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 completion 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.

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1. Introduction

Computational grids have been emerging as a new paradigm for solving large-scale problem in science, engineering and commerce (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 organizational 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...
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 MBDNAs (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 uncertainty 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 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: RDF (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 multi-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: RDF (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., GROA) can have one or more jobs (job1,...,jobk). Jobs submitted by GRCs into a cluster have varying requirements depending on GRC-specific needs and expectations. The GRC’s pth job characteristics (e.g., (GRC_job_prof,i)) 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 = 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 GRC, which is represented by a GRO agent (e.g., GROA), may possess k computing machines (which is denoted by (Mj1,...,Mjk)) for the grid environment. As noted in (Sim, 2006, p. 1384), “Each computing machine Mjk can be a single processor, a shared memory multiprocessor, or a distributed memory cluster of computers. Mjk can be formed by one or more processing elements {PE1,...,PEk}, and eachPEi can have different speeds measured in terms of MIPS (millions of instructions per second).” The GRO’s rth resource characteristics (e.g., GRC_resource_prof,r) include unique identifier, the architecture of computing resource (e.g., HPalpha server), list of computing machines (e.g., (Mj1,...,Mjk)), required bandwidth length, required memory capacity, and expected and reserved prices of leasing a computing machine.

The GRCAs (respectively, GROAS) should register each of its GRC_jobprof,i (s) (respectively, GRO_resource_prof,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...
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 (respectively, GRO_MBDNA) is generated according to GRCA (respectively, GROA), 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 δth trading partner of negotiator δi is denoted by δi'.

Following are the functions performed by δi (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 δi’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 δi_id field is equal to the identifier of one of δi’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 #GRNMδi—δi field of retrieved records by one.

And the functions that are performed by δj (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 δi, 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; ...}. In each period t∈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).

![Event diagram showing message-flow in the proposed four-phase scenario (for grid resource allocation).](image-url)
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_i's turn to move (e.g., determine the amount of concession), it proposes a deal from its possible negotiation set (e.g., \( \{IP_i, RP_i\} \), where \( IP_i \) and \( RP_i \) are, respectively, the initial and reserve prices of \( \delta_i \)).
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 \( \delta_i \) of type GRC_MBDNA is not equal to or greater than the reservation price of \( \delta_j \) 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 type GRO_MBDNA).

Also Sim (2005a, 2006) described a negotiation protocol for specifying the negotiation activities among GRCA 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.

For ease of analysis, the utility function of negotiator \( \delta_i \in \{\delta_1, \delta_2, \ldots, \delta_M\} \) 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 \( t \), \( \delta_j \) of type GRC_MBDNA makes the concession first and at the beginning of GRNM the negotiation round is set to zero):

\[
U_t^{\delta_i}(P_t^R \rightarrow \delta_j) = (RP_i - P_t^R)/(RP_i - IP_i)
\]

and

\[
U_t^{\delta_i}(P_t^R \rightarrow \delta_j) = (\delta_j - P_t^R)/(\delta_j - IP_i)
\]

where \( RP_i \) is \( \delta_i \)’s reserve price, \( IP_i \) is \( \delta_i \)’s initial price, \( P_t^R \) is \( \delta_i \)’s proposal at negotiation round \( t \) and \( P_t^R \) is \( \delta_i \)’s proposal at negotiation round \( t \). For example a GRC_MBDNA considers 100S to buy a special type of resource (i.e., \( RP_i = 100S \)) and starts the negotiation process with 20S (i.e., \( IP_i = 20S \)). From GRC_MBDNA’s perspective 20S is the best price that can be paid to buy that type of resource (as 20S generates the highest utility for GRC_MBDNA, \( \{(100S - 20S)/(100S)\} = 1 \) and saves 80S for him. Also from GRC_MBDNA’s perspective 100S is the worst price that can be paid to buy that type of resource (as 100 generates the lowest utility for GRC_MBDNA, \( \{(100S - 20S)/(100S)\} = 0 \) and saves nothing for him. Furthermore, let assume that the proposed price from \( \delta_k \) at negotiation round \( t-1 \) is 62S. At negotiation round \( t \) the negotiator \( \delta_i \) makes its potential concession amount by considering current market situation. Let assume that the potential concession amount of \( \delta_i \) that can be proposed to \( \delta_k \) is equal to 50S. Now \( \delta_i \) decides to accept 62S or continue the negotiation process by proposing 50S. This decision is made by computing the utilities generated from 62S and 50S as follows: \( U_t^{\delta_i}(P_t^R \rightarrow \delta_k) = \{(100S - 62S)/(100S)\} = 0.5 \) and \( U_t^{\delta_i}(P_t^R \rightarrow \delta_k) = \{(100S - 50S)/(100S)\} = 0.5 \). By comparing the generated utilities of 50S and 62S, \( \delta_i \) 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 \( \delta_i \in \{\delta_1, \delta_2, \ldots, \delta_M\} \) 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 \( t \)):

\[
U_t^{\delta_i}(P_t^R \rightarrow \delta_j) = (P_t^R - RP_j)/(IP_j - RP_j)
\]

and

\[
U_t^{\delta_i}(P_t^R \rightarrow \delta_j) = (P_t^R - RP_j)/(IP_j - RP_j)
\]

where \( RP_j \) is \( \delta_j \)’s reserve price, \( IP_j \) is \( \delta_j \)’s initial price, \( P_t^R \) is \( \delta_j \)’s proposal at negotiation round \( t \) and \( P_t^R \) is \( \delta_j \)’s proposal at negotiation round \( t \). For example a GRO_MBDNA cannot sell its resource less than 20S (i.e., \( RP_j = 20S \)) and starts the negotiation process with 100S (i.e., \( IP_j = 100S \)). From GRO_MBDNA’s perspective 100S is the best price that can be achieved in trading process (as 100 generates the highest utility for GRO_MBDNA, \( \{(100S - 20S)/(100S)\} = 1 \) and makes maximum revenue (i.e., 80S) for him. Also from GRO_MBDNA’s perspective 20S is the worst price that can be achieved in trading process (as 20 generates the lowest utility for GRO_MBDNA, \( \{(20S - 100S)/(20S)\} = 0 \) and makes no profit for him. Furthermore, let assume that the proposed price from \( \delta_k \) at negotiation round \( t-1 \) is 50S. At negotiation round \( t \) the negotiator \( \delta_i \) makes its potential concession amount by considering current market situation. Let assume that the potential concession amount of \( \delta_i \) that can be proposed to \( \delta_k \) is equal to 62S. Now \( \delta_i \) should decide to accept 62S or continue the negotiation process by proposing 50S. This decision is made by computing the utilities generated from 50S and 62S as follows: \( U_t^{\delta_i}(P_t^R \rightarrow \delta_k) = \{(62S - 50S)/(100S - 20S)\} = 0.5 \) and \( U_t^{\delta_i}(P_t^R \rightarrow \delta_k) = \{(62S - 20S)/(100S - 20S)\} = 0.5 \). By comparing the generated utilities of 50S and 62S, \( \delta_i \) decides to continue the negotiation process instead of accept the counter offer. Rationally, from
Negotiation strategy
In each round of the negotiation, δ_t’s choice is called a strategy. As MDAs and MBDNAs focus on single-issue (e.g., price) negotiation, the amount of concession determination, at negotiation round t, is a chosen strategy by δ_t. 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_t to its trading partner δ_k at round t is P^{t}_{d(t)} → δ_kt and the proposal of δ_k to δ_t at round t is P^{t}_{d(k)} → δ_k. Also, let U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] and U^{t}_{d(k)}[P^{t}_{d(k)} → δ_k] be the utilities of δ_t if δ_k accepts δ_t’s proposal and the best utility generated for δ_k if δ_k accepts the counter proposal of δ_t at {δ_kt, δ_k → δ_k | no.trading_partner | }, at t respectively. The (best) spread in the current cycle t is

\[ k_t = U^{t}_{d(t)}[P^{t}_{d(t)} → δ_kt] - U^{t}_{d(k)}[P^{t}_{d(k)} → δ_k] \]

(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:

\[ U^{t+1}_{d(t)}[P^{t}_{d(t)} → δ_k] = k_{t+1} + U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] \]

(4)

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

\[ con_t = k_t - k_{t+1} \]

(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}_{d(t)}), competition (C^{t}_{d(t)}) and deadline (T^{t}_{p(h)}) (Sim, 2005):  

\[ k_{t+1} = [O^{t}_{d(t)}(no.trading_partner)_{t}, U^{t}_{d(t)}[P^{t}_{d(t)} → δ_kt]U^{t}_{d(k)}[P^{t}_{d(k)} → δ_k]C^{t}_{d(t)}(no.trading_partner \times T^{t}_{p(h)}(t, \delta^{t}_{deadline})),] \]

(6)

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

(a) Opportunity function (O^{t}_{d(t)})
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_t’s opportunity function determines the amount of concession based on (1) trading alternatives (number of trading partners no.trading_partner) and (2) differences in utilities (U^{t}_{d(t)}[P^{t}_{d(t)} → δ_kt]) generated by the proposal of δ_t and the counter proposal(s) of its trading partner(s) (U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k]) and is calculated thus:

\[ O^{t}_{d(t)}(no.trading_partner_{t}, U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k], \langle U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] \rangle) = 1 - \prod_{j=1}^{n} \frac{U^{t}_{d(j)}[P^{t}_{d(j)} → δ_k] - U^{t}_{d(j)}[P^{t}_{d(j)} → δ_j] - c^{k_j}}{(U^{t}_{d(j)}[P^{t}_{d(j)} → δ_k] - c^{k_j})} \]

(7)

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

(b) Competition function (C^{t}_{d(t)})
As mentioned in Sim (2005, p. 714), since market-driven agents are utility maximizing agents, an agent δ_t is more likely to reach a consensus if its proposal is ranked the highest by some other agent δ_k. Let an agent δ_t have no.competitorδ_t and no.trading_partnerδ_t trading partners at round t. If the proposal of δ_t’s competitor agent (e.g., δC_t ∈ \{δC_1, δC_2, ..., δC_{no.competitorδ_t} \}) generates a utility \langle U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] \rangle for δ_k, and the proposal of δ_t generates a utility \langle U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] \rangle for δ_k, by considering the mentioned concept, the proposal of δ_t is ranked the highest by δ_k if U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] > \langle U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] \rangle \langle U^{t}_{d(t)}[P^{t}_{d(t)} → δ_k] \rangle. So, the probability of δ_t being considered the most preferred trading partner by at least one of δ_k ∈ \{δ_1, δ_2, ..., δ_{no.trading_partnerδ_t} \} is calculated thus:

\[ CC^{t}_{d(t)}(no.trading_partnerδ_t, no.trading_partnerδ_t) = 1 - [\text{no.trading_partnerδ_t}] \cdot [\text{no.competitorδ_t}] + 1 \cdot \text{no.trading_partnerδ_t} \]

(8)

(c) Time function (T^{t}_{p(h)})
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 what 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):

\[ T^{t}_{p(h)}(t, \delta^{t}_{deadline}) = 1 - \left( \frac{t}{t^{\delta^{t}_{deadline}}} \right)^{\lambda} \]

(9)

where δ_t’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_t’s deadline (e.g., a time frame by which δ_t needs negotiation result) by t^{\delta^{t}_{deadline}}, and current negotiation round by t. λ and Ψ 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 < λ < ∞) — δ_t makes smaller concession in early rounds and larger concession in later rounds.
ii. Linear (or Neutral: λ = 1) — δ_t makes a constant rate of concession.
iii. Concorlatory (or Conccder or Defensive): 0 < \lambda < 1 — \delta_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., \( c_n \)) through (5) where, the appropriate value of \( k_{t+1} \) is defined by considering market driven factors, negotiator \( \delta_i \)'s trading partner’s concession behavior, closeness of negotiator \( \delta_i \)'s proposal to average of its trading partners’ proposals, bargaining power of negotiator \( \delta_i \)'s trading partner and negotiator \( \delta_i \)'s time preference:

\[
k_{t+1} = F_{ST}^i \times k_t
\]

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

\[
F_{ST}^i = \kappa_1 [SPI_{t}^i + (PreBehav_Dependence_{t}^{i} \times IST_{t}^i)]
\]

where \( \kappa = 1/2 \) if \( [SPI_{t}^i + (PreBehav_Dependence_{t}^{i} \times IST_{t}^i)] \) is greater than one, else \( \kappa = 1 \). Also \( PreBehav_Dependence_{t}^{i} \) is previous concession behavior of negotiator \( \delta_i \)'s trading partner factor which is considered as penalty amount for misbehaved trading partners and \( IST_{t}^i \) is denoted by (12):

\[
IST_{t}^i = NC_{t}^i \times NTP_{t}^i \times FTP_{t}^i \times DTPAP_{t}^i \times TP_{t}^i
\]

where \( NC_{t}^i \), \( NTP_{t}^i \), \( FTP_{t}^i \), \( DTPAP_{t}^i \) and \( TP_{t}^i \) 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 \( F_{ST}^i \) are described in details:

(a) Number of competitors \( (NC_{t}^i) \)

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., \( no\_competitor_{t-1}^{i} / \text{no\_trading\_partner}_{t-1}^{i} + no\_competitor_{t-1}^{i} \)) 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., \( no\_competitor_{t-2}^{i} / \text{no\_trading\_partner}_{t-2}^{i} + no\_competitor_{t-2}^{i} \)) is considered. The new perspective of concession factor of trading competition is determined as

\[
IF \text{ it is a first } \delta_i \text{'s negotiation round OR (no\_competitor}_{t-1}^{i} = 0) \text{ THEN }
\]

\[
NC_{t}^{i} = 1 - \frac{\text{no\_competitor}_{t-1}^{i}}{\text{no\_trading\_partner}_{t-1}^{i} + \text{no\_competitor}_{t-1}^{i}}
\]

Else

\[
IF \text{ (no\_competitor}_{t-1}^{i} > \text{no\_competitor}_{t-1}^{i}) \text{ THEN }
\]

\[
NC_{t}^{i} = 1 - \left[ \frac{\text{no\_competitor}_{t-1}^{i}}{\text{no\_trading\_partner}_{t-1}^{i} + \text{no\_competitor}_{t-1}^{i}} \times \left( 1 + \frac{\text{no\_competitor}_{t-1}^{i}}{\text{no\_trading\_partner}_{t-1}^{i} + \text{no\_competitor}_{t-1}^{i}} \right)^2 \right]
\]

(b) Number of trading partners\( (NTP_{t}^i) \)

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 ratio of 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 number of current GRNM’s participants (i.e., \( \text{no\_trading\_partner}_{t-1}^{i} + \text{no\_competitor}_{t-1}^{i} \)) 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., \( \text{no\_trading\_partner}_{t-2}^{i} + \text{no\_competitor}_{t-2}^{i} \)) is considered. The new perspective of concession factor of trading cooperation is determined as

\[
IF \text{ (no\_trading\_partner}_{t-1}^{i} > \text{no\_trading\_partner}_{t-1}^{i}) \text{ THEN }
\]

\[
NC_{t}^{i} = 1 - \left[ \frac{\text{no\_trading\_partner}_{t-1}^{i}}{\text{no\_trading\_partner}_{t-1}^{i} + \text{no\_competitor}_{t-1}^{i}} \times \left( 1 + \frac{\text{no\_trading\_partner}_{t-1}^{i}}{\text{no\_trading\_partner}_{t-1}^{i} + \text{no\_competitor}_{t-1}^{i}} \right)^2 \right]
\]
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’s chance of reaching a consensus on its own terms increases as FTP tends to become one.

(c) **Flexibility in negotiator's trading partner's proposal (FTP)**

From an agent’s point of view, the difference between trading partners’ 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 δi’s trading partner increase as the difference between δi’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 δi’s trading partner’s bargaining power amount will be high and vice versa) and is reflected by flexibility concept.

It is assumed that the last two proposals of δi’s trading partner (e.g., δi0) are Pr and Pr−1 (recall that Rubinstein’s sequential alternating offer protocol is used in our work). In negotiation round t which it is an agent δi turn to make concession amount (i.e., Pt), it reacts to δi’s bargaining power amount (i.e., Pr−1−Pr) by considering a factor in name flexibility in δi’s trading partner’s proposal in the hope of reaching consensus with δi. When the next negotiation round which it is an agent δi turn to move (i.e., t = 2) is reached, since δi has reaceted to the changes of its δi’s bargaining power amount up to previous negotiation time which it was an agent δi turn to move (i.e., t), it is rational that δi just reacts to the last bargaining power amount of trading partner from that time.

A proposed factor in name flexibility in δi’s trading partner’s proposal is defined as the difference of ratio between Pr−1 and Pr−2 (i.e., the last two proposals of δi) to the difference between Pr−1 and Pr−2 (i.e., the last proposal of δi):

\[
FTP_i^t = \begin{cases} 
\frac{Pr-1 - Pr-2}{Pr-1 - Pr-2} & \text{for } t > 2 \\
1 & \text{for } 0 \leq t \leq 2 
\end{cases}
\]  

(15)

In fact, the bargaining power of δi’s trading partner decrease as FTP tends to become one. Consequently, with respect to FTP, a negotiator δi can make a smaller concession as FTP tends to become one.

(d) **Negotiator’s proposal deviation of the average of its trading partners’ proposals (DTPAP)**

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 

\[
\sum_{k=1}^{|no.trading._partner^t|} P_k^t / |no.trading._partner^t|
\]

denote the average of δi’s trading partners’ proposals at round t−1. FTP (see (16)) is the ratio of difference between δi’s last proposal (e.g., P-t,1) and the average of δi’s trading partners’ proposals at round t−1. In (16) we just consider the situation that is not suitable for negotiator δi, so if this is equal to or greater than the average of δi’s trading partners’ proposals at round t−1, the RD is considered to be zero:

\[
RD_i^t = \left(\frac{\sum_{k=1}^{|no.trading._partner^t|} P_k^t / |no.trading._partner^t| - P_{t-1}}{\sum_{k=1}^{|no.trading._partner^t|} P_{t-2} / |no.trading._partner^t| - P_{t-2}}\right) \quad \text{for } t \geq 2
\]

(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 δi should be increased as RD tends to become one (e.g., DTPAP tends to become zero).

(e) **Negotiator’s time preference (TP)**

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 δi has a lower chance of reaching a consensus”. Hence, the concession rate that is made by δi should be increased as TP tends to become zero (e.g., negotiator’s deadline is reached).

(f) **Previous concession behavior of negotiator’s trading partner (PrevBehave_Depend)**

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 meet each other previously in numbers of GRNs, so first of all we analyze work load traces from http://www.cs.hujii.ac.il/labs/parallel/workload/logs.html to investigate this. By analyzing work load traces we see that the main pattern observed in these traces is the following: when a grid’s resource allocators meet each other, they tend to make smaller concessions in the first rounds of negotiation, and then increase their concessions as the negotiation time passes.

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’s chance of reaching a consensus on its own terms increases as FTP tends to become one.
negotiations between $\delta_i$ and $\delta_{j_k}$ in all the GRNm they both participated (e.g., $\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}$) and the extent of departure from the average of negotiation time between $\delta_i$ and $\delta_{j_k}$ in $\#\text{GRNM}_{\delta_{j_k}}$ (e.g., $\text{Ave.negot.time}_{\delta_{j_k}}$ $\sum_{k=1}^{\text{no.trading.partner}_{\delta_{j_k}}}$ $\text{Ave.negot.time}_{\delta_{j_k}}$). This means that the $\delta_{j_k}$ whose ratio of $\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}$ is the lowest and its $\text{Ave.negot.time}_{\delta_{j_k}}$ is too far from zero (makes a longer negotiation) is a misbehaved trading partner and deserve to receive more penalty:

$$\text{PreBehave}_{\delta_{k_i}} = \frac{1}{\eta} \left(1 - \mu \times \rho \right)$$  \hspace{1cm} (19)

- $\text{IF}\left( (\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}) = 1 \right)$ AND $\left( \text{Ave.negot.time}_{\delta_{j_k}} > 0 \right)$ THEN $\left( \mu = 0 \right)$ AND $\rho = \text{Ave.negot.time}_{\delta_{j_k}} / \sum_{k=1}^{\text{no.trading.partner}_{\delta_{j_k}}} \text{Ave.negot.time}_{\delta_{j_k}}$

- $\text{IF}\left( \sum_{k=1}^{\text{no.trading.partner}_{\delta_{j_k}}} \text{Ave.negot.time}_{\delta_{j_k}} = 0 \right)$ THEN $\left( \mu = \sum_{k=1}^{\text{no.trading.partner}_{\delta_{j_k}}} \text{Ave.negot.time}_{\delta_{j_k}} \right)$ AND $\rho = 0$

- $\text{IF}\left( (\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}) < 1 \right)$ AND $\left( \text{Ave.negot.time}_{\delta_{j_k}} < 0 \right)$ THEN $\left( \mu = \sum_{k=1}^{\text{no.trading.partner}_{\delta_{j_k}}} \text{Ave.negot.time}_{\delta_{j_k}} \right)$ AND $\rho = \text{Ave.negot.time}_{\delta_{j_k}}$

- $\text{IF}\left( (\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}) = 1 \right)$ AND $\left( \text{Ave.negot.time}_{\delta_{j_k}} = 0 \right)$ THEN $\left( \mu = 1 \right)$ AND $\rho = 0$

If the type of $\delta_i$ is GRCMDBNA, then $\text{no.trading.partner}_{\delta_{j_k}} = N_i - 1$, where $N_i$ represents the number of negotiators of type GRCMDBNA at round $t$. Also, if the type of $\delta_i$ is GRCMDBN, then $\text{no.trading.partner}_{\delta_{j_k}} = M_i - 1$, where $M_i$ represents the number of negotiators of type GRCMDBNA at a 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 $\text{PreBehave}_{\delta_{k_i}}$ factor is modeled based on two parameters: $\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}$ and $\text{Ave.negot.time}_{\delta_{j_k}}$. The best value of $\text{PreBehave}_{\delta_{k_i}}$ factor (i.e., zero) is achieved in case of $\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}} = 1$ and $\text{Ave.negot.time}_{\delta_{j_k}} = 0$. So, when the $\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}$ is equal to one the effectiveness of the first parameter in $\text{PreBehave}_{\delta_{k_i}}$ factor is ignored (i.e., $\mu = 0$) also when the $\text{Ave.negot.time}_{\delta_{j_k}}$ is equal to zero the effectiveness of the second parameter in $\text{PreBehave}_{\delta_{k_i}}$ factor is ignored (i.e., $\rho = 1$). Similarly, when the $\#\text{Succ}^{\text{neg}^{\text{S}_i} / \#\text{GRNM}_{\delta_{j_k}}}$ is equal to one and the $\text{Ave.negot.time}_{\delta_{j_k}}$ is equal to zero the effectiveness of both parameters in $\text{PreBehave}_{\delta_{k_i}}$ factor are ignored (i.e., $\mu = 1$ and $\rho = 0$). A local database in name $DB_{\text{behave}}$ is considered to store the previous concession behavior of negotiator $\delta_i$’s trading partners who participated in GRNM previously. The data fields of a $DB_{\text{behave}}$ database’s record, together with their brief description, are shown in Table 1.

### 3.4. Terminating negotiation process and executing task

When the negotiation process between $\delta_i$ (which its type is GRCMDBNA) and $\delta_j$ (which its type is GRCMDBNA) of each pair
reaches an agreement, $\delta_i$ (respectively, $\delta_j$) performs the following tasks:

(a) If $\delta_i$ (respectively, $\delta_j$) 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 $\delta_i\_id$ (respectively, $\delta_j\_id$) and $\delta'_k\_id$ (respectively, $\delta'_l\_id$) fields correspond to $\delta_i$ (respectively, $\delta_j$) and $\delta'_k$ (respectively, $\delta'_l$) respectively is exist (among retrieved records), Then effect the following changes in the retrieved records from $DB_{behave\_database}$:**

1. Update the $\text{Ave.neg.time}^{\delta_i}_{k}$ field value using $\text{previous value} + \text{new negotiation time}$

2. Increase the $\text{#Suc.neg}_{\delta_i\_\delta'_k}$ (respectively, $\text{#Suc.neg}_{\delta_j\_\delta'_l}$) 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, respectively, GROA).

[Table 1]

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_i_id$</td>
<td>The identifier of $\delta_i$ (e.g., kth trading partner of $\delta_i$)</td>
</tr>
<tr>
<td>#GRNMs$_{\delta_i_\delta_j}$</td>
<td>Total number of GRNMs in which both $\delta_i$ and $\delta_j$ participate</td>
</tr>
<tr>
<td>#Suc_neg$_{\delta_i_\delta_j}$</td>
<td>Total number of successful negotiations between $\delta_i$ and $\delta_j$, in all GRNMs which both participate</td>
</tr>
<tr>
<td>Ave.neg.time$_{\delta_i_\delta_j}$</td>
<td>The average negotiation time between $\delta_i$ and $\delta_j$ in all GRNMs which both participate</td>
</tr>
</tbody>
</table>

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

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

(a) If $\delta_j$ (respectively, $\delta_i$) 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 $\delta_i\_id$ (respectively, $\delta_j\_id$) and $\delta'_k\_id$ (respectively, $\delta'_l\_id$) fields correspond to $\delta_j$ (respectively, $\delta_i$) and $\delta'_k$ (respectively, $\delta'_l$) respectively is exist (among retrieved records), Then update the Ave. neg.time$_{\delta_i\_\delta_j}$ (respectively, Ave.neg.time$_{\delta_j\_\delta_i}$) field value using $\text{previous value} + \text{new negotiation time}$**

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.

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.

Table 2
Summary and comparison.

<table>
<thead>
<tr>
<th>References</th>
<th>MDAs</th>
<th>MBDNAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negotiation protocol</td>
<td>Bilateral negotiation model</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Multilateral negotiation model</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Determine the specific amount of concession to each negotiator's trading partner instead of the same amount to all</td>
<td>No</td>
</tr>
</tbody>
</table>

4.2. Experimental settings

<table>
<thead>
<tr>
<th>Input</th>
<th>Possible values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>E-market type</strong></td>
<td>GRC-favorable</td>
</tr>
<tr>
<td></td>
<td>$P_{GRC} &lt; 0.5$</td>
</tr>
<tr>
<td>Market density</td>
<td>Sparse</td>
</tr>
<tr>
<td>$P_{cm}$</td>
<td>0.25</td>
</tr>
<tr>
<td>Grid_load</td>
<td>0 &lt; Grid_load ≤ 1 (0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9)</td>
</tr>
<tr>
<td>Deadline (No. of rounds)</td>
<td>Short: 100</td>
</tr>
<tr>
<td>Job size(MI)</td>
<td>10–100</td>
</tr>
<tr>
<td>Resource capacity(MIPS)</td>
<td>200–3000</td>
</tr>
<tr>
<td>Negotiation model</td>
<td>MBDNAs' negotiation model is described in Section 3</td>
</tr>
<tr>
<td>Amount of time-preference, type of strategy: abbreviation</td>
<td>MDBNA time-preferences</td>
</tr>
<tr>
<td>$i = 1/3$, Conciliatory: CC</td>
<td>$i = 1$, Linear: L</td>
</tr>
<tr>
<td>$i = 2$, Conservative: CS</td>
<td>$i = 2$, Conservative: CS</td>
</tr>
<tr>
<td>$i = 3$, Conservative: CS</td>
<td>$i = 3$, Conservative: CS</td>
</tr>
</tbody>
</table>

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

Q3: What are the input parameters for setting grid simulation testbed and their possible values?

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 $P_{gen}$ (i.e., the probability of a GRC generating a task that needs computing resources 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 Ms. 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.

$$\text{Grid load} = \frac{R_p}{C_c}, \quad \text{where} \quad 0 < \text{Grid load} \leq 1$$

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. GRC’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 described 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 categorized into three categories: Dense, Moderate and Sparse.

4.2.7. Strategic negotiation model

The proposed Multigent-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 successfully by the GRC agents, and the average utility ($P_{avg}$) of a GRC’s set of tasks that is accomplished successfully by the GRC agents.

$$P_{tc} = \frac{N_{tot}}{N_{tot}}$$

- Average utility: Average utility defines how efficiently the available budget was spent. Let assume that $P_r$ 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 ($N_{ir}$):

$$U_{ir} = \frac{N_{ur}}{N_{ir}}$$

We assume that the more grid resources are leased out to the GRCs, the higher the resource utilization level is:

- Average utility: Average utility defines how efficiently the revenue was received. Let assume that $P_r$ 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
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.

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 \( d_i \)) 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.](image-url)
of time to complete a deal the bargaining positions of both MBDBAs 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_MBDBAs 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., \( \lambda = 1.0 \)). 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_MBDBAs 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 MBDBAs always get higher utilities by using new negotiation strategy. This is because MBDBAs 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., MBDBAs and MDAs) to reach any consensus so they have to concede more to
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. So, in high grid loadings (e.g., Grid_load = 0.9 and Grid_load = 1.0) GRC_MBDNAs are more likely...
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 MDBNAs and MDAs are stronger and they both likely to complete deals successfully (i.e., have higher success rate). However, as MDBNAs 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-MDBNAs 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., MDBNAs and MDAs). (2) Given the same Grid_load, MDBNAs achieved higher success rate in leasing out resources than MDAs. This is because more appropriate factors are considered for designing MDBNAs 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 MDBNAs and MDAs are stronger and they both likely to complete deals successfully (i.e., have higher success rate). However, as MDBNAs 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-MDBNAs 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.

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

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Basic Definition</th>
<th>Symbol</th>
<th>Basic definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{Ave_neg_time}^t_{d_i} \text{d}_k</td>
<td>The average negotiation time between \text{d}_i and \text{d}_k in all GRNMs which both participate</td>
<td>no_competitor^t_{d_i}</td>
<td>Number of \text{d}_i’s competitors at round t</td>
</tr>
<tr>
<td>\text{C}_i</td>
<td>The total computing capacity of the grid</td>
<td>no_trading_partner^t_{d_i}</td>
<td>Number of \text{d}_i’s trading partners at round t</td>
</tr>
<tr>
<td>\text{e}^t_{d_i}</td>
<td>The worst possible utility for \text{d}_i (e.g., if the negotiation ends in disagreement)</td>
<td>\text{MC}_i^t</td>
<td>MBDNAs’ competition function</td>
</tr>
<tr>
<td>\text{CC}_i^t</td>
<td>MBDNAs’ competition function</td>
<td>\text{MDA}_i^t</td>
<td>MBDNAs’ opportunity function</td>
</tr>
<tr>
<td>\text{con}^t_{d_i}</td>
<td>The amount of concession at negotiation round t</td>
<td>\text{MDA}_i^t</td>
<td>The probability of an agent being GRC agent</td>
</tr>
<tr>
<td>\text{DTPAP}^t_{d_i}</td>
<td>MBDNAs’ closeness function (e.g., \text{d}_i’s proposal deviation of the average of its trading partners’ proposals)</td>
<td>\text{neg}^t_{d_i}</td>
<td>The probability that an agent will enter the GRNM in each round of negotiation</td>
</tr>
<tr>
<td>\text{FTP}^t_{d_i}</td>
<td>MBDNAs’ flexibility function (i.e., flexibility in \text{d}_i’s trading partner’s proposal)</td>
<td>\text{time}^t_{d_i}</td>
<td>\text{d}_i’s proposal at round t</td>
</tr>
<tr>
<td>\text{FST}^t_{d_i}</td>
<td>Final price-oriented strategy that is taken by \text{d}_i</td>
<td>\text{P}_{tc}</td>
<td>Proposal of \text{d}_i at round t</td>
</tr>
<tr>
<td>\text{FTP}^t_{d_i}</td>
<td>MBDNAs’ flexibility function (i.e., flexibility in \text{d}_i’s trading partner’s proposal)</td>
<td>\text{P}_{tc}</td>
<td>The price that a consensus is reached by both parties</td>
</tr>
<tr>
<td>\text{GRCA}_i</td>
<td>\text{i}th grid resource consumer</td>
<td>\text{PreBehave}^t_{\text{Depend}^t_{d_i}}</td>
<td>The probability of a GRC generating a task that needs computing resources at each negotiation round</td>
</tr>
<tr>
<td>\text{GRC}_i</td>
<td>\text{i}th grid resource consumer agent</td>
<td>\text{P}_{ic}</td>
<td>Percentage of a GRC’s set of tasks that is accomplished by successful negotiation and leasing grid resources</td>
</tr>
<tr>
<td>\text{GRC_job_prof}^t_{d_i}</td>
<td>\text{GRC}_i’s pth job characteristics</td>
<td>\text{Reserve_Price}^t_{\text{of}}</td>
<td>MBDNAs’ behavior function (e.g., previous behavior of \text{d}_i)</td>
</tr>
<tr>
<td>\text{Grid_load}</td>
<td>Utilization status of computing resources</td>
<td>\text{PreBehave}^t_{\text{Depend}^t_{d_i}}</td>
<td>The expected amount of processing requested per time interval</td>
</tr>
<tr>
<td>\text{grid_name}</td>
<td>Name of observed grids in workload traces (<a href="http://www.cs.huji.ac.il/labs/parallel/workload/logs.html">http://www.cs.huji.ac.il/labs/parallel/workload/logs.html</a>)</td>
<td>\text{R}^t_{no_trading_partner}</td>
<td>Ratio of difference between the average of negotiator \text{d}<em>i’s trading partners’ proposals at round \text{t} – \text{t} – 1 (e.g., \text{NP}</em>{\text{no_trading_partner}^{t_k}}) and negotiator \text{d}<em>i’s last proposal (e.g., \text{P}</em>{\text{no_trading_partner}^{t_k}}) to the average of negotiator \text{d}_i’s trading partners’ proposals at round \text{t} – 1.</td>
</tr>
<tr>
<td>\text{GRNM_jobrequestee_directory}</td>
<td>Storage for submitting \text{GRO_resource_prof}^t_{d_i} of \text{GRO}_i(s) in GRNM</td>
<td>\text{RP}^t_{\text{of}}</td>
<td>Represents percentage of grid_name’s users that are observed previously inunique_user_set_grid_name</td>
</tr>
<tr>
<td>\text{GRNM_jobrequester_directory}</td>
<td>Storage for submitting \text{GRC_job_prof}^t_{d_i} of \text{GRCA}_i(s) in GRNM</td>
<td>\text{RP}^t_{\text{of}}</td>
<td>Reserve Price of \text{d}_i</td>
</tr>
<tr>
<td>\text{GRO}_j \text{GRO}_j</td>
<td>\text{j}th Grid Resource Owner</td>
<td>\text{t}^t_{\text{of}}</td>
<td>Negotiation round</td>
</tr>
<tr>
<td>\text{GRO_job_prof}^t_{d_i}</td>
<td>\text{j}th Grid Resource Owner Agent</td>
<td>\text{U}_{d_i}</td>
<td>\text{d}_i’s deadline (e.g., a time frame by which \text{d}_i needs negotiation result)</td>
</tr>
<tr>
<td>\text{GRO_job_prof}^t_{d_i}</td>
<td>\text{j}th Grid Resource Owner Agent</td>
<td>\text{U}_{d_i}</td>
<td>Time preference function</td>
</tr>
<tr>
<td>\text{GRO_job_prof}^t_{d_i}</td>
<td>\text{j}th Grid Resource Owner Agent</td>
<td>\text{tr}^t_{\text{of}}</td>
<td>Resource utilization level</td>
</tr>
<tr>
<td>\text{GRCA}_j</td>
<td>\text{r}th resource characteristics</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>Utility of \text{d}_i’s at round t if \text{d}_i accepts the proposal from \text{d}_j (\text{d}_j_p^t)</td>
</tr>
<tr>
<td>\text{GRCA}_j</td>
<td>\text{r}th resource characteristics</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>Utility of \text{d}_j’s at round t if \text{d}_j accepts the proposal from \text{d}_i (\text{d}_i_p^t)</td>
</tr>
<tr>
<td>\text{IC}_j</td>
<td>Number of negotiators of type GRO_MBDNA at round t</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>The set of observed unique users in the grid_name’s SWF archive (<a href="http://www.cs.huji.ac.il/labs/parallel/workload/logs.html">http://www.cs.huji.ac.il/labs/parallel/workload/logs.html</a>)</td>
</tr>
<tr>
<td>\text{MC}_i^t</td>
<td>Number of negotiators of type GRO_MBDNA</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>Total number of GRNMs in which both \text{d}_i and \text{d}_j participate</td>
</tr>
<tr>
<td>\text{MDA}_i^t</td>
<td>Maximum number of potential unique users of a grid in grid_name</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>Total number of successful negotiations between \text{d}_i and \text{d}_j, in all GRNMs which both participate</td>
</tr>
<tr>
<td>\text{NC}_i^t</td>
<td>The number of tasks that are successfully scheduled and executed</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>Negotiator agent who its turn to make concession</td>
</tr>
<tr>
<td>\text{N}_{\text{task}}</td>
<td>Total number of tasks requested by a GRC</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>\text{i}th trading partner of \text{d}_i</td>
</tr>
<tr>
<td>\text{N}_{\text{task}}</td>
<td>Total number of tasks requested by a GRC</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>\text{i}th competitor of \text{d}_i</td>
</tr>
<tr>
<td>\text{N}_{\text{task}}</td>
<td>Total number of tasks requested by a GRC</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>\text{d}_i’s time preference</td>
</tr>
<tr>
<td>\text{N}_{\text{total}}</td>
<td>The total amount of GRO’s idle resources</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>\text{i}th competitor of \text{d}_i</td>
</tr>
<tr>
<td>\text{N}_{\text{total}}</td>
<td>The total amount of GRO’s idle resources</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>\text{i}th competitor of \text{d}_i</td>
</tr>
<tr>
<td>\text{N}_{\text{total}}</td>
<td>The ratio of the amount of GRO’s idle resources being leased out and utilized</td>
<td>\text{utility}^t_{\text{of}}</td>
<td>\text{i}th competitor of \text{d}_i</td>
</tr>
</tbody>
</table>
Acknowledgment

We want to express our gratitude to Dr. Hui Li who graciously provided us with the Standard Workload Format archives through which the used traces are made publicly available.

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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