A new fuzzy negotiation protocol for grid resource allocation

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ABSTRACT

In real-life trading, relaxing decisions in the face of trading pressure is common. Similarly, in market-based grid resource allocation problem designing negotiator agents with the flexibility to relax their decision to (quickly) complete a deal in the face of intense Grid Market Pressure (GMP) is essential. To make this idea possible, we design Enhanced Market- and Behavior-driven Negotiation Agents (EMBDNAs) that adopt new fuzzy negotiation protocol. The protocol focuses on both (1) enhancing Rubinstein’s sequential alternating offer protocol to handle multiple trading opportunities and market competition and (2) designing two new Fuzzy Grid Market Pressure Determination Systems (FGMPDSs) for both grid resource consumers and grid resource owners to guide negotiator agents in relaxing their bargaining terms under intense GMP to enhance their chance of successfully acquiring/leasing out resources. Implementing the idea in an agent-based testbed, an experiment for evaluating and comparing EMBDNA against EMDA (Enhanced Market-Driven Agent) and our previous work in name MBDNA (Market- and Behavior-driven Negotiation Agent) were carried out through stochastic simulations. While EMDA relaxes its bargaining term in the face of intense GMP by considering just two relaxation factors the MBDNA uses the same negotiation strategy as EMBDNA but does not relax its bargaining term in the face of intense GMP. The results show that adopting the new fuzzy negotiation protocol, EMBDNAs outperform MBDNAs and EMDAs.

1. Introduction

Grid computing is emerging as the foundation upon which virtual organizations can be built. Such organizations are becoming of increasing importance for tackling various projects, both in academic and in business fields (Arafah et al., 2007). 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 grid focuses on large-scale resource sharing, and because

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prudent rather than using other commonly referenced works (e.g., see (Wolski et al., 2001; Wolski et al., 2003; Buyya and Vazhkudai, 2001)). Also Sim Sim (2010)) pointed out the principal motivations for considering negotiation mechanisms among GROs and GRCs. Like most of the commonly previous works in providing grid resource management solutions (e.g., see (Rahwan et al., 2007; Srinivas and Varadhan, 2011; Pastore, 2008; Foster et al., 2005)), this approach provides negotiation mechanism for optimizing GROs' and GRCs' profit through providing software components (Agent).

Although there are many agent-based approaches for grid resource allocation via negotiation mechanism, the strategies of some of these agents are mostly static and may not necessarily be the most appropriate for changing in Grid Resource Negotiation Market (GRNM) situations. It means that this type of agents (i.e., fixed strategy negotiation agents) relax their bids (offers) at constant rate and do not properly address trading pressure in GRNM. From now we name the trading pressure of GRNM as Grid Market Pressure (GMP). The GMP is inspired from the concept of stock market pressure (Bhojraj and Libby, 2005) and is defined as a variable that captures the acceptability of the current grid resource negotiation market conditions. Obviously, the GMP arises from trade imbalances and local condition of each market participant. Previous empirical results in Sim and Wong (2001) show that in general, more flexible negotiation agents (e.g., Sim and Choi, 2003)) that relax their bids in face of GMP outperform fixed strategy market participant. Previous empirical results inSim and Wong (2001)show that in general, more flexible negotiation agents (e.g.,Sim

For instance, the only two relaxed-criteria of both GRCs and GROs inSim and Wang (2004)are eagerness and degree of competition, while the only two relaxed-criteria of GRCs and two relaxed-criteria of GROs inSim and Ng (2007)are recent statistics in GRC's failing/ succeeding in acquiring resources and GRC's demand for computing resources, and the amount of the GRO's resource(s) that is currently

In summary, the distinguishing features of this work are that:

1) Present an extended approach for determining GMP value (by consulting sets of fuzzy rules) to provide negotiation agents with more accurate GMP value (i.e., degree of relaxation).

2) Devise EAlternating offer protocol (i.e., enhancement of Rubinstein's sequential alternating offer protocol which is proposed in Rubinstein (1982), Sim and Ng (2007)) to handle multiple trading opportunities and market competition, overcome non-reasonable behavior of negotiation agents and relax bargaining criteria of negotiation agents (based on the value of GMP) and

3) Design new Enhanced Market- and Behavior-driven Negotiation Agents (EMBDNAs) by augmenting the MBDNAs (Market- and Behavior-driven Negotiation Agents that do not adopt the proposed fuzzy negotiation model) (Adabi et al., 2013) with the proposed negotiation protocol.

The remainder of the paper is structured as follows: Section 2 describes the proposed negotiation model of EMBDNAs that includes utility function of negotiator agents, near-optimal negotiation strategies and EAlternating offer protocol. The experimental results to study the performance of EMBDNAs are given in Section 3. Finally, the state-of-the-art flexible negotiation agents for grid resource management and conclusions are given in Section 4 and Section 5 respectively.


Table 1
Notation and basic terms used in the negotiation utility subsection of this paper (alphabetical sort).

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Basic definition</th>
</tr>
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<tbody>
<tr>
<td>( A_{child} )</td>
<td>( k )th instance of negotiator ( A )</td>
</tr>
<tr>
<td>( B_{p} )</td>
<td>( k )th trading partner of negotiator ( A )</td>
</tr>
<tr>
<td>GRC</td>
<td>Grid Resource Consumer</td>
</tr>
<tr>
<td>GRCA</td>
<td>Grid Resource Consumer Agent</td>
</tr>
<tr>
<td>GRC_EMBDNA</td>
<td>Grid resource consumer of type EMBDNA</td>
</tr>
<tr>
<td>GRC_job_prof (_p)</td>
<td>GRC's ( p )th job characteristics</td>
</tr>
<tr>
<td>GRNM</td>
<td>Grid Resource Negotiation Market</td>
</tr>
<tr>
<td>GRO</td>
<td>Grid Resource Owner</td>
</tr>
<tr>
<td>GROA</td>
<td>Grid Resource Owner Agent</td>
</tr>
<tr>
<td>GRO_EMBDNA</td>
<td>Grid resource owner of type EMBDNA</td>
</tr>
<tr>
<td>GRO_resource_prof (_t)</td>
<td>GRO's ( r )th resource characteristics</td>
</tr>
<tr>
<td>IP(_A)</td>
<td>Initial Price of negotiator ( A )</td>
</tr>
<tr>
<td>No_competitor(_t)</td>
<td>Number of negotiator ( A )'s competitors at round ( t )</td>
</tr>
<tr>
<td>no_trading_partner(_t)</td>
<td>Number of negotiator ( A )'s trading partners at round ( t )</td>
</tr>
<tr>
<td>( p_{r,child} )</td>
<td>( A_{child} )'s proposal at round ( t )</td>
</tr>
<tr>
<td>( p_{r} )</td>
<td>Proposal of ( B_{p} ) at round ( t )</td>
</tr>
<tr>
<td>( p_{consensus} )</td>
<td>The consensus price</td>
</tr>
<tr>
<td>( R_{PA} )</td>
<td>Reserve Price of ( A )</td>
</tr>
<tr>
<td>( t_{deadline} )</td>
<td>( A )'s deadline (e.g., a time frame by which ( A ) needs negotiation result)</td>
</tr>
<tr>
<td>( \theta )</td>
<td>The amount that is considered to distinguish the utilities between deals and no deals</td>
</tr>
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</tr>
<tr>
<td>( U_{r,child, p_{r,child}}^{\theta} \rightarrow B_{p} )</td>
<td>Utility of ( A_{child}'s ) at round ( t ) if its proposal is accepted by ( B_{p} )</td>
</tr>
<tr>
<td>( U_{r,child, p_{r}}^{\theta} \rightarrow A_{child} )</td>
<td>Utility that is generated for ( A_{child} ) by accepting the opponent's proposal ( p_{r} ),</td>
</tr>
</tbody>
</table>

The consensus price

It can be understood that considering more suitable relaxation criteria in the face of intense GMP.

For instance, the only two relaxed-criteria of both GRCs and GROs inSim and Wong (2004) are eagerness and degree of competition, while the only two relaxed-criteria of GRCs and two relaxed-criteria of GROs inSim and Ng (2007) are recent statistics in GRC's failing/succeeding in acquiring resources and GRC's demand for computing resources, and the amount of the GRO's resource(s) that is currently being used and recent requests from GRCs for resources respectively. Also even though agents in Kowalczyk and Bui (2000) are designed with the flexibility to relax trading conditions such as preferences, priorities and objectives, they were not designed to react to changing market situations such as competition and opportunities. It can be understood that considering more suitable relaxation criteria in determining the GMP's value can increase the chance of negotiation agents in making agreement with their opponents. This motivating consideration provides the impetus for designing flexible negotiation agents that not only focus put on applying near-optimal negotiation strategies but also devising a new negotiation protocol in name EAlternating offer protocol that model more new relaxation criteria from new perspective to optimize the negotiators' utilities, enhance the success rate and speed of negotiation (measured in number of rounds needed to reach an agreement) in the face of intense GMP. The proposed negotiation protocol focuses on augmenting the alternating offers protocol by designing two new fuzzy decision controllers (i.e., one modeling GRC's criteria, and one modeling GRO's criteria) for determining the amount of relaxation in a negotiation situation.

In summary, the distinguishing features of this work are that:

- Present an extended approach for determining GMP value (by consulting sets of fuzzy rules) to provide negotiation agents with more accurate GMP value (i.e., degree of relaxation).
- Devise EAlternating offer protocol (i.e., enhancement of Rubinstein's sequential alternating offer protocol which is proposed in Rubinstein (1982), Sim and Ng (2007)) to handle multiple trading opportunities and market competition, overcome non-reasonable behavior of negotiation agents and relax bargaining criteria of negotiation agents (based on the value of GMP) and
- Design new Enhanced Market- and Behavior-driven Negotiation Agents (EMBDNAs) by augmenting the MBDNAs (Market- and Behavior-driven Negotiation Agents that do not adopt the proposed fuzzy negotiation model) (Adabi et al., 2013) with the proposed negotiation protocol.

The remainder of the paper is structured as follows: Section 2 describes the proposed negotiation model of EMBDNAs that includes utility function of negotiator agents, near-optimal negotiation strategies and EAlternating offer protocol. The experimental results to study the performance of EMBDNAs are given in Section 3. Finally, the state-of-the-art flexible negotiation agents for grid resource management and conclusions are given in Section 4 and Section 5 respectively.
2. Negotiation model

The negotiation model has three parts (Kraus, 2001): (1) the used utility models or preference relationships for the negotiating parties, (2) the negotiation strategy applied during the negotiation process and (3) the negotiation protocol. Following, the negotiation’s strategy and utility function which are previously published in Adabi et al. (2013) are briefly discussed and then a new negotiation protocol that is called Alternating offer protocol is discussed in details. The three distinguishing features of Alternating offer protocol are: (a) handle multiple trading opportunities and market competition, (b) overcome non-reasonable behavior of negotiator agents during negotiation process and (c) relax bargaining criteria of negotiator agents by considering more accurate GMP. In addition the type of negotiation and negotiation assumptions are discussed in negotiation protocol subsection.

The negotiation agents that adopt proposed negotiation model are called EMBDNAs (Enhanced Market- and Behavior-driven Negotiation Agents).

The following three sub-sections address the three parts of negotiation model in the proposed EMBDNAs’ negotiation mechanism.

2.1. Negotiation utility

Any kind of behavior of each negotiator can be modeled with a suitable payoff or “utility function”. Each negotiator evaluates the resulting outcome through a payoff or “utility function” representing her objectives. For the benefit of readers the authors summarize in Table 1 the key symbols and their definitions used in the negotiation utility subsection of this paper.

The grid computational resource allocation mechanism in this paper is under budget and time constraints which means that a negotiator A of type GRC_EMBDNA (respectively, GRO_EMBDNA) makes computational resource acquiring (respectively, assigning) decisions within the budget and time constraints. That is, the negotiation objectives are the expected price that will be obtained via negotiation process and the negotiation time that will be spent in the grid resource allocation market. So, the negotiator A of type GRC_EMBDNA tries to purchase as much computational resource as possible with the objectives of spending the least possible amount of money (minimizing their payment) and minimizing its negotiation time, also the negotiator A of type GRO_EMBDNA tries to sell as much computational resources as possible with the objectives of maximizing its revenue and minimizing its negotiation time. By considering the mentioned issues we use a simple (for ease of analysis) linear utility function that considers not only the economy’s payoff but also the time’s payoff of a negotiator agent decreases as its spent money tends to the agent’s negotiation reserve price (i.e., the highest price a resource consumer is willing to pay for grid resource/service or the smallest price at which a resource owner is willing to sell a grid resource/service). Also the time’s payoff of a negotiator agent decreases as its spent time in the grid negotiation market tends to the agent’s negotiation deadline.

Let assume that number of negotiator agent A’s trading partners and competitors at round t are no.trading_partner\(t\) and no.competitor\(t\) respectively. Negotiator agent A duplicates itself according to no.trading_partner\(t\) and creates negotiator agent instances A\_CHILD\(t\) = {A\_child\(1\), A\_child\(2\), ... A\_child\(no.trading_partner\(t\)\)} to conduct negotiation process on behalf of it in the GRNM area that are assigned to. For understanding the meaning of GRNM area an example will be presented. Let assume that negotiator agent A has no.trading_partner\(t\) = 3 trading partners and no.competitor\(t\) = 6 competitors at round t. We consider that negotiator agent A finds competitor\(1\), competitor\(2\), competitor\(3\) and competitor\(4\) as the potential competitors against trading_partner\(1\), trading_partner\(2\), trading_partner\(3\) and competitor\(4\) against trading_partner\(3\). The GRNM area is composed of A\_child\(i\) (i.e., an instance of A), one of its trading partner and competitors who are found against that trading partner. Therefore as shown in Fig. 1, three GRNM areas are found in the described example.

Each GRC that is represented by a GRC agent (e.g., GRC) can have one or more jobs {job\(1\),...job\(y\}). 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\_prof\(p\)) include the following: unique identifier, job length measured in MI (millions of instructions), length of input and output data, earliest start time (i.e., the job cannot start before its earliest start time), the period of resource usage, job’s negotiation deadline (i.e., the latest start time of the job). Obviously, a job’s finish time = [earliest start time + period of resource usage, negotiation deadline - period of resource usage]), initial price, reservation price, and the originator of the job (Sim, 2006). Also, it is assumed that each GRO, which is represented by a GRO agent (e.g., GROA), may possess k computing machines (which is denoted by \(M\_j, ... M\_k\)) for the grid environment. As noted in Sim (2006), “Each computing machine \(M\_j\) can be a single processor, a shared memory multiprocessor, or a distributed memory cluster of computers. \(M\_j\) can be formed by one or more processing elements \(PE\_1, ... PE\_i\), and each \(PE\_i\) have different
speeds measured in terms of MIPS (millions of instructions per second).” The GRO’s r’th resource characteristics (e.g., GRO_resource_profj) include unique identifier, the architecture of computing resource (e.g., HPalpha server), list of computing machines (e.g., $M_1, ..., M_n$), required bandwidth length, required memory capacity, and expected and reserve prices of leasing a computing machine. From a GRC’s (respectively, GRO’s) perspective each of its tasks (respectively, computing machines) corresponds to “Agent A” in Fig. 1.

The utility of $A_{child}$ if $B_k$ (i.e., $A_{child}$’s trading partner in that GRNM area that $A_{child}$ is located) accepts $A_{child}$’s proposal (i.e., $P^A_{child,k}$ and the utility generated for $A_{child}$ if $A_{child}$ accepts the counter proposal of $B_k$ (i.e., $P^B_{k} = U^A_{child,k}P^A_{child,k}$) $\rightarrow B_k$ and $U^B_{child,k}P^B_{k}$ $\rightarrow A_{child}$ respectively. If the negotiation ends in disagreement, both negotiation sides (e.g., negotiator agent of type GRC_EMBDNA and negotiator agent of type GRO_EMBDNA) receive the worst possible utility (e.g., zero).

The linear utility function of $A_{child}$ of type GRC_EMBDNA and the linear utility function of $A_{child}$ of type GRO_EMBDNA considering $P^A_{child,k}$ to $B_k$ and $P^B_{k}$ to $A_{child}$ at negotiation round $t$ is defined as Eqs. (1) and (2) respectively

$$U^A_{child,k}(P^A_{child,k} \rightarrow B_k) = u_{min} + (1 - u_{min}) \left( \frac{t^A_{deadline} \rightarrow B_k}{t^A_{deadline}} + \left[ \frac{RPA - P^A_{child,k}}{(RPA - IP_A)} \right] \right)/2$$

$$U^B_{child,k}(P^B_{k} \rightarrow A_{child}) = u_{min} + (1 - u_{min}) \left( \frac{t^B_{deadline} \rightarrow A_{child}}{t^B_{deadline}} + \left[ \frac{IP_A - P^B_{k}}{(IP_A - RPA)} \right] \right)/2$$

where $RPA$ is $A$’s reserve price, $IP_A$ is $A$’s initial price, and $t^A_{deadline}$ is $A$’s negotiation deadline (e.g., a time frame by which $A$ needs negotiation result). Also $u_{min}$ is the parameter that used to distinguish the utilities between deals and no deals (since a negotiator agent receives a utility of zero if negotiation fails). Let assume that the price that a consensus is reached by both parties is $P^A_{optimal}$ and corresponds to negotiator’s reserve price (obviously this is the minimum utility that an agent receives for making a deal). Also the agreement is reached in $t^A_{deadline}$ (i.e., $t = t^A_{deadline}$). Without having $u_{min}$ the negotiator receives utility of zero which is as same as the utility if negotiation fails. Hence to avoid the non-reasonable utility of zero in the case that $P^A_{optimal} = RPA$ and $t = t^A_{deadline}$, parameter $u_{min}$ should be defined. The value of $u_{min}$ which is derived from Sim and Ng (2007) is defined as 0.1.

If the proposed deal from $A_{child}$ of type GRC_EMBDNA at round $t$ (e.g., $P^A_{child,k}$) is not greater than the one at round $t + 2$ (e.g., $P^A_{child,k}$), then $U^A_{child,k}(P^A_{child,k} \rightarrow B_k) > U^A_{child,k}(P^A_{child,k} \rightarrow B_k)$. Also, If the proposed deal from $A_{child}$ of type GRO_EMBDNA at round $t$ (e.g., $P^A_{child,k}$) is greater than the one at round $t + 2$ (e.g., $P^A_{child,k}$), then $U^A_{child,k}(P^A_{child,k} \rightarrow B_k) > U^A_{child,k}(P^A_{child,k} \rightarrow B_k)$. We should highlight that by using the Alternating offer protocol, negotiators in make alternate offers rather than moving simultaneously (see Section 2.3).

2.2. Negotiation strategy

In each round of the negotiation, a negotiator agent $A$’s choice is called a strategy. As EMBDNAs focus on single-issue (e.g., price only) negotiation (like Adabi et al., 2013; Li and Li, 2004; Li et al., 2005, 2009; Ghosh et al., 2004, 2005), the amount of concession determination, at negotiation round $t$, is a chosen strategy by $A$. For the benefit of readers the authors summarize in Table 2 the key symbols and their definitions used in the negotiation strategy subsection of this paper.

Following the negotiation strategies of proposed EMBDNAs which are derived from Adabi et al. (2013) is described. Sim (2005) 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 $A_{child}$ and the proposal of its trading partners at each round $t$. Coming to details, recall that the proposal of $A_{child}$ to its trading partner $B_k$ at round $t$ is $P^A_{child,k} \rightarrow B_k$ and the proposal of $B_k$ to $A_{child}$ at round $t$ is $P^B_{k} \rightarrow A_{child}$ also, $U^A_{child,k}(P^A_{child,k} \rightarrow B_k)$ and $U^B_{child,k}(P^B_{k} \rightarrow A_{child})$ are the utilities of $A_{child}$ if $B_k$ accepts $A_{child}$’s proposal at negotiation round $t$-2 and the best utility generated for $A_{child}$ if $A_{child}$ accepts the counter proposal of $B_k \in \{B_1, B_2, ..., B_{mn\text{trading\_partner}}\}$ which was proposed at negotiation round $t$-1 respectively. The (best) spread in the current cycle $t$
(before making new proposal) is

\[ k_t = U^A_{child}[P^A_{child} \rightarrow B_k] - U^A_{child}[P^B_{child} \rightarrow A_{child}] \]  

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:

\[ U^A_{child}[P^A_{child} \rightarrow B_k] = k_{t+1} + U^A_{child}[P^B_{child} \rightarrow A_{child}] \]  

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

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

Also, the appropriate value of \( k_{t+1} \) is defined by

\[ k_{t+1} = \text{FSTA}^A_{child} \times k_t \]  

where \( \text{FSTA}^A_{child} \) is a price-oriented strategy that is taken by \( A_{child} \) at round \( t \) and is defined through equation

\[ \text{FSTA}^A_{child} = \kappa \big( \text{IST}^A_{child} + \text{PreBehave}_t \times \text{ISTA}^A_{child} \big) \]  

where \( \kappa = 1/2 \) if \( \text{IST}^A_{child} + \text{PreBehave}_t \times \text{ISTA}^A_{child} \) is greater than one, else \( \kappa = 1 \). Also \( \text{PreBehave}_t \) is previous behavior of \( A_{child} \)’s trading partner factor (details can be found in part f of the current section) and \( \text{ISTA}^A_{child} \) is denoted by

\[ \text{ISTA}^A_{child} = N^A_{child} \times N^P_{child} \times F^A_{child} \times \text{DTPAP}^A_{child} \times T^A_{child} \]  

where \( N^A_{child} \), \( N^P_{child} \), \( F^A_{child} \), \( \text{DTPAP}^A_{child} \), and \( T^A_{child} \) 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 concepts of \( \text{FSTA}^A_{child} \)’s factors are described in (the whole definition of each \( \text{FSTA}^A_{child} \)’s factor and related calculation function are described in Adabi et al. (2013) in details).

a) Number of competitors (\( N^A_{child} \))

As described in previous works (see e.g., (Sim, 2010; Lang, 2005)), competition is one of the factors that contributes to power of negotiation. Adabi et al. (2013) consider two cases in defining the competition factor to handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain: (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. A negotiator \( A_{child} \) is more likely to reach an agreement if its number of competitors tends to become zero and/or the ratio of the total number of negotiator’s competitors to the total number of negotiator’s trading partners tends to become zero.

b) Number of trading partners (\( N^P_{child} \))

Sim and Choi (2003), Sim (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 [17, p. 249], “if there is a large number of trading alternatives, the likelihood that a negotiator proposes a bid/off that is potentially close to a trading partners’ offer/bid may be high”. Similarly to the definition of \( N^A_{child} \) factor, Adabi et al. (2013) consider two cases in defining the trading partner factor to handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain: (1) change in the number of negotiator’s trading partners and (2) change in the ratio of the total number of negotiator’s trading partners to the total number of negotiator’s competitors. A negotiator \( A_{child} \) is more likely to reach an agreement if its number of trading partners tends to become one and/or the ratio of the total number of negotiator’s trading partners to the total number of negotiator’s competitors tends to become one.

c) Flexibility in negotiator’s trading partner’s proposal (\( F^A_{child} \))

From an negotiator agent \( A_{child} \)’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 make concession amount, the agent computes \( F^A_{child} \) factor based on the ratio of \( B_k \)’s bargaining power amount (i.e., \( |P^B_{child} - P^A_{child}| \)) to the difference between \( P^B_{child} \) and its last proposal (i.e., \( P^{A_{child}}_{child} \)). A negotiator \( A_{child} \) is more likely to reach an agreement if the ratio of its \( B_k \)’s bargaining power amount to the difference between \( P^{A_{child}}_{child} \) and \( P^B_{child} \) tends to become one.

d) Negotiator’s proposal deviation of the average of its trading partners’ proposals (\( \text{DTPAP}^A_{child} \))

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. Hence, according to Adabi et al. (2013), \( \text{DTPAP}^A_{child} \) factor is defined as the ratio of the difference between average of \( A \)’s trading partners’ proposals at round \( t-1 \) and \( A \)’s last proposal to the average of \( A \)’s trading partners’ proposals at round \( t-1 \). 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.

e) Negotiator’s time preference (\( T^A_{child} \))

As noted by Binmore and Dasgupta (1987)” 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”. The effect of time discount
factor in negotiator's bargaining power can be modeled via time-dependent function. The present work focuses on time-dependent function that is given in Sim (2006) as follows:

$$TP_{A,\text{child}_k}(t, t^*_{\text{deadline}}, \lambda) = 1 - \left(\frac{t - t^*_{\text{deadline}}}{t^*_{\text{deadline}}} \right)^\lambda$$

(9)

where $A$'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) which is considered as agent's private information. Following are the three major classes of concession-making strategies with respect to the remaining trading time (details are discussed in Sim (2006, 2005)):

1. Conservative ($1 < \lambda < \infty$) — An agent $A_{\text{child}_k}$ makes smaller concession in early rounds and larger concession in later rounds.
2. Linear ($\lambda = 1$) — An agent $A_{\text{child}_k}$ makes a constant rate of concession.
3. Conciliatory ($0 < \lambda < 1$) — An agent $A_{\text{child}_k}$ makes larger concession in the early rounds and smaller concessions in the later rounds.

According to Eq. (9), the concession rate that is made by $A_{\text{child}_k}$ should be increased as $TP_{A,\text{child}_k}$ tends to become zero (e.g., negotiator's deadline is reached).

1) Previous concession behavior of negotiator's trading partner (PreBehave,Depend$\text{Bk}_k$) 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 the concession behavior of negotiator's trading partners should be modeled to determine the pattern of concession in grid resource allocation problem.

Adabi et al. (2013) model the concession behavior of $k$'th trading partner of negotiator agent $A$ (i.e., $B_k$) based on two following parameters: (1) the number of successful negotiations between $A$ and $B_k$ in all the GRNMs they both participated in ($\#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A}$) and 2) the ratio of average negotiation time between $A$ and $B_k$ in all GRNMs that both of them participate in ($A_{\text{negBk}_k} = \frac{\text{Ave.neg.time}_{B_k}}{\sum_{i=1}^{\text{no.}\text{GRNM}_{B_k-A}}} \text{Ave.neg.time}_{B_k}$). This means that the $B_k$, whose ratio of $\#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A}$ is the lowest and its Ave. neg. time$^{B_k}$ is too far from zero (makes a longer negotiation process), deserves to receive more penalty. For the benefit of readers, the calculation function of PreBehave,Depend$\text{Bk}_k$'s factor which is derived from Adabi et al. (2013) is shown in Eq. (10)

$$\text{PreBehave,Depend}^B_k = \frac{1}{\eta} \left[1 - (1 - \mu) \times \rho \right]$$

(10)

- **IF** ($\#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A} = 1$) AND (Ave. neg. time$^{B_k} < 0$) THEN ($\mu = 0$ AND $\rho = \text{Ave. neg. time}_{B_k} / \sum_{k=1}^{\text{no.\text{GRNM}_{B_k-A}}} \text{Ave. neg. time}_{B_k}$).
- **IF** ($\#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A} < 1$) AND (Ave. neg. time$^{B_k} = 0$) THEN ($\mu = 1$ AND $\rho = 1$).
- **IF** ($\#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A} > 1$) AND (Ave. neg. time$^{B_k} < 0$) THEN ($\mu = \#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A}$ AND $\rho = (\text{Ave. neg. time}_{B_k}) / (\sum_{k=1}^{\text{no.\text{GRNM}_{B_k-A}}} \text{Ave. neg. time}_{B_k})$).
- **IF** ($\#\text{Suc.neg}_{B_k-A}/\#\text{GRNM}_{B_k-A} = 1$ AND Ave. neg. time$^{B_k} = 0$) THEN ($\mu = 1$ AND $\rho = 0$).

where $\eta = 4$ is an experimental value (by experiment, it is believed to be an appropriate value for tuning the amount of concession). A negotiator agent $A$ has local database in name DB$_{\text{behave}}$ (see Table 3) that each of its data record contains the PreBehave,Depend$\text{Bk}_k$'s parameters.

2.3. Negotiation protocol

Type of negotiation protocol specifies the mechanism and the specific negotiation rules it uses for a particular negotiation. For the benefit of readers the authors summarize in Table 4 the key symbols and their definitions used in the negotiation protocol subsection of this paper.

In designing both types of EMBDNA (i.e., GRO,EMBDNA and GRC,EMBDNA), Rubinstein's sequential alternating offer protocol (Rubinstein, 1982) is enhanced. The negotiation procedure of Alternating offer protocol is as follows: the players (negotiators) can take actions only at certain times in the (infinite) set $T = \{1, 2, 3, \ldots, t\}$. In each period $t \in T$, one of the players, say $A$, proposes an agreement, and the other player $B$ 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 $B$ proposes an agreement, which player $A$ may accept if.

<table>
<thead>
<tr>
<th>Field name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_k$ id</td>
<td>The identifier of $B_k$</td>
</tr>
<tr>
<td>$#\text{GRNM}_{B_k-A}$</td>
<td>Numbers of GRNMs that both $B_k$ and $A$ participate in</td>
</tr>
<tr>
<td>$#\text{Suc.negot}_{B_k-A}$</td>
<td>Numbers of successful negotiations between $A$ and $B_k$ in all GRNMs that both of them participate in</td>
</tr>
<tr>
<td>Ave. neg. time$^{B_k}$</td>
<td>Average of negotiation time between $A$ and $B_k$ in all GRNMs that both of them participate in</td>
</tr>
</tbody>
</table>

Table 3 The data fields of DB$_{\text{behave}}$ database's record and their brief description Adabi et al. (2013).
that is designed to determine the relaxation amount is discussed in details. Alternating offer protocol (which is named as EAlternating offer protocol) is introduced.

Furthermore, having suitable flexibility under intense GMP can be a good approach to avoid risk of losing deals with other trading partners in a rational way is another important issue that should be considered especially in the case that the trading partner that is seemed to be a best opponent does not confirm the initial agreement from negotiator agent and the negotiation is not all these accept, seller A has one item and makes offers to multiple buyers and all these accept, buyer A must buy multiple items which is a non-reasonable behavior. Similarly, if seller A has one item and makes offers to multiple buyers and all these accept, seller A must provide more than one item which is a non-reasonable behavior. In addition, although the agreement from both sides of negotiation process is needed to avoid the non-reasonable behavior of negotiators, keep the chance of making agreement with other trading partners in a rational way is another important issue that should be considered especially in the case that the trading partner that is seemed to be a best opponent does not confirm the initial agreement from negotiator agent and the negotiation is not successfully completed. Furthermore, having suitable flexibility under intense GMP can be a good approach to avoid risk of losing deals in competition grid environment. To provide a solution for the mentioned issues an enhancement of Rubinstein’s sequential alternating offer protocol (which is named as EAlternating offer protocol) is introduced.

In the following, assumptions and rules apply in specifying the negotiation protocol are addressed and then the schema of the proposed EAlternating offer protocol is presented. Finally, Fuzzy Grid Market Pressure Determination System (FGMPDS) of EAlternating offer protocol that is designed to determine the relaxation amount is discussed in details.

### 2.3.1. Assumptions and rules

1. Time is discrete and is indexed by {0,1,2,...}—it is a logical and believable assumption, which is also made in other models [Sim, 2005; Osborne and Rubinstein, 1990].
3. Multiple pairs of negotiators can negotiate deals simultaneously since each pair is in a negotiation thread (We use the term “negotiation thread” for the single bargaining between negotiator agent A and its trading partner B).
4. All agents (including all resource consumers and owners) are selfish. That is, during negotiation, each agent chooses its negotiation strategy maximizing its (expected) utility; the assumption is intuitive, because the type of game is non-cooperative (negotiators make decisions independently with an arbitrary, finite number of negotiators. Also for the sake of simplicity it is assumed that the negotiator agents do not make coalition.

5. Each agent has incomplete information about the others. That is, negotiation begins with negotiators having private information (e.g., deadline, reserve price, time preferences, strategies and payoffs according to them). So, no negotiator knows the private information of the opponent.

6. For strategic reasons and according to Sim (2005), negotiators have information of only the index of the time period, their trading partners’ proposals and the existing number of competitors and trading partners (which is less restrictive or similar to the assumptions in most related work like Sim, 2004, 2006; An, 2011; Li et al., 2006; Nguyen and Jennings, 2005; Fatima et al., 2004).

7. Negotiation focuses on a single-issue (e.g., price-only). It is a plausible assumption which is also made in other models (Li and Li, 2004; Li et al., 2005, 2009; Ghosh et al., 2004, 2005).

8. A GRC (respectively, GRO) also faces market competition from other GRCs (respectively, GROS), which indicates that a negotiation agent needs to take the market situation into account to decide what is a necessary price to pay.

9. Typically, a negotiator proposes its most preferred deal initially (Sim, 2005).

10. Whenever it is the A’s turn to move (e.g. determine the amount of concession), it proposes a deal from its possible negotiation set (e.g., [IP_A, RP_A], recall that IP_A and RP_A are, respectively the initial and reserve prices of A).

11. If the initial price of A of type GRC_EMBDNA is not equal to or greater than the reservation price of Bk of type GRO_EMBDNA, the negotiation process terminates with conflict. This assumption is intuitive because a GRC_EMBDNA that its initial proposal is equal to or greater than GRO_EMBDNA's reserve price has enough budget to pay the minimum acceptable price of GRO_EMBDNA (i.e., reserve price) and from GRO_EMBDNA's point of view it is worthwhile to bargain with that GRC_EMBDNA in the hope of reaching consensus.

12. Negotiation process in GRM begins if only there are at least two negotiators of the opposite type (i.e., one negotiator of type GRC_EMBDNA and the other of type GRO_EMBDNA).

13. Negotiation consists of two stages: first negotiation stage and second negotiation stage. Details are described in Section 2.3.2.

14. A negotiator agent A makes initial agreement in first negotiation stage if either (i) the generated utility for agent A by received proposal PB_{t-1} from its trading partner B_k is greater or equal than the generated utility for agent A by its potential proposal to agent B_k or (ii) the sum of generated utility for agent A by received proposal PB_{t-1} from its trading partner B_k and market price value (i.e., GMP_value, that addresses the amount of relaxation and is determined by using FGMPDS) is greater or equal than the generated utility for agent A by its potential proposal to agent B_k (that is, an initial agreement can be reached if the offer does not totally match the agent's negotiation terms but is sufficiently close). Details of possible actions of negotiator A in first negotiation stage are described in First Stage Negotiation Algorithm (see Section 2.3.2).

15. A negotiator agent A makes final agreement in second negotiation stage based on Second Stage Negotiation Algorithm (details are discussed in Section 2.3.2).

16. If no agreement is reached, grid resource negotiation proceeds to the next round. At every round, the negotiator offers appropriate concession using the proposed multi factors function (Section 2.2).

17. Negotiation between two negotiators terminates (i) when a final agreement is reached, (ii) with a conflict when one of the negotiators’ deadline is reached or (iii) one of the negotiators decide to leave the GRNM.

18. At negotiation round t in which t=t_{deadline}, negotiator A would accept any proposal from agent B_k which gives it a utility not worse than zero.

19. When the negotiation ends, the history of negotiation is stored. This may be a good augmentation of database for future work.

2.3.2. Alternating offer protocol

Proposed Alternating offer protocol is designed with two stages which are considered for each negotiation thread: first negotiation stage and second negotiation stage. In presence of the two proposed agreement stages which aim at the development models of actual human behavior in negotiation process, a negotiator agent A is in the position to choose only the best received proposal from its trading partners and want to receive confirmation from that chosen trading partner (i.e., unlike the negotiation mechanism in Rubinstein (1982), a deal is made by having agreement from both sides of negotiation process) while keep the chance of making agreement that generates the same utility as the one that can be generated by the proposal of the chosen trading partner with other trading partners (this is useful especially in the case that the chosen trading partner does not confirm the agreement from negotiator agent A’s side and the negotiation is not successfully completed).

Following the first negotiation stage and second negotiation stage are described.

First negotiation stage—Let assume that no trading partner is, the number of negotiator A’s trading partners at negotiation round t-1. The action space of B_k ∈ {B_1, B_2, ..., B_n trading partner} in front of A childk is {A child, A child_2, ..., A child_m trading partner} at negotiation round t-1 is AS= {resource allocation process termination, initial accept, new price (amount of price), final accept} where resource allocation process termination action is made when the owner of B_k decides to terminate the negotiation process or B_k’s deadline is reached, initial accept action is made when B_k has agreed with the proposal of A child_k which is proposed in previous negotiation round t-2, new price (amount of price) action is made when B_k prefers to propose new price to A child_k and final accept action is made when initial accept action that is made by A child_k in previous negotiation round t-2 is confirmed by negotiator agent B_k.

The First Stage Negotiation Algorithm shows the decision making model of A child_k at negotiation round t in response to the possible actions that are made by B_k at negotiation round t-1 in the first negotiation stage. In details, at the first negotiation round which is A child_k’s turn to move, it needs to make an initial proposal to each trading partners. During each later round (0 < t ≤ t_{deadline}) which it is A child_k’s turn to move, it will always first check the type of its B_k’s action which is made in previous round t-1. If the type of B_k’s action is resource allocation process termination then A child_k finalizes the negotiation thread between himself and B_k as an unsuccessful negotiation and leave the GRNM. If the type of B_k’s action is final accept then A child_k finalizes the negotiation thread between himself

and $B_k$ as a successful negotiation and leave the GRNM. If the type of $B_k$’s action is initial accept then $A_{child_k}$ asks its parent (i.e., $A$) to continue the decision making process in second negotiation stage. Finally, if the type of $B_k$’s action is new_price then $A_{child_k}$ first evaluates the received price from $B_k$ using the First_Phase_Evaluation_of_received_proposal algorithm. According to the result of First_Phase_Evaluation_of_received_proposal algorithm two different decisions can be made: (1) if the generated utility for agent $A_{child_k}$ by received proposal $P_{B_k}^t$ from its trading partner $B_k$ is greater or equal than the generated utility for agent $A_{child_k}$ by its potential proposal to agent $B_k$ (which can be determined based on price-oriented strategy), then $A_{child_k}$ asks its parent to continue the decision making process in second negotiation stage else, 2) $A_{child_k}$ initiates the Second_Phase_Evaluation_of_received_proposal algorithm. The Second_Phase_Evaluation_of_received_proposal algorithm includes two steps. First step is to calculate GMP_value by using FGMPDS and the second step is to evaluate the received price from $B_k$ according to the calculated GMP_value. Two different decisions can be made according to the second step result: (1) if the sum of generated utility for agent $A_{child_k}$ by received proposal $P_{B_k}^t$ from its trading partner $B_k$ and GMP_value is greater or equal than the generated utility for agent $A_{child_k}$ by its potential proposal to agent $B_k$ (which is determined based on the price-oriented strategy), then $A_{child_k}$ asks its parent to continue the decision making process in second negotiation stage else (2) $A_{child_k}$ makes its potential price to $B_k$ by picking new_price action.

Second negotiation stage—The objectives of second negotiation stage are: (1) design rational negotiator agents that make at most one agreement (with a chosen trading partner) that its proposal generates the highest utility for negotiator agent $A$ and (2) keep the chance of making agreement that generates the same utility as the one that can be generated by the proposal of the chosen trading partner with other trading partners (this is useful especially in the case that the chosen trading partner does not confirm the agreement which is made by $A$ and the negotiation does not successfully completed and should be continued in the next round).

First_Phase_Negotiation_Algorithm: Decision making model based on initial negotiation stage of EA Alternating offer protocol

- Let assume $ANA_{set}^t$ is the set of GRNM’s active negotiation agents in negotiation round $t$.
- Let assume $A_{CHILD} = \{A_{child_1}, A_{child_2}, \ldots, A_{child_{no\_trading\_partner}}\}$ is the set of negotiator agent $A$’s children at round $t$.
- Let assume $B_k$ is $A_{child_k}$’s trading partner which is located in GRNM area that $A_{child_k}$ is responsible for.
- Let $P_{B_k}^t \rightarrow B$ is the proposal of negotiator agent $A$ to negotiator agent $B$ at negotiation round $t$.

1. In each negotiation round $t$ Do{

   1.1. For each negotiator agent $A \in A_{CHILD}^t$ Do{

      1.1.1.1. Switch case (action of trading partner $B_k$ in negotiation round $t-1$) {

         1.1.1.1.1. Case 1: resource_allocation_process_termination {

            1.1.1.1.1.1. Finalize unsuccessful negotiation process

            1.1.1.1.1.2. Leave GRNM }

         1.1.1.1.2. Case 2: initial_accept {

            1.1.1.1.2.1. Finalize successful negotiation process

            1.1.1.1.2.2. Leave GRNM }

         1.1.1.1.3. Case 3: new_price ($P_{B_k}^t$) {

            1.1.1.1.3.1. Second_Stage_Negotiation_Algorithm

        1.1.1.1.4. Case 4: action ${A_{child_k}}$ Do{

            1.1.1.1.4.1. First_Phase_Evaluation_of_received_proposal ($A_{child_k}, P_{B_k}^t$) Do{

            1.1.1.1.4.2. If go to second negotiation stage is returned

2. First_Phase_Evaluation_of_received_proposal (negotiator agent that has to make decision, proposal of that agent’s trading partner) Do {

   1. $A_{child_k}$ calculates $FST_{A_{child_k}}$ by adopting Eq. (7)

   2. $A_{child_k}$ determines $k_{t+1}$ by adopting Eq. (6)

   3. $A_{child_k}$ determines the amount of concession at round $t$ (e.g., $\Delta_t$) by adopting Eq. (5)

4. If the type of $A_{child_k}$ is GRC{

   4.1. $A_{child_k}$ sets $P_{t-1, child_k} = P_{t-2, child_k} + \Delta_t$

5. Else{

   5.1. $A_{child_k}$ sets $P_{t-1, child_k} = P_{t-2, child_k} - \Delta_t$

2. Second_Phase_Evaluation_of_received_proposal (negotiator agent that has to make decision, proposal of that agent’s trading partner) Do {

   1. $A_{child_k}$ determines final GMP_value by using FGMPDS (details are described in Section 2.3.3)

   2. If $U_{A_{child_k}}[P_{B_k}^t \rightarrow A_{child_k}] + GMP\_value \geq U_{A_{child_k}}[P_{B_k}^t \rightarrow B_k]$ Do{

      2.1. Return (go to second negotiation stage)

   3. Else{

      3.1. Return (make new price action)

6. $A_{child_4}$ calculates $U_{t-1}^{p_{child_4}}[p_{t-1}^{ch} \rightarrow A_{child_4}]
7. $A_{child_6}$ calculates $U_{t-1}^{p_{child_6}[p_{t-1}^{ch} \rightarrow B_6]}
8. If $U_{t-1}^{p_{child_4}}[p_{t-1}^{ch} \rightarrow A_{child_4}] > U_{t-1}^{p_{child_6}}[p_{t-1}^{ch} \rightarrow B_6]$ Do{
   8.1. Return (go to second negotiation stage)}
9. Else{
   9.1. Return (activate the next phase of evaluation)}

The first objective is covered by considering final_accept action that guarantees not having multiple finalized successful negotiation threads at a same time while A interested in successfully finalize only one negotiation thread. Suppose that more than one A’s trading partners made new_price(amount of price) action at negotiation round t-1. At negotiation round t of first negotiation stage that is A’s children turn to make an action in front of their trading partners, the A’s children whose trading partners made initial_accept action at negotiation round t-1 ask their parent (i.e., A) to continue decision making process in second negotiation stage. In second negotiation stage, A makes final_accept action against that trading partner who its initial_accept action generates the highest utility for A and resource_allocation_process_termination action against those trading partners who made initial_accept action in previous round t-1 but their initial_accept actions do not generate the highest utility for A. Doing this guarantees that negotiator agent A makes at most one agreement at a same time. Also suppose that more than one of A’s trading partner made new_price action at negotiation round t-1. At negotiation round t of first negotiation stage that is A’s children turn to make an action in front of their trading partners, the A’s children whose trading partners made the new_price action that generates the utility which is greater or equal than the utility of their potential proposals ask their parent (i.e., A) to continue decision making process in second negotiation stage. In second negotiation stage, A makes initial_accept action against that trading partner who its proposal generates the highest utility for A (which is named as selected trading partner) and new_price action against those trading partners who made new_price action in previous round t-1 but their proposals do not generate the highest utility for A (which are named as unselected trading partners). To keep the chance of making agreement that generates the same utility as the one that can be generated by the proposal of the selected trading partner with unselected trading partners, the concession amount of the new_price action that is made to unselected trading partners is set to the proposal of selected trading partner which generated the highest utility for A. This leads to speed up the negotiation process, increase price utility by jumping to the rational acceptable price (instead of following the price-oriented strategy) and increase success rate especially in a situation that final_accept action does not make by selected trading partner at negotiation round t+1 and negotiation process should be continued. By making two different actions in the mentioned situation, the second objective is covered.

Second_Phase_Evaluation_of_received_proposal shows the decision making model of negotiator agent A in second negotiation stage. During second negotiation stage, A will always first update its $INIT\_ACC\_ACT^t$ (i.e., container of initial_accept message(s) which is (are) received by A’s child (children)) and $New\_Price\_ACT^t$ (i.e., container of new_price message(s) which is (are) received by A’s child (children). The generated utility for A by considering this (these) new_price message(s) is greater equal than the utility of A’s potential proposal. Following, A checks whether $INIT\_ACC\_ACT^t$ is empty. If $INIT\_ACC\_ACT^t$ is not empty and the type of A is GRC then $INIT\_ACC\_ACT^t$ is sorted in a ascending order by A and the child whose received initial_accept message resides in the first position of $INIT\_ACC\_ACT^t$ (from now this child is named as $A_{child\_winner\_init}$) is asked to: (a) make final_accept action against his trading partner, (b) finalize the negotiation thread between himself and his trading partner as a successful negotiation and (c) leave the GRNM, also if $INIT\_ACC\_ACT^t$ is not empty and the type of A is GRO then $INIT\_ACC\_ACT^t$ is sorted in a descending order and the child whose received initial_accept message resides in the first position of $INIT\_ACC\_ACT^t$ is asked to repeat activities of A of type GRC which are discussed in parts (a), (b) and (c). Also other members of $INIT\_ACC\_ACT^t$ except $A_{child\_winner\_init}$ are asked to (a) make resource_allocation_process_termination action against their trading partners, (b) finalize the negotiation threads between themselves and their trading partners as an unsuccessful negotiation and (c) leave the GRNM.

If $INIT\_ACC\_ACT^t$ is empty and $New\_Price\_ACT^t$ is not empty and the type of A is GRC then: (i) $New\_Price\_ACT^t$ is sorted in a ascending order, (ii) the child whose received new_price message resides in the first position of $New\_Price\_ACT^t$ (from now this child is named as $A_{child\_winner\_newp}$) is asked to make initial_accept action against his trading partner and (iii) other members of $New\_Price\_ACT^t$ except $A_{child\_winner\_newp}$ are asked to make new_price action against their trading partners (the price value of this action is equal to the price value of the proposal of $A_{child\_winner\_newp}$’s trading partner). Finally, if $INIT\_ACC\_ACT^t$ is empty and $New\_Price\_ACT^t$ is not empty and the type of A is GRO then $New\_Price\_ACT^t$ is sorted in a descending order and parts (ii) and (iii) of A of type GRC are repeated.

Second_Phase_Evaluation_of_received_proposal: Decision making model based on final negotiation stage of Alternating offer protocol

- Let assume $INIT\_ACC\_ACT^t$ is the set of proposals that are initially accepted by A’s trading partners and are forwarded to A by $A_{CHILD}^t$’s members.
- Let assume $NEW\_PRICE\_ACT^t$ is the set of proposals that are sent by A’s trading partners and generate acceptable payoff for A (this can be evaluated by using First_Phase_Evaluation_of_received_proposal and (if necessary) Second_Phase_Evaluation_of_received_proposal). These proposals are forwarded by $A_{CHILD}^t$’s members to A.
- Let $A_{child\_winner\_newp}$ is A’s child who forwarded new_price message[where $B_k = B_{winner\_newp}$ and $B_{winner\_newp} = A_{child\_winner\_newp}$’s trading partner] that is located in the first position of ordered $NEW\_PRICE\_ACT^t$.
- Let $A_{child\_winner\_init}$ is A’s child who forwarded initial_accept message that is located in the first position of ordered $INIT\_ACC\_ACT^t$.

1. In each negotiation round t DO{
   1.1. Each negotiator agent $A \in ANA\_set\_DO$
      1.1.1. Update $INIT\_ACC\_ACT^t$ and $NEW\_PRICE\_ACT^t$ sets
      1.1.2. If $INIT\_ACC\_ACT^t$ is not NULL DO{
         1.1.2.1. If the type of negotiator agent A is GRO then {
            1.1.2.1.1 Sort $INIT\_ACC\_ACT^t$ in descending order }
2.3.3. Fuzzy grid market pressure determination system (FGMPSD)

The second distinguishing feature of EMBDNAs is that they have the flexibility of relaxing bargaining criteria in face of (intense) Grid Market Pressure (GMP) to enhance their chance of negotiating for resources more successfully and perhaps rapidly. In other words, the negotiation agents should be designed to slightly relax their bargaining terms or bargaining criteria (e.g., accepting a slightly lower price) by considering a suboptimal (or slightly more expensive) resource that can be allocated more quickly rather than the best (less expensive) resource which may be more difficult to acquire. Notions about parameters that make numerical value of GMP (i.e., GMP_value) are vague and uncertain to be expressed by crisp mathematical models. It is, however, often possible to describe the GMP_value by means of building fuzzy models. Two common sources of information for building fuzzy models are the prior knowledge and data (process measurements). Real data in the field of grid computing is rare and not available, hence it is prudent to construct Fuzzy Grid Market Pressure Determination System (FGMPSD) for determining GMP_value by using knowledge of experts.

We consider that, GMP can rise from three different sides: (1) competitors’ side (Competitor_side_GMP), (2) trading partners’ side (TP_side_GMP) and 3) GRNM’s global condition and negotiator’s conditions in acquiring/leasing resources (Condition & event_GMP). The FGMPSD composes of three types of fuzzy decision controller: Fuzzy Competitor_side GMP determinator, Fuzzy TP_side GMP determinator and Fuzzy Condition & event GMP determinator which are designed to determine the numerical values of Competitor_side_GMP, TP_side_GMP and Condition & event_GMP respectively. Final GMP_value is determined by considering the average of outputs of Fuzzy Competitor_side GMP determinator, Fuzzy TP_side GMP determinator and Fuzzy Condition & event GMP determinator to help negotiators in making near-optimal decisions during negotiation process (means rationally, a negotiator makes higher amount of concession as the relaxation criterion is discussed in detail.

Following the five components of each part of FGMPSD_GRC and FGMPSD_GRO are discussed.

2.3.3.1. Input and output variables of FGMPSD

2.3.3.1.1. Fuzzy Competitor_side GMP determinator. Output—The output of fuzzy Competitor_side GMP determinator is a numerical value of GMP from competitors’ side. Input set—Recall that a negotiator agent has less information about its competitors (according to strategic reasons) so the only relaxation criterion (from competitor side’s GMP perspective) that can influence a decision in the amount of relaxation of bargaining term includes change in number of competitors (NCN_chil). The rationale for considering NCN_chil criterion is given as follow. With a large number of competitors (i.e., high competition degree), an agent generally has a lower chance of reaching consensus with its trading partner and is more likely to be under pressure, and hence is more likely to slightly relax its bargaining criteria.

Following the NCN_chil relaxation criterion is discussed in detail.
i. Change in number of competitors (CNCA
_{childk}^t) Let CNCA
_{childk}^t \in \{0,1\} represents the degree of competition that an agent A_{childk} faces at negotiation round t. A negotiator agent A_{childk} \in A_{CHILD} determines its degree of competition at negotiation round t by considering the ratio of difference between number of A_{childk}'s competitors at negotiation round t (i.e., no.competitor
_{childk}^t \_A) and number of A_{childk}'s competitors at negotiation round t-1 (i.e., no.competitor
_{childk}^t \_A/C0) to the worst change in number of A_{childk}'s competitors (i.e., \text{WCC}_{A_{childk}}^t) that has been seen up to now in the current GRNM (i.e., Grid Resource Negotiation Market). At each negotiation round t, \text{WCC}_{A_{childk}}^t is determined thus:

\[
\text{WCC}_{A_{childk}}^t = \text{Max}(\text{no.competitor}_{A_{childk}}^t - \text{no.competitor}_{A_{childk}}^{t-1}, \text{no.competitor}_{A_{childk}}^{t-1} - \text{no.competitor}_{A_{childk}}^{t-2}, ..., \text{no.competitor}_{A_{childk}}^{0} - \text{no.competitor}_{A_{childk}}^{t-1})
\]

Also CNCA
_{childk}^t is determined as follows:

\[
\text{CNCA}_{A_{childk}}^t = \begin{cases} 
\frac{\text{no.competitor}_{A_{childk}}^t - \text{no.competitor}_{A_{childk}}^{t-1}}{\text{WCC}_{A_{childk}}^t} & \text{if } t > 0 \text{ and } (\text{no.competitor}_{A_{childk}}^t > \text{no.competitor}_{A_{childk}}^{t-1}) \\
0 & \text{if } t > 0 \text{ and } (\text{no.competitor}_{A_{childk}}^t < \text{no.competitor}_{A_{childk}}^{t-1}) \\
\text{CNCA}_{A_{childk}}^{t-1} & \text{if } t > 0 \text{ and } (\text{no.competitor}_{A_{childk}}^t = \text{no.competitor}_{A_{childk}}^{t-1}) \\
1 & \text{if } t = 0 
\end{cases}
\]

When no.competitor_{A_{childk}}^t < no.competitor_{A_{childk}}^{t-1} an agent A_{childk} faces with no GMP, hence the CNCA
_{childk}^t input of fuzzy Competitor_side GMP determinator will be set to the lowest possible value (i.e.\text{CNCA}_{A_{childk}}^t = 0). Also when no.competitor_{A_{childk}}^t is equal to no.competitor_{A_{childk}}^{t-1} the CNCA
_{childk}^t input of fuzzy Competitor_side GMP determinator is as same as the previous one (i.e.\text{CNCA}_{A_{childk}}^{t-1}). Obviously at the first negotiation round the CNCA
_{childk}^0 input of fuzzy Competitor_side GMP determinator is set to the worst value (i.e., one).

---

Consequently, with a higher (respectively, lower) value of \( CNTP_{A,\text{child}} \), an agent faces more (respectively, less) competition, and is more (respectively, less) likely to relax its bargaining criteria to reach an agreement. As the history of changing in competition degree is also considered in modeling the \( CNTP_{A,\text{child}} \), factor a negotiator benefits from a logical and accurate evaluation about the current market situation from the point of view of competition.

2.3.3.1.2. Fuzzy TP_side GMP determinator. As mentioned before TP_side_GMP_eva_agent is responsible to calculate the value of TP_side GMP and is equipped with TP_side GMP determinator.

Output—the output of fuzzy TP_side GMP determinator is a numerical value of GMP from trading partners' side.

Input set—Three relaxation criteria (from trading partner side's GMP perspective) that can influence a decision in the amount of relaxation of bargaining terms include (a) Distance between average of A's children's proposals and average of A's trading partners' proposals (DATPP\(_A^t\)), (b) Change in number of A's trading partners (CNTP\(_A^t\)) and (c) Acceptance degree of mutual behavior class between an agent A and its trading partners (AD_MBCTP\(_A^t\)). The rationale for considering criteria (a), (b) and (c) are given as follows. Since the chance of reaching consensus at the agent's own term will still be low, if the difference between the agent and the terms of all trading partners are very large (this cause that the probability that the agents will obtain a certain expected utility with at least one of its trading partners is low), it will be under more pressure to slightly relax its bargaining criteria with the hope of reaching consensus with at least one of its trading partners. Furthermore, with a few number of trading partners (i.e., low opportunity), an agent generally has a lower chance of reaching consensus with at least one of its trading partners (especially in stiff competition) and is more likely to be under pressure, and hence is more likely to slightly relax its bargaining criteria. In addition, it is intuitive that mutual behavior (that should be clearly explained and modeled) of the trading market participants of different types (i.e., one seller and one buyer) has great influence on the result of trading, this means that seller-buyer pair with suitable mutual behavior (which can be derived by analyzing previous markets that both participated) has higher chance to reach consensus and make deal in current market. Hence, a negotiator agent A that finds a few number of A-B\(_A\) pairs with suitable mutual behavior class (i.e., low AD_MBCTP\(_A^t\)) has lower chance to make an agreement and is more likely to relax its bargaining criteria to reach an agreement. The values of TP_side GMP determinator's input set are provided by negotiator agent A.

Following the three mentioned relaxation criteria are discussed in details.

i. Distance between average of A's children's proposals and average of A's trading partners' proposals (DATPP\(_A^t\)) Let DATPP\(_A^t\) \( \in [0,1] \) represents distance between the average of proposals of A's children and the average of proposals of A's trading partners. A negotiator agent A determines its DATPP\(_A^t\) at each negotiation round \( t \) by considering (1) the ratio of distance between the average of A's trading partners' proposals at negotiation round \( t-1 \) (i.e., ATP\(_R_{-1}\) which can be derived by considering new_price (amount of price) actions that are made by A's trading partners) and the average of A's children's proposals at negotiation round \( t-2 \) (i.e., AP\(_R_{-2}\)) to the average of A's trading partners' proposals at negotiation round \( t-1 \) (i.e., ATP\(_R_{-1}\)) and (2) the number of resource_allocation_process_termination actions that are made by A's trading partners at round \( t-1 \) as follows:

\[
DATPP_A^t = \frac{\alpha + \beta}{\text{no.trading._partners}_{t-1}}
\]

where

\[
\alpha = \begin{cases} 
\text{NTP.new_price}_{t-1} \times \frac{\text{ATPP}_{R_{-1}} - \text{AP}_{R_{-2}}}{\text{ATPP}_{R_{-1}}} & \text{if type of A is GRC} \\
\text{NTP.new_price}_{t-1} \times \frac{\text{AP}_{R_{-2}} - \text{ATPP}_{R_{-1}}}{\text{ATPP}_{R_{-1}}} & \text{if type of A is GRO}
\end{cases}
\]

\[
\beta = \text{NTP.resource_allocation_process_termination}_{t-1}
\]

\( \text{NTP.new.price}_{t-1} \) and \( \text{NTP.resource_allocation_process_termination}_{t-1} \) are the number of A's trading partners who made new_price(amount of price) action at negotiation round \( t-1 \) and the number of A's trading partners who made resource_allocation_process_termination action at negotiation round \( t-1 \), respectively. A high value of DATPP\(_A^t\) indicates that A is more under pressure to relax its bargaining criteria. As mentioned before receiving resource_allocation_process_termination message destroys the chance of having successful negotiation with that opponent who made this action in front of the negotiator. Obviously a negotiator's chance of reaching a consensus decreases as the number of receiving resource_allocation_process_termination messages increases. Also receiving new_price message from an opponent leads to have longer negotiation rounds and decreases the chance of having successful negotiation due to not have plenty of time. One can understand that a negotiator's chance of reaching a consensus decreases as the number of receiving new_price messages increases. In addition, if the distance(s) between the proposal of a negotiator agent and the proposals of its opponents are very large the probability of reaching consensus at the negotiator agent's own term will still be low, if the difference between the agent and the terms of all trading partners is low, it will be under more pressure to slightly relax its bargaining criteria with the hope of reaching consensus with at least one of its trading partners.

ii. Change in number of trading partners (CNTP\(_A^t\)) Let CNTP\(_A^t\) \( \in [0,1] \) represents the degree of opportunity that an agent faces at negotiation round \( t \). A negotiator agent A determines its degree of opportunity at negotiation round \( t \) by considering the ratio of difference between number of A's trading partners at negotiation round \( t-1 \) (i.e., no.trading._partner\(_A^{t-1}\)) and number of A's trading partners at negotiation round \( t \) (i.e., no.trading._partner\(_A^t\)) to the worst change in number of A's trading partners (i.e., WCTP\(_A^t\)) that has been experienced up to now in the current GRNM. At each negotiation round \( t \), WCTP\(_A^t\) is determined thus:

\[
\text{WCTP}_A^t = \max(\text{no.trading._partner}_{A}^{t-1} - \text{no.trading._partner}_{A}^t, 0)
\]

\[
- \text{no.trading._partner}_{A}^{t-2}, \ldots, (\text{no.trading._partner}_{A}^0)
\]

\[
- \text{no.trading._partner}_{A}^0, \ldots, (\text{no.trading._partner}_{A}^{t-1})
\]

Also CNTPA is determined as follows:

\[
\text{CNTPA} = \begin{cases} 
\text{no trading partner}_A - \text{no trading partner}_A, & \text{if } t > 0 \text{ and (no trading partner}_A > \text{no trading partner}_A) \\
0, & \text{if } t > 0 \text{ and (no trading partner}_A < \text{no trading partner}_A) \\
\text{CNTPA}_{t-1}, & \text{if } t > 0 \text{ and (no trading partner}_A = \text{no trading partner}_A) \\
1, & \text{if } t = 0
\end{cases}
\]

(16)

When no trading partner}_A < \text{no trading partner}_A, negotiator A faces with no GMP, hence the CNTPA input of fuzzy TP_side GMP determinator will be set to the lowest possible value (i.e., CNTPA = 0). Also when no trading partner}_A is equal to no trading partner}_A, the CNTPA input of fuzzy TP_side GMP determinator is as same as the previous one (i.e.,CNTPA). Obviously at the first negotiation round the CNTPA input of fuzzy TP_side GMP determinator is set to the worst value (i.e., one). Consequently, with a higher (respectively, lower) value of CNTPA, an agent faces less (respectively, more) opportunity, and is more (respectively, less) likely to relax its bargaining criteria. As the history of changing in trading opportunity degree is also considered in modeling the CNTPA factor a negotiator benefits from a logical and accurate evaluation about the current market situation from the point of view of trading opportunity.

iii. Acceptance degree of mutual behavior class between an agent and its trading partners (AD_MBCTP_A) The following three parameters Ave.neg.time_A, #Suc.neg.Bk_A and #GRNM_Bk_A that are introduced to model behavior factor PreBehave_Depend_B (see Section 2.2-part f) are used to describe mutual behavior class (i.e., Mutual_behavior_class_A) of each pair A–Bk (of opposite types). A new data field in name Mutual_behavior_class_A is added to the data fields of Table 3 to capture the value of mutual behavior class of each pair A–Bk.

The four mutual behavior classes are as follow:

1. Hasty and Royal (HR): means Ave.neg.time_A is close to zero and the #Suc.neg.Bk_A is close to the #GRNM_Bk_A (i.e., ratio of #Suc.neg.Bk_A/#GRNM_Bk_A tends to one).
2. Not Hasty but Royal (NHR): means Ave.neg.time_A is far from zero but the #Suc.neg.Bk_A is close to the #GRNM_Bk_A (i.e., ratio of #Suc.neg.Bk_A/#GRNM_Bk_A tends to one).
3. Hasty but Not Royal (HN): means Ave.neg.time_A is close to zero but the #Suc.neg.Bk_A is far from the #GRNM_Bk_A (i.e., ratio of #Suc.neg.Bk_A/#GRNM_Bk_A tends to zero).
4. Not Hasty and Not Royal (NHNR): means Ave.neg.time_A is far from zero and the #Suc.neg.Bk_A is far from the #GRNM_Bk_A (i.e., ratio of #Suc.neg.Bk_A/#GRNM_Bk_A tends to zero).

We use threshold ε = 0.5 (by experiment, it is believed to be an appropriate value) to determine the mutual behavior class of each negotiator agent pair A–Bk (of opposite types) as follows:

\[
\text{IF ( } \#\text{Suc.neg.Bk}_A / \#\text{GRNM}_B - A \geq \varepsilon \text{ THEN “Mutual_behavior_class}_A \text{ is tagged with } \text{HR} \text{ ELSE “Mutual_behavior_class}_A \text{ is tagged with } \text{NHR} \text{ IF ( Ave.neg.time}_A / \text{WNT}_{A_{up to now}} \geq \varepsilon \text{ THEN “Mutual_behavior_class}_A \text{ is tagged with } \text{NH} \text{ ELSE “Mutual_behavior_class}_A \text{ is tagged with } \text{NR} \text{ })}
\]

where WNT_A up to now is the worst negotiation time that A being spent in all GRNMs up to now. According to this new parameter a data field in name WNT_A up to now, is added to the data fields of Table 3 to capture the value of the worst negotiation time that A is being spent in all previous GRNMs. By terminating a negotiation process of A in each GRNM, WNT_A up to now is updated thus:

\[
\text{WNT}_{A_{up to now}} = \text{Max}(WNT_{A_{up to now}} , \text{neg.time}_{current - \text{GRNM}})
\]

(17)

where neg.time_{current - \text{GRNM}} is the negotiation time that A being spend in current GRNM. The value of WNT_A up to now is set to one for the first entrance of a negotiator to GRNM. Following we discuss the method of determining acceptance degree of mutual behavior class between an agent A and its trading partners (AD_MBCTP_A). It should be highlighted that the AD_MBCTP_A is determined and updated by an agent A individually.

Let assume that the percentage of A’s trading partners that have mutual behavior class of RH, NRH, RNH and NRNH with A at negotiation round t are percentage_RH, percentage_RNH, percentage_NRH and percentage_NRNH respectively. From A’s point of view, the trading partners with RH (respectively, NRNH) mutual behavior class in front of A make the best (respectively, the worst) situation for him as A has higher (respectively, lower) chance to make a successful deal with them. Also, the trading partners with NRH (respectively, NRH) mutual behavior class in front of A, have half of the part of the good behavior (cause by royal behavior (respectively, hasty behavior)) in comparison to the trading partners who have RH mutual behavior class in front of A and half of the part of the bad behavior (cause by not hasty behavior (respectively, not royal behavior)) in comparison to the trading partners who have NRNH mutual behavior class in front of A, so by having fifty percent good behavior and fifty percent bad behavior the trading partners with NRH and NRNHNH mutual behavior class are not considered in AD_MBCTP_A determination.

At each negotiation round t, AD_MBCTP_A is determined thus:

\[
\text{AD}_{MBCTP} = \frac{\text{percentage}_{\text{NH}} - \text{percentage}_{\text{RHN}}}{100} + 100
\]

(18)

In Eq. (18) AD_MBCTP_A is normalized to [0,1] where the worst case (i.e., percentage_{\text{NRNHN}} and percentage_{\text{RH}} are equal to 100% and 0% respectively) is normalized to one and the best case (i.e., percentage_{\text{NH}} and percentage_{\text{RHN}} are equal to 0% and 100% respectively)
normalized to zero. Consequently, a high value of $AD_{MBCTP_A}$ indicates that an agent $A$ has less trading partners with mutual behavior class of RH, so it is under more pressure to relax its bargaining criteria.

2.3.3.1.3. Fuzzy Condition & event GMP determinator of FGMPDS_GRC. As mentioned before Condition and event_GMPeva_agent is responsible to calculate the value of condition & event GMP and is equipped with condition and event GMP determinator.

Output—The output of fuzzy condition & event GMP determinator is a numerical value of GMP from both GRNM’s global condition and negotiator’s conditions in acquiring resources.

Input set- Three relaxation criteria (from condition & event side’s GMP perspective) that can influence a decision in the amount of relaxation of bargaining terms include (i) Recent statistics in failing/succeeding in acquiring resources ($FS_t$), (ii) Demand for computing resources ($DF_t$) and (iii) Ratio of a GRC_EMBDNA’s competitors to sum of numbers of GRC_EMBDNA’s competitors and trading partners ($RNCSCT_A^t$). The first and second relaxation criteria are derived from Sim and Ng (2007). As mentioned in Sim and Ng (2007)), the idea behind definition of these two criteria is that if a GRC is less successful in acquiring resources recently to execute its set of tasks will be under more pressure to slightly relax its bargaining criteria in the hope of completing a deal, also if it has a greater demand for computing resources it is more likely to be under more pressure to slightly relax its bargaining criteria. In addition, if the ratio of total number of GRC_EMBDNA’s competitors versus the sum of total number of GRC_EMBDNA’s trading partners and competitors tends to one (i.e., a GRC_EMBDNA has a lower chance of reaching a consensus at its own term with a few number of trading partners and also has a lower chance of being ranked the highest by its trading partner in face of high degree of competition), it will be under more pressure to slightly relax its bargaining criteria with the hope of completing a deal. The values of condition and event GMP determinator’s input set are provided by negotiator agent $A$.

i. Recent statistics in failing/succeeding in acquiring resources ($FS_t$) $FS_t \in [0, \infty)$ represents the ratio of the number of recent successful negotiations of a GRC (i.e., number of GRC’s tasks that successfully negotiate and reach agreement with resource owners) to the number of its recent successful negotiations by considering its negotiation history in the previous $n$ rounds of negotiation.

A negotiator agent $A$ of type GRC_EMBDNA determines $FS_t$ at negotiation round $t$ as follows:

$$FS_t = \frac{\sum_{i=t-n}^{t-1} f_i}{\sum_{i=t-n}^{t-1} s_i}$$

where $f_i$ and $s_i$ denote the number of unsuccessful and successful negotiations at negotiation round $t$, respectively, also according to the probability of GRC generating a task that needs computing resources at each negotiation round $t$ (i.e., $P_m$) and the number of negotiation results to be considered (i.e., $r$), $n$ can be defined as follows (more details can be found in Sim and Ng (2007))

$$n = \frac{r}{P_m}$$

A high value of $FS_t$ indicates that the agent is less successful in acquiring resources recently to execute its set of tasks, and it is under more pressure to relax its bargaining criteria.

ii. Demand for computing resources ($DF_t$) $DF_t \in [0,1]$ represents a GRC’s relative level of recent demand for computing resources. Let assume that the total resource demand capacity at round $t$ and the number of rounds to take the recent negotiation results into consideration at negotiation round $t$ are denoted by $d_t$ and $n$ respectively. $DF_t$ is determined by negotiator agent $A$ of type GRC_EMBDNA as follows (more details can be found in Sim and Ng (2007))

$$DF_t = d_t/\text{Max}(d_t-n,d_{t-n+1}+\ldots+d_1)$$

A high value of $DF_t$ indicates that the agent has greater demand for computing resources, and it is under more pressure to relax its bargaining criteria.

iii. Ratio of a GRC_EMBDNA’s competitors to sum of numbers of GRC_EMBDNA’s competitors and trading partners ($RNCSCT_A^t$) $RNCSCT_A^t \in [0,1]$ represents the ratio of (a) total number of competitors at negotiation round $t$ versus (b) sum of numbers of competitors and trading partners at negotiation round $t$ that can be shown formally as follows:

$$RNCSCT_A^t = \frac{\text{no. competitor}_t}{\text{no.trading partner}_t+\text{no.competitor}_t}$$

From RNCSCT_A^t’s perspective, the suitable situation is started by having no competitors (i.e., no.competitor_A^t=0) and will be bettered by increasing no.trading_partner_A^t. Hence, when no.competitor_A^t is equal to zero $A$ faces with no GMP and the RNCSCT_A^t input of fuzzy Condition & event GMP determinator will be set to lowest possible value (i.e.,RNCSCT_A^t=0). Consequently, when RNCSCT_A^t tends to one (i.e., no.competitor_A^t increases while no.trading_partner_A^t decreases), an agent is under more pressure to relax its bargaining criteria.

2.3.3.1.4. Fuzzy condition and event GMP determinator of FGMPDS_GRO. As mentioned before condition and event_GMPeva_agent is responsible to calculate the value of condition and event GMP and is equipped with condition and event GMP determinator.

Output—The output of fuzzy condition & event GMP determinator is GMP value from both GRNM’s global condition and negotiator’s conditions in leasing resources.

Input set—Three relaxation criteria (from Condition & event side’s GMP perspective) that can influence a decision in the amount of relaxation of bargaining terms include (i) Utilization level ($UL_A$), (ii) Request factor ($RF_t$) and (iii) Ratio of a GRO_EMBDNA’s competitors to sum of numbers of GRO_EMBDNA’s competitors and trading partners ($RNCSCT_A^t$). The first and second relaxation criteria are derived from Sim and Ng (2007). As mentioned in Sim and Ng (2007)), the idea behind definition of these two criteria is that if more of GRO’s resources are currently being used to execute its own tasks or have already been leased to other GRCs (i.e., the $UL_A$ is high), then GRO is
less likely to slightly relax its bargaining term, also if there are fewer recent demands from GRCs to lease its resources (i.e., the RFt is low), a GRO is more likely to slightly relax its bargaining criteria since it is under more pressure to trade its idle resources. In addition, if the ratio of total number of GRO_EMBDNA’s competitors versus the sum of total number of GRO_EMBDNA’s trading partners and competitors tends to one (i.e., a GRO_EMBDNA has a lower chance of reaching a consensus at its own term with a few number of trading partners and also has a lower chance of being ranked the highest by its trading partner in face of high degree of competition), it will be under more pressure to slightly relax its bargaining criteria with the hope of completing a deal. The values of condition and event GMP determinator's input set are provided by negotiator agent A.

i. Utilization level (ULt) Let assume that R0 is a GRO’s capacities that is currently being utilized to execute its own tasks or leased out to other GRCs to execute their tasks and RFt is a GRO’s total resource capacities. ULt ∈ [0,1] is determined by A of type GRO_EMBDNA as follows (more details can be found in Sim and Ng (2007))

\[ ULt = \frac{R0}{RFt} \]  

(23)

A high value of ULt indicates that the agent is under less pressure to lease out its resources hence it is under less pressure to relax its bargaining criteria.

ii. Request factor (RFt) Let assume that n is the number of rounds to take into consideration the recent total resource capacity requests which is determined as follows:

\[ n = h \times M_d \]  

(24)

where h and M_d are experimental parameter and a mid-range negotiation deadline for the GRO that provides an estimation for the number of rounds that a request for resource will persist for a GRO respectively. Let M_d=(I+u)/2 where I and u are the lower and upper bounds of a GRO’s negotiation deadline respectively.

\[ RFt = \frac{r_i}{\text{Max}(r_{i-n}, r_{i-n+1}, \ldots, r_1)} \]  

(25)

where ri is the total resource capacities requested by GRCs at negotiation round i. A low value of RFt indicates that there are fewer recent demands from GRCs to lease the agent A’s resources hence it is under more pressure to trade its resources and has to relax its bargaining criteria.

iii. Ratio of a GRO_EMBDNA’s competitors to sum of numbers of GRO_EMBDNA’s competitors and trading partners (RNCSCTA). The definition of RNCSCTA input of fuzzy Condition & event GMP determinator part of FGMPDS_GRO is the same as RNCSCTA input of fuzzy Condition & event GMP determinator part of FGMPDS_GRC that is described in Sections 2.3.3.1-(C-1)-iii.

2.3.3.2. Fuzzification interface (FI). The FI converts the (crisp) input data to the fuzzy decision controller into linguistic values. Based on the range of possible values of variables, several fuzzy sets are defined and a membership function \( \mu(x) \) is used for assigning the degree of membership of each crisp value of a variable in the fuzzy sets (Klir, 1995). Following we discussed about the range of possible values of input and output variables and the membership functions that are used to assign the degree of membership for that input and output variables in each fuzzy decision controller part of FGMPDS_GRC and FGMPDS_GRO (recall that Fuzzy Competitor_side GMP determinator and Fuzzy TP_side GMP determinator parts of FGMPDS_GRC are as same as Fuzzy Competitor_side GMP determinator and Fuzzy TP_side GMP determinator parts of FGMPDS_GRO respectively, but Fuzzy Condition & event GMP determinator parts of FGMPDS_GRC and FGMPDS_GRO are different).

2.3.3.2.1. Fuzzy competitor_side GMP determinator. Fuzzy values of output variable- Three fuzzy sets are defined for Competitor_side GMP determinator’s output variable: \( L_{\text{Competitor_side GMP}}, M_{\text{Competitor_side GMP}}, H_{\text{Competitor_side GMP}} \). That is, Competitor_side GMP output variable has three fuzzy values: [L(low), M(moderate), H(high)]. A membership function \( \mu_1(x) \) is used to assign the degree of membership for Competitor_side_GMP:

\[
\mu_1(x) = \begin{cases} 
-2x+1 & x \in [0, \frac{1}{2}] \\
p_1(2x+1)(-2x+1) & x \in [0, 1] \\
2x-1 & x \in [\frac{1}{2}, 1]
\end{cases}
\]  

(26)

where \( p_1 = 1 \) when \( x \in [0, \frac{1}{2}] \), and \( p_1 = 0 \) when \( x \in [\frac{1}{2}, 1] \). The linguistic terms of the membership function \( \mu_1(x) \) is shown in Fig.3(a).

Fuzzy values of input variable—Since notions such as “low” or “high” change in number of competitors are vague, it seems prudent to represent these concepts as fuzzy sets. Hence, several fuzzy sets are defined for Competitor_side GMP determinator’s input variable (i.e., CNC\_child\_Competitor). The fuzzy sets, fuzzy values and membership functions of CNC\_child\_Competitor input of Competitor_side GMP determinator are as same as those fuzzy sets, fuzzy values and membership functions of Competitor_side_GMP output of Competitor_side GMP determinator.

2.3.3.2.2. Fuzzy TP_side GMP determinator. Fuzzy values of output variable- Four fuzzy sets are defined for TP_side GMP determinator’s output variable: \( L_{\text{TP_side GMP}}, M_{\text{TP_side GMP}}, H_{\text{TP_side GMP}} \). That is, TP_side GMP output variable has four fuzzy values: [N(negligible), L(low), M(moderate), H(high)]. A membership function \( \mu_2(x) \) is used to assign the degree of membership for TP_side_GMP:

\[
\mu_2(x) = \begin{cases} 
-3x+1 & x \in [0, \frac{1}{2}] \\
p_2(3x+1)(-3x+2) & x \in [0, \frac{2}{3}] \\
p_3(3x-1)(-3x+3) & x \in [\frac{2}{3}, 1] \\
3x-2 & x \in [\frac{3}{2}, 1]
\end{cases}
\]  

(27)

where \( p_1 = 1 \) when \( x \in [0, \frac{1}{2}] \), \( p_2 = 1 \) when \( x \in [\frac{1}{2}, \frac{2}{3}] \), also \( p_2 = 1 \) when \( x \in [\frac{2}{3}, \frac{3}{2}] \), and \( p_2 = 0 \) when \( x \in [\frac{3}{2}, 1] \). The linguistic terms of the membership function \( \mu_2(x) \) is shown in Fig.3(b).
Fuzzy values of each member of input set—Since notions such as “close” to or “far” from average of trading partners’ proposals, “low” or “high” change in number of trading partners and “good”, “balance” or “bad” acceptance degree of mutual behavior class between an agent and its trading partners are vague, it seems prudent to represent these concepts as fuzzy sets. Hence, several fuzzy sets are defined for each \( TP_\text{side GMP determinator} \)’s input variable. The fuzzy sets, fuzzy values and membership functions of \( DATPP_4 \) and \( CNTP_4 \) inputs of \( TP_\text{side GMP determinator} \) are as same as those fuzzy sets, fuzzy values and membership functions of \( RNCSCTA \) input of \( Competitor_\text{side GMP determinator} \). Also, while the membership functions of \( AD_\text{MBCTP} \) input of \( TP_\text{side GMP determinator} \) are as same as the membership functions of \( CNCA_{\text{childk}} \) input of \( Competitor_\text{side GMP determinator} \), three different fuzzy sets \( (G_{\text{AD MBCTP}}, B_{\text{AD MBCTP}}, B_{\text{AD MBCTP}}) \) and three different fuzzy values: \{G(good), BL(balance), B(bad)\} are defined for \( AD_\text{MBCTP} \).

2.3.3.2.3. Fuzzy Condition & event GMP determinator of FGMPDS_GRC. Fuzzy values of output variable—The fuzzy sets, fuzzy values and membership functions of fuzzy Condition & event GMP determinator output are as same as those fuzzy sets, fuzzy values and membership functions of \( TP_\text{side GMP determinator} \) output.

Fuzzy values of each member of input set—Since notions such as being “less” successful in acquiring resources recently, “greater” demand for computing resources and “high” or “low” number of competitors in comparison to number of trading partners are vague, it seems prudent to represent these concepts as fuzzy sets. Hence, several fuzzy sets are defined for each \( Condition \& event GMP determinator \)’s input variable. The fuzzy sets, fuzzy values and membership functions of \( RNCSCCTA \) input of \( Competitor_\text{side GMP determinator} \) are as same as those fuzzy sets, fuzzy values and membership functions of \( CNCA_{\text{childk}} \) input of \( Competitor_\text{side GMP determinator} \), four fuzzy sets \( (N_{\text{LSF}}, M_{\text{FS}}, H_{\text{FS}}) \) and four fuzzy sets \( (N_{\text{DF}}, L_{\text{DF}}, M_{\text{DF}}, H_{\text{DF}}) \) are defined for \( FS\) and \( DF\) input variables respectively. That is, \( FS\) and \( DF\) input variables have four fuzzy values: \{N(negligible), L(low), M(moderate), H(high)\}. The membership functions \( \mu_3(x) \) and \( \mu_4(x) \) are used to assign the degree of membership for \( FS\) and \( DF\) respectively:

\[
\mu_3(x) = \begin{cases} 
-2x + 1 & x \in [0, \frac{1}{2}] \\
 p_1(2x + 1) - p_1(-2x + 2) & x \in [\frac{1}{2}, 1] \\
p_2(2x - 1) + (1 - p_2)(-2x + 3) & x \in [\frac{1}{2}, 1] \\
\min(1, 2x - 2) & x \in [1, \infty] 
\end{cases}
\]

(28)

where \( p_1 = 1 \) when \( x \in [0, 1/2] \), and \( p_1 = 0 \) when \( x \in [1/2, 1] \), also \( p_2 = 1 \) when \( x \in [1/2, 1] \), and \( p_2 = 0 \) when \( x \in [1, 3/2] \).

\[
\mu_4(x) = \begin{cases} 
-3x + 1 & x \in [0, \frac{1}{2}] \\
p_3(3x + 1) - p_3(-3x + 2) & x \in [\frac{1}{2}, 1] \\
p_2(3x - 1) + (1 - p_2)(-3x + 3) & x \in [\frac{1}{2}, 1] \\
3x - 2 & x \in [1, \infty] 
\end{cases}
\]

(29)

where \( p_3 = 1 \) when \( x \in [0, 1/3] \), and \( p_3 = 0 \) when \( x \in [1/3, 2/3] \), also \( p_2 = 1 \) when \( x \in [1/3, 2/3] \), and \( p_2 = 0 \) when \( x \in [2/3, 1] \).

The linguistic terms of the membership functions \( \mu_3(x) \) and \( \mu_4(x) \) are shown in Fig. 3(c) and (d) respectively.

2.3.3.2.4. Fuzzy Condition & event GMP determinator of FGMPDS_GRO. Fuzzy values of output variable—The fuzzy sets, fuzzy values and membership functions of fuzzy Condition & event GMP determinator output are as same as those fuzzy sets, fuzzy values and membership functions of \( TP_\text{side GMP determinator} \) output.

Fuzzy values of each member of input set—Since notions such as “more” resources currently being used, “fewer” recent demands and “high” or “low” number of competitors in comparison to number of trading partners are vague, it seems prudent to represent these concepts as fuzzy sets. Hence, several fuzzy sets are defined for each \( Condition \& event GMP determinator \)’s input variable. The fuzzy sets, fuzzy values and membership functions of \( RF\) and \( UL\) inputs of \( fuzzy Condition \& event GMP determinator \) of \( FGMPDS\_GRO \) are as same as those fuzzy sets, fuzzy values and membership functions of \( DF\) input of \( fuzzy Condition \& event GMP determinator \) of \( FGMPDS\_GRC \). Also


the fuzzy sets, fuzzy values and membership functions of RNCSCTA\textsuperscript{a}, input of fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRO} are as same as those fuzzy sets, fuzzy values and membership functions of RNCSCTA\textsuperscript{a}, input of fuzzy condition & event GMP determinator of FGMPDS\textsubscript{GRC}.

2.3.3.3. Fuzzy rule base (RB). The fuzzy rules that are shown in Tables 5–8, are consulted by fuzzy Competitor\_side GMP determinator, fuzzy TP\_side GMP determinator, Condition & event GMP determinator of FGMPDS\textsubscript{GRC} and Condition & event GMP determinator of FGMPDS\textsubscript{GRO} respectively.

2.3.3.4. Fuzzy negotiation decision making logic (DML)

A: DML of Fuzzy Competitor\_side GMP determinator By consulting the fuzzy rules in RB (see Table 5), the DML infers the linguistic value of Competitor\_side GMP and its corresponding membership degree \( \mu(\text{Competitor\_side GMP}) \) from the linguistic values and membership degrees of the fuzzified input \( \text{CNC}\textsubscript{child} \).

B: DML of Fuzzy TP\_side GMP determinator By consulting the fuzzy rules in RB (see Table 6), the DML infers the linguistic value of TP\_side GMP and its corresponding membership degree \( \mu(\text{TP\_side GMP}) \) from the linguistic values and membership degrees of the fuzzified inputs DATPP\textsubscript{a}, CNTP\textsubscript{a} and AD\_MBCTP\textsubscript{a}.

C-1: DML of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRC} By consulting the fuzzy rules in RB (see Table 7), the DML infers the linguistic value of condition & event side's GMP and its corresponding membership degree \( \mu(\text{condition & event side's GMP}) \) from the linguistic values and membership degrees of the fuzzified inputs \( F\textsubscript{r}, D\textsubscript{r}, \text{and RNCSCTA}\textsubscript{a} \).

C-2: DML of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRO} By consulting the fuzzy rules in RB (see Table 8), the DML infers the linguistic value of condition & event side's GMP and its corresponding membership degree \( \mu(\text{condition & event side's GMP}) \) from the linguistic values and membership degrees of the fuzzified inputs \( U\textsubscript{r}, R\textsubscript{f} \) and RNCSCTA\textsubscript{a}.

2.3.3.5. Defuzzification interface (DFI)

A: DFI of Fuzzy Competitor\_side GMP determinator The DFI of Fuzzy Competitor\_side GMP determinator is used to determine the crisp value of Competitor\_side GMP given its linguistic values with their respective membership degree being obtained from the DML of Fuzzy Competitor\_side GMP determinator.

B: DFI of Fuzzy TP\_side GMP determinator The DFI of Fuzzy TP\_side GMP determinator is used to determine the crisp value of TP\_side GMP given its linguistic values with their respective membership degree being obtained from the DML of Fuzzy TP\_side GMP determinator.

C-1: DFI of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRC} The DFI of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRC} is used to determine the crisp value of Condition & event GMP of FGMPDS\textsubscript{GRC} given its linguistic values with their respective membership degree being obtained from the DML of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRC}.

C-2: DFI of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRO} The DFI of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRO} is used to determine the crisp value of Condition & event GMP of FGMPDS\textsubscript{GRO} given its linguistic values with their respective membership degree being obtained from the DML of Fuzzy Condition & event GMP determinator of FGMPDS\textsubscript{GRO}.

Similar to Sim and Wang (2004, 2007) and Sim (2008) all the DFI(s) in this work adopt the weighted average method (Ross, 1995).

<table>
<thead>
<tr>
<th>Table 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy rules consulted by fuzzy Competitor_side GMP determinator. The output is Competitor_side GMP.</td>
</tr>
<tr>
<td>No</td>
</tr>
<tr>
<td>---</td>
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<tr>
<td>1</td>
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<table>
<thead>
<tr>
<th>Table 6</th>
</tr>
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<tbody>
<tr>
<td>Fuzzy rules consulted by fuzzy TP_side GMP determinator. The output is TP_side GMP.</td>
</tr>
<tr>
<td>No</td>
</tr>
<tr>
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<tr>
<td>1</td>
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Table 7
Fuzzy rules consulted by fuzzy Condition & event GMP determinator of FGMPDS_GRC. The output is condition & event_GMP.

<table>
<thead>
<tr>
<th>No</th>
<th>IFRNCSCT</th>
<th>And ULt</th>
<th>And RFt</th>
<th>Then output</th>
<th>No</th>
<th>IFRNCSCT</th>
<th>And ULt</th>
<th>And RFt</th>
<th>Then output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>L</td>
<td>M</td>
<td>H</td>
<td>N</td>
<td>9</td>
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<td>M</td>
<td>N</td>
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</tr>
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<td>2</td>
<td>L</td>
<td>M</td>
<td>H</td>
<td>N</td>
<td>10</td>
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<td>L</td>
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<td>L</td>
<td>M</td>
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<td>L</td>
<td>M</td>
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<td>L</td>
</tr>
<tr>
<td>8</td>
<td>L</td>
<td>M</td>
<td>H</td>
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<td>16</td>
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Table 8
Fuzzy rules consulted by fuzzy condition & event GMP determinator of FGMPDS_GRO. The output is condition & event_GMP.

<table>
<thead>
<tr>
<th>No</th>
<th>IFRNCSCT</th>
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<th>And RFt</th>
<th>Then output</th>
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<tbody>
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<td>M</td>
<td>H</td>
<td>N</td>
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3. Experimental results

3.1. Objectives

A series of experiments was carried out to compare the performance of EMBDNAs (that are programmed to slightly relax their bargaining criteria under intense GMP which is computed by using proposed FGMPDS) with MBDNAs (that do not adopt the proposed fuzzy negotiation protocol but apply the same negotiation strategy as EMBDNAs) (Adabi et al., 2013) and EMDAs (that is believed to be an appropriate negotiation protocol for comparison because it is equipped with fuzzy decision controller that uses fuzzy inputs with high similarity to EMBDNAs’ fuzzy inputs to determine the relaxation amount) (Sim and Ng, 2007) in a very wide variety of test environments. MBDNAs are described in details in Adabi et al. (2013), but EMDAs’ two fuzzy decision controllers (one modeling GRCs’ criteria, and one modeling GROs’ criteria) for determining the amount of concession of GRC agents and utilization level (ULt) and request factor (RFt) are used as criteria for determining the amount of concession of GRO agents. The calculation functions of FS\textsubscript{t}, DF\textsubscript{t}, ULt and RFt are shown in Eqs. (19), (21), (23) and (25) respectively. For benefit of readers, the generic structures of EMDAs’ fuzzy decision controllers from GRCS’ and GRO’s perspective are shown in Fig. 4.

3.2. TestBed

To evaluate the performance of EMBDNAs against MBDNAs (Adabi et al., 2013) and EMDAs (Sim and Ng, 2007), a testbed is developed. Implemented using C++, the testbed consists of: (1) a virtual e_market; (2) a society of negotiation agents comprising MBDNAs, EMBDNAs and EMDAs; and (3) a controller agent.

1) Virtual e_marketIn a virtual e_market, negotiation agents have one of the following roles: grid resource consumer (GRC) or grid resource owner (GRO).
2) Society of negotiation agentsThree kinds of negotiation agents: MBDNAs, EMDAs and EMBDNAs are simulated. For each negotiation agent of type EMBDNA a local database in name DB\_behave is considered. In addition, each EMBDNA is composed of two embedded agents: TP\_side\_GMPeva\_agent and Condition & event\_GMPeva\_agent.
3) Controller agentThe controller agent generates negotiation agents (EMBDNAs, MBDNAs and EMDAs), randomly determines their parameters (e.g., their roles as either GRC or GRO, initial prices (IP), reserve prices (RP), negotiation strategies (λ), deadlines, their competitors and trading partners) and simulate the entrance of agents to the GRNM following a uniform distribution.

3.3. Experimental scenarios

In the experiments, MBDNAs, EMDAs and EMBDNAs were subjected to different market densities, different market types (i.e., GRC\_favorable, Balanced and GRO\_favorable), different deadlines, different time preferences (i.e., λ) and different grid loads. Although both EMBDNA\_GRC and EMBDNA\_GRO agents are augmented with fuzzy decision controller to slightly relax their bargaining criteria,
but without loss of generality and because of lacking enough space, it suffices to demonstrate the properties of EMBDNAs from the perspective of GRC agents. So we conduct four types of experiments: (1) GRC agents are EMBDNAs and GRO agents are MBDNAs, (2) GRC agents are EMBDNAs and GRO agents are EMDAs and (3) GRC agents are MBDNAs and GRO agents are MBDNAs.

The reason that in the first (respectively, second) experiment just GRC agents are considered as EMBDNAs while GRO agents are considered as MBDNAs (respectively, EMDAs) is based on a common assumption in microeconomics, namely *ceteris paribus* (Salvatore, 1997). According to Salvatore (1997): “the effect of a particular factor can be analyzed by holding all other factors constant.” As mentioned before the purpose of the experiment is to compare the performance of EMBDNAs of type GRC against those negotiation agents that are not designed with our proposed FGMPDS (i.e., MBDNAs (respectively, EMDAs)), it seems prudent to avoid any possible influence on the negotiation outcomes when EMBDNAs of type GRC make relaxation based on the proposed FGMPDS. Hence in our experiment GRO agents are programmed as MBDNAs (respectively, EMDAs) because MBDNAs (respectively, EMDAs) are not designed with the proposed FGMPDS. Also, in the third (respectively, fourth) experiment we programmed both GRC and GRO agents as MBDNAs (respectively, EMDAs) to investigate the performance of EMBDNAs against MBDNAs (respectively, EMDAs) when both of them have the same type of opponents (i.e., MBDNAs (respectively, EMDAs)).

3.4. Experimental setting

All the following input parameters required for setting grid simulation testbed and their possible values are presented in Table 9: (a) the grid load (which is represented by Grid_load symbol), (b) the e_market type, (c) job size (measured in (MI)), (d) negotiation deadline for a GRC agent to complete its negotiation process, (e) the total resource capacity of a GRO agent (measured in (MIPS)), (f) Market density, (g) time-dependent strategy and (h) multiagent-based strategic negotiation model (described in Section 2). The values of the most mentioned parameters that are used to conduct simulation are derived from Sim and Ng (2007), Sim (2004, 2006, 2008). The following eight sub-sections address these eight parameters. Also Table 9 illustrated the simulation characteristics.

(a) 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 50–400 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.

\[
\text{Grid\_load} = \frac{R_p}{C_c} \quad \text{where } 0 \leq \text{Grid\_load} \leq 1
\]  

(b) E_market types. As the availability of grid resources varies continuously with time, the simulation should be carried out by considering different GRC_to_GRO ratios. These ratios characterize three types of e_market: GRC_favorable, GRO_favorable and Balanced. The GRC-favorable e_market addresses more GROAs and consequently more opportunity for acquiring resources; the GRO-favorable e_market addresses more GRCAs and consequently more opportunity for leasing out resources; the Balanced e_market addresses normal competition among GROAs and GRCAs. GRC_to_GRO ratio is controlled by the probability $P_{GRC}$ of an agent being GRCA (or GROA). $P_{GRC}$ follows a uniform distribution.

(c) Job size. The GRC’s job size is measured in millions of instructions (MI).

(d) GRC agent’s negotiation deadline. As described before, agent’s deadline constraint plays a major role in choosing the appropriate strategy. The values of an agent’s deadline, measured in time unit, were derived from Sim (2006). Space limitation precludes all
Measures are summarized in Table 10. According to Sim (2008), "since negotiation outcomes of each agent are uncertain (i.e., there are two possibilities: eventually reaching a consensus or not reaching a consensus), it seems more prudent to use expected utility (rather than average utility) as a performance measure because it takes into consideration the probability distribution over the two different expected utilities."

The negotiation activities are simulated in a series of 300 e-markets. Even though an extensive amount of stochastic simulations was carried out for all the combinations of the input data, space limitation preclude all results from being included here. Hence, this section only reports the results for experiments conducted in dense market.

### Table 9

<table>
<thead>
<tr>
<th>Input</th>
<th>Possible values</th>
</tr>
</thead>
<tbody>
<tr>
<td>E_market type</td>
<td>GRC_Favorable P_{GRC} &lt; 0.5</td>
</tr>
<tr>
<td></td>
<td>GRO_Favorable P_{GRC} &gt; 0.5</td>
</tr>
<tr>
<td></td>
<td>Balanced P_{GRC} = 0.5</td>
</tr>
<tr>
<td></td>
<td>GRO\textsubscript{to}\textsubscript{GRC} ={(1:100,1:50, 1:30, 1:10, 1:4, 1:2)}</td>
</tr>
<tr>
<td></td>
<td>GRC\textsubscript{to}\textsubscript{GRO} ={(100:1, 50:1, 30:1, 10:1, 4:1, 2:1)}</td>
</tr>
<tr>
<td>Market Density</td>
<td>Sparse P_{gen} = 0.25</td>
</tr>
<tr>
<td></td>
<td>Moderate P_{gen} = 0.5</td>
</tr>
<tr>
<td></td>
<td>Dense P_{gen} = 1</td>
</tr>
<tr>
<td>Grid_load (i.e., (\rho))</td>
<td>0 &lt; Grid_load &lt; 1  ({0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9})</td>
</tr>
<tr>
<td></td>
<td>Low: 0 &lt; Grid_load (\rightarrow 1)</td>
</tr>
<tr>
<td>Negotiation model</td>
<td>EMBDNAs' negotiation model is described in Section 2</td>
</tr>
<tr>
<td></td>
<td>MRDNAs' negotiation model is inspired by Adabi et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>EMDAs' negotiation model is inspired by Sim and Ng (2007)</td>
</tr>
<tr>
<td>Characteristics</td>
<td>Avg. no. of agents/round 400</td>
</tr>
<tr>
<td></td>
<td>720</td>
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</table>

### 3.5. Performance measure

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). Moreover, there is no general consensus on which metrics to use (Nemeth et al., 2004). As GRC's satisfaction function takes into account the number of tasks that are accomplished successfully, the price paid for the resources and average number of negotiation rounds needed to reach an agreement and GRO's satisfaction function takes into account the amount of resources being leased out, the revenue achieved for leasing out its resources and average number of negotiation rounds needed to reach an agreement so the GRC's metrics to be studied are success rate, expected utility and average negotiation round, and also the GRO's metrics to be studied are resource utilization level, expected utility and average negotiation round. These performance measures are summarized in Table 10. According to Sim (2008), "since negotiation outcomes of each agent are uncertain (i.e., there are two possibilities: eventually reaching a consensus or not reaching a consensus), it seems more prudent to use expected utility (rather than average utility) as a performance measure because it takes into consideration the probability distribution over the two different outcomes."

### 3.6. Observations

The negotiation activities are simulated in a series of 300 e-markets. Even though an extensive amount of stochastic simulations was carried out for all the combinations of the input data, space limitation preclude all results from being included here. Hence, this section only reports the results for experiments conducted in dense market.
Considering different e_market types are illustrated in Table 11 according to Figs. 5–7 and some examples in their bargaining terms under intense GMP, they are more likely to achieve higher expected utility than MBDNAs (that do not relax their bargaining terms). Additionally, it can also be observed from Figs. 5–10 that as EMBDNAs are designed with new positions of all EMBDNAs, MBDNAs and EMDAs are weaker (as under very extreme competition conditions, it may be extremely difficult to lease out computing machines). Also it can be observed from Figs. 11–13 positions (as there were fewer available resources in the grid, and it became difficult for all types of agents to successfully negotiate for trading) and they are both likely to make less concessions (i.e., have higher expected utility). Similarly, from Figs. 8–10 it can be observed of competition).

Observation 1: EMBDNAs achieved higher expected utility than MBDNAs and EMDAs when all types of agents are subjected to different deadlines and market types.

Figs. 5–7 show the performance of EMBDNAs against MBDNAs and EMDAs with different values for negotiation deadline and for all types of e_markets (i.e., GRC_favorable, Balanced and GRO_favorable). Also Figs. 8–10 show the performance of EMBDNAs against MBDNAs and EMDAs with different deadline ranges (i.e., Short, Moderate and Long) and different values for GRC_to_GRO ratio (i.e., different degree of competition).

From Figs. 5–7, it can be observed that when all types of agents (i.e., EMBDNAs, MBDNAs and EMDAs) are subjected to longer deadlines (in comparison to Moderate and Short deadlines), they have stronger bargaining positions (as they have plenty of time for trading) and they are both likely to make less concessions (i.e., have higher expected utility). Similarly, from Figs. 8–10 it can be observed that when the type of e_markets tends to be GRO_favorable (i.e., GRC_to_GRO=100:1, 50:1, 30:1, 10:1, 4:1, 2:1) in comparison to Balanced (i.e., GRC_to_GRO=1:1) and GRC_favorable (i.e., GRC_to_GRO=1:100, 1:50, 1:30, 1:10, 1:4, 1:2) e_markets the bargaining positions of all EMBDNAs, MBDNAs and EMDAs are weaker (as under very extreme competition conditions, it may be extremely difficult for all types of negotiators to reach any consensus) so they have to concede more to avoid the risk of losing grid resources (which leads to lower expected utility). Additionally, it can also be observed from Figs. 5–10 that, as EMBDNAs are designed with new FGMPDS to relax their bargaining terms under intense GMP, they are more likely to achieve higher expected utility than MBDNAs (that do not relax their criteria) and EMDAs (that use different method to compute relaxation amount). To show our claims some examples in deadline range 60–64 considering different e_market types are illustrated in Table 11 according to Figs. 5–7 and some examples in GRC_to_GRO ratio 4:1 considering different negotiation deadline ranges are illustrated in Table 12 according to Figs. 8–10.

Observation 2: EMBDNAs achieved higher expected utility than MBDNAs and EMDAs when all types of agents are subjected to different grid loads and market types.

Figs. 11–13 show the performance of EMBDNAs against MBDNAs and EMDAs in different Grid_loads and for all types of e_markets (i.e., GRC_favorable, Balanced and GRO_favorable). From Fig. 11 (respectively Fig. 12 and Fig. 13) it can be observed that when all types of agents are subjected to higher Grid_load (e.g., when more than 65% of the grid resources are occupied), they have weaker bargaining positions (as there were fewer available resources in the grid, and it became difficult for all types of agents to successfully negotiate for grid resources) and they all likely to concede more to avoid the risk of losing remain resources. Also it can be observed from Figs. 11–13 that in GRO_favorable e_markets (in comparison to Balanced and GRO_favorable e_markets) the bargaining positions of all EMBDNAs, MBDNAs and EMDAs are weaker (as from GRC’s perspective in GRO_favorable e_markets the probability that a GRO agent enters the market at any time is ~ 0.5) and if final agreement is reached, all of them are likely to make relatively more concessions (which leads to lower expected utility). Furthermore, according to Figs. 11–13 one can understand that, as EMBDNAs are designed with new FGMPDS to relax their bargaining terms under intense GMP, they are more likely to achieve higher expected utility than MBDNAs (that do not relax their criteria) and EMDAs (that use different method to compute relaxation amount). To show our claims some examples in Grid_load=0.8 considering different e_market types are illustrated in Table 13 and some examples in GRO_favorable e_market type considering different Grid_loads are illustrated in Table 14 according to Figs. 11–13.

Table 10

<table>
<thead>
<tr>
<th>Agent type</th>
<th>GRC</th>
<th>GRO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Success rate</td>
<td>$R_{success} = \frac{\sum_{i=1}^{N_GRC} \left( N_{GRC_i} \times N_{GRC_i} \right)}{N_{GRC} \times N_{GRC}}$</td>
<td>–</td>
</tr>
<tr>
<td>Resource utilization level</td>
<td>–</td>
<td>$U_d = \frac{\sum_{i=1}^{N_GRC} \left( TUCap_{GRO_i} / TCap_{GRO_i} \right)}{N_{GRO}}$</td>
</tr>
<tr>
<td>Expected utility</td>
<td>$U_{expected} = AL_{GRC_i} \times R_{success} + AL_{GRO_i} \times (1 - R_{success}) = AL_{GRC_i} \times R_{success}$</td>
<td>$U_{expected} = AL_{GRO_i} \times U_{GRO_i} + AL_{GRO_i} \times (1 - U_{GRO_i}) = AL_{GRO} \times U_{GRO_i}$</td>
</tr>
<tr>
<td>Average negotiation round</td>
<td>$R_{average} = \frac{\sum_{i=1}^{N_GRC} ST_{GRC_i} / \sum_{i=1}^{N_GRC} N_{GRC_i}}{N_{GRC}}$</td>
<td>$R_{average} = \frac{\sum_{i=1}^{N_GRO} ST_{GRO_i} / \sum_{i=1}^{N_GRO} N_{GRO_i}}{N_{GRO}}$</td>
</tr>
</tbody>
</table>

### Definition of used parameters

- $N_{GRC}$: Total number of GRC's tasks requiring resources
- $N_{GRC_i}$: Number of GRC’s task(s) that successfully negotiate
- $U_{Cap_{GRO}}$: Average utility of GRC agents that reached consensus.
- $R_{success}$: Success rate
- $ST_{GRC}$: Time that successful machine(s) of GRC used to reach a consensus.
- $TCap_{GRO}$: Total number of GRC agents
- $SU_{GRC_i}$: Sum of utility of successful machine(s) of GRC.
- $AL_{GRC_i}$: Average utility of GRC agents that did not reach consensus.
- $SU_{GRC_i}$: Sum of utility of successful GRC’s computing machine(s).
- $AL_{GRO_i}$: Number of GRO’s machine(s) that successfully negotiate
- $ST_{GRO_i}$: Time that successful task(s) of GRO used to reach a consensus.
- $Cap_{GRO_i}$: The time that GRO, spends in the negotiation market
- $T_{Cap_{GRO_i}}$: The total capacity of GRO’s machine(s) in negotiation round
- $U_{Cap_{GRO_i}}$: Average utility of GRO agents that did not reach consensus.
- $Cap_{GRO_i}$: The total used capacity of GRO’s machine(s) in negotiation round
- $T_{Cap_{GRO_i}}$: Sum of time that successful task(s) of GRC, used to reach a consensus

Observation 3: EMBDNAs achieved higher success rate than MBDNAs and EMDAs when all types of agents are subjected to different deadlines and market types.

Figs. 14–16 show the success rate of EMBDNAs against MBDNAs and EMDAs with different values for negotiation deadline and for all types of e_markets (i.e., GRC_favorable, Balanced and GRO_favorable). Also Figs. 17–19 show the performance of EMBDNAs against MBDNAs and EMDAs with different deadline ranges (i.e., Short, Moderate and Long) and different values for GRC_to_GRO ratio (i.e., different degree of competition).

From Figs. 14–16, it can be observed that when all types of agents are subjected to Longer deadlines (in comparison to Moderate and Short deadlines), they have stronger bargaining positions (as they have plenty of time for trading) and they all likely to complete deals successfully (i.e., have higher success rate). Similarly, from Figs. 17–19 it can be observed that when the type of e_markets tends to be GRO_favorable (i.e., GRC_to_GRO={100:1, 50:1, 30:1, 10:1, 4:1, 2:1}) in comparison to Balanced (i.e., GRC_to_GRO={1:1}) and GRC_favorable (i.e., GRC_to_GRO={1:100, 1:50, 1:30, 1:10, 1:4, 1:2}) e_markets the bargaining positions of all EMBDNAs, EMDAs and MBDNAs are weaker (as all types of negotiators have lower chance of being ranked the highest by their trading partners in face of high degree of competition) and it may be extremely difficult for all types of negotiators to reach any consensus (which leads to lower success rate). Additionally, it can also be observed from Figs. 14–19 that, as EMBDNAs are designed with new FGMPDS to relax their bargaining terms under intense GMP, they are more likely to achieve higher success rate than MBDNAs (that do not relax their criteria) and EMDAs (that use different method to compute relaxation amount). To show our claims some examples in deadline range 60–64 considering different e_market types are illustrated in Table 15 according to Figs. 14–16 and some examples in GRC_to_GRO ratio 30:1 considering different negotiation deadline ranges are illustrated in Table 16 according to Figs. 17–19.
Observation 4: EMBDNAs achieved higher success rate than MBDNAs and EMDAs when all types of agents are subjected to different grid loads and market types. Figs. 20–22 show the success rate of EMBDNAs against MBDNAs and EMDAs in different Grid_loads and for all types of e_markets (i.e., GRC_favorable, Balanced and GRO_favorable). From Figs. 20–22 it can be observed that when all types of agents are subjected to higher Grid_load (e.g., when more than 65% of the grid resources are occupied), they have weaker bargaining positions (as there were fewer available resources in the grid) and it became difficult for all types of agents to successfully negotiate for grid resources (i.e., have lower success rate) especially in GRO_favorable e_markets (in comparison to Balanced and GRC_favorable e_markets) where the competition degree is very high and probability that a GRO agent enters the market at any time is < 0.5. Furthermore, according to Figs. 20–22 one can understand that, as EMBDNAs are designed with new FGMPDS to relax their bargaining terms under intense GMP, they are more likely to achieve higher success than MBDNAs (that do not relax their criteria) and EMDAs (that use different method to compute relaxation amount). To show our claims some examples in Grid_load = 0.8 considering different e_market types are illustrated in Table 17 and some examples in GRO_favorable e_market type considering different Grid_loads are illustrated in Table 18 according to Figs. 20–22.

Observation 5: EMBDNAs take fewer negotiation rounds than MBDNAs and EMDAs when all types of agents are subjected to different deadlines and market types. Figs. 23–25 show the average negotiation time of EMBDNAs against MBDNAs and EMDAs with different values for negotiation deadline and for all types of e_markets (i.e., GRC_favorable, Balanced and GRO_favorable). Also Figs. 26–28 show the performance of EMBDNAs against MBDNAs and EMDAs with different deadline ranges (i.e., Short, Moderate and Long) and different values for GRC_to_GRO ratio (i.e., different degree of competition). It can be observed that EMBDNAs generally achieved lower average negotiation time than MBDNAs and EMDAs. For example, in Fig. 23, when the deadline is between 60 and 64, the average negotiation time is 34 for

EMBDNAs, 41 for EMDAs and 45 for MBDNAs, respectively. However, for very short deadlines, the average negotiation time of EMBDNAs is not significantly lower than the average negotiation time of MBDNAs and EMDAs. With very short deadlines, all EMBDNAs, EMDAs and MBDNAs have very little time for trading and EMBDNAs did not outperform MBDNAs and EMDAs in terms of average negotiation time for all types of e_markets. With longer deadlines, EMBDNAs clearly outperformed MBDNAs and EMDAs in terms of average negotiation time for all types of e_markets.

Observation 6: EMBDNAs take fewer negotiation rounds than MBDNAs and EMDAs when all types of agents are subjected to different grid loads and market types.

Table 11
Expected utility of EMBDNA, EMDA and MBDNA negotiation agents in different e_market types for deadline range 60–64.

<table>
<thead>
<tr>
<th>E_market type</th>
<th>Type of negotiation agent</th>
<th>EMBDNA</th>
<th>EMDA</th>
<th>MBDNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRC_Favorable</td>
<td>EMBDNA</td>
<td>0.42</td>
<td>0.38</td>
<td>0.36</td>
</tr>
<tr>
<td>Balanced</td>
<td>EMBDNA</td>
<td>0.40</td>
<td>0.37</td>
<td>0.35</td>
</tr>
<tr>
<td>GRO_favorable</td>
<td>EMBDNA</td>
<td>0.34</td>
<td>0.31</td>
<td>0.31</td>
</tr>
</tbody>
</table>

Fig. 9. Expected utility under different GRC_to_GRO ratios and Moderate deadline.

Fig. 10. Expected utility under different GRC_to_GRO ratios and Long deadline.

Figs. 29–31 show the average negotiation time of EMBDNAs against MBDNAs and EMDAs in different Grid_loads and for all types of e_markets (i.e., GRC-favorable, Balanced and GRO_favorable). From Figs. 29–31 it can be observed that when all types of agents are subjected to higher Grid_load (e.g., when more than 65% of the grid resources are occupied), they have weaker bargaining positions (as there were fewer available resources in the grid) especially in GRO_favorable e_markets (where the negotiators of type GRC face with stiff competition) and it became difficult for all types of agents to have lower negotiation rounds in successful negotiation process. However, by relaxing bargaining criteria of EMBDNAs, they clearly outperformed MBDNAs and EMDAs in terms of average negotiation time for all types of e_markets and different Grid_loads.

Table 12

<table>
<thead>
<tr>
<th>Negotiation deadline</th>
<th>Type of negotiation agent</th>
<th>EMBDNA</th>
<th>EMDA</th>
<th>MBDNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>EMBDNA</td>
<td>0.22</td>
<td>0.16</td>
<td>0.11</td>
</tr>
<tr>
<td>Moderate</td>
<td>EMDA</td>
<td>0.34</td>
<td>0.29</td>
<td>0.27</td>
</tr>
<tr>
<td>Long</td>
<td>MBDNA</td>
<td>0.40</td>
<td>0.35</td>
<td>0.30</td>
</tr>
</tbody>
</table>

Fig. 11. Expected utility under different grid loads and GRC_favorable market type.

Fig. 12. Expected utility under different grid loads and Balanced market type.

Figs. 29–31 show the average negotiation time of EMBDNAs against MBDNAs and EMDAs in different Grid_loads and for all types of e_markets (i.e., GRC-favorable, Balanced and GRO_favorable). From Figs. 29–31 it can be observed that when all types of agents are subjected to higher Grid_load (e.g., when more than 65% of the grid resources are occupied), they have weaker bargaining positions (as there were fewer available resources in the grid) especially in GRO_favorable e_markets (where the negotiators of type GRC face with stiff competition) and it became difficult for all types of agents to have lower negotiation rounds in successful negotiation process. However, by relaxing bargaining criteria of EMBDNAs, they clearly outperformed MBDNAs and EMDAs in terms of average negotiation time for all types of e_markets and different Grid_loads.
4. Related works

Few of the existing grid projects focus on working out decision-making model for trading participants (i.e., GRCs and GROs) in grid environment (Miao et al., 2006). There are usually two main approaches for decision-making models of negotiators. One approach is Game-theoretic models and another is Artificial Intelligence (AI)-based models. Game-theoretic models apply formal analysis (i.e. Game theory analysis) to find out an optimal negotiation strategy of a negotiation given all the possible outcomes of the negotiation (Miao et al., 2006). AI-based models make “satisfying” decisions based on heuristics and try to find a near-optimal strategy in the negotiation rather than the optimal strategy. However, in realistic dynamic uncertain grid environments it is often impossible to apply formal analysis. In addition, game theoretic analysis often makes strong assumptions about grid participants’ knowledge, which limits the practical applicability of game theoretic results. Furthermore, game theoretic solutions in which agents (on behalf of grid participants) are assumed to be fully rational cannot be applied to realistic negotiation problems as, in practice, it is not reasonable to assume agents’ full rationality (Miao et al., 2006). In contrast, agents adopting AI approaches often have bounded rationality and make near-optimal and satisfying decisions based on heuristics. So, AI-based models have been widely used by researchers as a decision-making approach to find approximate solutions (negotiation’s strategies in our work) in negotiation process. As fuzzy approaches (e.g., fuzzy constraint-based reasoning, fuzzy inference rules, and fuzzy decision controllers) provides a simple and easy way to draw a definite conclusion from ambiguous, imprecise or vague information (Luger, 2002) following we focus on the state-of-the-art flexible negotiation agents that using fuzzy approaches.

Wasfy and Hosni (1998) proposed fuzzy logic-based approach to deal with multiple-issue and two-party negotiations. In the negotiation process a negotiator defines his/her strategic profiles in advance to represent his/her concession size. A strategic profile consists of four fuzzy sets to represent the four concession tactics: no concession, small concession, medium concession and large concession.

Table 13
Expected utility of EMBDNA, EMDA and MBDNA negotiation agents in different e_market types for Grid_load=0.8.

<table>
<thead>
<tr>
<th>E_market type</th>
<th>Type of negotiation agent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EMBDNA</td>
</tr>
<tr>
<td>GRC_Favorable</td>
<td>0.49</td>
</tr>
<tr>
<td>Balanced</td>
<td>0.43</td>
</tr>
<tr>
<td>GRO_favorable</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Table 14
Expected utility of EMBDNA, EMDA and MBDNA negotiation agents considering different Grid_loads for GRO_favorable e_market.

<table>
<thead>
<tr>
<th>Grid_load values</th>
<th>Type of negotiation agent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EMBDNA</td>
</tr>
<tr>
<td>0.2</td>
<td>0.66</td>
</tr>
<tr>
<td>0.3</td>
<td>0.64</td>
</tr>
<tr>
<td>0.4</td>
<td>0.58</td>
</tr>
</tbody>
</table>
Also, to indicate which strategy profile should be adopted in which situation some rules are defined. During a negotiation process, the negotiator’s concession force which is affected by the negotiator’s power properties and his/her opponent’s power properties is calculated. A fuzzy weight is attached to each property by the negotiator. The concession force equals the difference between last price and reservation price divided by the fuzzy weighted sum of the power properties. The concession force is mapped to the selected strategy profile and the tactic with the largest common area with the concession force is chosen. The negotiator’s concession size at given time step can be determined by a translation of the fuzzy set of the chosen tactic. Whereas Wasfy and Hosni (1998) modeled negotiation power and (un) willingness to concede using fuzzy concepts, our work uses three sets of fuzzy rules to guide negotiator agents whether to reach agreements in multilateral negotiations.

In the multi-issue negotiation model of Matos et al. (1998), offers and counter offers are generated by case-based and fuzzy logic based strategies. While this model is adequate for dealing with the inherent uncertainties of bilateral negotiation, it cannot take advantage of the benefits of a constraint based approach. In other word, (Matos et al., 1998) ignores the benefit of fuzzy constraints in capturing the users’ requirements on attributes of a product/service. Matos et al. (1998)’s model uses previous knowledge and information of the environment state, from a case base, to change its negotiation behavior, a set of fuzzy rules to determine the values of the parameters of the negotiation model, and an evolutionary approach to determine which negotiation strategy is more successful. However, the issue of the users’ requirements on the desired outcome of negotiation is not addressed in their work. Whereas our work define GMP as an independent variable that captures the acceptability of the current grid resource allocation market condition, (Matos et al. 1998) did not address the users’ requirements on the desired outcome of negotiation.

Jennings et al. (2001) and Faratin et al. (2002) considered issues of time constraint, resource, and behaviors of negotiators in devising a negotiation model that defines a range of Negotiation Decision Functions (NDFs) for generating (counter-) proposals. In their works, fuzzy similarity is used to compute tradeoffs among multiple attributes during bilateral negotiations and cope with the inherent uncertainties in the negotiation process. From this basis, Faratin et al. (2002) developed a novel hill-climbing algorithm for performing trade-offs in multi-dimensional negotiations that involve both qualitative and quantitative decision variables. A negotiator agent first generates some potential contracts for which it receives a score $y$. After that, the negotiator agent finds the contract on the indifference curve for $y$, which has the maximum similarity degree to the last proposal from the negotiant. Although strategies in Jennings et al. (2001) and Faratin et al. (2002) are based on time, resource, and behaviors of negotiators, unlike our work, other essential factors such as competition (for multilateral negotiation) and trading alternatives were not considered.

Fuzzy e-negotiation agent (FeNA) of Kowalczyk and Bui (2000); Kowalczyk and Bui, 2000; Kowalczyk, 2002), modeled the multi-issue negotiation process as a fuzzy constraint satisfaction problem (FCSP). Their approach performs negotiation on individual solutions one at a time. FeNAs negotiate by exchanging offers and a consensus is reached when their private preferences, constraints, and objectives are satisfied. One of the distinguishing features of FeNAs is that the preferences, constraints and each party’s objectives are expressed as fuzzy constraints over these issues. Using this method, the FCSP is to find a solution that maximizes the satisfaction of all constraints of the parties. However, although FeNAs are designed with the flexibility to relax trading conditions such as preferences, priorities and objectives, they were not programmed to react to changing market dynamics. Also, while (Kowalczyk and Bui, 2000a,b; Kowalczyk, 2002) deal with bilateral negotiations, our work deals with multilateral negotiations.

Jennings et al. (2001) and Faratin et al. (2002) considered issues of time constraint, resource, and behaviors of negotiators in devising a negotiation model that defines a range of Negotiation Decision Functions (NDFs) for generating (counter-) proposals. In their works, fuzzy similarity is used to compute tradeoffs among multiple attributes during bilateral negotiations and cope with the inherent uncertainties in the negotiation process. From this basis, Faratin et al. (2002) developed a novel hill-climbing algorithm for performing trade-offs in multi-dimensional negotiations that involve both qualitative and quantitative decision variables. A negotiator agent first generates some potential contracts for which it receives a score $y$. After that, the negotiator agent finds the contract on the indifference curve for $y$, which has the maximum similarity degree to the last proposal from the negotiant. Although strategies in Jennings et al. (2001) and Faratin et al. (2002) are based on time, resource, and behaviors of negotiators, unlike our work, other essential factors such as competition (for multilateral negotiation) and trading alternatives were not considered.

Fuzzy e-negotiation agent (FeNA) of Kowalczyk and Bui (2000); Kowalczyk and Bui, 2000; Kowalczyk, 2002), modeled the multi-issue negotiation process as a fuzzy constraint satisfaction problem (FCSP). Their approach performs negotiation on individual solutions one at a time. FeNAs negotiate by exchanging offers and a consensus is reached when their private preferences, constraints, and objectives are satisfied. One of the distinguishing features of FeNAs is that the preferences, constraints and each party’s objectives are expressed as fuzzy constraints over these issues. Using this method, the FCSP is to find a solution that maximizes the satisfaction of all constraints of the parties. However, although FeNAs are designed with the flexibility to relax trading conditions such as preferences, priorities and objectives, they were not programmed to react to changing market dynamics. Also, while (Kowalczyk and Bui, 2000a,b; Kowalczyk, 2002) deal with bilateral negotiations, our work deals with multilateral negotiations.
Luo et al. (2003) developed a fuzzy constraint based framework for bilateral multi-issue negotiations in semi-competitive trading environments. Two knowledge models (i.e., one for the GRO agent and one for the GRC agent) are used to express the fuzzy constraint based framework. While the GRO agent’s domain knowledge consists of its multi-dimensional representation of the products or services it offers, the GRC agent’s domain knowledge consists of the GRC’s requirement/preference model (a prioritized fuzzy constraint problem) and GRC’s profile model (fuzzy truth propositions). The GRC and GRO agents exchange offers and counter-offers with additional constraints revealed or existing constraints being relaxed. Finally, a solution is found if there is one. The distinguishing features of (Luo et al., 2003) against previous works are: (1) the notion of Prioritized Fuzzy Constraint Satisfaction Problems (PFCSPs) was chosen as the

![Fig. 18. Success rate under different GRC_to_GRO ratios and Moderate deadline.](image)

![Fig. 19. Success rate under different GRC_to_GRO ratios and Long deadline.](image)

Table 15
Success rate of EMBDNA, EMDA and MBDNA negotiation agents in different e_market types for deadline range 60–64.

<table>
<thead>
<tr>
<th>E_market type</th>
<th>Type of negotiation agent</th>
<th>EMBDNA</th>
<th>EMDA</th>
<th>MBDNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRC_Favorable</td>
<td>EMBDNA</td>
<td>0.9</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>Balanced</td>
<td>EMDA</td>
<td>0.88</td>
<td>0.84</td>
<td>0.81</td>
</tr>
<tr>
<td>GRO_favorable</td>
<td>MBDNA</td>
<td>0.74</td>
<td>0.73</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Luo et al. (2003) developed a fuzzy constraint based framework for bilateral multi-issue negotiations in semi-competitive trading environments. Two knowledge models (i.e., one for the GRO agent and one for the GRC agent) are used to express the fuzzy constraint based framework. While the GRO agent’s domain knowledge consists of its multi-dimensional representation of the products or services it offers, the GRC agent’s domain knowledge consists of the GRC’s requirement/preference model (a prioritized fuzzy constraint problem) and GRC’s profile model (fuzzy truth propositions). The GRC and GRO agents exchange offers and counter-offers with additional constraints revealed or existing constraints being relaxed. Finally, a solution is found if there is one. The distinguishing features of (Luo et al., 2003) against previous works are: (1) the notion of Prioritized Fuzzy Constraint Satisfaction Problems (PFCSPs) was chosen as the
basis of the negotiation model, (2) enables negotiation to be carried out over fuzzy constraints of multiple issues of a product, (3) guarantees that the outcome of the negotiation is Pareto optimal and (4) incorporates the concept of a reward, from argumentation/persuasion-based models. The general difference between (Luo et al., 2003) and our work is that while (Luo et al., 2003) deals with bilateral negotiations, our work deals with multilateral negotiations.

Meng and Fu (Meng and Fu, 2004) presented a negotiation model based on a fuzzy multiple criteria decision-making for multi-issue negotiation problem. There are many uncertain factors in negotiation. First, negotiations’ preferences (weights) are uncertain and dynamic. It is difficult to get exactly negotiators’ preferences. Secondly, the evaluation of the solution is uncertain. Considering these uncertain factors, the degree of acceptance or rejection of the offer was measured by fuzzy members in (Meng and Fu, 2004). The success rate of negotiation agents in different negotiation deadlines for GRC_to_GRO:[30:1].

<table>
<thead>
<tr>
<th>Negotiation deadline</th>
<th>EMBDNA</th>
<th>EMDA</th>
<th>MBDNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>0.09</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.18</td>
<td>0.17</td>
<td>0.15</td>
</tr>
<tr>
<td>Long</td>
<td>0.35</td>
<td>0.31</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Fig. 20. Success rate under different grid loads and GRC_favorable market type.

Fig. 21. Success rate under different grid loads and Balanced market type.
Fuzzy linear weighted arithmetic average was used to obtain fuzzy evaluation of negotiators. Hamming gap is adopted to compute the similarity degree between the negotiation proposal and the ideal solution or the negative-ideal solution. Using the similarity degree between the proposal and the ideal solution and the similarity degree between the proposal and the negative-ideal solution, a negotiator’s satisfaction degree with the negotiation proposal was determined. The negotiation process is completed (i.e., an agreement is reached), if all negotiators’ satisfaction degrees are greater equal than the threshold of the satisfaction degree. Otherwise, the negotiators’ proposals are modified according to their evaluations, and the negotiation process continued until an agreement is reached, or the maximum number of sessions has been reached. The general difference between (Meng and Fu, 2004) and our work is that whereas (Meng and Fu, 2004) uses fuzzy concepts to represent negotiators’ preferences of issues and evaluations of issues, our work uses fuzzy concepts to determine GMP in different grid market conditions.

In (Lin et al., 2005) a general problem-solving framework for modeling multi-issue multilateral negotiation using fuzzy constraints is presented. Agent negotiation is formulated as a distributed fuzzy constraint satisfaction problem. Fuzzy constrains are thus used to naturally represent each negotiator agent’s desires involving imprecision and human conceptualization, particularly when lexical imprecision and subjective matters are concerned. This work enables a negotiator agent not only to systematically relax fuzzy constraints to generate a proposal, but also to employ fuzzy similarity to select the alternative that is subject to its acceptability by the opponents. The presented fuzzy constraint model has following important aspects: (1) multilateral negotiation, (2) fuzzy constraints on a combination of multiple attributes, (3) search offers only from a feasible region, (4) safe solution and (5) human cognition. More details can be found in (Lin et al., 2005). Whereas (Lin et al., 2005) focused on finding a joint agreement that satisfies all constraints and maximizes the agents' aggregated degree of satisfaction, our work adopts three sets of fuzzy rules to guide negotiator agents in relaxing their bargaining terms to enhance their chances of reaching agreements and reaching agreements more rapidly.

![Fig. 22. Success rate under different grid loads and GRO_favorable market type.](image)

<p>| Table 17 | Success rate of EMBDNA, EMDA and MBDNA negotiation agents in different e_market types for Grid_load=0.8. |</p>
<table>
<thead>
<tr>
<th>E_market type</th>
<th>Type of negotiation agent</th>
<th>EMBDNA</th>
<th>EMDA</th>
<th>MBDNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRC_Favorable</td>
<td>EMBDNA</td>
<td>0.60</td>
<td>0.50</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>EMDA</td>
<td>0.58</td>
<td>0.48</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>MBDNA</td>
<td>0.52</td>
<td>0.41</td>
<td>0.30</td>
</tr>
</tbody>
</table>

<p>| Table 18 | Success rate of EMBDNA, EMDA and MBDNA negotiation agents considering different Grid_loads for GRO_favorable e_market. |</p>
<table>
<thead>
<tr>
<th>Grid_load values</th>
<th>Type of negotiation agent</th>
<th>EMBDNA</th>
<th>EMDA</th>
<th>MBDNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>EMBDNA</td>
<td>0.58</td>
<td>0.41</td>
<td>0.38</td>
</tr>
<tr>
<td>0.8</td>
<td>EMDA</td>
<td>0.52</td>
<td>0.41</td>
<td>0.30</td>
</tr>
<tr>
<td>0.9</td>
<td>MBDNA</td>
<td>0.50</td>
<td>0.40</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Wang et al. Wang et al. (2006) presented a model of an intelligent negotiation agent based on fuzzy logic methodology to deal with one-to-one, multi-issue negotiations involving a third-party-driven virtual marketplace. The proposed negotiation agent model is particularly suitable to open environments, such as the Internet. In this model, fuzzy inference rules are used for determining the acceptance of an opponent’s offer. If the acceptance of the incoming offer is less than the minimum acceptance of the agent, then reject and terminate the negotiation. If the acceptance of the incoming offer is greater than the acceptance of the counter offer prepared by the agent, then accept the offer to achieve agreement with the opponent agent. Otherwise, if the acceptance of the incoming offer is less than the counter offer, then send the counter offer to the opponent negotiation agent. The exchange continued until an agreement is reached, or the maximum number of negotiation rounds or the maximum duration of negotiation is reached. Whereas (Wang et al., 2006) focused on modeling multi-issue, bilateral negotiations involving a third-party-driven virtual marketplace, our work adopts fuzzy rules for relaxing bargaining terms in multilateral negotiations in which there is no third party mediation.

Wu et al. Wu et al. (2006) proposed fuzzy based approach to deal with bilateral multiple-issue negotiations. Unlike most of the negotiation models that used Rubinstein’s sequential alternating offer protocol (Rubinstein, 1982) this work adopted the monotonic concession protocols (Rosenschein and Zlotkin, 1994). As negotiations’ preferences (weights) are uncertain and dynamic, the acceptability for each issue was measured by fuzzy members. During negotiation process, (counter-) offers were exchanged between the GRC agent and the GRO agent. If negotiator agent’s acceptability for its trading partner’s offer is less than the critical value (which was defined for each negotiation), the negotiator generates a new (counter-) offer or unsuccessfully exists the negotiation. Otherwise, the agreement is reached. The general differences between (Wu et al., 2006) and our work are that: (1) while (Wu et al., 2006) deals with bilateral negotiations, our work deals with multilateral negotiations and (2) whereas this work adopts an alternating protocol, (Wu et al., 2006)
adopted the monotonic concession protocols. In (Winito et al., 2005) shows that a non-monotonic-offers protocol can generate higher average surplus and a lower breakdown rate compared to a monotonic-offers protocol, and 3) while the acceptability for each issue was represented by a fuzzy value in (Wu et al., 2006), our work uses fuzzy concepts to determine GMP in different grid market conditions.

Sim and Wang (Sim and Wang, 2004) worked on designing Enhanced Market Driven Agents (i.e., EMDAs which are augmented with fuzzy decision controller) which are programmed to follow a set of fuzzy rules to slightly relax their bargaining terms under (intense) GMP. This work used (a) degree of competition \( u \) and (b) eagerness \( e \) as criteria for determining the amount of concession (these criteria are inputs to the fuzzy decision controller and the amount of concession is the output of the fuzzy decision controller). \( e \) represents how urgent it is for EMDA to acquire/ release a resource before a deadline. The idea behind definition of \( u \) and \( e \) criteria is that agent with very high \( e \) is also more sensitive to fast approaching deadline and under more pressure to slightly relax its bargaining criteria in the hope of completing a deal, also with a large number of competitors (i.e., high competition degree), an agent generally has a lower chance of reaching consensus with its trading partner and is more likely to be under pressure, and hence is more likely to slightly relax its bargaining criteria. As EMDAs are not designed to raise their expectations in extremely favorable market conditions (e.g., when a negotiator agent receives more than one counter-proposals that are equal or better than its own proposal), (Sim, 2004) complemented (Sim and Wang, 2004) by augmenting the designs of EMDAs with two additional fuzzy decision controllers. While the fuzzy decision controller in (Sim and Wang, 2004) guides an EMDA in relaxing trade aspirations, the two fuzzy decision controllers of an EMDA in (Sim, 2004) are used to guide a negotiator agent in determining whether to slightly raise its expectation. While just two relaxation criteria (i.e., degree of competition and eagerness) were used in (Sim and Wang, 2004), more effective relaxation criteria that have great role in

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determining the amount of GMP are used in our work. Also, while the fuzzy decision controller in our work guides negotiator agent in relaxing trade aspirations, the two fuzzy decision controllers in (Sim, 2004) are used to guide a negotiator agent in determining whether to slightly raise its expectation.

Sim and Ng (Sim and Ng, 2007) focuses on devising a relaxed-criteria bargaining protocol by augmenting the alternating offers protocol with the set of fuzzy rules to enhance the negotiators’ chance of successfully acquiring/leasing resources in face of (intense) GMP. To this, GRC and GRO agents are programmed with two different fuzzy controllers (one modeling GRCs’ criteria and one modeling GROs’ criteria) for determining the amount of relaxation in a negotiation situation. Unlike the relaxing criteria which are used in (Sim and Wang, 2004), (Sim and Ng, 2007) used (a) recent statistics in failing/succeeding in acquiring resources ($FSt$) and (b) demand for computing resources ($DFt$) as criteria for determining the amount of concession of GRC agents (these criteria are inputs to the GRC’s fuzzy decision controller and the amount of concession is the output of the GRC’s fuzzy decision controller). The idea behind definition of $FSt$ and $DFt$, criteria is that if a GRC is less successful in acquiring resources recently to execute its set of tasks will be under more pressure to slightly relax its bargaining criteria in the hope of completing a deal, also if it has a greater demand for computing resources it is more likely to be under more pressure to slightly relax its bargaining criteria. Also, the idea behind definition of $ULt$ and $RFt$, criteria is that if more of GRO are currently being used to execute its own tasks or have already been leased to other GRCs (i.e., the $ULt$ is high), then GRO is less likely to slightly relax its bargaining term, also if there are fewer recent demands from GRCs to lease its resources (i.e., the $RFt$ is low), a GRO is more likely to slightly relax its bargaining criteria since it is under more pressure to trade its idle resources.
more effective relaxation criteria that have great role in determining the amount of GMP are used in our work but also the Rubinstein’s sequential alternating offer protocol which is used by (Sim and Ng, 2007)’s negotiation agents is enhanced to overcome the limitations and provide more flexible and rational protocol.

Furthermore, Sim (Sim, 2008) designed another fuzzy controller for negotiation agents to determine the amount of relaxation in a negotiation situation. Unlike the relaxing criteria which are used in (Sim and Wang, 2004; Sim and Ng, 2007; Sim, 2008) used (a) degree of competition ($\nu$), (b) time pressure ($T_r$) and (c) the relative distance from trading parties’ proposals ($\delta$) as criteria for determining the amount of concession of negotiator agents (these criteria are inputs to the fuzzy decision controller and the amount of concession is the output of the fuzzy decision controller). While the idea behind definition of $\nu$ is discussed previously, the idea behind definition of $T_r$ and $\delta$ criteria is that when an agent’s deadline is fast approaching ($T_r \rightarrow 1$), it is under more pressure to relax its bargaining criteria also since the chance of reaching consensus at the agent’s own term will still be low, if the difference between the agent and the terms of all trading partners (i.e., $\delta$) are very large (this cause that the probability that the agent’s will obtain a certain expected utility with at least one of its trading partners is low), it will be under more pressure to slightly relax its bargaining criteria with the hope of reaching consensus with at least one of its trading partners. The distinguishing features of our work and (Sim, 2008) are as same as the distinguishing features of our work and (Sim and Ng, 2007).

Furthermore, some studies have focused on negotiation with nonlinear utility functions (e.g., (Marsa-Maestre et al., 2009; Marsa-Maestre et al., 2009; Hindriks et al., 2006)). For the sake of simplicity, in comparison to (Marsa-Maestre et al., 2009; Marsa-Maestre et al., 2009; Hindriks et al., 2006), our work uses linear utility function. In addition, (Marsa-Maestre et al., 2009; Marsa-Maestre et al., 2009; Hindriks et al., 2006)...

Hindriks et al., 2006) mainly focus put on designing nonlinear utility functions and ignore negotiation strategy and protocol which are considered in our work.

5. Conclusion and future works

The contributions of this work include: (a) enhancing Rubinstein’s sequential alternating offer protocol that is used in Sim and Ng (2007) to handle multiple trading opportunities and market competition, overcome non-reasonable behavior of negotiator agents during negotiation process and relax bargaining criteria of negotiator agents by computing more accurate GMP (Grid Market Pressure), (b) devising two new Fuzzy Grid Market Pressure determination Systems (FGMPDSs) for both GRCs (Grid Resource Consumers) and GROs (Grid Resource Owners) that determine the value of GMP (i.e., amount of relaxation) from GRCs’ and GRO’s perspectives, (c) designing new Enhanced Market- and Behavior-driven Negotiation Agents (EMBDNAs) that adopted the proposed fuzzy negotiation model, (d) conducting a series of experiments to evaluate the performance of GRCs under different market types (i.e., GRC-favorable, Balanced and GRO_favorable), different market density (i.e., Dense, Moderate and Sparse), different grid loads (i.e., Low and High) and different negotiator agent’s deadlines (i.e., Short, Moderate and Long).

Empirical results obtained from the simulations show that not only GRC_EMBDNAs generally take shorter average negotiation time, have higher success rate and achieve higher expected utility than MBDNAs and EMDAs of type GRC, but also GRO_EMBDNAs generally take shorter average negotiation time, have higher success rate and achieve better resource utilization level than MBDNAs and EMDAs of type GRO.

In future works we will work on two challenges: (1) building negotiation agents that not only have the flexibility of relaxing bargaining criteria using fuzzy rules, but can also evolve their structures by learning new relaxed-criteria fuzzy rules to improve their negotiation outcomes as they participate in negotiations in more e-markets, and (2) adopting the negotiation protocol to support coalition formation.

References


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