A SIMPLE SEMI-DYNAMIC COOPERATIVE BARGAINING APPROACH

F. NASSIRI-MOFAKHAM, Ph.D. Student
Computer Engineering Department
University of Isfahan, Isfahan, I. R. of Iran
email: fnasiri@eng.ui.ac.ir

M.A. NEMATBAKHSH, Ph.D.
Computer Engineering Department
University of Isfahan, Isfahan, I. R. of Iran
Corresponding Author:
email: nematbakhsh@eng.ui.ac.ir

N. GHASSEM-AGHAEE, Ph.D.
Computer Engineering Department
University of Isfahan, Isfahan, I. R. of Iran
email: aghaee@eng.ui.ac.ir

A. BARAANI-DASTJERDI, Ph.D.
Computer Engineering Department
University of Isfahan, Isfahan, I. R. of Iran
email: ahmadb@eng.ui.ac.ir

Abstract - The area of bargaining mechanisms has been well explored in both multi-agent systems and economics. In bargaining, participants raise/reduce their offers until an agreement is hopefully reached. In this dynamic environment, finding superior agreements without having the knowledge about the strategic private information of the counterpart is considerable. In this paper, we present a simple semi-dynamic cooperative bargaining, which deals with bargaining of single-buyer and single-seller in a multi-criteria single-good e-Marketplace. Both buyer and seller are equipped with medial agents that cooperatively want to win bargaining via a slight maneuver, over their own preferences that are unknown to each other. We show the results obtained using the simulation. This approach shows that the lack of intersection between threshold utility intervals of both parties does not necessarily yield a disagreement. On the other hand, if the party whose utility threshold is lower than the utility threshold of the other party makes the initial offer, the two parties will certainly have an agreement in a single round.

Keywords - Ecommerce, Bilateral Negotiation, Multi-Criteria Bargaining, Cooperation, Intelligent Agents.

INTRODUCTION

The area of bargaining [11] and negotiation mechanisms has been well explored in both multi-agent systems and economics. By using of autonomous agents which negotiate on behalf of their owners, a participant can obtain flexibility in prices and goods to distinguish between groups of buyers based on their preferences. Negotiation can be viewed as a distributed search through a space of potential agreements [8].

Recently, many researchers have been investigating on several bilateral and multilateral multi-criteria negotiations and some coalition extensions [1,4-6,10,14], and negotiation support system [2].

Negotiation and cooperation in multi-agent environments [9,16-18] and also machine learning approaches have entered the automated negotiation in electronic commerce [13]. Therefore, modeling the opponent [10] and learning his preference to make trade-offs are extremely challenging [3]. Finding superior agreements in this dynamic environment without having the knowledge and strategic private information of the counterpart is considerable.

According to Nash axioms, cooperative bargaining can take place in complete information games. However, in this paper, a simple semi-dynamic cooperative bargaining approach is introduced, where both buyer and seller agents are medial agents that cooperatively want to win bargaining via a slight maneuver, over their own preferences, that is unknown to the other party. This simple case deals with bargaining of single-buyer and single-seller in a multi-criteria single-good e-Marketplace. The paper consists of five sections. After this brief introduction, we then present the simple semi-dynamic mechanism which is followed by a discussion of a cooperative approach. Then the simulated results are given. Finally, the last part presents some concluding remarks and identifies the future directions of the research.

SIMPLE SEMI-DYNAMIC BARGAINING

Simple Semi-Dynamic Bargaining deals with bargaining of single-buyer and single-seller in a multi-criteria single-good e-Marketplace. Therefore, we dealt with a bilateral multi-criteria bargaining.

We assume that both buyer and seller agents are only seeking for preferable deals. Therefore, all agents behave medial so that they cooperatively want to win bargaining via a slight maneuver, over their own preferences, that is unknown to the other party. Nevertheless, a rational buyer is seeking contracts that conclude the best utility in their behavioral region. Hence, she prefers to drive first bargaining phases to an agreement concluding the best utility. However, if no agreement can be attained at this point, then she will continue bargaining in next levels of satisfaction. If the buyer cannot make an agreement in any alternatives, she will lose the chance of purchasing the good. The seller agent is also supposed the same but with its own preferences that may be in contrast to buyer's preferences. In the similar way, seller wants to sell his good based on his best utility during the first bargaining phases. However, if no agreement can be attained at this point, he will continue bargaining. Otherwise, he will lose the chance of selling the good to the buyer.

-HYPOTHESES IN FORMAL TERMS

In this part, we describe the problem in mathematical representations. To figure out the problem, we assume that this e-marketplace is lawful so that both buyer and seller know the legal interval of each good criterion value announced from a legal party. Since the e-marketplace is law-abiding, neither good's criteria have indefinite upper or lower boundary values to obtain greater profits for one party. Therefore, based on the e-marketplace legal authority, the good's criteria have *min_valid* and *max_valid* values. However, they can bargain with each other to buy/sell good based on the agreed point within the valid value intervals. Hence, both buyer and seller agents are created with this base knowledge on behalf of their owners.

Let the good in the e-marketplace have n_C criteria each with n_V different values, where the set of these criteria is constant during the bargaining. Therefore, the value intervals [min_valid_1, max_valid_1], [min_valid_2, max_valid_2], ..., [min_valid_{nC}, max_valid_{nC}] have been defined for criteria 1 through n_C.

Both buyer and seller agents have private utility functions based on different weightings on each criterion. During bargaining phases, both buyer and seller agents make offer and counter-offers based on their preferred utilities with the hope to reach a profitable agreement. However, the presence of the medial behavioral region increments the successful positions for both parties. Also, both buyer and seller agents are created with different ambition ratios to deal with this situation according to their own value interval.

When buyer and seller agents are created, they are assigned with his or her own arbitrary value intervals and the importance (i.e., weight) values related to each criterion. These value intervals are randomly generated within the related criterion valid value interval and are different between seller and buyer1.

Therefore, seller agent S has two sets containing nC criteria value intervals and their respective random W_C^S weights, i.e. $\{[\min_1^S, \max_1^S], ..., [\min_{n_C}^S, \max_{n_C}^S]\}$ and $\{W_1^S, ..., W_{n_C}^S\}$, respectively. That is, seller S evaluates the Cth criterion of good G based on the value within the interval using the weight W_C^S. Weights satisfy $\sum_{c=1}^{nc} W_C^S = 1$.

Similarly, each buyer B has two sets containing nc criteria value intervals[2] and their respective random weights, $\{[\min_1^B, \max_1^B], ..., [\min_{nc}^B, \max_{nc}^B]\}$ and $\{W_1^B, ..., W_{nc}^B\}$, where $\sum_{c=1}^{nc} W_C^B = 1$.

-THE OBJECTIVE FUNCTIONS

The buyer's and seller's aspiration (or reservation) values with respect to a particular criterion of a good are in opposite sides. In addition, for a typical agent A (A=B, S) $\max_C^A$ (or $\min_C^A$) is not necessarily his/her aspiration (or reservation) value of the good with respect to the criterion C. For example, according to the *price* and *quality* criteria, namely p and q, the buyer B desires to purchase a good with her $\min_p^B$ and $\max_q^B$ values, while the seller S is willing to sell the good with his $\max_p^S$ and $\min_q^S$ values. That is, if the buyer arranges the criterion p's values of good, she gives the highest score nv_p to $\min_p^B$

and the lowest score 1 to $\max_p^B$, where nvp is the number of values of the price criterion of the good.

Therefore, the aspiration values (not necessarily *max* values) related to all criteria, maximize the total utility, while the reservation values (not necessarily *min* values) make the total utility in minimum.

We denote each alternative offer from seller S to buyer B as O_B^S. Let us call the agent A's aspiration and reservation values for any criterion C of the good, AV_C^A and RV_C^A respectively. In addition, we define e_C^A *(alternative)*, which returns A's evaluated score of the value related to criterion C (Cth element) in the n_C-ary alternative. For example, e_C^B (O_B^S) is the score of the value related to criterion C of the good offered from seller S to buyer B, ranged between 1 through nv_C, in which C=1,...,n_C, and nvC is the number of values of criterion C.

Therefore, according to the MAUT (Multi Attribute Utility Theory) we can define the utility of a contract for a buyer B concerning offer O_B^S by

$$u^B(O_B^S) = f^B\left(f_1^B(e_1^B(O_B^S)),\cdots,f_{n_C}^B(e_{n_C}^B(O_B^S))\right) \qquad \text{(eq.1)}$$

where, for simplicity we assume linear functions

$$f^B\left(f_1^B(e_1^B(O_B^S)),\cdots,f_{n_C}^B(e_{n_C}^B(O_B^S))\right)=\sum_{C=1}^{n_C} W_C^B \cdot f_C^B(e_C^B(O_B^S)) \qquad \text{(eq.2)}$$

and

$$f_C^B(e_C^B(O_B^S)) = \frac{e_C^B(O_B^S) - RV_C^B}{AV_C^B - RV_C^B}. \qquad \text{(eq.3)}$$

Similarly, we define the utility of a contract for a seller S concerning the offer O_S^B from buyer B the same as the above formulas, by replacing S with B and vice versa.

-THE OBJECTIVE FUNCTION CONSTRAINTS

For a given agent A willing to deal a good, $M^A = f^A(f_1^A(AV_1^A),\ldots,f_{nc}^A(AV_{nc}^A))$ and $m^A = f^A(f_1^A(RV_1^A),\ldots,f_{nc}^A(RV_{nc}^A))$ are respectively the maximum and the minimum meaningful utility values. Figure 1 shows the sample Gold, White and Gray utility regions for typical two-criteria (i.e. horizontal and vertical axes) alternatives. Each buyer and seller agent can have five different ethics related to the interior or boundary of these three behavioral regions namely, greedy, semi-greedy, medial, semi-conservative, and full-conservative. The presence of the medial behavioral region increments the successful positions for both parties through cooperative bargaining. Then, we suppose two arbitrary threshold numbers Θ^A and θ^A within the interval $[m^A, M^A]$ representing the lower utility value bound related to medial behavioral region (i.e. white region) of agent A, so that $\theta^A \leq \Theta^A$. An offer O_B^S on good G from seller S to buyer B falls into the white utility region, if $\theta^A \leq u^B$ $(O_B^S) \leq \Theta^B$ where θ^B and Θ^B are the lower utility value threshod of the buyer B's gold and white region respectively.

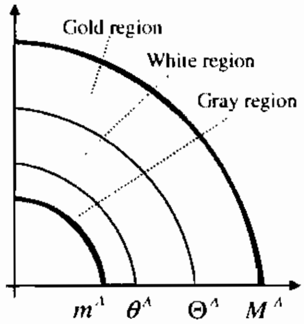

Figure 1: The sample gold, white and gray utility regions for typical two-criteria alternatives.

- CONSTRAINTS ON GENERATING AN OFFER AND COUNTER-OFFER

After a seller announces that he has a good, the buyer will be triggered and they will start bargaining by sending offers. On the other hand, a buyer can announce a good that she wants to purchase. Then, seller that sells the good will be triggered and they will begin bargaining by sending offers. Therefore, either party can make an initial offer to buy or sell the good.

Similar to evaluating the utility of arriving offers (see **The Objective Function Coustraints** above), a buyer B evaluates the utility of her own alternatives to submit the best alternative offer by calculating $u^B(O_S^B)$, where O_S^B is an alternative offer prepared from B to seller S. A medial buyer makes an offer yielding the utility $\theta^B < u^B(O_S^B) < \Theta^B$. In the same way, a medial seller makes an offer yielding the utility $\theta^S < u^S(O_B^S) < \Theta^S$. We also assign an agent A a risk factor $0.3 < R^A < 0.8$ that means a medial agent3.

SIMPLE SEMI-DYNAMIC COOPERATIVE BARGAINING

As we described in the previous sections, all agents in the e-marketplace has the base knowledge of their own behaviors and utility functions according to the e-marketplaces rules (legal valid values). In order to act cooperatively, we arm each agent with initial knowledge base containing alternative offers yield to one of *white* utility region on behalf of their owners (see **Hypotheses in Formal Terms** above). Since both parties entering to the bargaining often want to reach a profitable agreement, during the bargaining phases each agent only maneuvers over his/her own pre-calculated knowledge[4] and tries to pull the counterpart desires nearer to his/her own desires.

-THE KNOWLEDGE BASE PRE-CALCULATION

For the good with n_C criteria, we suppose the following n_C-dimensional matrix $\overline{P^A}$ in the size of $nv_1 \times \ldots \times nv_{nC}$ for each agent A, which represents the utility values of all possible preferences of A, where nv_C is the number of values of the Cth criterion of good from the

A's point of view (see **Hypotheses in Formal Terms**). Since, in this simple approach we use the evaluated score values of good's criteria as the matrix indices, therefore, according to (eq.1) and information given in **The Objective Functions** and **Constraints on Generating an Offer and Counter-Offers** sections, we define

$$\overline{P^A}\,[i_1, i_2, \ldots, i_{nc}] = u^A\,(alternative)$$

where,

$$i_1 = e_1^A\,(alternative),\ i_2 = e_2^A\,(alternative),\ \ldots,\ \text{and}\ i_{nc} = e_{nc}^A\,(alternative),$$

so that,

$$i_1 = 1, \ldots, nv_1,\ i_2 = 1, \ldots, nv_2, \ldots, \text{and}\ i_{nc} = 1, \ldots, nv_{nc},$$

and

$$\begin{gathered}[e_1^A]^{-1}(1) = AV_1^A, \cdots, [e_1^A]^{-1}(i_1) = \upsilon, \cdots, [e_1^A]^{-1}(nv_1) = RV_1^A \\ \vdots \\ [e_{n_c}^A]^{-1}(1) = AV_{n_c}^A, \cdots, [e_{n_c}^A]^{-1}(i_{n_c}) = \omega, \cdots, [e_{n_c}^A]^{-1}(nv_{n_c}) = RV_{n_c}^A \end{gathered} \qquad \text{(eq.4)}$$

in which, υ and ω are the intermediary values of the 1^{st} and n_c^{th} criteria of alternative in the viewpoint of agent A respectively.

After calculating the thresholds Θ^A and θ^A using m^A and M^A (see **The Objective Function Constraints**), we sort all of these utility values and then choose those which are within the corresponding behavioral interval for related bargaining decisions. That is, we reduce the calculation to a $d \times (n_C + 1)$ 2-dimensional matrix $\overline{Q^A}$, each row of which contains an alternative's criteria values and its corresponding utility value, where $d = |\{u|\theta^A \mid \theta^A < u^A < \Theta^A\}|$ (i.e., the number of alternative offers the utility values of which belong to the white region). That is,

$$\overline{\overline{Q^A}} = \begin{bmatrix} \alpha_1 & \cdots & \alpha_{n_c} & u^A(\alpha_1, \cdots, \alpha_{n_c}) \\ \vdots & \vdots & \vdots & \vdots \\ \gamma_1 & \cdots & \gamma_{n_c} & u^A(\gamma_1, \cdots, \gamma_{n_c}) \end{bmatrix}_{d \times (n_c + 1)} \qquad \text{(eq.5)}$$

where $\alpha_1, \ldots, \alpha_{n_c}$ are the criteria values of an offer which have led to the maximum utility $u^A\,(\alpha_1, \ldots, \alpha_{n_c})$ in the white region (the next value less than Θ^A), so that $\alpha_1 = C_1^A(alternative)$, $\ldots$, $\alpha_1 = C_{nc}^A(alternative)$ are the values of 1^{st} and n_c^{th} elements of the n_C-ary alternative $(\alpha_1, \ldots, \alpha_{n_c})$. Also, $\gamma_1, \ldots, \gamma_{nc}$ are the criteria values of the offer yielding to the minimum utility related to the white region (the next value more than θ^A).

On the other hand, u^A (*alternative*) values in the $\overline{Q^A}$ matrix are not unique and there may exist several alternative offers with the same utility value. Therefore, we do nested sorts for such situations according to the order of the critera weights. That is, if for example, the quality (C_2) is more important than delivery (C_3) and the latter is more important than price (C_1), then we first sort them based on C_2 values, next on C_3 values, and finally based on C_1 values. Then, we apply another internal sort on equal weight criteria according to their evaluated scores. So, all $\overline{Q^A}$ entries in the column $n_C + 1$ are just in the descending preference order.

-DISPATCHING KNOWLEDGEABLE BUYER AND SELLER AGENTS

According to discussions presented in previous sections, a buyer that wants to buy a good, generates an agent in a medial behavior. That is, she equips it with pre-calculated preference matrix $\overline{Q^B}$ along with the risk factor R^B describing her ambition ratio to bargain for grasping the good. In the same way, a seller will dispatch his agent with medial behavior equipped with a preference matrix and corresponding risk factor to bargain in order to sell good according to his own utility constraints. That is, we have the above mentioned discussion for seller agent by replacing B with S.

Since both parties maneuver over his/her own knowledge in order to pull the counterpart's desires near to his/her own desires we call this approach *semi-dynamic* because of the static pre-calculated knowledge matrices.

-GENERATING PRE-CONTRACT OFFER AND COUNTER-OFFERS

Buyer B and seller S have at most $nv_1 \times \ldots \times nv_{n_C}$ options to reach a mutual agreement. In the following, we describe special decisions each agent pursues according to its behavior. Agent A with the risk factor $0.3 < R^A < 0.8$ makes decisions according to the following algorithm.

- MEDIAL BARGAINING ALGORITHM

Offers:

- Each agent A initially offers an alternative offer at row q so that $\overline{Q^A}$ $[q, n_C + 1]$ has the first utility value equal to or larger than $u = \frac{R^A - 0.3)\,\Theta^A + (0.8 - R^A)\,\theta^A}{0.8 - 0.3}$.

Counter-Offers:

- For each O_B^S to buyer agent B,

* If $u^B\,(O_B^S) < \theta^B$ then B withdraws O_B^S.

* If $u^B\,(O_B^S) \geq \Theta^B$ then B accepts.

* If $u \leq u^B\,(O_B^S) <$ then

- If $R^B > 0.5$ then

\+ If $O_B^S <$ pre O_B^S then B accepts O_B^S,

\+ Else, B does nothing.

- Else, B accepts O_B^S.

* If $\theta^B \leq u^B\,(O_B^S) < u$, then B begins bargaining with S by generating counter-offer:

- She picks $\overline{Q^B}$ $[q, n_C + 1]$ where, the alternative offer at row q has the same utility as her previous offer O_S^B but the less distance with the last O_B^S, and offers this alternative (e.g.,

$$dist\ (n\text{ - }ary\ alternative\ a,\ n\text{ - }ary\ offer\ o) = \sqrt{\sum_{i=1}^{n} (a_i - o_i)^2}).$$

- If there is not any row with the utility equal to her previous offer O_S^B, then she picks $\overline{Q^B}$ $[r, n_C + 1]$where, the alternative offer at row r has the next utility value and offers this alternative.

- For buyer agent *B*, after at most *2d* levels, the above scenario results in a conclusion.
- For seller agent *S*, the above scenarios are pursued by replacing *S* with *B* and vice versa.

The trade-offs to offer alternatives near to opponent objectives are shown in Figure 2(a) for a typical 2-criteria bilateral bargaining. Agent *a* tries to find contract with the same utility for itself, but higher utility for opponent *b*, to increase probability of acceptance. Agent a proposes *P*, Agent b counteroffers *Q*, Concede on issue 2, demand on 1, leading to R, or vice versa for S. That is, the same utility for *a* and a higher utility for *b* [3].

Figure 2(b) shows the above mentioned scenario in three steps. After offering *x* from agent *a* in the counter of *y*, agent *b* calculates new contracts *S* with utility for agent *a*, which is slightly closer to *a's* target utility. Choose the one most similar to the last offer of the opponent and repeat from this new chosen contract until own iso-curve is reached [3].

SIMPLE SEMI-DYNAMIC COOPERATIVE BARGAINING SIMULATION

In this section, we investigate the results obtained via a multi-agent simulation system developed by Aglets [7] using the Medial Bargaining Mechanism. Aglets are Java-based autonomous agents that provide mobility capability to travel across a network and synchronous and asynchronous message passing to communicate with each other.

Simulations were run with a buyer and a seller agent in a single-good e-marketplace, where we assumed each good with three ShippingMethod, PaymentMethod, and Package Style criteria. The first criterion includes six methods coded from 1 through 6, namely: Normal, Registered, Certified, Express, DHL and Air express. The second criterion, denotes the three Cash, Credit and Check payment methods coded from 1 through 3. Finally, the third criterion is related to the packaging method in one of Nylon, Pocket, Carton and Box styles that are coded from 1-4.

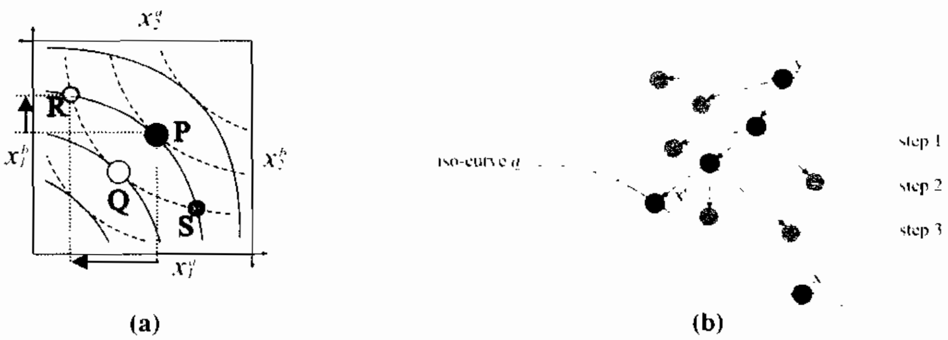

Figure 2: Trade-offs key feature of bargaining behavior [3].

Since buyer and seller aspiration and reservation values with respect to a particular criterion are in opposite sides, they individually score the criteria values. They act through their fix scoring methods. We suppose that all criteria are being scored within 0 to 100. Some criteria may fall out of their scoring range. In this case, buyer or seller scores the criterion with a zero value.

Buyer scores Shipping as 0, 90, 90, 100, 60 and 70 for Normal, Registered, Certified, Express, DHL, and Air Express methods, respectively. She similarly assigns the values of 60, 100 and 80 to Cash, Credit and Check Payment methods, as well as 0, 70, 100 and 80 to Nylon, Pocket, Carton and Box Packaging styles, respectively.

On the other hand, seller scores Shipping as 100, 90, 80, 70, 70 and 60 for Normal, Registered, Certified, Express, DHL, and Air Express methods, respectively. He similarly assigns the values of 100, 80 and 50 to Cash, Credit and Check Payment methods, as well as 90, 100, 80 and 80 to Nylon, Pocket, Carton and Box Packaging styles, respectively.

Moreover, the importance of the ShippingMethod, PaymentMethod and PackagingStyle for buyer and seller are 0.3, 0.2, 0.5, and 0.2, 0.5 and 0.3 respectively. Therefore, according to the scoring values mentioned above, we have:

$$
\begin{array}{ll}
AV^{B}_{Shipping}=100,\quad RV^{B}_{Shipping}=0, & AV^{S}_{Shipping}=100,\quad RV^{S}_{Shipping}=60,\\
AV^{B}_{Payment}=100,\quad RV^{B}_{Payment}=60, & AV^{S}_{Payment}=100,\quad RV^{S}_{Payment}=50,\\
AV^{B}_{Packaging}=100,\ RV^{B}_{Packaging}=0, & AV^{S}_{Packaging}=100,\ RV^{S}_{Packaging}=80,
\end{array}
$$

and

$$W^{B}_{Shipping}=0.3,\quad W^{B}_{Payment}=0.2,\quad W^{B}_{Packaging}=0.5$$

as well as

$$W^{S}_{Shipping}=0.2,\quad W^{S}_{Payment}=0.5,\quad W^{S}_{Packaging}=0.3.$$

According to the formulae 1, 2 and 3, each agent A ($A=B, S$) computes the utility of all 72 (= 6×3×4) possible alternatives related to all permutations of six Shipping methods, three Payment methods and four Packaging styles through preferences utility matrix $\overline{\overline{P^A}}$:

$$
\begin{aligned}
\overline{\overline{P^{A}}}[i,j,k] = {} & W^{A}_{Shipping}\cdot\frac{value^{A}(Shipping_{i})-RV^{A}_{Shipping}}{AV^{A}_{Shipping}-RV^{A}_{Shipping}}\\
& +W^{A}_{Payment}\cdot\frac{value^{A}(Payment_{j})-RV^{A}_{Payment}}{AV^{A}_{Payment}-RV^{A}_{Payment}}\\
& +W^{A}_{Packaging}\cdot\frac{value^{A}(Packaging_{k})-RV^{A}_{Packaging}}{AV^{A}_{Packaging}-RV^{A}_{Packaging}}\\
& i=0,\cdots,5 \qquad j=0,\cdots,2 \qquad k=0,\cdots,3
\end{aligned}
\qquad \text{(eq.6)}
$$

Then through formula 5, they sort all of their preferences' utilities into $\overline{\overline{Q^A}}$ $[r,3]$ $r=0,\ldots,71$, so that they arrange them based on the utility values and then on equal case, based on the individual criteria values according to the order of the critera weights. Therefore, *max* and *min* preferences' utility values (i.e., $\overline{\overline{Q^A}}$ [71,3] and $\overline{\overline{Q^A}}$ [0,3]) indicate

M^A and m^A for each agent A, respectively. Then, in order to resemble two different medial persons as buyer and seller agents, we assign θ^A and Θ^A random values in $[m^A, M^A]$ and $[\theta^A, M^A]$ respectively. In addition, a medial random risk factor R between 0.3 and 0.8 is assigned to agent A. Therefore, the agent can compute his best utility alternative according to the offer formula of medial bargaining algorithm in previous section **Generating Pre-Contract Offer and Counter-Offers.**

After initializing, without missing the generality, rational buyer agent makes an initial offer using search in the alternative criteria values the utility of which equals to her best utility value. Then, she moves toward seller agent to submit the offer. Then, seller analyzes the received offer using medial bargaining algorithm and after that they follow suitable action using interchanging offers and counter-offers.

-SIMULATED RESULTS

We investigate the results obtained via simulations run with a buyer and a seller agent in a single-good e-marketplace, where we assumed the good with three ShippingMethod, PaymentMethod, and PackageStyle criteria. Let us rewrite the value sets described at the beginning of this section as Tables 1-3. Therefore, according to (eq.6), Tables 4 and 5 show the planar form of three dimensional matrices $\overline{P^B}$ and $\overline{P^S}$ related to all alternatives for buyer and seller, respectively. Indices i, j and k are corresponding to Shipping, Payment and Packaging criteria.

Table 6 shows preferences values of buyer and seller in descending order. The sorting routine is a nested sort first based on the utility value and then (in equal cases) based on the values of each criteria in the descending order corresponding to their weights in Tables 1-3. Therefore, according to the first and last rows of Table 6, we have the meaningful utility value intervals for buyer and seller as $[m^B, M^B]$ = [0.00,0.80] and $[m^S, M^S]$ = [0.00,0.90], respectively.

Table 1: The shipping methods value scored by buyer and seller (i values).

Shipping Method	0=Normal	1=Registered	2=Certified	3=Express	4=DHL	5=Air Express	AV	RV	W
Buyer evaluation	0	90	90	100	60	70	100	0	0.3
Seller evaluation	100	90	80	70	70	60	100	60	0.2

Table 2: The payment methods value scored by buyer and seller (j values).

Payment Method	0=Cash	1=Credit	2=Check	AV	RV	W
Buyer evaluation	60	100	80	100	60	0.2
Seller evaluation	100	80	50	100	50	0.5

Table 3: The packaging styles value scored by buyer and seller (k values).

Packaging Style	0=Nylon	1=Pocket	2=Carton	3=Box	AV	RV	W
Buyer evaluation	0	70	100	80	100	0	0.5
Seller evaluation	90	100	80	80	100	80	0.3

Table 4: The buyer's alternatives utility values.

Utility	k = 0			k = 1			k = 2			k = 3		
i j	0	1	2	0	1	2	0	1	2	0	1	2
0	0	0.20	0.10	0.21	0.41	0.31	0.30	0.50	0.40	0.24	0.44	0.34
1	0.27	0.47	0.37	0.48	0.68	0.58	0.57	0.77	0.67	0.51	0.71	0.61
2	0.27	0.47	0.37	0.48	0.68	0.58	0.57	0.77	0.67	0.51	0.71	0.61
3	0.30	0.50	0.40	0.51	0.71	0.61	0.60	0.80	0.70	0.54	0.74	0.64
4	0.18	0.38	0.28	0.39	0.59	0.49	0.48	0.68	0.58	0.42	0.62	0.52
5	0.21	0.41	0.31	0.42	0.62	0.52	0.51	0.71	0.61	0.45	0.65	0.55

Table 5: The seller's alternatives utility values.

Utility	k = 0			k = 1			k = 2			k = 3		
i j	0	1	2	0	1	2	0	1	2	0	1	2
		0.80	0.60		0.90	0.70		0.70	0.50		0.70	0.50
			0.30			0.40			0.20			0.20
		0.75	0.55		0.85	0.65		0.65	0.45		0.65	0.45
			0.25			0.35			0.15			0.15
		0.70	0.50		0.80	0.60		0.60	0.40		0.60	0.40
			0.20			0.30			0.10			0.10
0		0.65	0.45		0.75	0.55		0.55	0.35		0.55	0.35
1			0.15			0.25			0.05			0.05
2		0.65	0.45		0.75	0.55		0.55	0.35		0.55	0.35
3			0.15			0.25			0.05			0.05
4		0.60	0.40		0.70	0.50		0.50	0.30		0.50	0.30
5			0.10			0.20			0			0

Table 6: The buyer's & seller's preferences values in descending order.

Priority	Utility_B	Shipping_B		Payment_B		Packaging_B		Utility_S	Shipping_S		Payment_S		Packaging_S	
		i	value	j	value	k	value		i	value	j	value	k	value
1	0.80	3	100	1	100	2	100	0.90	0	100	0	100	1	100
2	0.77	1	90	1	100	2	100	0.85	1	90	0	100	1	100
3	0.77	2	90	1	100	2	100	0.80	2	80	0	100	1	100
4	0.74	3	100	1	100	3	80	0.80	0	100	0	100	0	90
5	0.71	5	70	1	100	2	100	0.75	3	70	0	100	1	100
6	0.71	1	90	1	100	3	80	0.75	4	70	0	100	1	100

Priority	Utility_B	Shipping_B		Payment_B		Packaging_B		Utility_S	Shipping_S		Payment_S		Packaging_S	
		i	value	j	value	k	value		i	value	j	value	k	value
7	0.71	2	90	1	100	3	80	0.75	1	90	0	100	0	90
8	0.71	3	100	1	100	1	70	0.70	5	60	0	100	1	100
9	0.70	3	100	2	80	2	100	0.70	2	80	0	100	0	90
10	0.68	4	60	1	100	2	100	0.70	0	100	0	100	2	80
11	0.68	1	90	1	100	1	70	0.70	0	100	0	100	3	80
12	0.68	2	90	1	100	1	70	0.70	0	100	1	80	1	100
13	0.67	1	90	2	80	2	100	0.65	3	70	0	100	0	90
14	0.67	2	90	2	80	2	100	0.65	4	70	0	100	0	90
15	0.65	5	70	1	100	3	80	0.65	1	90	0	100	2	80
16	0.64	3	100	2	80	3	80	0.65	1	90	0	100	3	80
17	0.62	4	60	1	100	3	80	0.65	1	90	1	80	1	100
18	0.62	5	70	1	100	1	70	0.60	5	60	0	100	0	90
19	0.61	5	70	2	80	2	100	0.60	2	80	0	100	2	80
20	0.61	1	90	2	80	3	80	0.60	2	80	0	100	3	80
21	0.61	2	90	2	80	3	80	0.60	2	80	1	80	1	100
22	0.61	3	100	2	80	1	70	0.60	0	100	1	80	0	90
23	0.60	3	100	0	60	2	100	0.55	3	70	0	100	2	80
24	0.59	4	60	1	100	1	70	0.55	4	70	0	100	2	80
25	0.58	4	60	2	80	2	100	0.55	3	70	0	100	3	80
26	0.58	1	90	2	80	1	70	0.55	4	70	0	100	3	80
27	0.58	2	90	2	80	1	70	0.55	3	70	1	80	1	100
28	0.57	1	90	0	60	2	100	0.55	4	70	1	80	1	100
29	0.57	2	90	0	60	2	100	0.55	1	90	1	80	0	90
30	0.55	5	70	2	80	3	80	0.50	5	60	0	100	2	80
31	0.54	3	100	0	60	3	80	0.50	5	60	0	100	3	80
32	0.52	4	60	2	80	3	80	0.50	5	60	1	80	1	100
33	0.52	5	70	2	80	1	70	0.50	2	80	1	80	0	90
34	0.51	5	70	0	60	2	100	0.50	0	100	1	80	2	80
35	0.51	1	90	0	60	3	80	0.50	0	100	1	80	3	80
36	0.51	2	90	0	60	3	80	0.45	3	70	1	80	0	90
37	0.51	3	100	0	60	1	70	0.45	4	70	1	80	0	90
38	0.50	0	0	1	100	2	100	0.45	1	90	1	80	2	80
39	0.50	3	100	1	100	0	0	0.45	1	90	1	80	3	80
40	0.49	4	60	2	80	1	70	0.40	5	60	1	80	0	90
41	0.48	4	60	0	60	2	100	0.40	2	80	1	80	2	80
42	0.48	1	90	0	60	1	70	0.40	2	80	1	80	3	80
43	0.48	2	90	0	60	1	70	0.40	0	100	2	50	1	100
44	0.47	1	90	1	100	0	0	0.35	3	70	1	80	2	80
45	0.47	2	90	1	100	0	0	0.35	4	70	1	80	2	80
46	0.45	5	70	0	60	3	80	0.35	3	70	1	80	3	80
47	0.44	0	0	1	100	3	80	0.35	4	70	1	80	3	80
48	0.42	4	60	0	60	3	80	0.35	1	90	2	50	1	100

Priority	Utility_B	Shipping_B		Payment_B		Packaging_B		Utility_S	Shipping_S		Payment_S		Packaging_S	
		i	value	j	value	k	value		i	value	j	value	k	value
49	0.42	5	70	0	60	1	70	0.30	5	60	1	80	2	80
50	0.41	0	0	1	100	1	70	0.30	5	60	1	80	3	80
51	0.41	5	70	1	100	0	0	0.30	2	80	2	50	1	100
52	0.40	0	0	2	80	2	100	0.30	0	100	2	50	0	90
53	0.40	3	100	2	80	0	0	0.25	3	70	2	50	1	100
54	0.39	4	60	0	60	1	70	0.25	4	70	2	50	1	100
55	0.38	4	60	1	100	0	0	0.25	1	90	2	50	0	90
56	0.37	1	90	2	80	0	0	0.20	5	60	2	50	1	100
57	0.37	2	90	2	80	0	0	0.20	2	80	2	50	0	90
58	0.34	0	0	2	80	3	80	0.20	0	100	2	50	2	80
59	0.31	0	0	2	80	1	70	0.20	0	100	2	50	3	80
60	0.31	5	70	2	80	0	0	0.15	3	70	2	50	0	90
61	0.30	0	0	0	60	2	100	0.15	4	70	2	50	0	90
62	0.30	3	100	0	60	0	0	0.15	1	90	2	50	2	80
63	0.28	4	60	2	80	0	0	0.15	1	90	2	50	3	80
64	0.27	1	90	0	60	0	0	0.10	5	60	2	50	0	90
65	0.27	2	90	0	60	0	0	0.10	2	80	2	50	2	80
66	0.24	0	0	0	60	3	80	0.10	2	80	2	50	3	80
67	0.21	0	0	0	60	1	70	0.05	3	70	2	50	2	80
68	0.21	5	70	0	60	0	0	0.05	4	70	2	50	2	80
69	0.20	0	0	1	100	0	0	0.05	3	70	2	50	3	80
70	0.18	4	60	0	60	0	0	0.05	4	70	2	50	3	80
71	0.10	0	0	2	80	0	0	0.00	5	60	2	50	2	80
72	0.00	0	0	0	60	0	0	0.00	5	60	2	50	3	80

Then, to simulate different arbitrary buyer and seller pairs, different lower and upper threshold utility value pairs are generated in random within the related meaningful utility value intervals. Three separate runs for different medial buyer and seller pairs come in the following sections:

-FIRST BARGAINING RESULT SET: AN UNSUCCESSFUL BARGAINING

The lower and upper bargaining interval thresholds for first bargainer pairs were generated in random as $[\theta^B, \Theta^B] = [0.1621, 0.5909]$ and $[\theta^S, \Theta^S] = [0.7543, 0.7572]$. Moreover, to behave medial, the risk factors 0.6431 and 0.5437 are assigned to buyer and seller agents. Then, according to Medial Bargaining Algorithm, mentioned on page 21, an arbitrary medial rational buyer offers an alternative yielding the best utility 0.4563. This utility value falls between the rows 45 (=0.47) and 46 (=0.45) of Table 6. Then, row 45 corresponding to criteria values ShippingMethod (2:Certified)=90, PaymentMethod (1:Credit)=100 and PackagingStyle (0:Nylon)=0 is her best alternative.

In the same way, an arbitrary medial rational seller computes an alternative yielding the best utility 0.7557. This utility value falls between the rows 5 (=0.75) and 4 (=0.8). Then, row 4, correponding to criteria values ShippingMethod(0:Normal)=100, PaymentMethod (0:Cash)=100 and PackagingStyle(0:Nylon)=90, is his best alternative.

Both parties can make an initial offer. However, we assume that buyer makes initial offer and moves toward stationary seller agent to submit her offer. Then, seller analyzes the received offer using Medial Bargaining Algorithm and they follow suitable actions using interchanging offers and counter-offers. We assumed that the good is electronic information, and after a successful bargaining, the buyer requests bill and then the seller delivers invoice along with the good to the buyer agent.

As Table 7 shows, after 26 rounds offer and counter-offer argumentations within their threshold intervals (covered rows 45-70 of Table 6 in the buyer's side), they reached a dissagreement! Because, in row 108 the buyer finds that there is no acceptable alternative within her threshold interval. Therefore, the buyer informs the seller about her dissagreement to continue the bargaining.

Table 7. First bargaining result set: an unsuccessful bargaining within 26 rounds.

Row	History	u(Offer/C-Offer)
1	Buyer initialized with: M=0.80. m=0.00. **Theta=0.5909. theta=0.1621**. R=0.6431.	
2	**Best_u=0.4563**	
3	Seller initialized with: M=0.90. m=0.00. **Theta=0.7572. theta=0.7543**. R=0.5437.	0.4563(B)
4	**Best_u=0.7557**	0.4700(B)
5	Buyer: **making initial offer...**	
6	Buyer: offer-> [2.1,0]	0.5000(S)
7	Buyer: I arrived!	
8	Seller: analyzing...	
9	Seller: Denied-> [2.1,0]	0.4500(B)
10	Buyer: making counter offer...	0.5000(S)
11	Buyer: counter_offer-> [5,0,3]	
12	Seller: analyzing...	
13	Seller: Denied-> [5,0,3]	0.4400(B)
14	Buyer: making counter offer...	0.5000(S)
15	Buyer: counter_offer-> [0,1,3]	
16	Seller: analyzing...	
17	Seller: Denied-> [0,1,3]	0.4200(B)
18	Buyer: making counter offer...	0.5500(S)
19	Buyer: counter_offer-> [4,0,3]	
20	Seller: analyzing...	
21	Seller: Denied-> [4,0,3]	0.4200(B)
22	Buyer: making counter offer...	0.7000(S)
23	Buyer: counter_offer-> [5,0,1]	
24	Seller: analyzing...	
25	Seller: Denied-> [5,0,1]	0.4100(B)
26	Buyer: making counter offer...	0.7000(S)

Row	History	u(Offer/C-Offer)
27	Buyer: counter_offer-> [0,1,1]	
28	Seller: analyzing...	
29	Seller: Denied-> [0,1,1]	0.4100(B)
30	Buyer: making counter offer...	0.4000(S)
31	Buyer: counter_offer-> [5,1,0]	
32	Seller: analyzing...	
33	Seller: Denied-> [5,1,0]	0.4000(B)
34	Buyer: making counter offer...	0.2000(S)
35	Buyer: counter_offer-> [0,2,2]	
36	Seller: analyzing...	
37	Seller: Denied-> [0,2,2]	0.4000(B)
38	Buyer: making counter offer...	0.1500(S)
39	Buyer: counter_offer-> [3,2,0]	
40	Seller: analyzing...	
41	Seller: Denied-> [3,2,0]	0.3900(B)
42	Buyer: making counter offer...	0.4500(S)
	Buyer: counter_offer-> [4,0,1]	
	Seller: analyzing...	
43	Seller: Denied-> [4,0,1]	
44	Buyer: making counter offer...	
45	Buyer: counter_offer-> [4,1,0]	0.3800(B)
46	Seller: analyzing...	0.4500(S)
47	Seller: Denied-> [4,1,0]	
48	Buyer: making counter offer...	
49	Buyer: counter_offer-> [1,2,0]	0.3700(B)
50	Seller: analyzing...	0.2500(S)
51	Seller: Denied-> [1,2,0]	
52	Buyer: making counter offer...	
53	Buyer: counter_offer-> [2,2,0]	0.3700(B)
54	Seller: analyzing...	0.2000(S)
55	Seller: Denied-> [2,2,0]	
56	Buyer: making counter offer...	
57	Buyer: counter_offer-> [0,2,3]	0.3400(B)
58	Seller: analyzing...	0.2000(S)
59	Seller: Denied-> [0,2,3]	
60	Buyer: making eounter offer...	
61	Buyer: counter_offer-> [0,2,1]	0.3100(B)
62	Seller: analyzing...	0.4000(S)
63	Seller: Denied-> [0,2,1]	
64	Buyer: making counter offer...	
65	Buyer: counter_offer-> [5,2,0]	0.3100(B)
66	Seller: analyzing...	0.1000(S)
67	Seller: Denied-> [5,2,0]	
68	Buyer: making counter offer...	0.3000(B)
69	Buyer: counter_offer-> [0,0,2]	0.7000(S)

Row	History	u(Offer/C-Offer)
70	Seller: analyzing...	
71	Seller: Denied-> [0,0,2]	
72	Buyer: making counter offer...	0.3000(B)
73	Buyer: counter_offer-> [3,0,0]	0.6500(S)
74	Seller: analyzing...	
75	Seller: Denied-> [3,0,0]	
76	Buyer: making counter offer...	0.2800(B)
77	Buyer: counter_offer-> [4,2,0]	0.5500(S)
78	Seller: analyzing...	
79	Seller: Denied-> [4,2,0]	
80	Buyer: making counter offer...	0.2700(B)
81	Buyer: counter_offer-> [1,0,0]	0.7500(S)
82	Seller: analyzing...	
83	Seller: Denied-> [1,0,0]	
84	Buyer: making counter offer...	0.2700(B)
85	Buyer: counter_offer-> [2,0,0]	0.7000(S)
86	Seller: analyzing...	
87	Seller: Denied-> [2,0,0]	
88	Buyer: making counter offer...	0.2400(B)
89	Buyer: counter_offer-> [0,0,3]	0.7000(S)
90	Seller: analyzing...	
91	Seller: Denied-> [0,0,3]	
92	Buyer: making counter offer...	0.2100(B)
93	Buyer: counter_offer-> [0,0,1]	0.7000(S)
94	Seller: analyzing...	
95	Seller: Denied-> [0,0,1]	
96	Buyer: making counter offer...	0.2100(B)
97	Buyer: counter_offer-> [5,0,0]	0.6000(S)
98	Seller: analyzing...	
99	Seller: Denied-> [5,0,0]	
100	Buyer: making counter offer...	0.2000(B)
101	Buyer: counter_offer-> [0,1,0]	0.6000(S)
102	Seller: analyzing...	
103	Seller: Denied-> [0,1,0]	
104	Buyer: making counter offer...	0.1800(B)
105	Buyer: counter_offer-> [4,0,0]	0.6500(S)
106	Seller: analyzing...	
107	Seller: Denied-> [4,0,0]	
108	Buyer: making counter offer...	**0.1000(B)**
109	Buyer: **I'm Dissagree to continue bargaining!**	
110	Buyer: I'm back unsuccessful!	
111	Seller: I'm sited back unsuccessful!	

- - SECOND BARGAINING RESULT SET: A SUCCESSFUL BARGAINING

The lower and upper thresholds of bargaining intervals for second bargainer pairs were generated in random as $[\theta^B, \Theta^B] = [0.2437, 0.3492]$ and $[\theta^S, \Theta^S] = [0.1741, 0.6693]$.

The risk factors 0.5422 and 0.7333 were assigned to buyer and seller agents. This arbitrary medial rational buyer offers an alternative yielding the best utility 0.2948. This utility value falls between the rows 62 (=0.30) and 63 (=0.28) of Table 6. Then, row 63 correponding to criteria values ShippingMethod (3:Express)=100, PaymentMethod (0:Cash)=60 and PackagingStyle (0:Nylon)= 0 is her best alternative.

In the same way, the medial rational seller computes an alternative yielding the best utility 0.6033. Buyer makes initial offer and itineraries toward stationary seller agent to submit her offer. Then, seller analyzes the received offer and follows suitable actions using interchanging offers and counter-offers.

As Table 8 shows, after 3 rounds offer and counter-offer argumentation intervals (covered rows 61-64 of Table 6 in the buyer's side), they reached an agreement on ShippingMethod (1:Registered), PaymentMethod (0:Cash) and PackagingStyle (0:Nylon) yeilding the utility 0.2700 for the buyer instead of the initial offer utility 0.3000 but resulted in a better utility 0.7500 for seller beyond his threshold interval!

Table 8. Second bargaining result set: A successful bargaining within 3 rounds.

Row	History	u(Offer/C-Offer)
	Buyer initialized with: M=0.80, m=0.00, **Theta=0.3492, theta=0.2437**,	
	R=0.5422, **Best_u=0.2948**	
1	Seller initialized with: M=0.90, m=0.00, **Theta=0.6693, theta=0.1741**,	0.2948(B)
2	R=0.7333, **Best_u=0.6033**	0.3000(B)
3	Buyer: **making initial offer...**	
4	Buyer: offer-> [3,0,0]	**0.6500(S)**
5	Buyer: I arrived!	
6	Seller: analyzing...	
7	Seller: **suggest Continue up!**	0.2800(B)
8	Buyer: making counter offer...	0.1500(S)
9	Buyer: counter_offer-> [4,2,0]	
10	Seller: analyzing...	
11	Seller: Denied-> [4,2,0]	0.2700(B)
12	Buyer: making counter offer...	**0.7500(S)**
13	Buyer: counter_offer-> [1,0,0]	
14	Seller: analyzing...	
15	Seller: **Accepted-> [1,0,0]**	
16	Buyer: Bill Request [1,0,0]	
17	Seller: Delivered-> Invoice [1,0,0], Info [1,0,0]	
18	Buyer: I'm successful and back with Invoice&Info [1,0,0]!	
19	Seller: I'm sited back successful!	

- - THIRD BARGAINING RESULT SET: A SINGLE ROUND SUCCESSFUL BARGAINING

The lower and upper bargaining interval thresholds for third bargainer pairs were generated in random as $[\theta^B, \Theta^B] = [0.6544, 0.7505]$ and $[\theta^S, \Theta^S] = [0.3078, 0.4794]$. The risk factors 0.5730 and 0.7273 were assigned to buyer and seller agents. This arbitrary medial rational buyer offers an alternative yielding the best utility 0.7069. This utility value falls between the rows 8 (=0.71) and 9 (=0.70) of Table 6. Then, row 8 correponding to criteria values ShippingMethod (3:Express) =100, PaymentMethod (1:Credit)=100 and PackagingStyle (1:Pocket)= 70 is her best alternative.

In the same way, the medial rational seller computes an alternative yielding the best utility 0.4544. Buyer makes initial offer and moves toward stationary seller agent to submit her offer. Then, seller analyzes the received offer and follows suitable actions.

Table 9. Third bargaining result set: A successful bargaining within 1 round (no argumentation!).

Row	History	u(Offer/C-Offer)
1	Buyer initialized with: M=0.80, m=0.00, **Theta=0.7505, theta=0.6544,**	
2	R=0.5730, **Best_u=0.7069**	
3	Seller initialized with: M=0.90, m=0.00, **Theta=0.4794, theta=0.3078,**	0.7069(B)
4	R=0.7273, **Best_u=0.4544**	0.7100(B)
5	Buyer: **making initial offer…**	
6	Buyer: offer-> [3,1,1]	**0.5500(S)**
7	Buyer: I arrived!	
8	Seller: analyzing…	
9	Seller: **Accepted-> [3,1,1]**	
10	Buyer: Bill Request [3,1,1]	
11	Seller: Delivered-> Invoice [3,1,1], Info [3,1,1]	
	Buyer: I'm successful and back with Invoice&Info [3,1,1]!	
	Seller: I'm sited back successful!	

As Table 9 shows, after 1 round argumentation (covered row 8 of Table 6 in the buyer's side), they reached an agreement on ShippingMethod (3:Express), PaymentMethod (1:Credit) and PackagingStyle (1:Pocket) yeilding the utility 0.7100 and 0.5500 for buyer and seller, respectively. This bargaining resulted in a better utility than the best medial utility for buyer as well as the utility beyond the seller's threshold interval!

- DISCUSSIONS

As Tables 1-3 show, evaluation and weights values corresponding to each criteria options are independent and different in the viewpoints of buyer and seller agents while none of them has the knowledge about the utility function of the other party. Therefore, an alternative which makes a poor utility for one party may or may not result in a rich utility for the other party and encourage/prevent him/her to accept the offer.

Figure 3 shows the first bargaining result set. The horizontal axis describes round sequences. Rounds 1-26 correspond to offers [2,1,0], [5,0,3],…, [4,0,0] in Table 7. The

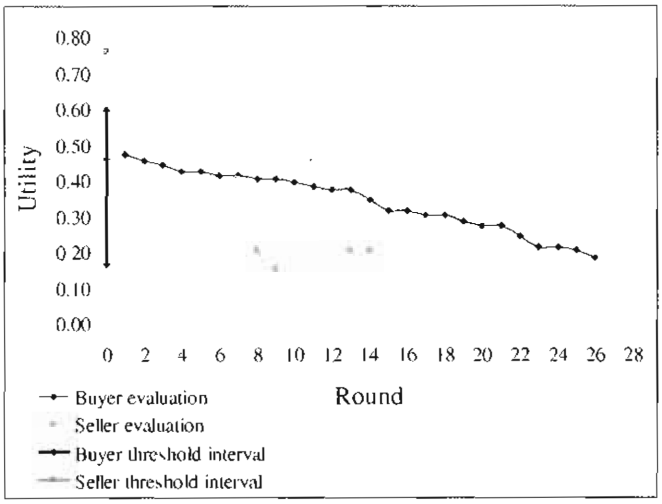

Figure 3: The offers' evaluated utilities of Table 7 (first bargaining result set).

vertical axis describes buyer and seller utility values related to each offer. In this Figure, threshold intervals of buyer and seller are shown in thick lines on utility axis in dark blue and red, respectively. The seller threshold interval is very short and far from the buyer threshold interval that is longer than the former.

According to the first bargaining result set on page 27 and shown in Figure 3, one may conclude that since the threshold intervals of buyer and seller agents have no intersection, reaching a disagreement is quite predictable. Figure 5, and its discussion, shows that it is not a generality.

In this paper we resembled agents as humanoid agents with particular behaviors based on their own objectives. Therefore, even medial agents may not agree upon any offer. Buyer has done her best to decrease her utility to reach an agreement with seller, but their objectives are not converged within the existed alternatives space. As Figure 3 shows, buyer and seller have a somehow similar evaluation about the offer in round 7, but they did not reach an agreement; because, this utility is out of the seller threshold interval. If the alternatives space was a little larger, they might hopefully reach an agreement but in the cost of the minimum utility for buyer. On the other hand, since the buyer threshold interval was below the seller threshold interval and buyer made the initial offer, they did not reach an agreement. In contrast, if seller had begun the bargaining process, they certainly had an agreement in a single round.

If we equip each agent with learning capabilities, they may be able to behave more rationally to find this type of divergence. Therefore, they can stay away from frustrated bargaining by adapting their behaviors (i.e., their threshold intervals) to reach an agreement cooperatively.

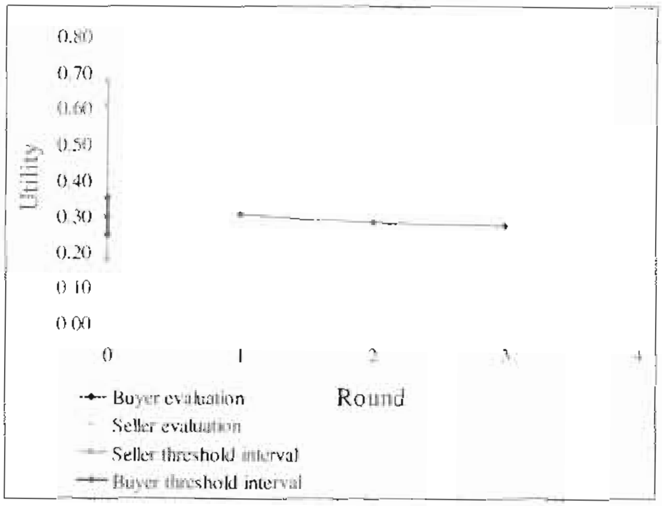

Figure 4: The offers' evaluated utilities of Table 8 (second bargaining result set).

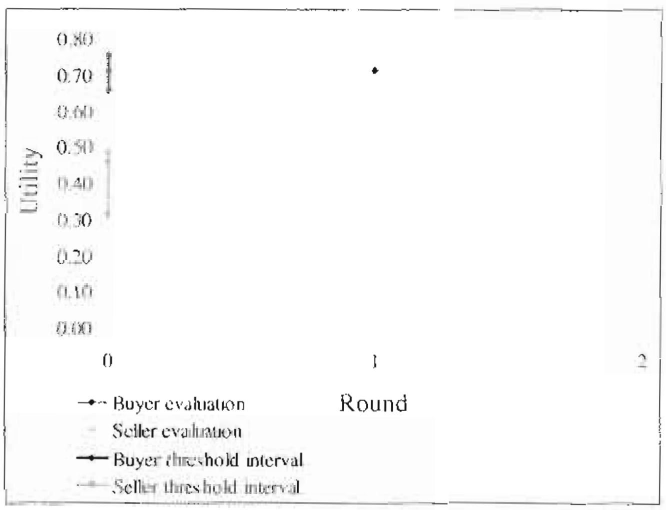

Figure 5: The offers' evaluated utilities of Table 9 (third bargaining result set).

As shown in Figure 4, in contrast to the first result set, in the second bargaining result set in section **second bargaining result set: A successful bargaining,** the threshold intervals of buyer and seller have intersection. Moreover, the seller threshold interval is very long in comparison to the buyer threshold interval. We can see that even the first offer is within the seller threshold interval, but according to Medial Bargaining Algorithm he likes to continue bargaining with the hope of gaining a higher utility (because, R^S = 0.7333>0.5) and therefore he did not show his acceptance and wanted the buyer to decrease her utility in order to present a better offer for him. However, the next offer of the buyer results in a utility downside of the threshold interval. Therefore, the seller denied this offer and then the buyer offered the other offer that yielded a utility beyond the seller threshold interval!

Figure 5 shows an empty intersection between buyer and seller threshold intervals. However, in contrast to Figure 3, since the buyer threshold interval is upper than the seller threshold interval, any offer from the buyer is immediately accepted by the seller. Therefore, they reach an agreement in a single round.

CONCLUSIONS

We presented a simple semi-dynamic approach to incomplete information cooperative bargaining mechanism which deals with bargaining of single-buyer and single-seller in a multi-criteria single-good e-Marketplace. In this paper, we supposed that both buyer and seller agents are medial agents that cooperatively want to win bargaining via a slight maneuver over their own preferences that are unknown to the other party.

All agents in the e-Marketplace have the base knowledge of their own behaviors and utility functions according to the e-Marketplace rules (legal valid values). In order to act cooperatively, we armed each agent with an initial pre-calculated knowledgebase containing alternative offers (preferences) on behalf of their owners along with a risk factor describing agent ambition ratio to bargain for grasping or outselling the good according to his own utility constraints. A rational buyer is looking for contracts that result in the best utility in their behavioral regions. Hence, the buyer prefers to drive the first bargaining phases to an agreement that will lead to the best utility. Nevertheless, both parties in the bargain often want to reach a profitable agreement, so during the bargaining phases, each agent only maneuvers over his or her own pre-calculated knowledge and tries to pull the counterpart desires closer to his/her own desires. However, if no agreement can be attained at this point, then she will continue bargaining in the next levels of satisfaction.

Our approach calculates the best offer that is close to the opponent's offer without prior knowledge about the criteria weights in the opponent viewpoint and is based only on his previous offer. If the buyer cannot make an agreement in any alternatives, she will lose the chance of purchasing the good. The seller agent is also supposed to do the same but with his own preferences that may be in contrast to the buyer's preferences. In a similar way, seller wants to sell his good based on his best utility during the first bargaining phases. However, if no agreement can be attained at this point, he will continue bargaining. Otherwise, he will lose the chance of selling the good to the buyer.

Via some simulation result sets, we showed that lack of the intersection between the threshold intervals of both parties does not necessarily yields a disagreement; because, the situation of intervals according to the party that offers first, is important. Moreover, risk factor plays a positive role in the degree of participation in bargaining. In addition, long threshold interval does not necessarily result in a successful bargaining, as well.

-FUTURE WORKS

In the simple approach to cooperative bargaining mechanism presented in this paper, we have not considered learning features. We have examined the effect of reinforcement learning based on the reputation and promotion in an e-Marketplace [15]. We have also recommended a better e-advertisement service to buyers with using sellers who learn from the history obtained from the similar prevoius buyer's purchases using *k*-NN learning [12]. Elegant machine learning techniques can be applied to learning during bargaining in order to learn how to rearrange the criteria's weights, or learn how to adjust utility functions, or learn to revise the behavior in a degree of tendency in behavioral tolerance to a slight maneuver over preferences belonging to the adjacent utility regions, or learn the counterpart's next decision and so on. Therefore, based on the successful dealing experiences, buyer and seller agents can arrange their own next deals with those desired parties.

In this paper, we generated a single behavioral agent for each buyer or seller. However, in a multi-good e-marketplace each seller has different preferences and sells many goods each with many criteria. For each good a buyer is willing to buy, if a buyer can attain a ubiquitous and omnipotent power to bargain with many sellers simultaneously, then she can purchase her desired goods at best utility around the market in competition with other buyers. Therefore, to achieve the best purchases, she can generate different behavioral agents and dispatch them around the e-marketplace. In this way a buyer transfers his knowledge to his agents and, therefore this will lead to the availability of a number of copies of a buyer in an e-marketplace. In the same way, to increase the chance of best selling a good, each seller can dispatch a group of seller agents with different behaviors for each good he sells. According to the opponent's behavior, that a cloned buyer agent may encounter with, many, one or none of them may obtain a successful result. Therefore, they must cooperatively communicate with each other in a rendezveous to coordinate to do the best deal and buy the designated good. That is, each agent has a different chance to win or lose the bargaining to buy a good on behalf of its owner. Similarly, sellers can do the same.

Therefore, each entity in the e-marketplace has to deal with four dimensions to get the best interest. These dimensions are: *many* buyers (with different preferences which may bargain on the same item from the same seller in concurrent), *many* sellers (with different preferences with which any buyer may concurrently bargain for their goods), *many* goods (which are provided by many sellers and which many buyers are after), and *many* criteria (related to each good the importance of which affects buyers'/sellers' preferences). We call this problem 4M-Bargaining Problem. [In the real world, where countries challenge to grasp many critical resources, the aforementioned situation is imaginable and suitable approaches must be adopted.]

This e-marketplace is loaded with many cloned agents and missed messages are very probable and the market will be full of many whispers. Hence, appropriate mechanisms for cooperation of these cloned agents must be developed.

Acknowledgement

The authors wish to thank the Office of Graduate Studies of the University of Isfahan for their support.

ENDNOTES

1. Due to the approach we introduce (e.g., necessitiy to refer to the values as the matrix indices), for all critera we assume discrete values within the intervals.
2. All min values are not necessarily equal to zero. Because, there are many ethical buyers that do not desire to present them goods in free.
3. We assume all agents A have different risk factors $0 \leq R^A \leq 1$. The risk factor $R^A = 0$ means a full conservative agent, while a greedy agent has the risk factor $R^A = 1$. We assume that with $0 < R^A \leq 0.3$ the agent behaves semi-conservative, while a semi-greedy agent has the risk factor $0.8 \leq R^A < 1$. The risk factor $0.3 < R^A < 0.8$ means a medial agent. We arbitrarily chose 0.3 and 0.8. These values can be assigned with any other predefined values as we did for min_valid and max_valid values.
4. In this paper, we have not considered learning features to gain and change the knowledge (see future works).

REFERENCES

[1] Breban, S. and Vassileva, J., "A Coalition Formation Mechanism Based on Inter-Agent Trust Relationships." in: L. Johnson & C. Castelfranchi (eds.), *Proceedings of the First International Joint Conference on Autonomous Agents & Multiagent Systems*, AAMAS 2002, Bologna, Italy, ACM Press, Available: at <http://julita.usask.ca /Texte/p225-breban.pdf>, pp. 306-307, 2002.

[2] Chiu, D. K.W., et al., "Developing E-Negotiation Support with a Meta-Modeling Approach in a Web Services Environment." *Decision Support Systems*, Vol. 40, pp. 51– 69, 2005.

[3] Coehoorn, R. M. and Jennings, N. R., "Learning an Opponent's Preference to Make Multi-Issue Negotiation Trade-Offs." Available: at <http://www.ecs.soton.ac .uk/~nrj/download-files/robert-icec04.pdf, http://www.icec04.net/Presentations /Coehoorn.ppt>, 2001.

[4] Deschner, D., et al., "Strategies for Software Agent Based Multiple Issue Negotiations." in: K. Bauknecht, S.K. Madria, and G. Pernul (Eds.): *Proceedings of the 2nd International Conference on Electronic Commerce and Web Technologies (EC-Web 2001)*, LNCS 2115, Springer-Verlag, pp. 206-215, 2001.

[5] Faratin, P., et al., "Simple Negotiating Agents in Complex Games: Emergent Equilibria and Dominance of Strategies." Available: at <http://ccs.mit.edu/peyman/pubs/ ATAL-

01.pdf>, 2000.

[6] Fatima, Sh., et al., "Optimal Negotiation of Multiple Issues in Incomplete Information Settings." AAMAS'04, Available: at <http://www.aamas2004.org/proceedings/131_fatimas_negotiation.pdf>, pp. 377-392, 2004.

[7] IBM Aglet Home Page, Available: at <http://www.trl.ibm.co.jp/aglets>.

[8] Jennings, N. R., et al., "Automated Negotiation: Prospects, Methods and Challenges." GDN2000 Keynote paper, Available: at <http://www.csc.liv.ac.uk/~mjw/pubs/gdn2001.pdf>, 2000.

[9] Kraus, S., "Negotiation and Cooperation in Multi-Agent Environments." *Artificial Intelligence*, Vol. 94, pp. 79-97, 1997.

[10] Mudgal C., and Vassileva, J., "Bilateral Negotiation with Incomplete and Uncertain Information: A Decision-Theoretic Approach Using a Model of the Opponent." *Proceedings of the 4th International Workshop on Cooperative Information Agents (CIA IV)*, Boston, pp. 107-118, 2000.

[11] Nash, J. F., "The Bargaining Problem." *Econometrica*, 18, pp. 155-162, 1950.

[12] Nassiri-Mofakham F. et al., "A k-NN-Learning-based Selling E-Advertising for Controlling E-Marketplace Resource Demands." 2006, (in submit).

[13] Oliver, J. R., "A Machine Learning Approach to Automated Negotiation and Prospects for Electronic Commerce." *Journal of Management Information Systems*, Vol. 13, No. 3, pp. 83-112, 1997.

[14] Rebstock, M., "An Application Architecture for Supporting Interactive Bilateral Electronic Negotiation." in: K. Bauknecht, S.K. Madria, and G. Pernul (Eds.): *Proceedings of the 2nd International Conference on Electronic Commerce and Web Technologies* (EC-Web 2001), LNCS 2115, Springer-Verlag, pp. 196-205, 2001.

[15] Roozmand, O., et al., "A Reputation and Learning Model for E-Commerce Agents." in: *proceedings of The North American Technology and Business Conference* (NATB05), Montreal, Canada, September 22-23, 2005.

[16] Shintani, T. and Ito, T., "Cooperative Meeting Scheduling Among Agents Based on Multiple Negotiations." in: C. Batini et al. (Eds.): *Proceedings of the 9th International Conference on Cooperative Infotmation Systems* (CoopIS2001), LNCS 2172, Springer-Verlag, pp. 95-107, 2001.

[17] Soh, L-K. and Luo, J., "Combining Individual and Cooperative Learning for Multi-agent Negotiations." *AAMAS'03, Melbourne, Australia,* pp. 1122-1123, 2003.

[18] Vassileva, J., et al., "Agent Reasoning Mechanism for Long-Term Coalitions Based on Decision Making and Trust." *Computational Intelligence*, Vol. 18, No. 4, pp. 583 – 595, 2002.