

# Buyer Agent Decision Process Based on Automatic Fuzzy Rules Generation Methods

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**Abstract**— Software Agents can assume the responsibility of finding and negotiating products on behalf of their owners in an electronic marketplace. In such cases, Fuzzy Logic can provide an efficient reasoning mechanism especially for the buyer side. Agents representing buyers can rely on a fuzzy rule base in order to reason for their next action at every round of the interaction process with sellers. In this paper, we describe a model where the buyer builds its fuzzy knowledge base using algorithms for automatic fuzzy rules generation based on data provided by experts and compare a set of such algorithms. Owing to such algorithms, agent developers spend less time and effort for the definition of the underlying rule base. Moreover, the rule base is efficiently created through the use of the dataset indicating the behaviour of the buyer and, thus, representing its line of actions in the electronic marketplace. In our work, we use such algorithms for the definition of the buyer behaviour and we provide critical insides for every algorithm describing their advantages and disadvantages. Moreover, we present numerical results for every basic parameter of the interaction process, such as the time required for the rule base generation, the Joint Utility of the interaction process or the value of the acceptance degree that each algorithm results.

## I. INTRODUCTION

NOWADAYS, due to the rapid evolution of Web, users deal with a huge amount of resources. Hence, they have the opportunity to search, find and purchase a number of products. However, this is a tedious task due to the above mentioned huge amount of shop resources. Users need an automatic way to find products in the Web. Intelligent autonomous software components, such as agents, seem to be the appropriate solution to this problem. Agents are capable of acting autonomously in order to achieve goals defined by their owners. They can undertake the responsibility of finding products in the Web with the minimum users intervention. The most important is that these products are those that best match to the users preferences and needs because intelligent agents have the capability of learning and adapting to their owners needs.

These software components can act in Electronic Markets (EMs) where entities not known in advance can negotiate about the exchange of products. This could be highly advantageous for the product discovery and acquisition. Agents can represent users (buyers) and providers (sellers) in an EM, thus, facilitating the automatic negotiation about the purchase of products. In this paper, we study a buyer-

seller interaction model and focus on the buyer's side. Our model implicates Fuzzy Logic theory [1] for the definition of the buyer knowledge base. This knowledge base consists of an efficient mechanism that yields the buyer decision at every step of the negotiation process. It should be noted, that our model is based on Game Theory (GT) due to the involved negotiation [2]. GT provides an efficient way to describe interactions between entities that try to maximize their profits. More specifically, entities in our model participate in a finite horizon Bargaining Game (BG) with alternating offers [2].

Fuzzy Logic (FL) can enhance the interaction between such entities. It is an algebra based on fuzzy sets [1] providing approximate reasoning mechanisms. FL deals with incomplete or uncertain information and helps at representing the knowledge of agents involved in an EM. Hence, agents can automatically decide during the interaction. An important decision for the buyer is the acceptance or rejection of the seller's proposals during negotiations. We use FL for representing the buyer knowledge and for calculating the Acceptance Degree (AD) of each proposal. The AD is based on important parameters of the interaction process. These parameters are fully described and analysed in the following Sections. Moreover, we study and compare models that are based on the automatic rule base extraction from expert data. In most of fuzzy systems, human experts define and tune the fuzzy rule base. This process requires time, experience and skills. This paper, presents a comparative analysis of a number of algorithms for automatic rule base generation for the specific scenario and we study the impact of each of them in the interaction process (number of agreements, required steps to reach an agreement, etc).

The rest of this paper is organized as follows: Section II reports prior work while in Section III we give the necessary description of the behaviour of a buyer in an Electronic Marketplace scenario. We fully describe the decision process of the buyer based on a fuzzy rule base. Section IV is devoted to the description of the fuzzy controller that results to the appropriate decision for the buyer according to the characteristics of products and the interaction process. In Section V, we describe the techniques used for the automatic generation of the buyer fuzzy rule base. In Sections VI and VII, we conclude the paper by presenting key findings. We give a qualitative as well as statistical comparison of the discussed algorithms when they are used by a buyer.

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## II. RELATED WORK

The automatic negotiation process between autonomous entities was the subject of a number of research efforts. Such architectures have the goal to define effective mechanisms for automatic negotiation between market participants.

Authors in [4] present a BG, which is held between buyers and sellers, describing a set of strategies for both sides. They describe symmetric and asymmetric scenarios concerning the knowledge of the opponent's parameters. A theoretical model regarding player's deadline is presented in [5]. The BG in [5] is between agents and the sequential equilibrium is studied. Authors define the game between two agents, which are of different types and have their own deadlines.

In [6] agents use a decision function at every round of a BG. This function deals with the current and last proposals by the two negotiating agents. Authors define three different strategies for the definition of counter-proposals. In [7], authors define functions for the definition of the proposals in alternating offers interaction and describe a set of tactics.

In [8] a bargaining scenario for agents participating in Information marketplaces is presented. The direct interaction between buyers and sellers is studied. This interaction involves a set of alternating offers for a specific product. Authors describe a mathematical model for the seller's deadline calculation. The authors in [9] describe a fuzzy model for deadline calculation. A set of fuzzy rules are defined according to experts' knowledge.

In [10] and [11], the authors adopt FL in agent systems. Specifically, 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. In [11], authors present the rationale of a fuzzy-based agent negotiating for e-commerce. Inference rules and decision strategies are also described.

The use of FL in Continuous Double Auctions (CDAs) is studied in [12]. The scenario involves the buyer and the seller. Authors present the algorithms used by 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. In [13], the authors adopt clustering algorithms for the automatic generation of a Fuzzy rule base for a seller agent. This rule base yields the deadline that the seller should adopt for a BG between buyers and sellers.

Multi issue negotiation under incomplete information is the subject of the research effort in [14]. Each agent participating in the negotiation builds a multi-dimensional fuzzy satisfaction set for specific attributes of a product. At every interaction step each agent submits an offer. This happens in a simultaneous mode. In [15], intelligent agents' negotiation is studied. Agents prepare offers and evaluate bids aiming at the highest possible profit.

An adaptive bilateral negotiation is studied in [16]. Self interested agents interact in a dynamic environment under time pressure. An algorithm for negotiations is presented that helps agents to adapt their behaviour in the market. It

chooses the optimal policy according to a Markov Decision Process.

In this paper, we try to define a model that imitates human behaviour for negotiations in marketplaces. This behaviour is modelled by a fuzzy rule base. The rule base provides, at every step of the interaction process of the buyer, with the necessary knowledge for the decision. Previous efforts deal with the use of fuzzy logic in such scenarios, however, they are based on specific fuzzy rules defined by the agent developers. The importance of our work is that through the presented algorithms, we indicate the procedure for the automatic rules definition which finally results to the decision process of the buyer. Our approach is characterized by simplicity, because it does not require any special effort for the definition of the fuzzy rule base. The definition of specific If – Then rules by the developers will probably not be efficient in all of the cases that the buyer agent will face in a dynamic environment such as an Electronic Marketplace. Hence, we adopt a scenario where autonomous software components can dynamically decide their actions using a fuzzy rule base created by using clustering or learning techniques based on simple data.

## III. ELECTRONIC MARKETPLACE SCENARIO

Electronic marketplaces can be considered as places where entities not known in advance can negotiate and agree upon the exchange of products. In such places two groups are the basic players: buyers and sellers. Buyers are entities seeking for products while sellers have a number of products in their property and try to sell them in the most profitable price. All of these entities can be represented by intelligent agents.

We focus on the direct interaction between buyers and sellers. This interaction can be modelled as a finite-horizon BG under incomplete information as reported in [2]. An entity involved in the BG has absolutely no knowledge about the characteristics of its opponent. 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 a player is not satisfied with the proposed offer, it has the right to reject it and issue a counter-proposal. In the case of an agreement, the BG ends with profit for both, or else, a 'conflict' is experienced leading to zero profit for both parties.

We note that, there is a specific time horizon for the BG. Both players have a specific deadline. If one of the deadlines expires and no agreement is reached then the BG ends with a conflict. The detailed description of the BG is beyond the scope of this paper. We focus on the buyer side and model its behaviour in the BG using a fuzzy rule base. Fuzzy rules

are automatically generated by data provided by experts as described in the following sections.

#### A. Buyer Behavior

Buyers play a BG with each seller for the specific time interval  $T_b$ . The buyer has a specific valuation about the product and it is not willing to pay more. The valuation is depicted by the variable  $V$ . Every buyer has classified all the sellers and their products according to their relevance with its interests. Such ranking is based on the descriptions of products. The relevance factor ( $r$ ) could be calculated by trustworthy middle entities or sellers based on a specific methodology imposed by the buyer in order to have an objective view. Moreover, a utility function indicates the buyer profit for specific product prices. A simple utility function for the buyer is defined as follows:

$$U_b = V - p \quad (1)$$

where  $V$  is the buyer valuation and  $p$  is the price of the specific product. This utility function is a linear function indicating that the buyer is neutral about the price of the product. However, we can adopt a more complicated utility function in order to describe a risk aware or risk averse policy of the buyer. Such analysis also falls beyond the scope of the paper.

Finally, there is a discount factor, which indicates that every buyer loses profit as the BG progresses. Specifically, the value of the discount factor indicates the urgency of the buyer to conclude the BG successfully (i.e., with an agreement). The discount factor for buyers is represented by  $\delta_b$ . The buyer knows absolutely nothing about the characteristics of the seller. The buyer's characteristics for the specific BG (product acquisition effort) include: valuation ( $V$ ), discount factor ( $\delta_b$ ), utility function ( $U_b$ ) and its deadline ( $T_b$ ). Moreover, the relevance factor ( $r$ ) of the seller is also known. The buyer wants to buy the product but is not willing to pay more than its valuation. It prefers to pay a high price (smaller than its valuation) rather than gain zero if the BG leads to a conflict. On every even round, it proposes a price according to a pricing function. Such function could be based on a specific distribution and/or be tuned by the buyer's pricing policy. The buyer can be patient (i.e., waits for certain rounds and tries to buy at the smallest possible price) or aggressive (i.e., tries to buy the product as soon as possible). In our model, we adopt the second case. The buyer proposes prices according to the following function:

$$p_t^b = p_0 + V \cdot (x \cdot T_b^{-1})^k \quad (2)$$

In the previous equation,  $p_t^b$  indicates the proposed price at round  $t$ ,  $p_0$  is an initial price,  $V$  is the buyer valuation,  $T_b$  is the buyer's time interval for the specific game,  $x$  is the index of the proposal and  $k$  indicates the buyer's policy. We can discern three policy types. A "patient" policy is followed when  $k$  is greater than 1. The higher the  $k$  is the more patience the buyer demonstrates. This policy describes a

buyer who waits in order to gain larger profits since it proposes low prices. In these cases there is the risk of the expiration of the deadline defined by sellers, thus, leading the BG to conflict. An aggressive policy implies that the buyer proposes high prices from the beginning of the BG in order to reach to an agreement as soon as possible. In these cases, the value of factor  $k$  is smaller than 1. Finally, a neutral (linear) policy is followed by the buyer when  $k$  is equal to 1.

#### B. Buyer Decision Process

At every odd BG round the buyer receives a proposal from the seller. The decision of the buyer can be either 'Accept' or 'Reject'. Rejection means that the buyer chooses to drop the offer and propose a counter offer to the seller. The decision of the buyer is based on a fuzzy rule base which contains a number of rules. The use of a fuzzy rule base offers a lot of advantages in the buyer side. Fuzzy rules are intuitive to us and they mimic the human decision process in accordance with tolerance to imprecise input data and therefore they can produce efficient results. It should be noted that the buyer knows nothing about the seller parameters. This means that the buyer has to discern the seller deadline. Hence, it builds a specific belief about the seller deadline. Finally, the generation of the fuzzy rules is an easy task especially when using automatic generation techniques as we discuss in the following sections.

In this paper, we propose a reasoning mechanism for the buyer adopted in order to decide if it will accept or reject the seller's offer. For this, we developed a Fuzzy Logic System (FLS), which is responsible for defining the buyer's reaction to the seller's proposals. The *Acceptance Degree (AD)* indicates when the buyer should accept the seller's offer and relies on the following parameters: a) the *relevance factor (r)*, which shows to which extent 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 BG and the buyer's deadline, and, e) the buyer's *valuation (V)* about the product.

The rules of the FLS are automatically generated through known techniques such as clustering. The rules generation is based on a set of data provided by experts and imitating human, product buying behavior. An efficient decision framework is, therefore, established for buyer negotiations.

## IV. BUYER FUZZY LOGIC SYSTEM

#### A. Fuzzy Logic Model

FL is appropriate for uncertain or incomplete information handling at the decision making phase. FL principles express human expert knowledge and facilitate the automated interpretation of the results. Allowing a degree of fuzziness at the decision stage makes a buyer more flexible and capable of automatically handling the seller's offers. We exploit FL in order to introduce a fuzzy rule-based system F

capable of adapting the decisions of the buyer to the characteristics of the product and the BG.

A fuzzy logic system  $F$  is a non-linear mapping between  $n$  inputs  $u_i \in U_i, i = 1, \dots, n$  and  $m$  outputs  $y_i \in Y_i, i = 1, \dots, m$ . The general architecture of the Fuzzy Logic System (FLS) is depicted in Fig. 1. The buyer maintains a Knowledge Base (KB) with the necessary information for the determination of the above described parameters. At every interaction round, the buyer receives the proposal of the seller and calculates the values of each parameter. These values are used by the FLS in order to determine the value of the AD. The FLS is a three step process: (a) the fuzzification step transforms the input values into a normalized fuzzy subset, (b) using the fuzzy rule base an inference takes place for the output value, and, (c) the defuzzification process converts the fuzzy conclusions into the crisp outputs for parameter AD.

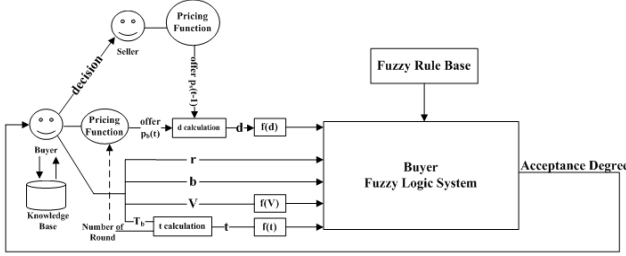


Fig. 1. The buyer FLS.

## B. Fuzzy Rule Base

As discussed in the previous Section, the inference procedure in the fuzzy controller follows a rule-based approach. There are two main models of inference in Fuzzy Systems. The Mamdani model [17] utilizes rules as the following:

$R_j$ : IF  $x_{1j}$  is  $A_{1j}$  AND/OR  $x_{2j}$  is  $A_{2j}$  AND/OR ... AND/OR  $x_{nj}$  is  $A_{nj}$  THEN  $y_j$  is  $B_j$

where  $R_j$  is the  $j^{\text{th}}$  Fuzzy rule,  $x_{ij}$  ( $i=1 \dots n$ ) is the inputs of the  $j^{\text{th}}$  rule,  $y_j$  is the output of the  $j^{\text{th}}$  rule and  $A_{ij}$  and  $B_j$  are membership functions usually associated by linguistic terms. Takagi-Sugeno model [18] involves the following form of rules:

$R_j$ : IF  $x_{1j}$  is  $A_{1j}$  AND/OR  $x_{2j}$  is  $A_{2j}$  AND/OR ... AND/OR  $x_{nj}$  is  $A_{nj}$  THEN  $y_j = a_{0j} + a_{1j}x_{1j} + a_{2j}x_{2j} + \dots + a_{nj}x_{nj}$

In this form, each rule has fuzzy antecedents and consequents being linear combinations of inputs. Such models allow easier application of learning techniques for their identification from data [19]. In our work, we use clustering techniques for the automatic Takagi-Sugeno like rules generation through data given by experts. This approach does not require special skills and experience. Furthermore, a lot of scenarios can be dealt with in a dynamic environment because the developer only defines a set of number combinations for the input and output parameters and it is not obligated to define specific rules to cover all these cases.

## V. FUZZY RULES GENERATION TECHNIQUES

Machine learning is a part of artificial intelligence. It covers algorithms for making decisions based on data. In our study, we emphasize on unsupervised learning, where we seek how a set of data is structured without previous knowledge (unlabeled data). The algorithms used for automatic fuzzy rules extraction belong to the data clustering methodologies. We shortly describe some of the most known algorithms used in our scenario and discuss the methodology for rules extraction. In this paper, we have used K-means, Fuzzy C-means, Subtractive, and Nearest Neighborhood Clustering algorithms.

Furthermore, except from unsupervised learning techniques, there are two intuitive approaches so as to construct fuzzy rules directly from input data. Such techniques differ from clustering algorithms. In clustering there are several steps of execution which try to optimize metrics such as a cost function. Learning From Examples (LFE) is an easy algorithm for constructing fuzzy rule bases. The algorithm relies on the knowledge of the membership functions. A template of membership functions is provided to the system for every dimension, distinguishing which dimensions needs more precision from others. Modified Learning From Examples (MLFE) is a generalization of LFE. In MLFE, we don't need to make estimations about dimensions and it does not need to have previous knowledge about the membership functions.

### A. K-means Clustering

The K-means clustering algorithm [20] is a simple algorithm that determines data clusters which minimize a cost function. The cost function is:

$$J = \sum_{i=1}^c J_i = \sum_{i=1}^c \left( \sum_{k, x_k \in G_i} \|x_k - c_i\| \right) \quad (3)$$

where  $c$  is the number of clusters,  $G_i$  is the  $i$ -th group,  $x_k$  is the  $k$ -th vector in group  $J_i$ , and  $\| \cdot \|$  represent the Euclidean distance between  $x_k$  and the cluster center  $c_i$ .

The partitioned groups are defined by using a membership matrix depicted by the variable  $U$ . Each element  $u_{ij}$  of this matrix is equal to 1 if the specific  $j$ -th data point  $x_j$  belongs to cluster  $i$ , and 0 otherwise. The element  $u_{ij}$  can be derived as follows:

$$u_{ij} = \begin{cases} 1, & \text{if } \|x_j - c_i\|^2 \leq \|x_j - c_k\|^2 \text{ for each } k \neq i \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

which means that  $x_j$  belongs to group  $i$ , if the  $c_i$  is the closest of all centers. Hence, the optimal center that minimizes equation (3) is:

$$c_i = \frac{1}{|G_i|} \cdot \sum_{k, x_k \in G_i} x_k \quad (5)$$

with:

$$|G_i| = \sum_{j=1}^n u_{ij} \quad (6)$$

### B. Fuzzy C-means (FCM) Clustering

In Fuzzy C-Means algorithm [21] & [22], a point could belong to more than one clusters. The algorithm is based on the minimization of the following function:

$$J_k = \sum_{i=1}^M \sum_{j=1}^C u_{ij}^k \|x_i - c_j\|^2 \quad (7)$$

where  $M$  is the number of data points,  $C$  is the number of cluster centers,  $1 \leq k \leq \infty$ ,  $u_{ij}$  is the membership degree of the  $x_i$  in the cluster  $j$ ,  $x_i$  is the  $i^{\text{th}}$  measured data, and  $c_j$  is the center of each cluster. The membership degree is calculated by:

$$u_{ij} = \left( \frac{\sum_{m=1}^C \left( \frac{\|x_i - c_j\|}{\|x_i - c_m\|} \right)^{\frac{2}{k-1}}}{\sum_{m=1}^C \left( \frac{\|x_i - c_j\|}{\|x_i - c_m\|} \right)^{\frac{2}{k-1}}} \right)^{-1} \quad (8)$$

with

$$c_j = \frac{\sum_{i=1}^M u_{ij}^k \cdot x_i}{\sum_{i=1}^M u_{ij}^k} \quad (9)$$

### C. Subtractive Clustering

In Subtractive clustering [23] every data point is rescaled to  $[0, 1]$ . For each of them, a potential degree  $P_i$  is defined according to its location to all other points. This potential depends on the Euclidean distance between the examined point and all other points. The point with the higher potential becomes the first cluster center and all the potentials for the other points are recalculated. The point with the highest potential becomes the next cluster center. The distance of the new candidate cluster center with all the previously defined cluster centers should fulfil a specific distance condition defined by the algorithm and ensures that cluster centers will have a minimum distance between them. If this condition is true then the point becomes the next cluster center or else it is rejected and its potential is set to 0. The potential degree for each point is calculated by:

$$P_j = \sum_{i=1}^N e^{-a \cdot |x_i - x_j|^2} \quad (10)$$

where

$$a = \frac{\gamma}{r_a} \quad (11)$$

and  $x$  is the data point,  $N$  is the number of points,  $\gamma$  is a variable and  $r_a$  is the cluster radius.

### D. Nearest Neighborhood Clustering (NNC)

The NNC algorithm assigns each point to its nearest neighbor that is clustered if the distance is sufficiently small [25]. NNC can be seen as an agglomerative single link clustering technique. At first the algorithm starts considering each sample as a singleton cluster and at each stage of the

process the closest pair of clusters are merged. After  $N-1$  steps a unique cluster is created through the merged sub-clusters. This process defines a hierarchical tree which can be cut at any level resulting to the desired number of clusters. The most important decision in the discussed process is the desired distance between clusters.

### E. Extracting Fuzzy Rules from Clusters

Clusters, created by the above described algorithms, consist of the main stage to the construction of fuzzy rules that will be the knowledge base of the buyer. Apart from the selected algorithm it is considered that every cluster corresponds to a fuzzy rule. For example, if  $x^*(x_1^*, x_2^*, \dots, x_n^*)$  is a cluster center, then the equivalent fuzzy rule is:

IF  $x_1$  is  $x_1^*$  AND  $x_2$  is  $x_2^*$  ... AND  $x_{n-1}$  is  $x_{n-1}^*$  THEN  $x_n$  is  $x_n^*$

This means that every dimension is also a fuzzy variable. The next step is to find the shape of membership functions for every fuzzy variable for every fuzzy rule. For this purpose, the most common technique is the projection of membership values of data points (belonging to a cluster) in each dimension. However, projection differs in every algorithm.

In FCM, every point belongs to several clusters. So, it has different membership degrees less than 1. The center of each cluster is laid in an area with membership degree  $\approx 1$ . We can approximate this projection by a truncated Gaussian function. Applying this methodology for every cluster, we are able to create the fuzzy rule base. In K-means, the process is different. Due to the fact that every point belongs to a cluster exclusively, a projection will have the form of a crisp set. We have to turn the orthogonal graphic representation into a Gaussian function. This approach results to the loss of data, but it is essential for the fuzzy rule base. In Subtractive clustering, each cluster is thought as a fuzzy rule. The degree of rule is given from the following equation:

$$\mu_i = e^{-a \cdot \|x - c_i\|^2} \quad (12)$$

where  $x$  is an input data applied to a fuzzy rule,  $c_i$  is  $i^{\text{th}}$  cluster center,  $\mu_i$  is the membership degree of  $i^{\text{th}}$  rule, and  $a$  is given by (11). Finally, in NNC, we can derive fuzzy rules from clusters using a distance parameter between clusters depicted by  $e_f$ . Every cluster is considered as a fuzzy rule and the membership functions are Gaussian functions whose dissemination is a constant depicted by  $\sigma$ .

In this point, we describe the methodology that we follow in order to produce fuzzy rules through clusters defined by the above described algorithms. In our scenario we construct MISO (Multi Input Simple Output) fuzzy rules based on the description of the buyer decision process. We choose Takagi-Sugeno fuzzy rules as their extraction does not need extended computational load. In case that a membership function has a wide range over the universe of discourse, i.e. when the dissimilarity measure gets values greater than 0.5,

we eliminate the given fuzzy variable from the fuzzy rule. The reason is simple: a membership function which will give values  $\approx 1$  for every input, makes no sense as it does not produce different results reflecting the position of a point. So it is useless to include in unnecessary computations. Finally, concerning the FCM, we use truncated Gaussian memberships functions as they are cost effective.

#### F. Learning From Examples (LFE) & Modified Learning From Examples (MLFE)

Both methodologies [25] do not belong to the clustering algorithms. In LFE technique, we construct fuzzy rules not only from an input set of data points but also from linguistic information. In this algorithm a template for every membership function is defined and accordingly based on an iterative process each data point is examined in order to create a new fuzzy rule. Moreover, a point can belong to an existing fuzzy rule. A point has a number of dimensions. For each dimension, we consider the point coordinate in order to compute a value (the membership degree) for all the membership functions and we choose the maximum one. As a result a data point creates a fuzzy rule because we have chosen for every membership variable (in the antecedent or the consequent part) the “most appropriate” membership function. On the other hand, it is possible that a point can create an existing fuzzy rule (with the same antecedent part). In this case, no further addition is done at the existing rule base.

MLFE works in a similar way. However, the most significant difference with the LFE is that MLFE tries on its own to compute the membership functions, without an input template for guiding the rule base construction. Initially, MLFE considers the first data point as if represents a fuzzy rule. Continuing the execution, it applies the next data point to the existing rule base. There, the difference between the result of the rule base and the value of the last coordinate (it is thought as the consequent part) is examined if it is smaller than the distance threshold  $e_f$ . If so, no new rule is added, otherwise, a new rule is derived by estimating the membership functions in order to enter the rule without distorting the previous rule base.

LFE is an easy to implement technique especially when the template of possible membership functions is defined for every dimension. It is a good practice to run first the FCM so as to get the truncated Gaussians functions and accordingly to apply the LFE algorithm. The problem in LFE is that we do not know beforehand which dimension membership functions are narrow and which are not. The results from FCM will give us a general aspect of the input data points. In MLFE there is a significant detail. The points must have unique coordinates. If not so, an assumption is made for the value of the dissimilarity measure.

## VI. RESULTS – COMPARISON OF TECHNIQUES

In Table I, we present the time required for the creation of the fuzzy rule base. The FCM requires a lot of time for the

creation of the rule base resulting to increased time for negotiations. The rest of the algorithms are at the same levels with an average of 21 ms. Such time overhead minimally impacts the negotiations between the buyer and the seller.

Concerning the interaction process, we performed simulations for specific values of basic parameters used by the two players. In our experiments, we consider a buyer agent that interacts with a seller agent and tries to successfully conclude a transaction. In this interaction, we define the agreement zone as the difference between the buyer valuation and the seller cost. Actually, this zone represents the possibility of an agreement. A positive zone means that there is a possibility for an agreement and the opposite stands when the zone is negative.

Algorithm	Rule Base creation time (ms)
Subtractive	35
FCM	2560
K-Means	25
LFE	20
MLFE	25
NNC	20

We deal with 8 different agreement zones. By using these zones, we aim to identify the result of the use of the fuzzy rule base defined by each algorithm and how it is used to conclude a transaction. For this, we define that an Acceptance Degree (AD) greater than 70 results to the acceptance of the seller proposal. The buyer proposes prices according to its pricing function defined in equation (2) and the seller produces prices using the following pricing function:

$$p_s^t = c + \varepsilon \cdot (1 - t \cdot T_s^{-1})^k \quad (13)$$

where  $c$  is the seller cost,  $\varepsilon$  is the profit,  $t$  is the current number of the proposal,  $T_s$  is the seller deadline and  $k$  defines its policy. In our case  $k$  is equal to 2 (impatient player).

It should be noted that each player does not know absolutely anything about the opponent’s parameters. Moreover, only the buyer uses the fuzzy rule base produced by the presented methodologies. The values for each parameter are depicted in Table II. The buyer starts from a price equal to 100 MUs and as the negotiation progresses it increases its prices, and the seller starts from a high price (=500 MUs) and during negotiation it decreases them.

Buyer Parameters		Seller Parameters	
Initial Price	100 MUs <sup>1</sup>	Cost	250 MUs
Valuation	255 MUs	Initial Profit	250 MUs

In order to have an objective view of our model, we adopt the normalized Joint Utility (JU) described in [26] and [27] as a measure of the particular interaction process. The JU is defined as follows:

<sup>1</sup> MU = Monetary Unit

$$JU = \frac{(P^* - C) \cdot (V - P^*)}{(V - C)^2} \quad (14)$$

where  $P^*$  is the agreement price,  $C$  is the seller cost and  $V$  is the buyer valuation.

In our experiments, we try to identify how the rule base derived by each methodology is used in the bargaining process. Hence, we use approximately equal deadlines (measured as the maximum number of the proposals for a specific player) for the two players and defined a number of scenarios concerning the agreement zone. The agreement zones used in our simulations are depicted in Table III. We only deal with cases where the agreement zone exists as in [26].

In Table IV, we see the results concerning the average JU for every scenario. Based on equation (14), we take that the theoretic maximum JU is equal to 0.25 [26]. In general, we can claim that the FCM and K-Means algorithms produce a rule base which gives us the maximum JU when the agreement zone is limited. Especially, in the 4<sup>th</sup> scenario the two algorithms reach close to the maximum theoretic JU. The reason is that the rule base produced by the discussed methods is very strict and forces the buyer to reach its deadline under the risk of a conflict. Hence, the buyer rejects the seller proposals at every round till the two proposed prices are very close. Should the agreement zone be extended, the MLFE algorithm produces a more efficient rule base.

TABLE III. THE SEVEN AGREEMENT ZONES

Buyer Valuation	Agreement Zone
255 MUs	5 MUs
260 MUs	10 MUs
270 MUs	20 MUs
300 MUs	50 MUs
500 MUs	250 MUs
700 MUs	450 MUs
1000 MUs	750 MUs

Another important observation is that the JU decreases as the agreement zone are at high levels (750 MUs). The reason is that the buyer valuation is greater than the maximum proposed price by the seller. In such cases (scenario 7), a price that will result the maximum JU should be equal to 650 MU. However, this is not possible because the seller starts its proposals from a price equal to 500 MUs. In cases where the valuation of the buyer is equal to maximum seller proposal (scenario 5) the average JU is close to the maximum theoretic. It should be noted that in [26] and [27] the maximum JU in all experiments was equal to 0.22.

Another interesting result refers to the AD values produced by the fuzzy rule base in each case. These values are defined as the average values for the agreements held in the above described scenarios. We see that FCM and K-Means have an average value below the threshold of 70 for the acceptance of the seller proposal. This means that in some scenarios the rule bases derived by these two algorithms force the buyer to reach its deadline rejecting the seller proposals. This forces the seller to offer smaller prices and the result of the interaction process is beneficial for the buyer. However, this

includes the risk of a conflict especially in cases where the player's deadlines have very large difference. On the other hand, the most 'optimistic' rule base is provided by the Subtractive methodology that results in higher AD values.

TABLE IV. JU RESULTS FOR DIFFERENT AGREEMENT ZONES

Scenario No	Agreement Zone	Average JU	Maximum JU	Algorithm
1	5 MUs	0.08	0.24	FCM, K-Means
2	10 MUs	0.14	0.24	FCM, K-Means
3	20 MUs	0.16	0.21	LFE
4	50 MUs	0.24	0.247	FCM, K-Means
5	250 MUs	0.238	0.24	MLFE
6	450 MUs	0.208	0.21	MLFE
7	750 MUs	0.17	0.172	MLFE

In Table VI, we see the average interaction time required to conclude transactions based on each of the considered algorithms. The FCM algorithm requires the largest average interaction time while the fastest process is held used the K-Means method. However, the computational overhead for using the discussed algorithms is not very high.

TABLE V. AVERAGE AD FOR THE STUDIED ALGORITHMS

Algorithm	Average AD Value
Subtractive	80.96
FCM	68.91
K-Means	62.84
LFE	72.65
MLFE	74.52
NNC	76.58

TABLE VI. AVERAGE INTERACTION TIME FOR ALL SCENARIOS

Algorithm	Average Interaction Time (ms)
Subtractive	523.4
FCM	4817.8
K-Means	434.2
LFE	510.0
MLFE	498.8
NNC	532.1

TABLE VII. AGREEMENTS PERCENTAGE

Algorithm	Agreements Percentage	Average JU
Subtractive	92%	0.217
FCM	69%	0.219
K-Means	69%	0.202
LFE	57%	0.223
MLFE	85%	0.244
NNC	86%	0.244

Finally, in Table VII, we present our results for the agreements that each algorithm achieves as well as the average JU in all these experiments. We take an agreement zone that corresponds to scenario 5 and run experiments for random deadlines for both players. The deadlines were defined as random numbers between 0 and 500. The rest of the parameters are defined as referred above. We observe that the highest number of agreements is achieved by the subtractive algorithm while the lowest number is achieved by the LFE. The highest average JU is achieved by the MLFE and NNC algorithms. This is due to the fact that these two algorithms force the seller to propose smaller prices which leads to smaller agreement prices (Fig. 2). The NNC results to the smallest average agreement price which

is equal to 355.30 MUs. The highest agreement price is obtained by the K-Means algorithm and is equal to 429.66 MUs. In general, the algorithm results to an acceptable number of agreements except in the cases where there is a very large difference in the deadlines of players. In such cases, there is an increased possibility of conflict because each player cannot very easily identify the opponent's deadline due to incomplete knowledge. This problem presents a future extension to our work.

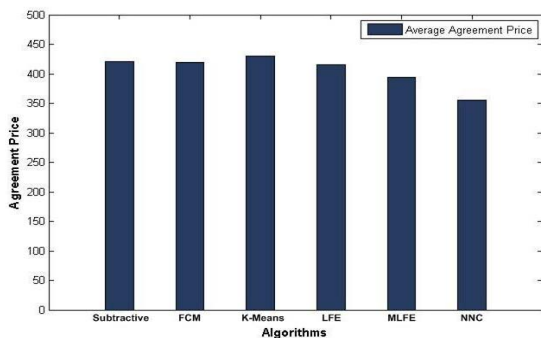


Fig. 2. Average agreement price.

## VII. CONCLUSIONS

In this work, we proposed a FL-approach for the decision process of a buyer agent acting in an electronic marketplace. We describe the behaviour of the buyer which shows when the buyer should accept or reject the seller proposal in the negotiation process. The buyer has a specific valuation for a product and it is not willing to pay more than this. The seller has a specific production cost and it is not willing to sell the product below this price.

We describe a set of algorithms for the automatic generation of the fuzzy rule base of the buyer. We present their characteristics as well as their pros and cons. Based on such algorithms, agent developers spend less time and effort for the definition of the underlying rule base. This production methodology guarantees efficiency in the development of the buyer fuzzy logic system. Finally, we present numerical results for every basic parameter of the interaction process, such as the time required for the rule base generation, the Joint Utility of the interaction process or the value of the acceptance degree that each algorithm results.

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