CYBER HAGGLER: WEB BASED BARGAINING USING GENETIC ALGORITHM

by

KUMAR UJJWAL

(Under the Direction of Jay E. Aronson)

ABSTRACT

In this thesis, we analyze the sequential bargaining problem from a different perspective. Instead of taking a game theoretic approach, we model bargaining as a search problem and use a genetic algorithm to find an equilibrium outcome. Users, as buyers or sellers, only have to specify the product details and reservation price. The bargaining process is done by buyer and seller software agents. We have also developed a fully functional website Cyber Haggler (http://www.cyberhaggler.com) to illustrate our concepts. The software agents are based on realistic assumptions of bounded rationality and they learn from trial-and-error over time. We also compare Cyber Haggler to both Kasbah and EBay.com. Results show that our model can be easily implemented commercially on the Internet. Thus, we have been successful in modeling real world human-like bargaining on the Internet.

INDEX WORDS: Genetic Algorithm, Software Agents, Bargaining Problem, Economic Equilibrium, Bounded Rationality

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DEDICATION

This thesis is dedicated to my adorable mom and doting dad.

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CHAPTER 1

INTRODUCTION

1.1 BARGAINING THEORY

Bargaining is a type of negotiation in which the buyer and seller of a good or service seek a mutually acceptable price. The bargaining process ends when the buyer and the seller agree upon a particular price. The deal price for the same product or service in different bargaining processes can be different. The agreed upon price is an equilibrium of the seller's anticipation and the customer's expectation. The bargaining process as proposed by [15] is shown in Figure 1.1.

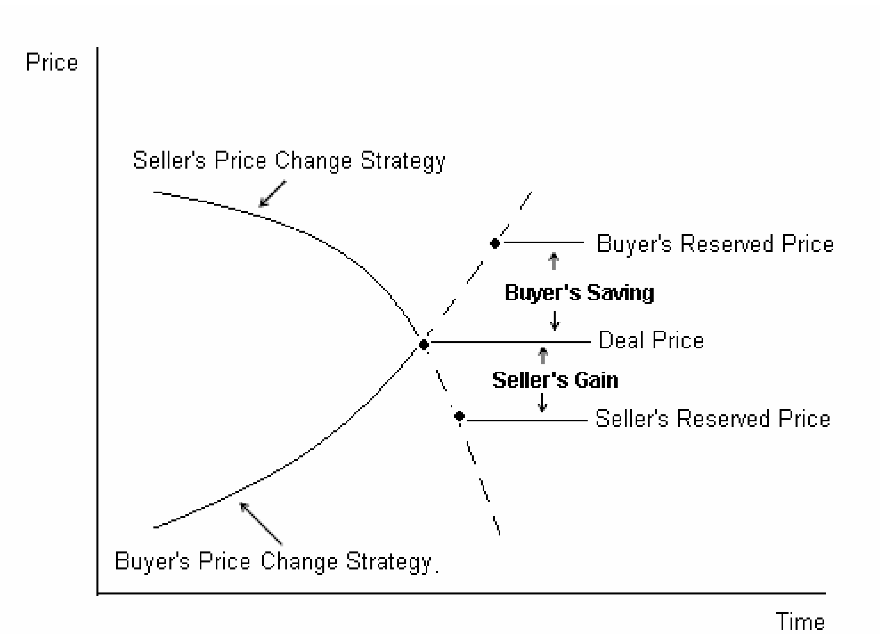

Figure1.1: Bargaining Process

Bargaining can be done on a single-issue or multiple-issues (e.g., price, quality, model, quantity, delivery date, payment method). This thesis focuses on one-to-one and one-to-many bargaining models for single-issue negotiations. We develop an ecommerce website, Cyber Haggler (http://www.cyberhaggler.com), where the bargaining process is automated on the single-issue of price. Users as buyers can log on to Cyber Haggler, find their product and start the bargaining process with the click of a button. Cyber Haggler will find a deal for the buyer (within the specified reserved price of the buyer). Similarly, users as sellers can sell their products by specifying the product details and a minimum reservation price in Cyber Haggler's database. We find an equilibrium (i.e., the deal price) using a genetic algorithm rather than the game theoretic techniques. We aim to design bounded rational (discussed in Section 1.3) agents that learn through trial-and-error to find an equilibrium price.

The game theoretic approach assumes perfectly rational agents with complete knowledge but in a genetic algorithm based approach, agents are assumed to be bounded rationally; learning through trial and error. From this point onwards we will be using the word 'bargaining' and 'negotiation' interchangeably ignoring any subtle difference(s) between them.

1.2 GAME THEORY AND THE NASH EQUILIBRIUM

Game Theory is all about the situations where the players (agents) choose different actions in an attempt to maximize their returns. Game theoretic models of bargaining [12, 13, 14] assume that the agents are perfectly rational and that this rationality is common knowledge. In a bargaining game between a buyer and a seller, knowledge includes what an agent knows about its own parameters (its reservation price, deadline, and utility function), and also what it knows about its opponent (the opponent's reservation price, the opponent's deadline, and opponent's utility function).

The following elements constitute a bargaining model as explained in [5]:

a) Bargaining protocol.

b) Bargaining strategies.

c) Information state of agents.

d) Bargaining equilibrium

a) Bargaining Protocol

The bargaining protocol refers to the set of rules that govern the interactions among players (i.e., buyers and sellers). The rules govern the valid states (e.g., offer acceptance/rejection, bargaining timeout) and the actions that cause changes in the bargaining state, like accepting an offer or leaving a bargaining session before timeout. In sum, the bargaining protocol defines the circumstances under which the interaction between agents takes place. The buyer and seller agents must be compatible before a bargaining process starts. In other words they should obey the same set of protocols.

b) Bargaining Strategies

The bargaining strategies employed by an agent decide the outcome of a bargaining process. The choice of a strategy depends on the bargaining protocol and the bargaining environment (e.g., one-to-one, one-to-many etc.). For instance, one strategy may be to bargain stingily until timeout, while another strategy may be to concede in the first round only [1, 9]. The strategy of a rational decision-maker always maximizes its expected utility.

c) Information State of Agents

An agent's information state at any point of time is the knowledge it possesses about itself and its opponents. Knowledge may include reservation price, utility function, deadline, or the bargaining strategy. Game theoretic models for bargaining can be divided into two types: those that deal with complete information and those that deal with incomplete information. In the former setting, agents have complete information about themselves as well as about the opponents. In this case, agents are supposed to have perfect rationality [8]. In the later case, agents may not have complete information about their opponent's utility function or deadline or strategy. In this case agents are supposed to have bounded rationality [12]. Clearly, bounded rationality is more realistic in today's world than perfect rationality.

d) Bargaining Equilibrium

Equilibrium forms the crux of a bargaining model. Nash [8] developed the mathematics for sequential offer protocols. The Nash solution to the bargaining problem maximizes the product of agent's utilities on the bargaining set. Two strategies are in Nash equilibrium [5] if each agent's strategy is the best response to its opponent's strategy. This is a necessary condition for system stability where both agents act strategically. The basic assumption of a Nash solution is that the agents act with perfect rationality and each agent will select an equilibrium strategy when choosing independently. Nash also describes some axioms for bargaining solutions. Some important ones include symmetry, monotonicity, and efficiency [5, 8]. The bargaining problem arises when a buyer values a product more than a seller, but a question arises; how to divide the difference? Let us consider a seller who is willing to sell his Dell laptop for $300 and a buyer who is looking for a Dell laptop and he is willing to pay $400. The margin between the buyer's reserved price and the seller's reserved price is $100. Is it logical to divide $100 in two equal parts and hence decide the equilibrium to be at $350? Game theory says that it may be the case, but not always. Attaining an equilibrium also depends on the number of rounds of negotiation and the discount factor of the buyer and the seller. The discount factor provides a means of evaluating future money amounts in terms of the current money amounts (i.e., net present value). Let us take the example of the Dell laptop once again. Suppose there are just two rounds of negotiation and the seller opens first. We also assume that the buyer and seller know each other's reserved price. Since the seller knows that the buyer is willing to pay $400 for the laptop, he will ask for $400 and the buyer will reject this offer and make a counteroffer of $300. Since both the players always prefer a deal to no deal and the counteroffer of $300 is equal to the seller's reserved price, the seller will accept this offer. Hence, the whole share of $100 goes to the buyer and $350 is not an equilibrium point. Let us consider this example again but this time, the buyer is first to start. Also, suppose that this time, the seller has a discount factor of 0.7. This means that the seller will accept any offer greater than or equal to $370 ($300+ 0.7*$100). Now if the buyer makes an offer of $340, the seller will immediately reject it and ask for $400. Since there are only two rounds of negotiation, an equilibrium price is attained at $400. But suppose the buyer offers $370 to the seller, then the seller will accept it since this was the expected threshold and the bargaining will end with an equilibrium price at $370. Hence, dividing the margin between the buyer's reserved price and the seller's reserved price equally is not always an equilibrium in a bargaining game. An equilibrium depends on the bargaining model, which in this context is a function of the reservation prices of the buyer and seller, rounds of negotiation and the discount factors of the buyer and seller.

1.3 PERFECT RATIONALITY VS. BOUNDED RATIONALITY

As discussed in Section 1.2, perfect rationality is idealistic, while bounded rationality is realistic. With respect to today's real world market (including e-commerce), the basic assumption of perfect rationality, (i.e., the agents always act in a rational way, and have complete knowledge about self and opponents) seems preposterous. Research work in economics suggests [11] that human beings utilize bounded rationality rather than perfect rationality. Human beings learn how to win games by playing them through trial-and-error, experimenting with different strategies, observing pay offs, and hence developing a best strategy. In this thesis, we focus mainly on bounded rationality where the agents do not have complete knowledge of its opponent's strategy and deadline. In Chapter 3, we discuss the basic assumptions of our model and the information state of the agents at length.

1.4 E-COMMERCE 2007: AUCTION VS. BARGAINING

In recent years, electronic commerce (e-commerce) has shown dramatic growth with the blossoming of the Internet. Prior to the advent of the Internet, the market typically had a fixed price for every product and service. However, the Internet has triggered a trend toward dynamic pricing where one can find the same product for different prices on different ecommerce websites. Bargaining and auctioning can be interpreted as forms of dynamic pricing on the Internet. Though the Internet is inundated with many auctioning websites like ebay.com, baazee.com, ebid.com, but online bargaining is less known. However, in the real world, bargaining exists in day-to-day life. Almost every major city has a flea market. For instance, the J&J Flea Market in Athens, Georgia boasts to have 10,000 visitors per day. Though auctioning is immensely popular on the Internet, research has shown that consumers prefer e-commerce websites that offer bargaining opportunities [7] even though they may not obtain the best price.

This thesis is about the design and implementation of a commercially viable model for automated bargaining, not auctioning. It is important to discuss the main differences between auctioning and bargaining. Auctioning has its own advantages and disadvantages. Auctioning can be frustrating [15] as a buyer may not tolerate waiting a few days for the close of an auction for an item such as a Dell laptop at ebay.com. Another disadvantage of auctioning is that sellers have little say in the process. The final price is always decided by the buyers. All of these things make auctioning a one sided game.

Unlike auctioning, bargaining includes the seller's input in determining the deal price, because an equilibrium is the result of the seller's anticipation and the buyer's expectation. As the seller is also actively involved in determining the price of the product, bargaining is a "win-win" [15] game as compared to auctioning which is clearly one sided.

1.5 CYBER HAGGLER: AN INTRODUCTION

Research has shown that even in simple single issue negotiations, people often reach suboptimal solutions, thereby "leaving money on the table" [9]. In the past, game theoretic models have been developed based on the unrealistic assumptions of perfect rationality and common knowledge. This thesis focuses on developing agents that have bounded rationality. They learn through trial and error, thereby choosing the strategies that have the maximum payoff. One way to accomplish this work would be to encode game theoretic strategies as IF-THEN rules and provide the agents with complete information from the start. But in this approach, the agents do not have any intelligence. Another way to solve the bargaining problem would be to design a neural network based on past data and use that network to predict the outcome of the negotiations. The problem with this approach is that the network needs to be constantly updated and the training time would increase considerably with increasing data. On the other hand, a genetic algorithm is very fast and does not need past data in the designing process. We aim to develop agents with "intelligence" that are capable of evolving and choosing the best strategies over a period of time. These agents should be able to learn through trial-and-error and finally conclude with a successful deal. We use a genetic algorithm (GA) based approach where we develop one-to-one and one-to-many bargaining models. The deal price is decided by the stable outcome of the GA model. We have developed a website http://www.cyberhaggler.com to demonstrate how the model works. We experiment with different parameter set-ups of the GA, different strategies, and summarize our results in Chapter 4. The rest of the thesis is organized as follows. Chapter 2 discusses some of the most relevant work related to our approach. Chapter 3 discusses the design and architecture of our model, along with the user interface. Chapter 4 discusses the results and Chapter 5 concludes the thesis.

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CHAPTER 2

ONLINE BARGAINING: STATE OF THE ART

2.1 THE KASBAH OPEN MARKETPLACE

Kasbah is an open web-based marketplace created by Chavez and Maes [2]. Like any real world marketplace, people can negotiate the purchase and sale of goods on Kasbah using software agents. For example, a user who wants to sell his digital camera can create a selling agent. Similarly, a user who wants to buy a digital camera can create his buying agent. These selling and buying agents can start a negotiation and end having a mutually acceptable deal. These user created agents have complete autonomy, but the users have the final say whether to accept or reject the deal. Also, the agents created by the users are not very smart; they do not use any kind of artificial intelligence techniques or machine learning. The user must clearly specify all the parameters when designing his or her agent. The parameters for a selling agent are:

a) Deadline: Time by which the product must be sold

b) Desired Price: Desired Price at which the product should be sold

c) Lowest Acceptable Price: Minimum Price below which no offer should be accepted

d) Negotiation strategy: Whether the discount factor should be linear, quadratic or cubic.

The buying agent must be similarly designed. Kasbah can be seen as a multi-agent system where various agents interact with each other to accomplish their goal. Before starting any negotiation, agents are checked for their compatibility. All agents must obey the same negotiation protocol. Chavez and Maes report that the user feedback was generally positive, but the participants were disappointed when their agents did “clearly stupid things,” such as accepting the first feasible offer when a second, better one was available. Kasbah appears to suffer from many inherent problems. For example, a layman does not know which strategy he should use to sell his camera. Also, for buying a camera, a buyer must give a deadline, but there is no guarantee that he will be successful in getting a deal. Cyber Haggler does not suffer from any of these problems. In Chapter 3 we highlight the differences between Cyber Haggler and Kasbah.

2.2 RELEVANT EVOLUTIONARY ALGORITHM MODELS

The literature is inundated with research papers that use evolutionary algorithms for multi-issue negotiation. In this section, we discuss only those papers which are tightly related to our work. We describe how our work is different from them and also point out some potential flaws in their work. Lau [10] presents an evolutionary learning approach for designing adaptive negotiation agents for multi-issue negotiation. Lau uses a genetic algorithm for heuristic search to derive potential negotiation solutions. The fitness function in Lau's work is designed so that the agents learn their opponent's preferences by trial-and-error. The initial population represents a subset of the feasible offers. Each chromosome is a possible offer and consists of a fixed number of fields representing the various attributes and the fitness value of that chromosome. The fitness function used by Lau captures three important issues to model real world bargaining behavior: an agent's own payoff, the opponent's partial preference (e.g., the most recent counteroffer), and the time pressure. The genetic operators such as crossover and mutation are only applied to the genes representing the attribute values of an offer. Lau has shown how a multi-issue negotiation system can be designed around an evolutionary approach. However, [10] seems to work well in a wholesale system where the buyer intends to buy something in bulk. Our work centers on the structure of today's e-commerce, where a buyer may buy just one or two camcorders. Therefore, quantity may not be a significant issue. Also, classical game theoretic models of bargaining are based on the concept of equilibrium, but [10] does not draw any kind of analogy from the classical game theoretic models. Finally, [10] does not guarantee a successful deal between a buyer and a seller even though both actively negotiate. Our work differs from [10] in the following ways: Cyber Haggler can work well for retail as well as wholesale, and a successful deal is guaranteed if a buyer indulges in a negotiation with a seller. Chapter 3 discusses more about the system design of Cyber Haggler.

Shaheen et al. [4, 5] compares the equilibria of game theoretic models and evolutionary models of bargaining. Our work is mainly based on [4, 5]. Our bargaining model is solely based on [4]. We have redefined the concept of strategy tuple described in [4] and extended the work. Our model includes one-to-one as well as one-to-many scenarios. We have developed an e-commerce website http://www.cyberhaggler.com (Cyber Haggler) in which bargaining can be automated in the backend, and users are required to specify just the reservation price. In Chapter 3, we discuss the system architecture in sufficient detail to give insight about the implementation of Cyber Haggler. In Chapter 4, we discuss the results of our experiments.

2.3 BAZAAR

Zeng and Sycara [16] have developed Bazaar, an experimental system for bilateral negotiations between two intelligent agents. Bazaar aims at developing an adaptive negotiation model which can capture a gamut of negotiation behaviors with minimal computational effort. Bazaar is a multi-agent learning system based on a sequential decision-making model and it uses a probabilistic framework using a Bayesian learning representation and updating mechanism. An application of Bazaar to the supply chain problem is shown in [16]. Zeng and Sycara [16] describe the following observations about Bazaar:

- Bazaar aims at modeling a multi-issue negotiation process. By incorporating multiple dimensions into the action space, Bazaar is able to provide an expressive language to describe the relationships between these issues and possible trade-offs among them.

- Bazaar supports an open world model. Any change in the external environment, if relevant and perceived by a player, will impact the player's subsequent decision making processes. This feature is highly desirable and is seldom found in other negotiation models.

- In most existing negotiation models, learning issues have been either simply ignored or oversimplified for theoretical convenience. Multi-agent learning issues can be addressed in Bazaar and conveniently supported by the iterative nature of sequential decision making and the explicit representation of beliefs about other agents.

Though our research focuses mainly on an evolutionary learning approach, we have discussed Bazaar mainly because Bazaar uses a different technique to solve this problem. However, we perceive Bazaar as a very complicated system because of reasons as discussed. For example, designing a Bayesian network is a very difficult task and it is highly problem dependent. Also updating all the probabilities for the external environmental impact is difficult because in a complicated environment there may be many factors affecting the players. Also, in a multi-issue environment the complexity of the model based on a Bayesian network is likely to increase.

CHAPTER 3

CYBER HAGGLER: WEB BASED BARGAINING VIA A GENETIC ALGORITHM

3.1 GENETIC ALGORITHM

A genetic algorithm (GA) is a powerful heuristic search scheme based on the model of Darwinian evolution. Since its inception in 1975 [6], genetic algorithms have been widely used in search and optimization problems. A set of randomly generated possible solutions (candidate solutions) to the problem at hand makes the initial population pool. The candidate solutions to the problem are encoded into “chromosomes,” which represent a solution or instance of the problem at hand. Traditionally binary encoding is done but the encoding mechanism is mostly problem dependent. The fitness of every individual in the population is evaluated. Then multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. There are three basic operations, selection, crossover and mutation, which guide the whole GA process. Our problem has two subpopulations, one is the buyer population and the other is the seller population. Sections 3.3 and 3.4 discuss the bargaining model and the system architecture in detail. We discuss the various parameter set up of our GA in Chapter 4.

3.2 BARGAINING AS A SEARCH PROBLEM

Bargaining is a search process. We can think of two player multi-issue integrative bargaining as an ‘N’ dimensional search space (where ‘N’ is the number of issues) where the players try to find a mutually acceptable point. The coordinates of this point in the multidimensional space become the bargaining solution. Each dimension represents an issue to be negotiated and each dimension can be real valued or discrete. In this thesis, we focus on a single-issue bargaining problem. The issue is the price of the product and we deal with only discrete values of the price. Since we have formulated the bargaining problem as a search problem, we can say that the use of GA is very well justified.

3.3 THE BARGAINING MODEL

In this section, we discuss the one-to-one and one-to-many bargaining models. We summarize the basic assumptions and explain our bargaining protocol.

3.3.1 ONE-TO-ONE

We start with a one-to-one bargaining model where a buyer 'B' with a reservation price 'RP^b' bargains with a seller 'S' with a reservation price 'RP^s'. The reservation price (RP^b) [4] of the buyer B is the maximum price he is willing to pay. B can never accept any offer which is more than his RP^b. Also, B will always make offers less than his RP^b. Similarly, the reservation price (RP^s) of the seller S is the minimum price he is willing to accept. S can never accept any offer which is less than his RP^s. Also, S will always ask for offers greater than his RP^s. This is a sequential model in which either the buyer B or the seller S can start the bargaining process. The interval [RP^s, RP^b] is referred to as the zone of agreement (from now onwards 'Z') [4]. Since a deal is always possible within the zone of agreement, our claim is that Cyber Haggler always guarantees a successful negotiation provided RP^s is less than RP^b. Suppose the buyer B starts off the bargaining process, then B will always make the offers starting from the seller's reservation price. Similarly the initial offer made by the seller S will always start from the buyer's reservation price. Let T^b and T^s represents the buyer's deadline and the seller's deadline respectively. This means that if $T^b < T^s$ then the bargaining process must conclude within T^b. Similarly if $T^b > T^s$ then the bargaining process must conclude within T^s. Figure 3.1 shows a buyer making offers starting from the seller's reservation price and reaching his own reservation price (RP^b) in time T^b. Boulware, linear and conceder are the various strategies followed by the buyer to reach his own reservation price starting from the seller's reservation price. Figure 3.2 shows a seller in addition to the buyer. The seller makes offers starting from the buyer's reservation price and reaches his own reservation price in time T^s.

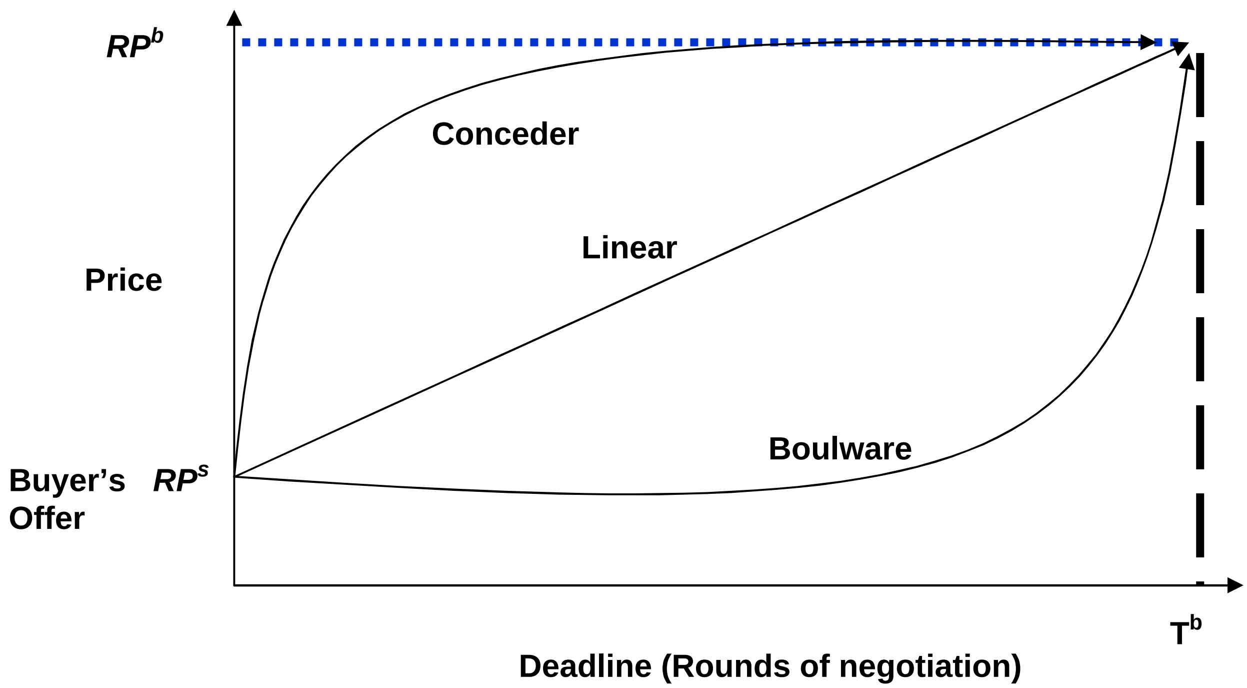

Figure 3.1 A buyer makes his offers starting from the seller's reservation price (RP^s)

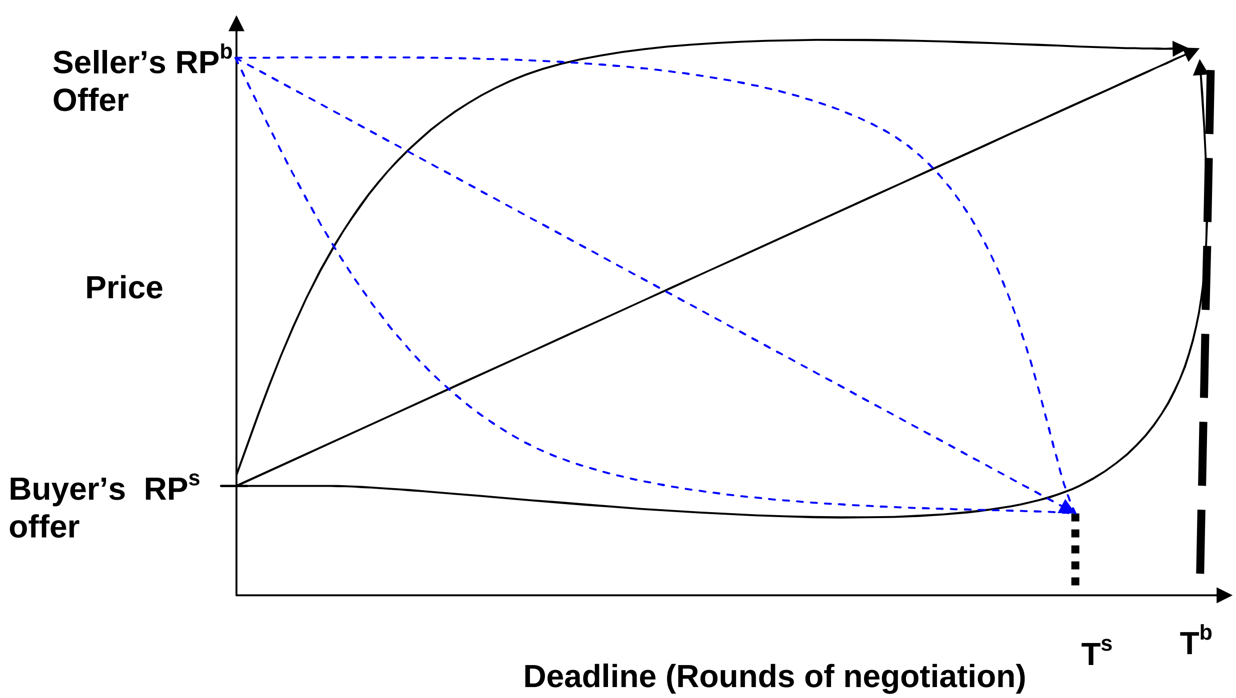

Figure 3.2 A seller makes his offers starting from the buyer's reservation price (RP^b). The buyer makes offers starting from the seller's reservation price (RP^s)

Let P (S→ B) represents the price proposed by seller S at any point of time to buyer B. Similarly, let P (B→ S) represents the price proposed by buyer B at any point of time to seller S. Then, the offers made by buyer B and Seller S at any point of time can be given by [4]:

$P(B \rightarrow S) = RP^s + F(t)*(RP^b - RP^s)$

$P(S \rightarrow B) = RP^s + (1-F(t))*(RP^b - RP^s)$

where F (t) is a negotiation decision function (NDF) and a wide range of functions can be chosen for this purpose. F(t) can be polynomial or exponential. Following NDFs have been defined in [3]:

(a) Polynomial:

$F^a(t) = \gamma^a + (1-\gamma^a)(\min(t, T^a)/T^a)^{1/\psi}$

where superscript a is used to refer a buyer or a seller, γ is a parameter close to zero, T^a is the deadline of the buyer if a refers to B, it is the deadline of the seller if a refers to S and ψ is the strategy of a (it can be a buyer B or a seller S).

(b) Exponential:

$F^a(t) = e^{\theta}$

where $\theta = (1-\min(t, T^a)/T^a)^{\psi} \ln \gamma^a$

The symbols have the same meanings as explained in (a).

For the purpose of our research, we use the polynomial function. It can be seen that a wide variety of strategies can be represented for different values of ψ. However, the following two sets show extreme behavior [4,9]:

(a) Boulware: For $\psi < 1$, the initial offer is maintained until time is up and the agent (buyer or seller) concedes to its reservation value. In other words the buyer B will start with an offer RP^s and will maintain this offer until T^b (if $T^b < T^s$), when it concedes by making an offer RP^b. Figure 3.3 shows the boulware tactics. If both the buyer and the seller stick to the boulware strategy throughout the bargaining game then the game theoretic equilibrium is (P,T) where T is minimum of the buyer and seller deadlines and P is equal to RP^s (if $T^s<T^b$) and RP^b (if

$T^s > T^b$). Since boulware is the best strategy for both the buyer and the seller, we will use only this strategy in our model.

(b) Conceder: For ψ>1, the agent (buyer or seller) reaches its reservation value very quickly. Figure 3.3 shows the conceder tactics. For ψ=1, an agent will show a linear behavior as shown in Figure 3.3.

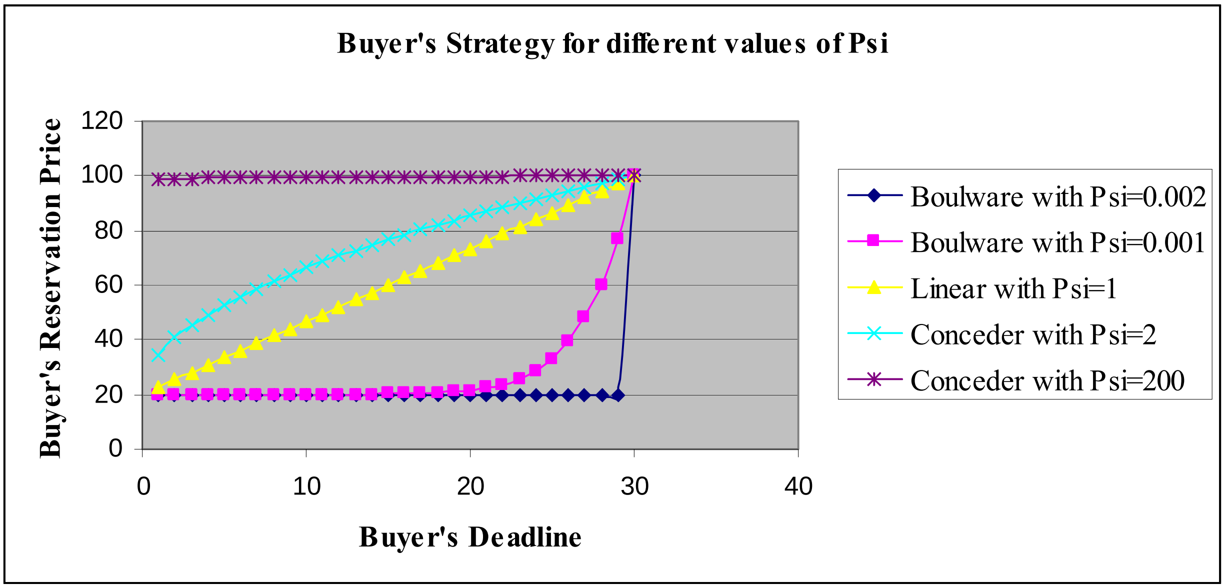

Figure 3.3 Buyer's strategy for different values of Psi (ψ)

Since our agents have bounded rationality with partial knowledge, the buyer doesn't know about the seller's utility function and deadline. Similarly the seller doesn't know about the buyer's utility function and deadline. A buyer's strategy tuple [4] can be defined as $S^b = < RP^s, RP^b, \gamma^b, \psi^b, T^b >$ where the symbols have their usual meanings. Similarly, a seller's strategy tuple can be defined as $S^s = < RP^b, RP^s, \gamma^s, \psi^s, T^s >$.

The utility function of the buyer at any time t is given as [4]:

$U_b(p,t) = (RP^b - p) + t$ where 'p' is the price offered by the buyer B.

The utility function of the seller at any time t is given as:

$U_s(p,t) = (p - RP^s) + t$ where 'p' is the price offered by the seller S.

3.3.2 ONE-TO-MANY

The one-to-many model is very similar to the one-to-one model except that a buyer can bargain with more than one seller at a given point of time. Let us take an example where we have one buyer and three sellers. Each of the three sellers has different reservation prices and hence different utility functions. The buyer B knows the reservation price of all the sellers and all the three sellers know the reservation price of the buyer. But the three sellers do not have any information about each other. Suppose B offers a price 'p' for some product. One of the sellers can accept this offer or all of them can reject this offer. If more than one seller accepts the offer, then one of them is chosen randomly to be the winner. Suppose all the three sellers reject the buyer's offer, then each one will make a counter offer 'p_1', 'p_2' and 'p_3' respectively. Out of these three counteroffers the one which has the maximum utility value will be chosen to be presented to the buyer. For example, suppose the reservation prices of the three sellers are 20, 40 and 60 respectively, while the reservation price of the buyer is 100. If the buyer makes an offer of 22, and the sellers make counteroffers of 90, 98 and 100 respectively then the utility value of the offers made by the three sellers according to following equation is 70, 58 and 40 at time t=0.

$U_s(p,t) = (p - RP^s) + t$ where 'p' is the price offered by seller S.

Hence the price chosen to be presented to the buyer is 90, since it has the maximum utility value. This model differs from the previous model only in the number of sellers. Apart from that, the equations used for this model are exactly same as the one-to-one case.

3.3.3 BASIC ASSUMPTIONS

In this section we describe the basic assumptions of our model.

- We deal with bounded rationality where a buyer knows the seller's reservation value but does not know about the seller's deadline and utility function, and the same is true about the seller with respect to the buyer.
- We have assumed a sequential model in which either the buyer or the seller can start the bargaining process. The bargaining process must conclude within time t where t = minimum

(T^b, T^s). In other words, the bargaining must conclude within the minimum of the buyer and seller's deadline.

- The buyer and the seller, each gain utility over time. Hence both have a tendency to reach a late agreement.
- A deal is always better than no deal. This essentially means that a buyer or a seller always wants to have a successful negotiation within the zone of agreement rather than a conflict.

3.3.4 BARGAINING PROTOCOL

The buyer and the seller must obey the bargaining protocol which is described as:

- The buyer or the seller is chosen randomly to start the bargaining process. If the buyer makes an offer to the seller, then the seller can accept the offer or reject the offer. Accepting the offer ends the bargaining process. If the seller rejects the offer, it must make a counteroffer to the buyer.
- Suppose the buyer B makes an offer p to the seller at time t. Then the seller S rates this offer by its utility function $U^s(p,t)$. If $U^s(p,t)$ is greater than the offer S is going to make at t+1, then S will accept p. Otherwise it will make a counteroffer. Exactly the same applies to the buyer.
- Suppose the buyer B makes an offer p to the seller at time 'T' where 'T' is the bargaining deadline (minimum of T^b and T^s), then the seller S must accept this offer. This is important because we have assumed that a deal is always better than no deal. Since rejecting the offer would mean a failed negotiation, the seller must accept it. Exactly the same behavior applies to the buyer, when the seller makes an offer p at time T.

3.4 GENETIC ALGORITHM DESIGN FOR CYBER HAGGLER

In this section we discuss the design of the genetic algorithm. We discuss the various parameter set up of our GA in Chapter 4.

3.4.1 OVERVIEW

Classical game theory assumes a single set of players playing the game with perfect rationality, but in the genetic algorithm design, we assume two subpopulations of players playing with bounded rationality. One population represents the buyer and the other population represents the seller. In Section 3.4.1 we define a buyer's strategy tuple as $S^b = < RP^s, RP^b, \gamma^b, \psi^b, T^b >$ and a seller's strategy tuple as $S^s = < RP^b, RP^s, \gamma^s, \psi^s, T^s >$ where the symbols have their usual meanings. A price proposed by either the buyer or the seller depends on the two variables γ and ψ, because RP^b, RP^s, T^b and T^s are constant. Since the buyers and the sellers have different utility functions, the bargaining problem becomes a case of co-evolution where the evolution of the parameters γ and ψ in one population affects the evolution of these parameters in the other population. The bargaining process starts with the initialization of both the populations with random values of γ and ψ as discussed in Section 3.4.1. Once initialized, agents in one of the populations, buyer or seller, starts the bargaining process. Figure 3.4 shows the design of our system. The first step is the initialization of the buyer and the seller population. Table 3.1 shows a sample initial buyer population initialized with boulware strategy. Table 3.2 shows a sample initial seller population initialized with boulware strategy. The last column in both the tables shows the calculated price based on the various parameters, as discussed in Section 3.3.1

Table 3.1: A sample initial buyer population

RP^s	**RP^b**	**γ^b**	**ψ^b**	**T^b**	**Calculated Price**
80	130	0.00509366666667	0.890770307656	10	84.0055216261
80	130	0.00600766666667	0.704543181894	10	82.192699161
80	130	0.00338633333333	0.145228492384	10	***80.16932315***
80	130	0.004954	0.0266991100297	10	80.2477

The fittest buyer in this subpopulation (Table 3.1) has a maximal utility value (or a minimum calculated price). The tuple corresponding to the calculated price of 80.16932315 (shown in italics) is the fittest buyer. This price is proposed to the seller. The seller may accept this offer leading to the termination of the bargain or reject the offer and propose the fittest seller from the seller subpopulation as a counter offer. The fittest seller in this subpopulation (Table 3.2) has a maximal utility value (or a maximum calculated price). The tuple corresponding to the calculated price of 129.996315265 (shown in italics) is the fittest seller. Since the difference between the fittest buyer and the fittest seller is considerable, this round of negotiation fails. The next buyer and the next seller subpopulations are created using the GA process of selection, crossover and mutation. The whole process is repeated until the deadline is reached or the bargaining process is terminated: if the buyer accepts the seller's offer or vice versa.

Table 3.2: A sample initial seller population

RP^b	RP^s	γ^s	ψ^s	T^s	**Calculated Price**
130	80	0.009161	0.092696910103	50	129.54195
130	80	0.00638166666667	0.979034032199	50	128.76714806
130	80	0.00736633333333	0.334155528149	50	129.631274647
130	80	0.00218533333333	0.415286157128	50	129.886688159
130	80	6.96666666667E-05	0.314922835905	50	***129.996315265***

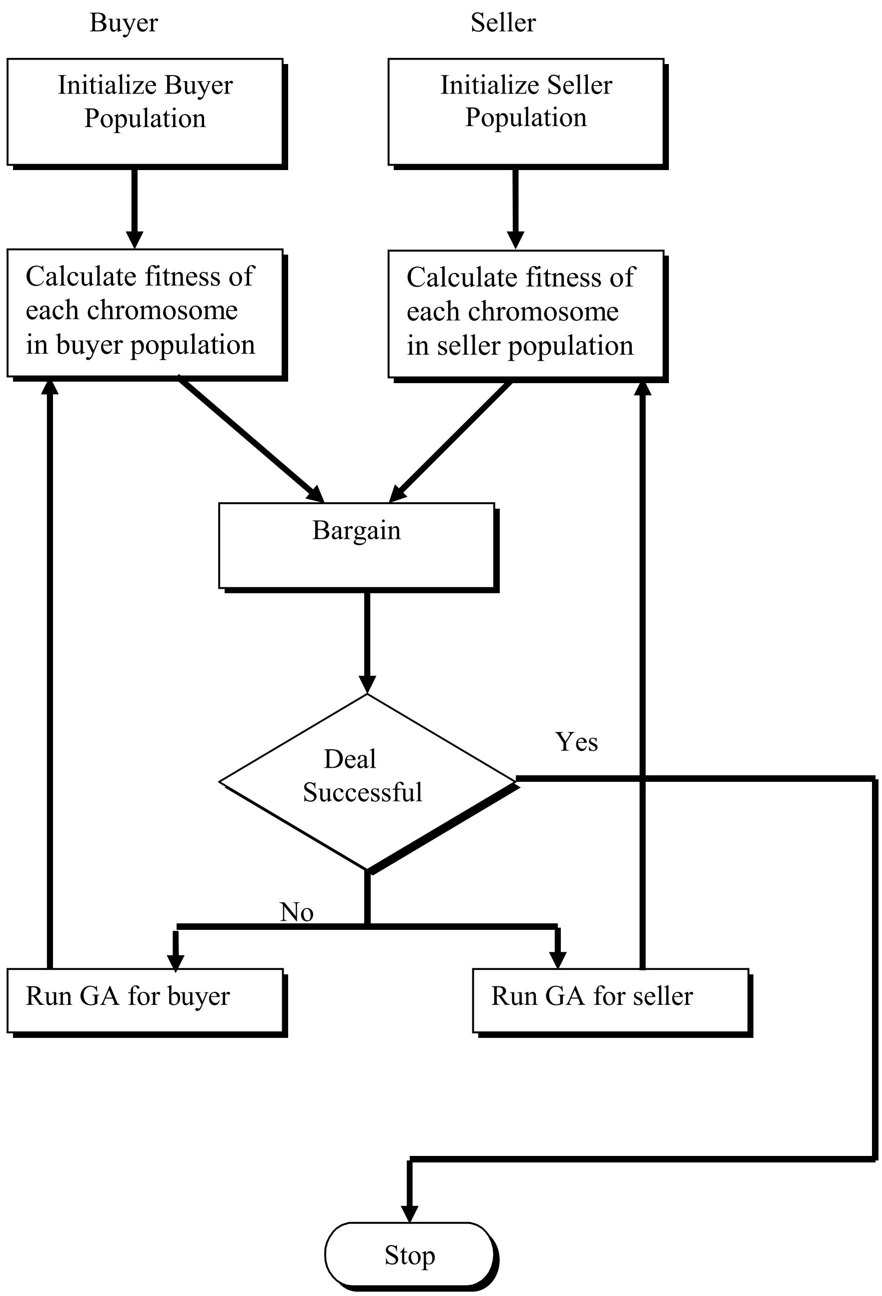

Figure 3.4: Design overview of Cyber Haggler

3.4.2 FITNESS FUNCTION

A fitness function aims at utility maximization. Hence, the utility function of the buyer and the seller defined below serves as the fitness function for the buyer's population and the seller's population.

The utility function of the buyer at any time t is given as:

$U_b(p,t)= (RP^b-p) + t$ where 'p' is the price offered by the buyer 'B.'

The utility function of the seller at any time t is given as:

$U_s(p,t)= (p-RP^s) + t$ where 'p' is the price offered by the seller 'S.'

This essentially means that the fittest buyer would have the highest utility value; similarly the fittest seller would have the highest utility value. As described earlier, the new offspring agents are created by the process of selection, crossover and mutation. We have used roulette wheel selection where the individuals are chosen with a probability proportional to their finesses [6]. Chapter 4 describes the various experiments we have carried out in detail.

3.4.3 OPERATORS

We used a uniform crossover technique. Let us consider the strategy tuple once again.

The buyer's strategy tuple is $S^b = < RP^s, RP^b, \gamma^b, \psi^b, T^b>$. Since γ^b and ψ^b are the variables and rest are constants, we generate a five bit key and generate offspring using uniform crossover. Here is an example:

Parent 1: 40,100, 0.647, 0.00495, 80

Parent 2: 40,100, 0.345, 0.00286, 80

Key: 0 1 1 0 1

Child 1: 40,100, 0.647, 0.00286,80

Child 2: 40,100, 0.345, 0.00495,80

We use the one point mutation as described in [6]. A random number 'r' is generated and if the mutation rate 'P_m' is greater than r then that bit is mutated randomly to another valid value; otherwise not. Only γ^b and ψ^b are mutated since the rest are constant. Suppose $P_m > r$ for γ^b then a random value of γ^b € [0,1] is chosen and the current value is replaced by this random value. In Chapter 4, we describe the various crossover and mutation rates we tested. We also describe how mutation rates and crossover rates affect the deal price.

3.5. USER INTERFACE

In this section, we discuss the detailed design of Cyber Haggler. We describe the various web forms[1] (web pages) available in the Cyber Haggler that facilitate the buying and selling of the products on the Internet.

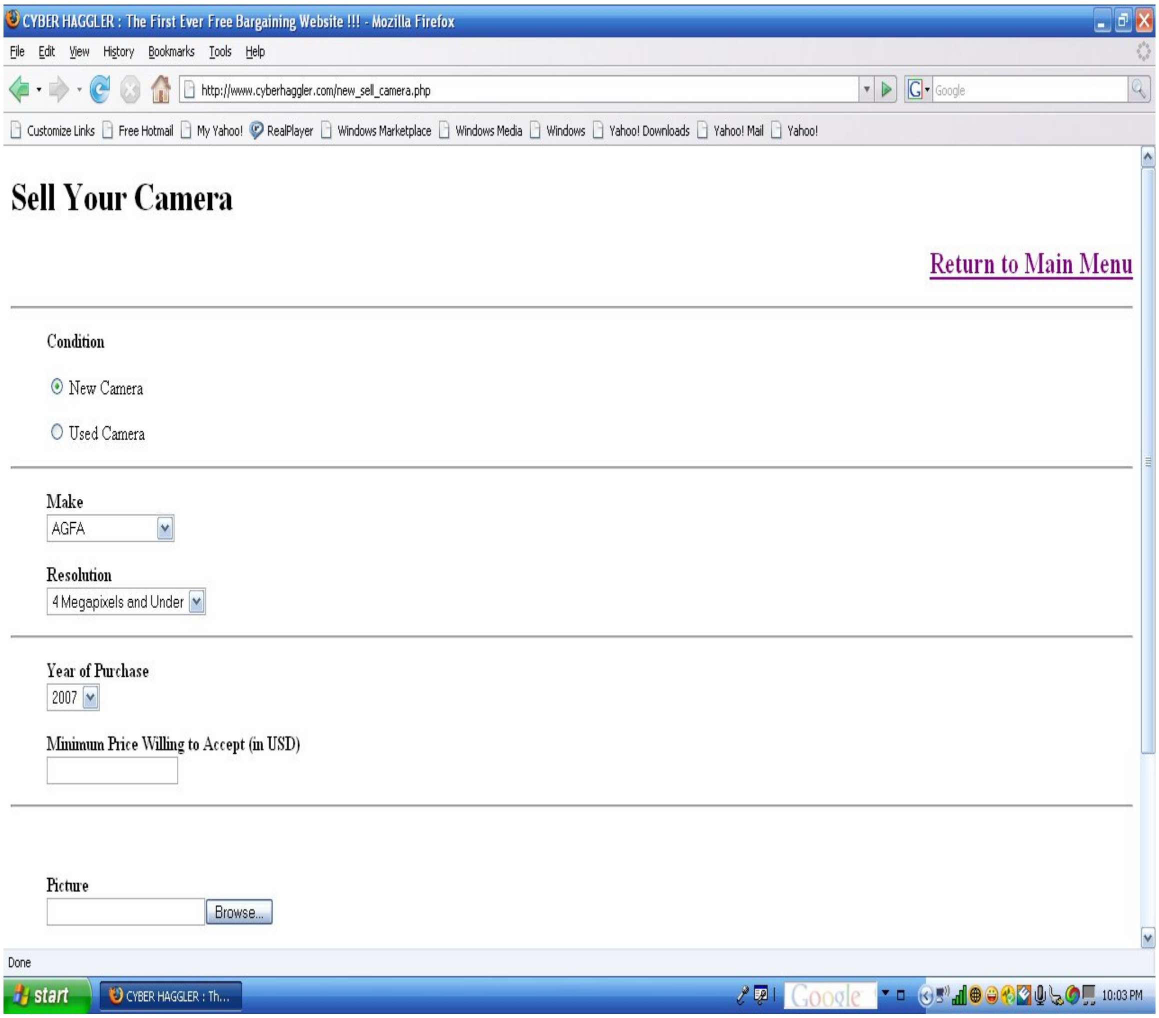

Figure 3.5: Cyber Haggler Form for selling a digital camera 3.5.1 SELLER SIDE

Consider an example where a user (human buyer) ‘Baron’ wants to purchase a digital camera and another user (human seller) ‘Sam’ wants to sell a digital camera. As a seller, Sam registers on Cyber Haggler and he submits the seller web form shown in Figure 3.5.

[1] Some of the interface screens were developed from the templates available for free use from www.freewebsitetemplates.com.

Once Sam submits the digital camera for sale, his product information is stored in the database of Cyber Haggler in the table named 'camera.' Figure 3.6 shows the successful submission of the digital camera in the database.

The form asks Sam to specify the following attributes of the digital camera:

a) Condition

b) Make

c) Resolution

d) Year of Purchase

e) Picture of camera

f) Minimum Price willing to accept (in USD)

g) Deadline (Time in days by which the submitted product should be sold)

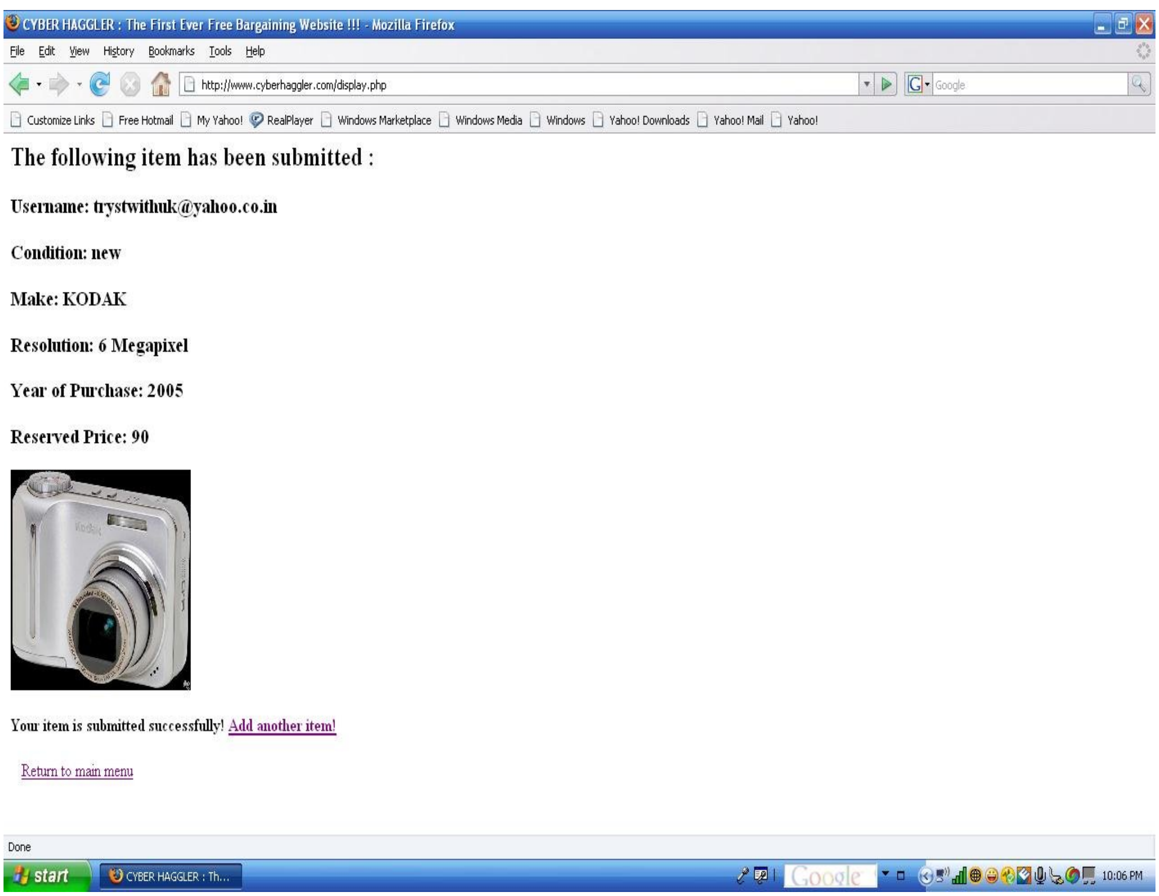

Figure 3.6: A successful product submission in Cyber Haggler's database

Once Sam submits the digital camera for sale, his product information is stored in the database of Cyber Haggler in the table named ‘camera.’ Figure 3.6 shows the successful submission of the digital camera in the database.

3.5.2 BUYER SIDE

The buyer Baron who is looking for a digital camera fills out the form shown in Figure 3.7, thereby specifying following attributes of the digital camera:

a) Search for (Condition)

b) Make

c) Resolution

d) Year of Purchase not earlier than

e) Maximum Price Willing to Pay (in USD)

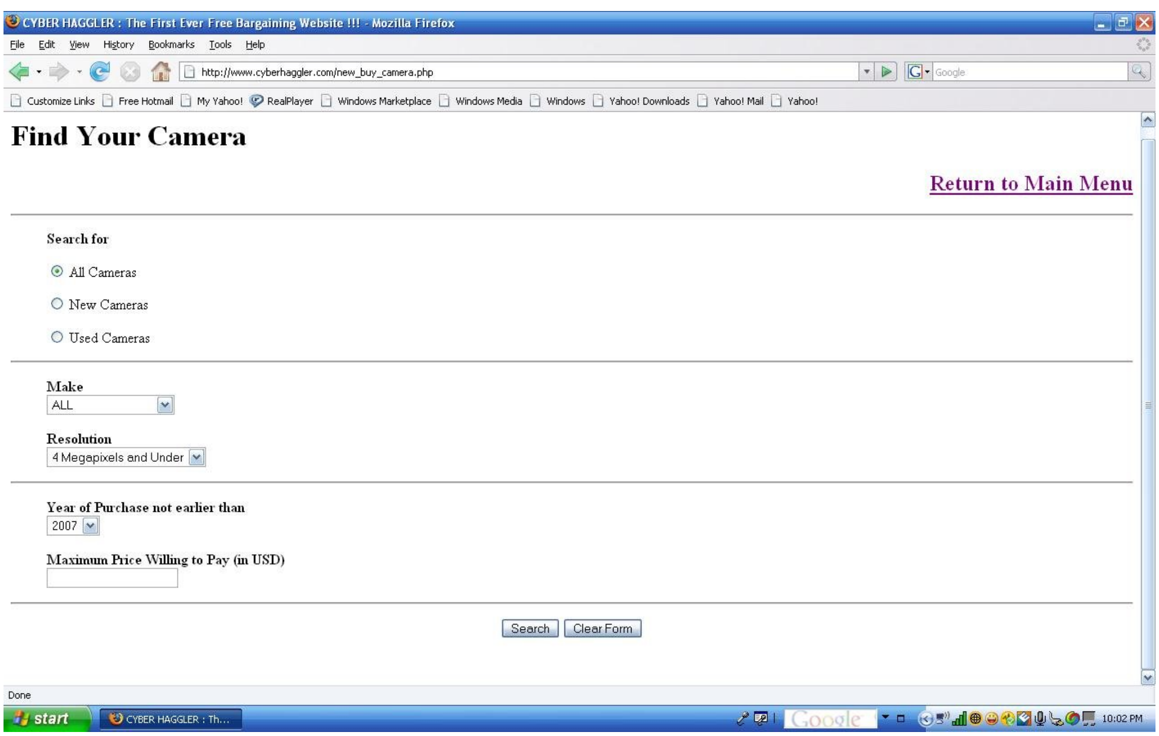

Figure 3.7: Cyber Haggler buyer form

On submission (by pressing the ‘Search’ button in Figure 3.7), a SQL query is generated corresponding to his search criteria. For example, suppose Baron’s search criteria are:

a) Search for (Condition): New

b) Make: Kodak

c) Resolution: 6 Megapixel

d) Year of Purchase not earlier than: 2005

e) Maximum Price Willing to Pay (in USD): 120

This will generate the following SQL query:

“SELECT seller_id, condition, make, resolution, picture, year _of_purchase FROM camera WHERE condition= ‘New’ and make= ‘Kodak’ and resolution = ‘6 Megapixel’ and year_of_purchase > 2005 and reservation_price < 120.”

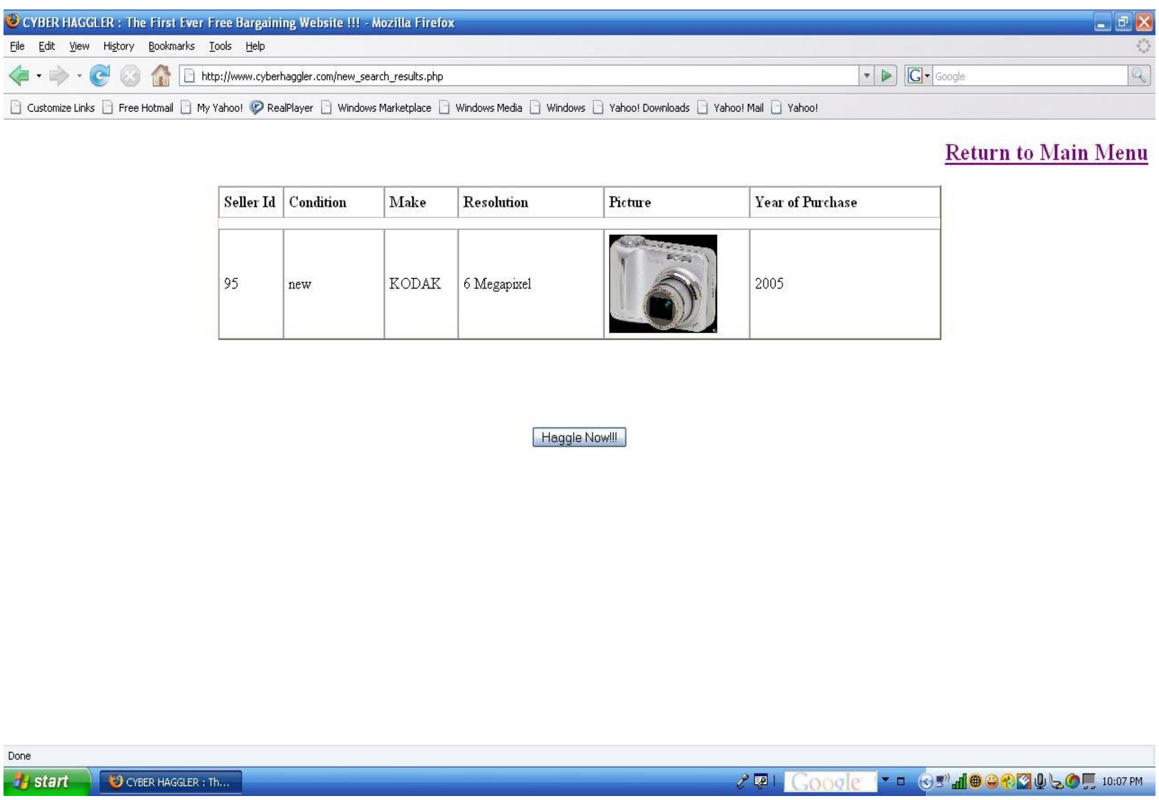

Figure 3.8: Cyber Haggler buyer’s search result

The result of this query is shown in Figure 3.8. The result lists all the sellers who are willing to sell a digital camera with the above search criteria. By pressing the 'Haggle Now' button in the 'Search Results Form' (Figure 3.8), Baron can initiate the bargaining process. The bargaining process starts in the background, and he gets a successful deal within his reservation price (RP^b). Figure 3.9 shows a successful deal with deal price = $113, which is within Baron's reservation price.

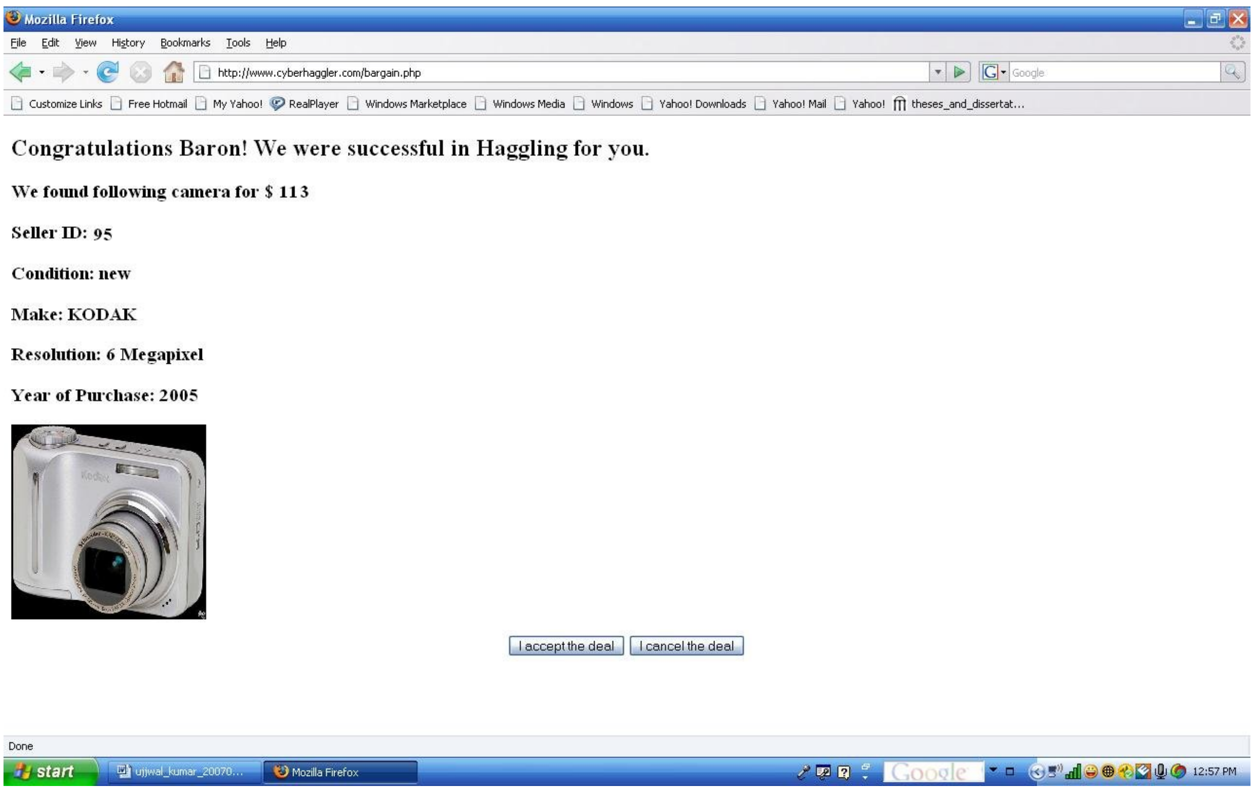

Figure 3.9: A successful deal at $113 when RP^s=80 and RP^b=120

3.6 CYBER HAGGLER VS. KASBAH

As discussed in Chapter 2, (Section 2.1) Kasbah is an open web-based marketplace where people can negotiate the purchase and sale of goods using software agents. On the other hand, we have designed and developed Cyber Haggler which is a bargaining website where users simply specify the reservation price for their product and the whole bargaining process is carried out by a population of buying and selling agents using a genetic algorithm. In this section, we summarize the main differences between Cyber Haggler and Kasbah. Table 3.3 gives insight as how Cyber haggler compares to Kasbah.

Table 3.3: Comparison of Cyber Haggler and Kasbah

Criterion	**Cyber Haggler**	**Kasbah**
Strategy	Automated (trial-and-error process, strategy evolves during many negotiations using Genetic Algorithm)	User Defined (users must choose between linear, quadratic or cubic strategies)
Bargaining Time	Maximum 2 minutes	May take days (users must define a deadline. It is very likely that the agents may not end in a successful negotiation within the deadline)
Bargaining Outcome	Always successful (Cyber Haggler always finds a successful deal if the reserved price of the buyer is greater than the reserved price of the seller)	May end in a conflict (the bargaining process is not guaranteed to end in a successful deal. It may end in a conflict)
Players	Population of buyers and sellers	Single set of buyer and seller
Intelligence	Agents evolve their strategy in time, hence learning through trial and error	No learning

3.7 CYBER HAGGLER VS. EBAY

EBay is an immensely popular auction website on the Internet. Cyber Haggler, on the other hand is an endeavor to develop a bargaining website. We have already discussed the main difference between auction and bargain in Section 1.4. In this section, we highlight the main differences between Cyber Haggler and EBay.

Table 3.4: Comparison of Cyber Haggler and EBay

Criterion	**Cyber Haggler**	**EBay**
Type	Cyber Haggler is a bargain website where users bargain on products	EBay is an auction website where users auction their products
Operating Time	Maximum 2 minutes. (buyers can search their product and start bargaining process, which can take a maximum of two minutes)	May take days. (buyers may have to wait for days before the auction ends and the winning bidder gets the product)
Outcome	Always successful (Cyber Haggler always finds a successful deal if the reserved price of the buyer is greater than the reserved price of the seller)	Not necessarily successful (bidder must win the auction to get the product. Hence, it depends on other buyers also)
Players	Players in the bargaining process involve populations of buying and selling agents	Many-to-many (EBay does not involve software agents in auctioning process. Auctioning process is done by human users only. Many buyers contend for a product being auctioned by a single seller)
Software Agents	Human users just specify the reservation price of the product and the bargaining process is done by software agents	There is no software agent involved in the auctioning process. (as per EBay conditions, using software agents for increasing the bid is not allowed)

CHAPTER 4

EXPERIMENTS AND RESULTS

4.1 EXPERIMENT 1

Here we present five experiments to test the model we have developed. The first experiment is done to find the optimal parameter setting for the genetic algorithm. The second experiment compares the results of random search with the genetic algorithm. The third experiment is done to measure the variation in deal price with the increasing size of the zone of agreement. The fourth experiment compares the performance of Cyber Haggler with human-to-human bargaining in five different bargaining games. The last experiment explores the one-to-many model of bargaining.

We utilize the following notation:

N= Population size. For simplicity, 'N' is same for both the buyer and the seller.

P_c = Crossover Rate

P_m = Mutation Rate

We start with the following set up:

Population Size (N) = 10

Crossover Rate (P_c) = 80%

Mutation Rate (P_m) = 0.005

Selection Method = roulette wheel

Stopping Criteria = 40 generations or the bargaining process termination, because of a mutually acceptable offer proposed by either agent within 40 generations.

Our goal is to find the optimal parameter settings for the stable outcome. To do this, we ran the genetic algorithm using every possible combination of the following settings:

N = 10 – 90 in increments of 10

P_c = 10% - 80% in increments of 10

P_m = .005 - .05 in increments of .005

Elitism=true or false

Selection Method = roulette wheel or tournament

We run the same GA set-up ten times and then take the average. We observe that having the elitism on or off does not make any significant difference because the stable outcome depends on both the subpopulations. We obtain the best performance for the following parameter set-up: N=20, P_c = 80%, P_m =0.005, roulette wheel selection, elitism=off and stopping criteria = 40 generations or the bargaining process termination, because of a mutually acceptable offer proposed by either agent within 40 generations. With this parameter set-up, we obtained decent results in almost all the experiments. The effect of varying the various parameters is discussed next. For each of the following experiments otherwise mentioned explicitly, we have assumed RP^b=130, RP^s=80, T^b=10, T^s=20 (if the seller's deadline > the buyer's deadline, otherwise T^b=20 and T^s=10), and the initial population is initialized with the boulware strategy for both the buyer and the seller populations. We compare the stable outcome in each case with the game theoretic equilibrium. If both the buyer and the seller follow the boulware strategy throughout the bargaining game then the game theoretic equilibrium is (P,T) where T is the minimum of the buyer and the seller deadlines and P is equal to RP^s (if T^s<T^b) and RP^b (if T^s>T^b). Since the assumptions of our model are different from that of a game theoretical model as discussed earlier, we do not expect that our stable outcome will exactly match that of the game theoretic equilibrium. However because our assumptions are based upon sound economic principles, we expect the stable outcome to be fairly close to the game theoretic equilibrium. Hence, if with increasing crossover rates, we get results closer to the game theoretic equilibrium, we will prefer a higher crossover rate to a lower crossover rate.

(a) Effect of population

We notice in Figure 4.1 that increasing the population size from 10 to 90 has no significant change in the concluding deal price. However, the running time for the GA to reach the stable outcome increases considerably with the increasing population.

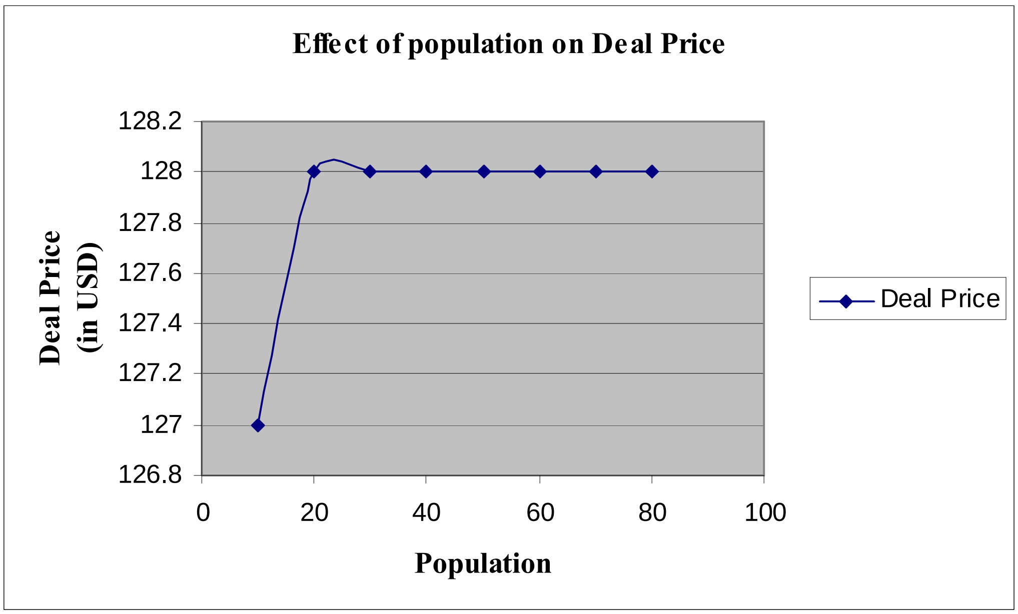

Figure 4.1 Effect of varying population size where $P_c = 80\%$, $P_m = 0.005$, selection method=roulette wheel, number of generations=40, elitism =false

(b) Effect of Selection Mechanism

We experiment with the roulette wheel selection as well as with the tournament selection. We run the same GA using two different selection mechanisms ten times and then average the results. The results in Figure 4.2 shows the outcome of five different bargaining games using two different selection methods when the seller's deadline is greater than the buyer's deadline. The (RP^s, RP^b) in these cases are (20,40), (40,80),(60,120),(80,160) and (100,200). On average, roulette selection outperforms tournament selection, but the difference is marginal. We decided to use roulette wheel selection for all of the subsequent experiments.

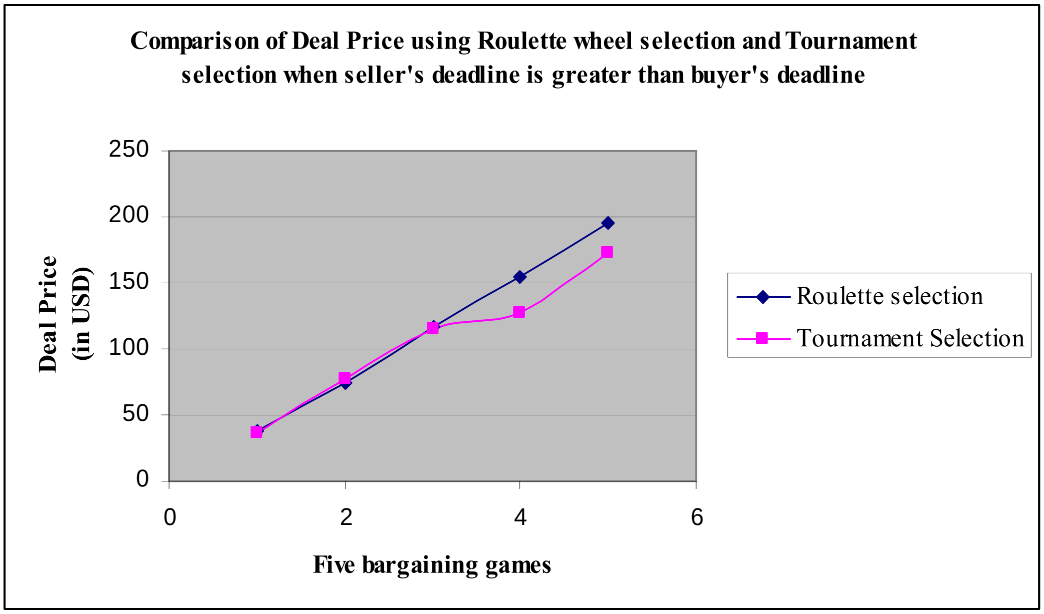

Figure 4.2 Comparison of Deal Price using Roulette wheel selection and Tournament Selection with tournament size of 2.

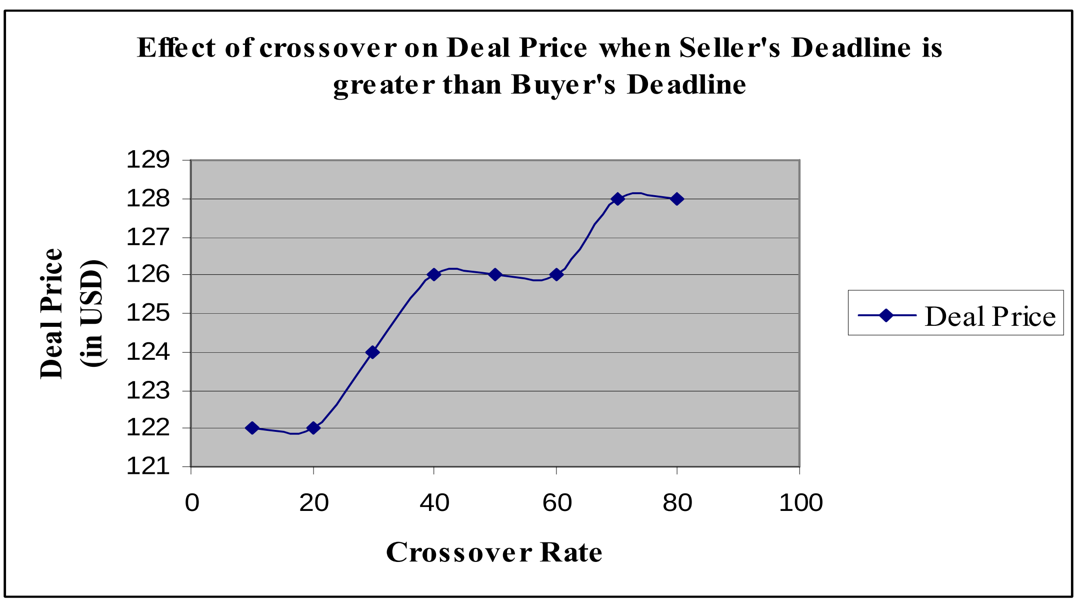

Figure 4.3 Effect of varying crossover rate where N=20, P_m=0.005, selection method=roulette wheel, number of generations=40, elitism =false, seller's deadline (T^s) > buyer's deadline (T^b)

(c) Effect of Crossover

In Figure 4.3, when the seller's deadline is greater than the buyer's deadline, we notice that a higher crossover favors the stable outcome to be 128, which is closer to the buyer's reserved price. The same trend can be seen in Figure 4.4 when the buyer's deadline is greater than the seller's deadline, where the stable outcome gets closer to the seller's reserved price with an increasing crossover rate.

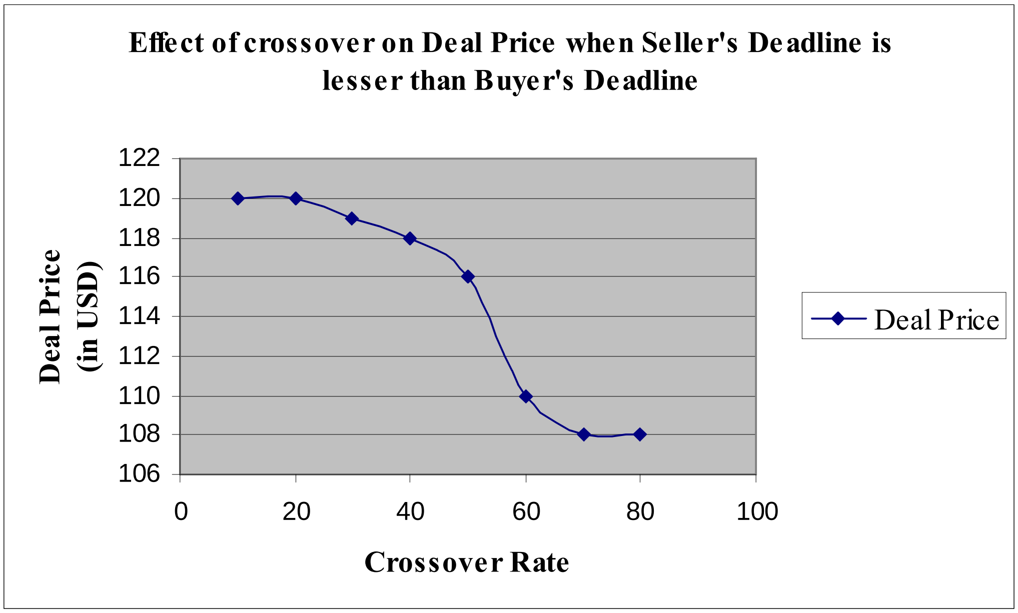

Figure 4.4 Effect of varying crossover rate where N=20, P_m=0.005, selection method=roulette wheel, number of generations=40, elitism =false, buyer's deadline (T^b) > seller's deadline (T^s)

(d) Effect of Mutation

In Figure 4.5, when the seller's deadline is greater than the buyer's deadline, we see that an increasing mutation rate starts deviating away from the buyer's reserved price. However, for the low mutation rate of 0.005, the stable outcome is closer to the equilibrium condition. The same trend can be seen in Figure 4.6 when the buyer's deadline is greater than the seller's deadline where the stable outcome is closer to the seller's reserved price for a low rate of mutation. The trend in both cases can be readily understood. With an increasing rate of mutation, the best solution is lost easily. This causes a shift from the equilibrium condition.

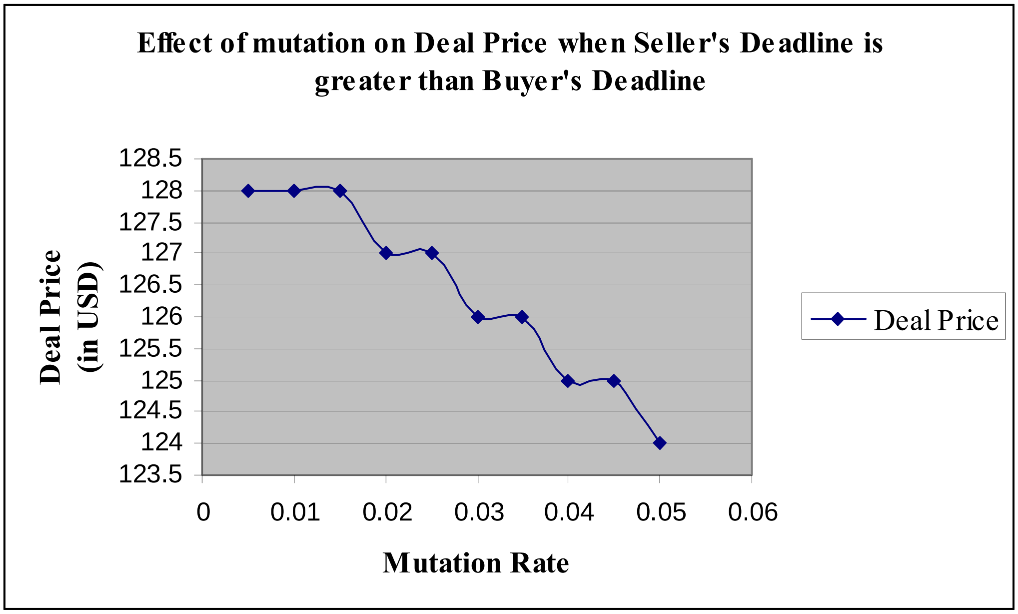

Figure 4.5 Effect of varying mutation rate where N=20, P_c=80%, selection method=roulette wheel, number of generations=40, elitism =false, seller's deadline (T^s) > buyer's deadline (T^b)

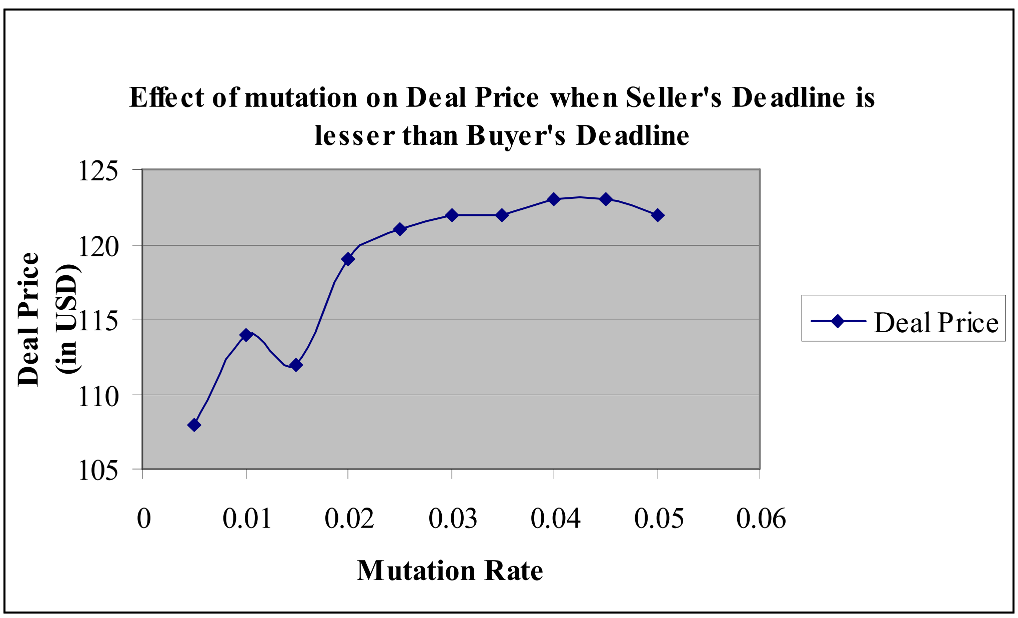

Figure 4.6 Effect of varying mutation rate where N=20, P_c=80%, selection method=roulette wheel, number of generations=40, elitism =false, seller's deadline (T^s) < buyer's deadline (T^b)

Using our best GA set-up, we find the stable outcome for one-to-one bargaining game for which RP^b=130, RP^s=80, T^b=10 and T^s=20. As discussed at the very start of this section, we run each GA set-up ten times and then take the average.

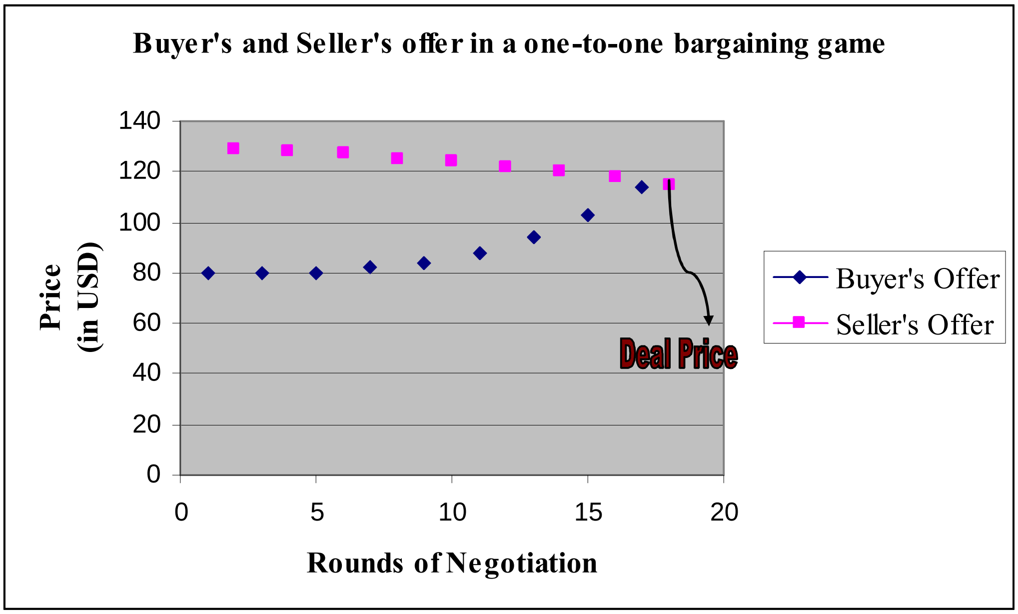

Figure 4.7: One-to-one bargaining game with RP^b=130, RP^s=80, T^b=10 and T^s=20

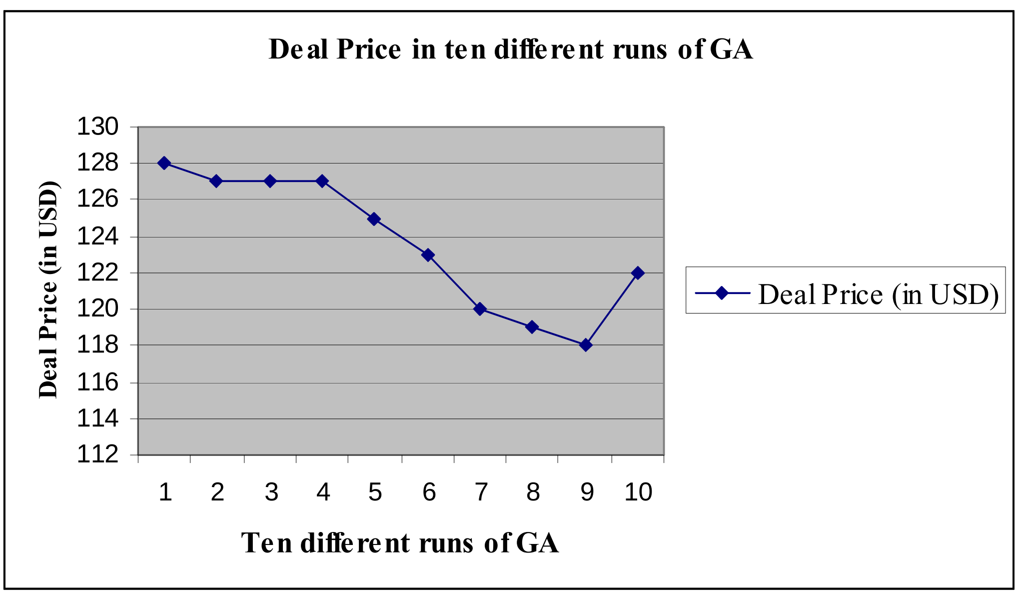

Figure 4.8 Result of ten runs of one-to-one bargaining game described in Figure 4.7

Figure 4.7 shows one such run displaying the successive offers made by the buyer and the seller in different rounds of negotiation. Figure 4.8 shows the deal price (stable outcome) in all ten experiments. It can be noticed that the GA does not give the same results and sometimes can give the sub-optimal results. This is why we run the same GA program ten times and then average the results. The average deal after ten experiments was found to be 123.

4.2 EXPERIMENT 2

In this experiment, we compare the performance of the genetic algorithm with random search. We find the stable outcome using these two methods where the (RP^s, RP^b) couplet is (80,130), T^b =10 and T^s=50 (if the seller's deadline is greater than the buyer's deadline, otherwise T^b =50 and T^s=10).

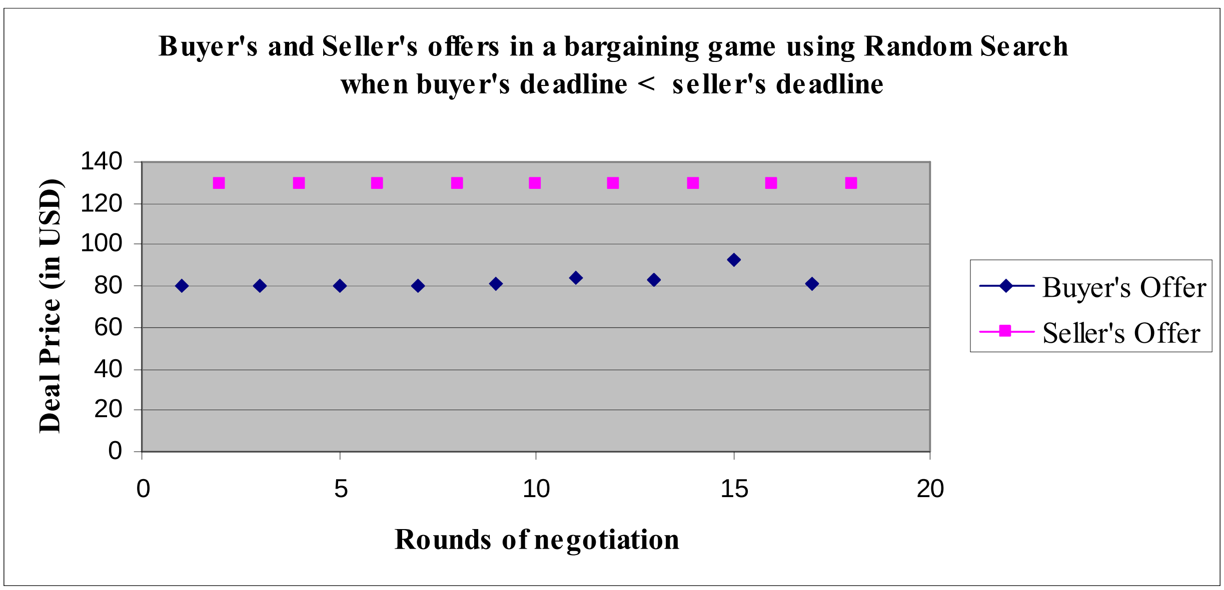

Figure 4.9 One-to-one bargaining game with RP^b=130, RP^s=80, T^b=10 and T^s=50 using random search

It is clear from Figures 4.9 and 4.10 that the random search does not converge but the genetic algorithm converges. In random search, when the seller's deadline is very high as compared to the buyer's deadline, the offers proposed by the seller remains almost constant and the buyer's offers keep on fluctuating. However, using the genetic algorithm, the buyer's offers converge fast because of a low deadline but the

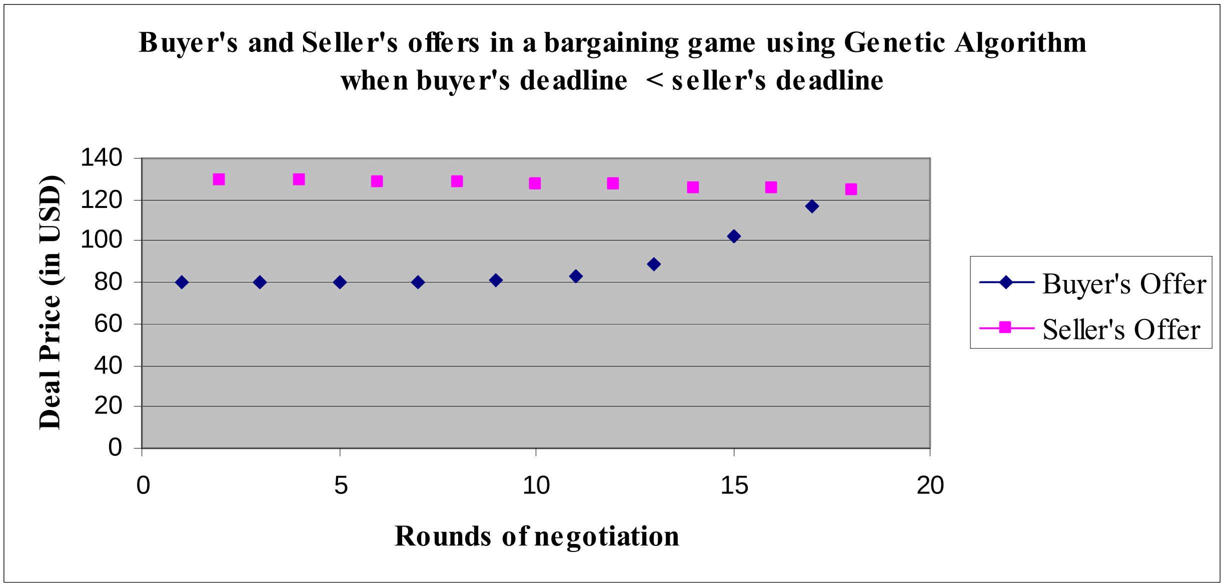

Figure 4.10 One-to-one bargaining game with RP^b=130, RP^s=80, T^b=10 and T^s=50 using genetic algorithm

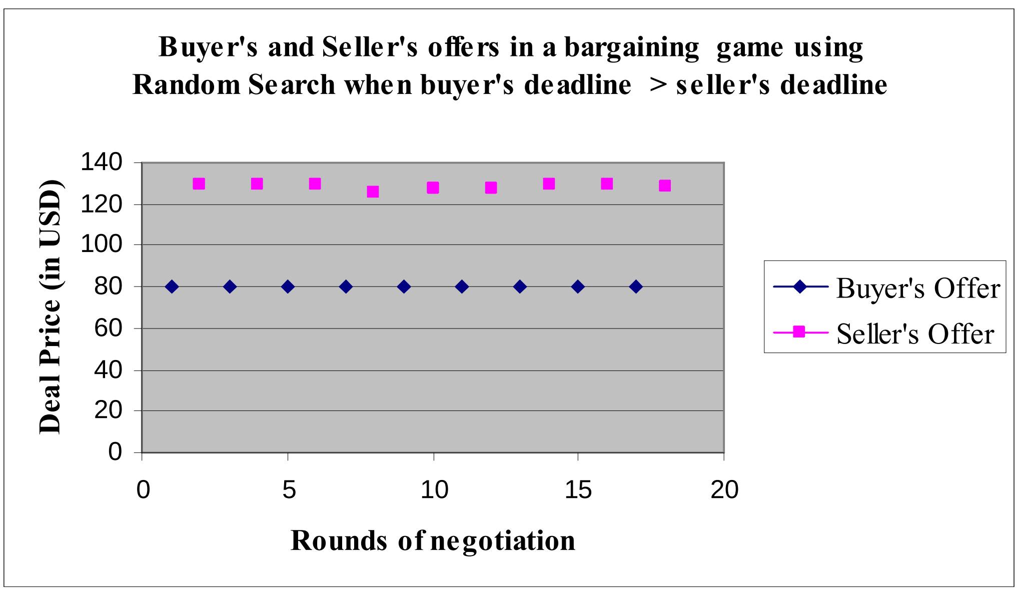

Figure 4.11 One-to-one bargaining game with RP^b=130, RP^s=80, T^b=50 and T^s=10 using random search

seller's offers converge very slowly because of a higher deadline. The stable outcome is fairly close to RP^b as expected. Similarly, in Figures 4.11 and 4.12, again we see that the random search fails to converge. The buyer's deadline is greater than the seller's deadline and the offers proposed by the buyer remains almost constant. The offers made by the seller keep on fluctuating. Again, using the genetic algorithm, we see in Figure 4.12 that the stable outcome is fairly close to RP^s, because the buyer's deadline is greater than the seller's deadline. Hence we conclude that the random search fails miserably when compared to the genetic algorithm.

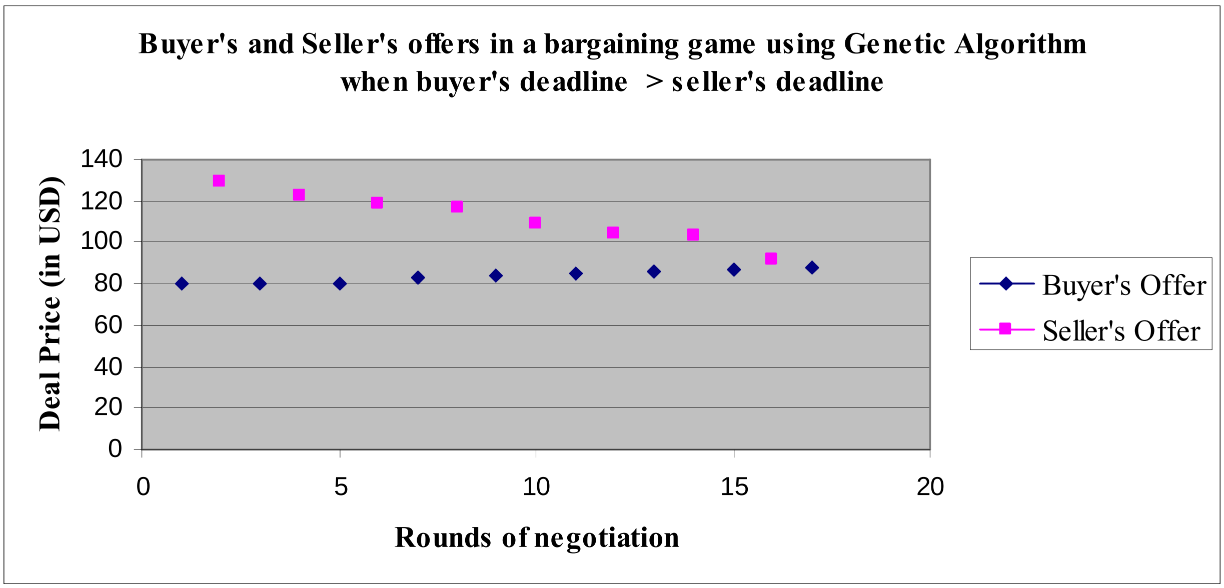

Figure 4.12 One-to-one bargaining game with RP^b=130, RP^s=80, T^b=50 and T^s=10 using genetic algorithm

4.3 EXPERIMENT 3

In Section 3.2, we described bargaining as a search problem where the genetic algorithm (GA) is used to find the stable outcome. In the game theoretic technique, we have the concept of equilibrium but in a genetic algorithm approach, the equilibrium is the stable outcome. Since a GA is not guaranteed to converge and give the same result each time it runs, we run the same GA ten times and then take the average. We notice that the variation in the stable outcome increases with an increasing size of the zone of agreement (Z). We calculate the variation in deal price as:

Variation in deal price (in %) = (Max. –Min)*100/Min

where Max = maximum value of the deal price obtained in ten runs of the GA

Min= minimum value of the deal price obtained in ten runs of the GA

In Figure 4.13 we show the variation in the deal price in five different cases. The (RP^s, RP^b) in these cases are (80,100), (80,200), (80,300) (80,400) and (80,500). Hence, the sizes of Z in these cases are 20, 120, 220, 320 and 420. We see that the variation in deal price increases with the size of Z. This is because the search space increases accordingly with the increasing size of Z and the GA does not converge at the same point, leading to variation in results. This also means that a buyer who has a very high reserve price pays more than the one with a lower reserve price.

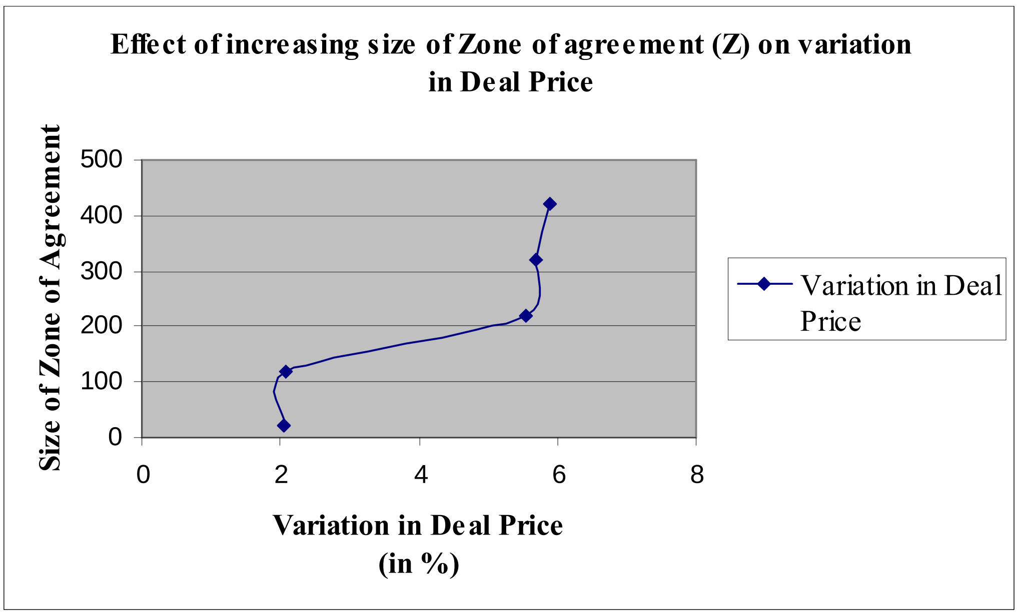

Figure 4.13: Effect of increasing the size of the zone of agreement (Z) on variation in Deal Price

4.4 EXPERIMENT 4

In order to measure the effectiveness of Cyber Haggler, we compare the performance of Cyber Haggler with human-to-human bargaining in five different games. The (RP^s,RP^b) couplet were (20, 40), (40,80), (60,120), (80,160) and (100,200). We analyze the results for two different situations. Firstly, when the seller's deadline is greater than the buyer's deadline and secondly, when the seller's deadline is less than the buyer's deadline. In human-to-human bargaining both the buyers and the sellers know each others reserved prices but do not know each other's deadlines. All the participants were students of The

University of Georgia. A third person acts as a mediator to start and end the bargaining in accordance with the bargaining protocol. Human-to-human bargaining is exactly the same as our proposed model except for the fact that it does not involve any computer program and uses a mediator to start and end the bargaining process.

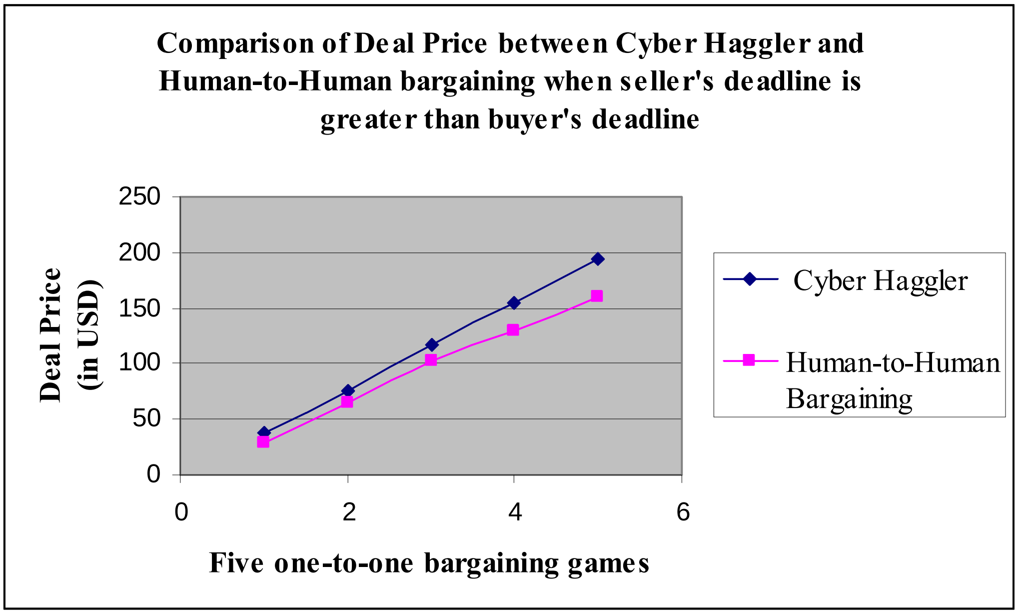

Figure 4.14: Comparison of Cyber Haggler with human-to-human bargaining in five different games with seller's deadline being greater than buyer's deadline

In Figure 4.14 we see that the stable outcome of Cyber Haggler benefits the seller more when compared to human-to-human bargaining. This is consistent with the game theoretic equilibrium when the seller's deadline is greater than the buyer's deadline. The same can be inferred from Figure 4.15. One limitation of this experiment is that the results of human-to-human bargaining depends on a number of factors such as whether the person is really good at bargaining or not, the utility function of bargainer, etc. In sum, the results of human-to-human bargaining can be different in different cases and it is very likely that they can outperform Cyber Haggler. However, our aim in this thesis is to develop intelligent and adaptive bargaining agents and we do not claim that Cyber Haggler will outperform every human bargainer.

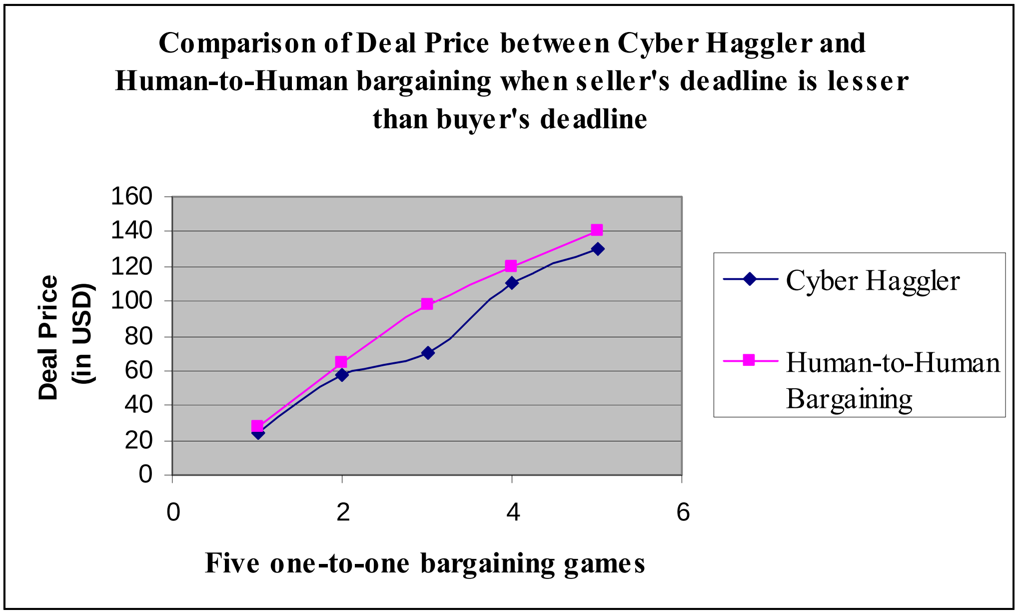

Figure 4.15: Comparison of Cyber Haggler with human-to-human bargaining in five different games with buyer's deadline being greater than seller's deadline

4.5 EXPERIMENT 5

In this experiment, we test our model in one-to-many bargaining game. The assumptions and the bargaining protocol for this model are same as discussed in Chapter 3. A buyer with $RP^b=130$ is bargaining simultaneously with three sellers each having different reservation price. $RP^{s1}=70$, $RP^{s2}=80$ and $RP^{s3}=90$. The deadline of the buyer is $T^b=10$ and the deadline of the sellers is $T^{s1} = 40$ (seller 1), $T^{s2} = 30$ (seller 2) and $T^{s3} = 20$ (seller 3). We see that the seller having the lowest reservation price has the highest deadline and vice versa. The reason for this choice was to examine the results in such a situation because a seller with the lowest reservation price as well as the lowest deadline will eventually win the deal over the other sellers. Figure 4.12 shows the offers made by different sellers and buyers in different rounds of negotiation. We see that the offers made by seller 1 are always lower than those of the other sellers and eventually seller 1 wins the deal in the final round of negotiation. Since seller 1 has the lowest reservation price, even though it has a longer deadline, it beats the other sellers, albeit marginally. Hence, it can be interpreted that the algorithm will always favor a seller with a lower reservation price and preferably a lower deadline. Even though the deadline is not the lowest, a very low reservation price can result in a successful deal as is evident from our experiment.

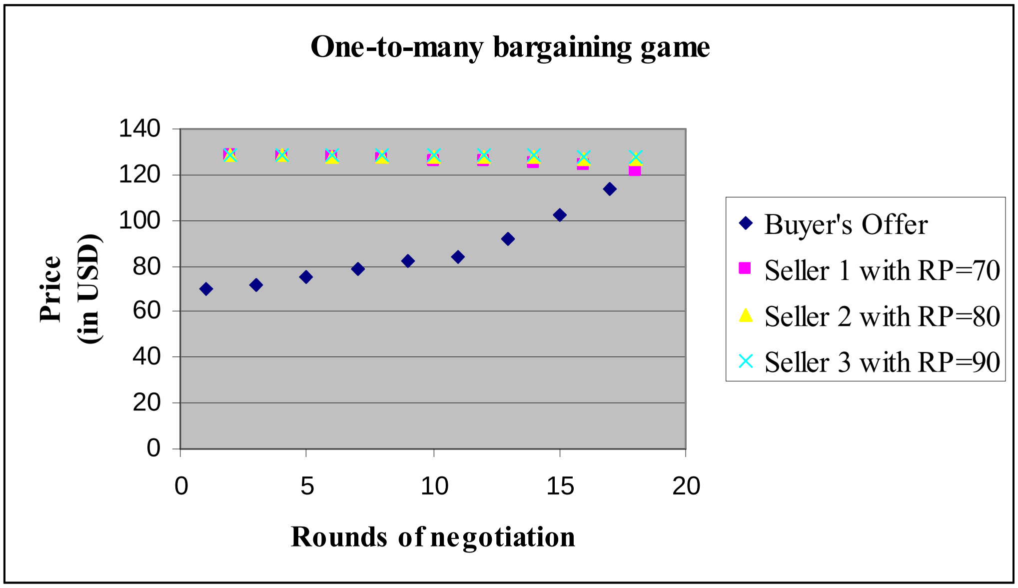

Figure 4.16: One-to-many bargaining game with one buyer and three sellers each having different deadline and different reservation price

CHAPTER 5

CONCLUSION

5.1 INTRODUCTION

In this Chapter we provide summary and potential directions for future research.

5.2 SUMMARY

We have developed a web-based bargaining website Cyber Haggler (http://www.cyberhaggler.com). Game theory has excessive research on the bargaining models under the assumption of perfect rationality. However, we are interested in one-to-one and one-to-many sequential bargaining models where the players (buyers and sellers) exhibit bounded rationality. Our aim in this thesis is to develop intelligent buyer and seller agents that learn from trial-and-error to reach a deal. They should be able to simulate human-type reasoning. For example: consider the situation of a haggler who goes to a flea market and starts bargaining for a product such as a used guitar. As a buyer, he sets a reserved price for the guitar and plans to make all offers up to and including his reserved price. Similarly, the guitar seller also sets a reservation price in his mind and plans not to accept any offer less than his reservation price. The buyer starts from a very small offer and increases it. Similarly the seller asks for a very high price and decreases it. The moment an offer is mutually acceptable a deal is made. We capture the same process and implement it as a genetic algorithm. We could have encoded game theoretic equilibrium rules into a well-structured knowledge-based system, but this approach cannot include automated learning. Also, this approach would have been very inflexible. Thus, we pose the bargaining problem as a search and optimization problem and use a genetic algorithm to find an equilibrium point in the search space. Also, while game theory assumes that the players have perfect rationality and complete knowledge, we make our model more realistic by assuming that the players have bounded rationality and partial knowledge. In our genetic algorithm model, we have two subpopulations, one for the buyer and the other for the seller.

We evolve these populations and the stable outcome becomes the deal price. While the game theoretic approach has an equilibrium point, the genetic algorithm approach has a stable outcome where the buyer and the seller populations offer the same price to each other. We started with a discussion on bargaining theory in Chapter 1. In Chapter 2, we discussed the most relevant work related to our thesis. Most importantly is Kasbah. In Chapter 3, we gave the details of our negotiation model. Also, we discussed the differences between Cyber Haggler and Kasbah, and Cyber Haggler and EBay. In Chapter 4, we conducted various experiments to test our model. Experiment 1 aimed at finding an optimal parameter set up for the genetic algorithm, Experiment 2 compared the performance of the genetic algorithm with random search, Experiment 3 showed the variation of the deal price with the increasing size of the zone of agreement, Experiment 4 compared Cyber Haggler with human-to-human bargaining; and Experiment 5 discussed the one-to-many bargaining model.

5.3 FUTURE WORK

Though we have developed a fairly significant and very realistic model of bargaining, there are many more aspects to be developed in a versatile real world bargaining model. We can extend our present work in the future. Future work may include the following:

- The present work deals with price as the only issue. The model could be extended to a multi-issue bargaining model including price, quality, quantity, delivery time, payment method, and more.
- In the present model, the buyer can search results in real time and haggle to get a deal immediately. The seller could utilize such capabilities. In this way, a seller can find all the interested buyers in real time and start the bargaining process to obtain a deal immediately.
- Currently, a default value is used for the buyer's deadline. A better idea would be to estimate the buyer's deadline based on attributes such as the utility value of the product, number of buyers contending for the product at any time, the buyer's per month transactions with Cyber Haggler, and so on.

Bargaining is a complex problem for which we have proposed a web-based and user-friendly model and an implementation. Cyber Haggler covers all the features of a good bargaining model. It may prove to be an important work in the development of web-based bargaining models.

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