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 competition, (3) negotiator’s time preference, (4) flexibility in negotiator’s trading partner’s proposal, (5) negotiator’s proposal deviation from the average of its trading partners’ proposals, and (6) previous concession behavior of negotiator’s trading partner. In our experiments, we compare grid resource consumer (GRC) of type MBDNAs (respectively grid resource owner (GRO) of type MBDNAs) with MDAs (Market Driven Agents) in terms of the following metrics: total tasks complementation and average utility (respectively resource utilization level and average utility). The results show that by taking the proposed factors into account, MBDNAs of both types make a more efficient concession amount than MDAs and are, therefore, considered an appropriate mechanism for grid resource allocation in different grid workloads and market types.

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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 organizations and administrative domains (Buyya et al., 2002, p. 1508). As the computational grid focuses on large-scale resource sharing, and because grid resource owners (GROs) and grid resource consumers (GRCs) may have different goals, preferences and policies, which are characterized and specified through a utility model (or utility function), an efficient resource management, is central to its operations. The term resource management refers to the operations used to control how capabilities provided by grid resources and services are made available to other entities, whether users, applications, or services (Foster and Kesselman, 2004).

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

Numerous economic models (Buyya et al., 2002), including microeconomic and macroeconomic principles for resource management, are proposed in literature (Buyya et al., 2000; Huhns and Stephens, 2000; Buyya, 2002; Lai et al., 2005; Chunlin et al., 2009; Chunlin, 2011; Aminul et al., 2011). Negotiation-like protocols may be more appropriate than other commonly referenced works (e.g., see (Wolski et al., 2003; G-Commerce, 2001; Buyya and Vazhikudai, 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.
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 Multigagent-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 Multigagent-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 Layjuan, 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 each negotiation market side but also change the balance of one market side's participants to other market side's participants and update its negotiation strategies according to these changes.

(d) Determining the specific amount of concession to each negotiator's trading partner separately, instead of the same amount to all. Although there are many agent-based systems for negotiation in e-commerce (e.g., just to name a few: NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (Guttman and Maes, 1998), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007), Zhao and Li (2009), An (2011), SNAP (Czajkowski et al., 1999, 2002, 2005),) the strategies of most of them make the same concession amount for all negotiators' trading partners. In contrast, our work considers different concession amount for different negotiator's trading partners (by applying muti-criteria decision function) which provides more flexibility in keeping the chance of making deal (by computing rational and sufficiently minimum price) with at least one trading partner.

(e) Formulating a new market- and behavior-driven negotiation strategy. In comparison to existing negotiation agents (e.g., just to name a few: NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (Guttman and Maes, 1998), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007), Zhao and Li (2009), An, 2011, SNAP (Czajkowski et al., 1999, 2002, 2005)) more negotiation factors which are inspired from real-life trading market are considered to determine minimally sufficient concession amount.

(f) Providing negotiation agents of both types (i.e., GRO_MBDNAs and GRC_MBDNAs) and equipped them with the new proposed negotiation model to improve the profits of both e_market sides (i.e., GRC_e_market side and GRO_e_market side). By considering this issue we show that MBDNAs are appropriate tools for both sides of negotiation.

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

2. Related works

In this section we review and compare the existing state-of-the-art negotiation agents from the issues for making negotiation model in Sim (2010) and our extra proposed issue for making appropriate negotiation model points of view.
Whereas the agents in NDF (Faratin et al., 1998), 2-phase negotiation (Lang, 2005), service negotiation (Lawley et al., 2003), Kasbah (Chavez and Maes, 1996), Tete-a-Tete (extended Kasbah, which focuses on multiple-issue negotiation rather than single-issue negotiation) (Guttman and Maes, 1998), MDAs and EMDAs (Sim 2005a, 2005b, 2006; Sim and Ng, 2006, 2007), Zhao and Li, 2009, An, 2011) and our work considered the issue of time constraint, the agents in SNAP (Czajkowski et al., 1999, 2002, 2005) and policy-driven negotiation (Gimpel et al., 2003) did not consider this issue in designing the agents.

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

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

Whereas SNAP (Czajkowski et al., 1999, 2002, 2005) addresses the influence of grid resource allocation 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), Venugopalan 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., GRC_A) can have one or more jobs \( \{job_1, ... , job_n\} \). Jobs submitted by GRCs into a cluster have varying requirements depending on GRC-specific needs and expectations. The GRC's \( p \)th job characteristics (e.g., \( \{GRC_job_profile_p\} \) ) include the following: unique identifier, job length, job price, and the originator of the job (Sim, 2006, p. 1384), "Each computing machine \( M_{b}\) can be a single processor, a shared memory multiprocessor, or a distributed memory cluster of computers. \( M_{b}\) can be formed by one or more processing elements \( \{PE_{1}, ... , PE_{n}\} \), and each \( PE_{k} \) can have different speeds measured in terms of MIPS (millions of instructions per second)."

The GRO's rth resource characteristics (e.g., GRO_resource_profile_r) include unique identifier, the architecture of computing resource (e.g., HP alpha server), list of computing machines (e.g., \( \{M_{1}, ... , M_{k}\} \) ), required bandwidth length, required memory capacity, and expected and reserve prices of leasing a computing machine.

The GRC_A (respectively, GRO_A) should register each of its GRC_job_profile_p(s) (respectively, GRO_resource_profile_r(s)) in GRNM_jobrequester_directory (respectively, GRNM_jobrequester_directory).

3.2. Creating MBDNAs and providing their required information

It was noted in Sim (2010, p. 245) that "software agents, in particular, negotiation agents, can play an essential role in realizing
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 \textit{GRC\_MBDNA} and \textit{GRO\_MBDNA} entities) are expected to realize the grid vision. A \textit{GRC\_MBDNA} (respectively, \textit{GRO\_MBDNA}) is generated according to \textit{GRCA} (respectively, \textit{GROA}), which is registered in GRNM to perform the negotiation process.

In the following sections, each \textit{GRC\_MBDNA} (respectively, \textit{GRO\_MBDNA}) is represented by $d$ symbol for ease of reading. Also let assume that $k$th trading partner of negotiator $d_i$ is denoted by $d_{0_k}$.

Following are the functions performed by $d_i$ (which its type is \textit{GRC\_MBDNA}) in the second phase of resource allocation scenario:

1. Start the process of resource discovery (e.g., discovering appropriate \textit{GRO\_MBDNA}(s) that match with the $d_i$’s requirements).
2. Query \textit{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 $d_{0_k}$\_id field is equal to the identifier of one of $d_i$’s trading partners. The retrieved records are used to calculate the previous concession behavior of negotiators’ trading partners (details are provided in Section 3.3.3 – MBDNAs part I).
3. Increase the \#\textit{GRNM\_GRNM\_d}$_{i_k}$ field of retrieved records by one.

And the functions that are performed by $d_j$ (which its type is \textit{GRO\_MBDNA}) in the second phase of resource allocation scenario are as same as the second and third functions performed by $d_i$ which its type is \textit{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; ...$t$}. In each period $t$ $\in T$, one of the players, say $i$, proposes an agreement, and the other player $j$ either accepts it or rejects it. If the offer is accepted, then the negotiation ends, and the agreement is implemented. If the offer is rejected, then the process passes to period $t+1$; in this period, player $j$ proposes an agreement, which player $i$ may accept or reject. The negotiation process will go on in this way.

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

1. Time is discrete and is indexed by $\{0,1,2,...\}$—it is a logical and believable assumption, which is made in other models also (Sim, 2005, p. 713) and (Osborne and Rubinstein, 1990, p. 152).

![Fig. 1. 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).

The negotiation objective is the expected price that will be obtained by the negotiator (respectively, assigning) decisions within the budget constraints.

3.3.2. Negotiation utility model

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

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

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

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 \(t\), \(\delta_i\) of type GRC_MBDNA makes the concession first and at the beginning of GRNM the negotiation round is set to zero):

\[
U_{GRC}^t[\delta_i \rightarrow \delta_j] = (RP_{\delta_i}^t - P_i^t)/(RP_{\delta_i}^t - IP_{\delta_i})
\]

and

\[
U_{GRO}^t[\delta_i \rightarrow \delta_j] = (P_j^t - RP_{\delta_i}^t)/(RP_{\delta_i}^t - IP_{\delta_i})
\]

where \(P_j^t\) is \(\delta_i\)'s reserve price, \(IP_{\delta_i}^t\) is \(\delta_i\)'s initial price, \(P_i^t\) is \(\delta_i\)'s proposal at negotiation round \(t\) and \(P_j^t\) is \(\delta_i\)'s proposal at negotiation round \(t\). For example a GRC_MBDNA considers 100$ to buy a special type of resource (i.e., \(RP_{\delta_i} = 100$) and starts the negotiation process with 20$ (i.e., \(IP_{\delta_i} = 20$). From GRC_MBDNA's perspective 20$ is the best price that can be paid to buy that type of resource (as 20$ generates the highest utility for GRC_MBDNA, (\(100$ - 20$)/(100$) = 1) and saves 80$ for him. Also from GRC_MBDNA's perspective 100$ is the worst price that can be paid to buy that type of resource (as 100$ generates the lowest utility for GRC_MBDNA, (\(100$ - 20$)/(100$) = 0) and saves nothing for him. Furthermore, let assume that the proposed price from \(\delta_i\) at negotiation round \(t-1\) is 62$. 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 \(\delta_j\) is equal to 50$. Now \(\delta_i\) should decide to accept 62$ or continue the negotiation process by proposing 50$. This decision is made by computing the utilities generated from 62$ and 50$ as follows:

\[
U_{GRC}^t[\delta_i \rightarrow \delta_j] = (P_j^t - RP_{\delta_i}^t)/(RP_{\delta_i}^t - IP_{\delta_i})
\]

\[
U_{GRO}^t[\delta_i \rightarrow \delta_j] = (P_j^t - IP_{\delta_i}^t)/(IP_{\delta_i}^t - RP_{\delta_i}^t)
\]

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

Also Sim (2005a, 2006) described a negotiation protocol for specifying the negotiation activities among GRCAs and GROAs in MDAs.
GRO_MBDA's perspective the price that makes more profit is considered as more appropriate price.

If the proposed deal from δ_i of type GRC_MBDA at round t (e.g., \(P^k_i\)) is not greater than the one at round \(t+2\) (e.g., \(P^k_{i+2}\)), then \(U^k_{+1}[P^k_i \rightarrow \delta_{k,i}] > U^k_{+1}[P^k_{i+2} \rightarrow \delta_{k,i}]\). Also, If the proposed deal from δ_j of type GRO_MBDA at round t (e.g., \(P^k_j\)) is greater than the one at round \(t+2\) (e.g., \(P^k_{j+2}\)), then \(U^k_{+1}[P^k_j \rightarrow \delta_{k,j}] > U^k_{+1}[P^k_{j+2} \rightarrow \delta_{k,j}]\). Recall that by using Rubinstein's sequential alternating offer protocol (Rubinstein, 1982), negotiators in make alternate offers rather than moving simultaneously.

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

### 3.3.3. Negotiation strategy

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

**Market Driven Agents (MDAs)** (Sim, 2005a, 2005b, 2006; Sim, 2002, 2003) investigated the way to assess the probability of successfully reaching a consensus in different market situations by considering the difference between the payoffs generated by the proposal of negotiator and the proposal of its trading partners at each round t. Coming to details, let assume that the proposal of δ_i to its trading partner δ_j at round t is \(P^k_i \rightarrow \delta_{k,i}\) and the proposal of \(\delta_j\) to \(\delta_i\) at round t is \(P^k_j \rightarrow \delta_{k,j}\). Also, let \(U^k_i[P^k_i \rightarrow \delta_{k,i}]\) and \(U^k_j[P^k_j \rightarrow \delta_{k,j}]\) be the utilities of \(\delta_i\) if \(\delta_j\) accepts \(\delta_i\)'s proposal and the best utility generated for \(\delta_j\) if \(\delta_i\) accepts the counter proposal of \(\delta_j\) in \([\delta_{k,j}, \delta_{k,j+1}, ..., \delta_{k,n}]\) at t respectively. The (best) spread in the current cycle t is

\[
k_t = U^k_i[P^k_i \rightarrow \delta_{k,i}] - U^k_j[P^k_j \rightarrow \delta_{k,j}]
\]

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:

\[
U^k_{+1}[P^k_i \rightarrow \delta_{k,i}] = k_{t+1} + U^k_i[P^k_i \rightarrow \delta_{k,i}]
\]

Finally, the amount of concession at round t (e.g., \(c_{tot}\)) is

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

In designing MDAs, the appropriate value of the expected difference \(k_{t+1}\) between the proposal of a agent and its trading partner is determined by examining the current market situation, taking into account factors such as opportunity (\(O^k_i\)), competition (\(C^k_i\)) and deadline (\(TP^k_i\)) (Sim, 2005):

\[
k_{t+1} = [O^k_i(no.trading.partner) \times U^k_i[P^k_i \rightarrow \delta_{k,i}] \times U^k_j[P^k_i \rightarrow \delta_{k,j}] \\ \times (no.competitor)^i \times no.trading.partner^j] \times TP^k_i(t, \tau_{deadline}, \lambda)
\]

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

(a) **Opportunity function (\(O^k_i\))**

In a multilateral negotiation, having outside options may give a negotiator more bargaining power. However, negotiators may still break down if the proposals between two negotiators are too far apart. The δ_i's opportunity function determines the amount of concession based on (1) trading alternatives (number of trading partners no.trading.partner^j) and (2) differences in utilities (\(U^k_i[P^k_i \rightarrow \delta_{k,i}]\)) generated by the proposal of δ_i and the counter proposal(s) of its trading partner(s) (\(U^k_j[P^k_i \rightarrow \delta_{k,j}]\)) and is calculated thus

\[
O^k_i(no.trading.partner) \times U^k_i[P^k_i \rightarrow \delta_{k,i}] < U^k_j[P^k_i \rightarrow \delta_{k,j}]
\]

\[
= 1 - \prod_{j=1}^{n} \left( \frac{U^k_j[P^k_i \rightarrow \delta_{k,i}] - U^k_j[P^k_j \rightarrow \delta_{k,j}]}{U^k_j[P^k_i \rightarrow \delta_{k,i}] - \delta_{k,i}} \right)
\]

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

(b) **Competition function (\(CC^k_i\))**

As mentioned in Sim (2005, p. 714), since market-driven agents are utility maximizing agents, an agent δ_i is more likely to reach a consensus if its proposal is ranked the highest by some other agent δ_j. Let an agent δ_i has no.competitor^j and no trading partners at round t. If the proposal of δ_i's competitor agent (e.g., δCi \(\in \{\deltaCI, \deltaC2, ..., \deltaCno.competitor\}^j\)) generates a utility \(U^k_i[P^k_i \rightarrow \delta_{k,i}]\) for δ_j.k and the proposal of δ_j generates a utility \(U^k_j[P^k_j \rightarrow \delta_{k,j}]\) for δ_i, by considering the mentioned concept, the proposal of δ_j is ranked the highest by δ_i, if \(U^k_i[P^k_i \rightarrow \delta_{k,i}] > U^k_j[P^k_j \rightarrow \delta_{k,j}] \forall U^k_j[P^k_j \rightarrow \delta_{k,j} \in \{\deltaCI, \deltaC2, ..., \deltaCno.competitor\}^j\). So, the probability of δ_i being considered the most preferred trading partner by at least one of \(\delta_j \in \{\deltaCI, \deltaC2, ..., \deltaCno.competitor\}^j\) is calculated thus,

\[
CC^k_i(no.competitor^j) \times no.trading.partner^j
\]

\[
= 1 - [(no.competitor^j) / no.competitor^j + 1]no.trading.partner^j
\]

(c) **Time function (\(TP^k_i\))**

As noted by Binmore and Dasgupta (see Binmore and Dasgupta, 1987, p. 14), the passage of time has a cost in terms of both dollars and the sacrifice of utility which stems from the postponement of consumption, and it will be precisely this cost which motivates the whole bargaining process. If it did not matter when the parties agreed, it would not matter whether they agreed at all. Lang, (2005), Lawley et al. (2003), Sim (2005a, 2005b, 2006), and Sim and Ng (2006) take into consideration the mentioned concept by introducing time discount factor in their proposed concession making strategies.

So, the effect of time discount factor in negotiator's bargaining power can be modeled via time-dependent function. Some state-of-the-art time-dependent functions are reviewed by Sim (2010), p. 253). MDAs' time function is calculated as Sim (2005).

\[
TP^k_i(t, \tau_{deadline}, \lambda) = 1 - \left( \frac{t}{\tau_{deadline}} \right)^\lambda
\]

where \(\delta_i\)'s time preference is denoted by \(\lambda\) (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, \(\delta_i\)'s deadline (e.g., a time frame by which \(\delta_i\) needs negotiation result) by \(\tau_{deadline}\), and current negotiation round by \(t\). \(\lambda\) and \(\tau_{deadline}\) are considered private information. Following are the three major classes of concession-making strategies with respect to the remaining trading time (details are discussed by Sim, 2005):

i. **Conservative (or Boulware or aggressive):** \(1 < \lambda < \infty\) — \(\delta_i\) makes smaller concession in early rounds and larger concession in later rounds.

ii. **Linear (or Neutral):** \(\lambda = 1\) — \(\delta_i\) makes a constant rate of concession.
iii. 

Conciliatory (or Conceder or Defensive: 0 < \( \delta \) < 1) — \( \delta \) 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., cont) through (5) where, the appropriate value of \( k_{1,t} \) is defined by considering market driven factors, negotiator \( \delta \)'s trading partner’s concession behavior, closeness of negotiator \( \delta \)'s proposal to average of its trading partners’ proposals, bargaining power of negotiator \( \delta \)'s trading partner and negotiator \( \delta \)'s time preference:

\[
k_{1,t+1} = FST_{1,t} \times k_t
\]

where \( FST_{1,t} \) is a price-oriented strategy that is defined to determine the amount of concession at round \( t \) and is defined through (11):

\[
FST_{1,t} = k[IST_{1,t} + (PreBehave_Depend_{1,t} \times IST_{1,t})]
\]

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

\[
IST_{1,t} = NC^{t}_{1,t} \times NTP^{t}_{1,t} \times FTP^{t}_{1,t} \times DTPAP^{t}_{1,t} \times TP^{t}_{1,t}
\]

where \( NC^{t}_{1,t}, NTP^{t}_{1,t}, FTP^{t}_{1,t}, DTPAP^{t}_{1,t} \) and \( TP^{t}_{1,t} \) are number of competitors, number of trading partners, flexibility in negotiator's trading partner's proposal, negotiator's proposal deviation of the average of its trading partners' proposals and negotiator's time preference factors respectively.

Following the factors that are included in a price-oriented strategy \( FST_{1,t} \) are described in details:

a. Number of competitors (\( NC^{t}_{1,t} \))

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 GRMN's participants (i.e., \( \frac{no\text{-}competitor^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}} \)) and the ratio of number of competitors in previous negotiation round \( t-1 \) to the total number of GRMN’s participants in previous negotiation round \( t-1 \) (i.e., \( \frac{no\text{-}competitor^{t-1}_{1,t}}{no\text{-}trading\text{-}partner^{t-1}_{1,t} + no\text{-}competitor^{t-1}_{1,t}} \)) is considered. The new perspective of concession factor of trading competition is determined as

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

\[
NC^{t}_{1,t} = 1 - \frac{no\text{-}competitor^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}}
\]

Else

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

\[
NC^{t}_{1,t} = 1 - \left[ \frac{no\text{-}competitor^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}} \times \left( 1 + \frac{no\text{-}competitor^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}} \right) \right]^{-2} - \frac{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}}
\]

b. Number of trading partners (\( NTP^{t}_{1,t} \))

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 partner's offer/bid may be high”. Hence, negotiators' bargaining power should be modeled by considering the number of trading partners. Even though the MDAs have shown good performance, there still exist some limitations which may restrict its application in the real world. In fact the current MDAs cannot handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain. To face with these limitations, we extend the concession factor of trading opportunity. There are two cases that need to be considered, namely: (1) change in the number of negotiator's trading partners and (2) change in the ratio of the total number of negotiator's competitors to the total number of negotiator's trading partners. In other word the deference between the ratio of number of current trading partners to the total number of current GRMN's participants (i.e., \( \frac{no\text{-}trading\text{-}partner^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}} \)) and the ratio of number of trading partners in previous negotiation round \( t-1 \) to the total number of GRMN’s participants in previous negotiation round \( t-1 \) (i.e., \( \frac{no\text{-}trading\text{-}partner^{t-1}_{1,t}}{no\text{-}trading\text{-}partner^{t-1}_{1,t} + no\text{-}competitor^{t-1}_{1,t}} \)) is considered. The new perspective of concession factor of trading opportunity is determined as

\[
NC^{t}_{1,t} = 1 - \left[ \frac{no\text{-}trading\text{-}partner^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}} \times \left( 1 + \frac{no\text{-}trading\text{-}partner^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}} \right) \right]^{-2} - \frac{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}}{no\text{-}trading\text{-}partner^{t}_{1,t} + no\text{-}competitor^{t}_{1,t}}
\]

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

(d) Negotiator’s proposal deviation of the average of its trading partners’ proposals (DTPAP$^{\delta_i}$; closeness factor)

Another criterion for making the pattern of concession is the relative distance between the proposal of a negotiator agent and all the proposals of its trading partners. 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 $\sum_{k=1}^{\text{no.trading.partner}_{i-1}} p_{k_{t-1}} / \text{no.trading.partner}_{i-1}$ denote the average of $\delta_i$’s trading partners’ proposals at round $t-1$. $RD^{\delta_i}$ (see (16)) is the ratio of difference between $\delta_i$’s last proposal (e.g., $P_{t-2}^{\delta_i}$) and $\sum_{k=1}^{\text{no.trading.partner}_{i-1}} p_{k_{t-1}} / \text{no.trading.partner}_{i-1}$ to the average of $\delta_i$’s trading partners’ proposals at round $t-1$. In (16) we just consider the situation that is not suitable for negotiator $\delta_i$, so if $P_{t-2}^{\delta_i}$ is equal to or greater than $\sum_{k=1}^{\text{no.trading.partner}_{i-1}} p_{k_{t-1}} / \text{no.trading.partner}_{i-1}$, the $RD^{\delta_i}$ is considered to be zero:

$$RD^{\delta_i} = \left\{ \begin{array}{ll}
1 - RD^{\delta_i} & \text{for } t \geq 2 \\
1 & \text{for } 0 \leq t < 2
\end{array} \right. \quad (17)$$

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 $\delta_i$ should be increased as $RD^{\delta_i}$ tends to become one (e.g., $DTPAP^{\delta_i}$ tends to become zero).

(e) Negotiator’s time preference ($TP^{\delta_i}$)

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

(f) Previous concession behavior of negotiator’s trading partner ($PreBehave$; Depend$^{\delta_i}$)

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

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 $\delta_i$’s chance of reaching a consensus on its own terms increases as $NTP^{\delta_i}$ tends to become one.

(c) Flexibility in negotiator’s trading partner’s proposal ($FTP^{\delta_i}$)

From an negotiator agent $\delta_i$’s point of view, the difference between its trading partner’s two proposals which are made in two consecutive negotiation rounds which that trading partner turn to move (e.g., determine the amount of concession) can be defined as that trading partner’s bargaining power amount. The bargaining power amount of $\delta_i$’s trading partner increase as the difference between $\delta_i$’s trading partner’s two proposals which are made in two consecutive negotiation rounds that its turn to move tends to become zero. The trading partner’s bargaining power amount may not be fixed (means in suitable market conditions an agent $\delta_i$’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 $\delta_i$’s trading partner (e.g., $\delta_j$) are $P_{t-1}^{\delta_j}$ and $P_{t-2}^{\delta_j}$ (recall that Rubinstein’s sequential alternating offer protocol is used in our work). In negotiation round $t$ which it is an agent $\delta_i$ turn to make concession amount (i.e., $P_t^{\delta_i}$), it reacts to $\delta_j$’s bargaining power amount (i.e., $|P_{t-2}^{\delta_j} - P_{t-1}^{\delta_j}|$) by considering a factor in name flexibility in $\delta_i$’s trading partner’s proposal in the hope of reaching consensus with $\delta_j$. When the next negotiation round which it is an agent $\delta_i$ turn to move (i.e., $t=2$) is reached, since $\delta_i$ has reacted to the changes of its $\delta_j$’s bargaining power amount up to previous negotiation time which it was an agent $\delta_i$ turn to move (i.e., $t=1$), it is rational that $\delta_i$ just reacts to the last bargaining power amount of trading partner from that time.

A proposed factor in name flexibility in $\delta_i$’s trading partner’s proposal is defined as the ratio of difference between $P_{t-2}^{\delta_j}$ and $P_{t-1}^{\delta_j}$ (i.e., the last two proposals of $\delta_j$) to the difference between $P_{t-2}^{\delta_j}$ and $P_{t-1}^{\delta_j}$ (i.e., the last proposal of $\delta_j$):

$$FTP^{\delta_i} = \left\{ \begin{array}{ll}
\frac{P_{t-1}^{\delta_j} - P_{t-2}^{\delta_j}}{P_{t-2}^{\delta_j} - P_{t-1}^{\delta_j}} & \text{for } t > 2 \\
1 & \text{for } 0 \leq t \leq 2
\end{array} \right. \quad (15)$$

$$\text{IF} \text{it is a first } \delta_i's \text{ negotiation round THEN}$$

$$NTP^{\delta_i} = \frac{\text{no.trading.partner}^{\delta_i} + \text{no.competitor}^{\delta_i}}{\text{no.trading.partner}^{\delta_i}}$$

$$\text{Else IF} \ (\text{no.trading.partner}^{\delta_i} > \text{no.trading.partner}^{\delta_i}_{t-1}) \ \text{THEN}$$

$$NTP^{\delta_i} = 1 - \left[ \frac{\text{no.trading.partner}^{\delta_i}}{\text{no.trading.partner}^{\delta_i}_{t-1} + \text{no.competitor}^{\delta_i}} \right]$$

$$\text{Else IF} \ ((\text{no.trading.partner}^{\delta_i} < \text{no.trading.partner}^{\delta_i}_{t-1}) \ \text{THEN}$$

$$NTP^{\delta_i}_{t-1} \times \left( 1 - \frac{\text{no.trading.partner}^{\delta_i}}{\text{no.trading.partner}^{\delta_i}_{t-1} + \text{no.competitor}^{\delta_i}} \right)$$

$$\text{Else IF} \ (\text{no.trading.partner} = \text{no.trading.partner}^{\delta_i}_{t-1}) \ \text{THEN}$$

$$NTP^{\delta_i}_{t-1} = \frac{\text{no.trading.partner}^{\delta_i}_{t-1}}{\text{no.trading.partner}^{\delta_i}_{t-1} + \text{no.competitor}^{\delta_i}}$$

$$(14)$$
traces from http://www.cs.huji.ac.il/labs/parallel/workload/logs.html, which are stored in Standard Workload Format (SWF), one can observe that GROs and GRCs repeat their supplies and demands respectively to the grid environment and in most instances, based on their supplies and demands, GROs (respectively GRCs) can find a number of their previous trading partners as the new trading partners in the current GRNM. To prove this claim, it is assumed that (based on the existing SWF archives (http://www.cs.huji.ac.il/labs/parallel/workload/logs.html)) grid.name represents the name of observed grid and also the maximum number of potential, unique users of a grid in grid.name which is called max._pot._usergrid.name corresponds to the total number of requested jobs found in grid.name’s SWF archive. Further, the set of observed unique users in that grid.name’s SWF archive are called unique._user_setgrid.name and the number of unique._user_setgrid.name’s members is called unique._user_set_memgrid.name. The percentage of grid.name’s users that are observed previously in unique._user_setgrid.name is denoted by repeated._usergrid.name and defined as (18). Hence, the variety of grid.name’s users increased as repeated._usergrid.name tends to become 0%:

\[
\text{repeated._usergrid.name} = \left(1 - \frac{\text{unique._user_set_memgrid.name}}{\text{max._pot._usergrid.name}}\right) \times 100 
\]

(18)

The results of SWF archives’ observations (http://www.cs.huji.ac.il/labs/parallel/workload/logs.html) from repeated._usergrid.name perspective are illustrated in Fig. 2.

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

To model the behavior of kth trading partner of negotiator \(\delta_i\) (i.e., \(\delta_{ki}\)) in grid resource allocation process we proposed a new factor \(\text{PreBehave}_\text{Depend}_{\delta_{ki}}\) based on the number of successful negotiations between \(\delta_i\) and \(\delta_{ji}\) in all the GRNMs they both participated (e.g., 
\#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}}) and the extent of departure from the average of negotiation time between \(\delta_i\) and \(\delta_{ji}\) in \#GRNM_{\delta_{ki}} (e.g., Ave.neg.time_{\delta_{ki}}) from the sum of \(\delta_{ki}\), Ave.neg.time_{\delta_{ki}} (e.g., \(\sum_{k=1}^{\text{no.trading.partner}}\) Ave.neg.time_{\delta_{ki}}). This means that the \(\delta_{ki}\) whose ratio of \#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} is the lowest and its Ave.neg.time_{\delta_{ki}} is too far from zero (makes a longer negotiation) is a misbehaved trading partner and deserves to receive more penalty:

\[
\text{PreBehave}_\text{Depend}_{\delta_{ki}} = \frac{1}{\eta} \left[1 - \left(1 - \mu\right) \times \rho\right] 
\]

(19)

- IF ((\#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} = 1) AND (Ave.neg.time_{\delta_{ki}} < 0)) THEN (\(\mu = 0\) AND \(\rho = \text{Ave.neg.time}_{\delta_{ki}} / \sum_{k=1}^{\text{no.trading.partner}}\text{Ave.neg.time}_{\delta_{ki}}\))
- IF ((\#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} < 1) AND (Ave.neg.time_{\delta_{ki}} < 0)) THEN (\(\mu = \#Suc.neg.\delta_{ki}/\#GRNM_{\delta_{ki}}\) AND \(\rho = \text{Ave.neg.time}_{\delta_{ki}} / \sum_{k=1}^{\text{no.trading.partner}}\text{Ave.neg.time}_{\delta_{ki}}\))
- IF ((\#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} < 1) AND (Ave.neg.time_{\delta_{ki}} > 0)) THEN (\(\mu = \#Suc.neg.\delta_{ki}/\#GRNM_{\delta_{ki}}\) AND \(\rho = \text{Ave.neg.time}_{\delta_{ki}} / \sum_{k=1}^{\text{no.trading.partner}}\text{Ave.neg.time}_{\delta_{ki}}\))

If the type of \(\delta_i\) is GRM.MBDNA, then no.trading.partner_{\delta_{ki}} = \text{N}_i - 1, where \(\text{N}_i\) represents the number of negotiators of type GRM.MBDNA at round \(r\). Also, if the type of \(\delta_i\) is GRC.MBDNA, then no.trading.partner_{\delta_{ki}} = \text{M}_i - 1, where \(\text{M}_i\) represents the number of negotiators of type GRC.MBDNA at round \(r\). 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 \(\text{PreBehave}_\text{Depend}_{\delta_{ki}}\) factor is modeled based on two parameters: \#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} and Ave.neg.time_{\delta_{ki}}. The best value of \(\text{PreBehave}_\text{Depend}_{\delta_{ki}}\) factor (i.e., zero) is achieved in case of \#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} = 1 and Ave.neg.time_{\delta_{ki}} = 0. So, when the \#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} is equal to one the effectiveness of the first parameter in \(\text{PreBehave}_\text{Depend}_{\delta_{ki}}\) factor is ignored (i.e., \(\mu = 0\)) also when the Ave.neg.time_{\delta_{ki}} is equal to zero the effectiveness of the second parameter in \(\text{PreBehave}_\text{Depend}_{\delta_{ki}}\) factor is ignored (i.e., \(\rho = 1\)). Similarly, when the \#Suc.neg.\(\delta_{ki}\)/\#GRNM_{\delta_{ki}} is equal to one and the Ave.neg.time_{\delta_{ki}} is equal to zero the effectiveness of both parameters in \(\text{PreBehave}_\text{Depend}_{\delta_{ki}}\) factor are ignored (i.e., \(\mu = 1\) and \(\rho = 0\)). A local database in name DB_behave is considered to store the previous concession behavior of negotiator \(\delta_i\)’s trading partners who participated in GRNM previously. The data fields of a DB_behave database’s record, together with their brief description, are shown in Table 1.

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

When the negotiation process between \(\delta_i\) (which its type is GRC.MBDNA) and \(\delta_j\) (which its type is GRO.MBDNA) of each pair of
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 are correspond to $\delta_i$ (respectively $\delta_j$) and $\delta_k$ (respectively, $\delta_l$), respectively exists among retrieved records, then effect the following changes in the retrieved records from $DB\_behave$ database:**

\[
\begin{align*}
 & (1) \text{ Update the Ave.neg.time}_{i}\_id^{(k)} (\text{respectively, Ave.neg.time}_{j}\_id^{(k)}) \text{ field value using } \frac{\text{previous value } + \text{ new negotiation time}}{2} \text{ for } \delta_i \text{ (respectively, } \delta_j), \\
 & (2) \text{ Increase the } #\text{Suc.neg}_{i\_id}^{(k)} \text{ (respectively, } #\text{Suc.neg}_{j\_id}^{(k)}) \text{ field value by one.} \\
 & \text{Otherwise:} \\
 & (3) \text{ Create a new record based on the template described in Table 1 and insert it into the } DB\_behave \text{ database.} \\
 & (c) \text{ Send negotiation results (e.g., the price for leasing the resource and the period of utilization) to corresponding } GRCA_i \text{ (respectively, } GROA_j) \text{.} \\
\end{align*}
\]

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

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

(a) If $\delta_i$ (respectively, $\delta_j$) is the negotiator agent who firstly terminates the negotiation process, then store the information of negotiation's transactions between itself and its opponents in $DB\_game\_history$ database. This may be a good augmentation of database for future work.

(b) **If a record which its $\delta_{i\_id}$ (respectively, $\delta_{j\_id}$) and $\delta_{k\_id}$ (respectively, $\delta_{l\_id}$) fields are correspond to $\delta_i$ (respectively, $\delta_j$) and $\delta_k$ (respectively, $\delta_l$), respectively exist among retrieved records, then effect the following changes in the retrieved records from $DB\_behave$ database:**

\[
\begin{align*}
 & (1) \text{ Update the Ave.neg.time}_{i\_id}^{(k)} \text{ (respectively, Ave.neg.time}_{j\_id}^{(k)}) \text{ field value using } \frac{\text{previous value } + \text{ new negotiation time}}{2} \text{ for } \delta_i \text{ (respectively, } \delta_j), \\
 & \text{Otherwise:} \]

Otherwise create a new record based on the template described in Table 1 and insert it into the $DB\_behave$ database.

Table 1: The data fields of an agent $\delta_i$'s local $DB\_behave$ database's record and their brief description.

<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>$#GRNM_{i_id}$</td>
<td>Total number of GRNMs in which both $\delta_i$ and $\delta_j$ participate</td>
</tr>
<tr>
<td>$#Suc_neg_{i_id}$</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$_{i_id}$</td>
<td>The average negotiation time between $\delta_i$ and $\delta_j$, in all GRNMs which both participate</td>
</tr>
</tbody>
</table>

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. MDA's (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., 2011; 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) MDA's 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 MDA's (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><strong>Negotiation protocol</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bilateral negotiation model</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Multilateral negotiation model</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Determine the specific amount of concession to each negotiator's trading partner instead of the same amount to all negotiator's competitors</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

| **Negotiation strategies** | | |
| Flexibility in negotiator's trading partner's proposal | No | Yes |
| Behavior of the negotiator's trading partner | dependent | |
| Change in the ratio of the total number of negotiator's competitors to the total number of negotiator's trading partners | No | Yes |
| Change in the number of negotiator's competitors | Yes | Yes |
| Change in the number of negotiator's trading partners | Yes | Yes |
| Remaining time to deadline | dependent | |
| Closeness of negotiator's proposal to its trading partners' proposals | dependent | |

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

<table>
<thead>
<tr>
<th>Input</th>
<th>Possible values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>E-market type</strong></td>
<td>GRC-favorable, GRO-favorable, Balanced</td>
</tr>
<tr>
<td><strong>Market density</strong></td>
<td>Sparse, Moderate, Dense</td>
</tr>
<tr>
<td><strong>Grid_load</strong></td>
<td>0 \rightarrow Grid_load \leq 1 {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}</td>
</tr>
<tr>
<td><strong>Deadline (No. of rounds)</strong></td>
<td>High: Grid_load \rightarrow 1</td>
</tr>
<tr>
<td><strong>Job size(MI)</strong></td>
<td>Low: 0 \rightarrow Grid_load, Moderate: 100, Long: 3100</td>
</tr>
<tr>
<td><strong>Resource capacity(MIPS)</strong></td>
<td>200-3000</td>
</tr>
<tr>
<td><strong>Negotiation model</strong></td>
<td>MBDNAs' negotiation model is described in Section 3, MDA's negotiation model is inspired by Sim (2005a, 2005b, 2006)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Amount of time-preference, type of strategy: abbreviation</th>
<th>MBDNA time-preferences</th>
<th>MDA time-preferences</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\lambda = 1)/3, Conciliatory: CC</td>
<td>(\lambda = 1)/3, Conciliatory: CC</td>
<td></td>
</tr>
<tr>
<td>(\lambda = 1), Linear: L</td>
<td>(\lambda = 1), Linear: L</td>
<td></td>
</tr>
<tr>
<td>(\lambda = 2), Conservative: CS</td>
<td>(\lambda = 2), Conservative: CS</td>
<td></td>
</tr>
<tr>
<td>(\lambda = 3), Conservative: CS</td>
<td>(\lambda = 3), Conservative: CS</td>
<td></td>
</tr>
</tbody>
</table>

4.2.1. Grid load

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

\[
\text{Grid load} = \frac{R_p}{C_c} \quad \text{where} \quad 0 < \text{Grid load} \leq 1 \tag{20}
\]

4.2.2. E_market types

As the availability of grid resources varies continuously with time, the simulation should be carried out by considering different GRC-to-GRO ratios. These ratios characterize three types of e-market: \( \text{GRC-favorable} \), \( \text{GRO-favorable} \) and \( \text{balanced} \). 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 GRC agents and GRC agents. GRC_to_GRO ratio is controlled by the probability \( P_{\text{GRC}} \) of an agent being GRC agent (or GRO agent). \( P_{\text{GRC}} \) 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 GRC's deadline from being included in depicting figures, and Table 3 only contains GRC'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 \( P_{\text{gen}} \) that an agent will enter the GRNM in each round of negotiation. \( P_{\text{gen}} \) 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 (\( P_{\text{tt}} \)) of a GRC's set of tasks that is accomplished by successfully negotiating and leasing grid resources; let \( N_{\text{tot}} \) denote the total number of tasks requested by a GRC and \( N_{\text{succ}} \) the number of tasks that are successfully scheduled and executed. \( P_{\text{tt}} \) is given as

\[
P_{\text{tt}} = \frac{N_{\text{succ}}}{N_{\text{tot}}} \tag{21}
\]

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

4.3.2. GRO's performance metrics

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

\[
U_{\text{rl}} = \frac{N_{\text{ur}}}{N_{\text{ir}}} \tag{22}
\]

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.
Fig. 3. (continued)
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) and evaluate the impact of each factor on performance metrics separately. Some of the proposed factors have greater impact on the GRC’s metric (respectively, GRO’s metric) of improving tasks complementation (respectively, improving resource utilization level) and the others on the GRC’s metric (respectively, GRO’s metric) of minimizing budget spent (respectively, maximizing received revenue). Following are the most important observations from the results:

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

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

![Fig. 4. Performance under different grid work loadings.](A) λ=1/3 Deadline=100, (B) λ=1/3 Deadline=1000, (C) λ=1/3 Deadline=3100, (D) λ=2.0 Deadline=100, (E) λ=1.0 Deadline=100 and (F) λ=1.0 Deadline=1600.
of time to complete a deal the bargaining positions of both MBDNAs and MDAs are weaker and if final agreement is reached, both of them are likely to make relatively more concessions (which leads to lower average utility). To show the weaker bargaining power of negotiators having short deadline in comparison to negotiators having moderate or long deadline an example is provided: in Fig. 3-GRC’s perspective (g)–(i), for GRC_to_GRO=1:5 and \( \lambda = 2.0 \), the average utility of GRC_MBDNAs increased from 2.51 with deadline=100 (i.e., short deadline) to 2.66 and 2.82 with deadline=1600 (i.e., moderate deadline) and deadline=3100 (i.e., long deadline) respectively.

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

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

Additionally, when the type of market tends to be GRC-favorable (e.g., the ratio of participants of GRO’s e_market side to participants of GRC’s e_market side increase), the average utilities of the both types of agents are close especially in the short deadline case since under very extreme competition conditions (i.e., GRC-favorable market type where GRC-to GRO ratio = \{1:2, 1:5\}), the bargaining power of GROs decreases and it may be extremely difficult for both types of negotiators (i.e., MBDNAs and MDAs) to reach any consensus so they have to concede more to
avoid the risk of losing the chance of leasing out their resources (which leads to lower average utility) and also with short deadline (in comparison to moderate and long) due to have no plenty of time to complete a deal the bargaining positions of both MBDNAs and MDAs are weaker and if final agreement is reached, both of them are likely to make relatively more concessions (which leads to lower average utility). To show the weaker bargaining power of negotiators having short deadline in comparison to negotiators having moderate or long deadline an example is provided: in Fig. 3-GRO’s perspective (g)–(i), for GRC_to_GRO = 1:5 and $\lambda = 2.0$, the average utility of GRO_MBDNAs increased from 0.48 with deadline = 100 (i.e., short deadline) to 0.91 and 1.32 with deadline = 1600 (i.e., moderate deadline) and deadline = 3100 (i.e., long deadline) respectively.

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

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

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

Observation 4: The experimental results in Fig. 4-GRO’s perspective show the following: (1) Negotiation results become more favorable with the increase of the Grid_load for both types of negotiators (i.e., MBDNAs and MDAs). (2) Given the same Grid_load, MBDNAs achieved higher success rate in leasing out resources than MDAs. This is because more appropriate factors are considered for designing MBDNAs which have great role in relaxing and adopting the bargaining criteria whenever the negotiation agents come under market pressure. This means that the negotiation agents can lease out more resources especially when the market conditions put them under pressure (i.e., Grid_load tends to zero). (3) Given the same Grid_load and time-preference, GROs of both types who have long deadline achieved higher success rate. With long deadline (in comparison to moderate and short) due to have plenty of time for trading the bargaining positions of both MBDNAs and MDAs are stronger and they both likely to complete deals successfully (i.e., have higher success rate). However, as MBDNAs are designed with more appropriate negotiation strategy, they are more likely to achieve higher success rate than MDAs especially under intense grid market pressure. As an example, in Fig. 4-GRO’s perspective (j), (k) and (l), for Grid_load=1 and λ=3.0, the success rate of GRO_MBDNAs increased from 83.1% with deadline=100 (i.e., short deadline) to 88.9% and 90.09% with deadline=1600 (i.e., moderate deadline) and deadline=3100 (i.e., long deadline) respectively.
Observation 5: To evaluate the impact of our most important factor, previous concession behavior of the 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 the 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 \( \lambda \in \{1, 2, 3\} \) and deadline \( \in \{100, 3100\} \) and \( \in \{100, 1600\} \) 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.time}_k)</td>
<td>The average negotiation time between (d_i) and (d_s) in all GRNMs which both participate</td>
<td>(\text{no competitor}_k)</td>
<td>Number of (d_i)'s competitors at round (t)</td>
</tr>
<tr>
<td>(C_i)</td>
<td>The total computing capacity of the grid</td>
<td>(\text{no trading partner}_k)</td>
<td>Number of (d_i)'s trading partners at round (t)</td>
</tr>
<tr>
<td>(C_l)</td>
<td>The worst possible utility for (d_i) (e.g., if the negotiation ends in disagreement)</td>
<td>(\text{MBDNA}_s)</td>
<td>MBDNA's competition function</td>
</tr>
<tr>
<td>(\text{CC}_t)</td>
<td>MBDNA's competition function</td>
<td>(\text{MBDNA}_s)</td>
<td>MBDNA's opportunity function</td>
</tr>
<tr>
<td>(\text{conc}_t)</td>
<td>The amount of concession at negotiation round (t)</td>
<td>(\text{MDA}_s)</td>
<td>MDA's opportunity function</td>
</tr>
<tr>
<td>(\text{DTPAP}_k)</td>
<td>MBDNA's closeness function (e.g., (d_i)'s proposal deviation of the average of its trading partners' proposals)</td>
<td>(\text{The probability of a grid being GRC agent})</td>
<td>The probability that an agent will enter the GRNM in each round of negotiation</td>
</tr>
<tr>
<td>(\text{FST}_k)</td>
<td>Final price-oriented strategy that is taken by (d_i)</td>
<td>(\text{Propose}_t)</td>
<td>Proposal of (d_i) at round (t)</td>
</tr>
<tr>
<td>(\text{FTP}_k)</td>
<td>MBDNA's flexibility function (i.e., flexibility in (d_i)'s trading partner's proposal)</td>
<td>(\text{Price}_t)</td>
<td>The price that a consensus is reached by both parties</td>
</tr>
<tr>
<td>(\text{GRCA}_k)</td>
<td>(i)th grid resource consumer</td>
<td>(\text{MBDNA}_s)</td>
<td>The probability of a GRC generating a task that needs computing resources at each negotiation round</td>
</tr>
<tr>
<td>(\text{GRCA}_k)</td>
<td>(i)th grid resource consumer agent</td>
<td>(\text{MBDNA}_s)</td>
<td>The probability of a GRC's set of tasks that is accomplished by successful negotiation and leasing grid resources</td>
</tr>
<tr>
<td>(\text{GRCA}_k)</td>
<td>(i)th grid resource consumer agent</td>
<td>(\text{MBDNA}_s)</td>
<td>The MBDNA's behavior function (e.g., previous behavior of (d_i))</td>
</tr>
<tr>
<td>(\text{GRNM}_\text{jobrequestee_directory})</td>
<td>Storage for submitting (\text{GRO}<em>\text{resource}</em>\text{prof}(s)) of (\text{GRO}(s)) in GRNM</td>
<td>(\text{MBDNA}_s)</td>
<td>The expected amount of processing requested per time interval</td>
</tr>
<tr>
<td>(\text{GRNM}_\text{jobrequester_directory})</td>
<td>Storage for submitting (\text{GRC}<em>\text{job}</em>\text{prof}(s)) of (\text{GRC}(s)) in GRNM</td>
<td>(\text{MBDNA}_s)</td>
<td>The ratio of difference between the average of negotiator (d_i)'s trading partners' proposals at round (t \rightarrow t-1) (e.g., (\frac{(\frac{1}{k_t}\sum_{k=1}^{t}\text{no trading partner}_k)}{\text{no trading partner}_k})) and negotiator (d_i)'s last proposal (e.g., (\text{Propose}_t)) to the average of negotiator (d_i)'s trading partners' proposals at round (t \rightarrow t-1).</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner</td>
<td>(\text{MBDNA}_s)</td>
<td>Represents percentage of grid.name's users that are observed previously in unique_user_set_mem_gridname.</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Reserve Price of (d_i)</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Negotiation round</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>(d_i)'s deadline (e.g., a time frame by which (d_i) needs negotiation result)</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Time preference function</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Resource utilization level</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Utility of (d_i)'s at round (t) if (d_i) accepts the proposal from (d_{\delta} (\text{Propose}_{t-1}))</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Utility of (d_i)'s at round (t) if (d_i) accepts the proposal from (d_{\delta} (\text{Propose}_{t-1}))</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</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{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Total number of GRNMs in which both (d_i) and (d_{\delta} ) participate</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Total number of successful negotiations between (d_i) and (d_{\delta} ), in all GRNMs which both participate</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>Negotiator agent who its turn to make concession</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>(\text{ith trading partner of } d_i)</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>(\text{ith competitor of } d_i)</td>
</tr>
<tr>
<td>(\text{GRO}_k)</td>
<td>(j)th Grid Resource Owner Agent</td>
<td>(\text{MBDNA}_s)</td>
<td>(d_i)'s time preference</td>
</tr>
</tbody>
</table>

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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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