A BBO based Procedure for Evolving Fuzzy Rules of Relaxed-criteria Negotiation in Grid Resource Allocation

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Abstract

Designing the negotiation agents and equipped them with the fuzzy decision controller to determine the relaxation amount in the face of intense grid market pressure leads to enhance both success rate and speed of negotiation. However, the market-oriented grids are unpredictable as new opportunities and threats are constantly being introduced as grid resource consumers and owners enter and leave a market. According to the grid market dynamics, it is needed to design adapting and self organizing negotiation agents that not only have the flexibility of relaxing the bargaining criteria using fuzzy rules but also have the ability to evolve their structures by learning and adapting new relaxed-criteria fuzzy rules. The impetus of this work is designing new negotiation agents in name *Ev_MBDNAs* that have two distinguishing features: 1) relaxing their bargaining term using *Fuzzy Grid Market Pressure Determination System* and 2) evolving their structures by learning new relaxed-criteria fuzzy rules to enhance their negotiation performance as they participate in a series of e_markets. The second feature of *Ev_MBDNAs* is provided by designing an evolutionary procedure that invokes Biogeography-based optimization (BBO) algorithm. In our experiments, we compare the proposed *Ev_MBDNAs* with EMBDNAs (i.e., negotiation agents with fixed relaxed-criteria fuzzy rules). The results show that by designing a BBO-based evolutionary procedure for learning effective relaxed-criteria fuzzy rules, *Ev_MBDNAs* generally outperformed EMBDNAs in different types of e_markets.

Keywords: *Grid resource allocation; Automated negotiation; Intelligent agent; Fuzzy decision controller; Biogeography-based optimization (BBO).*

1. Introduction

Grid computing emerging as a new paradigm for next-generation computing enables the sharing, selection, and aggregation of geographically distributed heterogeneous resources for solving large-scale problems in science, engineering, and commerce [1]. The resource management in such large-scale distributed environment is a complex task. The term resource management in grid computing can be defined as those operations that control the way that grid resources and services are made available for use by entities like users, applications and services [2] to ensure efficient utilization of computer resources and for optimization performance of specific tasks. Resource allocation is one of the major parts of resource management. Designing an efficient mechanism and strategies for solving grid resource allocation problem is essential for realizing the vision of grid computing environments. It is proven that one of the best solutions for grid resource allocation is usage of economic based models [3]. Numerous economic models [1] are proposed in literature [4-9]. As negotiation-like protocol is found to be suitable when the participants cooperate to create the value of objects[10], adopting negotiation mechanism for successfully reconciling the differences between **Grid Resource Owners (GROs)** and **Grid Resource Consumers (GRCs)** seems to be more prudent rather than using other commonly referenced works (e.g., see [11-13]). Although there are many agent-based approaches for grid resource allocation which are considered negotiation mechanisms among GROs and GRCs for successfully reconciling the differences between them, 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. In other word, this type of agents (i.e., fixed strategy negotiation agents) relaxes their offers at constant rate and do not properly address trading pressure in GRNM [14]. The trading pressure in GRNM (i.e., **GMP: Grid Market Pressure)**, which is raised from trade imbalances and local condition of each market participant, is defined as a variable that captures the acceptability of the current grid resource negotiation market conditions. Providing negotiation agents with more accurate GMP value (i.e., degree of relaxation) has a significant role in increasing the chance of flexible negotiation agents in making agreement with their opponents in the face of intense GMP. This consideration motivated Adabi *et al*. [14] to design flexible negotiation agents in name EMBDNA (**Enhanced Market- and Behavior-driven Negotiation Agent)** that adopt a proposed negotiation protocol in name *EAlternating offer protocol* (i.e., enhancement of *Rubinstein's sequential alternating offer* protocol which is

proposed in [15, 16]). The *EAlternating offer* negotiation protocol [14] 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 degree of relaxation in a negotiation situation. But, the fuzzy rules in [14] were manually constructed and the system structure of EMBDNA negotiation agent remained generally fixed throughout its operation in different electronic markets (i.e., e_markets). As the parameters that make e_market (like numbers of trading partners, numbers of competitors, number of participants, behavior of negotiator agents, negotiator agents' deadline,…) are subject to change given varying market conditions it is difficult to find a fixed set of fuzzy rules that is suitable for all electronic markets. Hence, the new feature of this work is that design an evolutionary procedure that invokes a BBO (Biogeography-based optimization) algorithm for evolving and adapting the relaxed-criteria rules as the EMBDNA participate in negotiation activities in a series of electronic markets. Consequently, a *new* negotiation agent in name Ev_MBDNA (i.e., EMBDNA with relaxed-criteria fuzzy rules that are evolved using the evolutionary algorithm) that has **both** the ability to slightly relax its bargaining criteria in the face of (intense) GMP and evolve its structure by learning new relaxed-criteria fuzzy rules is designed to improve the *success rate*, *expected utility* and *average negotiation round* from GRC's perspective and *resource utilization level*, *expected utility* and *average negotiation round* from GRO's perspective.
The remainder of the paper is structured as follows. Section 2 describes briefly the negotiation model of Ev_MBDNAs. In section 3 a BBO-based evolutionary procedure that is designed for evolving relaxed-criteria (fuzzy) rules is discussed. The experimental results to study the performance of Ev_MBDNAs are given in section 4. Finally, the state-of-the-art flexible negotiation agents for grid resource management and conclusions are given in section 5 and section 6 respectively.

2. Negotiation model

The negotiation model has three parts [17]: 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. As the negotiation model of Ev_MBDNAs is as same as the negotiation model of EMBDNAs [14], the negotiation model of EMBDNAs is briefly discussed. More details can be found in [14].

2.1 Negotiation utility model

Any kind of behavior of each negotiator can be modeled with a suitable payoff or "*utility function*". Each negotiator evaluates the resulting outcome through a payoff or "*utility function*" representing her objectives. The negotiation objectives of EMBDNAs 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. For the sake of simplicity, the EMBDNA negotiation agent and its opponent (i.e., trading partner) are named as A and B respectively. Also $P_t^A \longrightarrow B$ and $P_t^B \longrightarrow A$ represent the proposal of A to B at negotiation round t and the proposal of B to A at negotiation round t respectively. The linear utility function of negotiation agent A of type GRC and the linear utility function of negotiation agent A of type GRO considering $P_t^A \longrightarrow B$ and $P_t^B \longrightarrow A$ is defined as Eq. (1) and Eq. (2) respectively [14]:

$$U_t^A[P_t^A \longrightarrow B] = u_{min} + (1-u_{min})[(\frac{t^A_{deadline}-t}{t^A_{deadline}}) + [(RP_A - P_t^A)/(RP_A - IP_A)]]/2 \quad \text{And} \quad U_t^A[P_t^B \longrightarrow A] = u_{min} + (1-u_{min})[(\frac{t^A_{deadline}-t}{t^A_{deadline}}) + [(RP_A - P_t^B)/(RP_A - IP_A)]]/2 \tag{1}$$

$$U_t^A[P_t^A \longrightarrow B] = u_{min} + (1-u_{min})[(\frac{t^A_{deadline}-t}{t^A_{deadline}}) + [(P_t^A - RP_A)/(IP_A - RP_A)]]/2 \quad \text{And} \quad U_t^A[P_t^B \longrightarrow A] = u_{min} + (1-u_{min})[(\frac{t^A_{deadline}-t}{t^A_{deadline}}) + [(P_t^B - RP_A)/(IP_A - RP_A)]]/2 \tag{2}$$

where RP_A 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). The value of u_{min} which is derived from [15] is defined as 0.1.

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, the amount of concession determination, at negotiation round t, is a chosen strategy by A. Sim [18] 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 and the proposal of its trading partners at each round t. The (best) spread in the current cycle t (before making new proposal) is:

$$k_t = U_t^A[P_{t-2}^A \longrightarrow B] - U_t^A[P_{t-1}^B \longrightarrow A] \tag{3}$$

We should highlight that by using *EAlternating offer protocol* (i.e., the negotiation protocol of [14]), negotiators in make alternate offers rather than moving simultaneously. According to [19]: "*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

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making a suitable concession the *expected utility* of each negotiator's next proposal is determined by itself as follows:

$$U_t^A[P_t^A \longrightarrow B] = k_{t+1} + U_t^A[\,P_{t-1}^B \longrightarrow A] \tag{4}$$

Finally, according to [19] the amount of concession at round *t* (e.g.,Δ_t) is:

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

Also, the appropriate value of k_{t+1} is defined by:

$$k_{t+1} = FST_t^A \times k_t \tag{6}$$

where FST_t^A is a price-oriented strategy that is taken by A at round *t* and is defined through Eq. (7) [19]:

$$FST_t^A = \kappa[\,IST_t^A + (\,PreBehave\_Depend_t^B \times IST_t^A)] \tag{7}$$

where κ =1/2 if $[IST_t^A + (\,PreBehave\_Depend_t^B \times IST_t^A)]$ is greater than one, else κ =1. Also $PreBehave\_Depend_t^B$ is *previous behavior of A's trading partner* factor (details can be found in part *f* of the current section) and IST_t^A is denoted by Eq. (8) [19]:

$$IST_t^A = NC_t^A \times NTP_t^A \times FTP_t^A \times DTPAP_t^A \times TP^A \tag{8}$$

where NC_t^A, NTP_t^A, FTP_t^A, $DTPAP_t^A$ and TP^A 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 FST_t^A's factors are described in brief.

a) ***Number of competitors*** $(\boldsymbol{NC_t^A})$**:** If there is a few number of competitors, the likelihood that a negotiator *A* proposes a bid/offer that is potentially close to a trading partners' offer/bid may be high.

b) ***Number of trading partners*** $(\boldsymbol{NTP_t^A})$**:** If there is a large number of trading alternatives, the likelihood that a negotiator proposes a bid/offer that is potentially close to a trading partners' offer/bid may be high.

c) ***Flexibility in negotiator's trading partner's proposal*** $(\boldsymbol{FTP_t^A})$**:** According to [19]:"*From a negotiator agent A's point of view, the difference between its trading partner's two proposals which are made in two consecutive negotiation rounds which that trading partner turn to move (e.g., determine the amount of concession) can be defined as that trading partner's bargaining power amount. The bargaining power amount of A's trading partner increase as the difference between A's trading partner's two proposals which are made in two consecutive negotiation rounds that its turn to move tends to become* **zero***. The trading partner's bargaining power amount may not be fixed (means in suitable market conditions an agent A's trading partner's bargaining power amount will be high and vice verse) and is reflected by flexibility concept. A negotiator A is more likely to reach an agreement if the bargaining power amount of its opponent agent A decreases*."

d) ***Negotiator's proposal deviation of the average of its trading partners' proposals*** $(\boldsymbol{DTPAP_t^A}$***:closeness factor)*****:** 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. 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*** $(\boldsymbol{TP^A})$: The passage of time sacrifices of negotiation utility and has an effect on negotiator's bargaining power. Considering the mentioned concept, the following time-dependent function is used [14]:

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

where A's time preference is denoted by λ (e.g., concession rate with respect to time) which is considered as agent's private information. According to [18] and [20] there are three major classes of concession-making strategies with respect to the remaining trading time:

- **i.** *Conservative* *(1<λ<∞)* – An agent *A* makes smaller concession in early rounds and larger concession in later rounds.
- **ii.** *Linear* (λ=1) – An agent *A* makes a constant rate of concession.
- **iii.** *Conciliatory* *(*0<λ<1) – An agent *A* makes larger concession in the early trading rounds and smaller concessions in the later rounds.

According to Eq. (9), the concession rate that is made by *A* should be increased as TP^A tends to become **zero** (e.g., negotiator's deadline is reached).

f) ***Previous concession behavior of negotiator's trading partner*** $(\boldsymbol{PreBehave\_Depend_t^B})$: Negotiators should view their trading partners' behavior to select suitable tactics and strategies [21]. Adabi *et al*. [19] modeled the concession behavior of the trading partner of negotiator agent *A* $(i.e.,\ B)$ based on two following parameters: 1) the number of successful negotiations between *A* and *B* in all the GRNMs they both participated and 2) the average negotiation time between A and B. This means that the trading partner *B* that makes fewer successful negotiation with A and also makes a longer negotiation process deserves to receive more penalty.

2.3 Negotiation protocol

Type of Negotiation Protocol specifies the mechanism and the specific negotiation rules it uses for a particular negotiation. The most important issues that are considered in *EAlternating offer protocol* [14] (which is used as a negotiation protocol of Ev_MBDNA) are as follows: "I*n*

Rubinstein's sequential alternating offer protocol [16], the players (negotiators) can take actions only at certain times in the (infinite) set T = {1; 2; 3; ...t}. In each period t∈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 or reject. Hence, in this protocol, if buyer A makes offers to multiple sellers 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." Considering the mentioned issues, the three distinguishing features of *EAlternating offer protocol* [14] 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.

2.3.1 Assumptions and rules

Following all the assumptions and rules apply in specifying the *EAlternating offer protocol* are addressed [14]:

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 ([18] and [22]).
2. Grid resource negotiation progresses in a series of rounds.
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 logical, 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 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 [18], negotiators have information of only the index of the time period, their trading partners' proposals and the existing number of competitors and trading partners.
7. Negotiation focuses on a single-issue (e.g., price-only).
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 [18].
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 is not equal to or greater than the reservation price of B of type GRO, the negotiation process terminates with conflict. This assumption is intuitive because a GRC that its initial proposal is equal to or greater than GRO's reserve price has enough budget to pay the minimum acceptable price of GRO(i.e., reserve price) and from GRO's point of view it is worthwhile to bargain with that GRC in the hope of reaching consensus.
12. Negotiation process in GRNM begins if only there are at least two negotiators of the opposite type (i.e., one negotiator of type GRC and the other of type GRO).
13. Negotiation consists of two stages: *first negotiation stage* and *second negotiation stage*.
14. A negotiator agent A makes initial agreement in *first negotiation stage* if either (i) the generated utility for agent A by received proposal P^B_{t-1} from its trading partner B is greater or equal than the generated utility for agent A by its potential proposal to agent B or (ii) the sum of generated utility for agent A by received proposal P^B_{t-1} from its trading partner B and market pressure value (i.e., *GMP_value*, that addresses the amount of relaxation and is determined by using ***Fuzzy Grid Market Pressure Determination System*** (see section 2.3.2)) is greater or equal than the generated utility for agent A by its potential proposal to agent B (that is, an initial agreement can be reached if the offer does not totally match the agent's negotiation terms but is sufficiently close). The negotiation process will be continued in *second negotiation stage* if

the negotiator agent *A* makes initial agreement in *first negotiation stage*. This is because the agreement should be confirmed by both sides of negotiation thread not the only one side. Details of possible actions of negotiator *A* in *first negotiation stage* are described in [14].

15. A negotiator agent *A* makes final agreement in *second negotiation stage.* The objectives of *second negotiation stage* are: a) 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 b) 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). Details are discussed in [14].
16. If **no agreement** is reached, grid resource negotiation proceeds to the next round. At every round, the negotiator offers appropriate concession using the mentioned multi factors function.
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 $t = t^{A}_{deadline}$, negotiator *A* would accept any proposal from agent *B* 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 Fuzzy grid market pressure determination system (FGMPDS)

According to [14]: "*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 world, 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*." As the notions about parameters that make *GMP_value* are vague and uncertain to be expressed by crisp mathematical models, a fuzzy model can be a suitable method to describe the *GMP_value*. Adabi *et.al* [14] considered three types of GMP: 1) GMP from competitors' side (*Competitor_side_GMP*), 2) GMP from trading partners' side (*TP_side_GMP*) and 3) GMP from GRNM's global condition and negotiator's conditions in acquiring/leasing resources (*Condition & event_GMP*). For determining the numerical value of the mentioned types of GMP three fuzzy decision controllers were designed [14]: a) *Fuzzy Competitor_side GMP determinator* to determine the numerical values of *Competitor_side_GMP, b) Fuzzy TP_side GMP determinator* to determine the numerical values of *TP_side_GMP* and c) *Fuzzy Condition & event GMP determinator* to determine the numerical values of *Condition & event_GMP*. These three fuzzy controllers made **Fuzzy Grid Market Pressure Determination System** (*FGMPDS).* Also the 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 value of the final *GMP_value* tends to become one (maximum market pressure)).

The *FGMPDS* for *GRC_EMBDNA* and *GRO_EMBDNA* are named *FGMPDS_GRC* and *FGMPDS_GRO* respectively and the generic structures of them are shown in Fig.1. While *Fuzzy Competitor_side GMP determinator* and *Fuzzy TP_side GMP determinator* parts of *FGMPDS_GRC* are the same as *Fuzzy Competitor_side GMP determinator* and *Fuzzy TP_side GMP determinator* parts of *FGMPDS_GRO* respectively, *Fuzzy Condition & event GMP determinator* parts of *FGMPDS_GRC* and *FGMPDS_GRO* are different. The reason is that the local conditions of resource consumer agents and resource owner agents are influenced by different factors.

A fuzzy decision controller is composed by 1) input and output variables, 2) a *fuzzification interface (FI),* 3) a *fuzzy rule base (RB)*, 4) a fuzzy negotiation *decision making logic* (*DML)* and 5) a *defuzzification interface (DFI).* Similar to [15, 23-24] all the DFI(s) in [14] adopt the weighted average method [25]. Following the five components of each part of *FGMPDS_GRC* and *FGMPDS_GRO* are briefly discussed.

2.3.2.1 Fuzzy Competitor_side GMP determinator

A: ***Input variable-*** According to strategic reasons a negotiator agent has less information about its competitors, hence, the only relaxation criterion that can influence a decision in the amount of relaxation of bargaining term includes change in number of competitors (CNC^{A}_{t}). With a large number of competitors, 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.

B: ***Output variable -*** The output is a numerical value of *GMP* from competitors' side.

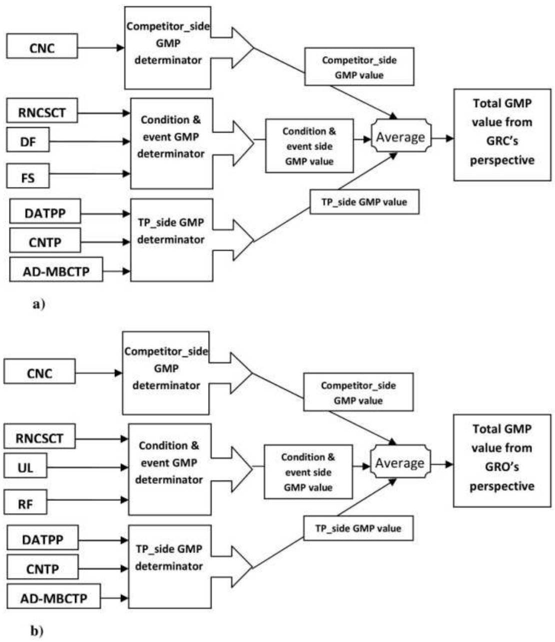

Fig1. **a)** An abstract view of EMBDNAs' *FGMPDS*_GRC and **b)** An abstract view of EMBDNAs' *FGMPDS*_GRO. [14]

C: ***Fuzzification interface*** **–** Three fuzzy sets are defined for output variable: (L, M, H). That is, the output variable has three fuzzy values: {L(low), M(moderate), H(high)}. The linguistic terms of the membership function $\mu_1(x)$ that is used to assign the degree of membership for the value of $Competitor\_side\_GMP$ is shown in Fig.2-(a). Also, the fuzzy sets, fuzzy values and membership functions of CNC_t^A 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*.

D: ***Fuzzy rule base (RB)*** **–** The fuzzy rules that are shown in Table 1 is consulted by *fuzzy Competitor_side GMP determinator*.

E: ***Fuzzy negotiation decision making logic (DML)-*** By consulting the fuzzy rules in RB (see Table 1), the DML infers the linguistic value of *Competitor_side GMP* and its corresponding membership degree μ(*Competitor_side GMP*) from the linguistic values and membership degrees of the fuzzified input CNC_t^A.

Table 1. Fuzzy rules consulted by *fuzzy Competitor_side GMP determinator*. The output is *Competitor_side_GMP* [14].

No	IF *CNC*	Then *output*
1	L	L
2	M	M
3	H	H

F: ***Defuzzification interface (DFI)-*** The DFI 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*.

2.3.2.2 Fuzzy TP_side GMP determinator

A: ***Input variable-*** From trading partners' side perspective three relaxation criteria can influence a decision in the amount of relaxation of bargaining terms: (a) Distance between A's proposal and average of A's trading partners' proposals ($DATPP_t^A$), (b) Change in number of A's trading partners ($CNTP_t^A$) and (c) Acceptance degree of mutual behavior class between an agent A and its trading partners ($AD\_MBCTP_t^A$). The rationale for considering criteria (a), (b) and (c) are given as follow [14]: "*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* $A - B$ *pairs with suitable mutual behavior class (i.e., low* $AD\_MBCTP_t^A$*) has lower chance to make an agreement and is more likely to relax its bargaining criteria to reach an agreement.*"

B: ***Output variable*** **-** The output is a numerical value of *GMP* from trading partners' side.

C: ***Fuzzification interface*** **–** Four fuzzy sets are defined for output variable: (N, L, M, H). That is, the output variable has four fuzzy values: {N(negligible), L(low), M(moderate), H(high)}. The linguistic terms of the membership function $\mu_2(x)$ that is used to assign the degree of membership for the value of TP_side_GMP is shown in Fig.2-(b). Also, The fuzzy sets, fuzzy values and membership functions of $DATPP_t^A$ and $CNTP_t^A$ inputs of *TP_side GMP determinator* are as same as those fuzzy sets, fuzzy values and membership functions of $\mathrm{CNC}_t^{\mathrm{A}}$ input of *Competitor_side GMP determinator*. In addition, while the membership functions of $\mathrm{AD\_MBCTP}_t^{A}$ input of *TP_side GMP determinator* are as same as the membership functions of $\mathrm{CNC}_t^{\mathrm{A}}$ input of *Competitor_side GMP determinator*, three different fuzzy sets (G, BL, B) and three different fuzzy values: {G(good), BL(balance), B(bad)}are defined for $\mathrm{AD\_MBCTP}_t^{A}$.

D: ***Fuzzy rule base (RB) –*** The fuzzy rules that are shown in Table 2 is consulted by *fuzzy TP_side GMP determinator*.

E: ***Fuzzy negotiation decision making logic (DML)-*** By consulting the fuzzy rules in RB (see Table 2), the DML infers the linguistic value of *TP_side GMP* and its corresponding membership degree μ(*TP_side GMP*) from the linguistic values and membership degrees of the fuzzified inputs $\mathrm{DATPP}_t^{\mathrm{A}}$, $\mathrm{CNTP}_t^{\mathrm{A}}$ and $\mathrm{AD\_MBCTP}_t^{A}$.

F: ***Defuzzification interface (DFI)-*** 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*.

Table 2. Fuzzy rules consulted by *fuzzy TP_side GMP determinator*. The output is *TP_side_GMP* [14].

No	IF *DATPP*	And *CNTP*	And *AD_MBCTP*	Then *output*	No	IF *DATPP*	And *CNTP*	And *AD_MBCTP*	Then *output*	No	IF *DATPP*	And *CNTP*	And *AD_MBCTP*	Then *output*
1	L	L	BL	N	8	M	M	G	L	15	H	L	BL	M
2	L	M	G	N	9	H	L	G	L	16	H	M ∨ H	G	M
3	L ∨ M	L	G	N	10	L	M ∨ H	B	M	17	L ∨ M	H	BL	M
4	L	L	B	L	11	M ∨ H	L	B	M	18	M ∨ H	H	B	H
5	L	M	BL	L	12	M ∨ H	M	BL	M	19	H	M	B	H
6	L	H	G	L	13	M	M	B	M	20	H	H	BL	H
7	M	L	BL	L	14	M	H	G	M					

2.3.2.3 Fuzzy Condition & event GMP determinator of FGMPDS_GRC

A: ***Input variable-*** 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 ($\mathrm{RNCSCT}_t^{\mathrm{A}}$). The first and second relaxation criteria are derived from [15]. As mentioned in [15], 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.

B: ***Output variable -*** The output is a numerical value of *GMP* from both GRNM's global condition and negotiator's conditions in acquiring resources.

C: ***Fuzzification interface –*** 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_side GMP determinator* output. The fuzzy sets, fuzzy values and membership functions of $\mathrm{RNCSCT}_t^{\mathrm{A}}$ input of *Condition & event GMP determinator* are as same as those fuzzy sets, fuzzy values and membership functions of $\mathrm{CNC}_t^{\mathrm{A}}$ input of *Competitor_side GMP determinator*. Four fuzzy sets (N, L, M, H) are defined for both FS_t and DF_t input variables. That is, FS_t and DF_t input variables have four fuzzy values: {N(negligible), L(low), M(moderate), H(high)}. The linguistic terms of the membership functions μ_3(x) and μ_4(x) that are used to assign the degree of membership for FS_t and DF_t are shown in Fig.2- (c) and Fig.2- (d) respectively.

D: ***Fuzzy rule base (RB) –*** The fuzzy rules that are shown in Table 3 is consulted by *fuzzy Condition & event GMP determinator*.

E: ***Fuzzy negotiation decision making logic (DML)-*** By consulting the fuzzy rules in RB (see Table 3), the DML infers the linguistic value of *condition & event* side's *GMP* and its corresponding membership degree μ(*condition & event* side's *GMP*) from the linguistic values and membership degrees of the fuzzified inputs FS_t, DF_t and $\mathrm{RNCSCT}_t^{\mathrm{A}}$.

F: ***Defuzzification interface (DFI)-*** The *DFI of Fuzzy Condition & event GMP determinator* of *FGMPDS_GRC* is used to determine the crisp value of *Condition & event_GMP* of *FGMPDS_GRC* given its linguistic values with their respective membership degree being obtained from the *DML of Fuzzy Condition & event GMP determinator* of *FGMPDS_GRC.*

2.3.2.4 Fuzzy Condition & event GMP determinator of FGMPDS_GRO

A: ***Input variable-*** From *condition & event* side's *GMP* perspective three relaxation criteria can influence a decision in the amount of relaxation of bargaining terms: (i) Utilization level (UL_t), (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 ($\mathrm{RNCSCT}_t^{\mathrm{A}}$). The first and second relaxation criteria are derived from [15]. As mentioned in [15], 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.,

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the UL_t 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 RF_t 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.

Table 3. Fuzzy rules consulted by *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC*. The output is *Condition & event_GMP* [14].

No	IF *RNCSCT*	And *FS_t*	And *DF_t*	Then *output*	No	IF *RNCSCT*	And *FS_t*	And *DF_t*	Then *output*	No	IF *RNCSCT*	And *FS_t*	And *DF_t*	Then *output*
1	L	N	N v L	N	9	M	L	NvLvM	L	17	H	N	M v H	M
2	L	L v M v H	N	N	10	M	MvH	N	L	18	H	L	L v M	M
3	L	L	LvMvH	L	11	H	N	L	L	19	H	M	L	M
4	L	N v M v H	M	L	12	H	-	N	L	20	M	H	H	H
5	L	H	L	L	13	L	M vH	H	M	21	M v H	M	H	H
6	L	N	H	L	14	M	H	L v M	M	22	H	L	H	H
7	L v M	M	L	L	15	M	L	H	M	23	H	M	M	H
8	M	N	-	L	16	M	M	M	M	24	H	H	LvM v H	H

B: ***Output variable*** **-** The output is a numerical value of *GMP* from both GRNM's global condition and negotiator's conditions in leasing resources.
C: ***Fuzzification interface*** **–** 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_side GMP determinator* output. The fuzzy sets, fuzzy values and membership functions of RF_t and UL_t inputs of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRO* are as same as those fuzzy sets, fuzzy values and membership functions of DF_t input of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC*. Also the fuzzy sets, fuzzy values and membership functions of RNCSCT_t^A input of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRO* are as same as those fuzzy sets, fuzzy values and membership functions of RNCSCT_t^A input of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC*.
D: ***Fuzzy rule base (RB)*** **–** The fuzzy rules that are shown in Table 4 is consulted by *fuzzy Condition & event GMP determinator*.
E: ***Fuzzy negotiation decision making logic (DML)*-** By consulting the fuzzy rules in RB (see Table 4), the DML infers the linguistic value of *condition & event* side's *GMP* and its corresponding membership degree μ(*condition & event* side's *GMP*) from the linguistic values and membership degrees of the fuzzified inputs UL_t, RF_t and RNCSCT_t^A.

F: ***Defuzzification interface (DFI)*-** The *DFI of Fuzzy Condition & event GMP determinator* of *FGMPDS_GRO* is used to determine the crisp value of *Condition & event_GMP* of *FGMPDS_GRO* given its linguistic values with their respective membership degree being obtained from the *DML of Fuzzy Condition & event GMP determinator* of *FGMPDS_GRO.*

3. Proposed approach for evolving relaxed-criteria rules

As previously discussed, the EMBDNA negotiator agents [14] is equipped with a fuzzy decision controller to slightly relax their bargaining criteria in the face of intense GMP, but the relaxed-criteria fuzzy rules are manually constructed by using knowledge of experts. The construction of the relaxed-criteria fuzzy rules based on the appropriate expert knowledge can be quick and effective. On the other hand, it is difficult to find a fixed set of fuzzy rules that is suitable for all different types of electronic markets. As the system structure of EMBDNA negotiator agents [14] remained generally fixed in unpredictable market conditions, it is essential to design new negotiation agents that not only use fuzzy rules to relax their bargaining criteria but also have the ability to evolve their structures by learning new relaxed-criteria fuzzy rules to enhance their negotiation performance as they participate in negotiations in a series of different electronic markets. To construct adaptive and self improving negotiation agents operating in a series of electronic markets an evolutionary approach that invokes a Biogeography-based optimization (BBO) algorithm is adapted. The following subsections include: a) a brief description of BBO and b) a description of the proposed evolutionary procedure that invokes BBO algorithm for evolving and adapting relaxed-criteria fuzzy rules in details.

Table 4. Fuzzy rules consulted by *fuzzy Condition & event GMP determinator* of *FGMPDS_GRO*. The output is *Condition & event_GMP* [14].

No	IF *RNCSCT*	And *UL_t*	And *RF_t*	Then *output*	No	IF *RNCSCT*	And *UL_t*	And *RF_t*	Then *output*	No	IF *RNCSCT*	And *UL_t*	And *RF_t*	Then *output*
1	L	M	H	N	9	H	H	-	L	17	H	M	L v M	M
2	L	H	-	N	10	H	M	H	L	18	M	N	N	H
3	L	L v N	Lv M v H	L	11	H	L	M v H	M	19	H v M	L	N	H
4	L	M	Nv L v M	L	12	L	N v L	N	M	20	H	M	N	H
5	M	M	Lv M v H	L	13	M	N	L v M	M	21	H	L	L	H
6	M	H	-	L	14	M	M	N	M	22	H	N	Nv L v M	H
7	M	N	H	L	15	M	L	L	M					
8	M	L	M vH	L	16	H	N	H	M					

3.1 Biogeography-based optimization (BBO)

Biogeography Based Optimization [26] is a population based global optimization technique based on the science of biogeography, i.e., study of the distribution of animals and plants among different habitats over time and space. The environment of BBO corresponds to an archipelago, where every possible solution to the optimization problem is an island (or habitat) [27]. In BBO, the island's features

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that characterize habitability are called suitability index variables (SIV). The goodness of each solution is called its habitat suitability index (HSI). A good solution is analogous to an island with a high HIS, and a poor solution represents an island with a low HSI. High HSI solutions resist change more than low HSI solutions. The method to generate the next generation in BBO is by immigrating solution features to other islands, and receiving solution features by emigration from other islands. High HSI solutions tend to share their features with low HSI solutions. Logically, poor solutions accept a lot of new features from good solutions. Each solution is modified based on other solutions. It means that, each habitat H_i has immigration rate λ_i and emigration rate μ_i. Suppose that k'th habitat (i.e., H_k) is selected to be modified. The λ_k of H_k is used to probabilistically decide whether or not to modify each H_k's SIV. If a given SIV in a given solution is selected to be modified, then the emigration rate μ_s of the other solutions are used to probabilistically decide which of the solutions should migrate a randomly selected SIV to solution. Then mutation is performed for the whole population in a manner similar to mutation in Genetic Algorithm (GA). According to [27]: "*After tests on many benchmarks, and comparisons with many other widely used heuristic algorithms like GAs, stud GAs, and others, BBO outperformed most of the other algorithms on most of the benchmarks*", so BBO is a perfect choice for evolving the relaxed-criteria fuzzy rules of EMBDNAs.

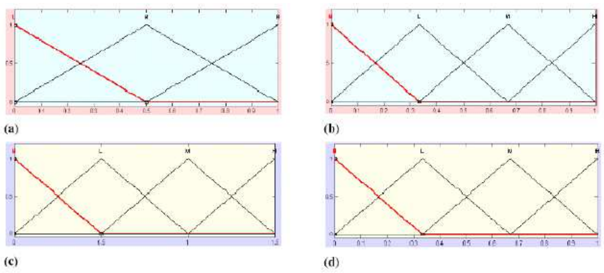

Fig 2. **(a)** Linguistic terms of the membership function $\mu_1(x)$, **(b)** Linguistic terms of the membership function $\mu_2(x)$, **(c)** Linguistic terms of the membership function $\mu_3(x)$, **(d)** Linguistic terms of the membership function $\mu_4(x)$ [14].

3.2 Evolutionary procedure for evolving and adapting relaxed-criteria fuzzy rules

An evolutionary procedure (see Fig. 3) is designed to improve the negotiation outcomes of EMBDNAs by evolving their relaxed-criteria fuzzy rules as they participate in negotiations in more electronic markets $\{M_0, M_1, \ldots\}$. First of all, a set R_0 of manually designed relaxed-criteria fuzzy rules is generated. We should highlight that EMBDNA is designed with three fuzzy controllers in names: *Fuzzy Competitor_side GMP determinator*, *Fuzzy TP_side GMP determinator* and *Fuzzy Condition & event GMP determinator*. Also recall that while *Fuzzy Competitor_side GMP determinator* and *Fuzzy TP_side GMP determinator* parts of *FGMPDS_GRC* are the same as *Fuzzy Competitor_side GMP determinator* and *Fuzzy TP_side GMP determinator* parts of *FGMPDS_GRO* respectively, *Fuzzy Condition & event GMP determinator* parts of *FGMPDS_GRC* and *FGMPDS_GRO* are different. The authors focus on evolving the relaxed-criteria rules of *Fuzzy TP_side GMP determinator* and *Fuzzy Condition & event GMP determinator*. Hence, in the case of evolving fuzzy rules of *Fuzzy TP_side GMP determinator* , *Fuzzy Condition & event GMP determinator* part of *FGMPDS_GRC* and *Fuzzy Condition & event GMP determinator* part of *FGMPDS_GRO* the rule set R_0 is as same as the rule set of Table 2, Table 3 and Table 4 respectively. At any relaxed-criteria fuzzy rules evolution and adaption just one fuzzy controller part of *FGMPDS_GRC* (respectively, *FGMPDS_GRO*) is picked and the evolution and adaption procedure of fuzzy rule set is started to create new fuzzy rule set while the fuzzy sets of other fuzzy controller parts of *FGMPDS_GRC* (respectively, *FGMPDS_GRO*) are hold same as before. During the negotiation process in electronic market M_0, EMBDNAs adopt R_0 as their relaxed criteria rule sets in their fuzzy decision controllers for determining if agreements should be reached. By terminating the negotiation process of M_0, the crisp values of inputs and output of fuzzy controller that have successfully reached agreements are recorded as a data set D_0. For example, if the *Fuzzy TP_side GMP determinator* is picked and the evolutionary procedure is started for learning effective relaxed-criteria negotiation rules, the data set D_0 is constructed based on the crisp values of three inputs of *Fuzzy TP_side GMP determinator* in names DATPP_t^A, CNTP_t^A and $\mathrm{AD\_MBCTP}_t^A$ and one output of *Fuzzy TP_side GMP determinator* in name *TP_side GMP value* of EMBDNAs that have successfully reached agreements. Also, if the *Fuzzy Condition & event GMP determinator* part of *FGMPDS_GRC* is picked and the evolutionary procedure is started for learning effective relaxed-criteria negotiation rules, the data set D_0 is constructed based on the crisp values of three inputs of *Fuzzy Condition & event GMP determinator* in names FS_t, DF_t and RNCSCT_t^A and one output of *Fuzzy Condition & event GMP determinator* in name *condition & event side GMP value* of EMBDNAs that have successfully reached agreements. By having both D_0 and R_0 the proposed BBO-based solution (see section 3.2.1) is invoked to evolve and adapt a set of new fuzzy rules and the D_0 and R_0 are used as inputs of BBO. The output of the BBO-based solution is a set of newly evolved fuzzy rules which replaces some of the rules in R_0 to form a new rule set R_1. The process continues such that at each M_i: a) EMBDNAs adopt R_i as their relaxed-criteria fuzzy rule set, b) by terminating the negotiation process of M_i, the crisp values of the inputs and output of fuzzy decision

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controller of EMBDNAs, that is picked to evolve its fuzzy rule set, that have successfully reached agreements are recorded as data set D_i and c) using both D_i and R_i as inputs, the BBO is invoked to evolve a new set of fuzzy rules which replaces some of the rules in R_i to form a new rule set R_{i+1} which will be adopted by EMBDNAs in M_{i+1}.

3.2.1 Proposed BBO-based solution

This section contains the BBO-based solution (see Fig. 4) that is proposed for evolving relaxed-criteria fuzzy rules. First of all, the encoding and decoding methods of the proposed BBO-based solution are described. Following the initial population generation, HSI calculation, three operators in names migration operator, mutation operator and repair operator are discussed. At the end the elitism parameter is introduced.

i. ***Encoding Relaxed-criteria rules as SIVs:*** In this paper, we encode relaxed-criteria rules as string with fixed length. Each string is an abstract representation of a relaxed-criteria fuzzy rule and is illustrated as "$m_1m_2m_3m_4$" where m_1, m_2 and m_3 represent the antecedents and m_4 represents the conclusion of a fuzzy rule. Recall that each fuzzy control system of *FGMPDS* (from both GRC and GRO sides) that is picked in the evolutionary procedure for evolving relaxed-criteria fuzzy rules has three inputs and one output, hence the abstract representation of a relaxed-criteria fuzzy rule can be used for a fuzzy rule in all three fuzzy controller systems. The value domain for each variable in the antecedent and conclusion of a fuzzy rule depends on which fuzzy controller system is evolved. It means that, by considering *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC* the string m_1, m_2 and m_3 represent RNCSCT_t^A, FS_t and DF_t respectively and the value domain for m_1 is {0,1,2,3} whereas "1", "2" and "3" are used to represent the fuzzy values "L", "M" and "H", respectively, "0" represents that the corresponding variable does not appear in the fuzzy rule (i.e., each string may encode several different rules) and the value domain for both $m_2$and m_3 is {0,1,2,3,4} whereas "1", "2", "3" and "4" are used to represent the fuzzy values "N", "L", "M" and "H", respectively, "0" represents that the corresponding variable does not appear in the fuzzy rule. By considering *fuzzy Condition & event GMP determinator* of *FGMPDS_GRO* the string m_1, m_2 and m_3 represent RNCSCT_t^A, UL_t and RF_t respectively and the value domain for m_1 is as same as the value domain for m_1 in fuzzy rule of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC* and the value domain for m_2 and m_3 is as same as the value domain for m_2 (or m_3) in fuzzy rule of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC.* Also, by considering *fuzzy TP_side GMP determinator* the string m_1, m_2 and m_3 represent DATPP_t^A, CNTP_t^A and $\mathrm{AD\_MBCTP}_t^A$ respectively and the value domain for both $m_1$and m_2 is {0,1,2,3} whereas "1", "2" and "3" are used to represent the fuzzy values "L", "M" and "H", respectively, "0" represents that the corresponding variable does not appear in the fuzzy rule and the value domain for m_3 is {0,1,2,3} whereas "1", "2" and "3" are used to represent the fuzzy values "G", "BL" and "B", respectively, "0" represents that the corresponding variable does not appear in the fuzzy rule. In addition, the value domain for m_4 for all three fuzzy controllers is {0,1,2,3,4} whereas "1", "2", "3" and "4" are used to represent the fuzzy values "N", "L", "M" and "H", respectively, "0" represents that the corresponding variable does not appear in the fuzzy rule. For example, string "1211" of *fuzzy TP_side GMP determinator* represents the rule "***IF*** DATPP is **L** and CNTP is **M** and AD_MBCTP is **G** then TP_Side GMP is **N**" and string "3<u>0</u>12" of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC* represent following four rules: a) ***IF*** RNCSCT is **H** and FS_t is **<u>N</u>** and DF_t is **N** then Condition & event GMP is **L**, b) ***IF*** RNCSCT is **H** and FS_t is **<u>L</u>** and DF_t is **N** then Condition & event GMP is **L,** c) ***IF*** RNCSCT is **H** and FS_t is **<u>M</u>** and DF_t is **N** then Condition & event GMP is **L** and d) ***IF*** RNCSCT is **H** and FS_t is **<u>H</u>** and DF_t is **N** then Condition & event GMP is **L**.

ii. ***Decoding SIVs to relaxed-criteria rules:*** Each string can be decoded to one or several relaxed-criteria rules containing three variables in the antecedent and one variable in the conclusion. Recall that, since "0" in a string represents that the corresponding variable does not appear in a fuzzy rule, the variable can be mapped into any value in the domain. For example, considering a string "21<u>0</u>2" that represents a rule of *fuzzy Condition & event GMP determinator* of *FGMPDS_GRC* can be translated into four different rules.

iii. ***Initialization of the population (n islands):*** The size of population (i.e., *POPSIZE*) is set to 100 [24]. All the rules in R_0 are copied into the initial population as part of the habitats. Additionally, other new habitats are randomly generated, with the values for each variable randomly generated from the value domain [24].

iv. ***HSI function:*** In this paper the HSI of each habitat *m* with a string "$m_1m_2m_3m_4$" is calculated as Eq. (10) [28]:

$$\mathrm{HSI(m)}=\frac{TP}{TP+FN}\times\frac{TN}{FP+TN} \tag{10}$$

where according to [24] :"*A data record is positive (P) if it is covered by m, and it is negative (N) if it is not covered by m. If a data record is predicted to be P (i.e., the antecedent is covered by m, and it is predicted that m also covers the conclusion) and the outcome is actually P (i.e., the conclusion is actually covered by m), then it is called a true positive [29]. However, if the conclusion is actually N (i.e., the conclusion is actually not covered by m), then it is called a false positive. Conversely, a true negative occurs*

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when a data record is predicted to be N (i.e., the antecedent is not covered by m, and it is predicted that the conclusion is also not covered by m) and the outcome is actually N (i.e., the actual conclusion is not covered by m). A false negative occurs when a data record is predicted to be N but the outcome is actually P. Hence, TP (true positives) [29] is the number of data records that are covered by the antecedent and conclusion of m. FP (false positives) [29] is the number of data records that are covered by the antecedent but not the conclusion of m. TN (true negatives) [29] is the number of records that are not covered by both the antecedent and conclusion of m. FN (false negatives) [29] is the number of records that are covered by m's conclusion but not its antecedent." The next two decisions that should be made are: a) how a data record *d* is covered by the antecedent of habitat *m* and b) how a data record *d* is covered by the conclusion of habitat *m*. Both the first and second decisions are made based on [24] as follows: **a)** If $\min\{\mu_{m1}(d_1), \mu_{m2}(d_2), \mu_{m3}(d_3)\} \geq \varepsilon$, then it is considered that data record *d* is covered by the antecedent of habitat *m* (if $m_i = 0$, then $\mu_{mi}(d_i)$ is ignored and deleted from the formula $\min\{\mu_{m1}(d_1), \mu_{m2}(d_2), \mu_{m3}(d_3)\}$, i = 1, 2, 3); **b)** If $\mu_{m4}(d_4) \geq \varepsilon$, then it is considered that data record *d* is covered by the conclusion of habitat *m*. The inputs of fuzzy controller system are represented by d_1, d_2 and d_3 and the output of fuzzy controller system is represented by d_4. If the crisp value of *i*th variable is d_i and its linguistic value is represented by m_i(i = 1, 2, 3, 4), $\mu_{mi}(d_i)$ denotes the membership degree of the *i*th variable. The threshold ε is set to 0.5 [24]. For the benefit of readers an example is provided. Suppose that *fuzzy TP_side GMP determinator* is picked in the evolutionary procedure for evolving relaxed-criteria fuzzy rules. The habitat *m* = "2212" represents the rule "***IF*** DATPP is **M** and CNTP is **M** and AD_MBCTP is **G** then TP_Side GMP is **L**". If we have data record $d = \{0.2, 0.4, 0.1, 0.05\}$ then $\mu_{m1}(d1) = \mu_M(0.2) = 0.4$, $\mu_{m2}(d2) = \mu_M(0.4) = 0.8$, $\mu_{m3}(d3) = \mu_G(0.1) = 0.8$, and $\mu_{m4}(d4) = \mu_N(0.05) = 0.15$. According to the values of $\mu_{m1}(d1)$, $\mu_{m2}(d2)$ and $\mu_{m3}(d3)$ the $\min\{\mu m1(d1), \mu m2(d2), \mu m3(d3)\} = 0.4 < \varepsilon$, hence, *d* is not covered by the antecedent of *m*. Also according to the value of $\mu_{m4}(d4)$, *d* is not covered by the conclusion of *m* (i.e., $\mu m4(d4) = 0.15 < \varepsilon$).

v.*Migration operator:* As mentioned previously, each habitat H_i has immigration rate λ_i and emigration rate μ_i. Good solutions have high emigration rates and low immigration rates. Bad solutions have low emigration rates and high immigration rates. Through various migration models [30] in the biogeography, every habitat can get different immigration and emigration rates. In this paper the immigration rate λ_i and emigration rate μ_i is calculated as Eq. (11) and Eq. (12) respectively [26] :

$$\lambda_i = I\left(1 - \frac{k(i)}{n}\right) \tag{11}$$

$$\mu_i = E\left(\frac{k(i)}{n}\right) \tag{12}$$

where *I* is the maximum possible immigration rate; *E* is the maximum possible emigration rate; *k* is the number of species of the *k*th habitat; *n* is the maximum number of specie which is set to population size.

Procedure for evolving relaxed-criteria rules
1. Manually design a fuzzy rule set R_0 containing fuzzy rules (see Table 2).
2. Incorporate R_0 into the Fuzzy TP side GMP determinator of EMBDNAs and simulate the negotiation process of EMBDNAs in e-market M_0
3. Record the crisp values of *DATPP,CNTP,AD_MBCTP*, and *TP_side_GMP* of EMBDNAs that have reached agreements as a data set D_0.
4. Set the iteration count *i* to 0.
5. **While** not stop,
   a. Invoke procedure ***BBO***(R_i,D_i) to evolve a set of new fuzzy rules.
   b. Replace the corresponding rules in R_i with the newly evolved fuzzy rules, and copy all the rules in to a new fuzzy rule set R_{i+1}.
   c. Incorporate R_{i+1} into the Fuzzy TP_side GMP determinator of EMBDNAs and simulate the negotiation process of EMBDNAs in e-market M_{i+1}.
   d. Record the crisp values of *DATPP,CNTP,AD_MBCTP*, and *TP_side_GMP* of EMBDNAs that have reached agreements as a data set D_{i+1}.
   e. Increment *i* by 1

a

Procedure for evolving relaxed-criteria rules
1. Manually design a fuzzy rule set R_0 containing fuzzy rules (see Table 3).
2. Incorporate R_0 into the Fuzzy Condition & event GMP determinator of EMBDNAs and simulate the negotiation process of EMBDNAs in e-market M_0.
3. Record the crisp values of *RNCSCT*,FS_t, DF_t and *Condition & event_GMP* of EMBDNAs that have reached agreements as a data set D_0.
4. Set the iteration count *i* to 0.
5. **While** not stop,
   a. Invoke procedure ***BBO***(R_i,D_i) to evolve a set of new fuzzy rules.
   b. Replace the corresponding rules in R_i with the newly evolved fuzzy rules, and copy all the rules in to a new fuzzy rule set R_{i+1}.
   c. Incorporate R_{i+1} into the Fuzzy Condition & event GMP determinator of EMBDNAs and simulate the negotiation process of EMBDNAs in e-market M_{i+1}.
   d. Record the crisp values of *RNCSCT*,FS_t, DF_t and *Condition & event_GMP* of EMBDNAs that have reached agreements as a data set D_{i+1}.
   e. Increment *i* by 1

b

Procedure for evolving relaxed-criteria rules
1. Manually design a fuzzy rule set R_0 containing fuzzy rules (see Table 4).
2. Incorporate R_0 into the Fuzzy Condition & event GMP determinator of EMBDNAs and simulate the negotiation process of EMBDNAs in e-market M_0.
3. Record the crisp values of *RNCSCT*,UL_t, RF_t and *Condition & event_GMP* of EMBDNAs that have reached agreements as a data set D_0.
4. Set the iteration count *i* to 0.
5. **While** not stop,
   a. Invoke procedure ***BBO***(R_i,D_i) to evolve a set of new fuzzy rules.
   b. Replace the corresponding rules in R_i with the newly evolved fuzzy rules, and copy all the rules in to a new fuzzy rule set R_{i+1}.
   c. Incorporate R_{i+1} into the Fuzzy Condition & event GMP determinator of EMBDNAs and simulate the negotiation process of EMBDNAs in e-market M_{i+1}.
   d. Record the crisp values of *RNCSCT*,UL_t, RF_t and *Condition & event_GMP* of EMBDNAs that have reached agreements as a data set D_{i+1}.
   e. Increment *i* by 1.

c

Fig 3. a) Procedure for evolving relaxed-criteria rules of *Fuzzy TP_side GMP determinator* , **b)** Procedure for evolving relaxed-criteria rules of *Fuzzy Condition & event GMP determinator* part of *FGMPDS_GRC* and **c)** Procedure for evolving relaxed-criteria rules of *Fuzzy Condition & event GMP determinator* part of *FGMPDS_GRO*.

vi.*Mutation operator:* The purpose of mutation is to increase diversity among the population. The mutation probability is inversely proportional to the solution probability [26], and is defined by Eq (13):

$$m_i = m_{max}\left(1 - \frac{P_i}{P_{max}}\right) \tag{13}$$

where m_{max} is the user-defined maximum mutation probability, $P_{max} = argmaxP_i, (i = 1, \ldots, n)$, n (n is population size), and P_i is the solution probability. More details can be found in [26].

vii. *Repair operator:* As "0" may appear in habitats, some of the habitats may be invalid and should be modified. There are three cases that result in an invalid fuzzy rule (or habitat): 1) all the values in the antecedents are zero, 2) the value of conclusion is zero and 3) all the values of antecedents and conclusion are zero. To overcome this problem the *repair operator* [31] is introduced. Two tasks should be done by repair operator: first, it validates the antecedent and conclusion of habitat in the population of rules and second corrects the antecedent and/or conclusion of the invalid rules. If the first case of invalid fuzzy rule is detected, a nonzero value in the domain will be randomly introduced by repair operator to a randomly picked position. If the second case of invalid fuzzy rule is detected, repair operator will modify the conclusion to a random nonzero value in predefined value domain. If the third case of invalid fuzzy rule is detected, the repair operator modifies both antecedent and conclusion parts of a rule by using the two mentioned correction techniques.

viii. ***Elitism parameter:*** The termination criterion of 450 iterations is set for the BBO. It should be reported that generally the coverage is reached more rapidly.

4. Experimental results

4.1 Objectives

A series of experiments was carried out to compare the performance of Ev_MBDNAs (that have the flexibility of evolving their relexed-criteria fuzzy rules by using the proposed BBO-based solution) with EMBDNAs [14] (i.e., MBDNAs [19] with relaxed-criteria fuzzy rules that are manually constructed to make relaxation decision in face of (intense) GMP) in a very wide variety of test environments. While the relaxed-criteria fuzzy rules of Ev_MBDNAs are evolved and adapted using the proposed BBO-based solution, the same set of fuzzy rules for EMBDNAs is used throughout the different series of electronic markets.

4.2 TestBed

To evaluate the performance of Ev_MBDNAs against EMBDNAs [14], a testbed is developed. Implemented using C++, the testbed consists of: 1) a virtual e_market; 2) a society of negotiation agents comprising Ev_MBDNAs and EMBDNAs; and 3) a controller agent.

1)Virtual e_market: In a virtual e_market, negotiation agents have one of the following roles: GRC or GRO.

2) Society of negotiation agent: Two kinds of negotiation agents: EMBDNAs and Ev_MBDNAs are simulated.

3)Controller agent: The controller agent generates negotiation agents (EMBDNAs and Ev_MBDNAs), 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.

4.3 Experimental scenarios

In the experiments, EMBDNAs and Ev_MBDNAs 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 Ev_MBDNA_GRC and Ev_MBDNA_GRO agents are augmented with fuzzy decision controller to slightly relax their bargaining criteria and evolve their relaxed-criteria fuzzy rules by using an evolutionary BBO algorithm, but without loss of generality and because of lacking enough space, it suffices to demonstrate the properties of Ev_MBDNAs from the perspective of GRC agents. So we conduct two types of experiments:1) GRC agents are Ev_MBDNA and GRO agents are MBDNAs[19] and 2) GRC agents are EMBDNAs and GRO agents are MBDNAs[19]. The reason that in the first (respectively, second) experiment just GRC agents are considered as Ev_MBDNAs (respectively, EMBDNAs) while GRO agents are considered as MBDNAs is based on a common assumption in microeconomics, namely *ceteris paribus* [32]. According to [32]: "*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 Ev_MBDNAs of type GRC against EMBDNAs, it seems prudent to avoid any possible influence on the negotiation outcomes when negotiation agents of type GRC make relaxation. Hence in our experiment GRO agent are programmed as MBDNAs because MBDNAs are not designed with relaxation ability.

4.4 Experimental setting

All the following input parameters required for setting grid simulation testbed and their possible values are presented in Table 5: **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. The reason for choosing the range [10-70] for GRCs' negotiation deadlines is that, in experimental setting it was found that for very *Short* deadline (<10), very few negotiation agents that follow the relaxed-criteria protocol can complete deals and also for deadline>70, there is little or no difference in performance of two types of agents, **e)** the total resource capacity of a GRO agent (measured in (MIPS)), **f)** Market density and **g)** time-dependent strategy. The values of the most mentioned parameters that are used to conduct simulation are derived from ([26, 44-45, 47]). Also Table 5 illustrated the simulation characteristics. More details can be found in [14].

```
Procedure BBO (R_i, D_i)
1. Set the generation counter g to 0.
2. Set POPSIZE to 100.
3. Copy all the rules in R_i to POP(0).
4. Set the number of habitats N in POP(0) to be the number of rules in R_i.
5. While N<POPSIZE,
   a. Randomly generate a habitat for POP(0).
   b. Execute Repair operator for the new habitat.
   c. Increment N by 1.
6. Calculate HSI value for each habitat in POP(0) from D_i.
7. While the maximum number of generation is not reached
   {
   a. Copy all the habitats in POP(g) into a temporary population TPOP(g).
   b. Compute immigration rate λ and emigration rate μ for each habitat in POP(g) based on HSI.
   c. For each habitat in POP(g)
      {
      i. For each SIV
         {
         1. Select habitat H_i with probability ∝ λ_i.
         2. If H_i is selected then
            {
            a. For all habitats in POP(g) except H_i
               {
               i. Select habitat H_j with probability ∝ μ_j.
               ii. If H_j is selected then
                  {
                  1. Execute Migration operator and H_i(SIV)← H_j(SIV).
                  2. Execute Repair operator for habitat H_i.
                  3. Copy H_i to i'th habitat of TPOP(g).
                  }
               }
            }
         3. Select H_i(SIV) based on mutation probability m_i.
         4. If H_i(SIV) is selected then
            {
            a. Execute Mutation operator for H_i(SIV).
            b. Execute Repair operator for habitat H_i.
            c. Copy H_i to i'th habitat of TPOP(g).
            }
         }
      ii. Recomputed HSI value.
      }
   d. Elitism.
   e. Copy TPOP(g) to POP(g+1) to obtain a new population POP(g+1).
   f. Increment g by 1.
   }
8. Decode the best habitats into relaxed-criteria rules and return the rules.
```

Fig 4. BBO-based solution for evolving relaxed-criteria fuzzy rules.

Table 5. Input parameters for setting grid simulation testbed and their possible values [14].

Input	*Possible values*		
E_market type	**GRC_Favorable**	$P_{GRC} < 0.5$	*GRC_to_GRO={1:100,1:50, 1:30, 1:10, 1:4, 1:2}*
	GRO_favorable	$P_{GRC} > 0.5$	*GRC_to_GRO={100:1, 50:1, 30:1, 10:1, 4:1, 2:1}*
	Balanced	$P_{GRC} = 0.5$	*GRC_to_GRO={1:1}*
P_{GRC}: Follows a uniform distribution and is a probability an agent being a GRC.			
Market Density	**Sparse**	**Moderate**	**Dense**
P_{gen}	0.25	0.5	1
P_{gen}: Follows a uniform distribution and is a probability of generating an agent per round			
Grid_load (i.e., $\frac{R_p}{C_c}$)	0<Grid_load<1 {0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9}		
	Low: 0 ← *Grid_load*		*High: Grid_load* ⟶ 1
R_p: The expected amount of processing requested per time interval *C_c: The total computing capacity of the grid*			
Negotiation deadline (No. of rounds)	**Short**	**Moderate**	**Long**
	10-29	30-59	60-70
Job size(MI)	50-400		
Resource capacity(MIPS)	200-3000		
λ[20]	λ={1/3,1,2,3,20}		
Characteristics: -Avg. no. of agents/round	320	600	890
-Max. no. of agents/round	400	720	1200

4.5 Performance measure

According to the dynamic nature of grids, the benchmarking and evaluating of grids is difficult (specially, market-oriented resource allocation algorithms are very difficult to analyze analytically). As EMBDNAs of type GRC take into account *success rate*, *expected utility* and *average negotiation round* as performance measures and EMBDNAs of type GRO take into account *resource utilization level*, *expected utility* and *average negotiation round* as performance measures, and because the objective of this paper is to compare the performance of the proposed negotiation agents Ev_MBDNAs with EMBDNAs [14] the performance metrics that are considered in our study are as same the ones in [14]. The performance measures are summarized in Table 6.

4.6 Observations

The negotiation activities are simulated in a series of 300 consecutive 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. Furthermore, the results of the last twenty consecutive e_markets are plotted in the figures of simulation results. The reason is that, in the first several e_markets the Ev_MBDNAs do not outperform EMBDNAs as most of the manually designed relaxed-criteria fuzzy rules were used by them. However, by negotiating in more e_markets, new relaxed-criteria fuzzy rules were evolved which lead to a significant improvement in the performance of Ev_MBDNAs against EMBDNAs.

Table 6. Performance measures [14].

Agent type	*GRC*	*GRO*
Success rate	$R_{succ}=[\sum_{i=1}^{N_{tot}^{GRC}}(N_{succ}^{GRC_i}/N_{tot}^{GRC_i})]/N_{tot}^{GRC}$	-
Resource utilization level	-	$U_{rl}=[\sum_{i=1}^{N_{tot}^{GRO}}(TUCap_{GRO_i}/TCap_{GRO_i})]/N_{tot}^{GRO}$
Expected utility	$U_{expected}=AU_{succ}^{GRC}\times R_{succ}+AU_{fail}^{GRC}\times(1-R_{succ})=AU_{succ}^{GRC}\times R_{succ}$	$U_{expected}=AU_{succ}^{GRO}\times U_{rl}+AU_{fail}^{GRO}\times(1-U_{rl})=AU_{succ}^{GRO}\times U_{rl}$
Average negotiation round	$R_{time}=\sum_{i=1}^{N_{tot}^{GRC}}ST_{N_{succ}^{GRC_i}}/\sum_{i=1}^{N_{tot}^{GRC}}N_{succ}^{GRC_i}$	$R_{time}=\sum_{i=1}^{N_{tot}^{GRO}}ST_{N_{succ}^{GRO_i}}/\sum_{i=1}^{N_{tot}^{GRO}}N_{succ}^{GRO_i}$

Definition of used parameters			
$N_{tot}^{GRC_i}$	Total number of GRC_i's tasks requiring resources	$TUCap_{GRO_i}$	$\sum_{j=0}^{TS_{GRO_i}} UCap_j^{GRO_i}$
$N_{succ}^{GRC_i}$	Number of GRC_i's task(s) that successfully negotiate	$SU_{N_{succ}^{GRC_i}}$	Sum of utility of successful GRC_i's task(s)
N_{tot}^{GRC}	Total number of GRC agents	AU_{succ}^{GRC}	Average utility of GRC agents that reached consensus. $AU_{succ}^{GRC}=\sum_{i=1}^{N_{tot}^{GRC}}SU_{N_{succ}^{GRC_i}}/\sum_{i=1}^{N_{tot}^{GRC}}N_{succ}^{GRC_i}$
TS_{GRO_i}	The time that GRO_i spends in the negotiation market	AU_{fail}^{GRC}	Average utility of GRC agents that did not reach consensus. $AU_{fail}^{GRC}=0$
N_{tot}^{GRO}	Total number of GRO agents	$SU_{N_{succ}^{GRO_i}}$	Sum of utility of successful GRO_i's computing machine(s).
$N_{succ}^{GRO_i}$	Number of GRO_i's machine(s) that successfully negotiate	AU_{succ}^{GRO}	Average utility of GRO agents that reached consensus (based on achieved utilities by leasing out computing machines). $AU_{succ}^{GRO}=\sum_{i=1}^{N_{tot}^{GRO}}SU_{N_{succ}^{GRO_i}}/\sum_{i=1}^{N_{tot}^{GRO}}N_{succ}^{GRO_i}$
$Cap_j^{GRO_i}$	The total capacity of GRO_i's machine(s) in negotiation round j	AU_{fail}^{GRO}	Average utility of GRO agents that did not reach consensus. $AU_{fail}^{GRO}=0$
$UCap_j^{GRO_i}$	The total used capacity of GRO_i's machine(s) in negotiation round j	$ST_{N_{succ}^{GRC_i}}$	Sum of time that successful task(s) of GRC_i used to reach a consensus
$TCap_{GRO_i}$	$\sum_{j=0}^{TS_{GRO_i}} Cap_j^{GRO_i}$	$ST_{N_{succ}^{GRO_i}}$	Sum of time that successful machine(s) of GRO_i used to reach a consensus

Observation 1: *Ev_MBDNAs achieved higher expected utility than EMBDNAs when both types of agents are subjected to different deadlines and market types.*

Figs. 5 (a-c) show the performance of Ev_MBDNAs against EMBDNAs with different values for negotiation deadline and for all types of e_markets (i.e., *GRC-favorable*, *Balanced* and *GRO_favorable*). From Figs. 5 (a-c), it can be observed that when both types of agents (i.e., Ev_MBDNAs and EMBDNAs) 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). Additionally, it can also be observed from Figs.5

(a-c) that, as Ev_MBDNAs evolve and adapt their relaxed-criteria fuzzy rules by using BBO-based solution, generally they are more likely to achieve higher expected utility than EMBDNAs (that equipped with a fix set of relaxed-criteria fuzzy rules).

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

Figs.5 (d-f) show the performance of Ev_MBDNAs against EMBDNAs in different *Grid_loads* and for all types of e_markets (i.e., *GRC-favorable*, *Balanced* and *GRO_favorable*). From Fig.5(d) (respectively Fig.5(e) and Fig.5(f)) it can be observed that when both types of agents are subjected to higher *Grid_load* (e.g., when more than 62% of the grid resources are occupied), they have weaker bargaining positions (it became difficult for both types of agents to successfully negotiate for grid resources due to there were fewer available resources in the grid,) and they both likely to concede more to avoid the risk of losing remain resources. Also it can be observed that in *GRO_favorable* e_markets (in comparison to *Balanced* and *GRO_favorable* e_markets) the bargaining positions of both Ev_MBDNAs and EMBDNAs 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, one can understand that, as Ev_MBDNAs evolve and adapt their relaxed-criteria fuzzy rules by using BBO-based solution, generally they are more likely to achieve higher expected utility than EMBDNAs (that equipped with a fix set of relaxed-criteria fuzzy rules). The results are good evidences to show the effect of the proposed BBO-based solution to adopt and evolve the fixed-criteria fuzzy set of EMBDNAs.

Observation 3: Ev_MBDNAs achieved higher success rate than EMBDNAs when both types of agents are subjected to different deadlines and market types

Figs.6 (a-c) show the success rate of Ev_MBDNAs against EMBDNAs with different values for negotiation deadline and for all types of e_markets (i.e., *GRC-favorable*, *Balanced* and *GRO_favorable*). From Figs.6 (a-c), it can be observed that when both 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). Additionally, as Ev_MBDNAs evolve and adapt their relaxed-criteria fuzzy rules by using BBO-based solution, generally they are more likely to achieve higher success rate than EMBDNAs (that equipped with a fix set of relaxed-criteria fuzzy rules).

Observation 4: Ev_MBDNAs achieved higher success rate than EMBDNAs when both types of agents are subjected to different grid loads and market types.

Figs.6 (d-f) show the success rate of Ev_MBDNAs against EMBDNAs in different *Grid_loads* and for both types of e_markets (i.e., *GRC-favorable*, *Balanced* and *GRO_favorable*). From Figs.6 (d-f) it can be observed that when both types of agents are subjected to higher *Grid_load* (e.g., when more than 62% 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. Additionally, as Ev_MBDNAs evolve and adapt their relaxed-criteria fuzzy rules by using BBO-based solution, generally they are more likely to achieve higher success rate than EMBDNAs (that equipped with a fix set of relaxed-criteria fuzzy rules).

Observation 5: Ev_MBDNAs take fewer negotiation rounds than EMBDNAs when both types of agents are subjected to different deadlines and market types

Figs.7 (a-c) show the average negotiation time of Ev_MBDNAs against EMBDNAs with different values for negotiation deadline and for all types of e_markets (i.e., *GRC-favorable*, *Balanced* and *GRO_favorable*). It can be observed that Ev_MBDNAs generally achieved lower average negotiation time than EMBDNAs. It can be observed that, for very *Short* deadlines, the average negotiation time of EMBDNAs is not significantly lower than the average negotiation time of EMBDNAs. With very *Short* deadlines, both Ev_MBDNAs and EMBDNAs have very little time for trading and Ev_MBDNAs did not outperform EMBDNAs in terms of average negotiation time for both types of e_markets. With longer deadlines, Ev_MBDNAs clearly outperformed EMBDNAs in terms of average negotiation time for all types of e_markets.

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

Figs.7 (d-f) show the average negotiation time of Ev_MBDNAs against EMBDNAs in different *Grid_loads* and for all types of e_markets (i.e., *GRC-favorable*, *Balanced* and *GRO_favorable*). It can be observed that when both types of agents are subjected to higher *Grid_load*, 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 both types of agents to have lower negotiation rounds in successful negotiation process. However, by evolving relaxed-criteria fuzzy rules relaxing, Ev_MBDNAs clearly outperformed EMBDNAs in terms of average negotiation time for all types of e_markets and different *Grid_loads*.

5. Related works

Following we focus on the state-of-the-art flexible negotiation agents that using fuzzy approaches to relax their bargaining terms for improving their negotiation outcomes.

A fuzzy logic-based approach to deal with multiple-issue and two-party negotiations is proposed by Wasfy and Hosni [33]. In the negotiation process, a negotiator defines its concession tactics based on four fuzzy sets. Also, to indicate which concession tactic 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. In the next step, the tactic with the largest common area with the calculated concession force is chosen. The negotiator's concession amount at given time step can be determined by a translation of the fuzzy set of the chosen tactic. Whereas [33] modeled negotiation power and (un) willingness to concede using fuzzy concepts, the proposed negotiation agents (i.e., Ev_MBDNAs) not only use three sets of fuzzy rules to relax their bargaining terms but also evolve their fuzzy rule sets to enhance their performance and achieve better outcomes in different e_markets..

In the multi-issue negotiation model of Matos et al. [34], offers and counter offers are generated by case-based and fuzzy logic based strategies. Matos et al. [34]'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. While our work defines GMP as an independent variable that captures the acceptability of the current grid resource allocation market condition by using fuzzy decision controller and uses an evolutionary procedure to evolve the negotiators' fuzzy rule sets , [34] did not address the users' requirements on the desired outcome of negotiation.

Jennings et al. [35] and Faratin et al. [36] 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. Although strategies in [35] and [36] 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.

In Fuzzy e-negotiation agent (*FeNA*) of [37, 38-39], the preferences, constraints and each party's objectives are expressed as fuzzy constraints over these issues. *FeNAs* negotiate by exchanging offers and a consensus is reached when their private preferences, constraints, and objectives are satisfied. Using this method, a solution is the one that maximizes the satisfaction of all fuzzy constraints of the parties. However, although *FeNAs* are designed with the flexibility to relax trading conditions, they were not programmed to react to changing market dynamics. Also, while [37, 38-39] deal with bilateral negotiations, our work deals with multilateral negotiations. In addition, unlike [37, 38-39], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Luo et al. [40] developed a fuzzy constraint based framework for bilateral multi-issue negotiations in semi-competitive trading environments. Two knowledge models of [40] are: 1) GRC agent's domain knowledge which consists of the GRC's requirement/preference model (a prioritized fuzzy constraint problem) and GRC's profile model (fuzzy truth propositions) and 2) GRO agent's domain knowledge which consists of its multi-dimensional representation of the products or services it offers. 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 general difference between [40] and our work is that while [40] deals with bilateral negotiations, our work deals with multilateral negotiations. In addition, unlike [40], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Meng and Fu [41] 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 negotiators for the offer was measured by fuzzy members in [41]. The general difference between [41] and our work is that whereas [41] 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 addition, unlike [41], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

In [42] 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's desires involving imprecision and human conceptualization. The [42] 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. Whereas [42] 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. In addition, unlike [42], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Wang et al. [43] 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. In this model, fuzzy inference rules are used for determining the acceptance of an opponent's offer. Whereas [43] 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. In addition, unlike [43], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Wu et al. [44] proposed a fuzzy based approach to deal with bilateral multiple-issue negotiations. As negotiations' preferences (weights) are uncertain and dynamic, the acceptability for each issue was measured by fuzzy members. While the proposed Ev_MBDNA negotiation agents of this paper adopt *Enhanced Rubinstein's sequential alternating offer protocol* [14], deal with multilateral negotiations and use fuzzy concepts to determine GMP in different grid market conditions, the negotiation agents of [44] adopt monotonic concession protocols [45], deal with bilateral negotiations and represent the acceptability for each issue by a fuzzy value. In addition, unlike [44], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Sim and Wang [23] 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* and (b) *eagerness* 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). As EMDAs are not designed to raise their expectations in extremely favorable market conditions, [46] complemented [23] by augmenting the designs of EMDAs with two additional fuzzy decision controllers. While the fuzzy decision controller in [23] guides an EMDA in relaxing trade aspirations, the two fuzzy decision controllers of an EMDA in [46] are used to guide a negotiator agent in determining whether to slightly raise its expectation. The distinguishing features of our work in comparison to [23] are: 1) while [23] considers just two relaxation criteria in names degree of competition and eagerness, our work consider more effective relaxation criteria in determining the amount of GMP and 2) unlike [23], our work considers evolutionary procedure to enhance the outcomes of the negotiation process. Also, The distinguishing features of our work in comparison to [46] are: 1) while the fuzzy decision controller in our work guides negotiator agent in relaxing trade aspirations, the two fuzzy decision controllers in [46] are used to guide a negotiator agent in determining whether to slightly raise its expectation and 2) unlike [46], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Sim and Ng [15] focuses on devising a relaxed-criteria bargaining protocol by augmenting the alternating offers protocol with the set of fuzzy rules. To this, each GRC and GRO agent is programmed with a fuzzy controller for determining the amount of relaxation in a negotiation situation. Unlike the relaxing criteria which are used in [23], [15] used (a)*recent statistics in failing/succeeding in acquiring resources* and (b) *demand for computing resources* as criteria for determining the amount of concession of GRC agents, also (a) *utilization level* and (b) *request factor* are used as criteria for determining the amount of concession of GRO agents. These criteria are inputs to the fuzzy decision controller and the amount of concession is the output of it. While not only 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 [15]'s negotiation agents is enhanced to overcome the limitations and provide more flexible and rational protocol. Also, unlike [15], our work considers evolutionary procedure to enhance the outcomes of the negotiation process.

Furthermore, Sim [24] 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 [23, 15], the negotiator agents of [24] used (a) *degree of competition* (υ), (b) *time pressure* and (c) *the relative distance from trading parties' proposals* 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). In addition, in [24] an evolutionary algorithm (that invokes a genetic algorithm (GA)) for adapting and evolving relaxed-criteria fuzzy rules is developed to construct adaptive and self improving negotiation agents in a series of e_markets. In comparison to [24], our work not only considers a negotiation model that uses enhanced *Rubinstein's sequential alternating offer* protocol [14] and two fuzzy decision controllers (one for GRCs and the other for GROs) to determine relaxation degree in the face of GMP by modeling more new relaxation criteria from new perspective, but also uses a new evolutionary procedure that invokes a BBO algorithm to evolve and adapt the relaxed-criteria fuzzy rule sets for improving the chance of successfully acquiring/leasing out resources. Although BBO is applicable to many of the same types of problems that other evolutionary algorithms (like GA, PSO,…) are used for, according to some distinguishing features of BBO that are unique among biology-based optimization methods generally BBO outperforms GA [26-27]. This motivates the authors to consider the BBO as evolutionary algorithm to evolve the system structures of the negotiation agents.

Adabi *et.al* [14] proposed a negotiation model which has the following distinguishing features: **a)** enhancing *Rubinstein's sequential alternating offer protocol* that is used in [15] 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 and **b)** devising two *Fuzzy Grid Market Pressure determination Systems* (one for GRCs and the other for GROs) to determine the value of GMP. In comparison to [14] our work proposes *new* negotiation agents in name Ev_MBDNAs that not only relax their bargaining term in the face of GMP but also evolve and adapt their relaxed-criteria fuzzy rule sets by participating and negotiating in different e_markets using a *new* evolutionary procedure that invokes a BBO algorithm.

6. Conclusion and future works

Although there are many negotiation agents that are designed with the flexibility to relax their trading conditions using fuzzy approaches (specially in the face of intense grid market pressure) in the hope of enhancing the chances of successfully reaching agreements and perhaps reaching agreements more rapidly, the system structures of most of these negotiation agents are remained fixed. It can be understand that as these fixed structure negotiation agents do not have the ability to evolve their structure they cannot improve their outcomes in different e_markets with many varying parameters. Considering the mentioned concept, *new* negotiation agents in name Ev_MBDNAs that not only relax their bargaining term in the face of intense grid market pressure but also evolve and adapt their relaxed-criteria fuzzy rule sets by participating and negotiating in different e_markets using the proposed BBO (Biogeography-based optimization)-based solution are designed. According to the BBO characteristics that generally result in better optimization in comparison to other optimization algorithms (like GA, PSO,…) [26-27], it is the perfect choice for adapting and evolving relaxed-criteria fuzzy rules of negotiation agents. Also to the best of authors' knowledge, this work is one of the earliest works that developed a BBO-based solution to construct adaptive and self improving negotiation agents. To evaluate the effectiveness of the proposed BBO-based solution for adapting and evolving relaxed-criteria rules, a test bed to simulate the negotiation activities of both Ev_MBDNAs (EMBDNAs with relaxed-criteria rules that are evolved using the BBO-based solution) and EMBDNAs (that use fixed relaxed-criteria fuzzy rule set)[14] is developed. Empirical results obtained from the simulations show that Ev_MBDNAs generally take shorter average negotiation time, have higher success rate and achieve higher expected utility than EMBDNAs. In future work using the BBO-based approaches to tune other parts of *FGMPDS* (like modifying membership functions and term sets) should be investigated.

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