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UNIVERSITI TEKNOLOGI PETRONAS

FUZZY LOGIC BASED NEGOTIATION IN E-COMMERCE

By

MOUSTAPHA TAHIR ATEIB

The undersigned certify that they have read, and recommend to the Postgraduate Studies Programme for acceptance this thesis for the fullfilment of the requirements for the degree stated.

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FUZZY LOGIC BASED NEGOTIATION IN E-COMMERCE

by

MOUSTAPHA TAHIR ATEIB

A Thesis

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BANDAR SERI ISKANDAR

PERAK

JANUARY 2011

DECLARATION OF THESIS

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To my beloved family

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ABSTRACT

The evolution of multi-agent system (MAS) presents new challenges in computer science and software engineering. A particularly challenging problem is the design of various forms of interaction among agents. Interaction may be aimed at enabling agents to coordinate their activities, cooperate to reach common objectives, or exchange resources to better achieve their individual objectives. This thesis is dealing with negotiation in e-commerce: a process through which multiple self-interested agents can reach agreement over the exchange of scarce resources.

In particular, we present a fuzzy logic-based negotiation approach to automate multi-issue bilateral negotiation in e-marketplaces. In such frameworks issues to negotiate on can be multiple, interrelated, and may not be fixed in advance. Therefore, we use fuzzy inference system to model relations among issues and to allow agents express their preferences on them.

We focus on settings where agents have limited or uncertain information, ruling them out from making optimal decisions. Since agents make decisions based on particular underlying reasons, namely their interests, beliefs then applying logic (by using fuzzy logic) over these reasons can enable agents to refine their decisions and consequently reach better agreements. I refer to this form of negotiation as: Fuzzy logic based negotiation in e-commerce.

The contributions of the thesis begin with the use of fuzzy logic to design a reasoning model through which negotiation tactics and strategy are expressed throughout the process of negotiation. Then, an exploration of the differences between this approach and the more traditional bargaining-based approaches is presented. Strategic issues are then explored and a methodology for designing negotiation strategies is developed. Finally, the applicability of the framework is simulated using MATLAB toolbox.

ABSTRAK

Evolusi sistem multi-agent (MAS) menyajikan cabaran baru dalam ilmu komputer dan kejuruteraan perisian. Masalah khususnya mencabar adalah rekaan pelbagai bentuk interaksi antar agen. Interaksi mungkin bertujuan untuk membolehkan agen untuk menyelaraskan kegiatan mereka, bekerja sama untuk mencapai tujuan bersama, atau sumber-sumber daya pertukaran yang lebih baik mencapai matlamat masing-masing. Penyelidikan ini berkaitan dengan perundingan dalam e-dagang: proses melalui mana agen kepentingan sendiri beberapa dapat mencapai kesepakatan atas pertukaran sumber daya yang langka. Secara khusus, kami menyajikan pendekatan perundingan berasaskan logik fuzzy untuk mengotomatisasi perundingan multi-isu bilateral dalam e-marketplaces. Dalam isu-isu seperti rangka kerja untuk berunding di dapat beberapa, saling berkaitan, dan mungkin tidak ditetapkan sebelumnya. Oleh kerana itu, kami menggunakan sistem inferensi fuzzy untuk model hubungan antara isu-isu dan untuk membolehkan agen mengekspresikan keutamaan mereka pada mereka. Kami fokus pada tatacara di mana agen mempunyai maklumat yang terhad atau tidak pasti, berkuasa mereka dari membuat keputusan yang optimum. Sejak agen membuat keputusan berdasarkan alasan yang mendasari tertentu, iaitu kepentingan mereka, keyakinan kemudian menerapkan logik (dengan menggunakan logik fuzzy) atas alasan-alasan ini boleh memungkinkan agen untuk memperbaiki keputusan mereka dan akibatnya mencapai kesepakatan yang lebih baik. Saya lihat bentuk perundingan sebagai: Logik Fuzzy berasaskan rundingan dalam e-dagang. Sumbangan tesis bermula dengan menggunakan logik fuzzy untuk merancang sebuah model penalaran melalui perundingan taktik dan strategi disajikan selama proses perundingan. Kemudian, sebuah eksplorasi perbezaan antara pendekatan ini dan pendekatan berasaskan tawar-menawar yang lebih tradisional disajikan. Isu strategik ini kemudian dieksplorasi dan metodologi untuk merancang strategi perundingan dibangunkan. Akhirnya, pelaksanaan rangka disimulasikan menggunakan toolbox MATLAB.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

With the advancement of internet technology, business transactions have grown rapidly over the last couple of decade. Today, as the world witnesses growing businesses going online, there has been a tendency about shifting to a complete or automated type of online business activities. Electronic commerce provides efficiency, cost savings, productivity to many business entities. The ongoing improvements in internet technology through reliability, security, higher seeds (broadband) and cheaper costs, has permitted e-business to grow rapidly over the web. E business is now globally flourishing and moving with a remarkable trend. E-business is helping transform business into a network structure thus providing greater value for their products, less costs and access to their customers. E-business brings production and consumption closer and enterprises gain a wider and competitive market while consumers gain more choices and more personalized services [33].

As of today, one of the most significant parts of e-business that businesses have not paid attention and focus to is the automation of negotiation in e-business. That is how to completely automate e-business in a way one can be able to negotiate a deal with a counterpart. There is a need for a more sophisticated automated negotiation in e-business. Negotiation is a critical activity in business transactions. Defined as an interactive process, “negotiation” aims to achieve a mutually beneficial deal for the seller and buyer [31]. Negotiations can be done mutually in e-business, for example using emails, but it is not timely and cost effective. There is a need for automated negotiation process using agent technology to negotiate a solution autonomously for a more efficient and objective result.

Agents are considered to be the new trend of software system and object oriented computing. Currently, they have been used for information retrieval and for offering recommendations such as finding product information, comparing product prices, and offering suggestions on product and services based on customer's interest and preferences [27]. According to Zambonelli and Parunak [12], there exist four main characteristics that stand between the future software systems from traditional ones:

1. *environment*: this designates the context of an environment which can be influenced or being influenced by;
2. *Openness*: this is about the dynamism and decision power a software can acquire
3. *Locality in Control*: this characteristic represents the autonomist and proactive loci control within software system component.
4. *Locality in interaction*: regardless of full connectivity, software system still depends on local (geographical or regional) interaction.

These characteristics have drawn ways for agents to possess a new paradigm – an agent paradigm which offers a powerful set of metaphors, concepts and techniques for conceptualizing, designing, implementing and verifying complex distributed systems [46]. An agent is viewed as an encapsulated computer system that is situated in an environment and is capable of flexible, autonomous action in order to meet its design objectives [32]. Applications of agent technology have ranged from electronic trading and distributed business process management, to air-traffic and industrial control, to health care and patient monitoring, to gaming and interactive entertainment [32; 35].

Agents are highly customizable and personalization enhances interactivity. Agents also interact with other agents to achieve mutually agreeable terms and conditions of a business transaction. However, different types of interaction mechanisms suit different types of environments and applications. Agents are able to and can facilitate information exchange, coordinate activities in a coherent manner, collaborate with other agents to achieve a common goal, and so on. One such type of interaction that is gaining increasing prominence in the agent community is negotiation. The following definition of negotiation, adapted from work on the philosophy of argumentation by [8] suits the objective:

Negotiation is a form of interaction in which a group of agents, with conflicting interests and a desire to cooperate try to come to a mutually acceptable agreement on the division of scarce resources.

Let us have the following illustration in figure1.1 below

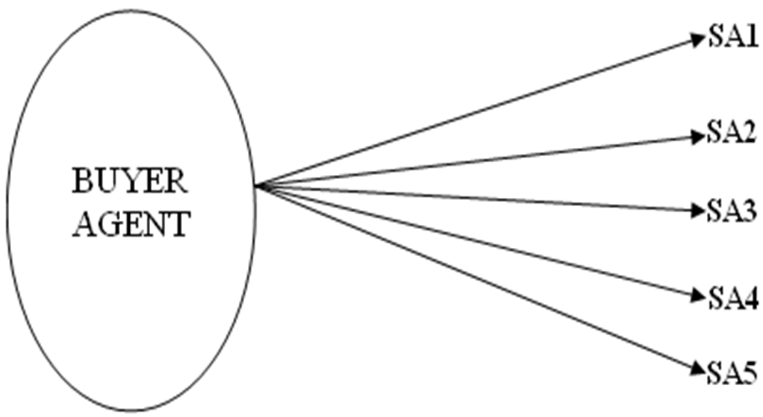


Figure.1 1: Automated Negotiation Scenario

The above figure depicts a software agent (Buyer agent) acting on behalf of a manufacturer in negotiation with various supplier agents (SA), in order to secure the delivery of various components. In this scenario, the negotiation mechanism involves allocating money and commodities (goods/service). Each party aims at making more money, and hence the different commodities suppliers compete over contracts with the buyer. Typical issues that arise in this situation include: What trading mechanism should agents use? What negotiation protocol to use? What happens if a supplier fails to delivery on time, or has produced an excess supply? Do we need some measure of the reliability of different suppliers, and how do we use such measure in making decisions about allocation? And so on.

Beyond these concerned and as an answer to them, there are properties of which designers of negotiation mechanisms aim at. Here are the list of some properties adapted from the work of Rosenschein and Zlotkin [21]:

1. *Simplicity*: A mechanism property that asks for less computational processing and communication overhead.

2. *Efficiency*: an efficient mechanism which produces good outcome is preferred.

3. *Decentralization*: decentralization is one of these properties that are also acceptable.

4. *Symmetry:* the mechanism should not be biased for or against some agent whatever the condition.

5. *Stability*: a stability is much preferred; at least agent won't have the incentive of deviation from some agreed upon strategy or set of strategy. And above them all;

6. *Flexibility:* a mechanism should be flexible in handling situation where there is lack of complete and private information in relation to their own decisions and preferences.

Various interaction and decision mechanisms for automated negotiation have been proposed and studied. Frameworks for automated negotiation have been studied analytically using game-theoretic techniques [21; 49] and logic- based techniques [32], as well as experimentally by programming and testing actual systems [38; 47; 46]. These negotiation frameworks are mainly based on the exchange of offers such as a bid in an English Auction is an example of an offer. Analytical and empirical techniques have helped produce mechanisms that satisfy the properties discussed above to varying degrees. However, the *flexibility* property has only begun to receive attention in the multi-agent community.

1.2 Problem Statement

Most frameworks [49; 38; 46; 35] for automated negotiation are often based on the assumption that agents have complete, pre-set and fixed preferences over negotiation outcomes, as well as a complete awareness of the space of possible outcomes. This means that agents are in advance aware of what they need and how different deals they can satisfy. And all that is needed is to jointly find a deal that is satisfactory enough for all parties. If that is so, it means simply that negotiation using agents represents the exchange of suggested potential deals, which are then evaluated against the predetermined preferences until an agreement is reached. However, agent flexibility suggests otherwise. Limited, uncertain or false information, due to imperfect sensing of the environment or due to the lack of time or computational resources needed to fully process information are not going to affect or influence (in a deviating manner) a well sound flexible negotiation agent mechanism. Beside, of the various researches done in this area, many of them (33, 46, 51, 52) based their evaluation mechanism in a complete mathematical set – a Boolean kind of programming. That means it is either zero or one. Hence, there exists a lot of numbers between zero and one which these mechanisms designers do not take into consideration. For instance, an agent might be programmed to carry on the purchase of a black Gen2 car. As such any Gen 2 car which is not black is not acceptable and no possible deal is going to happen within this framework. Although the buyer's preference is for a black car, the buyer may wish to relax this constraint under certain circumstances. Again, in this sense, not only the notion of flexibility is lost but also efficiency is made ineffective.

Against this background, we are proposing a negotiation mechanism that is based on fuzzy logic. By fuzzy, we mean to unlock the deadlock between zero and one, making the negotiation decision paradigm flows – be flexible. A comprehensive reasoning model anticipates the making of a human like negotiation mechanism.

1.3. Objectives and contribution

To alleviate much of today's problems, such as high inefficiency, subjectivity, etc., inherent in human negotiations, this research begins in an attempt to answer the following question:

How can we design an agent capable of negotiating effectively, by incorporating the notion of fuzzy logic throughout the process of negotiation – from generating offers, evaluating them and make decision?

This thesis revolves around answering this question. In fact, I contend that flexibility in choices (option available for a deal) through fuzziness can enable agents to reach the desired outcome.

To this end, I first present the generic framework for automated negotiation. I then introduce the dawn of fuzzy logic in negotiation. Finally, I present a comprehensive reasoning model based on fuzzy expert system, which allows agent to generate offers and counter offers, evaluate incoming offers and make decision with regard to the outcome of the negotiation.

Primarily, my work is restrained to a problem in negotiation in e-commerce, specifically: the design of negotiation mechanism capable of resolving conflicts over resources. Though there are concepts in this thesis drawn from other theories such as game theory, the philosophy of argumentation, and so on; I do not - and do not claim to - make a contribution to these areas. In fact the main concept of modeling presented in this thesis is to express the agents' negotiation tactics as fuzzy rules so that a more promising negotiation interaction can be made.

As such, the objectives of my research are:

To propose a negotiation mechanism based on fuzzy logic.

To design a reasoning model capable of handling fuzzy and qualitative preferences

1.4.Overview of thesis

This thesis is structured into the following chapters:

- Chapter 1 covers the introduction, problem statement, and objective and contribution.
- Chapter 2 presents a review of related literature on negotiation approaches; which has been already done. This chapter examines the general concept of these methods and their drawback.
- Chapter 3 covers the methodology of the research that will be used as framework. It is divided into two parts. The first part gives an overview of fuzzy logic and the second part highlights how fuzzy logic negotiation is to be conducted.
- Chapter 4 proposes our negotiation model using fuzzy logic and

- Chapter 5 discusses the simulation and results of the proposed model.
- Finally, conclusion and recommendation of future work is discussed in chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter discusses and analyzes existing research on automated negotiation; particularly fuzzy logic negotiation. It first gives a brief insight on negotiation in general and what has been done so far in the area. In particular, this chapter discusses and reviews negotiation using fuzzy logic.

2.2 Overview of the Negotiation

Negotiation as defined from the previous chapter suggests that the need for an automation of negotiation arises only when agents have conflicting objectives and a desire to cooperate. Agents typically conflict over issues which are to be resolved through negotiation. These issues range from goods, services, delivery, price, quality and so on.

Numerous theories have been proposed and studied in the area of automation of negotiation in MAS. Theses researches include: game-theory based bargaining [14, 10, 11]; Heuristic-based approaches [38, 46, 35]; and Multi-attribute decision theory [44]. Thus, the remaining of this chapter is organized as follows. The next section presents and discusses concepts essential to understanding the automated negotiation problem; followed by discussion and criticism of game-theory bargaining in section 2.3. Heuristic based approaches discussion and critics in section 2.4 and fuzzy logic based approaches followed by multi-attribute decision making theory in section 2.5.The chapter finally ends with summary and discussion in section 2.6.

2.3 Fundamental Concept

This section is dedicated to discussing some fundamental concept used in the automated negotiation literature more precisely.

2.3.1 The Negotiation Space Agreement

Negotiation as it happened, aims at resolving issues over which agents have conflicting interest. That is allocating resources that are acceptable to both parties. In this sense, negotiation can be seen as a “distributed search through a space of Potential agreements” [3, 4, 51]. There are, however, different ways of characterizing this particular agreement space. The space, in a way, can be seen as a set of deals $\Omega = \{\Omega_{1 \ldots}\ \Omega_n\}$ where *n* is the size of the search space.

Another way of characterizing the search space is in terms of atomic program which is conceived as a combination of actions that can change the state of the world. In this characterization, agreement is defined as a set of attributes $A_1, \ldots, A_n$ where each attribute A_i can take a set of value $a_{i,1}, a_{i,2} \ldots, a_{i,m}$. for illustration purpose the following example is to take place.

Example 1. Let BA represents a buyer agent and SA, a seller agent, negotiating over an issue which is Hand phone. The issue to be resolved has ‘brand’ and ‘price’ as attribute. Suppose the attribute brand is either ‘Nokia’ or “Samsung” and the price can take an integer value between 1 and $700. Therefore, every combination of brand/price noted as *(brand, price)* such as (Nokia, $500) or (Samsung, $200) is a deal. Hence the size of possible deals is 2 x 700 = 1400. This means, since we have two brands $(m_1=2)$ and the respective value $(m_2 =700)$, then the possible deal $m_1 m_2$ *is 2 x 700.*

Referring to the above example, we can note that using a set of attribute over a range of a domain size means that as the number of attribute *n* and the number of possible values m_1 increases, accordingly the agreement space increases. This makes it complex and infeasible to consider every possible set of agreement when we deal with a very large space of possible deal. An ideal example would be when we have a negotiation mechanism, which uses time constraints. Normally, a negotiation mechanism using time constraints is lock down between a specific time frame within which the agent has to conclude a deal or else refrain from the negotiation. Therefore, when an agent has a very large combination of deal, it will obviously take more time to go through than the originally assigned time frame.

Going back to example 1, we can see that the combination *(Nokia, $500)* is easily understood and interpreted as: the Nokia hand phone is to be given to the buyer in exchange for $500. However, this may not be the case if we were to use explicit specification for agents are themselves associated with the allocation.

Example 2. Let say a university authority assigning different courses to different lecturers, need to explicitly detail or specify which lecturer should take which subject and so on. Suppose, we have three subjects to be assigned to two lecturers; therefore there will be a need to specify which subject goes to whom. Possible combination of this scenario, however, may be represented as follows: *(Lecrturer1, (course1, course2)) and (Lecturer2, course3).*

Again, as we noticed, no matter explicit or implicit a scenario might be, the space of possible deals still increases when allocation increases. Nevertheless, it is obvious and fundamental to first somehow characterize the set of possible allocation and its domain.

2.3.2 Negotiation Mechanism

The ideal about the automation of negotiation is that, where everything is constant, agent must find or realize the better possible deal or outcome. To do that agents require certain mechanism or strategy in which rules of encounter are specified. An example of this type of agent using rules of encounter would be an auction place where there are players as bidders (buyers) and a seller, a person to whom is entrusted the selling of a property.

Another example of mechanism would be bargaining; where two agents exchange offers until an agreement is reached.

Each mechanism presents different properties depending on what the agent is to achieve. Nevertheless, certainly, there are number of features which any mechanisms would find it fit to include. There are:

1) Flexibility:
2) Simplicity:
3) Efficiency:
4) Stability:
5) Independent:

2.4 Game – Theoretic Approach to Negotiation

This section discusses game theoretic approach to negotiation followed by the limitation of this specific approach.

2.4.1 Overview of Game Theoretic approach

As in [1], a game theory is a branch of economics in which strategic interactions between self-interested economic agents are studied. Game theory is rooted from the work of von Neuman and Morgenstern [25] and has been extensively used to study and engineer interaction between self-interested computational agents [49, 32]. It is also widely acknowledged to provide a useful set of tools for the design of Multi-agents architecture.

There exist two main core game theory classified as cooperative and non-cooperative. The difference in these two branches is mainly in how they formalize interdependence among the players.

- Non cooperative game theory: in this theory, a game is a detailed model of all the moves available to the players, whereas
- Cooperative theory abstracts away from this level of detail, and describes only the outcomes that result when players come together in different combinations.

Since the non-cooperative game theory is the one widely used, therefore any mention of game theory throughout this section will refer to the non-cooperative game theory. For its own, The non-cooperative game theory includes tools for conducting two types of analysis:

- Optimal behavior analysis of individuals or organizations; and
- Analysing how to design optimal mechanisms, given that agents behave strategically.

2.4.1.1 Behavior analysis concept

The behavior analysis concept revolves around a game in which each player is presented by a set of alternative actions (choices or strategies) and given to some rules with set of actions available and the outcome of the encounter.

The most popular example of game theory is the so-called prisoner's dilemma [4, 41]. In the so-called prisoner's dilemma game, the players are considered to be two criminals held by the police and being interrogated in two separate rooms. Each criminal has to give individual testimony, without being influenced by the other, wherein both fates are analyzed. Each player has the option to confess or not to confess. Should neither of the suspect confesses, then both of them go free and split the proceeds of their crime; each one of them receiving a certain utility. However, if one confesses and testifies against the other, then he only will be set free and get the entire proceeds, while the other goes to jail and get nothing. Nevertheless, should both of them confess, they are entitled to reduced term and of course getting certain utility.

Example 3*: we present the above-mentioned concept in a matrix representation table below. This table details the action and outcome of the game. The first row shows the actions available to player 1, while the first column shows actions available to player 2. The numbers in the upper right hand of each cell represent the utility (or payoff) received by player 1 from that action combination, while the bottom left number represents the utility of player 2. Note that higher numbers are better (more utility).*

Table 2.1 The Prisoner's Dilemma

	Not Confess	Confess
Not Confess	8 8	16 0
Confess	0 16	4 4

Given the above prisoner's dilemma matrix representation, the following analysis is due to help and understand the optimal behavior analysis of the game theory.

Assume that player 1 knows the set of actions available to him and to player 2, and that player 1 also has complete information about the payoffs in the matrix. Player 1 reasons strategically as follows: suppose player 2 does not confess! In this case, I would rather confess, because I would get a utility of 16 (compared to 8 for not confessing). Suppose, instead, that player 2 confesses, then I would also rather confess, because I get a utility of 4 (compared to 0 for not confessing). Hence, for every possible action of player 2, player 1 is better off confessing. For player 1, confession is the dominant strategy, because it got nothing to lose. The exact same analysis can be followed from the point of view of player 2, leading to a dominant strategy to confess. As a result of both agents confessing, they will get a payoff of 4 each. Note that in this case, both agents are worse off than they would be if they both did not confess (in which case they would receive a utility of 8 each). In other words, even though the outcome resulting from mutual no confession strictly dominates the outcome resulting from mutual confession, *rational* agent behavior will lead to the latter.

This optimal behavior analysis of the game leads us to understand that the notion of "equilibrium" constitute a fundamental or core concept for game theory. An ideal type of equilibrium would be the so-called *Nash equilibrium*, where no player has an incentive to deviate from a particular strategy, given that other players stick to their strategies.

2.4.1.2 Design analysis mechanism

The concept of mechanism design is meant for resource allocation mechanism to be designed in such a way that each agent behavior is directed toward maximizing its utility.

The popular mechanisms used are the ones using notions of dominant behavior and equilibrium. An example of desired mechanism properties is incentive compatibility. A mechanism is said to be incentive compatible if, under that mechanism, the dominant strategy for all agents is to tell the truth about their preferences (often referred to as their types). This is a powerful concept, since by guaranteeing incentive compatibility; mechanism designers make sure agents cannot strategically manipulate the outcome by lying about their types. This property is an example of the stability requirement mentioned earlier in section 2.2.3. In economics, mechanism design principles are used to design various negotiation mechanisms, ranging from auctions, to voting, to bilateral bargaining [48].

2.4.2 Game Theory for Automated Negotiation

Game theory is known for providing a very powerful and useful tool for studying and engineering strategic interaction among self-interested computational agents in general, and to automated negotiation in particular [50]. As discussed earlier on, game theory can be applied to study and engineer both the strategies as well as the mechanism. The field of computational mechanism design [18] uses mechanism design techniques in order to construct mechanisms for allocating resources in multi-agent systems. Some of the most influential uses of game theory in studying automated negotiation.

2.4.2.1 A Domain Theory for Automated Negotiation

The use of mechanism design to automated negotiation is mainly and thoroughly used in the work of Rosenschein and Zlotkin [21]. In their work, they came out with a domain theory for automated negotiation distinguishing three different domains:

1) *Task-oriented domains*: this domain deals with the decision of tasks to execute; the utility function associated with different task allocations; and the individual evaluation of agent for the cost of the task to be executed. Here the utility function is determined in terms of cost associated with different tasks.

2) *State-oriented domains*: this domain is about what state agents will achieve; the utility function is measured in terms of preference over states that result from different deals; each agent tries to get to a more preferable state to itself.

3) *Worth-oriented domains:* domains involving a joint decision about what goals to achieve; the utility function is measured in terms of the number of goals each deal achieves; each agent tries to achieve as many goals as possible.

Rosenschein and Zlotkin [21] emphasize on the study of agent strategies in different domains and under different mechanisms. They derived and design the agent strategies mainly from concepts of game theory and mechanism design theory. Their goal is to design a mechanism that produces an outcome based on the information agents reveal about them. The authors show that, in certain situations, an agent can benefit from strategic manipulation, for example by lying about the tasks it has to perform or about its preferences over states. This analysis was then used in order to design incentive compatible mechanisms, i.e. mechanisms that force agents to be truthful. However, such mechanisms are restricted by certain conditions. For example, the authors were able to construct incentive compatible mechanisms when agents have incomplete information about each other's preferences over states, but not when they have incomplete information about each other's goals.3. Worth-oriented domains: domains involving a joint decision about what goals.

2.4.2.2 Mechanisms for Combinatorial Auctions

Sandholm [49] used game-theoretic techniques in order to construct eMediator, an electronic commerce server that uses algorithmic and game-theoretic techniques to allocate resources among multiple agents. eMediator includes the eAuctionHouse, a configurable auction server that can handle a number of combinatorial auctions and exchanges; and the eCommitter, a contract optimiser that determines the optimal contract price and decommitting penalties for the different parties, taking into account that agents may decommit strategically. The author is concerned with achieving optimal outcomes using a mechanism that ensures agents do not deviate from the desired strategies. In related work, Sandholm [48] presents an algorithm for optimal winner determination in combinatorial auctions (auctions where bidders can bid on combinations of items). Conitzer and Sandholm [50] explore viewing the mechanism design problem itself as a computational problem, and present algorithms that produce preference aggregation mechanisms at run-time, given a particular setting.

2.4.3 Limitations of Game Theory

An adequate evaluation of game theory is beyond the scope of this thesis. Therefore, I focus my discussion on issues relevant to automated negotiation, and particularly to the topic of this thesis.

In game-theoretic analysis, researchers usually attempt to determine the optimal strategy by analysing the interaction as a game between identical participants, and seeking its equilibrium [23, 29, 49,]. The strategy determined by these methods can sometimes be made to be optimal for a participant, given the game rules, the assumed payoffs, and the goals of the participants. Assuming further that participants behave according to the assumptions of rational-choice theory [36], then this approach can guide the design of the interaction mechanism itself, and thus force such agents to behave in certain ways [37].

Classical game theory assumes, among other things, that agents:

1) Have unbounded computational resources,
2) Have complete knowledge of the outcome space, and
3) Are optimisers of utility in the sense of rational-choice theory

From a computational perspective, these assumptions imply unrealistic assumptions about the negotiating software agents. The first assumption implies that no computation or communication cost is incurred in order to reach a deal. In most realistic computational environments, however, this assumption fails due to the limited processing and communication capabilities of information systems. The size of the set of possible deals grows exponentially with the number of attributes and attributes values. Calculating and evaluating all of these may require more time and computation than can be afforded. Similarly, in a bargaining encounter, exchanging every possible offer may be impractical, given time and communication bandwidth limitations. Classical game-theoretic models do not provide a way to account for these costs and study their impact on strategic decisions.

The second assumption implies that not only does the software agent have unbounded computational resources to evaluate every possible resource allocation, but it also has all preference information needed to perform such evaluation. In many domains, however, it may be impractical for the user to specify its complete preference information to the agent.

The third assumption implies that agents always make decisions that optimise their utility. Game theory requires this because an agent must first reason about the "optimal strategy of the opponent before deducing the best response to that strategy. However, software agents may be resource-constrained (as discussed above), altruistic, malicious, or simply badly-coded, so that participant behaviour may not conform to the assumptions of rational choice theory. Hence, if game theory's predictions are inaccurate, its prescriptive advice becomes unreliable.

Game theory can also be critiqued from a "software-engineering" point of view. Game theory is normative since it is concerned with what constitutes an optimal decision given a game description. Hence, classical game theory has nothing to say about how to implement agents that reason optimally. It is worth pointing out that an emerging sub-area of game theory, termed evolutionary game theory [38], is concerned with some of the limitations discussed above. Evolutionary game theory relaxes the assumption of unbounded rationality. Instead of calculating optimal strategies, games are played repeatedly and strategies are tested through a trial-anderror learning process in which players gradually discover that some strategies work better than others. However, other assumptions, such as the availability of a preference valuation function, still hold. Another limitation is the modelling of bounded rationality" by explicitly capturing elements of the process of choice, such as limited memory, limited knowledge, approximate preferences (that ignore minor difference between options) etc. [2, 39]. These frameworks are primarily aimed at producing models that better explain and predict human behaviour in real economic and social scenarios. Their insight into the building of multi-agent systems requires further exploration and is relevant to heuristic approaches discussed in the next section.

2.5 Heuristic Based Approach

When agent designers relax some of the assumptions of game theory, particularly regarding unbounded rationality, they immediately fall outside the region of predictability of classical game-theory. This implies that analytical results (e.g. about optimal strategies) become hard to achieve. Instead, approximate strategies (or heuristics) must be devised. Heuristics are rules of thumb that produce good enough (rather than optimal) outcomes. For heuristic approaches, experimentation through simulation becomes a more viable option for studying the properties of different strategies. The support for a particular heuristic is usually based on empirical testing and evaluation in comparison with other heuristics [7, 17, 46; 47]. In general, these methods offer approximations to the decisions made according to game-theoretic studies. The heuristic approach has been applied both to bargaining mechanisms as well as auction-based mechanisms. In the next section, I survey some major frameworks in each category.

2.5.1 Heuristics for Bargaining

A number of heuristic methods have been employed in a service-oriented negotiation framework presented by Faratin, Sierra and Jennings in a number of papers [see 36, 37, 38]. In this framework, different heuristic decision functions are used for evaluating and generating offers in multi-attribute negotiation [7]. Instead of exploring all possible deals, agents exchange offers based on heuristic functions that depend on time deadlines and resource availability. Moreover, in order to improve the convergence to a deal, the authors present a method that enables an agent to generate offers that are "similar" to previous offers made by its negotiation counterpart [42] (where, "similarity" representation is based on fuzzy-logic techniques [43]). The intuition is that such offers are more likely to be accepted by the counterpart.

Kowalczyk and Bui [42] present a negotiation model with decision procedures based on distributed constraint satisfaction [53]. This enables agents to use heuristics used in the constraint satisfaction literature in order to improve the process of generating and evaluating offers. This framework was later extended to allow for multiple concurrent negotiations [45] and to accommodate fuzzy (as opposed to "crisp") constraints [46]. The idea of using fuzzy constraint satisfaction is further investigated by Luo et al. [47].

Kraus [48] presents a negotiation framework based on Rubinstein's model for alternating offers [49]. The framework has been used to solve data allocation, resource allocation and task distribution problems, and was verified via empirical simulation and (to a certain extent) related analytically to game-theoretic concepts. In related work, Fatima et al. [46; 16; 5] studied the influence of information and time constraints on the negotiation equilibrium in a particular heuristic model.

2.5.1.1 The Trading Agent Competition

Another example of the use of heuristics in negotiation is the Trading Agent Competition (TAC): an annual competition, which involves multiple competing agents bidding in simultaneous auctions. I discuss TAC-02 as an example.

Eight agents participated in each TAC-02 game. Each agent performed the role of a travel agent attempting to provide booking for eight clients travelling from TACtown to Tampa and back during a five-day period. Each client was characterised by a random set of preferences for arrival and departure dates, hotels and entertainment tickets. Utility was gained by purchasing a complete package and was calculated based on comparison with the corresponding client's preferences. Package constituents were sold in separate simultaneous auctions, each with certain price dynamics. Airline tickets were sold in single round continuous auctions with biased random pricing that was more likely to increase. Hotel bookings were sold in ascending English auctions clearing every minute, while entertainment tickets were traded in continuous double auctions. The score of an agent was the difference between the total utility gained for its clients and the agent's expenditure.

TAC represents a real challenge for automated negotiation, where game-theoretic techniques fail. This is mainly due to the complexity of the problem and the time limitations. Agents participate in 28 different auctions over a period of 12 minutes. Each agent has to solve a combinatorial assignment problem, where goods must be packaged into bundles. Moreover, agents' bidding behaviour must be strategic, taking into account the strategies of other agents in order to decide when to buy and how much to bid. A consequence of these complications is that `there is no known way to compute the best course of action' [50]. TAC-02 participants used techniques ranging from Linear Programming for finding optimal bundles, to Machine Learning for modelling other agents' behaviours, to Genetic Algorithms for evolving adaptive strategies.

2.5.2 Limitations of Heuristic Approaches

Heuristic methods do indeed overcome many of the shortcomings of game-theoretic approaches. However, they also have a number of disadvantages [25].

Firstly, the models often lead to outcomes that are sub-optimal because they adopt an approximate notion of rationality and because they do not examine the full space of possible outcomes. And secondly, it is very difficult to predict precisely how the system and the constituent agents will behave. Consequently, the models need extensive evaluation through simulations and empirical analysis.

Another limitation of heuristic approaches is that, like game-theoretic approaches, they assume that agents know what they want. In other words, agents have a precise and correct way of calculating the quality of the negotiation outcome (usually using numerical utility functions). As I shall argue in depth in the following section, this requirement cannot always be satisfied, in which case alternative techniques would be needed.

2.6 Fuzzy Logic based Approaches to Negotiation

The core challenge facing the theory of negotiation model stated above is their ability to handle qualitative negotiation preferences. In the following paragraphs I will argue that existing game-theoretic, heuristic approaches and auction based negotiation do not satisfy those properties. Then, I will show how an emerging family of negotiation frameworks, based on the notion of fuzzy logic has the potential to overcome this limitation. Such frameworks have been termed negotiation using fuzzy logic frameworks. Nevertheless, it is worth mentioning that couple of researches have been done in negotiation using the notion of fuzzy logic as in [33, 53, and 16]. Although they use different fuzzy techniques, in most part it leads to a common purpose.

In [33] the authors have raised the issue of autonomous negotiation and propose a fuzzy logic based bidding strategy for autonomous agents in continuous double actions. While [53] in his model expresses the idea of making trade offs (relaxing on an attribute), M.He and al. structures their modelling based on auctioning. They argue that the seller and buyer constitute the continuous double actions or CDAs within which negotiation is to take place. Therefore, negotiation among them is like an auction in a different environment. It is always give and take. However auction based theory lacks to some extent the dynamism of producing an ideal negotiation. In the auction based theory, preferences of both buyer and seller are known and predetermined, making it easy for other party to determine one’s moves.

Meanwhile, H. Al-Ashmaway and al [16] in their paper expressed the importance of incorporating fuzzy logic to the automation of negotiation in an effort to deal with ambiguities in the negotiation. They proposed a reasoning model just to try to determine the degree to which the negotiating agent is satisfied with an incoming offer while the concession rate which constitutes the ratio that allows calculating the next offer is applied using heuristic based theory. Nevertheless, the satisfaction degree calculated using fuzzy logic is merely used for its specific purpose and does not contribute any part in determining the concession rate which constitutes the main output of the negotiation. it could therefore be said that the model lacks to stand for its expectation to be a fuzzy logic based negotiation. The trade-off or the main factor of the negotiation model proposed is yet based on time, resource or imitation technique to allow the flow of offer and counter offer.

Another category of negotiation theory is the multi-attribute decision making theory. Pei-you and Yi-Ling [52] have worked in this type of theory. The latter is based on multi-criteria decision making [53]. In [53], the main idea is on how to generate weight. The author provides the model to deal with problem of ranking and site selection. The paper again is destined to deal with a problem of quantitative nature and as it is based on concept of accurate measure and crisp evaluation. Through this footstep, Pei-you and Yi-Ling have proposed a negotiation model based on uncertainty multi-attribute decision making. Their main objective is to develop a decision making operator based on the application of vague mathematics to evaluate negotiator's preference for different attribute. In the process fuzzy membership and Bayesian learning theory is to be the methodology. However, conceptually, their model is as same as [53, 16] but different approach used. One can note that the fuzzy membership incorporated is, if not at all, defined. Their paper is more tied and focused on Bayesian learning mechanism and rather the combination of it with fuzzy membership. Thus, the effect or incorporation of fuzzy logic here is inexistent.

Either case (whether paper [33, 53, 16 or 7]) their application of fuzzy logic is partial and is only involved where vague or uncertain attributes are concerned. Pei-you and Yi-ling in particular have combine fuzzy membership with Bayesian learning mechanism to determine the preference of either buyer or seller on a particular attribute or issue; whereas [53, 16] have used fuzzy to determine the satisfaction degree of either buyer or seller on a particular offer.

2.7 A Closer Look at the existing Models

The existing approaches to automated negotiation mostly assume that agents' utilities or preferences are completely characterised prior to the interaction. Thus, an agent is assumed to have a mechanism by which it can assess and compare any two proposals. This may be easy, for example, when the utility of the negotiation object is defined in terms of a monetary value. However, in more complex negotiation situations, such as trade union negotiations, agents may well have incomplete information, which limits this capability. Thus, agents might:

- lack some of the information relevant to making a comparison between two potential proposals and,
- have limited resources preventing them from acquiring such information,
- have the information, but lack the time needed to process it in order to make the comparison,
- have inconsistent or uncertain beliefs about the environment,
- have unformed or undetermined preferences (e.g. about products new to them), or
- have incoherent preferences.

The situations described above do exist in the human negotiation world (bearing in mind that the objective of this thesis is to design a human like negotiation). For example, consumers form their preferences based on information available to them. They acquire and modify their preferences as a result of interaction with the environment and other consumers [26]. Advertising capitalises on this idea, and can be seen a process of `argumentation' in which marketers attempt to persuade consumers to change their preferences among different products [13].

Allowing flexibility in negotiation increase both buyer and seller interest to perform an action using agent. Designing a human like is an important part of a sound negotiation. If that is so, a reasonable question to ask is: can computational agents be able to deal with common sense that human deal with during negotiation? For existing frameworks, the answer is mostly No for the following reasons:

- In most game-theoretic and heuristic models, agents exchange proposals (i.e. potential agreements or potential deals). This, for example, can be a promise to purchase a good at a specified price in an English auction, a value assignment to multiple attributes in a multi-dimensional auction [13], or an alternate offer in a bargaining encounter [5]. Agents are not allowed to exchange any additional information other than what is expressed in the proposal itself.
- Agents' preferences over proposals are assumed to be proper in the sense that they reflect the true benefit the agent receives from satisfying these preferences. For example, an agent attempting to purchase a car might assign a high value to a particular brand based on a false belief that this brand makes safer cars than other brands. In this case, the preferences do not properly reflect the agent's actual gain if it was to purchase that car.
- Game-theoretic and heuristic approaches assume that agents' utilities or preferences are fixed. A rational agent would only modify its preferences upon receipt of new information, and traditional automated negotiation mechanisms do not facilitate the exchange of such information.

Against this background, our model attempts to overcome the above limitations by allowing agents to negotiate by exchanging offers and be able to make decisions based on the use of fuzzy logic.

CHAPTER 3

FUZZY LOGIC METHODOLOGY

3.1 Introduction

This chapter presents the methodology used to model our negotiation scenario. It extensively include an overview of fuzzy logic

3.2 Overview of Fuzzy Logic

In the words of Bertrand Russell [44]: "*All traditional logic assumes that precise symbols are being employed. It is therefore not applicable to this terrestrial life, but only to an imagined celestial one. The law of excluded middle is true when precise symbols are employed but it is not true when symbols are vague, as, in fact, all symbols are*". The principle foundation of mathematics invented by the Greek philosopher Aristotle came up with the binary logic (0, 1). It was based on one law: A or not A; it is either this or not this. For example: a glass of water can be full of water or not full of water; a man can be old or not old and so on. Moreover, every statement can be true or false. Such is Aristotle's law of bivalence and was philosophically correct over couple of thousands years.

During 1960's, a professor from the University of Berkely by the name of Lotfi Zader introduces fuzzy logic – a logic that disapproves Aristotle's law of bivalence. He (Zader) based his logic on the concept of certain degree and multivalence. He argues that between the binary logic (0, 1) there exist many numbers that are useful to count.

3.3 Fuzzy set

George Cantor [9] proposed the conventional set theory; which says that conventional set are crisp. This means a set has a rigid and well defined boundary. However, realistically (in a real world) things are rather fuzzy, uncertain and vague than crisp.

Illustration 3.1: let us consider the following set of theory: “when we take a grain from a heap, the heap is still there, but when we keep taking grains from the heap until one grain is left, do we still consider it as a heap?.” Such was the dilemma posed by ancient Greek; which caused a real problem to logicians and mathematicians. How do we solve this type of paradox?

Well, using conventional set theory, we have to set a bound. A heap can be formed by *n* grains but it is not heap if only *n-1* grain is left. However, using common sense, we cannot really fell the boundary. The setting of bound using conventional theory is not clear and this makes the conventional set theory unrealistic.

Lotfi Zader, the father of fuzzy set makes it possible for such dilemma to be solved. He introduces the concept of graded membership – a graded membership, which preceded the characteristic function of conventional set that only takes 1 or 0 indicating whether an element is a member.

Definition 1: *a membership function of a fuzzy set A denoted U_A is defined by a set of ordered pairs* $A=\{(x, u_A(x))|x \in A\}\ 0 \leq u_A(x) \leq 1$.

The above definition means a membership function of a fuzzy set A, $U_A(x)$ means that the membership function can take any value between 0 and 1; a function that outclasses the conventional set theory of either 0 or 1. The larger the value of $U_A(x)$, the greater or higher the degree of membership.

Let us look at another example where a person wishes to characterize the cost of dinner at a restaurant. Over the range of prices, a person might have three preference values or sets: Low, medium and high. If the cost of the dinner is low, the person is happy. If the cost of dinner is medium, the person is neutral. Consequently, if the dinner cost is high then the person will be unhappy. Classically, one might model this illustration with discrete threshold points at which price transitions from low to medium and medium to high occur. However, this approach does not correctly model what happens in the real world since each individual has a different, imprecise range over which those preference transitions actually occur. Nevertheless, this natural imprecision and vagueness can be effectively handled by using fuzzy set introduced by Zadeh [30].

3.3.1 Definitions and Discussion of theory

Unlike conventional logic, Fuzzy set theory, assumes that an element can belong to more than one set at a time and that its membership in a set is a matter of degree. A parameter's specific or crisp value's degree of membership in a fuzzy set is determined by the membership function of that set also called truth-value. A fuzzy set is defined by all membership function for a given variable over its range or origin of discourse. A common example is shown is figure 3.1.

In rule driven fuzzy logic application, the memberships in the fuzzy sets present themselves in the antecedent or consequents of the rules presented in the linguistic expressions. In practise, triangular and trapezoidal membership functions are typically used because of their computational simplicity. The value of the membership function for any crisp parameter value indicates the degree of membership (truth-value 0 and 1) in the related set. Adjacent membership functions overlap to a certain degree to reflect the fuzziness or vagueness of the set classification. The convention that all membership functions total 1 for any parameter value is utilized here.

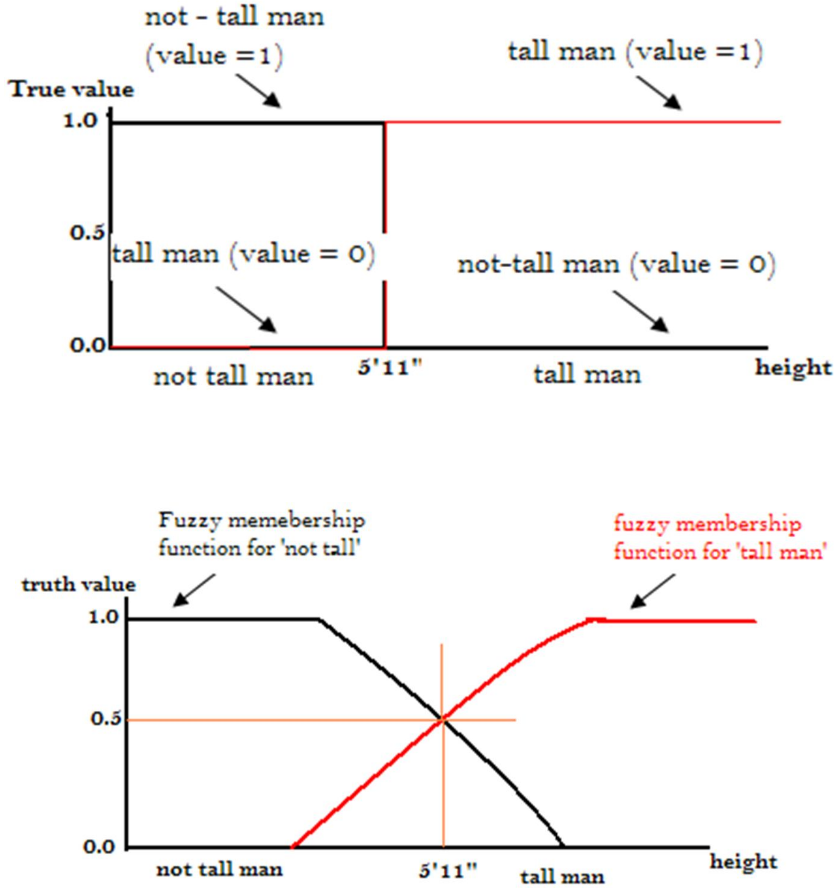


Figure 3.1 Membership function

Figure 3.1 illustrates the concept of fuzzy logic. It describes the concept of tallness, which depend upon the height of the observer, and the concept of its use. In conventional logic, based on the figures above, a person would have to be classified either as a "not tall" person with membership equals to 0 or as "tall" person with membership equals to 1 as seen in the area ≥ 5'11'' of figure 1. In the more general fuzzy logic, the membership function shown in figure 2 could be utilized. Below 5'7'' a person is clearly no tall; above perhaps 6'3", a person is clearly tall and at 5'11'' a person might be considered half "not tall" and half "tall" with membership 0.5 in each fuzzy set. There is a gradual transition between these situations; perhaps between 5'7" and 6'3". The vagueness will certainly vary between describing jockeys at a race track or players of an NBA. The ability to be tall and not tall at the same time is against the conventional set theory law of contradiction, which states that x cannot be in set A and set not-A at the same time.

If the evaluated person weight is added to the above discussion, one can see how another dimension can expand the input fuzzy sets. The question might arise if someone is at risk by a heart condition? This question cannot be answered by looking at the person weight alone since height also has to be taken into consideration when deciding whether a person is at risk or not. Fuzzy theory allows us to combine the ambiguity of both height, weight over a range of values, and help us more realistically classify if a person is at risk of a heart condition and at what risk factor. A fuzzy system is a good candidate to describe complex and not well-defined system.

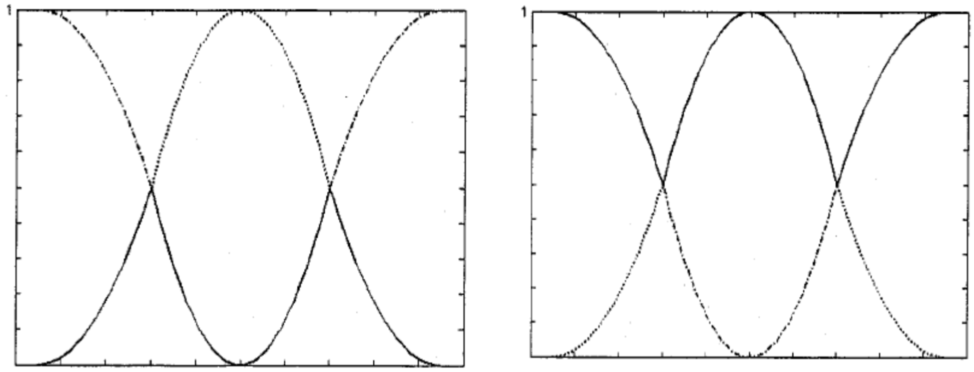
3.3.2 Fuzzy Operators

Mathematically, the conventional logic can be written as $f(x)$*:* $x \rightarrow \{0, 1\}$ which states that the membership function maps x to either 0 or 1. Fuzzy logic maps x to any value between 0 and 1. This can be written as $f(x)$*:* $x \rightarrow [0, 1]$.

Fuzzy logic consists of basic operations such as union (OR) and intersection (AND). let us consider the following letters F, Y, Z to denote our fuzzy set used along this thesis and their corresponding membership functions are: $U_F(x)$, $U_Y(x)$ *and* $U_Z(x)$ *respectively*. To represent our fuzzy operators, we consider F, Y as fuzzy set defined in the universe U, we then have the following list of operators.

- Equality: if F = Y, then $U_F(x) = U_Y(x)$ and $x \in U$
- Inclusion: if F ⊆ Y, then $U_F(x) \subseteq U_Y(x)$ and $x \in U$
- Proper subset: if F ⊂ Y, then $U_F(x) \subseteq U_Y(x)$ and $x \in U$
- Intersection: if F ∩ Y, then $U_{F\cap Y}(x) = \min(U_F(x), U_Y(x))$, $x \in U$
- Union: if F ∪ Y, then $U_{F\cup Y}(x) = \max(U_F(x), U_Y(x))$, $x \in U$

By observing the fuzzy operators denoted above, we can say that the law of excluded middle expressed by $F \cup F = U$ and $F \cap F = \phi$ is not valid in fuzzy set anymore. This is also represented graphically as in the following figure.



$A \cap \bar{A} \neq \emptyset$ $\quad$ $A \cup \bar{A} \neq U$

Figure 3.2: The law of excluded middle as it happened graphically

Briefly, fuzzy sets are flexible and more suitable in describing vagueness and processes with incomplete and imprecise information.

3.4 Fuzzy Logic

Fuzzy logic has emerged as an extension of classical logic – a two value logic in which prepositions are either true or false. The truth value of the classical logic denoted T_2 which contains 0 for false representation and 1 being true.

Back in 1923, Lukasiewicz introduced the law of many-value logic where the truth T_n has so many values beside 0 and 1 [29]. Along with Lukasiewicz, one can say that fuzzy set is a derivation of this many value logic. Therefore, we can see the relations between classical sets, classical logic, fuzzy set and many value logic as in figure 3.3.

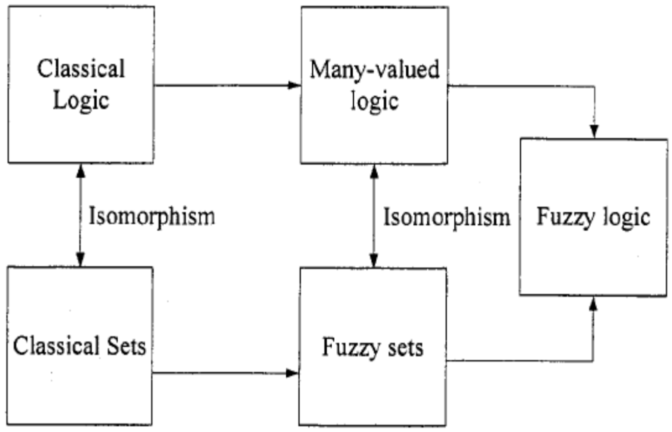


Figure 3.3: Evolvement of fuzzy Logic

Fuzzy logic is made fit to reasoning with imprecise and vague prepositions, which deal with natural language easily. Therefore, a methodology is made possible for fuzzy logic to treat linguistic variable and expressing modifiers like *High, Medium, Low and so on.* It reflects both the vagueness and rightness of natural language in common sense reasoning.

3.4.1 Traditional fuzzy system

Fuzzy system provides a nonlinear mapping between crisp numerical input variables and crisp numerical output variables and allows the use of linguistic expressions for the rules that define the input – output relationship. The rules are expressed for all possible combinations of the active input fuzzy sets.

3.4.1.1 Linguistic variable

As in [28], linguistic variables are those, which take values of words or sentences in natural or artificial languages. For example: height as a person height is word in natural language. To transform it into linguistic variable, we first have call upon modifiers; then a person height is expressed as {very short, short, medium tall, very tall}. These are called term of linguistic variable "height" and described by fuzzy set with corresponding membership function on a universe set $U \subset R^+$.

The following figure describes the linguistic variable ‘height’.

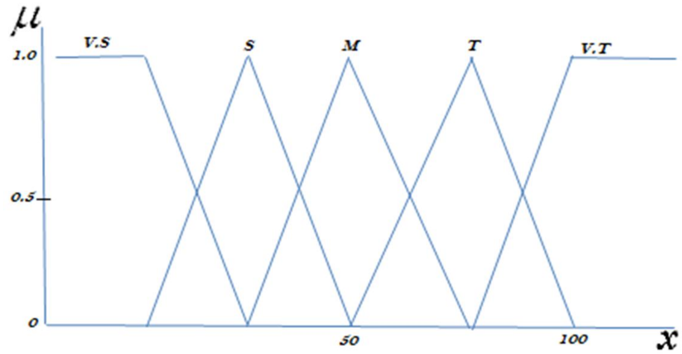


Figure 3.4: linguistic variable “Height”

The fig maps the linguistic variable Height on the universe set U = [0, 100] with V.S = very short, S = short; M = medium; T = tall and V.T = very tall.

3.4.1.2 Composition rule

Composition is an operation occurring between two propositions p and q joined by logical connectives. Assuming A and B two fuzzy sets with $A = \{(x, \mu_A(x)/x \,\square A \subset U_1\}$ *and* $B = \{(y, \mu_B(y)/y \,\square\, B \subset U_2\}$; and let us also assume that proposition P states that x is A and proposition q states that y is B. therefore the corresponding membership functions ($\mu_A(x)$, $\mu_B(y)$) represent the truth value of the propositions p and q and their composition list is shown in figure 3.5.

Conjunction: $p \wedge q$	$\mu_{A \times B}(x, y) = \min(\mu_A(x), \mu_B(y)), (x, y) \in A \times B$
Disjunction: $p \vee q$	$\mu_{A \times B}(x,y) = \max(\mu_A(x), \mu_B(y)), (x,y) \in A \times B$
Implication: $p \rightarrow q$	$tr(\text{if p then q}) = \min(1, 1 - \mu_A(x) + \mu_B(y)), (x,y) \in A \times B$
Complementation: $\overline{A}$	$\mu_{\overline{A}}(x) = 1 - \mu_A(x), x \in U$
Intersection: $A \cap B$	$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)), x \in U$
Union: $A \cup B$	$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)), x \in U$

Figure 3.5: Composition rules for fuzzy proposition

3.4.2 Fuzzy Expert System

A fuzzy expert system is an expert system that uses fuzzy logic instead of Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to reason about data. Unlike conventional expert systems, which are mainly symbolic reasoning engines, fuzzy expert systems are oriented toward numerical processing.

The rules in a fuzzy expert system are usually of a form similar to the following:

If x is low and y is high then z is medium

where *x* and *y* are input variables (names for known data values), *z* is an output variable (a name for a data value to be computed), *low* is a membership function called also fuzzy subset defined on *x*, *high* is a membership function defined on *y*, and *medium* is a membership function defined on *z*. The part of the rule between the "if" and "then" is the rule's premise or antecedent. This fuzzy logic expression describes to what degree the rule is applicable. The part of the rule following the "then" is the rule's conclusion or consequent. This part of the rule assigns a membership function to each of one or more output variables. Most tools for working with fuzzy expert systems allow more than one conclusion per rule. A typical fuzzy expert system has more than one rule. The entire group of rules is collectively known as a rule-base or knowledge base.

With this in hand, we now need to know how to apply this knowledge to specific values of the input variables to compute the values of the output variables. This process is referred to as inference. In a fuzzy expert system, the inference process is a combination of five sub processes:

1. Fuzzification
2. Inference Rules
3. Evaluation of inference rule
4. Defuzzification

The figure below depicts the generic modelling of all these sub processes.

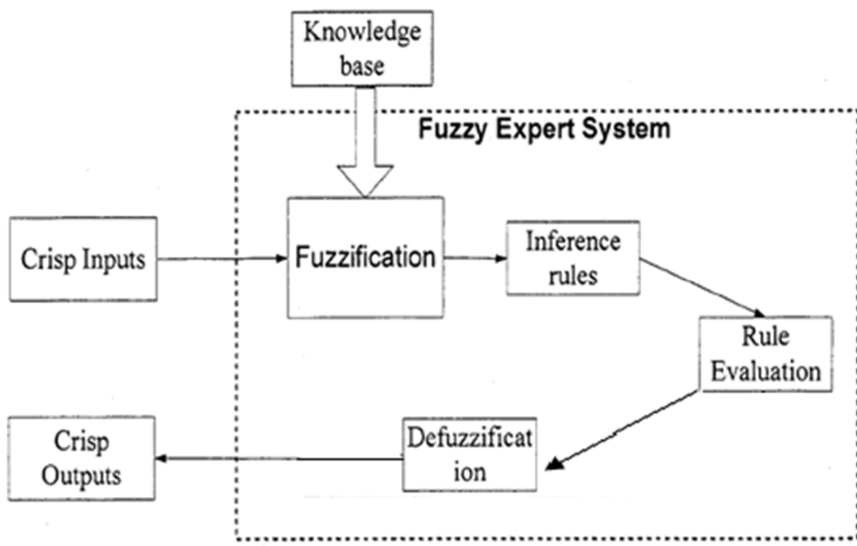


Figure 3.6: Block diagram of fuzzy expert system

3.4.3 Fuzzification

In a conventional fuzzy system, fuzzification is the procedure that converts crisp inputs into membership in a fuzzy set or sets and calculate the truth-value for these fuzzy sets. To demonstrate fuzzification, a two inputs example has been developed.

Assuming two inputs variables, height and weight of an individual; each variable will have its own membership functions for their input fuzzy variables as in figure 3.8.

The fuzzy output variable is the risk factor for having a heart attack. For this example, each fuzzy input variable has three fuzzy set membership possibilities and the output has four membership possibilities. Due to the linguistic component of fuzzy logic each membership function of the input variables can be classified as thin, average and heavy for the weight fuzzy variable and short, average and tall for the height fuzzy variables. The labelled fuzzy set for each input variables and output variables can be written as weight = {thin, average, heavy}; Height = {short, average, tall}; and risk factor = {low risk, average risk, moderate risk, high risk}.

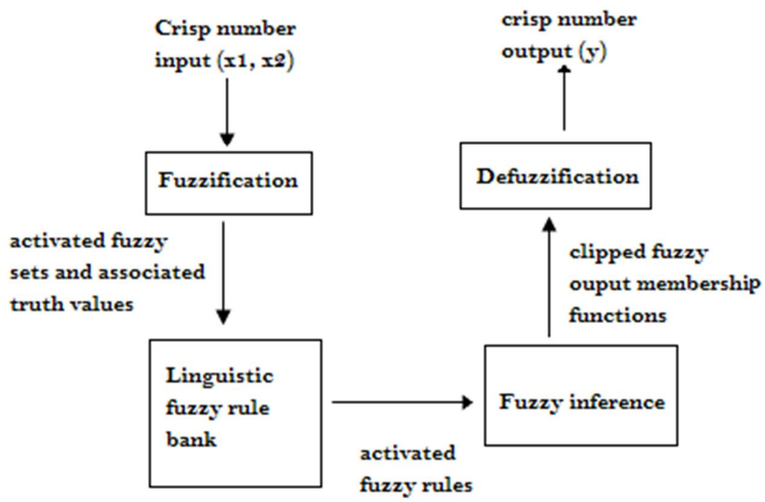


Figure 3.7: Schematic diagram of traditional fuzzy system

For this particular example, imagine we want to evaluate this system with a weight value of 130 pound and a height of 5’3”. Figure 3.8 displays that a weight value of 130 pound would belong to a fuzzy set {thin} with a membership function of 0.5 and the fuzzy set {average} with truth-value of also 0.5. Similarly, if height were evaluated at 5’3” it would belong to the fuzzy set {short} and {average} with truth-value of 0.8 and 0.2 respectively. This example shows how a crisp fuzzy value inputs are mapped to the appropriate fuzzy set membership and associated a truth-value.

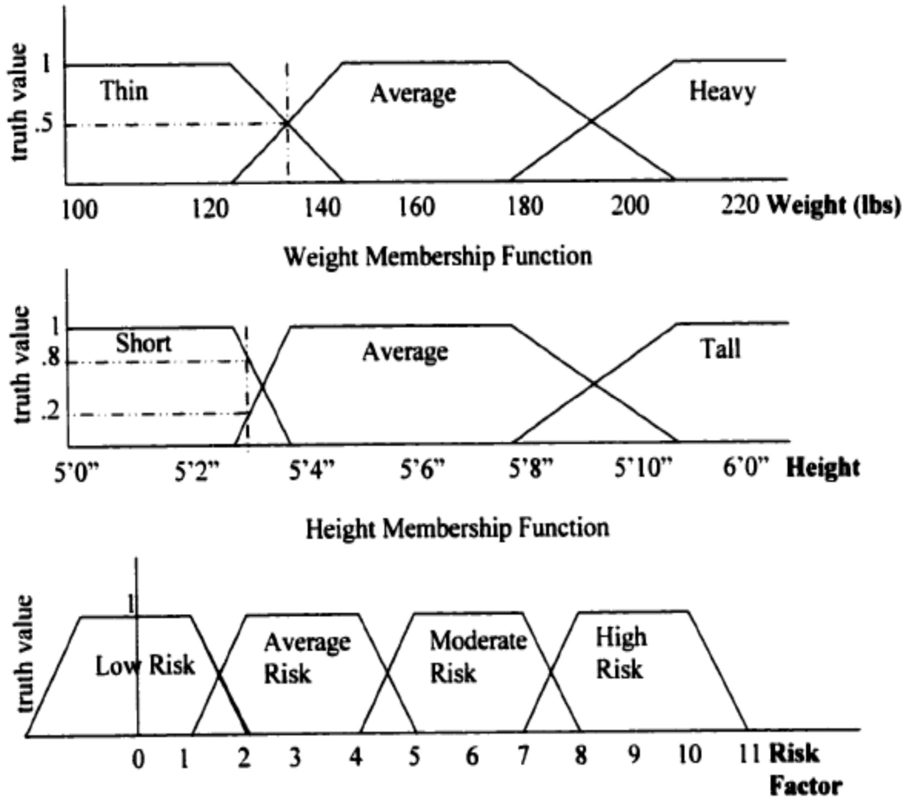


Figure 3.8: Two inputs example

3.4.4 Inference Rules

Inference rules are the next step in the fuzzy process. The fuzzy rules are the rules that form the logic that makes up the fuzzy system. These rules are linguistic expressions that link the membership in input set to membership in output set. Fuzzy rules consist of an antecedent (input) and a consequent (output) correlated by "If…..and …. Then" rule format. In logic, a rule of inference (also called a transformation rule) is a function from sets of formulae to formulae. The argument is called the premise set (or simply premises) and the value the conclusion. They can also be viewed as relations holding between premises and conclusions, whereby the conclusion is said to be inferable (or derivable or deducible) from the premises. If the premise set is empty, then the conclusion is said to be a theorem or axiom of the logic.

From figure 3.8 and using the fuzzy rule bank in table 3.1 and two examples of linguistic expressions, we can have the following illustration:

- If Weight is Thin and Height is Short then The risk factor is Low.
- If Weight is Average and Height is Short then the Risk factor is Moderate.

If we have *n* terms of A and *m* terms of B, the total number of rule we can get is *nm;* and the rules make *l* different outputs. A typical rule can be written as follows:

$$\textit{If } X_i \textit{ is } A_i \textit{ and……and } X_m \textit{ is } A_{m,} \textit{ Then } Y \textit{ is } C \qquad (3.1)$$

In expression (3.1), $X_{i\ and}$ Y are fuzzy variables and A_i and C are fuzzy sets. There are an ever-growing number of fuzzy operators, but for this thesis, we only concentrate on the fuzzy operator AND as used in [60].

The fuzzy rule bank forms the structure of a fuzzy system. In a typical fuzzy system, the number of input variables and the number of fuzzy sets determine the number of rules in a fuzzy rule bank that each input variable can be assigned. The number of fuzzy rule within fuzzy rule bank can be written as:

$$\prod_{i=1}^{m} N_i; \qquad (3.2)$$

In equation 3.2, m is the number of fuzzy variables and N_i is the number of fuzzy set defining variable *i.* thus the number of fuzzy rules for this example is 3 x 3 = 9.

In a fuzzy expert system, inference rules stem from the knowledge of human experts, the preference of clients, or the common sense of everyday life. They can be redesigned at any time when there is change in the knowledge base.

3.4.5 Fuzzy Inference

Fuzzy logic based systems use RULES to represent the relationship between observations and actions. These rules consist of precondition (IF-part) and a consequence (THEN-part). The precondition can consist of multiple conditions linked together with AND or OR conjunctions. The computation of fuzzy rules is called Fuzzy Inference.

3.4.5.1 Inferencing

Inferencing determines the fuzzy subset of each output variables for each rule. Usually only MIN or PRODUCT is used as inference rules. In MIN inference, the output membership function is clipped off at a height corresponding to the rule premise's computed degree of truth (fuzzy logic AND).

In PRODUCT inference, the output membership function is scaled by the rule premises computed degree of truth. Since we are using AND operator, let us look at the figure 3.9, in this example the truth value for Thin membership function is 0.5 and truth value for short membership function is 0.8. Therefore, the consequent activated fuzzy set, Low risk, is clipped at 0.5 at seen by the shaded area A.

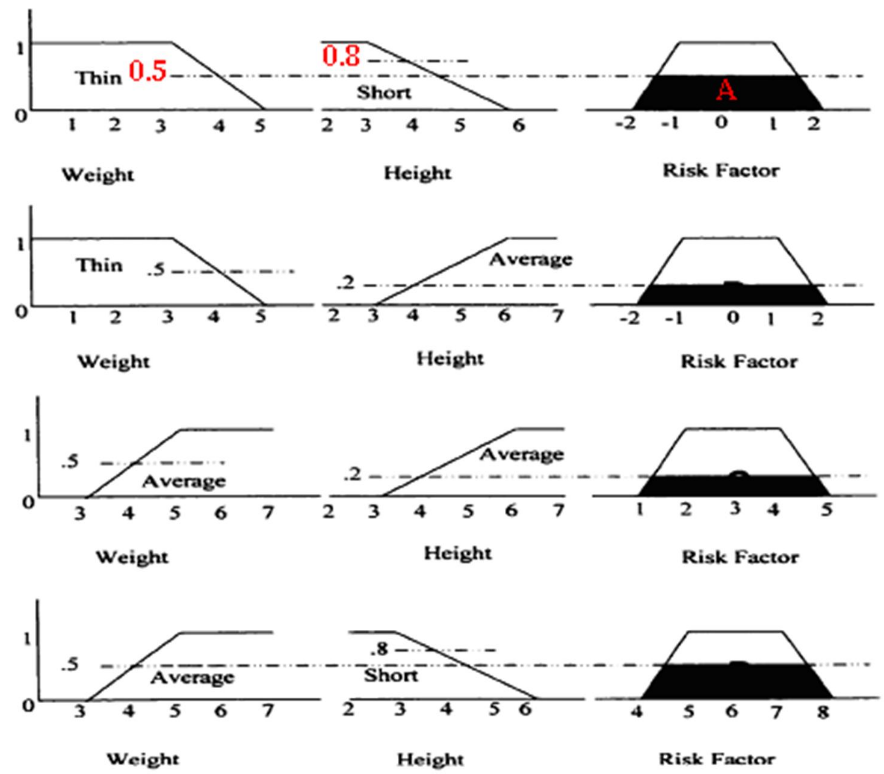


Figure 3.9: Inference system

Inference can be also represented using fuzzy matrix. A fuzzy matrix is a matrix associated with the linguistic expressions that map fuzzy input variable set to the fuzzy output variable set. Table 3.1 shows the rule matrix for the example above. The column on the left side of the matrix contains the possible fuzzy input set Height, while the row above the matrix contains the possible fuzzy input set Weight. Within the fuzzy output set that correspond to the fuzzy linguistic rules are contained in the cells of the matrix. There are our shaded cells in the matrix below. The shading represents the activated fuzzy rules for this example that were created by the linguistic rules of the fuzzy system.

Table 3.1 Fuzzy rule matrix

	Thin	Average	Heavy
Short	Low Risk	Moderate risk	High risk
Average	Low Risk	Average risk	High risk
Tall	Low Risk	Low Risk	Moderate risk

The four rules represented by the four active cells are called fired rules.

3.4.5.2 Composition

Composition combines the fuzzy subsets for each output variable into a single fuzzy subset. Usually MAX or SUM are used. In MAX composition, the combined output fuzzy subset is constructed by taking the point wise maximum over all of the fuzzy subsets assigned to variable by inference rule. In SUM composition, the combined output fuzzy subset is constructed by taking the point wise sum over all of the fuzzy subset assigned to the output variable by the inference rule.

IF-THEN rules are a common way of representing and communicating knowledge in everyday conversation. Anyone who has written a program or machine code knows how complicated (and difficult to debug, read and maintain) the if-then lines can get.

Fuzzy rules offer a way of getting around that by trading the precise representation of the values that variables must assume with much more intuitive representation.

Generally, a rule, by itself, does not do much. What is needed are a set of rules that can play of one another. The fuzzy inference methodology allows “fair” competition between these rules to produce sophisticated answers using seemingly simple premises.

3.4.6 Defuzzification

This stage is the final function of a fuzzy system and is used to convert output set to a crisp number. There are several methods to be used in order to perform defuzzification. The most common techniques used are the Centroid and Maximum methods. In the Centroid method the crisp value of the output variable is computed by finding the value of the center of gravity of the membership function. In the Maximum method, the crisp value of the output variable is the maximum truth-value of the fuzzy subset. For a more detailed look on how different defuzzification method affects the output, refer again to [10]. However, we apply Centroid method for the purpose of this thesis.

Centroid defuzzification as mentioned earlier on, is simply the act of finding the x location of the center of mass of the clipped output fuzzy sets. This function can be expressed as:

$$\text{Defuzzify crisp output} = \frac{\sum_{j=1}^{q} z_j * \mu_c(z_j)}{\sum_{j=1}^{q} \mu_c * (z_j)}; \quad (3.3)$$

CHAPTER 4

FUZZY LOGIC BASED NEGOTIATION

4.1 Introduction

In this chapter, I present the framework of my research, fuzzy logic based negotiation. The framework, as also highlighted earlier, is about implementing a negotiation scenario based on fuzzy logic.

4.2 Proposed Fuzzy Logic Based Negotiation

As mentioned earlier on the introduction, the purpose of applying fuzzy to negotiation is to make it simple and comprehensive. To start, the negotiation framework is as depicted in the figure below:

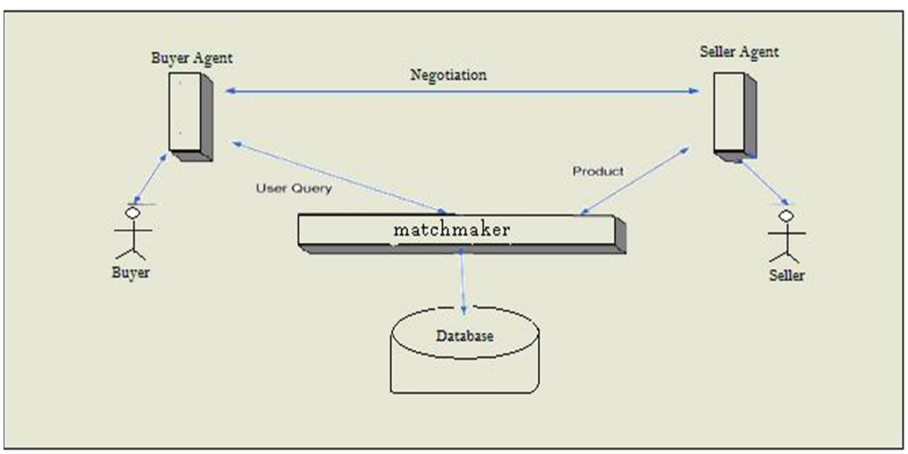


Figure 4.1: Negotiation framework

The above framework looks simple and straightforward. It involves three main components: the Buyer agent (BA), the Matchmaker (MA) and the Seller agent (SA).

At any time, when the need of buying arises, the buyer sends the description of the item it needs to the BA, whereas on the other side, the seller updates the MA about what it has to offer. Hence, when a request from a buyer agent is received, the matchmaker checks to see which seller agent has the description of the item requested. Once a seller is located, its profile will be sent to the BA and negotiation between BA and SA begins.

Our model follows an alternating-offers protocol, which means the negotiators propose and respond alternatively until an agreement is reached or quit the negotiation. The outcome of a negotiator at each step in this protocol includes: accept, reject and propose an offer, quit [11]. The intelligence of the negotiation agent is concentrated on the reasoning component model detailed in section 4.1.4; which in particular focuses on the processes of generating initial/counter offers, evaluating the incoming offers, and making decisions.

4.2.1 Negotiation Process

The negotiation scenario described two agents (seller and buyer) each with contradictory demands, seeking to reach a deal by the exchange of proposals. These exchanges of proposal are also called the sequence of offers and counter-offers. Negotiation happened over the range of pre-defined issues. Those issues are classified into two parts:

- Hard constrains issues: there are issues, which cannot be negotiated. For example a buyer wants to buy a car, however when the seller presented him/her with an airplane, it is obvious there will not be any negotiation because the core object or item which makes room for a negotiation is not available.
- Soft constrain issues: there are issues that make the negotiation possible and there represent the issues over which agents negotiate. For example, price of an item. The price of an item is one of the many soft constrain issues to be negotiated over for an agreement to be reached.

Once the issues to be resolved are identified by both agents; then they start negotiating those issues by exchanging offers and counter offers.

4.2.2 The negotiation setup

Let x ($x \in \{x_1, x_2 \ldots x_m\}$) represents the buyer agent (BA) and y ($y \in \{y_1, y_2 \ldots y_n\}$) be the supplier agent. In addition, let then i ($i \in \{i_1, i_2 \ldots i_n\}$) be the issues under negotiation, such as price, volume, duration, quality and so on. Each agent assigns to each issue i a weight w_i, denoting the relative importance of that issue to the agent. Hence, w_i^x represents the importance of issue i to agent x. each agent assign a value to each of the issues represented by: $V_i \in [min_i; max_i]$. This means for each issue i there is a value V_i which carries a minimum and maximum value attributed to issue i. thus a scoring function f of an issue is presented by:

$$f_i^{\alpha}: [min_i, max_i] \rightarrow [0, 1].$$

Therefore, the utility function of an offer (o) is denoted as:

$$U(o) = \frac{\sum_{i=1}^{m} w_i . f_i(v_i)}{\sum_{i=1}^{m} w_i}; \quad (4.1)$$

Where U (O) is the overall utility for the offer O (= $[O_1 \ldots O_m]$ T) and f_i (v_i) is the individual scoring function for issue i for $v_i \in [0, 1]$ and the preference degree of an agent to an issue i is denoted as $w_i \in [0, 9]$. Each agent also specifies a border proposal, which is characterized by a minimum and maximum limit called utility level $[U_{max}, U_{min}]$ to determine if an offer is acceptable. The intersection between the two agents' border proposals defines what we call the deal range. If the deal range is empty, it means it is not reachable [8] as in fig.4.2. The utility level or border proposals are kept hidden from the opponent.

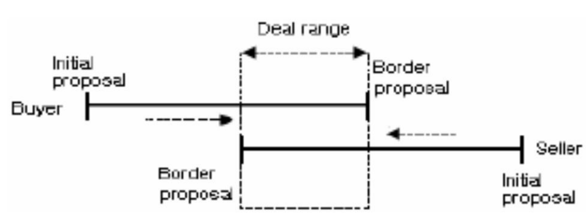


Figure 4.2: Deal range

Illustration: suppose two agents are negotiating on the price of a specific product. Each agent has its own border proposal hidden and each one of the two know what its reservation price is – a reservation price is or RP represents how much the agent is willing to pay or get on the object in question.

4.2.3 Negotiation Scenario

The negotiation scenario is as follows:

Step 1: Initialization

1.1 A participant agent enters the e-marketplace and identifies itself as either a buyer or a supplier through an agent.

1.2. Then, it submits an offer to the system (in our case, the system is characterized by the moderator).

Step 2: Matching

2.1 The system's matching agent finds M most similar opponents to the participant.

2.2 The matching agent notifies the participant and the N most similar opponents.

Step 3: Negotiation

3.1 The participant's agent evaluates the offers from the opponents. If the offers are acceptable, the negotiation process goes to Step 4; otherwise, the process continues to Step 3.2.

3.2 The participant's agent used fuzzy inference systems to generate an offer. If the offer is not good enough for the other participant, it will counter it. This succession of offers and counter offers continue until a deal is made or deadline is reached or withdrawal of one party.

Step 4: The participant chooses the best offer from the complete set of negotiated contracts or rejects all of them.

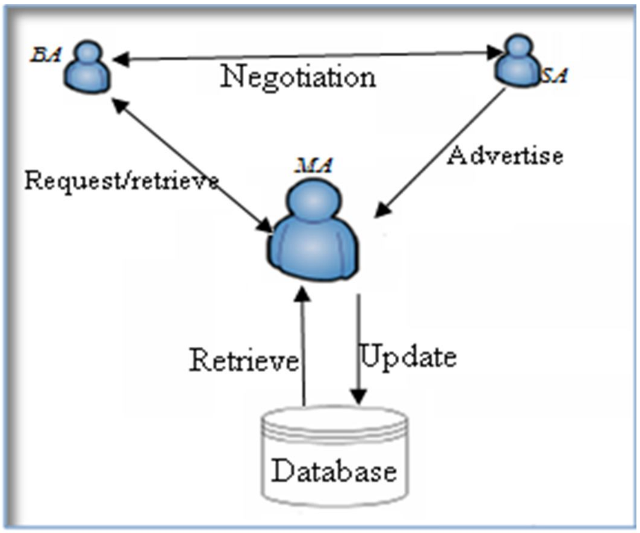


Figure 4.3: Agents' interactions

4.2.3.1 Break down of step

As mentioned above, the first step is for initialization. In this step, each of the two agents has a role to play. The seller agent will advertize or update the matchmaker agent about any new development regarding its goods or services. The buyer agent, in the other hand, enquires from the matchmaker agent when there is a need of buying any goods or services. The matchmaker agent is confined with a database, which allows it to save and register all entries from suppliers' agents and be able to retrieve them when there is a request after successfully matching the buyer agent request with the data of suppliers it has (this is done in step 2 matching). How the matchmaker agent stores data, manages them, retrieve them and/or matching does not constitute the object of this research.

After the matchmaker agent has successfully indentifies seller agents with the right products/services as requested by the buyer agent. It presents to the latter with the list from which the buyer agent will enter into negotiation with as in step 3. The whole flow is again depicted in figure 4.3.

4.2.3.2 Negotiation on the mark

This part is concerned with step 3; the negotiation. For a negotiation to start, an agent (BA) just needs to send an utterance to the seller agent expressing its intention to buy. For example:

BA: I want to buy a laptop x, how much?

SA: I give you for $4,500.

Or it could be stated:

BA: I want to offer you $1500 for your "x" laptop?

SA: I rather want $4,500 for it.

Either case the buyer agent now uses the offer sent by the seller and evaluates it to see whether it really worth spending that much for "laptop x". Now throughout the thesis, we are going to use the second format of communication or inquiry. For agent BA to counter this offer, there are a number of things that need to be considered. First, BA has to look at the quality of the laptop, then warranty and all other preferences; for example, the color of the laptop, brand name, casing and so on.

For instance, the quality feature of BA preferred laptop should include the following:

Product = { (brand) ∧ (price) ∧ (warranty)}

Computer = { (Notebook)¬(Laptop)}

Model = {(age<1yr) ∧ processor { (Intel Pentium IV dual core); (built in 518MB VGA)} ∧ Memory {RAM (3GB); hard disk (200 GB)} ∧ software {windows (original vista); Anti virus (Kapersky); Adobe (PDF, Illustrator)}}.

Meanwhile, let us say the SA has the following to offer:

Product = { (brand) ∧ (price) ∧ (warranty)}

Computer = { (Notebook)¬(Laptop)}

Model = {(age<1yr) ∧ processor { (Intel Pentium IV dual core); (built in 518MB VGA)} ∧

Memory {RAM (2.5GB); hard disk (180 GB)} ∧ software {windows (original vista);

Anti virus (Kapersky); Adobe (PDF, Illustrator)}}.

As we can from the two product specifications, there are almost the same. The difference is only on the memory which realistically very slight one. The BA requested for a 3GB RAM and 200 GB while the SB has 2.5 GB of RAM and 180 GB of hard disk. Well, in such condition can BA or we conclude or take decision of no deal? Mathematically yes, because both specifications are not exactly the same. In fact, what SA has to offer could well satisfy the purpose of which Agent wants to purchase the laptop for; it is just that there are not identically the same (in term of specification). Therefore, to be able to successfully engage into negotiation, we must include the notion of fuzzy logic. As for the above-mentioned illustration, how BA is to respond? The answer is BA will counter SA using fuzzy inference rule which we are going to illustrate in the following sections.

4.2.4 The Reasoning Model

The reasoning model consists of three blocks as shown in figure 4.4:

➢ Offer/counter offer generation block: the role of this block is to generate new offers/counter offers;

➢ Offer evaluation block: the offer evaluation block holds the task of evaluating or analysing any incoming offer to see the degree to which this offer is acceptable and finally

➢ Decision block: this block does the final wrapping up of the negotiation. It makes decision whether to accept, reject or withdraw from the negotiation.

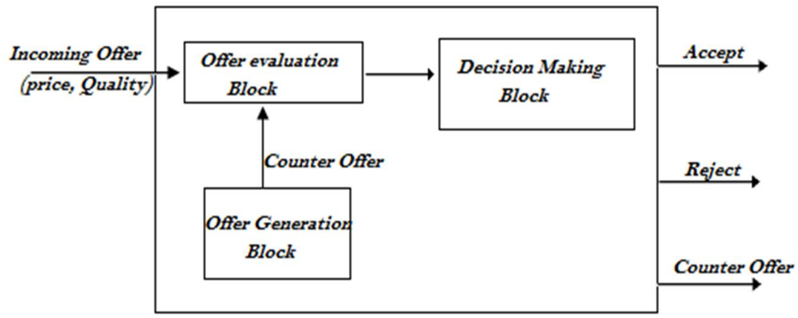


Figure 4.4: The reasoning model of the negotiation

Figure 4.4 describes the flow of the negotiation. It started with an incoming offer (notably from the seller agent), then BA evaluates it using the offer evaluation block, makes a decision through decision making and if there is anything about counter offer, then it has to be done through offer generation block.

Hence, we can conclude that the reasoning model answers the following questions:

- What counter offer should be sent out?
- What is the range of acceptable agreement?
- When negotiation should be abandoned?
- And when agreement is reached?

4.2.4.1 Offer Evaluation Block

The offer evaluation block contains the task of evaluating incoming and counter offers in order to analyse the extent to which the opponent accepts the incoming or counter offer. It can be seen as a fuzzy expert system because of its capability of measuring the human preference, which is considered as vague and uncertain. Having conventional mathematical methodology to evaluate the degree of acceptance of the incoming offer is too complicated, especially when the numbers of issues grow. Hence, fuzzy expert makes it easy and simple to deal with such situation.

The offer evaluation block is characterized by two inputs and an output as depicted in the picture below. The inputs are: price and quality while the output represents the satisfaction degree denoted as *G*. This is to measure the level of satisfaction of the buyer with respect to the quality and price quoted by the seller on that particular item.

The degree of satisfaction is represented by integers from 0 to 100 with 0 represents the least satisfaction level and 100 the most satisfaction level.

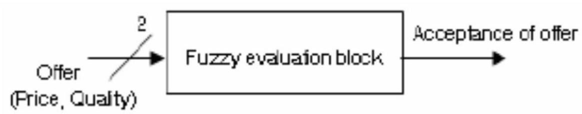


Figure 4.5: Offer evaluation model

We use fuzzy expert system to determine the satisfaction degree as in the steps depicted in fig.4.6.

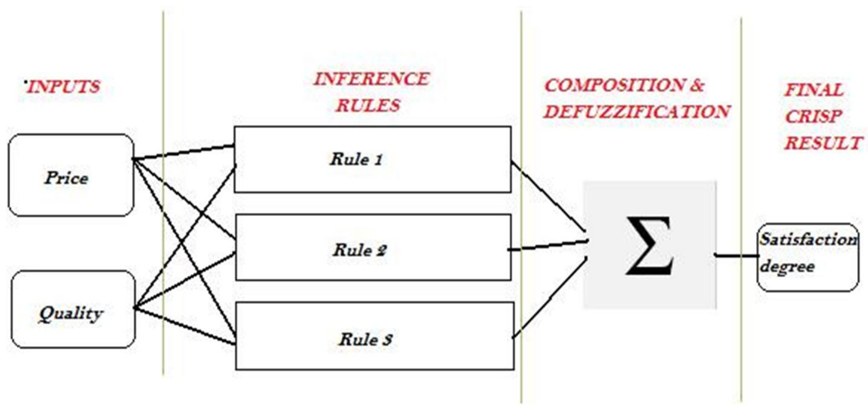


Figure 4.6: Fuzzy expert system steps

1) *Fuzzification of rules:* the fuzzification of rules comprises the modelling of the inputs and output into fuzzy sets and then set their corresponding membership function. The inputs and output are modelled as follows:

- *Input 1: Offer Price = A = {Low, medium, high}*
- *Input 2: Quality = Q = {Low, medium, high}*
- *Output: Satisfaction degree = G= {Low, medium, high}*

L = *Low; M = medium; and H = high*.

The next step of the fuzzification is to attribute to those defined fuzzy sets membership functions.

Membership functions as also outlined in chapter III represents the generalization of the indicator in classical sets. In fuzzy logic, they represent the degree of truth as an extension of valuation. Therefore our membership functions for the above mentioned linguistic variables can be noted as follows:

$$u_{Low}(x) = \begin{cases} 1; & 0 \le x \le a \\ \frac{m-x}{m-a}; & a \le x \le m \end{cases} \quad (4.2)$$

$$u_{Medium}(x) = \begin{cases} \frac{x-a}{m-a}; & a \le x \le m \\ \frac{b-x}{b-m}; & m \le x \le b \end{cases} \quad (4.3)$$

$$u_{High}(x) = \begin{cases} \frac{x-m}{h-m}; & m \le x \le h \\ 1; & h \le x \end{cases} \quad (4.4)$$

With these equations (4.2); (4.3) and (4.4) in hand and using a *trimf* membership function, we can easily map them into membership graph as in fig.4.6. *Trimf* is a membership function that uses a collection of three points forming a triangle.

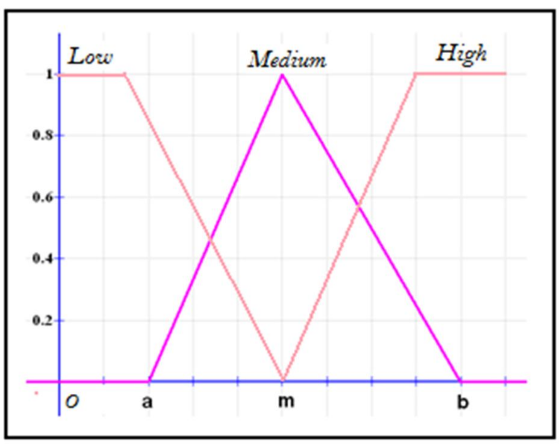


Figure 4.7: Membership function

Figure 4.6 shows which range is attributed to the linguistic variable Low, Medium and High. For instance the linguistic variable Low is any variable from 0 to a.

so if a = 2 then any value between 0 and 2 are considered to be Low, so on and so forth for the other linguistic variables Medium and High. Thus, after successfully determining our membership functions, we have to define our rules and this is done in the next section.

2) Rule Inference

Inference rules are the complete set of inference rules that map the inputs to the outputs. Each of the rules depends on resolving the inputs into a number of different fuzzy linguistic sets: Price is Low, Quality level is Moderate or price is high and so on. The Inputs price and quality level have to be fuzzified according to each of these linguistics sets before any evaluation takes place. For instance, we might want to know to which extent price is to be low? The membership function graph, which represents that extent, is on fig.4.8.

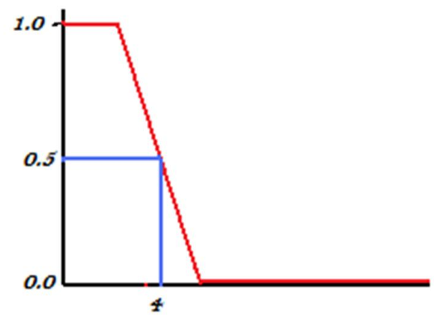


Figure 4.8: Membership function graph of price

Figure 4.7 depicts a membership function of the input variable Price = 4. As we can see in the figure, the rated price = 4, given our definition of low, corresponds to a membership of $u = 0.5$.

Inference rules are based on common sense simply because as always a buyer would like to go for a product with high quality and low price and vice versa. The rules constitute the tactic of negotiation to determine G. The L, M, and H are linguistic terms and describe the importance level of the inputs.

The complete sets of inference rule we can get are in table 4.1.

Table 4.1: Rule bank

	Antecedent			*Consequent*
Rules	*Input 1*	*Operator*	*Input 2*	*Output*
R1	*If Price is Low*	*And*	*Quality is Low*	*Then Buyer satisfaction Degree is Moderate*
R2	*If Price is L*	*And*	*Quality is M*	*Then BSD is H*
R3	*If Price is L*	*And*	*Quality is H*	*Then BSD is H*
R4	*If Price is M*	*And*	*Quality is L*	*Then BSD is L*
R5	*If Price is M*	*And*	*Quality is M*	*Then BSD is M*
R6	*If Price is M*	*And*	*Quality is H*	*Then BSD is H*
R7	*If Price is H*	*And*	*Quality is L*	*Then BSD is L*
R8	*If Price is H*	*And*	*Quality is M*	*Then BSD is L*
R9	*If Price is H*	*And*	*Quality is H*	*Then BSD is M*

L = Low; M = Moderate; H = High and BSD = Buyer satisfaction degree.

Examining these rules defined in table 4.1, we note that they are composed of:

a) *Antecedent:* antecedents are the inputs around which rules are formed or defined.

b) *Consequent:* consequent represents the output or the consequence resulting from the combination of the inputs.

c) *Operator*: Operators are connectors. Their role is to join the inputs together in order to give a meaningful output. There exist two essential operators: AND which account for the minimum value of two inputs and OR which takes the maximum value for any two or more inputs.

Illustration: let us consider price = {0 1 2 3 4} and Quality = {2 1 3 4 5}. Assuming the combination between price and quality using AND, OR operators give us C, we will have the following result shown in table 4.2 and 4.3 respectively.

Table 4.2: Combination of Price, Quality using AND operator

P AND Q		C
Price	Quality	min(P,Q)
0	2	0
1	1	1
3	3	3
4	5	4
5	4	4

Table 4.3: Combination of Price, Quality using OR operator

P OR Q		C
Price	Quality	max(P,Q)
0	2	2
1	1	1
3	3	3
4	5	5
5	4	5

Table 4.2 depicts a combination of price, quality using AND operator. As we can see, when using AND, the combination price and quality results in taking the least or minimum value among them. However, applying OR operator results in taking the maximum value of the two inputs as in Table 4.3.

3) Composition

Composition or aggregation is the process or step in which all the rules must be combined in some manner in order to give a decision. The task of the composition is to combine all the fuzzy sets that represent the output into a single fuzzy set. Figure 4.9 explains how composition takes place by applying rule 1 and 6.

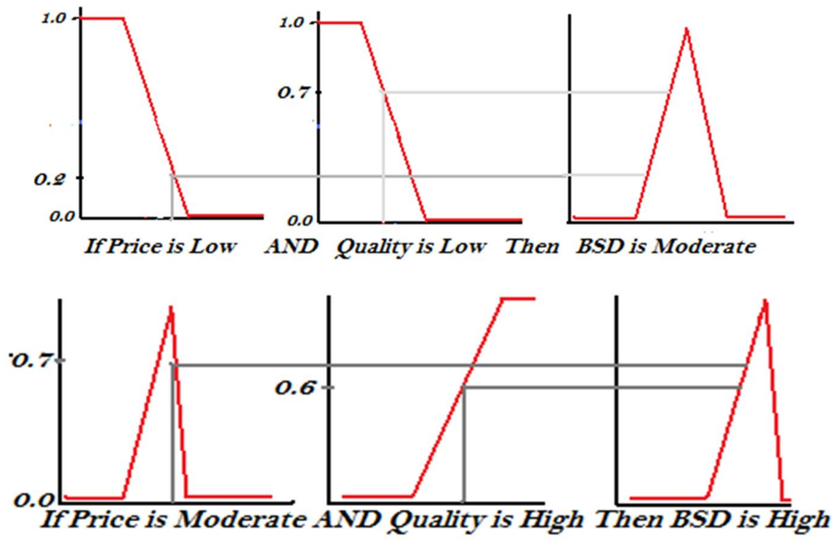


Figure 4.9: Composition of rule

As depicted in figure 4.9, all the output of the rules (constituting the BSD) will be combined together and difuzzify.

4) Defuzzification

Defuzzification is now the process of transforming those rules specified in the inference rules into something quantifiable. Defuzzification also requires conversion of the fuzzy output into a crisp single number. When applying defuzzification, there are methods we need to apply. The most common defuzzification method is the Centroid method which we use in this thesis. A Centroid method of defuzzification just returns the center of an area under curve. This means to difuzzify, we need to group all the BSD shape resulting from the rules in a single shape and calculate the center of that curve. Figure 4.10 illustrates this.

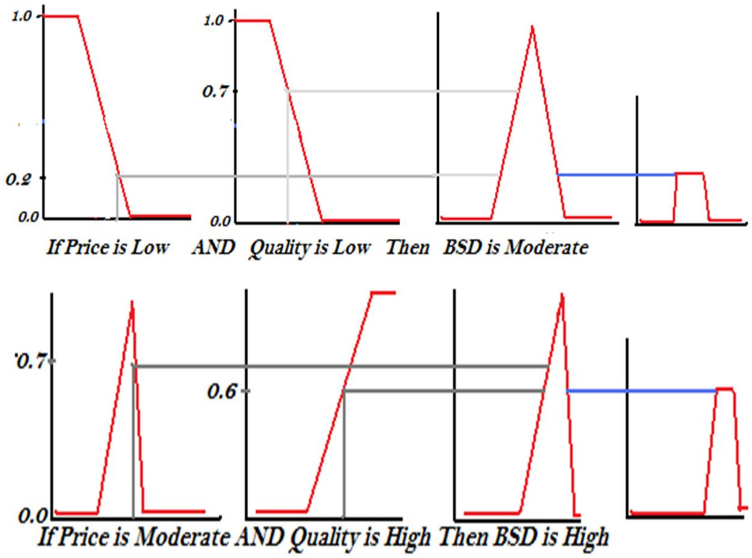


Figure 4.10: Defuzzification

The last graph in the right side of figure 4.10 represents the result of defuzzification from each rule. Now, we need to combine both figures in order for us to get a shape and later using Centroid method to determine our crisp output. Figure 4.11 shows the defuzzified shape.

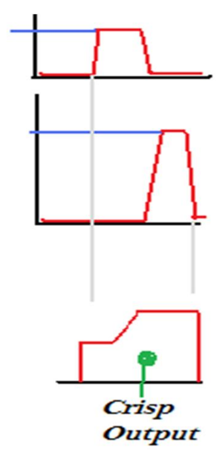


Figure 4.11: Defuzzified crisp output

Illustration 4.1 (finding satisfaction degree): for illustration purpose, let us go back to our previous example about a buyer agent BA who desires to purchase a laptop from a seller agent SA.

BA: I want to offer you $1500 for your "x" laptop?

SA: I rather want $4,500 for it.

Now, BA has to evaluate this offer and see whether it is a good bargain. This done by using fuzzy expert system as mentioned above. To determine the buyer satisfaction degree by means of fuzzy expert system manually is complex; therefore, we use MATLAB to simulate the output.

At the beginning of the process of using MATLAB, we have to set the utility value of our variables. The variables in question are Price and Quality.

- Price: $\begin{cases} u_{min} = 800 \\ u_{max} = 4700 \end{cases}$
- Quality: $\begin{cases} u_{min} = 0 \\ u_{max} = 10 \end{cases}$
- Satisfaction degree: $\begin{cases} SD_{min} = 0 \\ SD_{max} = 100 \end{cases}$

The above notation simply means for example price is chosen from 800 to 4700. This is to say that price offered or received below 800 is considered out of the deal. On the other hand, price that exceeds 4700 will neither constitute the object of negotiation.

Quality range has also to be between 0 being the least and 10 highest. The same thing also goes to the satisfaction degree. This is computed as in figure 4.12.

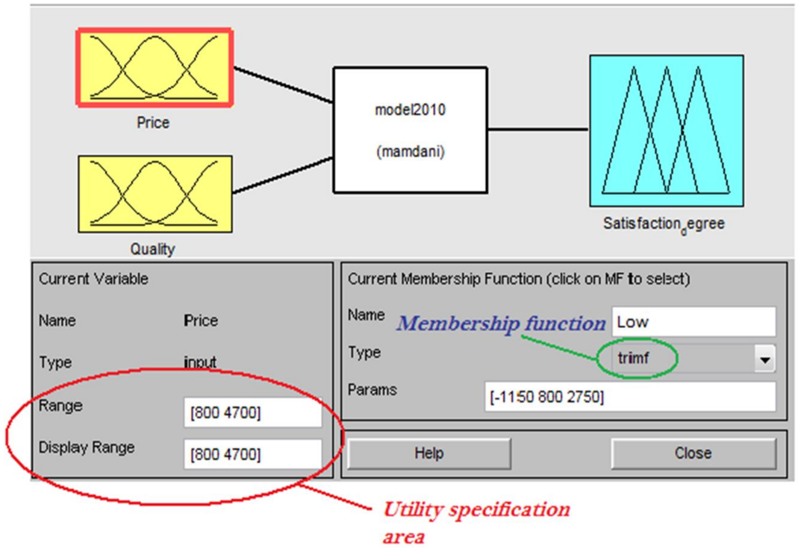


Figure 4.12: Screen shot from Matlab utility specification window

Figure 4.12 shows where to key in the utility function for the input price as well as the membership function we use. The same goes to Quality and satisfaction degree.

Later comes the specification of rules in figure 4.13 below:

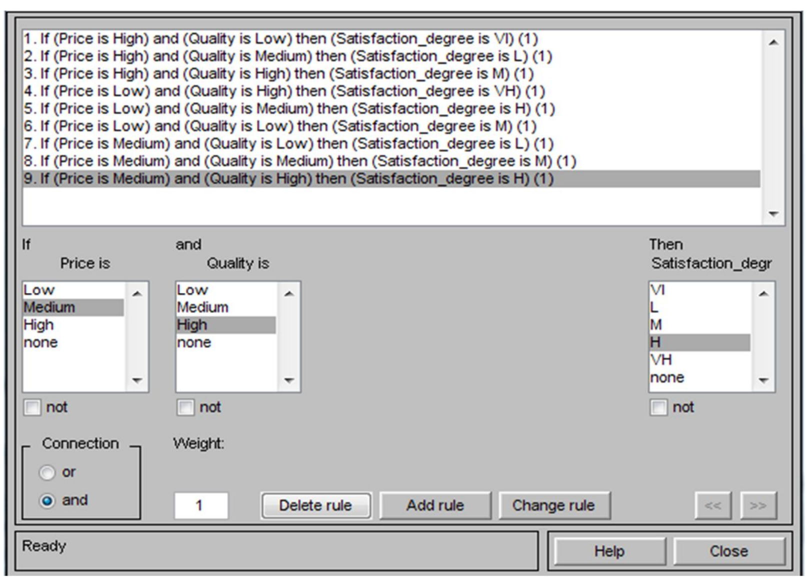


Figure 4.13: Rule editor

Lastly, the system runs it, gives us the result in terms of surface, and rules in figure 4.14 and 4.15 respectively. The rule evaluation figure is to make our job easier because it contains a rectangular box down in the left where you can specify your input value and simultaneously it will give you the corresponded crisp output. With this, one does not need to repeat the process every time there is a change in the value of price or quality.

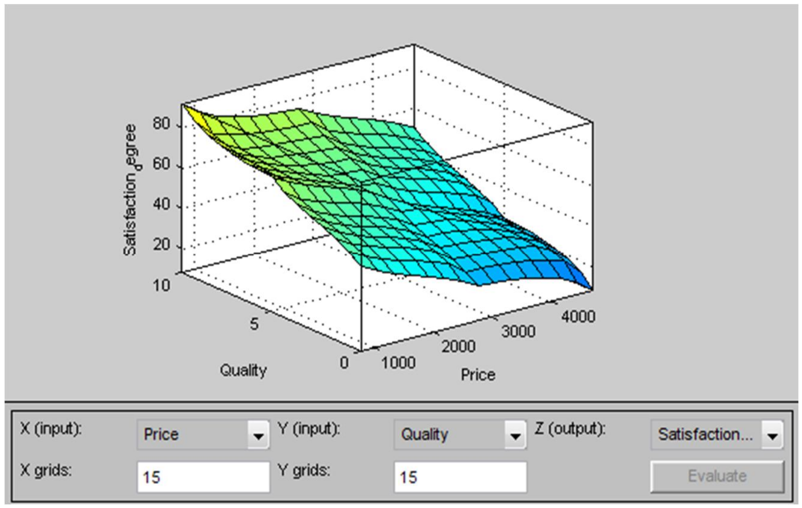


Figure 4.14: Screenshot of surface viewer

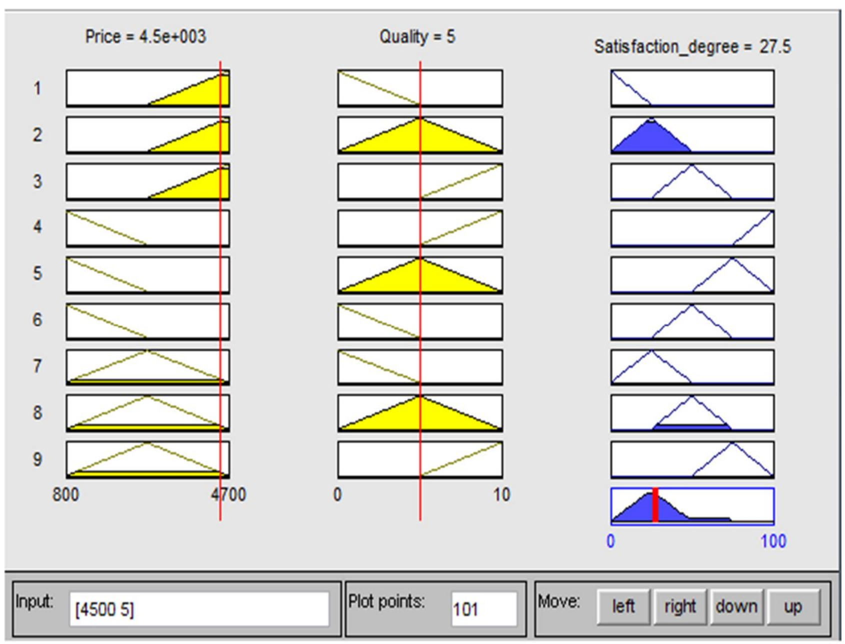


Figure 4.15: Matlab rule evaluation screen shot

The rule evaluation screen shot is a comprehensive figure where you can see how many inputs and output are taken into consideration, how many rules are defined and what are the ranges or utilities over which these inputs and output are set. Nonetheless, at the top of the figure, we can clearly see, at medium Quality of the laptop (quality = 5) and with the price the seller quotes which is = 4500, the buyer satisfaction degree is 27.5%. This value (27.5%) represents the defuzzified crisp value of the illustration. The crisp value found there above represents rule 2 which states that:

Rule 2: If Price is High, Quality is Medium, Satisfaction Degree is Low

The satisfaction degree found above justifies rule 2 and it can be computed using the center of gravity (COG) defuzzification method formula.

$$COG = \frac{\sum_{j=1}^{q} z_j * \mu_c(z_j)}{\sum_{j=1}^{q} \mu_c * (z_j)}; \quad (4.5)$$

Where q = number of quantization levels of the output

z_j = the amount output at quantization level j

$\mu_c(z_j)$ = membership value in C.

To compute rule 4 manually, we need to again use the help of figure 4.15 and reproduce the concerned graph in 4.16 below

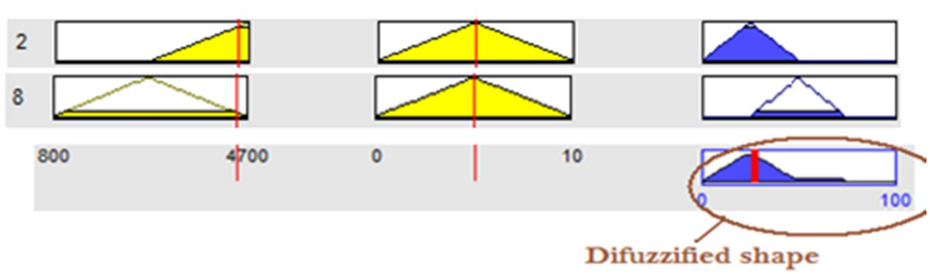


Figure 4.16: Defuzzified shape of R4

The Matlab evaluation system does not run the rules individually. This means if you have inputs and want to find out the output, the Matlab system runs through every single rule that has been computed before determining the output. This is because what we are using is a fuzzy system and when dealing with fuzzy logic we are often faced with membership function. For instance when we define our input price = 4500, we know for sure it is high, but we don't know how high it is? So in order to understand how high is 4500, we need to refer to its membership. And as outline in fig 4.15, Price = 4500 is considered to be high at approximately 0.9 of membership and consequently 0.1 medium.

Going back to figure 4.16, we now understand that in order to transform R4 into something quantifiable, we need also to involve R8 to certain degree. Let us then evaluate those two rules:

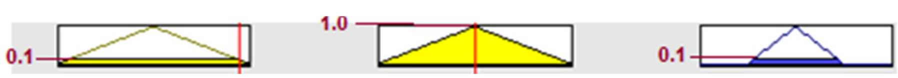
Rule 2: If Price is High **AND** Quality Medium, then Satisfaction degree is Low

Therefore $z_j = \mathbf{min}\,(\mu_c(P), \mu_c(Q))$

$$z_j = \mathbf{min}(0.9; 1)$$

$$\boldsymbol{z_j = 0.9}$$

Rule 8: If Price is Medium **AND** Quality is Medium then Satisfaction Degree is Medium.



Therefore $z_j = \min\,(\mu_c(P), \mu_c(Q))$

$$z_j = \mathbf{min}(0.1; 1)$$

$$\boldsymbol{z_j = 0.1}$$

Applying equation 4.4 the COG = $\frac{(0\ x\ 0.9)+(25\ x\ 0.1)+(50\ x\ 0.9)+(75\ x\ 0.1)}{0.9+0.1+0.9+0.1}$

$$\mathbf{COG} = \frac{\mathbf{55}}{\mathbf{2}} = \mathbf{27.5}$$

Now that the buyer agent has evaluated the incoming offer from the seller agent, the reasoning model suggests that the seller agent will look into decision block to see if the current offer made by the seller agent is acceptable. What action should be taken, given the seller agent offer? Would it be an acceptance, rejection or countering? We will surely find the answer in the decision making block in the next section.

4.1.4.2. Decision Making Block

The function of the decision block model is to make decision after the evaluation block has finished its task. The decision function gives the final verdict whether to accept any incoming offer rejects it or counter it with an offer. It can be simplified according to simple and comprehensive rules as follows:

- Reject the Offer: $\begin{cases} if\ SD_n < SD_{min} \\ if\ O_{incoming} > U^o_{max} \end{cases}$; (4.6)

- Accept/counter the Offer: $\begin{cases} if\ O_{incoming} \leq U^o_{min} \\ else,\ Counter \end{cases}$ (4.7)

With SD_n = satisfaction degree at time n; SD_{min} = minimum satisfaction degree set by the buyer; $O_{incoming}$ = Incoming Offer from the seller; U^o_{max} = Maximum utility offer of the buyer; U^o_{min} = Minimum Utility Offer of the buyer.

Equation (4.6) suggests that if the buyer satisfaction degree is less than the minimum satisfaction degree or if the incoming offer is greater than the maximum utility of the offer, then the buyer agent rejects the offer proposed by the seller. However, equation (4.7) states that if the incoming offer is less or equal to the minimum utility offer of the buyer, buyer agent will have to accept the proposal of the seller; else, buyer agent goes into countering the seller proposal. However, this decision making block is too easy to avoid an impasse in a negotiation process. Hence, we assume two external constrains limit the negotiation process: the round of negotiation and duration, which are predefined by the user at the start of the negotiation to avoid an endless negotiation process.

Referring to the above-determined evaluation and considering the decision function in equation (4.6) and (4.7) we now can have a clear picture on what the BA decision is going to be? With 27.5% satisfaction degree, the BA will automatically counter the offer for a good bargain. Well, countering an offer is a subject of Offer generation Block.

4.1.4.3.Offer Generation Block

The offer generation block determines what counter offer should be sent out. Offer generation engine/block can be seen as Distributed Fuzzy Constraint Satisfaction Problem. The modelling of this block has been done using functions called tactics. The way those tactics were tuned in using weight are called strategies. Tactics are the set of functions that determine how to compute the value of an issue using a single criterion such as time, behaviour, resource and so on…a lot of research has been done in this area using those criterion as in [1, 44, and 54].

However, our model uses a quite different methodology. In line with our objective of designing a fuzzy logic based negotiation agent, we decided to incorporate the notion of fuzzy logic throughout the process of negotiation. Therefore, our offer generation engine has been designed using fuzzy set theory. So in order to determine the counter offer, we need to define our concession rate ‘r’. Hence, we call upon two linguistic variables, which will help us determine our Counter offer as depicted in figure 4.17 below.

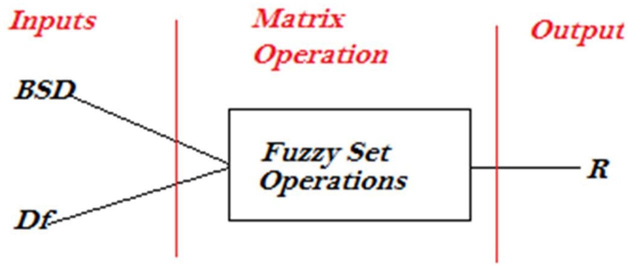


Figure 4.17: Inference method using max product

Figure 4.16 details the process from which the ratio for the next round "r" is going to be determined. To do so, we need to call upon two linguistic variables to constitute our inputs.

The first linguistic variable is the buyer satisfaction degree (BSD) mentioned in fig 4.17. The second linguistic variable, which we are going to determine, is the ratio for the difference between buyer and seller proposal. It is formulated as follows:

$$Df = \frac{x_n - y_{n-1}}{x_n} \quad (4.8);$$

With x_n = initial price proposed by the seller at time n; y_{n-1} = price the buyer proposes at time $n-1$.

We, then, need to transform the crisp values of those linguistic variables *SD* and *Df* into grade of membership for linguistic terms of fuzzy sets. This fuzzy sets is characterized each by 5 linguistic terms {VL, L, M, H, VH} denoting Very Low; Low; Medium; High; and Very High respectively. For each linguistic term, there is a membership function associated with it and so the membership functions of the two linguistic variables *SD* and *Df* are as follows:

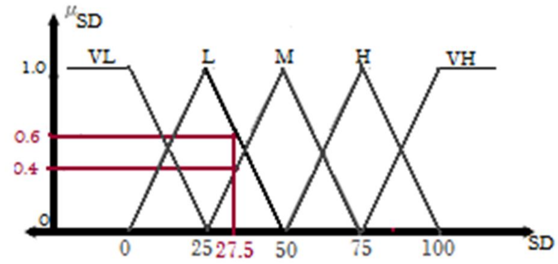


Figure 4.18: Membership function of SD

Figure 4.17 maps the satisfaction degree of the buyer equals to 27.5% as found in illustration 4.1. therefore at SD = 27.5%, we found that the 5 linguistic terms {VL; L; M; H; VH} are {0; 0.6; 0.4; 0; 0}.

If we may again recall illustration 4.1 here above; the offer price the buyer agent has proposed initially was RM 1500, while the seller counter that offer by proposing an amount of RM 4500. Considering these two offer prices and apply equation 4.8, we get a ratio of difference *Df of:*

$$Df = \frac{4500-1500}{4500} = 0.66$$

Therefore, at Df = 0.66, we have the following graph membership function.

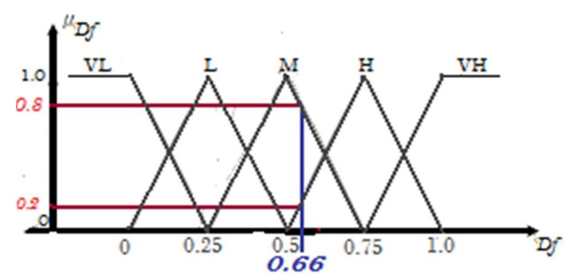


Figure 4.19: Membership function of D*f*

At Df = 0.66, our five linguistic terms are {0; 0; 0.8; 0.2; 0}.

Now we have defined our two variables, so to get something out of them we have to use inference method with *max product.* The output of this method is the grades of membership for the 5 linguistic terms of linguistic variable *C*. to determine the value of the linguistic variable *C*, there are two steps involved:

➢ The first step is to generate the product of grades membership out of *SD* and *Df*. So given the grades of membership of the two variable {0; 0.6; 0.4; 0; 0} for *SD* and {0; 0; 0.8; 0.2; 0} for *Df*, the product of these two grades *SD x Df* which represent C is a set of matrix Ґ shown in figure below.

Table 4.4: Inference matrix

$$Ґ = \begin{bmatrix} SD/Df & 0 & 0.6 & 0.4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.12 & 0.08 \\ 0 & 0 & 0 & 0 & \mathbf{0.48} & \mathbf{0.32} \\ 0.8 & 0 & 0.48 & 0.32 & 0 & 0 \\ 0.2 & 0 & 0.12 & 0.048 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The matrix Ґ in table 4.2 is characterized as follows. The first row represents the linguistic variables for the satisfaction degree *SD* and the first column represents the linguistic variable for the ratio of difference *Df* .

➢ The second step consists of selecting the maximum value as the grade of membership for each linguistic term. Therefore, the grades of membership for C are {0; 0.48; 0.32; 0; 0}.

Now that we have determined C with its corresponding linguistic variable or grade of membership, we difuzzify it in order to get our '*r*' that represents the ratio that determines the next counter offer from the buyer agent. The defuzzification method adopted is again the *Centroid* method. The output of this method is a crisp value of a linguistic variable, the x-axis position of the gravity center of some areas, which are derived from the grades of membership of the linguistic variable. For this case, the output is a crisp value of linguistic variable *C*, the concession rate, denoted by r_{n+1}. The rate is used to compute the counter offer in $(i+1)^{\text{th}}$-round proposal.

So given the grades of membership {0; 0.48; 0.32; 0; 0} for linguistic variable *C*, apply the Center of Gravity method to difuzzify and obtain a crisp value 0.14. This value represents the value of r_{n+1} as deduced in figure 4.19

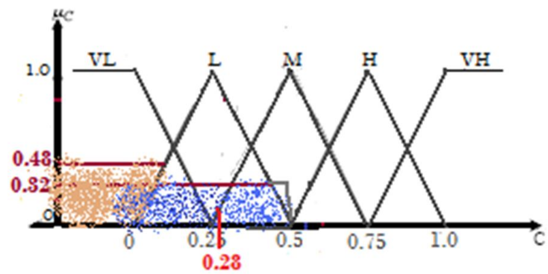


Figure 4.20: Membership function of linguistic variable C

This crisp value of 0.28 is finally used as a ratio to compute the counter offer using equation 4.9.

$$x_{n+1} = x_n(1 + r_{n+1}); \quad (4.9)$$

With $x_{n+1} = next\ proposal$; x_n = previous proposal and r_{n+1} = concession rate for this round.

- *Illustration 4.2:* referring back to our illustration 4.1 we will have the following scenario.

o *BA: I want to offer you $1500 for your "x" laptop.*

o *SA: I rather want $4,500 for it.*

o (From here the buyer agent needs to use fuzzy logic in order to counter/give another offer suitable. Process of evaluation has been carried out in section 4.1.4.1, followed by decision taking in 4.1.4.2).

o The decision taken in 4.1.4.2 is to counter. The task of counter the offer has been explained in section 4.1.4.3 and we came out with a ratio of 0.28 for the next offer, the buyer agent needs to use. Hence, applying equation 4.9; the next offer the buyer agent is to send to the seller is:

1500*(1+0.28) = **1920**

CHAPTER 5

SIMULATION AND RESULT

5.1 Introduction

This chapter discusses result and analysis of our simulation based on the model discussed in chapter four. The simulation is based on a buyer agent and a seller agent with the willingness of striking a deal with one another. At the outset of the negotiation, both buyer and seller determine or set their objectives. For example; for this thesis, we place ourselves in the buyer side, a buyer has to key in all necessary information in term of task to be performed to the computer for the buyer agent to carry on.

5.2 Simulation

The simulation is based on two scenarios. The first scenario evaluation is based on three inputs namely: Price, Quality and Warranty and an output that is the satisfaction degree. That means the buyer agent here is bound to make a decision based on these three attributes/inputs. However, the first thing to do when presented with such a scenario is to determine the satisfaction degree of the buyer agent (or seller agent) upon reception of an input from the seller agent. This is primordial for the buyer agent to first know the extent of its satisfaction towards the negotiation. The satisfaction degree as explained in chapter 4 in section 4.1.4.1 has to go through fuzzification of its inputs until the step of defuzzification in order to present/compute out a crisp output constituting the extent to which the agent is satisfied. To begin with scenario one, it is imminent to define the setting from which the scenario is based upon or derived from.

__Scenario I__

The inputs and output utility functions are defined as follows:

- Price: $\begin{cases} u_{min} = 800 \\ u_{max} = 4700 \end{cases}$
- Quality: $\begin{cases} u_{min} = 0 \\ u_{max} = 10 \end{cases}$
- Warranty: $\begin{cases} Wty_{min} = 1 \\ Wty_{max} = 3 \end{cases}$
- Satisfaction degree: $\begin{cases} SD_{min} = 0 \\ SD_{max} = 100 \end{cases}$;

These utilities are the same as the one used in illustration 4.1 with the exception of warranty, which constitute a new addition. The warranty is scaled over 1 year to 3 years with 1 being the least and 3 the highest. It is important to define the utility functions of each attribute or issue as this makes the system know from where we are going. Should the price utilities for example be forgotten or unidentified, the system will not be able to accurately understand or calculate how much the agent is willing to propose. In addition, it will be difficult for the system to tell at what price, the item that is being negotiated is considered to be high. It could be noted that the utilities are to help the system make boundaries or limit its domain. Moreover, the settings of these utilities are not meant to fix the price to a specific amount but rather serve as a range for the flow of negotiation. The evaluation of all rules in table 5.1 is depicted in the figure below (fig 5.1) using Matlab. Table 5.1 below details the rules deduced from the available inputs and output.

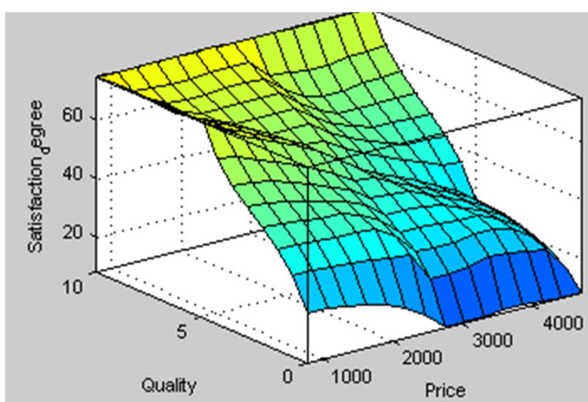


Figure 5.1: Rules surface

Table 5.1: Rule Bank

1.	IF P is L	Q is L	Wty is L	SD is L
2.	IF P is L	Q is L	Wty is M	SD is L
3.	IF P is L	Q is L	Wty is H	SD is M
4.	IF P is L	Q is M	Wty is L	SD is M
5.	IF P is L	Q is M	Wty is M	SD is H
6.	IF P is L	Q is M	Wty is H	SD is H
7.	IF P is L	Q is H	Wty is L	SD is H
8.	IF P is L	Q is H	Wty is M	SD is H
9.	IF P is L	Q is H	Wty is H	SD is VH
10.	IF P is M	Q is L	Wty is L	SD is VL
1	IF P is M	Q is L	Wty is M	SD is VL

1.				
12.	IF P is M	Q is L	Wty is H	SD is L
13.	IF P is M	Q is M	Wty is L	SD is M
14.	IF P is M	Q is M	Wty is M	SD is M
15.	IF P is M	Q is M	Wty is H	SD is M
16.	IF P is M	Q is H	Wty is L	SD is M
17.	IF P is M	Q is H	Wty is M	SD is H
18	IF P is M	Q is H	Wty is H	SD is H
19.	IF P is H	Q is L	Wty is L	SD is VL
20.	IF P is H	Q is L	Wty is M	SD is VL
21.	IF P is H	Q is L	Wty is H	SD is L
22.	IF P is H	Q is M	Wty is L	SD is L
23.	IF P is H	Q is M	Wty is M	SD is L

24.	IF P is H	Q is M	Wty is H	SD is M
25.	IF P is H	Q is H	Wty is L	SD is M
26.	IF P is H	Q is H	Wty is M	SD is H
27.	IF P is H	Q is H	Wty is H	SD is H

P = Price; Q= Quality; Wty = Warranty; SD= Satisfaction degree

VL = Very Low; L = Low; M = Medium; H = High; VH = Very High

Now that we have the rules in order, we now must determine the satisfaction degree resulting from it.

Table 5.2: Satisfaction degree vs. change in price

Price	**Quality**	**Warranty**	**Satisfaction Degree**
$4700	0	1	8%
4500	0	1	8.11%
4300	0	1	8.34%
4100	0	1	8.66%
3900	0	1	8.71%
3700	0	1	8.78%
3500	0	1	8.86%

3300	0	1	8.92%
3100	0	1	8.97%
2900	0	1	9.07%
2700	0	1	9.18%
2500	0	1	13.7%
2300	0	1	16.8%
2100	0	1	19.1%
1900	0	1	20.9%
1700	0	1	22.2%
1500	0	1	23.3%

Table above shows the different satisfaction degree to be obtained when price varies; whereas quality and warranty remained fixed. It details the percentage or the satisfaction degree resulting from each combination of price, quality and warranty. If one may recall the objective of this thesis is to incorporate the notion of fuzzy logic throughout the process of negotiation. However, one of the elements of fuzzy logic is the mapping of input through output using fuzzy rule as shown in table 5.1. This has allowed us to determine the different percentage or changes in the satisfaction degree in table 5.2. Since the satisfaction degree constitutes a key element in the notion of fuzzy logic, this makes it easier for us to determine the counter offer provided that we also find the ratio of difference between the last two successive offers using equation 4.8 in section 4.1.4.3. The analysis of Table 5.2 and figure 5.2 suggests that for any price change the satisfaction degree also varies. This is to say that satisfaction degree is function of all the tree attributes/issues. Any change in them could result in a change in the satisfaction degree. nevertheless, figure 5.2 demonstrates how practical the satisfaction degree is; for it doesn't only determine the satisfaction degree but it also make sense to the sense that it, to some extent simulate the possible behavior humans create vis-à-vis negotiation. For instance, when the price is \$4700, quality is zero and warranty = 1, then the buyer satisfaction degree is 8%. But when the price shifts to \$3500 for example, the satisfaction degree rises to 8.86% even though quality and warranty remain unchanged. This fact again highlights the importance of specifying fuzzy rule as shown in table 5.1.

To further highlight the importance and stability of the system with regard to determining the satisfaction degree, we made another simulation but this time, by keeping the price fix and have the quality varies. The table and figure 5.2 explain another relationship. Keeping price level fix at \$ 800, the above-mentioned table and figure detail the sensitivity of the satisfaction degree when the quality level of the item varies. If we look at table 5.2 first row, we realize when the price is \$4700, quality = 0 and warranty is 1, the satisfaction degree of the buyer is 8%. However, table 5.3 returns a 25% satisfaction degree to the buyer when the price is reduced to a lower value of \$800.

Now as stated earlier on that we need at first to compute the satisfaction degree to understand how satisfied the buyer/seller is given a particular offer/proposal; we then need to determine the next offer concession, as satisfaction degree alone is not enough to make a decision as we have demonstrated in chapter 4. Consequently, we also need to define our ratio of difference denoted as *Df* as in section 4.1.4.3. This is because for every proposal, there will be a new price offer and as such, the ratio of difference plays an important role in determining the next counter offer.

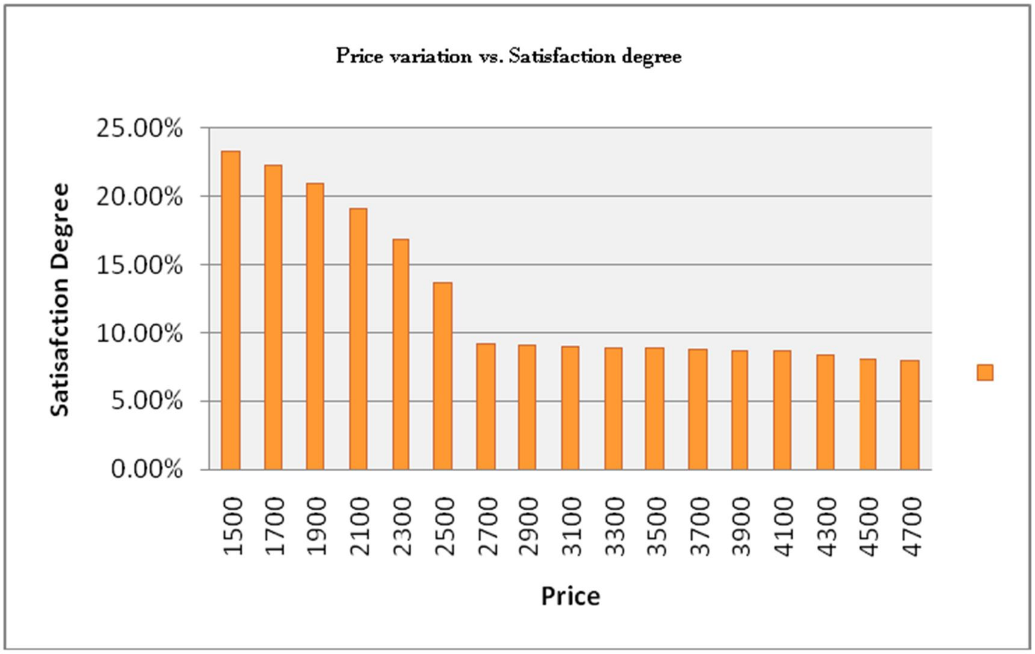


Figure 5.2: Price variation vs. Satisfaction degree

Table 5.3: Quality changes vs. Satisfaction degree

Price	Quality	Warranty	Satisfaction Degree
800	0	1	25%
800	1	1	31%
800	1.2	1	32%
800	1.4	1	32.9%
800	1.6	1	33.8%
800	1.8	1	34.7%
800	2	1	35.5%

800	2.2	1	36.3%
800	2.4	1	37.1%
800	2.6	1	37.9%
800	2.8	1	38.7%
800	3	1	39.5%
800	3.2	1	40.3%
800	3.4	1	41.2%
800	3.6	1	42.1%
800	3.8	1	43%
800	4	1	44%
800	4.2	1	45%
800	5	1	50%
800	7	1	60.5%
800	9	1	69%
800	10	1	75%

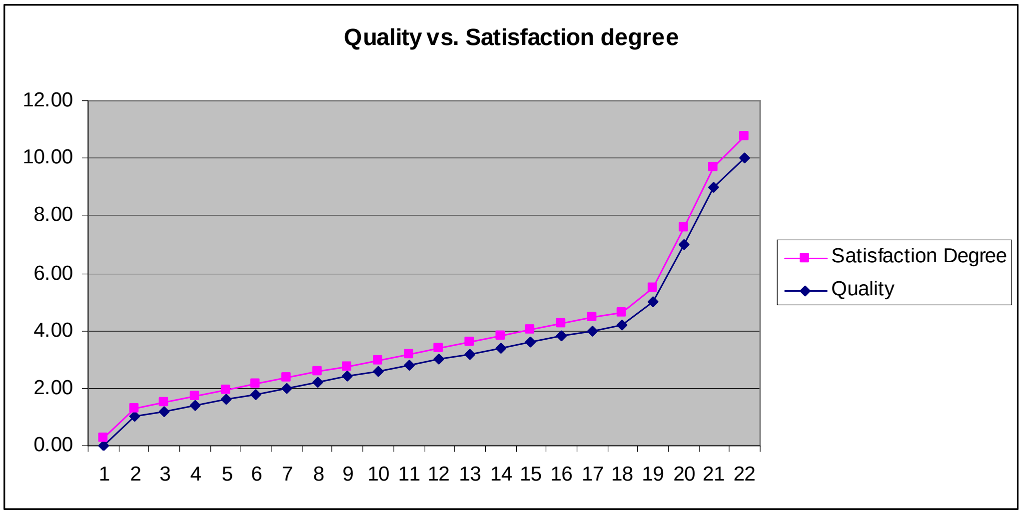


Figure 5.3: Satisfaction degree vs. quality

Table 5.4 as well as figure 5.4 details the different satisfaction and their respective concession rate. For every different satisfaction degree, there is also one different concession rate. Now the concession rate (as explained in section 4.1.4.3) determines how much the buyer/seller needs to advance, in the form of a ratio, as an addition to his current proposal for the deal to happen. That means if the buyer agent receives a counter offer from the seller agent and it (BA) satisfaction degree rose to 9.07%, then it is very luckily that the BA next counter offer will be in excess of 19.75% from the previous offer. Subsequently, if another counter offer has been sent to the BA and this time the satisfaction degree of BA is 20.9%, then the BA is likely to improve its previous offer by 38.9%. Moreover, the offer and counter offers continue until one agent is satisfied and/or the negotiation is terminated.

Table 5.4: Satisfaction Degree vs. Concession rate

Satisfaction Degree	**Concession rate** r_{n+1}
8%	0.195
9.07%	0.1975

13.7%	0.0925
16.8%	0.195
19.1%	0.3125
20.9%	0.389
22.2%	0.405
23.3%	0.4115
25%	0.1115
31%	0.3675
32%	0.3325
33%	0.3025
34%	0.283
35%	0.119
40%	0.242
45%	0.220
50%	0.1967
55%	0.560

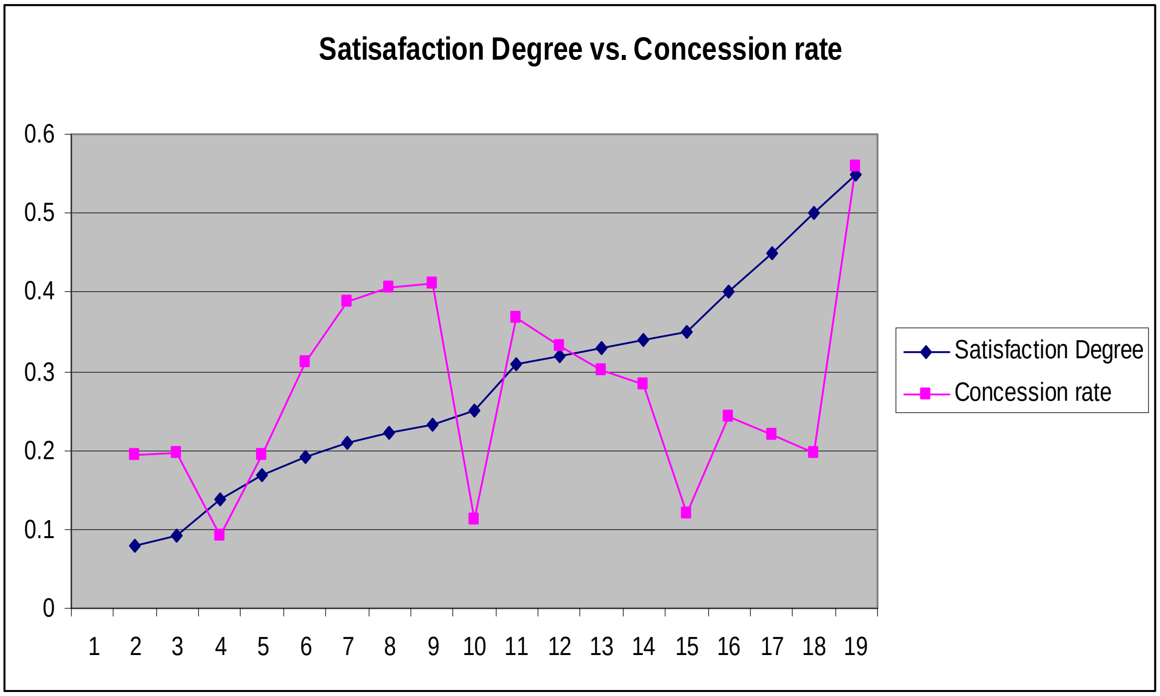


Figure 5.4: Satisfaction degree vs. concession rate

Proposals of Scenario I:

- *BA: First offer for "x" laptop → $1500*
- *SA: First Offer for "x" laptop → $4,500*
- *BA: First Counter Offer →$ 1920*
- *SA: First Counter Offer → $3825*
- *BA: Second counter Offer→ $2617*
- *SA: Second Counter Offer → **$3199***
- *BA: Third Counter Offer → $3275*

The above Scenario proposal depicts sequences of offers between the buyer agent and the seller agent. The respective amounts displayed for both agents are determined through the modelling process discussed in chapter four. In this scenario, we can see that each buyer and seller is receiving an offer from its counterpart, determine whether the incoming offer is acceptable, and then make decision of a counter. for example, at offer $1920 sent by the buyer to seller agent, the latter has to determine its satisfaction degree which is computed and shown in appendix A under "*satisfaction degree as in the rules viewer*". The seller then determines the ratio of difference using equation 4.8. Moreover, the fuzzy linguistic variables title in appendix A explains and shows the different combinations and variable values concerned before reaching to the final offer. In fact, when we look at appendix A under fuzzy linguistic variables, the incoming offer of $1920 received from BA has satisfied the seller agent at 39.9%. At this stage of the negotiation, the ratio of the difference is 0.57(equation 4.8) which resulted in a counter offer ratio of 0.85 after determining both linguistic variables for SD, DF and concession rate.

In this scenario, the acceptable price that enables the buyer agent to finalize the negotiation is $3199. In fact, the buyer agent has already determined an offer to send to the seller agent and that offer is quite good for the seller agent than its own counter offer of $3199. However, the buyer agent third counter offer is obviously greater than the earlier incoming offer from the seller agent. Therefore, the buyer agent accepts the seller second counter offer to maximize its utility. This also highlights one of the qualities of the agent to realize an optimum outcome and an added advantage for the agent not to make excessive offer. Another interesting remark is that, whenever negotiation is on and the seller agent keeps decreasing its initial offer, the buyer agent satisfaction degree rises. As we can see in the scenario, the buyer satisfaction degree increases from the initial degree of 27.5% (found in illustration 4.1) to 35.4% and 49.7% (appendix A).

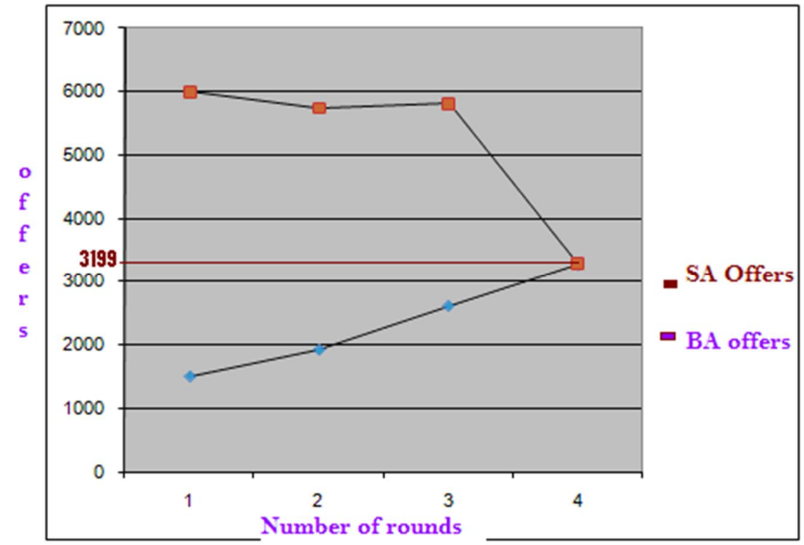


Figure 5.5: Successive offers between buyer and seller

Appendix A. shows more on how these counter offers value were coming from. Besides fig.5.4 displays the successive movements of offers between buyer and seller and the agreed price of $3199, as we can see in the figure, is right above the intersection range.

Scenario II:

The scenario II is based on scenario I with the exception of attributes or issues, which are in excess from the previous one. This means that scenario II is simulated using four attributes/issues namely: Price, Quality, Warranty, and Delivery time. The utilities' settings are the same as scenario I except for delivery time, which is in the range of [1-3].

- *Determining the satisfaction degree*

Figure 5.6 shows the different satisfaction degree of scenario II (satisfaction degree SC II) and how variant these values are from the satisfaction degree of scenario I (satisfaction degree SC I). The figure 5.6 is drawn out from the satisfaction degree of scenario II in table 1B; which is in appendix B. This is done in an effort to understand how efficient the negotiation will be when several issues are taken into consideration. In this scenario, we are trying to see, among others, the difference this one inclusion of issue delivery time has in the resulting output compared to scenario I. at first, we notice that there exists a difference in the satisfaction degree for scenario I and II as outlined in tables 1B and 2B in appendix B.

After process of determining satisfaction degree, decision-making until concession rate have been duly gone through, here are the possible interaction and offer exchange that result from the simulation. For complete and comprehensive details on how these figures or interaction value below were obtained, please refer to appendix B under fuzzy linguistic variables.

Offer Exchanges between BA and SA

- *BA: First offer for "x" laptop → $1500*
- *SA: First Offer for "x" laptop → $4,500*
- *BA: First Counter Offer →$ 1975*
- *SA: First Counter Offer → $3208.5*
- *BA: Second counter Offer→* ***$2786***
- *SA: Second Counter Offer → $2444.49s*

The above offer exchange shows the interactions BA and SA went through to reach an agreed price of $2786 for the item 'x" laptop. From the initial price of $1500, BA offered to the SA, the BA has managed to increase his offer until a price of $2786. Meanwhile, the SA has decreased his pricing of $4500 to the same final offer of $2786. Both seller and buyer agent has gone through the same process of determining the satisfaction degree once an offer has been received, deciding whether to quit, accept or counter and finally make an offer if there is. On the other hand, in scenario, both agents SA and BA came to an agreement in the price of $2786 compared to $3199 in scenario I. This difference is characterized by the addition of delivery time coming into the scenario. Although the delivery time range is from 1 to 3 but it made a significant difference from the satisfaction degree to the final price (from $3199 to $2786). Table 1B and 2B in appendix B show the difference between the satisfaction degrees of scenario I and II when price changes and Quality changes simultaneously. Finally, as we look at figure 5.7, one can also realize that for this scenario or this particular buyer and seller agents, it only took at least 3 proposals to realize an agreement. Meanwhile, it has taken the BA and SA 4 round of proposals to reach an agreement in scenario I.

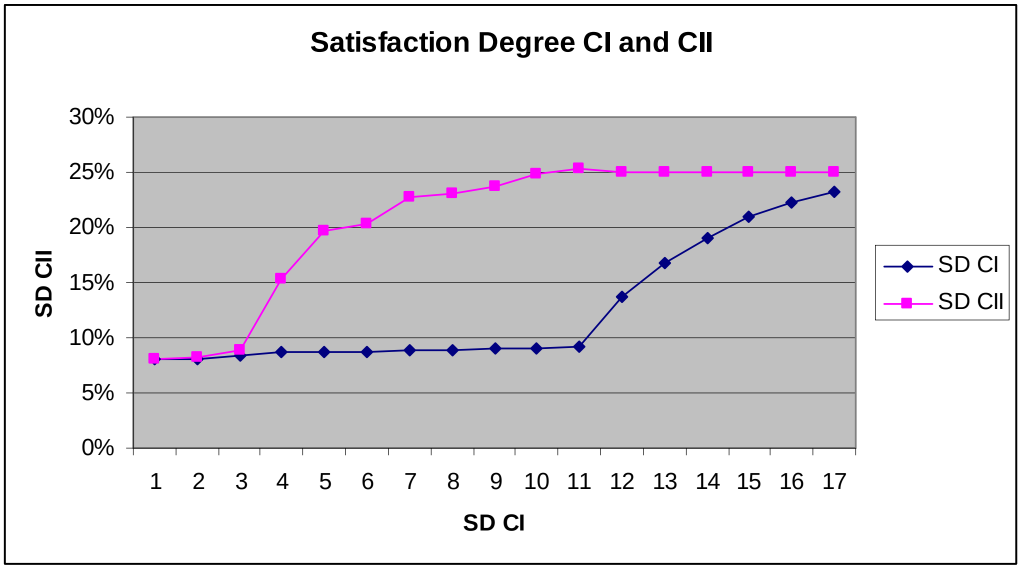


Figure 5.6: Satisfaction degree SCI vs. SCII

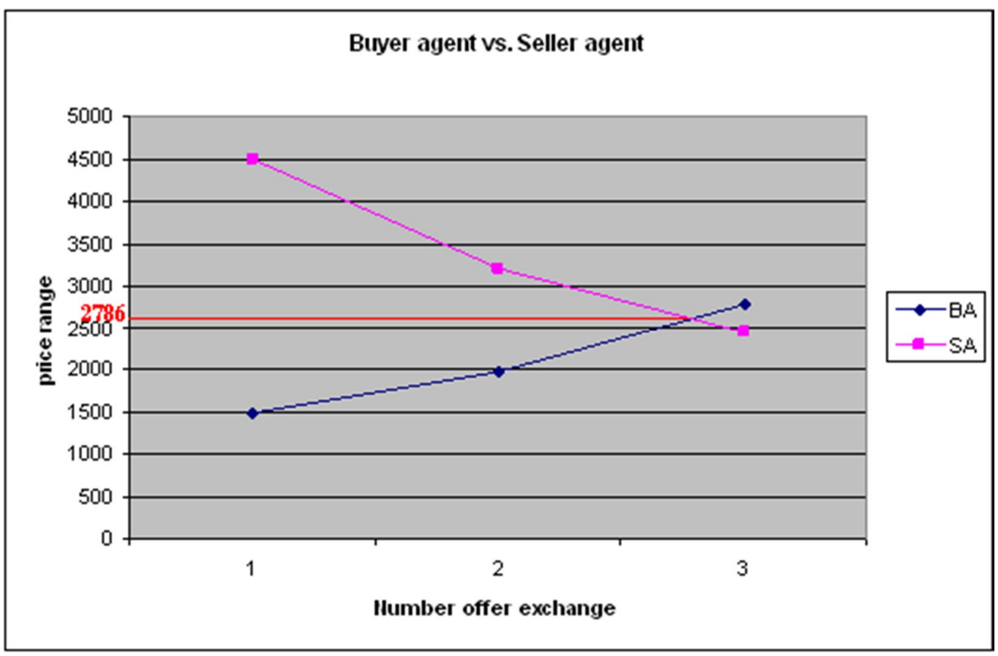


Figure 5.7: BA and SA proposals exchange

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Introduction

This chapter is divided into two sections; the first is the conclusion of our works. The second section presents recommendations for future works.

6.2 Conclusion

The model presented in this thesis work is a form of negotiation using fuzzy logic approach. The main contribution entails with the application of fuzzy logic to agent-mediated negotiations. Our proposal first intends to make negotiation scenario more human, and second, it also intends to make the negotiation approach more profitable for buyers and seller. This work provides a contribution to the area of electronic negotiation since it gives the user a simple yet powerful tool that allows him/her to quickly discard proposals that are not well sound.

The model presented in this thesis work is based upon fuzzy logic, which allows it to be able to solve complex problems plagued with uncertainty and vagueness. Albeit these researches [1, 44, 54, and 55], which also use fuzzy logic to model their work, at some points their use of fuzzy logic, are not to a large extend. They prefer to incorporate the notion of fuzziness to a certain aspect. This paper makes it possible to design and model a negotiation using fuzzy logic through out the whole phase of negotiation. This means this thesis work applies fuzzy logic from evaluating offers/proposals; making decision about them and finally generating a counter offer if needed. As we witness, today the business industry is developing at extremely fast rates; new industries and forms of businesses are emerging; thus making the business environment so complex. These complexities can be translated into issues to be resolved during the course of negotiation. As such the vaguer these issues can be the more complex the negotiation modelling would become. For instance, modelling an issue like “Delivery time” or “Privacy” can be very much complicated if we were to use mathematical or heuristic methodology. In fact, these issues are relatively intangible; therefore, it is difficult to attribute exact values to any of them.

The model designed in this thesis allows the user first to measure the degree of attractiveness the seller proposal could present. This allows the system to be prepared for the decision to be followed. Should the decision is to go for a counter offer, the system will again use the same ration or degree of attractiveness value to determine the right counter offer. By doing so, the system will be able to make its concession or the ratio for its next counter offer accordingly and not heuristically. For instance [54] uses also fuzzy logic to model its negotiation. Its model is divided into two parts, which are connected in parallel. The first part uses fuzzy logic to measure the buyer acceptance degree and the second part uses time dependant tactic to generate counter offers. However, one might wonder what is the use of determining the satisfaction degree? Perhaps to allow the system to make a decision on whether to accept, reject or counter the offer. Nevertheless, when it comes to counter offer, the system excludes the acceptance degree to be part of the determination of counter offer and yet uses a different approach of negotiation modelling (time dependant approach). This model uses rather a simple and powerful approach in fuzzy logic. This simplicity makes this work attractive in e-negotiation department and allows a fast and efficient way of human wise negotiation approach.

The main contribution of this research can be highlighted out in two main points. Firstly, the application of fuzzy sets to evaluate negotiators’ preference/degree of satisfaction in different proposal has enhanced the bargaining efficiency. In our model, neither time nor resource constitutes the deciding factor for agents’ decision making or making a counter offer. Agents, here, make decisions based on the outcome of the satisfaction degree; which is characterized by the issues or element involved in the negotiation (issues ranging from price, quality, warranty and so on). Secondly, the use of fuzzy logic to determine the concession rate, which constitutes the key factor for the proposition of a new offer. Fuzzy logic has been widely acknowledged for its ability to design vagueness and model qualitative data into something of crisp value. In addition, this algorithm once refined to each area under the industry of software development can be used for subsequent projects, saving large percentages of time, money, and effort, without sacrificing quality.

6.3 Limitations and Future Work

This thesis opens up a realm of possibilities where future researchers can produce a more powerful, user friendly software that can analyze and design issues in negotiation that are qualitative and vague. Our experimental result particularly the 2 scenarios suggest that the fuzzy-based model often takes fewer numbers of rounds to finish the negotiation. Exchanging fuzzy values as offers leads to a more flexible negotiation. Intuitively, when agents play more flexibly, the risk of coming to a failure should be less. In this work, we have used the simplest format to keep our model easy and to focus more on the concept of negotiating with qualitative values. Many open questions are left for future work. For instance, the impact of having too many issues could be an object of another research. Our research choices up to 4 issues in the experiments which is in line with the fact that in business there are no many issues to deal with. If one feels with the need of buying an item, the relevant issues that affect the transaction is quality, warranty, price, delivery time and perhaps couple of policies if any. Moreover, our fuzzy defuzzification method used in this thesis is “Memdani” for its simplicity and popularity whenever the use of fuzzy logic is used. Therefore it is also imminent to know how well is modeling this type of negotiation with sugeuno. Finally, negotiation over predefined linguistic values could also do the object of a future investigation.

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APPENDIX A

Seller agent settings:

Price range [800 4700]

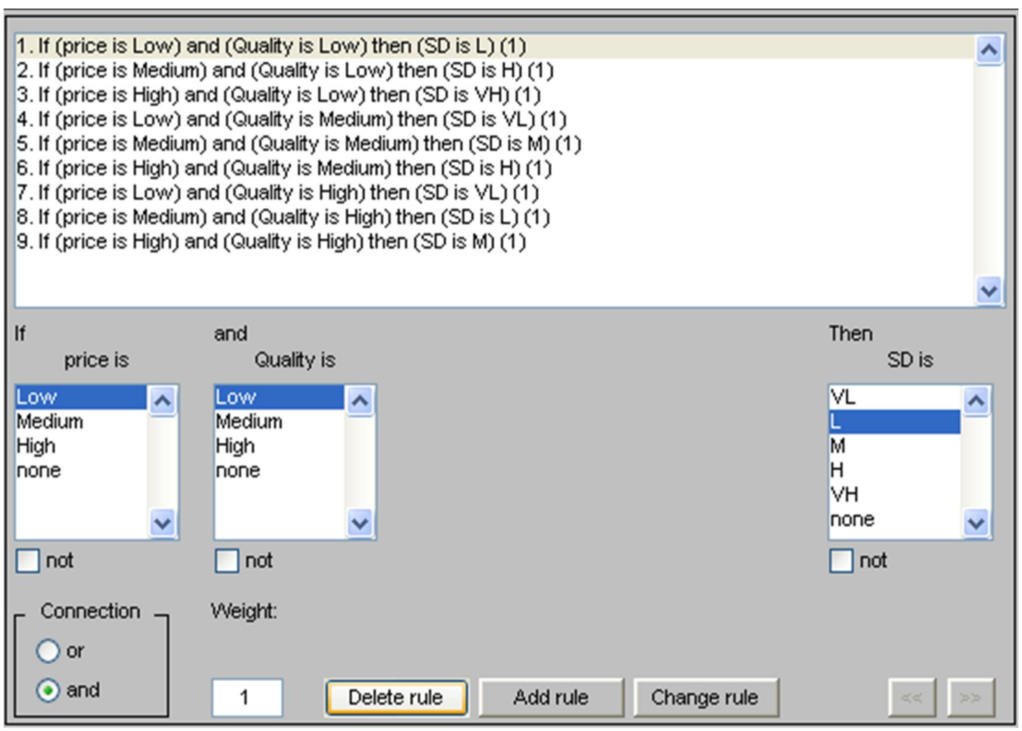
Quality [0 10]

Satisfaction degree [0 100]

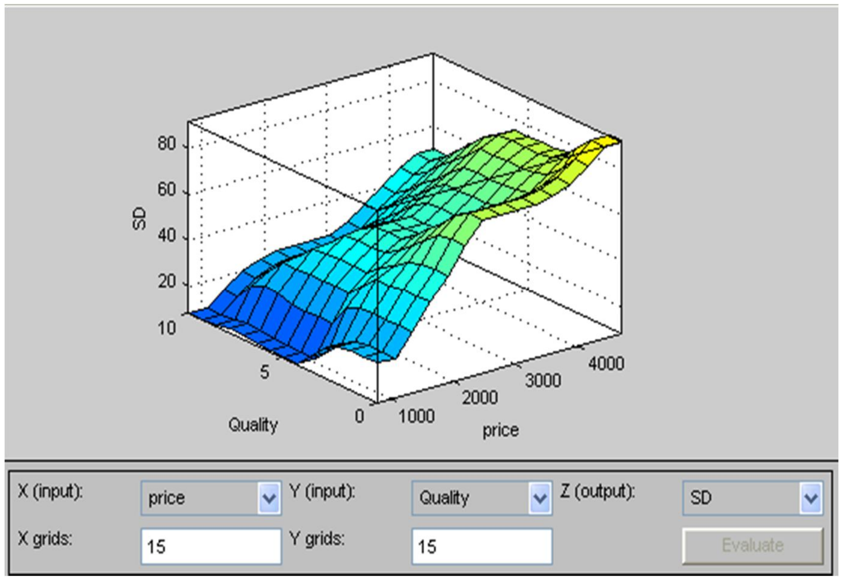
Matlab settings and results

The matlab setting and result represents the evaluation of seller agent only. For the buyer agent, please refer to illustration 4.1.

Rules bank

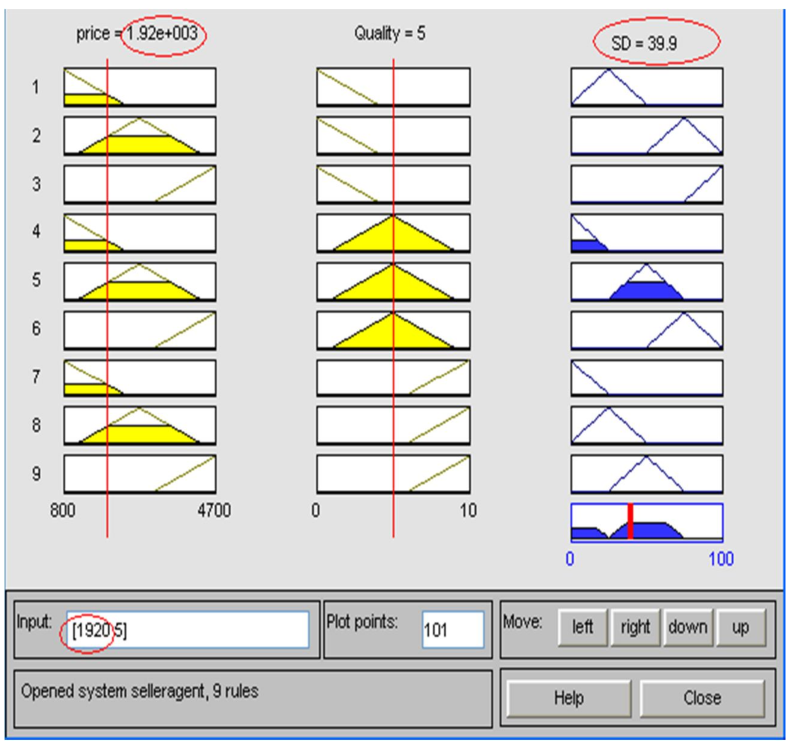


Evaluation of the rules

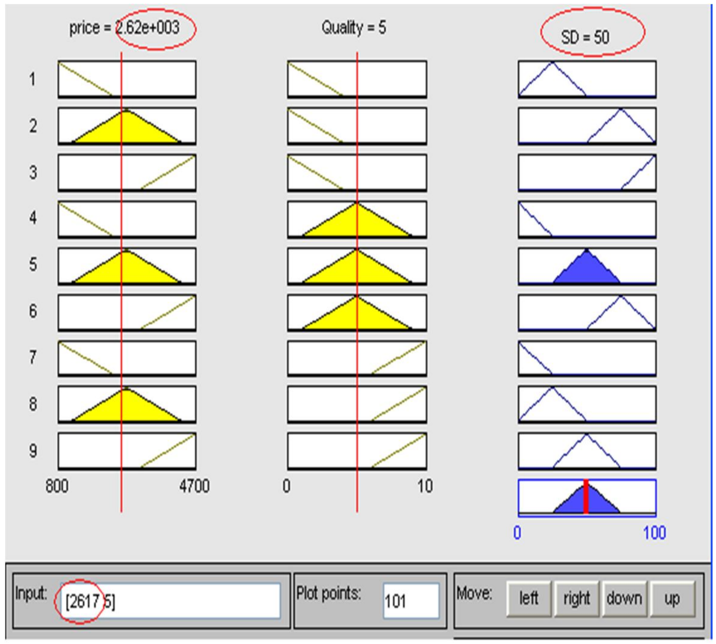


Satisfaction degree as in the rules viewer

- when the seller agent satisfaction degree is 39.9%



- *When the seller agent satisfaction degree is 50% we have:*



Fuzzy Linguistic variables

- ➢ Incoming Offer received from BA ($1920). At this price:
- ✓ Satisfaction degree of Seller agent; SD = 39.9%
- ✓ Df = 0.57
- ✓ Linguistic variable for SD = {0; 0.399; 0.601; 0; 0}
- ✓ Linguistic variable for Df = {0; 0; 0.722; 0.278; 0}
- ✓ Concession rate C = {0; 0.288; 0.434; 0; 0}
- ✓ Seller agent first counter offer ratio is **0.8.**

- ➢ Incoming Offer received from SA ($3825); so at this price BA:
- ✓ Satisfaction Degree is : SD = 35.4%
- ✓ Df = 0.49
- ✓ Linguistic variables for SD = {0; 0.548; 0.452; 0; 0}
- ✓ Linguistic variables for Df = {0; 0; 1; 0; 0}
- ✓ Concession rate C = {0; 0.548; .452; 0; 0}
- ✓ Buyer agent second counter offer rate is **0.363**.

- ➢ Incoming Offer received from BA ($2617); at this price SA:
- ✓ Satisfaction Degree is: SD = 50%
- ✓ Df = 0.315
- ✓ Linguistic variables for SD ={0; 0; 1; 0; 0}
- ✓ Linguistic variables for Df = {0; 0.76; 0.24; 0; 0}
- ✓ Concession rate C = {0; 0; 0.76; 0; 0}
- ✓ Seller agent second counter offer rate is **0.836**

- ➢ Incoming Offer received from SA ($3199); at this price BA:
- ✓ Satisfaction Degree is: SD = 49.7%
- ✓ Df = 0.155
- ✓ Linguistic variables for SD = {0; 0.012; 0.988; 0; 0}
- ✓ Linguistic variables for Df = {0.29; 0.71; 0; 0; 0}
- ✓ Concession rate C = {0; 0.852; 0.7015; 0; 0}
- ✓ Buyer agent third counter offer rate is **0.2514**

APPENDIX B

Fuzzy Linguistic variables

- ➢ Incoming Offer received from BA ($1975). At this price:
- ✓ Satisfaction degree of Seller agent; SD = 43.3%
- ✓ Df = 0.57
- ✓ Linguistic variable for SD = {0; 0.433; 0.567; 0; 0}
- ✓ Linguistic variable for Df = {0; 0; 0.722; 0.278; 0}
- ✓ Concession rate C = {0; 0.312; 0.409; 0; 0}
- ✓ Seller agent first counter offer ratio is **0.713.**

- ➢ Incoming Offer received from SA ($3208.5); so at this price BA:
- ✓ Satisfaction Degree is : SD = 48.1%
- ✓ Df = 0.3844
- ✓ Linguistic variables for SD = {0; 0.475; 0.535; 0; 0}
- ✓ Linguistic variables for Df = {0; 0.482; 0.518; 0; 0}
- ✓ Concession rate C = {0; 0.228; .277; 0; 0}
- ✓ Buyer agent second counter offer rate is **0.411**.

- ➢ Incoming Offer received from BA ($2617); at this price SA:
- ✓ Satisfaction Degree is: SD = 50%
- ✓ Df = 0.131
- ✓ Linguistic variables for SD ={0; 0; 1; 0; 0}
- ✓ Linguistic variables for Df = {0; 0.35; 0.65; 0; 0}
- ✓ Concession rate C = {0; 0; 0.65; 0; 0}
- ✓ Seller agent second counter offer rate is **0.762**

Table 1B: Satisfaction degree scenario I vs. satisfaction degree scenario II

Price	**Quality**	**Warranty**	**Satisfaction Degree SC I**	**Satisfaction Degree SC II**
$4700	0	1	8%	8%
4500	0	1	8.11%	8.16%
4300	0	1	8.34%	8.86%
4100	0	1	8.66%	15.3%
3900	0	1	8.71%	19.6%
3700	0	1	8.78%	20.3%
3500	0	1	8.86%	22.7%
3300	0	1	8.92%	23.01%
3100	0	1	8.97%	23.7%
2900	0	1	9.07%	24.8%
2700	0	1	9.18%	25.3%
2500	0	1	13.7%	25%
2300	0	1	16.8%	25%
2100	0	1	19.1%	25%
1900	0	1	20.9%	25%
1700	0	1	22.2%	25%
1500	0	1	23.3%	25%

Table 2B: Satisfaction Scenario I vs. satisfaction degree scenario II;

Price	Quality	Warranty	Satisfaction Degree SC I	Satisfaction Degree SC II
800	0	1	25%	26.9%
800	1	1	25%	28.7%
800	1.2	1	25.3%	30.3%
800	1.4	1	25.7%	31.9%
800	1.6	1	26.4%	33.5%
800	1.8	1	27.1%	35%
800	2	1	29.08%	36.6%
800	2.2	1	30.1%	38.2%
800	2.4	1	30.3%	39.7%
800	2.6	1	30.5%	41.3%
800	2.8	1	30.6%	42.8%
800	3	1	32.2%	44.4%
800	3.2	1	33%	46.1%
800	3.4	1	33%	47.9%
800	3.6	1	45%	49.7%
800	3.8	1	47.7%	58.8%
800	4	1	50%	59.2%

800	4.2	1	50%	63.3%
800	5	1	50%	68.8%
800	7	1	63%	84.7%%
800	9	1	75%	91.5%%
800	10	1	75%	92%

APPENDIX C

Publication Records

- **Ateib, MT .** and J. Jubair (2009). Agent based Negotiation in E-commerce. Proceedings The 4thInternational International Symposium on Information Technology (ITSim 2010), IEEE Computer Society, vol 3, pp 1286-1297, Kuala Lumpur - Malaysia.