On the Use of Fuzzy Logic in a Seller Bargaining Game

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Abstract

Information marketplaces are places where users search and retrieve information goods. Intelligent Agents could represent the participating entities in such places, i.e, assume the role of buyers and sellers of information products. In this paper, we introduce a finite horizon bargaining model between buyers and sellers. We examine the seller's side and define a method for the 'bargaining' deadline calculation based on Fuzzy-Logic (FL). Such deadline indicates the time for which it is profitable for a seller to participate in the bargaining procedure, i.e., the time threshold for his offers. We represent the seller's knowledge / policy adopting the Fuzzy Set Theory and provide a fuzzy inference engine for reasoning about the bargaining deadline. The result of the reasoning process defines the degree of patience of the seller agent, thus, affecting the time for which that seller participates in the bargaining game.

1. Introduction

With the rapid development of the Web, information has become the most important trading commodity in modern societies [1]. A huge amount of information sources are available to users. Simultaneously, due to the abundance of information sources, finding information becomes a demanding procedure. Users have to browse and process numerous sources in order to find the information that best meets to their interests.

Intelligent Agents could be a solution to the above problem. Agents are software or hardware components capable of acting exactingly in order to accomplish tasks on behalf of their owners [2]. Their intelligence mostly refers to their capability to learn the preferences of their owners, thus, increases their performance. Hence, agents can undertake the responsibility of finding information in the Web with the minimum intervention by users.

Information Markets (IMs), could provide a place where autonomous entities representing users try to locate the desired information products. In IMs, participants negotiate for the exchange of information commodities. Usually, there are two main groups of participants: the *buyers* and the *sellers*. However, in IMs, an additional group of entities may be responsible for administration or mediation tasks facilitating buyers and sellers in their negotiation.

The combination of the technologies of agents and IMs is highly advantageous for the information discovery and acquisition processes. Agents represent users in an IM, where there are sellers that offer information goods. We study the combination of the Intelligent Agent and IM technologies and present a buyer-seller interaction model. The objective of our work is to define an economic model for the IM organisation. Our model enables the engineering of algorithms and protocols for more efficient transactions. This model is based on Game Theory (GT) [3]. GT provides an efficient way to describe interactions between entities that try to maximize their profits.

A methodology that could offer a number of advantages in interaction models is Fuzzy Logic theory. Fuzzy Sets [4] can be seen as an extension of the Boolean set theory. Fuzzy Logic (FL) is an algebra based on fuzzy sets and provides reasoning mechanisms that are *approximate* rather than *precise*. FL deals with ambiguous information and helps at representing the knowledge of the agents involved in an IM in order to automatically assume decisions during the bargaining process. An important decision is the calculation of the correct time for which an agent will participate in the game. The calculation of that *deadline* affects the behaviour of a seller concerning the proposed prices. We adopt FL for: (i) representing the seller-expert knowledge, and (ii) inferring the

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appropriate deadline for a seller involved in a bargaining game by adapting to the popularity of the bargained product and the current profit of the seller.

The rest of this paper is organized as follows: Section 2 reports related work. Section 3 describes Information Markets and analyses the method that is followed by agents in order to buy / sell information products. Such method is a Bargaining Game (BG) [5] held every time a buyer wants to buy a product. We analytically describe the BG. Section 4 is devoted to the description of the seller's behaviour in the BG. We shortly describe the characteristics of the seller and focus on the estimation of the 'bargaining' deadline. This deadline represents the time interval for which the BG is efficient from the seller's viewpoint. In Section 5, we discuss the fuzzy inference rules and the adaptation mechanism used for the deadline estimation. Finally, in Sections 6 and 7 we conclude the paper by presenting our key findings.

2. Related Work

Nowadays, one can find very interesting efforts in the design and development of virtual marketplaces. A key pursuit in such architectures is to define effective mechanisms for automatic negotiation between market participants. Moreover, particular emphasis is placed on the important issues of payments and registration of members.

Intelligent agents in electronic marketplaces are discussed in [6]. In this architecture, there are three types of agents: buyers, sellers and intermediaries. Agents represent the needs of their owners. An intermediary agent coordinates information related to buyers, sellers and the traded commodity. It is in the *middle* of the market connecting buyers and sellers and handling their transactions. The intermediary agent handles issues like interaction security, fraud and payment. However, there is a risk of market breakdown if the middle entity fails to meet the objectives.

MAGMA [7] is an agent-based market architecture where agents can buy or sell products. It supports manual and automatic negotiation. In this system, administration mechanisms are defined, including product manipulation and payments. MAGMA includes an advertisement server where product descriptions are matched against buyer needs, a bank that is responsible for payments and a number of trader agents which are involved in the market for buying, selling or negotiating prices. Finally, a relay server facilitates the communication between trader agents, storing and manipulating the exchanged messages among members of the community.

The aforementioned systems implement general architectures where agents represent their owners. However, there are research efforts focusing on the interactions between buyers and sellers [8]. The authors in [8] present a BG, which is held between buyers and sellers, and describe a set of strategies for both sides. They describe symmetric and asymmetric scenarios concerning the knowledge of the opponent's parameters. The examined parameters are the player's deadline, the reservation price and the discount factor. The BG involves a set of alternating offers: each player proposes a price for the examined product at every round. The optimal strategy of the player is studied w.r.t. a product pricing scheme. Three types of functions are defined: linear over time, boulware (the player reaches its final proposed price slowly) and conceder (the player reaches its final proposed price quickly). It should be noted that, the final proposed price is reached at the deadline of each player.

A theoretical model regarding player deadline is presented in [9]. The BG in [9] is between agents and the sequential equilibrium is studied. The authors formulate the game between two agents, which are of different types and have their own deadlines. The involved parties do not share knowledge (i.e. type of the opponent and deadline. Analysis for games of continuous and discrete time shows that the only sequential equilibrium is achieved when agents wait until the first deadline expires. At this point players concede everything to the other and this applies both to pure and mixed strategies.

In [10] and [11], the authors adopt FL in agent systems. The discussed work describes the reasoning mechanisms used for the negotiations between agents. Specifically, the authors in [10] present a sequential bargaining technique based on FL for the estimation of acceptable prices of parties trying to form joint ventures (JV) of companies. The objective is to help the involved parties choose the appropriate bargaining strategy. In [11], the authors present the rationale of an intelligent fuzzy-based agent negotiating in an e-commerce environment. The inference rules and the decision strategies are described along with the relevant implementation.

The use of FL in Continuous Double Auctions (CDAs) is studied in [12]. The scenario involves buyer and seller. Authors present the algorithms used by the agents participating in such places and employ a number of heuristic fuzzy rules and fuzzy reasoning mechanisms in order to determine the optimum bid for specific products. Moreover, through the discussed framework, agents are capable of dynamically adapting to variations of demand and supply, thus, achieving efficiency in their bidding strategies.

3. Bargaining Setting

An electronic marketplace can be considered as a virtual location where entities cooperate in order to achieve common goals [13]. An IM can be defined as the place where there are groups of entities trying to buy or sell information products. Information goods can be images, videos, music, software code and electronic articles. The market participants are:

- The group of buyers (consumers or customers).
- The group of sellers (information providers).
- The group of middle entities.

Intelligent agents can represent market participants. Fig. 1 depicts a general scenario of an information market where users dispatch agents to search for information and sellers are agents that act as front-ends of information sources.

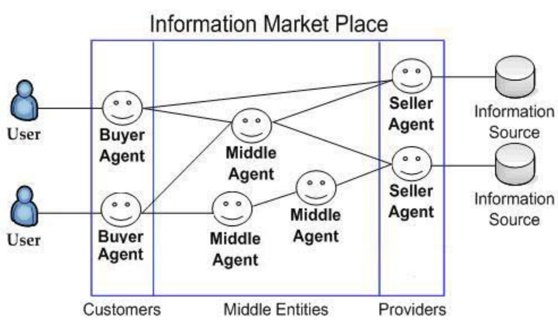

Fig. 1. A general IM scenario.

We examine the case where buyers have direct interactions with sellers in order to conclude an agreement about the price of a certain product. We model the direct buyer-seller interaction as a finite-horizon BG under incomplete information reported in [3]. The BG lasts for a finite period of time (horizon) and involves a number of alternating offers. At every round, entities propose a specific price for the product. If this price is accepted by the opponent then the BG ends with an agreement and specific profit for both entities. The seller starts first and the buyer follows if the proposed offer is rejected. We adopt a sequential numbering scheme for rounds. The seller proposes at odd rounds (1, 3, 5, …) and the buyer proposes at even rounds (2, 4, 6, …). If a player is not satisfied with the proposed offer, it has the right to reject it and issue a counter-proposal. If an agreement is reached then the BG ends with profit for both. Otherwise, a "conflict" is experienced leading to zero profit for both involved parties.

We note that, there is a specific time horizon for the BG. The buyer has a specific deadline posed by its owner, while the seller calculates its deadline, as discussed below. If one of the deadlines expires and no agreement is reached then the BG ends with a conflict. From the description of the BG, we can discern that, each player will reject the opponent's offers if it anticipates acceptance of its future proposed price. A player can anticipate future acceptance if it is likely that, the opponent's deadline does not expire in the next round. This is because, players prefer to pay (sell) the product at a higher (lower) price rather than gain zero profit. Hence, each player starts from an initial price and as long as the opponent's prices are not acceptable, it proposes its own offers only when is certain about the continuation of the BG.

An entity that is involved in the BG does not have any knowledge about the characteristics of its opponent. This means that, the seller does not know the deadline and the valuation of the buyer, and vice versa. Hence, the entities should reason at every round and decide whether they want to continue the BG rejecting the current offer, thus, anticipating better profit in the future.

4. The Behavior of the Seller

In this section, we briefly describe the behaviour of the seller (a more extensive discussion can be found in [14]). The seller retrieves information from information sources and behaves like a caching server, in the sense that, it can deliver information to interested parties more than once. The information goods, available at the seller, are ranked according to their *popularity*. The seller has a certain utility function that reflects the attained profit according to the product's price and the seller's cost. An increase in the price of a product triggers an increase in the seller's profit. In the worst case, the seller's profit is equal to zero. At every even BG round, the seller receives the buyer's offer and proceeds as follows:

- If the deadline of the seller, the price proposed by the buyer and, the estimate of the buyer's deadline indicate that, the BG is to carry on then the seller rejects the buyer's offer and issues a new proposal.
- Otherwise, the seller fears a sudden termination of the BG and accepts the current offer.

Since both entities do not want to terminate the BG with zero profits then a very important issue is the estimation of the opponent's deadline.

The buyer does not know the seller's characteristics. The seller characteristics include: the *cost* (c), the *discount factor* (δ_s), the *utility function* (U_s) and the *deadline* for non-zero profit (T_s). The discount factor indicates that, the seller loses profit as the BG keeps on. Furthermore, the seller knows the popularity of the product, which affects its pricing policy. The price proposed by the seller depends not only on the cost but, also, on the popularity ranking. This means that, it is possible to sell products of high popularity in smaller prices than other products with low popularity. Popular products yield an added value to their owner since they are sold numerous times to interested buyers. For instance, when we have a cost of 5 monetary units (MU), it is more convenient to sell a product with profit of 1 MU to 100 buyers than to sell it with profit of 20 MU to 5 buyers. The first case is more attractive to buyers because the price of product is 6 MU, in contrast to the second case, where the price of the product is 25 MU. In every odd round, the seller proposes prices using a pricing function, which takes into account the current BG round and the popularity ranking of the product.

The seller proposes prices using the following function:

$$p^s(x) = \frac{\varepsilon}{x^{q+1}} + c, \qquad x = 1,2,.... \quad (1)$$

The term $p^s(x)$ denotes the seller's price at the seller's round x (i.e., x=2 implies the second proposal from the seller issued at the third BG round), ε denotes the profit, c is the product's cost, x indexes the seller's round and q is the popularity measure (non-normalized probability of reference) for item i according to Zipf's law [15]. It stands:

$$q = i^{-\lambda} \qquad (2)$$

where i is product's popularity ranking, λ is the Zipf parameter.

Based on the analysis in [14], we can conclude that, there is a time limit, T_s, beyond which all proposed prices by the seller change marginally. T_s is the *threshold for the termination* of the offers proposed by the seller. Hence, from its point of view, if the buyer has not accepted its prices up to this time limit, it is aimless for the seller to continue the BG. This is because the policy of the buyer is to wait for the next rounds in order to achieve higher profit insisting on proposing quite small prices and on rejecting the seller's proposals. For this reason, the seller defines this time limit for its involvement in the BG. This time limit is calculated as:

$$t \cong \left(\alpha \cdot \varepsilon \cdot \left(q+1\right)\right)^{\frac{1}{q+2}} \quad (3)$$

The parameter α, in Equation (3), is a *scaling factor*, which depends on the seller's policy; specifically, if the seller follows a *patience policy*, the α factor assumes a high value. For example, the value of α=100 shows that the seller slowly reaches its lower cost bound, in contrast to a value of α=20. Smaller values for α indicate an *impatient* seller that proposes a few prices and concludes rapidly the BG.

Equation (3) indicates from which time instant the seller converges to a price that has marginal differences with all the upcoming offers. Specifically, the offers are close enough to the seller's cost and it is meaningless for the seller to continue the BG if the buyer, up to the current time instance, has rejected all the preceding offers.

5. Fuzzy Logic Reasoning

The time limit, for which it is profitable for the seller to participate in the BG, depends on the scaling factor α. Hence, the α parameter reveals the impatience of the seller. However, α depends on the parameters q and ε.

The FL is appropriate for real-time decision-making with a certain degree of uncertainty [16]. FL principles express human expert knowledge and facilitate the automated interpretation of the results. Allowing a degree of fuzziness not only at the time limit estimation but also at decision-making (e.g., determining the best patience policy for a BG) makes a seller more flexible and capable of handling the buyer's offers. We exploit FL in order to apply a fuzzy rule-based system Fψcapable of adapting the decisions of the seller to the product's characteristics and current value of profit.

A fuzzy system F is a non-linear mapping between n inputs $u_i \in U_i$, i =1, …, n and m outputs $y_i \in Y_i$, i = 1, …, m. The inputs are crisp, i.e., they are real numbers (not fuzzy sets). The *fuzzification* process converts the crisp inputs into fuzzy sets, the *inference mechanism* uses the fuzzy rules in the rule-base to produce fuzzy conclusions, and the *defuzzification* process converts these fuzzy conclusions into the crisp outputs. The ordinary sets U_i and Y_i are called *universes of discourse* --domains-- for u_i and y_i, respectively. To specify rules for the rule-base, the expert (the seller) uses linguistic descriptions for both u_i and y_i. We call such descriptions linguistic variables $l(u_i)$ and $l(y_i)$ for the input u_i and y_i, e.g., an input to the fuzzy system F might be described as a product with *high* popularity ($l(u_i)$ = *high*, u_i = popularity ranking degree); a linguistic variable ($l(u_i)$) takes linguistic values ($l(u_i)$ = *high*) that are used to describe characteristics of the variable (u_i). If A_{ij} denotes the j^{th} linguistic value of the variable u_i then $l(u_i)$ takes values from the set $A_i = \{A_{ij} : j = 1, \ldots, N_i\}$. Each element A_{ij} is a *fuzzy set* defined as $A_{ij} = \{(u_i, \mu_j(u_i)) : u_i \in U_i\}$, where $\mu_j(u_i)$ is called *membership function* and maps U_i to [0,1]. In this paper, we use triangular membership functions with centers c_{ij} and spreads s_{ij}.

Moreover, FL incorporates a rule-based approach for inference. Hence, the mapping of the inputs to the outputs of a fuzzy system is characterized by a set of *condition* → *action* rules. We adopt the multi-input single-output (MISO) form of a linguistic rule R_j, with $q = u_1$, $\varepsilon = u_2$ and $y = a$, that is,

$$R_j : \text{If } q \text{ is } A_{1(j)} \text{ AND/OR } \varepsilon \text{ is } A_{2(j)} \text{ Then } a \text{ is } B_{(j)}.$$

where $A_{i(j)}$ and $B_{(j)}$ is the fuzzy set representing the j^{th} linguistic value for the input parameter i and for the output parameter a, respectively. The fuzzy system F learns to control decisions through a set of linguistic rules. Such system autonomously adapts to the current profit ε of the seller and the popularity measure of the product q. However, adjustment and estimation of the c_{ij} and s_{ij} values can be achieved through statistical learning systems [17] in order to obtain a more accurate representation of the BG semantics.

5.1. The Fuzzy Rule-base

The linguistic expressions of the values for the parameters q, ε and a are defined in the sets $A_1 = A_2 = B_1$ {*low*, *medium*, *high*} and the corresponding trapezoidal fuzzy sets are depicted in Fig. 3. Specifically, a fuzzy value *low q* indicates that, the product is at the Region B of the cache ranks (Fig. 2). A value of *medium q* denotes that, the product is at the middle popularity positions (Region C) and a value of *high q* refers to the fact that, the product is within the Region D of the cache items. For a more fine-grained resolution of the fuzzy linguistic values of q, we use the linguistic modifier *very*; $very(\mu(q)) = \mu(q)^2$. Specifically, *very low q* denotes that the product is at the lower 10% of the cache (Region A) and *very high q* denotes that, the product is at the top 10% of the cache (Region E). The values of q are in the interval (0,1].

Moreover, a *low* value of ε denotes that, the seller's initially intended profit value is low, while, a *medium* and a *high* value of ε indicate medium and high values for profit (Fig. 4), respectively. The value of ε is a positive number indicating the initially intended profit. However, this number is bounded from above. The range of values of ε is $[0, \varepsilon_{max}]$ where ε_{max} is defined by the seller. We consider a sigmoid function of ε in order to produce values in the range [0,1], that is,

$$f(\varepsilon) = \frac{1}{1 + e^{-\left(\varepsilon - \frac{\varepsilon_{max}}{2}\right)}} \quad (4)$$

Hence, a value of $f(\varepsilon)$ close to 1 shows that, the seller aims to the higher possible profit or a value close to 0 indicates that the seller aims to profit marginally higher than 0.

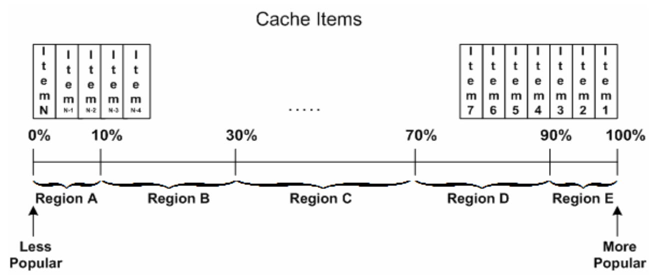

Fig. 2. Cache popularity rank regions.

Concerning the scaling factor α (Fig. 5), a fuzzy value *low a* indicates that, the seller is an impatient player which stays for a few rounds in the BG. A *medium* and a *high* value of *a* indicates a medium and high value of patience respectively. For a more fine-grained resolution of the fuzzy linguistic values of *a*, we use the linguistic modifier *very*; $very(\mu(a)) = \mu(a)^2$. Specifically, *very low a* denotes that the seller wants to sell the product as soon as possible participating in only a few BG rounds and *very high a* denotes that, the seller is a very patient player.

The policy of the seller is based on the following scheme:

- When a product is not popular then the seller has to stay in the BG as much as possible in order to attain higher profits insisting in large prices.
- When a product is popular then the seller has the opportunity to sell it in lower prices because its profit increases through the increased number of buyers.

Such policy can be mapped into a set of fuzzy rules in order for the seller to estimate / calculate the time limit *a* for the specific BG with a specific buyer. We present the five most important rules that represent the seller's knowledge and decision tasks with respect to the calculation of parameter *a*.

R_1: If (q is *very low* AND (ε is *low* OR ε is *medium*)) Then *a* is *very High*

Explanation: The R_1 rule means that, if the product's popularity rank is very low (the product is located at the 10% lower places of the cache – Region A) and the pursued profit is low or medium then the value of a should be very high because the seller has to stay as much as possible in the BG in order to secure its profit. This stands because there is a decreased number of buyers interested in the specific product and the seller targets to a small initial profit.

R_2: If (q is *very low* AND ε is *high*) OR (q is *low* AND (ε is *low* OR ε is *medium*)) Then a is *high*

Explanation: If the seller targets to high initial profit and the product is located at the lower places (Region A) of the cache then the value of a should be high. The same is when the product's rank is low (Region B) and the seller aims to a low or medium initial profit. The rationale is that, the seller should stay in the BG for adequate time insisting on high prices because the product's popularity rank is quite low.

R_3: If (q is *low* AND ε is *high*) OR (q is *medium*) OR (q is *high* AND ε is *low*) Then a is *medium*

Explanation: The parameter a should have a medium value when the seller tries to sell products with a medium popularity (Region C). The same holds true, when the product is located at the least popular places of the cache and the intended profit is high (or vice versa). In such cases, the seller follows a *neutral* policy and pays equal attention on the product's popularity rank and the pursued profit.

R_4: If (q is *high* AND (ε is *medium* OR ε is *high*)) OR (q is *very high* AND ε is *low*) Then a is *low*

Explanation: When the product is located at the most popular places of the cache, the seller has the opportunity to sell it in smaller prices due to the increased number of buyers. Hence, the value of a is low if the popularity rank is high or very high (Regions D and E). However, the seller tries to stay some time in the BG in order to gain higher profit, especially in cases where the initial profit has low values (medium or low).

R_5: If (q is *very high* AND (ε is *medium* OR ε is *high*)) Then a is *very low*

Explanation: The final case refers to a product located at the most popular places of the cache (Region E). The seller does not have to stay in the BG for long because there might be an increased number of buyers for the specific product. Hence, its higher profits could be derived through this large number of buyers selling the specific product with smaller profit.

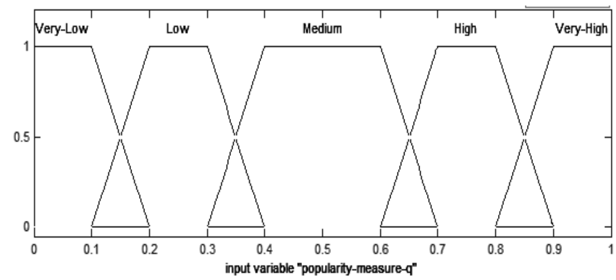

Fig. 3. Fuzzy sets for the input parameter q (popularity measure).

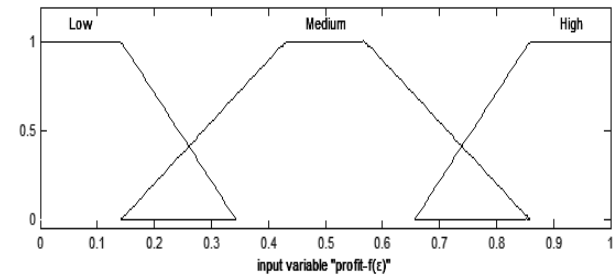

Fig. 4. Fuzzy sets for the input parameter $f(\varepsilon)$.

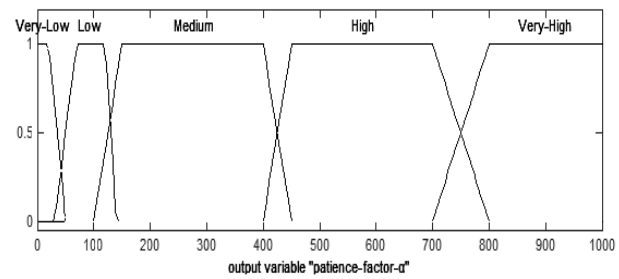

Fig. 5. Fuzzy sets for the scaling factor α.

6. Analysis on the Fuzzy Reasoning Results

In Fig. 6, we give the 3D diagram for the fuzzy inference engine described in Section 5. We use an upper limit for the value of a denoted as a_{max} (e.g., a_{max} = 1000). The seller defines this upper limit during the bootstrapping of the transaction. In Table 1 we show the values of a based on the fuzzy-based approach described in this paper. We compare our findings to the calculations provided in [14]. For our calculations, we define a maximum profit of 20 MU.

From Table 1 and Fig. 6, we can observe that, the seller tries to secure its profit when the product is not popular and the profit is low. Hence, in such cases, a large value of a implies a *very patient* policy. At the opposite case, the seller is eager to lose profits when the product is at the most popular places in the cache. As already explained, in such scenarios, the seller covers its losses through the increased number of buyers interested in the specific product. When the popularity ranking measure q assumes values close to 1, the values produced for a are small. This leads to an *impatient* policy, which forces the seller to quickly decrease its proposed prices. This stands true regardless of the values of ε.

Table 1. Seller's deadline calculation

Profit (ε)	**$f(\varepsilon)$**	**Popularity Ranking measure q**	**T_s for a = 20 (from [14])**	**a value in our fuzzy approach**	**New T_s**
5	*0.067*	*1*	*6*	*89.4*	*10*
5	0.067	0.4	8	275	23
10	*0.5*	*1*	*7*	*15.8*	*7*
10	0.5	0.4	10	275	31
10	0.5	0.7	9	89.4	15
10	0.5	0.2	**12**	588	**56**
20	1	1	9	15.8	9
20	1	0.4	14	275	42

Table 2. Seller's deadline calculation special cases

Profit (ε)	**$f(\varepsilon)$**	**Popularity Ranking measure q**	**T_s for a = 50 (from [14])**	**a value in our fuzzy approach**	**New T_s**
10	*0.5*	*1*	*10*	*15.8*	*7*
20	1	1	13	15.8	9

Moreover, from Table 1, we can observe the advantage of using FL as an inference mechanism for the deadline calculation. The seller, based on the FL rules, reasons at the beginning of the transaction in order to decide the maximum BG participation time. Our model becomes quite efficient as the seller operates using knowledge expressed by human experts. For instance, in the 6th row of Table 1, one can see that, there is a large difference in the calculation of T_s compared with that of [14]. Without the use of FL, the seller would determine the value of a based on the sharp / *crisp* boundaries of a. If the value of a is defined equal to 20, or even 100, the T_s is calculated as 12, or 25, respectively. In that case, if the seller adopts the FL reasoning, the result for the a value is 588 and, thus, T_s is equal to 56. This means that, for the specific values of ε and q, the seller should stay in the BG for more time trying to attain profit.

Another important characteristic of our model is that, the seller is capable of changing its deadline for different products and intended profit. Rows 1 and 3 of Table 1 present such an example. For a very popular product, the seller chooses, in the 1st row, to stay more in the BG due to smaller pursued profit. This means that, the seller wants to assure that, it will gain some profit from the transaction. In the 3rd row, the seller aims to challenge the buyer by suddenly decreasing its offers. This can be done due to the higher pursued profit. From the above examples, it is reasonable that, there is a real-time adaptation to the parameters of each BG. The seller plays a number of BGs with potential buyers. At the beginning of every BG, the seller, based on the popularity of the requested product and the profit that it wants to attain for that specific product, determines the time limit for which the seller will stay in the BG.

Two very interesting cases are depicted in Table 2. The entries of the table show that our fuzzy mechanism indicates smaller deadline than in cases where we use crisp values for the definition of parameter α. We can see that by using a value for α equal to 50 for the specific products the deadline is calculated as 10 and 13 respectively. However, based on the fuzzy rules the seller should define its deadline equal to 7 and 9 in contrast to the above mentioned values. Hence, the seller for these two products should stay less in the game and the use of large crisp value for α could be a wrong decision.

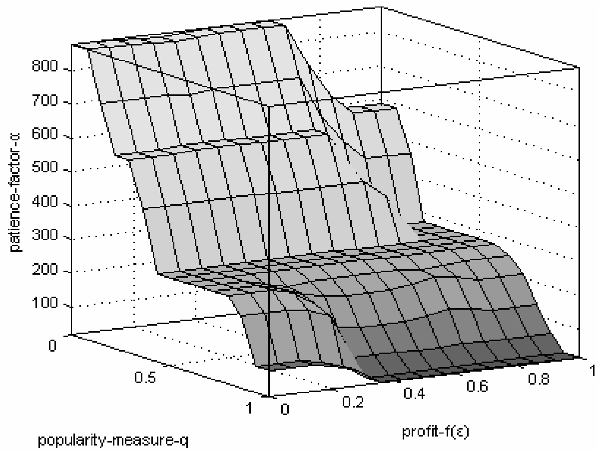

Fig. 6. The inference surface for the scaling factor α.

7. Conclusions

In this paper, we propose a FL-based approach for the deadline calculation of a seller agent bargaining in IMs. We describe the BG and present the behavior of the seller. The seller proposes prices for a specific number of rounds based on a certain policy. This policy refers to the patience exhibited by the seller. A patient seller should stay in the BG as long as possible. An impatient seller tries to sell the product as soon as possible by rapidly decreasing its prices.

The policy of the seller is implied by a scaling factor α. We describe a fuzzy model and the corresponding reasoning mechanism for the determination of a, and thus, the calculation of the BG participation deadline. The value of a is affected by the popularity ranking of the product in the cache and the initial intended profit. The seller should reason at the beginning of the BG and decide the time limit for which it will participate in the BG proposing prices to the interested buyer.

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