Automated Negotiations between Intelligent Entities Participating in Electronic Markets

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Abstract. Automated negotiations comprise an interesting research domain for many years. A scenario, mostly depicting real life negotiations, defines that entities act under no knowledge on the characteristics of the rest of them. This means that their behavior should incorporate mechanisms for handling uncertainty imposed by the lack of knowledge as well as intelligent methods for modelling every aspect of the discussed scenario. In this thesis, we adopt computational intelligence techniques in order to propose efficient mechanisms for the definition of the behavior of entities participating in Electronic Markets. We cover the entire framework defined in a marketplace by proposing methodologies for the definition of basic parameters together with decision making models. We take into consideration the uncertainty in such scenarios in combination with profit maximization. The proposed models are based on Fuzzy Logic, Swarm Intelligence, Optimal Stopping Theory and Machine Learning techniques. We describe methods for the selection of middle entities and products. We utilize Quality of Service parameters in order to increase the efficiency of the proposed models. We study negotiations between one buyer and one seller as well as concurrent negotiations between a buyer and multiple sellers.

Keywords. Negotiations, Fuzzy Logic, Prediction, Neural Networks, Swarm Intelligence, Optimal Stopping Theory

1 Dissertation Summary

Nowadays, users are confronted with a huge amount of information resources. Apart from information, users are able to find and purchase a very large number of products. Providers can find new ways to reach customers in an open and dynamic environment such as Web. However, a number of difficulties are present in purchasing products. The first is the number of product resources. It is out of human capabilities to find and navigate in a huge amount of Web stores. Moreover, it is very difficult for users: a) to collect the necessary information for various products, and b) to identi-

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fy providers' intentions. For example, customers cannot be aware of the providers' pricing strategies. Therefore, customers should spend a lot of time and effort in order to conclude successful transactions.

The solution to the above mentioned problems can be the combination of the intelligent agent technology with Electronic Markets (EMs). An Intelligent Agent (IA) is a software or hardware component capable of acting in order to accomplish the tasks delegated by its owner. EMs are virtual environments where a set of entities try to agree upon the exchange of goods. Usually, there are groups of market members such as: the buyers, the sellers and members that are in the middle between them helping in their tasks. Buyers aim to buy products while sellers offer a number of specific products. Middle entities deal with administration or mediation tasks.

In this dissertation, we focus on modelling the behavior of entities as well as on the negotiation between them. The interaction between autonomous entities for exchanging offers with the final objective of dealing for purchases can be defined as negotiation. Usually, in negotiations, entities are selfish and try to maximize their profit. Negotiations could be either single (bilateral) or concurrent (multi-lateral). Bilateral negotiations are related to the negotiation between a buyer and a seller. The negotiation could involve either a single issue (product characteristic) or multiple issues (e.g., price, delivery time, etc). Finally, a negotiation could involve a complete or an incomplete information setting related to the knowledge of the opponent characteristics (e.g., deadline, pricing strategy, etc).

A number of research efforts focus on the discussed domain. The majority of them are based on Game Theory while others adopt Fuzzy Logic. Both of them are used for defining various parameters of the negotiation. However, the proposed approaches have a number of disadvantages. For example, game theoretic models require the definition of players' strategies and, in many cases, assume common knowledge of some of the characteristics of players (e.g., deadlines distribution). Additionally, fuzzy logic schemes are based on a specific rule base that describes the actions followed at every round. The following list summarizes the use of fuzzy logic in negotiations:

- for evaluating the difference of issues values or the attributes of each offer or specific constraints in successive rounds of the negotiation.
- for predicting the reservation prices (e.g., upper – lower acceptable price) of the opponent.
- for deciding the appropriate action at every round of the negotiation.
- for evaluating the satisfaction level that an offer produces in the players' decision mechanism.

In this thesis, we deal with a number of open issues in negotiations. These issues are:

- The efficient definition of specific behavior parameters for each player.
- The definition of the equilibrium path under no knowledge on the players' characteristics.
- The definition of an efficient decision making mechanism to be used by the buyer and the seller.

- The definition of an efficient mechanism for selecting the appropriate products and middle entities.
- The definition of an efficient trust framework to be used in dynamic environments like EMs.

In the above listed issues, we propose specific methodologies and models. Computational Intelligence techniques can provide the basis for solving problems arising when entities interact with each other. A real life scenario defines that entities have no knowledge on the characteristics of other entities also involved in the EM setup. We adopt computational intelligence techniques in order to propose efficient mechanisms for the definition of the behavior of entities participating in EMs. We cover the entire framework defined in a marketplace by proposing methodologies for the definition of basic parameters together with decision making models at every step of the negotiation. We take into consideration the uncertainty in such scenarios in combination with profit maximization. We propose decision making models that are based on different aspects of the discussed scenario in order to reveal the optimal one. We cover the research gap by proposing an efficient decision making mechanism, for the buyer [3] and the seller side, based on fuzzy logic [9] and utilizing a number of parameters (instead of using a limited number as research efforts found in the literature).

We describe methods for the selection of middle entities [4] and products [5]. The proposed methods result the appropriate middle entity or product that best matches the buyers' needs. We utilize Quality of Service parameters in order to increase the efficiency of the proposed model. We study negotiations between one buyer and one seller as well as concurrent negotiations between a buyer and multiple sellers. In the first case, we rely on the game theory principles with the objective to provide a model that maximizes the expected profit. For the second case, we rely on Swarm Intelligence theory in order to have a framework where threads, used by the buyer, converge to the best solution (the best agreement) through a team work. Additionally, Optimal Stopping Theory gives us the tool to change the view of the problem. Based on Optimal Stopping Theory, we propose models trying to find the best time to take a decision instead of finding the best action as the response to the opponent move.

Finally, we propose a technique for defining the trust level of entities [11]. The reason is that our scenario involves an open and very dynamic environment like EMs. The trust level of an entity affects the decision taken by the rest of them for their involvement in negotiations with her. If the entity is very trusted, then the risk of negotiations with an unknown entity (we are not sure that the entity is going to offer what is promoting) is eliminated. From the above, we see that we try to cover all the aspects of negotiations starting from the selection of entities to negotiate with, to decision making mechanisms. We reveal the problems in the specific research area and propose specific solutions.

2 Results and Discussion

2.1 Negotiation Setup

At every round of the negotiation, the involved entities propose a specific price to the opponent. Should this price be accepted, the negotiation ends with an agreement and specific profit for both parties. The seller starts first and the buyer follows if the proposed offer is rejected. If a player is not satisfied with the offer then she has the right to reject it and issue a counter-proposal. If an agreement is reached then the negotiation ends with profit for both parties. A conflict leads to zero profit for both.

In this interaction, there are two factors that affect the decision making of the entities. The first factor is the seller's cost and the second one is the buyer's valuation about the product. The proposed offers have a lower limit defined by the cost (seller side). The buyer has a specific valuation about the product and is not willing to pay more than this value. Evidently, only in the case where the seller's cost is smaller than the buyer's valuation an agreement can be reached. However, the two players do not know if this pre-condition holds true. Finally, there is a specific time horizon for the negotiation [10]. The buyer has a specific deadline posed by her owner while the seller calculates her deadline as discussed in [7, 8]. If one of the deadlines expires and no agreement is reached till then the negotiation ends with a conflict.

The characteristics of the buyer are: the *valuation* about the product (V), the *discount factor* (δ_b), the *utility function* (U_b), the *deadline* (T_b) and the *pricing strategy* (p_b). On every round, she proposes a price according to the following pricing strategy:

$$p_b(i) = p_0 + \left(V - p_0\right) \cdot \left(i \cdot T_b^{-1}\right)^k \tag{1}$$

where p_0 is the first proposed price (usually it is a very small price) and i is the current round. The parameter k defines the strategy and could be: patient, aggressive, neutral.

The seller negotiates for a number of products with a number of buyers. It is of high importance to note that the buyer is not aware of any of the seller's characteristics. The characteristics of the seller are: the product *cost* (c), the *discount factor* (δ_s), the *utility function* (U_s), the *deadline* (T_s), the intended *profit* (ε) and the *pricing strategy* (p_s). Usually, the seller starts by proposing a large price which equals to c + ε and according to her strategy she can reduce the offers as the negotiation progresses. Furthermore, she can change the strategy at every negotiation round. There can be four types of sellers: a) *neutral*, b) *patient*, c) *impatient* and d) sellers that change the strategy at every round (*mixed behavior*). These strategies are reflected by:

$$p_s(i) = c + \varepsilon \cdot (1 - i \cdot T_s^{-1})^k \tag{2}$$

where i is the round index. The parameter k denotes the policy of the seller. An aggressive seller wants to conclude the negotiation process as soon as possible. Following this strategy, her intention is to quickly reduce her prices in order to challenge the buyer to accept her offers. For this, we propose the strategy defined in [8]. The proposed pricing function fully adapts the resulting values to the product characteristics. The goods, available at the seller, are ranked according to their popularity. We can defined the product popularity based on Zipf's Law. The proposed pricing strategy is:

$$p_S(i) = \frac{\varepsilon}{i^{q+1}} + c \tag{3}$$

where q is the popularity measure. The described pricing function indicates a very aggressive seller that tries to conclude as many transactions as she can in a certain period of time. Based on the above described strategy, we adopt the deadline calculation process proposed in [6, 7, 8]. The seller deadline is calculated as follows:

$$T_s \approx (\alpha \cdot \varepsilon \cdot (q+1))^{\frac{1}{q+2}} \tag{4}$$

where α is a scaling factor which depends on the seller's strategy. If the seller follows a patient policy the α factor assumes a relatively high value.

In [7], we present a fuzzy logic system for the derivation of the α value. The proposed system is based on parameters q, ε and the final result is the value of α. For each parameter, specific linguistic values are defined $A_1 = A_2 = B_1$ {low, medium, high} as well as the corresponding trapezoidal fuzzy sets. Concerning the scaling factor α, 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, thus, participating in only a few negotiation rounds and *very high a* denotes that, the seller is a very patient player. The strategy of the seller is mapped into a set of fuzzy rules in order for the seller to estimate / calculate the time limit *a* for the specific negotiation with a specific buyer. Finally, in [6], we propose the automatic fuzzy rules generation from data provided by experts. The proposed methodology is simple, yet, efficient as experiments show.

2.2 Sequential Equilibrium Definition

The outcome of the negotiation mainly depends on two issues: a) the players' deadlines, and, b) the players' strategies. However, as no knowledge is present, players should predict both issues based on the offers made in order to take the most appropriate decision. Let us examine first the prediction of deadlines. We describe the buyer side. A similar approach stands for the seller side. We consider that the buyer could adopt a Uniform distribution for the seller deadline estimation:

$$P(t \le T_S \le t + \Delta_t, \Delta_t \to 0) = \frac{1}{t_{max}}, \text{if } 0 < t < t_{max} \tag{5}$$

where $P(t \le T_S \le t + \Delta_t, \Delta_t \to 0)$ represents the probability that the seller deadline is equal to t. If $t \ge t_{max}$, we consider that the probability of the seller deadline expiration is equal to 1. For the pricing strategy distribution estimation, we adopt the known Kernel Density Estimation (KDE) methodology. KDE is a methodology for estimating the PDF of an unknown distribution. The Kernel estimator of this distribution is defined by the following equation:

$$\hat{f}_h(x) = \frac{1}{N \cdot h} \sum_{i=1}^{N} K\left(\frac{x - x_i}{h}\right) \tag{6}$$

where x is the examined variable, N is the sample's size, h is the bandwidth of the kernel and K(·) is the Kernel function. In our model, we use the Gaussian function and, thus, the probability distribution of the seller pricing strategy can be given by:

$$P(x) = \frac{1}{N \cdot h} \cdot \sum_{i=1}^{N} K\left(\frac{x - p_{si}}{h}\right) \tag{7}$$

In our scenario, without loss of generality and for simplicity in our calculations, we take the bandwidth equal to 1. Thus, Equation (7) is transformed to the following:

$$P(x) = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{1}{\sqrt{2 \cdot \pi}} \cdot e^{-\frac{(x - p_{si})^2}{2}} \tag{8}$$

In the above equations, p_{si} depicts the seller price proposed at every round of the negotiation. Based on the above analysis, we take the cumulative distribution function of the seller pricing strategy:

$$CDF(x) = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{1}{2} \cdot \left(1 + erf\left(\frac{x - p_{si}}{\sqrt{2}}\right)\right) \tag{9}$$

Definition: *After an offer made by the seller, the buyer decides on the next action to be taken based on:*

$$D_b^t(p_s^t, V, t) = \begin{cases} \text{Accept}, & \text{if } [[(T_s = t) \text{ or } (T_s = t+1)] \text{ and } (p_s^t \le V)] \text{ or } [U_b(p_s^t) \ge U_b(p_b^t)] \\ \text{Defect} & \text{if } [(T_b = t) \text{ or } (T_b = t+1)] \text{ and } (p_s^t > V) \\ \text{Reject and Propose} & \text{otherwise} \end{cases} \tag{10}$$

The utility that the buyer gains at round t of the negotiation process is given by the following equation:

$$\delta_b^{t-1} \cdot U_b^t \cdot P(accept) \tag{11}$$

Where P(accept) represents the probability that the buyer accepts the seller offer. Based on the KDE methodology, we can make the following proposition:

Proposition: *For the negotiation model described in (10) there is a strategy combination which satisfies the sequential equilibrium. If the buyer adopts a Uniform distribution for estimating the seller deadline and the KDE for estimating the seller pricing strategy the buyer should reject the seller's offers at every round of the negotiation and accept only when:*

$$p_s^t \le \begin{cases} V - \dfrac{t_{max} \cdot (V - p_b^t) \cdot z'}{2 \cdot z + z' \cdot t_{max} - 2 \cdot z \cdot z'}, & \text{if } t < t_{max} \\ V - \dfrac{(V - p_b^t) \cdot z'}{2 \cdot z + z' - 2 \cdot z \cdot z'}, & \text{if } t \ge t_{max} \end{cases} \tag{12}$$

with

$$z = \sum_{i=1}^{N} \frac{1}{2} \cdot \left(1 + \sqrt{1 - e^{-Q \cdot \frac{\frac{4}{\pi} + a \cdot Q}{1 + a \cdot Q}}} \right) \quad Q = \frac{(V - p_{si})^2}{2} \tag{13}$$

$$z' = \sum_{i=1}^{N} \frac{1}{2} \cdot \left(1 + \sqrt{1 - e^{-W \cdot \frac{\frac{4}{\pi} + a \cdot W}{1 + a \cdot W}}} \right) \quad W = \frac{(p_b^t - p_{si})^2}{2} \tag{14}$$

and N is the number of seller proposals till the current round.

2.3 Seller Decision Making Mechanism

In the seller side, we also propose a decision making mechanism based on fuzzy logic. The proposed mechanism is used at every round in which the buyer proposes a price. The decision refers to whether the seller should accept or reject the proposed offer. The decision is based on the *Acceptance Degree* (AD) which shows when the seller should accept the buyer’s offer and depends on the following parameters: a) the *time difference* between the current time of the negotiation and the seller’s deadline (t), b) the *belief* about the expiration of the buyer’s deadline (b), c) the absolute value of the *price difference* between the buyer’s proposal and the upcoming seller’s offer (d), and, d) the *number of buyers* waiting/interacting for/with the seller (N). For the reasoning process, an input to the fuzzy system might be described as: a round which has increased time difference with the deadline T_s is represented by the value high ($l(u_i)$ = High), medium difference ($l(u_i)$ = Medium) or low difference ($l(u_i)$ = Low) where u_i = the time difference between the current round and the deadline of the seller. The same rationale stands for the remaining parameters. The form of the rules is:

R_j : If t is $A_{1(j)}$ AND b is $A_{2(j)}$ AND d is $A_{3(j)}$ AND N is $A_{4(j)}$ Then AD 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 AD, respectively. The linguistic expressions of the values for the parameters t, b, d, N and AD are defined in the sets $A_1 = A_2 = A_3 = A_4 = B_1$ {Low, Medium, High} and we use for them trapezoidal fuzzy sets. We consider three sigmoid functions for parameters t, d, and N in order to produce values in the range [0,1]. Concerning the acceptance degree AD, *Low AD* indicates that the seller should not accept the buyer’s proposal and make a counter offer, a *Medium* and *High AD* indicates a neutral and positive attitude to the buyer’s offer. Specially, a high AD value means that the seller should accept the buyer’s proposal and conclude the negotiation before the expiration of her deadline. Finally, the strategy of the seller can be mapped into a set of fuzzy rules in order for the seller to decide if she will accept or reject the buyer’s offer. Rules are defined by experts.

2.4 Buyer Decision Making Mechanism

In this section, we focus on the buyer side and shortly describe the reasoning mechanism adopted by her in order to decide on the acceptance or rejection of a seller's offer [3]. We developed a fuzzy logic system, which determines the buyer's reaction to the seller's proposals. We define as *Acceptance Degree* (AD) the capability of the buyer to accept the seller's offer. The AD parameter reflects the willingness of the buyer to accept the price for a product offered by the seller hoping to maximize her utility. High AD degree indicates that the buyer accepts the seller's offer and concludes the negotiation. Specifically, the *AD* degree depends on the following parameters: a) the *relevance factor* (r) which shows to which extend the product corresponds to the buyer's needs, b) the absolute value of the *price difference* (d) between the seller's proposal and the upcoming buyer's offer, c) the *belief* (b) about the expiration of the seller's deadline, d) the *time difference* (t) between the current time of the negotiation and the buyer's deadline, and, e) the buyer's *valuation* (V) about the product. The system relies on a rule base for inference. We adopt the multi-input single-output (MISO) form of the linguistic rule R_j, with $r = u_1$, $d = u_2$, $b = u_3$, $t = u_4$, $V = u_5$ and $y = AD$, that is,

R_j : If r is $A_{1(j)}$ AND d is $A_{2(j)}$ AND b is $A_{3(j)}$ AND t is $A_{4(j)}$ AND V is $A_{5(j)}$ Then AD is $B_{(j)}$.

where $A_{i(j)}$ and $B_{(j)}$ are the fuzzy sets representing the j^{th} linguistic value for the input parameter i and for the output parameter AD, respectively. The system involves a three-step process: a) the fuzzification step transforms the input parameter-values into fuzzy subsets, b) using the fuzzy rule base an inference takes place for the output value (fuzzified AD), and c) the defuzzification process converts the output of the fuzzy inference into the crisp outputs for the parameter AD. For the defuzzification process, we use the *Center-of-Gravity* (COG) approach. The linguistic expressions of the values of the parameters r, d, b, t, V and AD are defined in the sets $A_1 = A_2 = A_3 = A_4 = A_5 = B_1 = \{low, medium, high\}$ while we utilize trapezoidal fuzzy for each of them. Specifically, a linguistic value of *low r* indicates that, the relevance of the product with the buyer's needs is low. A linguistic value of *medium r* denotes that, the relevance of the product is medium and a linguistic value of *high r* indicates that the product has increased relevance with the buyer's needs. For a more fine-grained resolution of the linguistic values of *r*, we use the linguistic modifier very: $very(\mu(r)) = \mu(r)^2$. We adopt three sigmoid functions in the range [0, 1] for parameters *d*, *t*, and *V*. Concerning the AD, a fuzzy value of *low AD* indicates that, the buyer should not accept the seller's proposal while a *medium* and a *high* value of *AD* indicate a neutral and positive attitude to the seller's offer respectively. Through the fuzzy rule-base, we imitate the human behavior when acting in a trading environment with no information on the characteristics of the other party (i.e., the seller). Our system contains ten fuzzy rules, which are defined by experts on the e-commerce domain. Our results (Table 1) show an increased utility value better than those reported in the literature (maximum value is to 0.9 with the vast majority to be equal to 0.6).

We extend the proposed fuzzy system and propose and adaptive mechanism for the buyer side [2]. The adaptive mechanism of the buyer consists of two parts: a) the *seller price predictor*, and, b) the *fuzzy controller*. The price predictor is responsible for estimating the upcoming seller proposal. The fuzzy controller receives the estimation *error* and the *error change* at every round and produces the appropriate values for basic parameters of the buyer strategy such as the *belief (b)* and the *pricing policy (k)*. Belief shows how much the buyer beliefs that the negotiation ends at the upcoming round while the pricing policy influences the upcoming buyer price.

The seller price predictor should be objective and efficient. For this reason, we use three sub-predictors: A *linear*, a *polynomial* and a *neural network predictor*. The values provided by these predictors can be linearly combined in order to produce the final predicted price. The final predicted price is used in a fuzzy controller in order to obtain two important parameters: the buyer *pricing policy factor* and the buyer *belief* about the intentions and the deadline of the seller. In Fig. 1, we compare the performance of the 'simple' fuzzy system with the adaptive system. Both of them are compared with an optimal stopping model. We see that the agreement percentage is at the same level as well as the steps required for an agreement. However, the adaptive model achieves better agreement price compared to a theoretical optimal model.

Finally, we propose a scheme for the automatic generation of the fuzzy rule base [5]. Based on the proposed scheme, the fuzzy rule base is extracted by a number of crisp values defining the behavior of the buyer. The discussed process is more efficient as we do not need experts to define specific rules that are very difficult to cover all the aspects of a negotiation.

Table 1. Average intrinsic utility for the proposed fuzzy system.

V	Average Intrinsic Utility
5	0.70
20	0.84
50	0.95
80	0.97
100	0.95
150	0.98
200	0.97

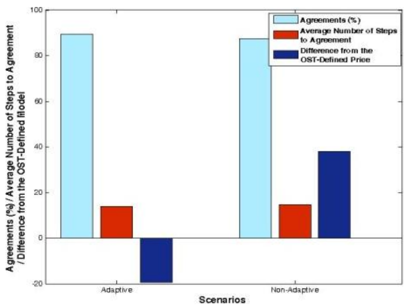

Fig. 1. Comparison between the 'simple' fuzzy system and the adaptive case.

2.5 Selection of Products

We extend the work presented in [2, 3] and provide a methodology for defining the product *relevance factor (r)* [1]. The proposed methodology is based on the buyer request description and the product description. The buyer request can be described by: a) the context, b) the description of the desired product by using a set of keywords or simple sentences and c) a set of constraints. At the seller side, we adopt a similar approach for product description. Thus, a product description could be defined by: a) the context, b) the description by using simple sentences and c) a set of attributes. Every attribute has a name and a value.

The proposed methodology is based on the use of similarity algorithms. We choose to utilize linguistic similarity as semantic techniques require more time and resources. In order to have efficiency, we utilize a large number (16) of similarity algorithms. By using so many algorithms, we aim to avoid extreme results (e.g., very pessimistic or very optimistic). Every time we obtain the algorithms results, we calculate the values variance. If the variance is over a pre-defined threshold, we reject the minimum and the maximum value from those 16 similarity values. The final similarity value is the average of the results. It should be noted that in case where the variance is over the threshold we can reject the first and the last two values from the ranked list of algorithms' values. The developer can choose the scenario that best matches to her needs. We apply the similarity measure on the product context (request / demand) and the product description. The request context is matched against the seller product context and the request keywords are matched against the seller product description. The same process is applied for matching constraints with attributes. If the request context matches to the product context, we obtain two results: (a) keywords similarity (kFactor), and, (b) constraints similarity (cFactor). Furthermore, we combine those results with results concerning the QoS characteristics of the product. The final relevance factor value could be calculated by following a '*hard'* or a '*soft'* approach. Based on '*hard'* approach the relevance factor is calculated by the following equation:

$$r = \mathrm{kFactor} \cdot \mathrm{cFactor} \cdot \mathrm{QoSFactor} \tag{16}$$

where:

$$\mathrm{kFactor} = \frac{k}{|\,\mathrm{keywords}\,|} \qquad \mathrm{cFactor} = \frac{c}{|\,\mathrm{constraints}\,|} \tag{17}$$

with the number of successful matches for keywords and c is the number of successful matches for constraints. Symbols | | depict the number of keywords/constraints. QoSFactor calculation is based on price, delivery time and seller trust. Following the '*hard'* approach, the buyer is very pessimistic in characterizing a product as relevant to her goals. Following the '*soft'* approach in the calculation process, the relevance factor could be calculated through the following equation:

$$r = w_1 \cdot \mathrm{kFactor} + w_2 \cdot \mathrm{cFactor} + w_3 \cdot \mathrm{QoSFactor} \tag{18}$$

2.6 Concurrent Negotiations

In concurrent negotiations, the buyer could negotiate with a number of sellers trying to achieve the best agreement. For this, she is based on a number of threads. We propose a model that utilizes the Particle Swarm Optimization (PSO) algorithm in order to reach to the best solution (best agreement price). Each buyer thread can be considered as particle in the PSO algorithm. They should converge to the optimal solution which is the best price for the specific group of sellers.

The buyer will accept offers that are below her valuation. Each particle initially defines its own pricing strategy. The buyer threads follow the equilibrium path. All the buyer threads have the same deadline. Each particle negotiates autonomously with a specific seller. If an agreement is "reached" then the specific thread sends the agreement message to the rest of them. We consider that the communication time is negligible. The personal best position is the smallest price for which each particle negotiates with the seller. The global best is the smallest agreement price defined in a negotiation. The global best is defined when an agreement takes place. If no agreement is present then all the particles have velocity equal to 0 and continue to propose prices according to the pricing strategy. If a particle does not have an agreement and receives an agreement message from another particle then it switches its state and: a) if her current negotiated price is smallest than the global best, she remains at the current status or b) if the global best is smaller than current negotiated price, she changes the pricing strategy in order to reach the global best position. Particles velocity is defined when particles want to change their position (an agreement was "announced" in a better price). The velocity is initially calculated when an agreement is announced and for every round after that. If the global best is not smaller than the current price the velocity is set equal to 0 or else the velocity is calculated by the PSO algorithm. The velocity affects the pricing strategy and the proposed by the buyer price respectively.

3 Conclusions

The interaction between autonomous entities in dynamic environments (such as EMs) is a very interesting research issue. In this thesis, we present decision making mechanisms for the buyer and the seller side. The mechanism utilizes fuzzy logic that is appropriate for handling uncertainty. We also propose models for choosing the most appropriate product in the buyer side while we analyze the equilibrium path for the negotiation process with a seller. Moreover, we propose a prediction mechanism for the seller pricing strategy. The prediction engine in combination with the negotiation parameters provides the necessary information for the buyer to adapt her behavior. Additionally, we study concurrent negotiations and propose the use of the PSO algorithm. The advantage is that buyer threads through a team work find the optimal solution. The difference of our work from the efforts found in the literature is that we do not any coordination between threads. Experimental results show increased number of agreements in combination with the increased utility for both parties. The fuzzy logic system is proved to be very efficient for both the buyer and the seller.

References

1. Kostas Kolomvatsos, and Stathes Hadjiefthymiades, ‘An Extended Q-Gram Algorithm for Calculating the Relevance Factor of Products in Electronic Marketplaces’, accepted for publication in *Elsevier Electronic Commerce Research and Applications (ECRA)*, 2013.
2. Kostas Kolomvatsos and Stathes Hadjiefthymiades, 'Buyer Behavior Adaptation Based on a Fuzzy Logic Controller and Prediction Techniques', *Elsevier Fuzzy Sets and Systems (FSS)*, February 2012, pp. 30-52.
3. Kostas Kolomvatsos, Christos Anagnostopoulos, and Stathes Hadjiefthymiades, 'A Fuzzy Logic for Bargaining in Information Markets', *ACM Transactions on Intelligent Systems and Technology (ACM TIST)*, February 2012, vol. 3(2), pp. art. No 32.
4. George Boulougaris, Kostas Kolomvatsos, and Stathes Hadjiefthymiades, 'Building the Knowledge Base of a Buyer Agent Using Reinforcement Learning Techniques', In Proc. of the *2010 IEEE World Congress on Computational Intelligence (WCCI 2010), IJCNN*, July 18th - 23rd, Barcelona, Spain, pp. 1166-1173.
5. Roi Arapoglou, Kostas Kolomvatsos, and Stathes Hadjiefthymiades, 'Buyer Agent Decision Process Based on Automatic Fuzzy Rules Generation Methods', In Proc. of the *2010 IEEE World Congress on Computational Intelligence (WCCI 2010), FUZ-IEEE*, July 18th - 23rd, Barcelona, Spain, pp. 856-863.
6. Kostas Kolomvatsos and Stathes Hadjiefthymiades, 'Automatic Fuzzy Rules Generation for the Deadline Calculation of a Seller Agent', In Proc. of the *9th International Symposium on Autonomous Decentralized Systems (ISADS 2009)*, Athens, Greece, March 23-25, 2009, pp. 429-434.
7. Kostas Kolomvatsos, Christos Anagnostopoulos, and Stathes Hadjiefthymiades, 'On The Use of Fuzzy Logic in a Seller Bargaining Game', In Proc. of the *32nd Annual IEEE International Computer Software and Applications Conference (COMPSAC 2008)*, July 28th - August 1st, Turku, Finland, 2008, pp. 184-191.
8. Kostas Kolomvatsos and Stathes Hadjiefthymiades, 'Implicit Deadline Calculation for Seller Agent Bargaining in Information Marketplaces', In Proc. of the *2nd International Conference on Complex, Intelligent and Software Intensive Systems (CISIS 2008)*, March 4th - 7th, Polytechnic University of Catalonia, Barcelona, Spain, 2008, pp. 184-190.
9. Kostas Kolomvatsos and Stathes Hadjiefthymiades, 'On the Use of Fuzzy Logic in Electronic Marketplaces', in the book 'Cross Disciplinary Applications of Artificial Intelligence and Pattern Recognition: Advancing Technologies', ed. Vijay Mago, IGI Global, 2011.
10. Kostas Kolomvatsos and Stathes Hadjiefthymiades, 'Defining Time Constraints for Sellers in Electronic Markets', in the 'Encyclopedia of E-Business Development and Management in the Global Economy', ed. In Lee, IGI Global, 2010.
11. Kostas Kolomvatsos and Stathes Hadjiefthymiades, 'How Can We Trust Agents in Multi-Agent Environments?', Chapter in 'Intelligence Integration in Distributed Knowledge Management', eds D. Krol and N. T. Nguyen, IDEA Group Inc., 2008.