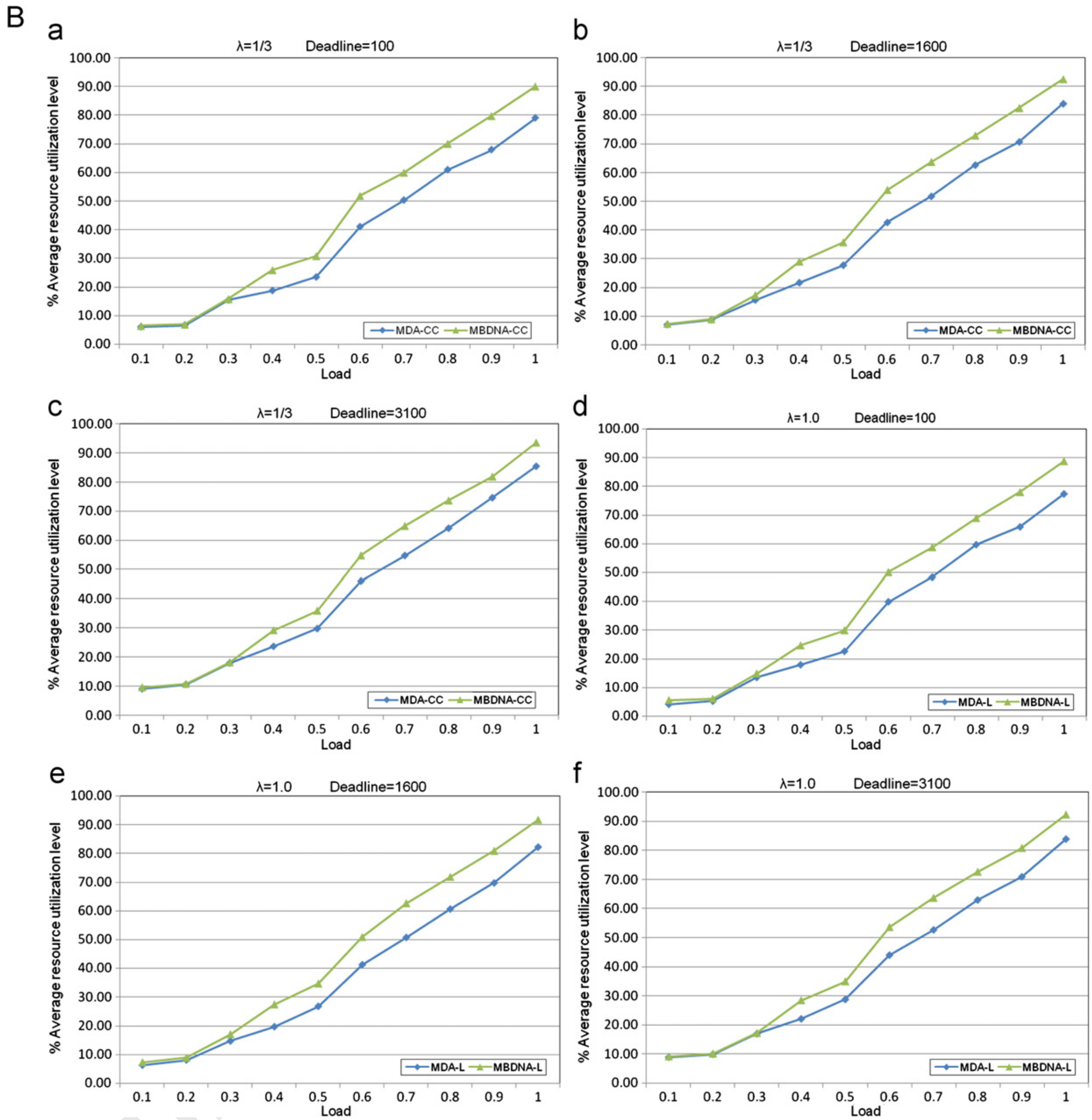

Fig. 4. (*continued*)

avoid the risk of losing the chance of leasing out their resources (which leads to lower average utility) and also with *short* deadline (in comparison to *moderate* and *long*) due to have no plenty of time to complete a deal the bargaining positions of both MBDNAs and MDAs are weaker and if final agreement is reached, both of them are likely to make relatively more concessions (which leads to lower average utility). To show the weaker bargaining power of negotiators having *short* deadline in comparison to negotiators having *moderate* or *long* deadline an example is provided: in Fig. 3-GRO's perspective (g)–(i), for GRC_to_GRO=1:5 and $\lambda=2.0$, the average utility of GRO_MBDNAs increased from 0.48 with deadline=100 (i.e., *short* deadline) to 0.91 and 1.32 with deadline=1600 (i.e., *moderate* deadline) and deadline=3100 (i.e., *long* deadline) respectively

Furthermore given the same deadline and GRC_to_GRO ratio, GRCs of both types achieved higher utilities by adopting conservative strategies (i.e., $\lambda>1$). As an example, in Fig. 3-GRO's perspective (a), (d) and (g), for GRC_to_GRO= 5:1 and deadline=100 (i.e., long deadline), the average utility of GRO_MBDNAs increased from 1.92 with $\lambda=1/3$ (i.e., *conciliatory* strategy) to 2.42 and 2.51 with $\lambda=1.0$ (i.e., *linear* strategy) and $\lambda=2.0$ (i.e., *conservative* strategy) respectively. The proof is provided in *Sim* (Sim, 2005).

Observation 3: The experimental results in Fig. 4-GRC's perspective show the following: (1) Negotiation results become more unfavorable with the increase of the Grid_load for both types of negotiators (i.e., MBDNAs and MDAs). With the increase of Grid_load, there were fewer available resources in the grid, and it became increasingly difficult for both types of agents to successfully negotiate for resources. (2) Given the same Grid_load, MBDNAs achieved higher success rate in acquiring resources than MDAs. This is because more appropriate factors are considered for designing MBDNAs which have great role in relaxing and adopting the bargaining criteria whenever the negotiation agents come under market pressure. This means that the negotiation agents can achieve more resources especially when the market conditions put them under pressure. So, in high grid loadings (e.g., Grid_load=0.9 and Grid_load=1.0) GRC_MBDNAs are more likely

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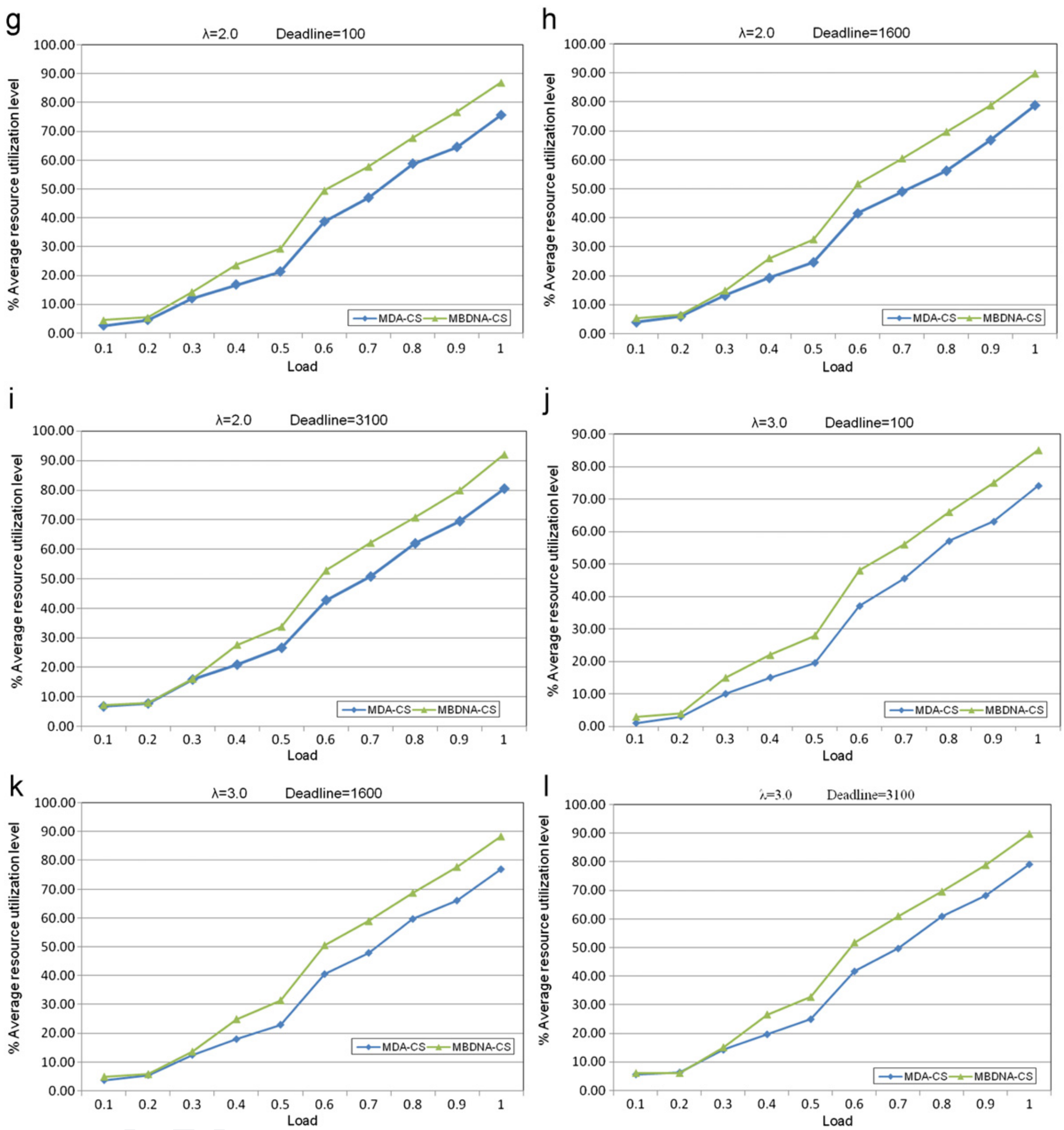

Fig. 4. (*continued*)

to be successful in acquiring resources in comparison to MDAs. (3) Given the same Grid_load and time-preference, GRCs of both types who have *long* deadline achieved higher success rate. With *long* deadline (in comparison to *moderate* and *short*) due to have plenty of time for trading the bargaining positions of both MBDNAs and MDAs are stronger and they both likely to complete deals successfully (i.e., have higher success rate). However, as MBDNAs are designed with more appropriate negotiation strategy, they are more likely to achieve higher success rate than MDAs especially under intense grid market pressure. As an example, in Fig. 4-GRC's perspective (d), (e) and (f), for Grid_load$=$1 and $\lambda=1$, the success rate of GRC_MBDNAs increased from 96.03% with deadline$=$100 (i.e., *short* deadline) to 96.9% and 100% with deadline$=$1600 (i.e., *moderate* deadline) and deadline$=$3100 (i.e., *long* deadline) respectively.

Observation 4: The experimental results in Fig. 4-GRO's perspective show the following: (1) Negotiation results become more favorable with the increase of the Grid_load for both types of negotiators (i.e., MBDNAs and MDAs). (2) Given the same Grid_load, MBDNAs achieved higher success rate in leasing out resources than MDAs. This is because more appropriate factors are considered for designing MBDNAs which have great role in relaxing and adopting the bargaining criteria whenever the negotiation agents come under market pressure. This means that the negotiation agents can lease out more resources especially when the market conditions put them under pressure (i.e., Grid_load tends to zero). (3) Given the same Grid_load and time-preference, GROs of both types who have *long* deadline achieved higher success rate. With *long* deadline (in comparison to *moderate* and *short*) due to have plenty of time for trading the bargaining positions of both MBDNAs and MDAs are stronger and they both likely to complete deals successfully (i.e., have higher success rate). However, as MBDNAs are designed with more appropriate negotiation strategy, they are more likely to achieve higher success rate than MDAs especially under intense grid market pressure. As an example, in Fig. 4-GRO's perspective (j), (k) and (l), for Grid_load$=$1 and $\lambda=3.0$, the success rate of GRO_MBDNAs increased from 83.1% with deadline$=$100 (i.e., *short* deadline) to 88.9% and 90.09% with deadline$=$1600 (i.e., *moderate* deadline) and deadline$=$3100 (i.e., *long* deadline) respectively.

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Observation 5: To evaluate the impact of our most important factor *previous concession behavior of negotiator's trading partner* a common assumption in microeconomics, namely *ceteris paribus* (Salvatore, 1997) is considered. As mentioned in Salvatore (1997): "the effect of a particular factor can be analyzed by holding all other factors constant." Since the purpose is to only compare MBDNAs and MDAs from the *previous concession behavior of negotiator's trading partner* factor perspective, it seems prudent to avoid any possible influence on the negotiation outcomes when MBDNAs make concession amount. Hence, for depicting Figs. 5 and 6, MBDNAs are designed with the same MDA's factors (i.e., *opportunity, competition* and *deadline*) and extra proposed factor in name *previous concession behavior of negotiator's trading partner.* Space limitation precludes all results from being included here, and Figs. 5 and 6 only report the results for experiments conducted from GRC's perspective when negotiators have $\lambda \in \{1/3,1,2\}$ and deadline$\in\{100,3100\}$ and $\lambda \in \{1,2,3\}$ and deadline$\in\{100,1600\}$ respectively. The results show that considering larger penalties for *misbehaved* trading partners not only increases the chance of reaching a consensus with *well-behaved* trading partners in different market types but also puts *misbehaved* trading partners under pressure to have better behavior in next meeting (to avoid achieving low success rate and/or loosing utility). This idea is inspired from real-life trading where the negotiators analyze their opponents' behavior and categorized them into *misbehaved* and *well-behaved* opponents. Then, during negotiation process, the negotiators consider penalties for *misbehaved* opponents to put them under pressure to refine their behavior and reward for *well-behaved* opponents to encourage them in continuing their good behavior. Consequently the achieved utility and success rate of negotiators will be bettered by participating in more numbers of trading markets.

5. Conclusion

This paper presents an approach to allocate resources in grid environment via negotiation between GRC_MBDNAs (Grid Resource Consumer Market- and Behavior-driven Negotiation Agents) and GRO-MBDNAs (Grid Resource Owner Market- and Behavior-driven Negotiation Agents) to enhance the success rate and utility of negotiation agents. The scenario of resource allocation proposed here in the economy-aware grid environment includes the following four major phases:

(1) *Registering GRCs and GROs.*
(2) *Creating MBDNAs and providing the required information (that is necessary for starting negotiation).*
(3) *Starting negotiation based on proposed strategic negotiation model.*
(4) *Terminating negotiation process and executing task (if negotiation is successful).*

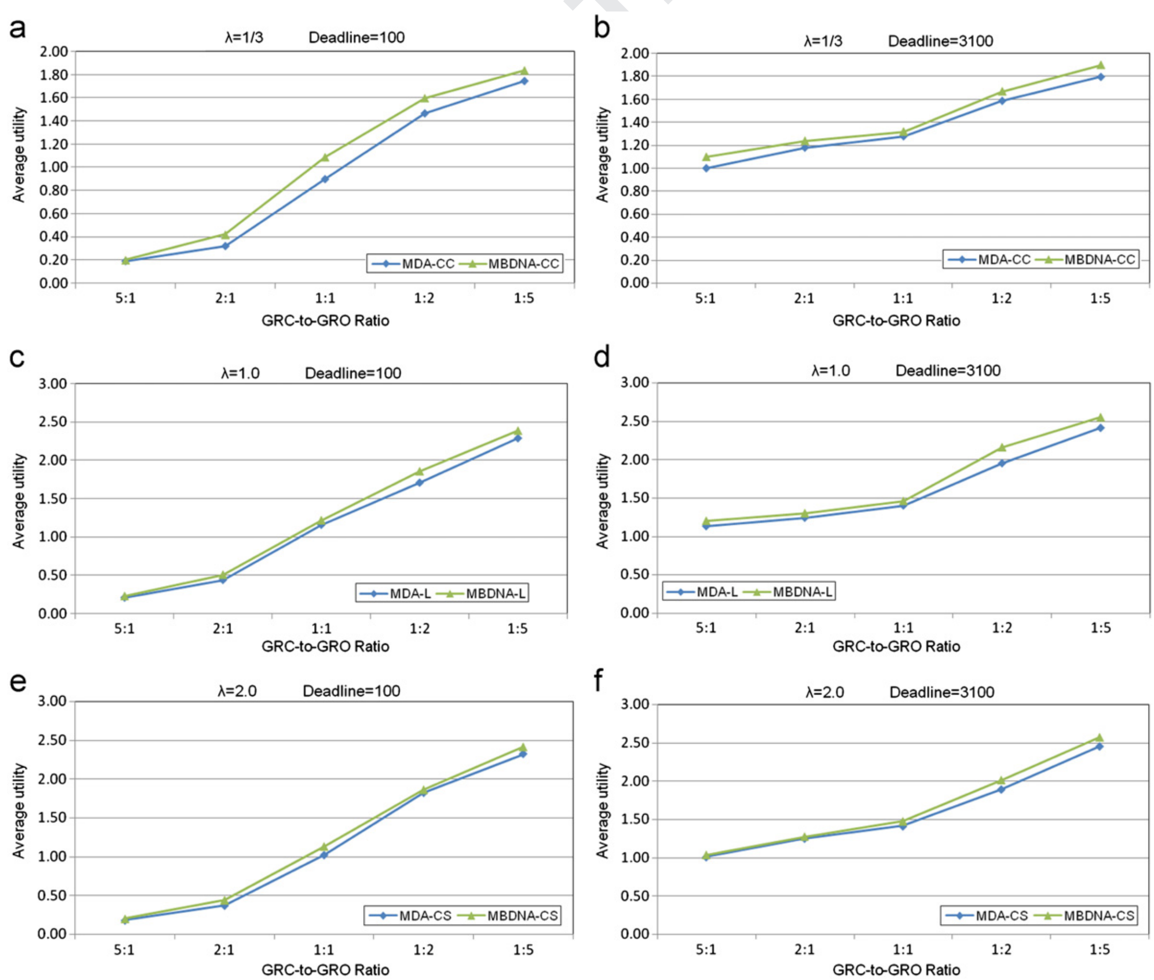

Fig. 5. Performance under different market types (considering behavior factor and MDA's competition, opportunity and time factors for making MBDNA's negotiation strategy).

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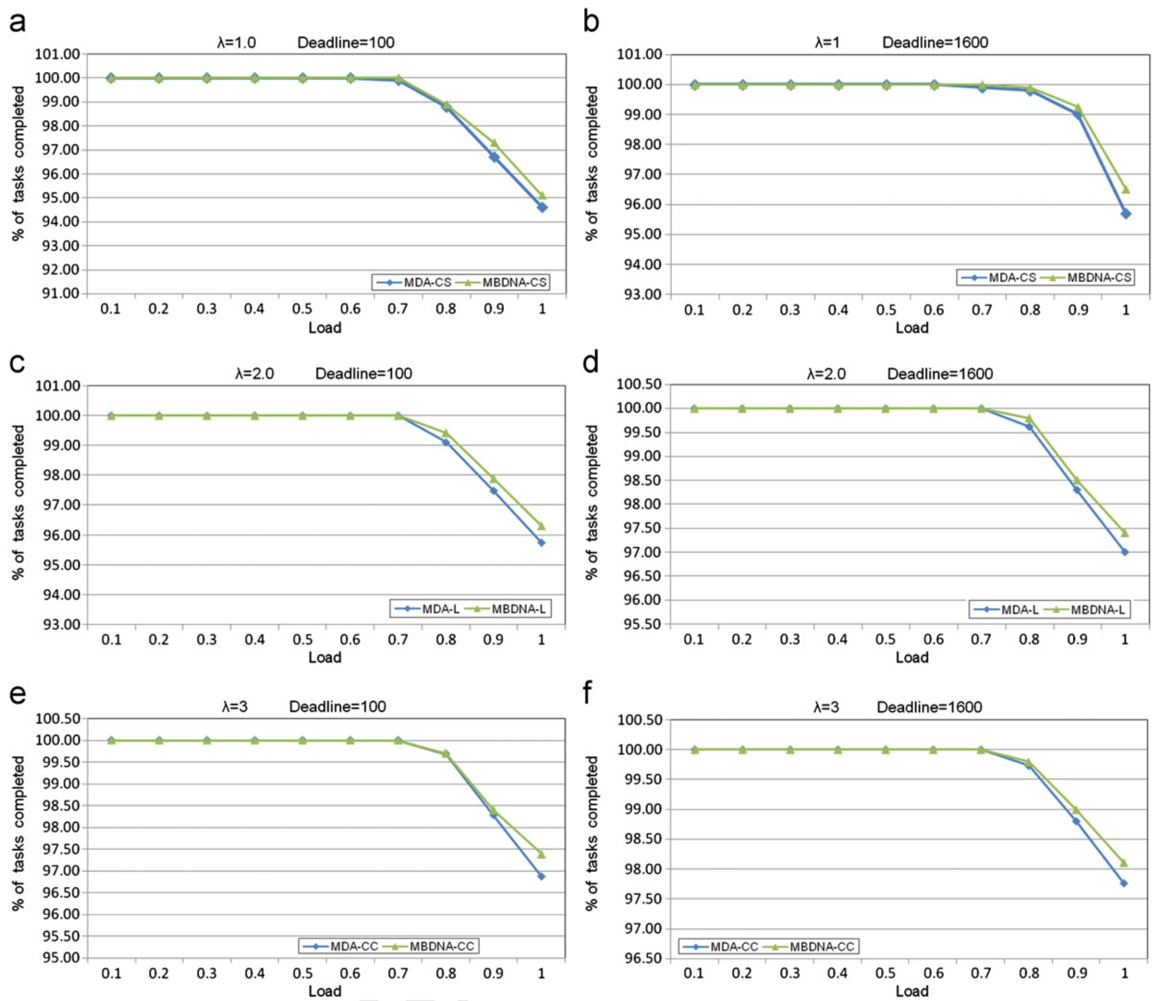

Fig. 6. Performance under different grid work loadings (considering behavior factor and MDA's competition, opportunity and time factors for making MBDNA's negotiation strategy).

The strategic negotiation model presented here (as the heart of the proposed four-phase scenario for grid resource allocation) has three parts: (1) the negotiation protocol (2) the used utility models or preference relationships for the negotiating parties, and (3) the negotiation strategy that is applied during the negotiation process. The main goals of this work are introducing rational negotiation protocol and negotiation strategy that model the effective factors used by negotiators of real-life trading market for making concession amount in negotiation process. The strategy of MBDNAs determine the amount of concession that has to be given at negotiation round *t*, based on the proposed factors: *number of negotiator's trading partners, number of negotiator's competitors, negotiator's time preference, flexibility in negotiator's trading partner's proposal, negotiator's proposal deviation of the average of its trading partners' proposals and previous concession behavior of negotiator's trading partner.*

Thus, in this approach, the authors investigated the benefit of the proposed negotiation factors in designing the negotiation agents of both types (e.g., GRC_MBDNAs and GRO_MBDNAs) so as to handle resource allocation in a computational grid environment, as also in a simulated environment. Simulation results show that by considering the new proposed negotiation factors besides new perspective of previous exist factors, MBDNAs of both types leaves a much higher profit for both GRC_MBDNAs and GRO_MBDNAs in market_based resource allocation in comparison to MDAs (Sim, 2005a, 2005b, 2006). In addition, the proposed approach better deals with the dynamic nature of the Grid and generates more optimal allocations compared to existing approaches used for NP-hard resource allocation problems.

Although there is good opportunity for grid applications to benefit from MBDNAs in regulating the supply (grid resources which are provided by resource owners) and demand (grid resource consumers' requirements) in grid computing environments, there are still many challenges that need to be overcome before designing more effective negotiation agents. Some of these challenges are as follows: (1) designing negotiation agents that not only applying near optimal negotiation strategies but also have the flexibility of relaxing their bargaining criteria to quickly complete a deal in the face of intense grid market pressure and (2) designing negotiation agents that not only react to current market situations but also to future market situations. One way to deal with the first challenge is to design negotiation agents that have the flexibility of relaxing bargaining criteria using fuzzy rules and a way to deal with the second challenge is to design negotiation agents with learning and predicting capabilities by analyzing negotiation history between negotiation agents and their opponents.

It is hoped that this approach of designing negotiation agents (e.g., MBDNAs), based on the proposed negotiation factors for regulating supply-and-demand in grid computing environment allows one to move closer to being able to allocate resources in grid computing environment via rational and effective negotiation agents.

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Table 4
Notation and basic terms used in the paper (alphabetic sort).

Symbol	**Basic Definition**	**Symbol**	**Basic definition**
$Ave.neg.time_{\delta_i}^{\delta'_i}$	The average negotiation time between δ_i and $\delta'_{k,i}$ in all GRNMs which both participate	$no.competitor_t^{\delta_i}$	Number of δ_i's competitors at round t
C_c	The total computing capacity of the grid	$no.trading\_partner_t^{\delta_i}$	Number of δ_i's trading partners at round t
c^{δ_i}	The worst possible utility for δ_i (e.g., if the negotiation ends in disagreement)	$NC_t^{\delta_i}$	MBDNAs' competition function
$CC_t^{\delta_i}$	MDAs' competition function	$NTP_t^{\delta_i}$	MBDNAs' opportunity function
con_t	The amount of concession at negotiation round t	$O_t^{\delta_i}$	MDAs' opportunity function
$DTPAP_t^{\delta_i}$	MBDNAs' closeness function (e.g., δ_i's proposal deviation of the average of its trading partners' proposals)	P_{GRC}	The probability of an agent being GRC agent
$FST_t^{\delta_i}$	Final price-oriented strategy that is taken by δ_i	P_{gen}	The probability that an agent will enter the GRNM in each round of negotiation
$FTP_t^{\delta_i}$	MBDNAs' flexibility function (i.e., flexibility in δ_i's trading partner's proposal)	$P_t^{\delta_i}$	δ_i's proposal at round t
GRC_i	*i*th grid resource consumer	$P_t^{\delta'_{k,i}}$	Proposal of $\delta'_{k,i}$ at round t
$GRCA_i$	*i*th grid resource consumer agent	P_c	The price that a consensus is reached by both parties
$GRC\_job\_prof_p^i$	GRC_i's *p*th job characteristics	P_m	The probability of a GRC generating a task that needs computing resources at each negotiation round
Grid_ load	Utilization status of computing resources	P_{tc}	Percentage of a GRC's set of tasks that is accomplished by successful negotiation and leasing grid resources
grid.name	Name of observed grids in work load traces (http://www.cs.huji.ac.il/labs/parallel/workload/logs.html)	$PreBehave\_Depend_t^{\delta'_{k,i}}$	MBDNAs' behavior function (e.g., previous behavior of $\delta'_{k,i}$)
GRNM	Grid Resource Negotiation Market	R_p	The expected amount of processing requested per time interval
GRNM_jobrequestee_directory	Storage for submitting *GRO_resource_prof*(s) of *GROA*(s) in GRNM	$RD_t^{\delta_i}$	Ratio of difference between the average of negotiator δ_i's trading partners' proposals at round $t-1$ (e.g., $(\sum_{k=1}^{no.trading\_partner_{t-1}^{\delta_i}} P_{t-1}^{\delta'_{k,i}} / no.trading\_partner_{t-1}^{\delta_i})$ and negotiator/ δ_i's last proposal (e.g.,$P_{t-2}^{\delta_i}$) to the average of negotiator δi's trading partners' proposals at round $t-1$.
GRNM_jobrequester_directory	Storage for submitting *GRC_job_prof*(s) of *GRCA*(s) in GRNM	$repeated\_user_{grid.name}$	Represents percentage of *grid.name*'s users that are observed previously in$unique_user_set_{grid.name}$
GRO_j	*j*th Grid Resource Owner	RP_{δ_i}	Reserve Price of δ_i
$GROA_j$	*j*th Grid Resource Owner Agent	$\boldsymbol{t}$	Negotiation round
26	GRO_j's *r*th resource characteristics	$t_{deadline}^{\delta_i}$	δ_i's deadline (e.g., a time frame by which/δ_i needs negotiation result)
	Initial Price of negotiator δ_i		Time preference function
	Initial price-oriented strategy that is taken by δ_i	U_{rl}	Resource utilization level
k_t	The (best) spread in current cycle t		Utility of δ_p's at round t if δ_p accepts the proposal from δ_r $(\delta_r(p_t^{\delta_r}))$
k_{t+1}	The expected difference between the proposal of an agent and its trading partner		Utility of δ_p's at round t if δ_r accepts the proposal from δ_p $(\delta_p(p_t^{\delta_p}))$
M_t	Number of negotiators of type *GRO_MBDNA* at round t	$unique\_user\_ set\_mem_{grid.name}$	The set of observed unique users in the *grid.name*'s SWF archive (http://www.cs.huji.ac.il/labs/parallel/workload/logs.html)
	Maximum number of potential unique users of a grid in *grid.name*		Total number of GRNMs in which both $\delta'_{k,i}$ and δ_i participate
N_{suc}	The number of tasks that are successfully scheduled and executed		Total number of successful negotiations between δ_i and $\delta'_{k,i}$, in all GRNMs which both participate
N_{tot}	Total number of tasks requested by a GRC	δ_i (e.g., *GRC_MBDNA*|*GRO_MBDNA*)	Negotiator agent who its turn to make concession
N_t	Number of negotiators of type *GRC_MBDNA* at round t		*k*th trading partner of δ_i
N_{ir}	The total amount of GRO's idle resources	$\delta C_{l,i}$	*l*th competitor of δ_i
N_{ur}	The ratio of the amount of GRO's idle resources being leased out and utilized	λ	δ_i's time preference

Acknowledgment

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Appendix

For the benefit of readers, the authors summarize in Table 4 the key symbols and their definitions used in this paper.

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