Notre Dame University

Faculty of Natural and Applied Sciences
Department of Computer Science

Agent Negotiation in a Virtual Marketplace

Master Thesis

Roger Kahwagi

Advisor:
Dr. Hikmat Farhat

Agent Negotiation in a Virtual Marketplace:
Improving the Negotiation Behavior of the DALIA Agents

By
Roger Kahwagi

Approved by:

HIKMAT FARHAT

Hikmat Farhat: Assistant Professor of Computer Science
Advisor.

Omar Rifi: Assistant Professor of Computer Science
Member of Committee.

Mario Missakian: Assistant Professor of Computer Science
Member of Committee.

Elias Saleeby: Assistant Professor of Mathematics
Member of Committee.

Date of Thesis Defence: March 8^{th}, 2007

Abstract

This thesis examines the different types of agents, and how they help evolve the world around, most particularly the way businesses are undertaken and handled.

The following work is based upon the DALIA environment, which stands for Distributed Autonomous and Linguistically Competent Agents.
In this work I have extended and improved the DALIA agent negotiation aspect, where two agents are involved in an offer and counter-offer negotiations.

The model presented by DALIA for the offers and counter offers is investigated and the weak points in the negotiation paradigm are identified. A strategy is devised to overcome these weak points and provide more reliable functions and strategies to make sure the different mental attitudes would dramatically affect the agents' strategies and the negotiation outcome.

Further enhancements are added to the agents and to their negotiation strategies to make them more aware of the negotiation environment and of the changing circumstances affecting the negotiation.
The agents would then try to adapt to these changes and would try to make them work to their advantage, while making sure they respect their mental attributes' priorities.

Table of Contents

List of figures and tables

List of abbreviations

AA: International Conference on Autonomous Agents

BDI: Belief, Desire and Intention

DALIA: Distributed, Artificial and Linguistically Competent Negotiation Agents

E-Commerce: Electronic Commerce

EDI: Electronic Data Interchange

ETA: Estimated Time of Arrival

JEPI: Joint Electronic Payment Initiative

MAGMA: Minnesota AGent Marketplace Architecture

MAS: Multi-Agent Systems

MIT: Massachusetts Institute of Technology

PAAM: International Conference on the Practical Application of Intelligent Agents on Multi-Agent technology

SET: Secure Electronic Transaction

UPP: Universal Payment Protocol

XML: Extensible Markup Language

Acknowledgments

Many people helped make this thesis a reality, either directly or indirectly. But the first thank you should go to my advisor, Dr. Hikmat Farhat, for without his help and guidance, this work would not have materialized.

I also owe my family a very big thank you for all the encouragement and support they provided through out all the duration of the work. They helped provide a great working environment, and were always there to push me towards achieving this work.

A final thank you would have to go to all my friends, who supported me and provided me with all the help and encouragement that I needed to be able to successfully complete this thesis.

Chapter 1: Introduction and problem definition

1.1 Introduction to the general problem

With the increasing importance of the time factor in daily business, comes the need to accelerate and automate many tedious and time consuming tasks. "Time is money" is the key sentence that defines the need for all this automation. This time factor can be enhanced in many ways: the introduction of computers and machinery to business and industries was a first step at increasing the time needed to finishing tasks quicker without any deterioration in quality, and with an improved reliability.

The main concept behind the revolution in the way business runs is the automation of tasks, making them quicker and more reliable.

Historically, the need for more speed at car factories was the reason behind the creation of assembly lines. The need for more speed and more reliability at the assembly line was the driving force behind the introduction of automated machinery. With the introduction of machines at the factory, the only job left for the humans was the actual running of these machines and making sure the assembly line keeps running smoothly.

With the evolution of computers, and as they became faster and more reliable, a new era was also introduced for the evolution of business. Computer software introduced even more automation at a level not experienced before, and it wasn't long before all accounting tasks and inventory management tasks became automated. Even better all results were stored in databases that can hold more data than any other manual storage system that can be accessed and viewed at the press of a button.

As computers became more complex, and more capable, computers took an increasingly important role in corporation, analyzing data and business trends and providing the help top managers need when making critical decisions- so computers evolved into decision support system. And with the recent status that the internet has reached, and the role it has taken as the premium communication medium, computers were once again about to change the very way business is alone.

With the help of the internet, businesses were able to defeat time itself: E-stores open 24 hours a day always there to provide the customer with what he needs and when he needs it. Even more e-stores were able to track customers' habits and suggest personalized offers that might interest the buyer and make him feel more at home.

The same advantages are found in the new business to business relation and even helps in the foundation of virtual companies: low on stock for product x? An automated request email can be sent to the provider- the request is instantaneously processed and the order will be dispatched as soon as possible- perfect harmony.

On the other hand, customer to customer e-commerce wasn't as successful as the other two media, and is mainly restricted to online auctions; Practical, but not as popular or successful as the other two variants.

Technology is once again imposing a new dimension on the way business is run, with the introduction of a virtual market place. Eliminating the need for a business trip in a foreign country is one of the many advantages that can be provided by the virtual market place. Bringing down the space and time barriers, it is the evolution of e-business and is the merger of all e-business trends, where anyone can trade and negotiate the trade with anyone else and for anything.

The introduction of customizable agents can be configured according to their user's priorities and preferences to be his virtual representatives on the net. The agents would be able to trade, negotiate, conclude deals, analyze opponents' offers and bring back recommendations that would be of interest to the user, and all that will leave the human to do what he does best: make a choice. Especially that the agent will take into consideration, market trends and requirements trade-offs in order to bring the user the best possibly deals.

1.2 Problem definition

The establishment of the virtual market place as a world-wide standard for trading and doing business still has a long way to go. All components needed to achieve this virtual market are still under research, and not enough are developed and implemented.

The three major components needed to run this virtual market place are the following: The agent, the negotiation protocol and the communication protocols that are needed to ensure that all parts can communicate and understand each other.

The agents aren't supposed to be inherently compatible, yet they are supposed to have enough compatibility and adaptability in order to be able to deal with the different circumstances available at the different marketplaces and with the different agents. The negotiation protocols are the essence of the market, and they don't have to be using the same negotiation algorithms. Yet the different agents should be able to deal with each other regardless of the negotiation protocols adopted by every agent. And finally the communication protocols should allow the different agents to deal and communicate with each other regardless of their heterogeneous backgrounds.

All the issues regarding agents, negotiations and communications will be discussed at a later stage in their relevant sections.

Even though the achievement of this virtual market place would revolutionize the way business is done, we are still a long way from achieving it. Some experiments are making some break through, but they remain few compared to the magnitude of the project, and all results are achieved in a closed, limited, restricted and controlled environment where most variables are defined... The true virtual market place will have no boundaries and will be as large as the net itself with an endless number of agents, goods and sources of information for market trends analysis.

Despite the fact that the agents as a technology are growing more popular and are starting to earn a place everywhere in the industry such as in some rocket components for NASA, or even in some online engines, they still aren't mature enough and don't have all it takes to deal with all the variations that such an open ended environment can break: the autonomous agent needs to understand the needs of the user, be able to search for products that satisfy the User's criteria, to make compromises when fetching these goods, such as quality-price trade-offs for example. The agent needs to understand the market trends, to know whether the purchase of a certain product is favorable at the moment and what would be considered as a good price.

Then comes the negotiation process itself which involves having the agent bargaining with other agents via proposing offers and counter offers. The agent has to propose offers, receive others, analyze them, check with the market trends, his history and the other agent's offers, and decide accordingly on a course of action. The agent would continuously monitor his opponent's offers and accept a favorable offer if the situation is right, reject and quit the negotiation when the offers become completely unacceptable, or propose a counter-offer with the purpose of getting a more favorable deal.

When it comes to understanding website content and looking for items in websites, when it comes to "talking" and listening to other agents, when it comes to analyzing market trends and predicting market fluctuations, the agent needs to understand natural languages as opposed to having to adapt all the net, for agents to be able to operate.

In short, the agent is supposed to achieve all these tasks as if he was his human counterpart. Search, and analyze an enormous amount of data, trade and negotiate with lots of other agents before eventually returning a set of potential products that will be of interest to the user if not conclude the deal and return the item that would satisfy most the user's needs and expectations.

The negotiation needs to be either standardized or the agents have to be configured so they can deal with any type of negotiation. A current popular type of negotiation is online auctions with automated agents: the agents try to outbid each other while conforming to the regulations needs and expectations of the user. Another type currently available is the two way auctions where agents can negotiate with each other as well as try to outbid each other. But the virtual market place will bring two more types of negotiation: the one to one relationship where one buyer negotiates directly with one seller in an obvious sequence of offers and counter offers until the negotiation ends with either success or failure. The other type is having one buyer or seller negotiating with many sellers or buyers respectively, or more typically is to have many buyers negotiating with many sellers. This last type of negotiation can be broken down to a simpler one to one negotiation repeated many times without changing one of the participants, to mimic the one to many, or even the two can be changed to mimic the many-to-many negotiation.

Finally, the communication is the last challenge facing the virtual market place. The agents are supposed to communicate over secure connections through the net in order to be able to keep the privacy of the user and the security of the money being transferred. The agents are supposed to search a wide range of internet available material, raging from online shopping websites to market pricing and analysis pages, to different data bases with a wide variety of information up to threaded postings from other agents. What complicates the searching is that the agents need to understand the content of these pages in order to be able to analyze them. Which leaves us with two major approaches to a solution: either update the existing pages for the agents to be able to understand them or even better, make the agents "smart" enough to be able to understand and analyze natural languages. Even more, having all agents adopt the natural languages approach, will allow them to easily communicate with each other over a unified existing language and will allow them to interact seamlessly and efficiently with other human users with no additional technical requirements.

1.3 Research objectives

Starting from the virtual market place perspective, we will be trying to build upon the existing infrastructure and improve it to make it fit into our own perspective of the virtual market place, autonomous agents, and negotiation. For that, the agent will have to be rebuilt from scratch to be able to fit the "negotiation with an attitude" schema that this research is trying to achieve, and to this should be added a negotiation schema that will fit with the agents' mental attitude criteria.

By introducing the mental attributes, the user would feel more in contact with the agent, and even more, the agent will be able to satisfy the user's expectations more closely. By knowing what the user expects, the agent will be able to know better how to look and how to negotiate with others in order to provide the best deal possible for the user.

The negotiation process itself needs to be fixed in order to allow the agents to be able to integrate the new mental attitudes requirements and cope with the changes that the new situation suggests and the adaptation required to successfully manage the negotiation and to be able to get the best possible results out of the given situation.

With the introduction of a time constraint the inter agent negotiations will become more disputed and as one of the agents' time start running out he will have to play all his cards in order to be able to achieve a satisfactory end for the negotiation. The time factor will also allow the agent to know when a negotiation is not in his favor anymore and thus allow him to leave it just for time constraint reasons, thus resulting in a failed negotiation. This will help the agent make sure that the final negotiation outcome is always fair and that the negotiation will not favor his opponent due to the other agent's more favorable circumstances.

In short, the research objectives are to investigate the different negotiation schemas, and then integrate and expand them to allow for more refined negotiation which develops according to the user's, and subsequently to the agent's, mental preferences and priorities. Achieving the custom negotiation while taking into consideration the user's mental attitude would be the cornerstone in the development and evolution of sustainable online virtual marketplaces.

1.4 Approach and main results

The main approach followed by this research in order to better understand the way agents, negotiation and virtual markets work is to build a simulation. The simulation is based on the DALIA approach, where DALIA stands for Distributed, Artificial and Linguistically competent Intelligence Agents. In the rush towards the virtual market place the DALIA setting provides a new and interesting approach.

The agents are linguistically competent meaning that they can communicate with the user, and with each other the same way people talk. This will allow for easier market analysis and the search for the adequate item will come very naturally, the same way any person will look for any product. But most importantly is the ability of the agent to cope with the priorities of the user via the importance of the price, time, and commitment.

This research covers the feasibility of the DALIA agents, specifically the mental attributes approach, and by rectifying the functions it uses in order to ensure it satisfies the primary specifications. We have added specifications and features to the agents found in other approaches in order to enhance the overall agent performance and ensure a smoother user experience. Some additional rules were taken from Sun Tzu's "The Art of War" and applied to the negotiation schema in order to enhance the agent's negotiation paradigm.

The first stage of the thesis was to verify the existing functions used as part of the DALIA agents. Upon the validation of the existing agent negotiation functions, many shortcomings were revealed. For instance, the variation of the agent's attitudes did not result in a dramatic change in the final negotiation outcome. This was due to the initial scope of the functions and the way they were designed.

The second stage of the thesis involved fixing and refining the agents' negotiation functions to allow them to better reflect the agents' mental attributes in the final negotiation outcome. Applying the functions resulted in more realistic negotiations with more meaningful results and a final outcome that better reflects both the agents' mental attributes and priorities.

The final stage of the thesis saw the addition of adaptability rules for the agents. These rules, based on "The Art of War", would allow the agents to better read the environment and better know their opponents, thus resulting in even more realistic agent behavior and even more accurate final negotiation outcome. The rules allowed for the introduction of a variable step, that is agents would increase, or decrease, their offers by variable amounts as required by their current negotiation situation. This resulted in having agents' offers curves that vary from logarithmic to exponential, dynamically according to the agent's mental attitudes and priorities and preferences.

Chapter 2: Background and Motivation

The background for this thesis covers the definition of Autonomous Agents, Agent Negotiation, Virtual Marketplace, and the DALIA Agents. Each of these topics will be defined and analyzed and its contribution to the current work made clearer.

2.1 *Autonomous Agents*

The autonomous agents subsection tries to define what autonomous agents are, what are their characteristics, and their different categories. Then, we move to investigate the need for agents, and their impact on current industries. And finally, this chapter concludes by exposing the current research being undertaken on agents, and the different challenges facing both multi agents systems and personal agents' development.

2.1.1 Autonomous Agent Definition:

The definition of an autonomous agent is not an easy task. Many definitions can be found in the literature, depending on the agent design and purpose, making it more difficult to pinpoint what an agent is. Furthermore, given that the agent is nothing but a piece of code, another problem arises to determine what makes an agent what it is and how to differentiate it from ordinary programs.

For the MuBot agent creators, "The term agent is used to represent two orthogonal concepts. The first concept relates to the agent's ability for autonomous execution. The second concept is the agent's ability to perform domain oriented reasoning."[34]. The AIMA agent creators, Russell and Norvig in their 1995 publication, provide another definition: "An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors." [27]. As for the Maes agent, as published in Maes 1995, the definition is similar to the two preceding definitions: "Autonomous agents are computational systems that inhabit some complex dynamic environment, sense and act autonomously in this environment, and by doing so realize a set of goals or tasks for which they are designed."[24]. Following the same ideology as the previous definitions, Barbara Hayes-Roth of Stanford's Knowledge Systems Laboratory in her 1995 publication, insists that "Intelligent agents continuously perform three functions: perception of dynamic conditions in the environment; action to affect conditions in the environment; and reasoning to interpret perceptions, solve problems, draw inferences, and determine actions".[15]. And finally, the IBM agent was designed according to the following premise: "Intelligent agents are software entities that carry out some set of operations on behalf of a user or another program with some degree of independence or autonomy, and in so doing, employ some knowledge or representation of the user's goals or desires."[11].

But the two definitions that fit most closely the agent implemented in this work come from The SodaBot Agent and The Brustoloni Agent, provided by Coen and Brustoloni each in their respective publications, who provide respectively the following definitions: "Software agents are programs that engage in dialogs [and] negotiate and coordinate transfer of information."[6] and "Autonomous agents are systems capable of autonomous, purposeful action in the real world."[4].

All these attempts at defining what an agent is remain none categorical. That is, these definitions do not explicitly specify what an agent is and what isn't. This is due to the fact that agents are closer to the real world than to the mathematical realm and thus cannot be classified into distinct categories but rather belong to the fuzzy world. Yet all definitions seem to agree on one concept defining an agent as one who acts, or one who can act. [16].

2.1.2 What is an autonomous agent?

In order to best answer this question, one would need to go to the essence of agents and delve into the definitions themselves, testing them on the extreme in order to be able to clarify the fuzzy boundaries. A formal definition can be deduced following the mentality just presented and combining it to the different definitions exposed before:

"An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future."

By checking the limits of this definition, one would get at the upper extreme a human being, guided by all his senses and driven by his own mind calculations, agenda and future plans. At the other extreme of this definition, one could find a thermostat: a one sensor, one action device. Both these extremes verify our definition, and so to some extent in a fuzzy kind of way, both can be considered in essence as agents. Yet both are not the agents we are studying to design. [16]

By contrast, ordinary programs cannot be described as agents:
The payroll program for example fails the agent test for two reasons. Even though it interacts with the real world via its input and output, its output does not affect what it will sense later on. Moreover, the payroll program fails the temporal continuity test, meaning it gets fetched then executed. However, once its job is done, the program is put to sleep until it gets executed another time. During its sleep time, the program neither senses nor affects its environment.

Similarly, agents are not defined by their tasks. A spell checker that only executes when it is called cannot be considered as an agent. On the other hand, a spellchecker that starts with your word processor and checks words then correct them on the fly can be considered as an agent.

Autonomous agents live in a predefined world. Outside their world, or by changing some characteristics of their world, a previously verified agent can lose its status and become useless. For example, a robot that only relies on visual sensors in an environment deprived of light becomes useless and is no longer described as agent.

From another point of view, an agent can also have his sub-routines managed by other agents. Then the agent would analyze its own agents' feedback and decide on a course of action. A robot, for example, fits this category. It can have its visual sensors and their respective tools managed together by an agent in order to fulfill a certain job. While a "super agent" coordinates with his visual subagent described before and the walking functionality in order to achieve the robot's agenda. [16]

For Jennings and Wooldridge, an agent is a self contained problem solving entity which exhibits some or all of the following properties: autonomy, social ability, responsiveness, pro-activeness, adaptability, veracity, rationality and mobility.

Autonomy: Agents should be able to operate with minimal control from the user, if not none. They should also have control over their internal states and decisions.

Social ability: Agents should be able to interact with other human or agents when they see fit in order to be able to solve their own problems or to help others better achieve their goals and activities.

Responsiveness: Agents should be aware of the environments in which they operate, and of all changes that occur in this environment then react in a timely fashion to these changes as they happen.

Pro-activeness: Agents should not only react to changes in the environment as they occur, they should also be able to act upon their environment in order to better fulfill their goals and change the environment to their favor, that is, they should exhibit opportunistic goal directed behavior and take actions whenever appropriate.

Adaptability: The agent should be able to cope with any environment changes by changing his own behavior over time in order to be able to better solve the problems he faces as his knowledge and experience increases.

Veracity: Agents should operate under the assumption that they wouldn't knowingly communicate false or erroneous information.

Rationality: Agents should always operate and act in such a way to best achieve their goals, and they won't do any actions that can or may prevent them from achieving their goals without having a good reason for it.

Mobility: Agent should be able to change its physical location in order to be able to better solve their problems and achieve their goals. [20]

2.1.3 Agent Classification:

In their paper, "Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents", Franklin and Graesser from the Institute for Intelligent Systems of the University of Memphis suggest the following agent category classifications table.

Property	Other Names	Meaning
reactive	(sensing and acting)	responds in a timely fashion to changes in the environment
autonomous		exercises control over its own actions
goal-oriented	pro-active purposeful	does not simply act in response to the environment
temporally continuous		is a continuously running process
communicative	socially able	communicates with other agents, perhaps including people
learning	adaptive	changes its behavior based on its previous experience
mobile		able to transport itself from one machine to another
flexible		Actions are not scripted
character		believable "personality" and emotional state.

Table 1: Agent Category Classification

This table follows from the "formal definition" presented earlier in the same paper.

All agents can be usefully categorized according to the criteria they fulfill these categories, keeping in mind that all agents need to fulfill the first four categories, meaning that all agents should be reactive, autonomous, goal-oriented and temporally continuous.

Other categorization schemas can be envisaged according to the tasks executed by the agent, information gathering or email filtering for example. Agents can also be classified according to their control architecture, the range and sensitivity of their senses, or by the range and effectiveness of their actions, or by how much internal state they possess, or even according to the environment in which they operate. Other schemas for agent classification are also suggested by Brustoloni's and by Franklin and Graesser each in their respective publications. [16].

Nicholas Jennings and Michael Wooldridge, in Jennings and Wooldridge 1995 and 1998, also present another schema for agent classification. They indicate that agents are used to relate to a broad range of software and computational entities. These entities are distributed generally over three categories that range from the simple, like Microsoft's tip wizard available in all Microsoft Office iterations, or the desktop assistant [24], up to the very large interoperable and expert systems involving huge and distributed database systems, such as ARCHON [19].

To keep it simple, these categories can be defined as follows: First and simplest are "gopher" agents that execute simple and straightforward commands based on pre-defined rules and assumptions, like reminding you of the time and space of your next lecture, or any other similar command for that matter. The next level of more complex agents is service performing agents that can, for example, arrange a meeting for you, or plan your next flight. And at the highest level of agent sophistication one can find "predictive/proactive" agents that determine the appropriate time to volunteer information and or services for the user without being asked. Agents that fall into this category can handle tasks such as monitoring the net for certain information of interest for the user and then keeping him up to date whenever a new interesting change occurs. [18][20]

Agents have as many definitions as the number of researchers that have already worked on the subject. There is no one agent that can fill all the definitions that have already been presented, but there is a minimal set that everybody would agree that it satisfies an agent's definition. The importance of agents is discussed in the following section.

2.1.4 Why agents

Agents have had such a boost lately because of their potential for problem solving previously hard to manage and solve problems. Agents can handle problems that were previously considered beyond the scope of automation, either because no technology was available or adequate for that certain problem to be solved, or because it was very hard and expensive to solve the problem with the available technologies. Even more, agents can handle problems in a better way than the original and traditional solutions. They provide a more natural interface for problem solving, which can be coupled with an easy, efficient and fast approach at both problem solving and development; making them the ideal choice for the more complex problems we face everyday.

Jennings and Wooldridge, in Jennings and Wooldridge 1998, indicate that agents are ideal when dealing with "Open problem situations", that is a system in which not all components are known from the beginning, or where the components can change over time. Even more, agents can help you deal with heterogeneous systems where every part is built independently of all others without knowing a priori how every part works internally. An example of such an "Open Domain" is the internet, where every part is built independently of all others, and the only way to be able to make the best out of all the subsystems that are on offer is to use software that can work independently of all others and that can put to good use all the different parts, and agents are the perfect candidates to fulfill such a role. [20]

Agents can fill the role of a natural metaphor. The notion of an autonomous agent acting by himself on your behalf is the easiest way of representing the set of functionalities that it does. When it comes to checking for appointments and scheduling meetings, the most natural way of representing such a task fulfilling software is via the use of an autonomous agent acting as a personalized digital assistant that takes your preferences into consideration. The same also applies in computer games (35) and virtual reality systems [3] where individual characters can naturally be represented by an autonomous agent, which is a self contained social, problem solving entity. [20]

Agents have a wide use, and they can be the most natural approach yet to many problems that have always faced the software industry. But at the same time, agents are not a panacea that can solve all problems and that can be used in all situations. Before using an agent approach it would be better to check whether it would beneficial to use agents at all, and if there exists cheaper and simpler and thus more adequate alternatives. Agents are best used when the they fit the solution naturally; that is when the solution feels that it requires an agent to best handle it, whether digital or human agent. The industry is starting to adopt the agents as a new standard and a new approach to better solve the problems it faces.

2.1.5 Agents and the Industry:

Agents won't change the industry with a bang. Instead, they will slowly, but steady, gain market share, creeping into the industries from the backdoors handling an increasing amount of tasks as they gain increasing confidence. According to Richard Lazarus, manager of the enterprise architectures group at BBN, the agents' technology is "going to be revolutionary, but it will occur incrementally." [31]

To show the potential of agents, we pay a visit to NASA, a company that needs no introduction especially when it comes to the field of technology, a company who is already testing the agents' technology and introducing agents to their technologies, spacecrafts and critical missions.

Such an example of mission goal that NASA delegates for an autonomous agent is the apparently simple goal of not wasting any fuel. Looking further into this goal, it proves to be more complex than first expected, with the agent having to manage many, and sometimes conflicting, tasks such as staying on course, keeping experiments running, and dealing with the unexpected. The usual software paradigm, that programmers are good at, usually relies on "if-then" conditions. In contrast, NASA's agents are model-based, and are designed to achieve certain goals and intentions, as opposed to responding to a set of predefined events. This practically means that the agent can react to unimagined events, while making sure that the spacecraft does not waste fuel as well keeping to its mission. Controlling the fuel consumption, which is now handled by an agent, used to be previously handled by a team of ground controllers. And thus you can see how important the agents can play in industries, doing by themselves the job that a team used to do, only quicker and more efficiently. But as NASA's Steve Chien likes to put it, the cost efficiency potential of the agents is not emphasized, as "nobody like their budget reduced." On the other hand, what's emphasized is the additional scientific research that can be generated by the use of agent-based software. [31]

Andersen Consulting and Comshare have established the Commander Exception Monitor Agent. This agent is currently used by Hertz, the car rental company, to be able to analyze the pricing structure in the car rental business. The agent works by analyzing 28000 spreadsheets full of relevant data about the car rental business, and reduces the information to something that can be easily managed and analyzed by the pricing executives in order to be able to provide optimal strategies.

These companies and many others are starting to depend on agents and, lots of research is currently under way in order to improve agents' involvement in all aspects of industries and businesses. The most promising industries for agent integration appear to be markets, supply chains and telecommunications, especially when coupled with agents that can learn, interact, discover interactions and react to them, exchange information, set priorities and negotiate.

2.1.6 Agents and research:

Building an agent requires the amalgamation of many disciplines most notably game theory, economics and psychology. Thus, in order to be able to handle such complex disciplines and routines a new approach at design and development is required. [31]

The development of agents systems requires a new paradigm for design and development in order to be able to achieve satisfactory results. The traditional software engineering approach, which provides a complete system approach and then implements it in a number of rigid components, is not appropriate for the development of agents, and agent controlled application. The agent based system development approach involves building complex, self-contained components that can interact with similar independently developed components. Interactions, in such a model, are no longer rigid and through a pre-determined interface, but have to be rather achieved through negotiation and persuasion, followed by commitment and agreement between the different parties, in this case agents, involved. This will lead to non-determinist system behavior, which will rather emerge out of the different interactions of the different agents, which are the different parts of the system, at runtime.

Agents, through the wide range of types, applications and tasks they need to achieve, employ problem solving approaches that can vary from the purely deliberative to the purely reactive. Agents also vary from the totally generic, which can be used in many to achieve many tasks, to the hand crafted agents, that are designed to achieve very specific and customized tasks. Applications also vary from systems were multi-agents are all working towards achieving a single goal, to systems were different agents each have their own individual goals that can even be conflicting with each other.

But the agent paradigm also suffers from some drawbacks that are as serious as the interesting opportunities they offer. The first and most obvious drawback is that the overall system behavior can be unpredictable and non-deterministic. There is no way to be sure of how agents will interact with each other and in which ways can not be determined in advance. Even more, since the agents are autonomous and act according to their own agendas, there is no guarantee that the dependencies between agents can be managed effectively, which can lead to infinite deadlocks and starvation. The second major disadvantage is that the overall system behavior and properties cannot be determined at design time, but are rather specified by the agents themselves at runtime. Agents can be made to act according to certain rules and specifications, and can be made to act as desired, but the whole systems which depends on the interaction between the different agents can not be predetermined and will necessarily emerge at runtime. [20]

A lot of research is currently under way in order to be able to overcome these shortcomings. Jennings, Wooldridge and Kinny in 2000, have proposed Gaia, an agent oriented analysis and design methodology. The Gaia paradigm offers a tailored methodology for the design and implementation of agents based systems, where the same approach and paradigm covers a wide range of systems, and where the emphasis is on the agents as well as the overall performance and behavior of the whole system. [21]

Having covered how the design of agents should be and how they are implemented, their strong points and drawbacks, we move on to describing in detail how the agents are actually designed and how they should work.

2.1.7 Multi-Agents Systems Challenges:

From a technical point of view, agents are, unofficially, split into two major categories: multi-agent systems and autonomous interface, information agents. This split is also visible in both the AA and PAAM conferences, which respectively stand for the International Conference on Autonomous Agents, and International Conference on the Practical Application of Intelligent Agents on Multi-Agent technology. [25]

The Multi-Agent systems have a clear goal that has been proven over many years and lots of research. It involves creating a system operated by many separately developed agents that can communicate with each other in order to ensure operability and functionality beyond the capabilities of a single agent.

But Multi-Agent Systems are far from being a reality. Even though they have the potential of becoming one, they are still plagued with many problems that hinder their progress and need to be solved in order to be able to jump with the technology to the mainstream so it can be adopted by the industry. The figure below shows how things need to be done and what each agent has to do and how they should communicate together. This figure represents both the potentials and problems of such a system, and each of these parts will be dissected in order to show how close to reality it has become, or how much research it still needs in order to be achieved.

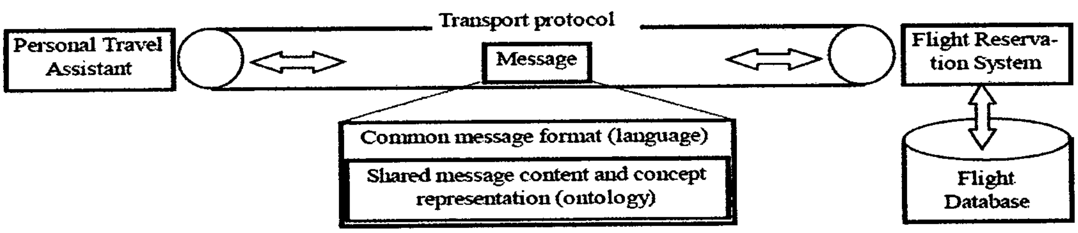

Figure 1: Agent Communications

The first problem such agents face, is the gathering of information: these agents are meant to operate in an open environment, typically the Internet. Moreover, it is of prime importance to integrate address trackers into these agents so they can know where to look for reliable sources of the information they need in order to ensure smooth and reliable performance. But then it would be very hard for every agent to know where everything is, especially in a very large and constantly changing environment such as the Internet. Ergo the need for agents specialized in address look up. These agents would be the yellow pages for other agents. They would have to constantly update their address tables and be on the constant hunt for better deals in order to ensure optimal performance for the agents that would request their services. [25]

The second problem Multi-Agent Systems face is communication. The communication problem itself faces three challenges in order to be successfully overcome. The first problem is how actual agents would communicate over the net, and what protocol they would use. The second challenge that presents itself is the availability of a common language that can be understood and manipulated by both agents in order to form a basis for communication. XML can go some way into solving this problem but won't be enough to ensure agent compatibility. The final challenge to be raised is the ontology problem. The ontology problem is basically the content of the message being sent from one agent to another, how it is structured and what are the meanings of the terms used in the message so that the other agent can understand and process the information in the message without ambiguity. All these challenges need to be solved and require intensive research in order to create favorable ground to be able to take the agents technology from the labs test beds to their rightful place in the industry. [25]

Another major problem faced by Multi-Agent Systems is the reasoning and coordination problem. "This process necessitates reasoning, planning and constraint satisfaction capabilities in order to deal with timing and other dependencies" in order to satisfy the user's requirements. In essence, the agent "needs to co-ordinate the services of the different service providers so that as a whole, the service providers behave coherently in their attempt to provision an integrated service."

"Agent researchers have had some considerable successes tackling the coordination and reasoning problem. The reasoning problem is handled in most multi-agent systems using AI techniques such as rule-based inference, classical planning, various logic formalisms, and constraint satisfaction techniques. Co-ordination to ensure coherent functioning of the multi-agent society is also handled with a variety of approaches including organizational structuring, contracting, multi-agent planning, negotiation and coordination." [25]

And as we conclude this section that covers the problems facing Multi-Agent Systems with the pitfalls and thus potential research topics for improving these agents, we move on to another type of agents, the autonomous agents. Autonomous agents, whether personal or information agents, are more modern as a concept and have only recently jumped to the highlight. These are agents that reduce work information overload.

2.1.8 Personal Agents Challenges:

Personal agents were first introduces in 1994 by MIT's Pattie Maes. These agents' role would be able to communicate with the user at the user level in order to help better navigate in a certain work environment. The agents would work by observing the user and his actions, try to understand his motives and what he wants then suggest new ways of achieving the required job that would be better and easier for the user. In such an environment and facing such a task, it becomes invaluable for the agent to learn, from the user and from his old actions, on what suits best the user's needs.

But in order to be able to better serve and provide useful suggestions, the agent would need to have a full understanding of the functionality and usability of the environment in which the agent and user are both operating. Even more, the agent would then need to continually model the user in order to be able to provide personalized assistance. More importantly, the personal agent would even have to understand the tasks that the user is trying to achieve in order to be able to provide any help what so ever. Thus the agent would need to be built with knowledge covering, the work domain of the application in which it is operating, a model of the user, a list of strategies that can help the user better achieve his actions, and a list of typical problems that are faced by the user when working in the defined environment. [25]

It is the requirements that we just stated that make Maes' agents more of a theory or an end goal rather than a reality. In the real world we generally face two kinds of problems, either the mundane that wouldn't really require any agent assistance, or the really complex where an agent would have lots of trouble providing any meaningful help, unless they possess deep knowledge of both the system and the user, which is highly unlikely. And so an alternate proposition was presented. Instead of having the agent look over your shoulder and learn from you are doing and try and guess what you want to do, he is offered a profile of the user. And then the agent would take the user profile, analyze it and then check how he can help the user in the most efficient and customizable way.

According to Nwana et al, a special category of personal agents is the personal information agents. The undeniable reason behind the existence of such agents is the explosive growth of information, particularly online. The growth of online businesses also makes the existence of personal agents more essential as they help their user better search for the items he is looking for, thus increasing the probability of finding relevant items. With the explosive growth of the net, it has become less probable and rather unrealistic to manually search for anything, be it information or other. All these problems add up to make the existence of personal information agents even more urgent. But even with all the need for such agents we are still miles away from getting anything that can satisfy the criteria of personal information agent. [25]

Some of the problems hindering the progress of personal information agent are shared with the Multi-Agent Systems such as information discovery, ontology, dealing with older inadaptable systems, and reasoning. The communication problem is less of a problem with such agents, as they don't have to interact with other machinery but rather all their communication is limited with their user. But still, the communication that needs to be made with the user has to be made over some medium. [25]

The final challenge facing agents would have to be their design and implementation. The development of a methodology for analyzing and designing agent oriented systems need to be put in place and proven to allow agents to be considered for large applications. A formal mechanism then needs to be introduced to verify the validity and robustness of the design. Formal tests and benchmarks would also need to be introduced to evaluate the reliability and performance of the agents.

Once these two design and testing issues have been solved, or at least better researched in order to allow for a certain foundation to be put in place, the agents research and development would become more fertile and the whole industry would thus become more productive and reliable. When the foundations for better agents are in place it would become much easier for the agents industry to mature and ergo to break through to the commercial and mainstream industries and fulfill its potentials.

2.2 Negotiation and Agents

The Negotiation and Agents chapter start by defining what is negotiation and its different types, cooperative and competitive. The competitive negotiation is the dissected and explained from the "Game Theory" point of view and from the "E-Commerce" point of view. This is followed by further explaining the cooperative model by introducing the cyclic model for cooperative negotiation. And finally this section concludes by introducing the different negotiation strategies, and explaining how the negotiation outcome can be enhanced by enhancing the agent and allowing it to predict his opponent, to deal with time constraints and to learn from previous experience.

2.2.1 Defining Negotiation:

Having defined the agent interactions, exposed their needs and their different types; the next step is to define agent "negotiation", how it can be used for the best of all agents and its different types...

Negotiation is a means that can be used to coordinate agent actions and behaviors; negotiation can be used for conflict resolution and thus it can implicitly lead to coordination. Defining negotiation is as elusive as its importance for the modeling and coordination of Multi Agent Systems, very. Some may even say that there are as many definitions of negotiations as there are negotiations researchers, yet a basic definition is provided by Bussmann and Muller (1992):

"....negotiation is the communication process of a group of agents in order to reach a mutually accepted agreement on some matter."

In other words, the basic idea behind negotiation, the goal of negotiation is reaching an agreement. To achieve optimal results and negotiate effectively, the agent may have to reason about beliefs, intentions and desires of other agents. This has lead to a wide use of all sorts of AI and mathematical techniques including but not restricted to logic, case-based reasoning, belief revisions, optimization and game theory. [7]

In practice, everyone offers his own vision for negotiation. The business negotiation literature defines negotiation as the decision making process of resolving a conflict involving two or more parties over a single mutually exclusive goal. The economics literature describes negotiation more specifically as the effects on market price of a limited resource, given the supply and demand among self-interested parties. And finally the game theory literature describes negotiation as a zero-sum game where one party's gain is exactly the other party's loss. [14]

Whenever agents reach a level where they actually care about equity and social welfare, and not only about their own individual utility, it becomes possible to develop collaborative agents and systems. When such a situation is achieved, agents will know that the better the overall situation of the whole system, the more their individual situation will improve. [22]

Negotiation is usually divided in two major categories, Competitive Negotiation and Cooperative Negotiation; this depends on the attitude and behavior of the agents involved in the negotiation.

2.2.2 Cooperative and Competitive Negotiation:

Agents are usually designed according to one of two schemas: they are either cooperative problem solving agents, or self-interested agents.

The premise behind the cooperative agents is that agents are designed by one person, with the only goal of helping each other out for the greater good of the whole system. The agents are developed by the designer in such a way to help each other to achieve certain tasks with enhanced system performance and reliability, rather than optimized towards the performance of the individual agents. Such agents are considered cooperative. [7]

The competing agents were designed at a later stage. They take in to consideration the self-interest and motivation of every agent. This branch was developed because systems could not count on multiple agents being developed by a single user and having them cooperate only because of the way they were designed.

The situation of total cooperation, also known as the benevolent agent is often assumed by agent researchers and designers, unfortunately, real world situations and circumstances often mean that the different agents are faced with conflicting goals. A simple example of such conflicting goals is the scheduling scenario where every agent tries to schedule a meeting to best suit his user's needs and requirements. Other more complicated and complex scenarios can be easily imagined and faced.

In order for multi agents systems to be able to solve problems, they need to communicate with each other, coordinate their actions and activities and negotiate when facing a conflict situation. Conflicts can be due to a variety of reasons ranging from limited resources sharing to more complex decision making choices due to the variety of expertise and goals that the agents may be facing. In short, coordination is required to determine the organizational structure amongst the different agents and to allocate the different resources and tasks efficiently; Negotiation is required for detecting and resolving conflicts whenever they occur. [7]

Coordination can be easily achieved in familiar circumstances: when everything is behaving as expected, it is easy to determine what every agent should do or should be doing, setting the tasks is trivial and synchronizing the different agents to achieve optimal performance is feasible.

However, "coordination decreases as the situation becomes less familiar, as more analysis and reasoning is required, which is laborious and could result in conflicts between agents". Therefore, it becomes a necessity to add some laws, social laws for example, to allow the agents to map unfamiliar circumstances to more familiar situations. This can be achieved by adding stored patterns of predefined procedures that map directly observations to actions. Using this model of case based reasoning it becomes easier for agents to deal with unexpected and unpredictable situations. Adding social rules can enhance the agents' performance significantly. Adding coordination rules can enhance the way agents deal with each other, since coordination rules can enhance the way agents organize their tasks. Adding social collections can create groups and introduce hierarchies, which will facilitate the way groups of agents deal with each other. [7]

2.2.3 Competitive Negotiation:

Competitive Negotiation marks the situations where the different agents involved in the negotiation have disparate interests and are attempting to make a group choice over many well-defined alternatives. The agents are usually independent from one another with independent and potentially conflicting goals, they are not a priori willing to cooperate, share information or back down from their set objectives and goals. [7]

2.2.3.1 Competitive Negotiation using Game Theory:

Game theory in negotiation is used to provide coordination amongst a set of rational and autonomous agents that do not operate with an explicit built-in coordination mechanism. In short it allows the agents to operate and coordinate without pre- assumptions that the agents will behave benevolently.

Game Theory for negotiation and coordination is achieved according to the following concepts: Utility Functions, Space of Deals, Strategies and Negotiations Protocols.

The negotiation procedure itself will evolve as follows:

The utility values for each outcome of some interactions for each agent are built into a pay-off matrix. The pay-off matrix is common knowledge to both agents involved in the negotiation.

Then, in turn, every agent presents an offer and a counter offer in which every agent tries to choose a deal that maximizes his utility value. That is, every agent will present an offer that will maximize his goal value to actual cost ratio. To do so, the agent will have to evaluate the other agent's offer in terms of his own strategy then adapt his strategy accordingly to maximize his profits in the given situation. [7]

Unfortunately, this approach is not without inconvenience, as Nwana (1996) explains: He argues that the agents are assumed to be fully rational and able to maximize their profits using predefined strategies, which is not obvious. Even more, all agents have full knowledge of the pay-of matrix and have therefore full knowledge of the other agent's preferences, which his highly unlikely and unrealistic. In the real world, agents usually have partial knowledge of their own domains, and even less of others'; ergo it become very unrealistic for all agents to have full knowledge of all the situation's characteristics, and this makes the whole setting similar to the benevolent agent situation. Finally, this setting is based on two agents having negotiation, whereas in real life a large number of agents are involved in the negotiation process.

In short, although mathematically and theoretically successful, this approach faces many challenges and will unlikely be adopted by the industry. [7]

2.2.3.2 Competitive Negotiation and Electronic Commerce:

Electronic Commerce on the Internet has been growing fast lately due to its convenience and preservation of time: It is much quicker to purchase a product or a service from the Internet. Yet the huge amount of information found on the net creates lots of problems for both consumers and sellers, rather than facilitate the procedure. Agents can help facilitate if not solve the problem of information overdose.

KASBAH and MAGMA are two systems involving Personal Assistants that represent buyers and sellers and operate in a virtual marketplace where the negotiations are performed and deals concluded. Both systems operate using the same basic premise where you ask your Assistant to perform what needs to be done and under what circumstances: for example you can ask your Personal Assistant to sell this laptop for the best possible price; then you will have to trust it to figure a way to best accomplish this task.

The negotiation in this scheme happens between agents where a selling agent first post an item for sale at the highest desired price, and then according to the presented offers and the time limit, the Personal Assistant will lower the price until the date of sale arrives; finally the deal will go through, after the user's approval, at a price close the lowest acceptable price. The same applies for the buyers with an opposite procedure.

2.2.4 Cooperative Negotiation:

Cooperative Negotiation marks the situations where all agents have a global task envisioned for the system and all are working to achieve it. This is a situation where agents are not self interested or at least the importance of achieving the global system goals is more important than achieving their own goals, or when their personal goal is to ensure that the system achieves its global goals. The agents can also be called collaborative. [7]

2.2.4.1 Cooperative Negotiation using a Cyclic Model:

In this cooperative model, the agents collaborate to achieve a common goal for the best interests of the system as a whole.

The general strategy proposed by Bussmann and Muller [Bussmann & Muller, 1992] involves a cyclic negotiation model both general and simple where the negotiation begins with one, some or all agents making proposals. Then every agent evaluates the proposals and lists how it helps them achieve their preferences and how it hinders their goals. Then the agents update their knowledge about the other agents' preferences and then propose a new alternative to the initial proposal that suits better all agents. And with every negotiation cycle the proposals are refined until they all agree on something that suits everyone.

Such a system can be achieved by using Mentalistic Notions:

Rao and Georgedd (1995) characterize their agents in terms of three mentalistic notions; Belief, Desire and Intention (BDI). An agent's beliefs, correspond to information the agent has about the world, which may be incomplete or incorrect. An agent's desires intuitively correspond to the tasks allocated to it (its goals). An agent's intentions represent desires that it has committed to achieving.

The intuition is that an agent will not, in general, be able to achieve all its desires, even if these desires are consistent. Agents must therefore fix upon some subset of available desires and commit resources to achieving them. These chosen desires, which the agent has committed to achieving, are intentions. An agent will typically continue to try and achieve an intention until either it believes the intention is satisfied, or else it believes the intention is no longer achievable.

The final data structure is a plan library, which is a set of plans (or recipes) which specify courses of actions that may be followed by an agent in order to achieve its intentions.

The interpreter is responsible for updating beliefs from observations made of the world, generating new desires, or tasks, on the basis of new beliefs, and selecting from the set of currently active desires some subset to act as intentions. Finally, the interpreter must select an action to perform on the basis of the agent's current intentions and procedural knowledge.

This BDI agent framework is currently undergoing parallel evaluation trials at Sydney airport, receiving live data from the radar. Essentially, each aircraft agent estimates its Estimated Time of Arrival (intentions), based on its beliefs (e.g., current wind velocity) and desires (desired ETA) and using accessible world semantics.

2.2.5 Negotiation Strategies:

Negotiation usually takes place by alternating offers from the buyer and seller, where each player either accepts the opponent's offer or proposes a counter offer for the opponent to evaluate. The strategies adopted by the players can be very varied and some more suitable to certain situations than others. Strategy may depend on profitability and whether bargaining anymore may be worth any additional significant gain. Players may fake their attitudes and offers as a strategy, and masquerade as tougher or weaker opponents. Players may also take into considerations certain negotiations equilibrium such as the dominant strategy equilibrium, Nash's equilibrium or sub-game perfect equilibrium. Most situations involve many strategies and equilibriums making it very hard to analytically prefer one strategy over another, even though some equilibriums and strategies are more favorable than others in certain situations.

All strategies and negotiation equilibriums offer their unique advantages. Each of the strategies would work best only when operating in the special circumstances it was meant to work with. Further tweaks can be added to the negotiation strategies to enhance the agent behavior. Such tweaks can include the agent's ability to predict and adapt to his opponent's offers to be able to grab an edge in the negotiation outcome.

2.2.5.1 Predictive Agents:

To make sure the agent does not end up on the bad side of the negotiation, some validation techniques need to be introduced. This can be achieved by introducing a guessing mechanism that will analyze the opponent's offers and try to guess their next offer. By knowing the other agent's preferences, and being able to predict his moves, one can protect himself and be able to better deal with the negotiated situation.

According to Jonlker and Robu, the guessing can be achieved by analyzing the opponent's offers and accordingly try to guess the opponent's preferences and requirements, and subsequently the next opponent's offer. If the opponent is willing to share some, or maybe all of requirement and preferences, even a more accurate estimation can be achieved.

Assuming our agent was able to get hold of the opponent's preferences, then he will try to put introduce a certain formula that will help him when combined with the opponent's previously submitted offers to try and find an accurate prediction of the opponent's next offer. When a prediction can be achieved with a reasonable amount of accuracy, then our agent will have an edge in the negotiation that will ensure he gets the better end of the deal when the negotiation is finished.

If the opponent is not willing to share his information, then again according to his offers and the way they vary, one can deduce the importance of these attributes. First the attributes will be classified as those that can be deduced from previous offers and those that cannot. And the next offer's prediction will be adjusted according to the previous offers and according to the continually evaluated values of the opponent's preferences. [22]

2.2.5.2 Negotiating with Time Constraints and Incomplete Information:

As already stated, agents usually have to negotiate in circumstance where incomplete information is usually the rule rather than the exception. Thus, the agents need to be optimized to deal with such circumstances. And to make the negotiations more realistic, time needs to be taken as a factor in the negotiation criteria itself and should be considered by the agents as an offer affecting factor.

Negotiating with a time constraint and with incomplete information, or more specifically aggressive bargaining over the price and with specific deadlines that every agent needs to respect, is a topic approached by Fatima, Wooldridge and Jennings. Time is a very important aspect often neglected in negotiation theories that has a deep impact over negotiations in general and in real world scenarios over the final outcome of the situation. As the negotiation evolves, an agent might be making profit from the passing of time and from a prolonged negotiation whereas the other might be losing…

The effect that time can have on a negotiation can be directly observed and can affect the flow of the negotiation process according to the following:

- The benefits that an agent can gain from a deal at the current time are more advantageous to gaining the same rights in the future.
- The bargaining process in itself might be of some expensive cost to the agent.
- An agent can have a deadline beyond which he cannot proceed with the negotiation.

Even more, the agents can not be assumed to have complete knowledge of their opponent's preferences, as this would be unrealistic… yet it is not unlikely that an agent can have approximate information about his opponent's preferences and deadline...

In their approach, Fatima, Wooldridge and Jennings assume that their agents have a probabilistic knowledge about their opponent's information most notably their preferences and their deadline limit. Using this knowledge about their opponent and their preferences and time constraints, the agent can devise a near optimal strategy to maximize his utility from the time and price.

As opposed to game theory which usually assumes complete information availability, and then pre-computes a perfect solution and ignores any aspect of time; which is very unrealistic due to the usual scarcity of available information about the opponent, and because time has a significant impact on the negotiation process; this proposed approach will give near optimal result even with lack of information and time constraints...

This approach assumes two agents, a buyer and a seller, with alternating offers. Every agent has a range of acceptable values and a time deadline. The negotiation starts with the first offer being presented. The offer is evaluated by the other agent according to the time and price utility. The other agent can either accept the offer or present a counter-offer. If one of the agents reaches his deadline he has to quit the negotiation.

Thus, due to the importance of time, it is obvious that both agents use time dependant strategies that vary as time goes on and as the negotiation lasts. A wide range of time dependant functions can be defined that can vary the way the offers are evaluated and proposed. However the functions must ensure the respect of the agent's accepted range and never stray outside of it.

According to the use of these functions, many strategies can be devised ranging from the very conservative to the very aggressive. Thus an agent can, at one end of the spectrum, be very hesitant and keep offering values that are close to his initial bid, until he almost runs out of time; this is when he will offer a value very close to his other internal limit. This is called the Boulware strategy. On the opposite end is the Conceder strategy where the agent goes from one internal limit to the other very quickly at the beginning of the negotiation and then stagnates at the opposite end till the end of the negotiation. Obviously the first strategy considers price as the most valuable asset and doesn't try to play all his cards until he starts running out of time. The second strategy considers time as the most valuable, and the agent makes it clear that concluding a quick deal is of a high priority at the expense of price. In between these two strategies is an infinite amount of other time dependant functions and strategies.

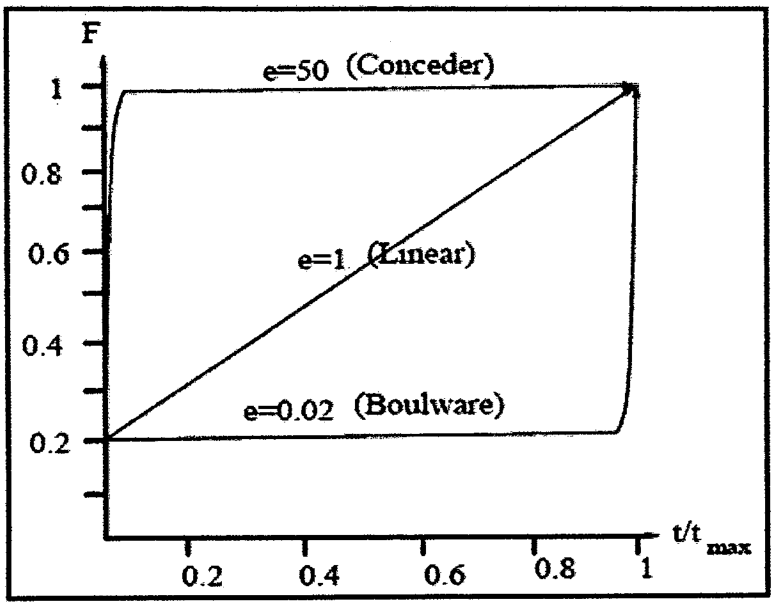

Figure 2: Functions for the Computation of F(t)

Depending on the circumstances of the current agent and what he assumes are his opponent's attributes, many strategies can be employed to good, or bad effect, among the strategies stated before. For example, given a buyer who loses with time and who has a deadline that will occur before the seller's, it would be more beneficial for the seller to play a more conservative game when it comes to offering the buyer just high enough prices to keep him going. The situation will go the seller's way as long as he concludes the deal before the buyer's deadline is reached and consequently having him forfeit the negotiation.

Consequently, in their analysis, Fatima, Wooldridge and Jennings were able to determine that the agent with the longest deadline would generally end up at the better end of the deal, and thus make more profit from the negotiation.

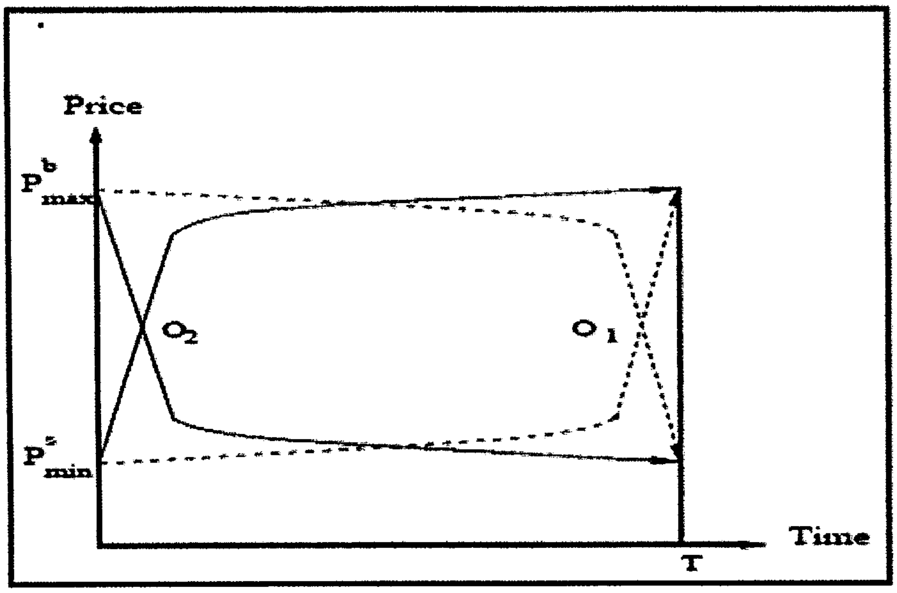

Figure 3: Negotiation outcome for the Boulware and Conceder Functions

As for the effect of time on the negotiation, whenever at least one of the agents gains with time and thus makes more profit from a prolonged negotiation, the agreement tends to occur close to the first deadline. When both agents consider the time as a very important factor, they tend to agree and stop the negotiation as soon as it begins.

When considering the situation where one of the agents gains with time and the other loses from a prolonged negotiation, the agent that gains on time, that is the agents who profits from a long negotiation, gets the same utility as compared to the case where both gain with time. The agent that loses on time, that is he who loses as time passes by, gets a lower utility when compared to the case where both agents, gain or both lose with time. [10]

2.2.5.3 Learning from Previous Negotiations:

A final enhancement that can be added to agents in order to improve their negotiating abilities is the learning from past experiences tweak. By making the agents remember which strategies work better and under which circumstances, and then making good use of what they already know and what they have already experienced can dramatically improve the agents' performance.

The experience can be gathered from previous negotiations and applied to the current situation. The agent may have past experiences dealing with the same product, the same agent, the same preferences and the same environmental constraints… Experience can also be used from simultaneous negotiation threads.

According to Jennings et al., an agent's past experience can be quantified. Definitely the higher the experience the more weight it will have when considering multiple choices according to the success or failure of a certain strategy in the past.

The experience from previous negotiation of an agent X with another agent Y can be classified into three major categories:

- Failed negotiations and the circumstances that lead to the failure
- Accepted offers and the circumstances for their acceptance
- Quality of the deals with the opponent

These previous negotiations can be stored in a database where each row indicates the relevant information. When negotiating, the agent will try and make the best use of what he already knows about a certain item, agent and negotiation circumstances in order to be able to make better decisions. The influence value will then be normalized and added to the computed offer. If the agent is sure from previous experience from the efficiency of a certain strategy, then the weight of the previous experience will be large and will thus largely affect the way the current negotiation is tackled... the agent will try the same approach that worked before on the current circumstances and negotiation. If the experience weight is minimal, then the agent will put less emphasis on past experiences and rather concentrate on different strategies such as the time based strategies. After the negotiation is over, the past experience table will be updated again according to the outcome of the current negotiation and its circumstance... [26]

After introducing all of these enhancements that can be added to agents to better their negotiation performance, we find it worthy to indicate that no one agent has been designed to include all theses strategies. These strategies, each on its own, have not been optimized so far either. As stated before, every proposed negotiation strategy is only optimized for its given circumstances, and can result in a different outcome in different conditions.

2.3 Virtual Markets and Agents

The virtual market section tries to define a virtual marketplace and to pinpoint the requirements its introduction, both the business and technical pre-requisites. Then it moves on to talk about the search capabilities in these markets and the need for intermediate agents, Broker Agents, to satisfy this role and how they can make use of Ontologies to increase their search capabilities. Interface and Tent agents are also introduced as intermediate agents to successfully translate the user commands into market language. And finally, this section ends by checking on real virtual marketplaces, particularly Kasbah and MAGMA.

2.3.1 Creating a Virtual Marketplace:

The traditional marketplace is a site where many buyers and sellers gather and interact in order to buy and sell the different items that they need or have. Marketplaces are characterized by the products being traded, the trading terms and regulations, dealing protocols and standardized means of transaction. These policies, regulations and protocols organize the allowed interactions between the different parties, and that these parties are obliged to follow. They also define the accepted standards for inter-party dealing and product exchange. They finally define the market classification where all these parties are operating, whether this is an open market or an auction market, or maybe some other type...

According to Jonker et al., the Virtual Marketplace tries to create an imitation of its traditional counterpart, while adding the benefits of the modern computers era, trying to abolish some of the inherited drawbacks of the traditional marketplace and trying to overcome some of the new problems introduced by the new technological era. The creation of virtual marketplaces requires setting-up product and product-related ontologies with which knowledge structures can be defined and demand offers can be formulated. In other words, to be able to successfully create a virtual market place, may things need to be put in place, mechanism that would allow the different and competing virtual marketplace parties to be able to make advanced analysis on the product supply and demand, and the different product characteristics and to be able to make cross product comparisons, even if the product don't have the same characteristics. The different regulations and guidelines have to be defined imposed and maintained in order to be able to provide a safe and secure environment for the parties interacting within the marketplace. And finally, security, privacy and safety need to be addressed and maintained within the virtual marketplace to provide a user-trusted environment. [1]

The introduction of global networking and World Wide Web has enforced a new approach on the way people make business. Thus the interactions with the markets became more customer-oriented, and even more, the customer became an active participant in this area. The development of e-commerce enforced an Internet redefinition of the market infrastructure. The new market that satisfies the conditions of this new age is very different from the old market, especially with its lack of a physical environment, and its evolved customer-oriented interaction.

This new environment brings new advantages to both buyers and sellers:

For the customers, they now have access to greater amounts for information and products, thus increasing their choice and facilitating their decisions. The huge amount of available information that can all be gathered form one place also decrease the search time previously required by the user in order to be able to gather all he needed information.

As for the sellers, the web offers a distribution channel with unlimited exposure potential, thus increasing cost efficiency and time efficiency, and closes the gap between them and the buyers. The customizations that can be offered for the customer to make use of, improve their relationship with their potential buyers, and create a new kind of marketing to customer support. [1]

2.3.2 Virtual Markets Business Pre-Requisites:

On the other hand, current available virtual markets still suffer from many drawbacks that are keeping them from achieving their potential as the future of e-commerce. Such drawbacks include the lack of diversity of items in certain marketplaces, such as letsbuyit.com. And when you couple this problem with special naming terminology as imposed by certain sites such as www.shopping.com, these markets become user troublesome and not very friendly thus decreasing their reputation.

Even more, the electronic trading introduces new conditions that arise due to a set of trade conditions that are unique to electronic commerce: first of all, in electronic marketplaces, there are more dynamic variations in demand at sellers' sites resulting in occasional shortages of goods. Second of all, there is a loss of long-term customer-buyer relationships due to the anonymity of both the buyer and the seller. And finally, and due to the relative ignorance of the buyers with the actual stocks management and situations, a group of sellers can easily manage the stocks and orders according to their own discretion to maximize their profits.

This is due to the fact that buyers can remain anonymous and in general, buyers are unaware of competitor buyers. These two facts make it that buyers have no precise insight on the actual stock level of the sellers more so than in traditional markets. On the other hand, sellers too are not aware of the number of potential buyers, and thus cannot be certain of the volume of the orders to be placed, in an environment where the pace of trading is very quick. Thus demands at the sellers' sites vary dynamically and dramatically, making the market demand impossible to predict, thus leading to shortages in stock.

The anonymity of the buyers makes it impossible to benefit from personalized long term customer relation management; which is a turn off for both buyers and sellers as all deals are based on the best offers, and where it is impossible to maintain a personalized customer-dealer relationship.

Furthermore, the buyers are not aware of the extent of the competition or the actual stock levels of the sellers. This situation can easily allow sellers to manage orders and stocks at their own discretion thus opening new opportunities to create alliance between them and enforce monopolies over the market in order to maximize their profits. [1]

On another level, and according to Jonker et al., the interactions with the user are also limited. The human-market interaction is limited and forced upon the user: the user can only communicate with the market according to the vocabulary introduced and comprehended by the market, thus creating a certain distance between the buyer and the seller. Even though some aspects of the market can be customized by the user to better suit his tastes, many standards will still be enforced upon the user such as the vocabulary used to describe the available merchandize or the even the information itself being available for the user. From the market standpoint, all items being traded have to be identified and "tagged" according to a certain standard. All information displayed has to be managed in some way to allow for efficient searching. This effectively means that only selective information about every item will be available. And this information has to be inserted in such a way to allow searching to take place. For the user this means that he won't have access to all the information he might require, but alternatively, he won't be overwhelmed by the amount of information being displayed. As for the tagged attributes, they are definitely a plus for the user as they facilitate the searching for the user and thus allow for smarter decisions as the user will only have to relevant information that he needs to make a decision. [1]

2.3.3 Virtual Markets Technical Pre-Requisites:

In addition to the presentation and business problems facing the marketplace, many technical problems also challenge the development of an established online market. At the top of the list of technical challenges is the security related problems. Privacy, security and safety are pre-requisites for the establishment of online marketplace, as no exchange of money or goods can be successfully achieved without these security measures successfully implemented and in place. The development of EDI, SET and XML standards are improvements in the online security issues, but are still not enough to grant the establishment of a fully working virtual marketplace. [1]

Safety and security issues are one of the most important aspects facing the development of virtual marketplaces for which no adequate solutions have been found so far. The trust of individuals and businesses is a must in order to allow for the virtual marketplaces to flourish. For this to happen, a minimum amount of security is required. Even more, many users have difficulties with online payments and don't even trust the idea of online market concepts.

In order to overcome these problems, digital cash needs to become the standard protocol for transaction processing, and needs to be coupled with a standard and safe electronic transaction protocol. One example of such protocols is the UPP (Universal Payment Protocol), which was developed as part of the JEPI (Joint electronic Payment Initiative) project, sponsored by Commerce Net and other organizations. The UPP protocol allows for the different parties using it to be able to negotiate about payment mechanism they prefer. [1]

On a different note, Virtual marketplaces must be able to handle millions of transactions and product searches simultaneously and on a continuous basis. To be able to handle such requests, both hardware and software need to be of very high standards, and must be built up to very tough specifications. Technological improvements help towards achieving such a highly technical and demanding system.

The agents that operate within the marketplace need to be designed and implemented in such a way that would allow them to be efficiently integrated into the market, and the efficient running of these agents is essential to be able to obtain a maintainable system. The design of the different agents and parts of the marketplace need to be transparent and compositional in order to obtain a virtual marketplace that is as a whole, easy to maintain and extend. [1]

And the final challenge facing virtual marketplaces is the introduction of reliable search facilities. The virtual marketplace's search facilities need to be able to cope with many demanding tasks such as having an updated list of the different buyers and sellers as well as available products. The search facilities also need to accommodate and deal with the different languages that the different agents speak as well as that used in the market itself.

2.3.4 Broker Agents as Search Mediators:

According to Jonker et al., marketplaces would be useless without searching facilities that facilitate the user interaction with the market and the finding of relevant information to the user's request. For this end, brokers can be introduced. Brokers can be described as agents working as intermediaries between buyers and sellers.

Using brokers can reduce the search costs, as it is an agent specialized in searching, it can maintain data on the different providers and consumers thus helping them better find each other out. And given the fact a huge amount of transactions take place every minute, brokers can fit the role of maintaining what goes where and how too access it.

On another note, brokers would also help return more interesting and relevant search hits, they can alleviate the problems introduced by naming inconsistencies that can be found between different agents by acting as intermediary platform between the different ends translating the available information into something that every agent can understand and making sure that an agent's requirement are fully met.

From another angle, brokers can guarantee the privacy of the different parties involved in a search or even in a negotiation. They can only provide information on a need to know basis thus making sure that all parties have satisfactory data to make a decision without revealing any private information they might hold. Even more, the broker can himself handle the transaction, making sure that both participants, if need be, ignore each other's identity. Even more, brokers can enhance security by ensuring that all deals are respected, and that no suspect deals take place that might violate the market rules.

And last but not least, brokers can help avoid pricing inefficiencies by maintaining a balance throughout the market that ensures that all prices respect a certain mechanism and none of them are unfair or at odds with the rest of the market. [1]

2.3.5 Introducing Ontology:

In their work, Gruber et al., introduce ontologies to increase the searching efficiency. Ontologies help the different agents better communicate and better understand each other and thus allowing them to better serve each other. Ontology is, and here we quote Gruber, an "explicit specification of a conceptualization". It provides a vocabulary for talking about a domain. Gruber explains: "An ontology is an explicit specification of a conceptualization. The term is borrowed from philosophy, where an Ontology is a systematic account of Existence. For AI systems, what 'exists' is that which can be represented. When the knowledge of a domain is represented in a declarative formalism, the set of objects that can be represented is called the universe of discourse. This set of objects, and the describable relationships among them, are reflected in the representational vocabulary with which a knowledge-based program represents knowledge. Thus, in the context of AI, we can describe the ontology of a program by defining a set of representational terms. In such an ontology, definitions associate the names of entities in the universe of discourse (e.g. classes, relations, functions, or other objects) with human readable text describing what the names mean, and formal axioms that constrain the interpretation and well-formed use of these terms. Formally, an ontology is the statement of a logical theory." [12]

And then Gruber explains that for an ontology to be successfully designed and implemented it needs to respect some of the following rules:

An ontology needs to be clear. The objectiveness of the definitions is an essential and integral part to the design of a well-defined ontology. This means that all definitions in the ontology must be independent of any social or computational context, making them universally understood by all users and in all circumstances. This clarity directly affects the terms' definitions, which helps the different users better communicate and better understand each other. These definitions need to be documented in natural languages.

An ontology needs to be coherent. All the different definitions and the defining axioms need to be logically consistent with each other. The same consistency should also be applied to informal definitions of concepts. Contradictions at any level between definitions axioms or informal concepts, violates the coherency principles of the ontology.

Finally, an ontology should be extendible. It should provide means to define new terms and extensions to the original set without having to modify the requirements or having to revise the original already existing ontology. Adding new terms, concepts, and relations to an existing vocabulary should not require a total or partial revision of the existing ontology. [13]

2.3.6 Broker Agents and Ontologies:

The broker agent needs to be aware of these ontologies as he will be using them in his searching and are required for him to be able to successfully achieve his job. In an advanced marketplace, at last two ontologies are required to be able to achieve good searching, and to be able to return relevant user results: The product-related ontology and the consumer and provider perspective ontologies.

The product related ontology model needs to be split into three categories: the Generic Information Types, Domain Specific Information Types and Reference Information Types.

Generic Information Types are general, domain independent concepts and their relations are identified here. In this category only general specifications are stated such as specifying that a physical, functional, and presentational model exist, without giving details about domain specific contents for these models.

Domain Specific Information Types are more specific and detailed concepts and terms that extend the Generic Information Types into a certain domain. For example, when considering a generic concept such as a car, specifying that it has a motor, chassis or wheels would be the domain specific information extension of the generic car.

Reference Information Types represent the merger of both generic information types and domain-specific information types. Continuing with the car example, the generic information and domain-specific information are taken together and then a reference information type is used to merge these two types together in order to be able to define a complete car product model.

Obviously all categories and sub-categories are completely independent from one another, thus making it easier to fill the relevant information by someone specialized in each field. For instance when talking about the car chassis, only an expert in car chassis is required to describe that part, other specialists will fill the other parts. This will ensure that all descriptions are relevant and that no one person will be overwhelmed when filling data, as his part will be limited to his knowledge.

In addition to the different information types, rules and facts are required to be able to describe the relationships between the different aspects and parts of a product. The rules will be applied to the product parts in order to derive new facts about a specific product. For instance, the presence of airbags, safety belts and bumpers in a car, which are facts, would enhance safety, which is derived fact from the applied rules. [1]

Consumer and provider ontologies are how both buyers and sellers define and view their products from their own perspectives. Personal agents acting on behalf of a consumer or provider are also considered to be of the same type as their respective user. To be able to determine how the consumer or provider relates to a certain product, many aspects need to be covered such as how does the user look at and understand the product, and what aspects of the product are most important for the user.

Average consumers are not usually aware of the specific details and properties of the product, and so they should be treated accordingly. Thus the consumer when looking for a product he usually expects answers related to the meaningful quality and functionality related aspects of the product, and how they relate to his lifestyle, rather than the aspects concerning the physical attributes and properties of the product. For example, an average consumer would be more interested to know, even if it was in brief details, how safe a certain car is and how it compares relatively to others, rather than having a detailed description of its safety belts, brake types of the number of airbags.

As for the advanced user, who is more interested in the technical details, he could easily check the initial models and views that were used in order to provide the final consumer related view.

From the producer point of view, he would prefer providing the technical attributes of the product, he could do just that, and the marketplace routines would analyze the requirements and build the more consumer friendly views and information. [1]

2.3.7 Interface and Tent Agents:

The broker agent is not the only agent for the efficient running of the virtual marketplace. Even though he plays a central role in helping the different parts communicate with each other and helping other agents to find relevant products to their needs, other agents are also essential for the successful running of the marketplace. Agents such as the "Interface agents" and the "Tent agents" are also essential for the smooth and efficient running of virtual markets.

Interface agents manage the communications between the customers and the marketplace. These agents will be the interface for the users and user agents and they will manage their inputs and outputs. These agents will gather the user's requirements and then communicate these requirements to the broker agents using the marketplace's communications standards. Then after the broker agents have gathered the required results, he will transmit them back to the interface agents who will display them according to the user's specifications, requirements, customizations and needs.

In other words, the introduction of Interface agents can solve the communications problem between the users and the markets: the user will communicate his needs in the language he prefers to his personalized agent, and from there on, the agent will take care of communicating with as many parties as needed, mainly with the broker agents, in order to best achieve the user's needs in terms of requirements and presentation.

Tent agents are agents whose responsibility is managing the available marketplace inventory. Every Tent agent represents a category of products. Within their assigned category, Tent agents control the availability and the flow of products. For example, vehicles are classified in one category and have their respective tent agent; Furniture products are classified as another category, and are managed by a different tent agent. Within the vehicles category, the tent agent will keep track of all the available products and whenever a certain criteria is queried by the broker agents, it would be the job of the tent agent to check for its availability and he will be the one returning the required results to the broker agent.

The broker agent will assimilate and analyze the results set and return the required results to the interface agent, who will, in turn reorganize these results and re-forward them to the relevant user.

2.3.8 Existing Virtual Marketplace:

Moving away from the theory, we make a round up of the currently available commercial marketplaces, their architectures, designs, and future visions.

Many agents and virtual marketplaces are already in setup and offer some kind of service for customers...

Agents such as Bargain Finder (http://www.bf.cstar.ac.com) and FireFly (http://www.agents-inc.com) are online shopping services that help users search for and locate their needs. But again, such agents do not satisfy the requirements of a virtual marketplace as they are searching facilities rather than complete shopping platforms with the required infrastructure for automated purchasing and agent cooperation.

2.3.8.1 Introducing Kasbah:

As for the marketplaces, Kasbah has to be one of the most interesting promises. Designed and developed at MIT, with many prominent researchers behind it such as Chavez, Maes, Dreilinger and Guttman. Kasbah is a multi-agent web-based system, where agents interact with each other within the confinement of the virtual market domain in order to buy and sell goods on behalf of their respective owners. [1]

Kasbah offers a common blackboard which is used to post offers. The users configure their respective agents with their requirements. The agents then monitor the blackboard, looking for something that might fit the user's requirements. When any interesting postings are found, the agents notify their users and then go into a price negotiation with the posting user's agent. [1]

The negotiation in Kasbah takes place between a buyer and a seller, where the first uses "price raise" functions and the other decay functions. The seller first offers his lowest desired price, and then gradually raises his offers according to his price raise functions. The user has the choice between linear, quadratic or cubic functions. The same applies in reverse to the seller. After a while the two agents should be settled on a certain price; the final price will depend on the users' choice of negotiation functions. Finally, after negotiating with many agents, the seller will report back to the user who will choose one of the negotiated offers; most probably the highest. Even more, the user can check at any time the negotiated deals and how they went, and will thus be able to fine-tune his agent in order to be able to get the deal he had envisaged at the beginning. [7]

Security wise, Kasbah runs on proprietary server side system, making it private and independent from the rest of the net thus avoiding any security risks. Thus no special security solutions are introduced, but rather preventive measures are what keep the system safe. [1]

After a user logs in to Kasbah, he has the opportunity to create an agent. The agent is created in the server side inside a lisp image. Thus all agents are created the same way and they all reside inside the same space. This means that communication problems are solved since all agents are compatible with each other and with the system. This also means that the system as a whole is secure since it is self-contained. All transactions and communications are done inside the system, and only a minimal set of communications is required with the outside, thus the system is inherently secure since no one can easily jeopardize the server side security. But as a drawback, everything is being processed on a single server thus creating a huge overhead on the private server causing a performance problem. [5]

The current marketplace architecture is agent independent, meaning that the agents are free to behave and use any algorithm they want, as long as they speak the marketplace's common language. But then having the agents exist on the server side where they are supposed to trade creates lots of limitations on their design and functionalities. In order for an agent to be able to successfully trade inside the marketplace, it has to respect many architectural and design constraints that are enforced on it by the marketplace's routines and algorithms. [5]

Kasbah offers currently little administrative and law enforcing utilities. The current used agents being not very complex, they are only allowed to do legal transactions. But as the agents become smarter, one can easily imagine the development of malicious agents who will try to take advantage of more honest agents and try to get into unfair deals. For this end Kasbah has plans in developing some law enforcing utilities that will make sure the market stays a safe place for trading. The introduction of regulator agents that would roam through the marketplace to make sure no illegal activities take place can go some way into creating a safe trading space. [5]

Kasbah offers many advantages and drawbacks. The use of a blackboard system allows agents to post classified ads and then sleep until some interest is shown in their product. The advantage of this system is that users don't have to stay logged in all the time to be able to get some deals going. But unfortunately, it has some shortcomings that keep it from being a true virtual marketplace. [33]

First of all the Kasbah agents are very limited messaging agents which hinders the development of any real inter agent negotiation. This also limits the agent interactions with other external entities such as banks and advertisers thus limiting both the exposure of the marketplace and its financial capabilities. Even more, Kasbah is a proprietary server-side system, which makes it impossible to use a heterogeneous mix of agents in the market. The system is built and resides inside one Lisp image on the server, which bypasses and partially the communications problem, but on the other hand, this will also limit the overall capacity and capability of the system. This makes Kasbah more of a solution for privately run commercial web-servers rather than a complete and scalable virtual marketplace. [33]

2.3.7.2 Introducing MAGMA:

The Minnesota AGent Marketplace Architecture, MAGMA, whose architecture was designed by Tsvetovattyy, Gini, Mobasher, and Wieckowski, is an experiment intending to create a marketplace where autonomous agents participate in the trading of goods. The purpose of magma was to recreate an architecture that would allow the development of such a project. The main challenges that magma tries to overcome are:

- The establishment, development and implementation of the infrastructure that would allow a successful agent based market place to thrive.
- How can a purchasing marketplace be transformed into an investment marketplace and what are the required algorithms and changes that need to be introduced to the agents in order to cope with such situations.
- And finally what are the good strategies for creating successful inter-agent alliances. [32]

MAGMA is one of the most serious competitors to Kabah. MAGMA was first established as agent-based virtual marketplace with a developed infrastructure that would allow the simulation of a real market. The infrastructure includes communication protocols, mechanisms for transfer and storage of goods in addition to banking and monetary transactions support. Magma is an open system relying on the open-standard messaging API. [1]

MAGNET, developed by Collins, Youngdahl, Jamison, Mobasher, and Gini, is the evolution of MAGMA, where all the experiences learned from MAGMA were implemented in MAGNET. Whereas MAGMA puts more emphasis on multi-agent negotiation, MAGNET shifts the emphasis to creating a market architecture which can be exploited to negotiate and maintain contracts.

Since MAGMA and MAGNET are open systems, they require an enhanced security. And security is exactly one of the highlights of this system. MAGMA and MAGNET provide an open system where hybrid agents are allowed to participate and coordinate using an open-standard messaging API, and that does not compromise on security: agents are allowed to make the deal and transfer the money in a very secure environment where these important transactions cans be successfully achieved. [1]

Even more, this enhanced and open architecture security would allow for the market and agents to connect directly with the current banking systems and networks, even with the legacy systems. To this end, many layers of enhanced security are used such as encryption and safeguards… [33]

The communication is an integral part of the market and thus should be very robust and built into the core system. Such a system cannot and should not rely on a central hub, but should rather rely on a mesh of redundant hubs, something similar to the current mailing facilities; as a matter of fact, the current facilities could be used as part of the infrastructure for the system. The communications system should be built on open standards to allow developers to build platform independent plugins that could be easily integrated into the system. The marketplace communications system is agent independent, but still some basic agent-market communications are required for the agents to be able to achieve their purpose in the market. More specifically, agents need to have access to global blackboards where the buy and sell offers are posted by the different agents. In addition, agents must use a common language for all inter-agent and agent-market communications. A minimal language subset must include posting offer, responding to them, negotiating with other agents and executing transactions. [32]

Goods need to be stored and handled correctly. The software objects and virtual goods need to display the same characteristics as their counterparts. Goods need to be handled correctly and protected against theft. Only the allowed agents should have access and should be allowed to deal with their respective goods. When transferring goods, a new storage place where these goods can fit must first be found, and the different items need to be stored correctly to allow easy access to the required merchandise… [32]

Advertising is a key part of any marketplace and thus should have a place in its virtual counterpart. Obviously, the flashing drawing usually appealing the human psychic would have little effect on the agents, thus creating the need to find alternative solutions and approaches to the advertising problem.

One approach to solve this problem would be to create an advertising agent with a knowledgebase of all available items and make him respond to buyer and seller agents by quickly providing them with relevant results.

Another approach would involve the creation of some sort of a facilitator agent or broker agent that would help the different agents finds their requirements and needs. They can also provide extra information about competing agents or about the items that the user may be interested in, and then charging for their services. They can also help the different agents try and reach a deal conclusion and facilitate the communications and finding a middle ground between the different competing parties where a deal would be easier to conclude. [33]

A central administration should be in place to monitor the agents' activities and transactions and make sure that no illegal transactions take place. They also collect sales taxes and commissions, as well as maintaining a credit and service rating for agents. [32]

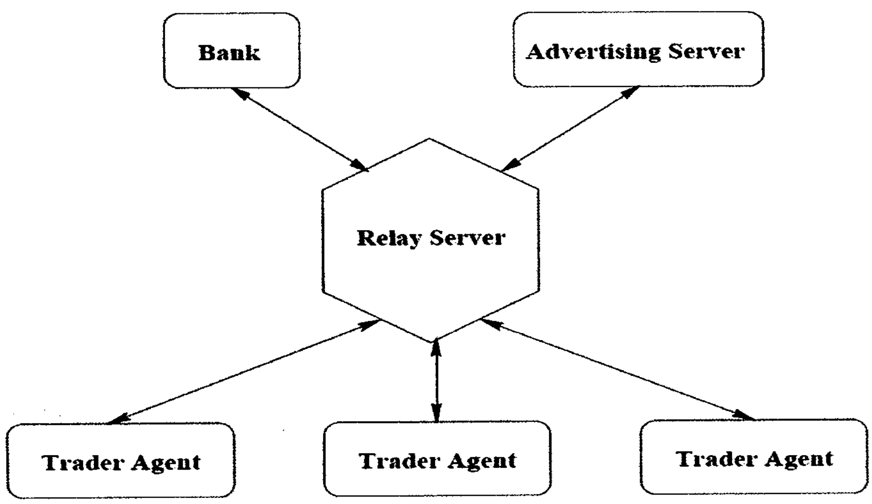

Figure 4: Magma Architecture and Module Interaction [33]

The openness of the communications API would allow for any inter-agent negotiation to happen according to the desires of the participating agents. Thus direct agent-to-agent negotiation can be allowed with every agent using any negotiation strategies that he likes. The use of intermediate agents to conclude inter-agent deals is also allowed. The use of some kind of auction systems can also be used for inter agent negotiation where every agent can only offer bid and the deal finally goes to the highest bidder, or any sort of variation of that model. In short, all negotiation formats are allowed as long as the used agents can support and abide by the marketplace rules which are enforced by the administration. [33]

The basic inter-agent communication and negotiation follows the following pattern: The agents have access to a blackboard called "offer board" where agents post their offers. Sellers indicate the items they have for sale along with the requested price. Buyers indicate to their agents their requirements, and the numbers of hits they want. Buyer agents will make the search and return the relevant results; then buyers will indicate to their agents which deals they'd like to follow up on. Finally the buyer agent will send accept offers to the relevant agents indicated by the user. [7]

Many promises are offered by the development and expansion of the virtual marketplaces. Their development might one day change the way we deal with other people, the way commerce is done. But before reaching that point, many challenges are still facing this new bread of marketplaces: security and money transfer issues are still a huge problem. Agent interaction and the way agents understand and cooperate and help each other better fulfill their needs still has a long way to go before it matures and becomes a full grown up game on its own.

2.4 DALIA- Towards Distributed, Artificial and Linguistically Competent Intelligent Agents

This final background section focuses on DALIA, which is an alternate approach to agents and virtual markets. This section introduces the DALIA agent characteristics and market; then introduces the negotiation with an attitude model, unique to the DALIA agents. DALIA agents can even learn from past experience, and are adept at both competitive and cooperative negotiation. And finally, this section concludes by identifying the linguistic capabilities of the DALIA agents and the potential this opens up for the DALIA agents.

2.4.1 DALIA Agents Characteristics:

Towards Distributed, Artificial and Linguistically Competent Intelligent Agents, DALIA, is a novel approach to virtual marketplaces and negotiation agents. The DALIA approach shifts the emphasis from the Marketplace to the agents and introduces mental state negotiating agents that take into consideration some metal attributes of their parent user. DALIA is the brainchild of Saba et al., who managed to build the theoretical infrastructure with the help of Farhat and Sathi.

The DALIA agents are "intelligent agents", meaning that they display a minimum set of characteristics that would allow them to operate efficiently and effectively on their own. Most import the agents have to be autonomous systems that are expected to experts at performing certain tasks, they also have to be aware of the dynamic environment in which they operate, and finally, they are expected to be capable of performing some kind of reasoning as well as exhibiting flexible problem solving behavior. Some additional important agents' characteristics include learning, mobility and communication. [30]

DALIA is an environment of distributed, artificial and linguistically competent intelligent agents that are able to communicate using natural language as well as perform common sense reasoning in a highly dynamic and uncertain environment. In the end, the agents' should be able to reason in situations similar to the following:

- It is very likely that product X will keep going down for a while.
- The user can wait for a few months before buying product X.

Drawing from these two premises, the agent should be able to conclude that it would be better to wait for a few months before buying X unless we find a very good deal.

If in the first statement, the term "very likely" would be "highly unlikely" the agent should be able to cope with these changes and purchase the product X at the first opportunity. The agent would also have to define what would actually be a "very good deal" and put into formal numerical values that can easily be determined and compared. If the user was "must' actually make a purchase, then it would a completely different story and the agent would also have to cope with such a change and react accordingly. Ultimately the agents should be able to do such reasoning. Unfortunately, formalizing such logic is not a trivial task, and the research is currently a long way from achieving such a complexity level. [30]

The DALIA agents need to be linguistically competent. Meaning they should be able to understand and reason in plain English. English would be the primary inter-agent and agent-user communication medium, thus removing many standardization problems and introducing many others. The most important challenge in this field would be how the agents would be able to understand English in the first place given that the language is very flexible, undetermined, and context sensitive; for example the same word can have different meanings in different situations. [8]

The DALIA agents are supposed to learn from previous experiences and from the different approaches and market settings under which the negotiation is taking place. The agents are supposed to try to optimize their mental states configuration, which was saved from previous negotiations, in order to try and get better deals in the future. [28][29]

And finally the agents are supposed to operate according to mental states attributes. This means that the agents would have to take into consideration when searching, negotiating and making deals, some user custom preferences such as the importance of time and price. [28]

2.4.2 The DALIA Marketplace:

As mentioned previously, the DALIA approach shifts the emphasis from the marketplace and makes sure that the agents are very capable of handling themselves on their own. This means that the marketplace is rather simpler than previous approaches, but its simplicity is what makes it more feasible and realistic.

The DALIA marketplace has at any point in time a list of all available buyers and sellers. The buyers and sellers are supposed to have access to two knowledge sources that should be made available within the marketplace:

- An ontology of domain specific product information.
- A set of general common sense rules.

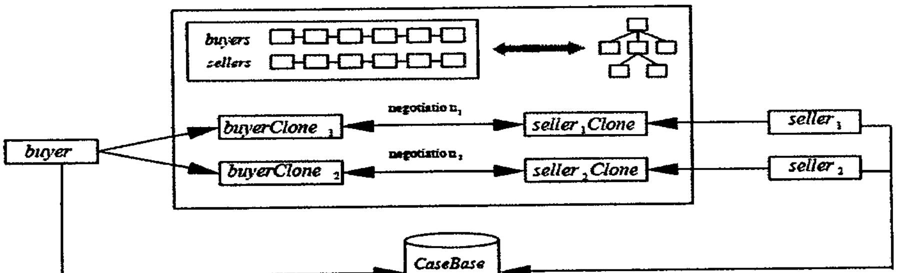

Figure 5: Basic DALIA Marketplace Architecture

The process starts when a user creates his agent, either buyer or seller, and submits it to the marketplace. The agent will be added to the list of currently available agents. Then the buyer agents will go looking for suitable seller agents who have products posted for sale that the buyer agent and his user might be interested in.

Hereafter, we will reproduce the procedure of creating a buyer agent and searching to buy a certain product X.

- First the user creates the agent.

- The buyer agent would go look for the available public maximum and minimum prices that are being dealt in the marketplace. These values should be part of the product ontology.
- Based on his mental states attributes the agent would compute his private minimum and maximum prices. That is, he would compute his personal valuation of the product based on the publicly available prices. These prices would represent how much and how little the agent would be willing to pay for the product.
- The buyer would then query the environment looking for sellers, exhibiting the product of interest.
- After finding an appropriate agent seller, the agent would send a product negotiation request. Requests can be sent to all found agents simultaneously.
- The seller will have to respond to the request by either accepting or rejecting it.
- After receiving the accept negotiation response, the buyer agent would create a negotiation thread for every accepting agent seller.
- Then the two agents would start the negotiation process. More than one negotiation can take place simultaneously.
- The buyer agent would start bidding his minimum computed value, the seller his maximum. And then as offers and counter offers go, the buyer would steadily increase his minimum price and offer it, and the seller would decrease his maximum, and offer it back
- The negotiation ends with success when the buyer's re-evaluated minimum reaches the seller re-evaluated maximum.
- The negotiation ends with a failure when the buyer reaches his maximum and the seller won't accept it as an accepted deal, or vice versa, when the seller reaches his minimum and the buyer rejects the offer as a final deal.
- Both buyer and seller would finally save the negotiation characteristics as experience and for future tuning. [30]

The ontology is the final part of the marketplace. It provides domain-specific product information. Such information includes the public maximum and minimum prices of the product thus providing its price range. It also provides product specific information that can be used by the agents in order to be able to make product comparisons.

The product comparison would allow the agent to compare products of the same type. Thus the agent would have the chance to compare the products not only based on their price but also on their features. This would go some way into helping the agent determine what would be a "very good deal" given the user's priorities and mental attributes. Thus, the agent would be able to make some price\quality compromises in order to better suit the user's needs. As an example, when buying a certain mp3 player, the agent would be able to compare the different products and their different characteristics and options, and not only their price, and then determine if it would of better value to the user if the mp3 player also had an extra radio tuner for a certain additional amount of money.

The ontology would also allow the agent to use his experience in purchasing a certain product in order to benefit from it while purchasing a different product from the same category. Thus the previous experience will have a more versatile role and won't be restricted to very niche situations. For example, when buying a computer scanner, the agent can use the previous experience of purchasing a computer printer and apply his previous experience to his current situation. Such experience might include brand reliability and the importance of an extended warranty. [30]

2.4.3 DALIA Agents and Mental Attributes:

Agents themselves are based on mental state model. Every agent has a set of relevant attributes. These "relevant" attributes will be the only ones that will be taken into consideration by the agent when negotiating. For example, "price" will be a relevant attribute for agents competitively negotiating the sale of an item, while "public safety" would be a relevant attribute for agents cooperatively deliberating the issue of public smoking in restaurants.

Every agent has a relevant "attitude" concerning each and every one of his relevant attributes. This attitude will indicate the importance of its relevant attribute. For example, the "price" attribute might be very important for an agent whereas the "time" attribute is of lesser importance. This actually means that agent puts a higher importance on price and is very interested in getting a good price no matter how long the process takes; the agent would sacrifice some time in favor of getting a better deal. The attitude values vary between 0 and 1 where 0 indicates that the attribute has little importance for the agent and 1 indicating that the current attribute is of prime importance for the user and would be the decisive factor in the negotiation. [28]

The success, or failure, of a negotiation depends on the agreement between the different agents on a set of distinguished attributes. For example, the agreement on "price" might be the deciding factor in the success of negotiation between a buyer agent and a seller agent negotiating the sale of a certain specific product in a virtual marketplace. On the other hand, when dealing with the issue of banning smoking in restaurants, when factors and attributes might need to be taken into consideration, but agreeing on "public safety" might just be the decisive factor and attribute. [28]

For every "distinguished attribute", it is assumed that every agent has access to publicly available value given as a range with a minimum value and a maximum value. Using these publicly available values, the agents compute their private values relatively to their public counterparts. The agent's own attitude set towards the different attributes would help him in the calculation of his private attributes' values. For example, given the range [1000, 5000] as the public price for a PC, the agent would calculate a sub range that would take into consideration the agent's attitudes and priorities; the agent's private range might be [1000, 3500] given the case that the buyer agent would like to get a very good price and has the time to spare in order to be able to get such a deal. [28]

To illustrate the agent negotiation algorithm, we hereafter use the example of buying and selling agents negotiating the price of a certain item. When negotiating, the buyer hides his maximum value from the seller, and offers his minimum computed value. The logic behind this is that the buyer would always like to get the best deal, thus offering his minimum, and would definitely like to hide his maximum, that is the most he is willing to pay, in order not allow the seller agent to take advantage of this information. The seller agent, on the other hand, would offer his maximum and conceal his minimum from the buyer, according to an opposing logic to that used by the buyer.

After getting an offer, the buyer evaluates it, and compares it with his next offer. If the buyer was to offer more in his next turn, then he accepts the seller's offer and the negotiation would end with success.

If the offer was higher than buyer was going to propose, then he increases him minimum by a certain value and re-offers it.

If the seller has already offered his maximum and he is not willing to increase his offers anymore, then he will forfeit the negotiation, which will end in failure.

The exact opposite applies to the seller agent.

A negotiation is a success, if both agents were able to agree on all distinguished attributes. If agents fail to reach an agreement on any of the distinguished attributes, then the negotiation ends with failure, even if an agreement was reached on some of the distinguished attributes. [28]

2.4.4 Negotiating with an Attitude:

The agent's mental states and attitudes have been given little attention in the previously designed virtual marketplaces. But these mental states define a new overall context of negotiation which consequently affect the agent's strategy and ultimately determines how a negotiation will proceed.

In the current model, DALIA's agents have the price, time and commitment attributes to be regarded as mental attributes, and thus affecting the course of negotiations. The agent's past experience is also a factor that can affect the current mental attributes in order to guarantee a better deal. [28]

Thus when dealing with virtual marketplace model, DALIA offers two types of agents, a buyer and a seller. These agents when negotiating have their offers affected by their price, time and commitment mental states and priorities, in addition to their previous experiences.

These mental attributes can take any value from the open interval [0, 1], where 0 indicates that the attribute is of little importance and 1 means that the attribute is of prime importance.

The time attribute indicates how urgent it is for the agent to conclude a deal.

The price attribute indicates whether the agent is looking for an opportunistic price, or if he has no problem spending as much as it takes in order to get the desired item.

And finally the commitment attribute indicates how desperate the agent is to get the negotiated item.

For example, given the set <price, time, commitment> with the respective values <0.8, 0.2, 0.6> means that the agent would like to find a rather good price, no matter how long it takes, and that the agent would rather like to get the involved item, but is not dying to buy it.

Price is assumed to be the only "distinguished attribute"; that is the negotiation is only affected by the price. Once both agents agree on a certain price, the negotiation end with a success and the deal can take place. [28]

After getting the public price range of a certain product from the marketplace ontology, the agent, and with respect to his mental attributes, will calculate his own private range. Many functions can be used to calculate the private range.

What needs to be taken into consideration when designing the buyer functions are the following rules:

- The minimum private price should be higher than the public price in the case when the item is an important factor. This is due to the fact that the lower the minimum and starting price, the longer it takes to reach an agreement, thus the need to raise the minimum in the case if high time importance.
- A high commitment level means that the agent's private maximum should be close to the public maximum, as this will indicate a situation of urgency for the buyer where the agent is desperate to get the item, no matter how much he pays.
- The price attribute balances with the commitment level, and creates a sort of equilibrium that would make the price ranges more reasonable, or in extreme cases, closer to the extremes, either low or high.

When reasoning for the seller in order to design his functions, exactly the opposite direction of the rules stated above should be used. [28]

For the calculation of the private values, the following formulas are proposed:

- For the buyer:
  - privMin= pubMin+T*(pubMax-pubMin)/10
  - privMax=pubMax-(pubMax)*P*(1-C)/10
- For the seller:
  - privMin=pubMin+(pubMin)*P*(1-C)/10
  - privMax=pubMax-T*(pubMax-pubMin)/10

Where:
privMin is the agent's private calculated Minimum value.
privMax is the agent's private calculated Maximum value.
pubMin is the given product's domain specific public Minimum value.
pubMax is the given product's domain specific public Maximum value.
T is the agent's time commitment value.
P is the agent's price commitment value.
C is the agent's commitment value. [28]

The current inter-offer buyer's increment value and seller's decrement value are calculated according to the following formula:-

Step=(PublicMaximum-PublicMinimum)/100 [8]

The buyer and the seller will use the formulas stated above to calculate their private values. Then when the negotiation starts, the buyer will start by offering his private minimum and the seller his private maximum. In case the offer was not accepted, the buyer will increment his minimum value by the "step" formula described above, and then re-offer his re-evaluated minimum again; as for the seller, he will decrement his maximum by the "step" value and then re-offer it back. Both agents will repeat the same process until they reach an agreement or until one of them reaches his threshold value and aborts the negotiation.

But again in order to reach optimal solutions for the formulas described above, a lot of experiments and work needs to be done so that the agents behave more realistically. The formulas will also have to be tweaked so that the agents do not increment their offers by a value that is beyond his opponent's desire. For example, if an agent has a high priority for the Time factor, one can expect him to have a step relatively large so that the negotiation converges quicker than the usual. But at the same time, the step should not be too large, so that the agent will not end up paying more than he was initially supposed to pay... [28]

2.4.5 The Experience Factor:

After every negotiation, and regardless of its outcome, both buyer and seller agents are supposed to save their experience in a "case base" for future use. When dealing with case base, one has to carefully consider a strategy for case representation, case indexing and retrieval, case matching and finally case adaptation.

The DALIA model presents the following case base structure:

- Product Category
- Public Price Range
- Agent's Private Price Range
- Agent's Attitude
- Supply/Demand Ratio
- Negotiation, offers/counter offers and final outcome

Cases are to be indexed according to Product Category and Average Public Price. Agents should learn from experience by using old cases that are similar to the current negotiation and their outcome in order to better adjust their attitude and their increment/decrement step. The agent before starting any negotiation would try to search for any cases that are similar the current conditions. This can be done by checking both the Product Category and the Average Price Range, in addition to the agent's attitude and the supply and demand ratio... [28]

The retrieved matching cases are separated into two groups, those that ended in success and those that ended in failure. Afterwards the agent would increment the step and fix the mental states attributes so that they assure higher values than the previously used attributes and step in the failed negotiations. But the agent would also have to make sure that the new incremented values remain lower than the values used in previously successful negotiations. Thus the agent would be using a new set of attributes that are more favorable than the previously failed negotiations' attributes yet less favorable than those of previously successful negotiations. Thus the agent would in theory be guaranteeing himself a deal that is better than the previous similar negotiated cases, and yet not unfavorable for his opponent agent in order for him not to reject it. [28]

2.4.6 Cooperative and Competitive Negotiations:

Using the agents' attitude model can be used in cooperative environments as well as competitive environments such as the marketplace example described earlier. Whereas in competitive negotiation situations, the agents don't need to share any attributes, in cooperative situations, such as deliberations, all agents must at least share one of their mental attributes.

Even competitive negotiations can transform into cooperative games when both the buyer and the seller agree on some essential attribute in their mental states.

For example, given the situation where a buyer agent, b, and a seller agent, s, both have very high commitment values, 1 for example, meaning that they are both committed towards making a deal; b is rather desperate to buy the object and s just wants to sell it.

In this case, the whole negotiation process will be more cooperative than competitive. The buyer will have a rather high starting bid, close to his maximum, and his increment step would also be relatively high to reflect his desperation to buying the desired item. On the other hand, the seller, who is also dying to sell the item, would start bidding with a relatively low value, closer to his minimum than his maximum, and would also have a rather large decrement step to show his commitment to selling the object.

This means that the buyer's initial bid should be very close to the seller's initial bid and the number he is willing to accept to conclude a deal. Given that both agents have a rather high increment/decrement step, the whole negotiation process would quickly converge and both agents should be concluding a deal in no time.

Thus this given process, where both agents are dying to strike a deal, looks more like cooperation rather than competitive negotiation. [29]

The cooperation model in a competitive environment can be made even further clearer if both agents were to agree on two attributes, such as commitment and time. By highlighting the extreme case where both agents would have a very high priority for price and time, wouldn't care less about the price, the cooperation would be even made clearer.

Given the example where <P, T, C> indicate the importance of Price, Time and Commitment respectively, and where both agents share the same mental states <0, 1, 1> indicating that they have very little importance for price, meaning that the buyer is willing to pay as much as it takes in order to get the given item and that the seller has no problem selling the item for his minimum price, and have very high levels of commitment and time is also of prime importance, meaning that both agents would like to conclude a deal as fast as possible and both agents are very committed to making the deal. The buyer desperately wants to buy the item and the seller desperately wants to sell it.

In this case of total agreement by both agents, they would both compute very similar price ranges, and they would both have very high steps. Thus both agents would find themselves quickly offering each other suitable prices, and quickly agreeing to each other's offers. And the negotiation wouldn't take long before both agents agree to a price, and conclude the deal. Such a process looks more like a cooperation rather than competition. [29]

Thus the DALIA environment and agents can be easily extended to deal with cooperative situations such as deliberations. The agents seem to be able to naturally move from a competitive to a cooperative dialog type. Thus, with the introduction of the mental states to the agents' environment, the competitive and cooperative models become just two extreme points of a continuum that is defined by the degree to which the negotiating agents share their attitudes and mental states attributes. [29]

2.4.7 Linguistically Competent Agents:

As discussed before, the DALIA agents are supposed to be linguistically competent. Their linguistic competency is an essential aspect that is needed in order for them to successfully complete their jobs. Meaning that in order to be able to perform some common sense reasoning in a dynamic and highly uncertain environment as well as perform some trading duties, the agent would need search for the required information on the desired topic to be able to perform good reasoning as well as conclude beneficial deals. Thus comes the need for the agents to exhibit sophisticated linguistic capabilities, as opposed to less adequate traditional key-word systems.

Given the following statements:

- Support for leftist rebels in Latin America (1)
- Aid for Marxist guerrillas in South America (2)

An agent must be able to understand that conceptually, these two statements are very similar even though they use very different words.

In order to be able to perform conceptual matching of such topics, as presented in the example above, requires lexical disambiguation as a pre-requisite. For example, while "aid" and "support" have several meanings, it is only the specific meaning of each word that is conceptually similar. Even more, to be able to do efficient and effective conceptual matching of topics that are expressed in a complex syntax requires that well-defined compositional semantics are available for compound nominals.

To be able to deal with such a problem, one must first determine how compound concepts are formed from more primitive concepts. Applying this problem to information retrieval can be expressed in the following example:

- Computer Book sale (3)
- Information Retrieval System (4)

When removing the middle noun from (3), the sentence subject matter changes considerably, whereas applying the same to (4) does not affect the overall sentence meaning. Thus Saba and Farhat, and in order to overcome such a problem used conceptual subject matching in order to be able to extract the key topics in a document. [8]

Another pre-requisite to achieving language understanding is the design and development of an ontology of common sense knowledge. The design of such an ontology would also help in information retrieval.

Thus, for the building of such an ontology of common sense knowledge, one must use the language itself as a design guide.

In other words, the understanding of natural languages, is for the most part, a common sense reasoning process at the pragmatic level, thus comes the "understanding as reasoning" paradigm. This paradigm is used as a basis in order to allow the DALIA agents to understand common languages, and to reason in common languages. [8]

The basic strategy in using the language as basis for the design of an ontology of common sense knowledge is based on Frege's conception of Compositionality. According to Frege, "the sense of any given sentence is derived from our previous knowledge of the senses of the words that compose it, together with our observation of the way in which they are combined in that sentence." This paradigm is based on an observation regarding the way in which words are supposed to acquire a sense. Thus the principal of Compositionality is based on the concept that our understanding of those words "consists in our grasp of the way in which they may figure in sentences in general, and how, in general, they combine to determine the truth-conditions of those sentences."

The following idea forms the basis of the design of an ontology of commonsense knowledge that was adopted for the DALIA agents: "what languages allows one to say about a concept, tells us a lot about the concept under consideration." In other words, the meaning of words can be discovered from the way in which the words themselves are used in the every day language.

Assuming that language reflects thought, then by analyzing patterns of everyday language and words use, should provide clues to structure of commonsense knowledge. [8]

In short, DALIA's agents use natural languages themselves as source for an ontology that helps them better understand and reason in that given language. And thus by having agents that can reason in natural languages, the whole internet cyberspace has the potential of becoming the playground of the DALIA agents. Thus the marketplace role would come down to supplying lists of available agents and their trading artifacts. And the agents themselves would search the net for price ranges, and product specifications and market predictions and accordingly, they will be able to decide how much they should be paying for a certain item and whether it would be more profitable to make a purchase straightaway or whether a better deal can be made by waiting... and finally, the agent would be able to make quality/price comparisons and thus determine whether it would be valuable if he spent more money for an extra feature or for an item of a different brand...

Chapter 3: Contributions

3.1 Introduction

Creating an agent and improving his negotiation abilities and skills is the challenge undertaken in this thesis, and particularly in this chapter.

To this end, the DALIA marketplace and agents will be used as the cornerstone for creating a simulation. In the following we will propose modified agents with mental states that affect the way they negotiate and interact with the other agents.

The negotiation model and formulas proposed for the DALIA agents will be first simulated and analyzed. And then according to the analysis results, some modifications will be introduced into the negotiation schema to make it more realistic and flexible at the same time. Thus the new agents that will be proposed will be able to behave more realistically according to their mental states and attributes.

The goal of the simulation is only to concentrate on analyzing and improving the negotiation aspect of the DALIA agents. For this purpose, any searching, communication aspects, security standards or linguistic competencies won't be implemented and will be taken for granted. The simulation will assume that the buyer has already found a seller with the requested item, and now the two agents have agreed to start the price negotiation over this item. The simulation will start from this point onwards, covering the negotiation that the two agents will go, up until the negotiation's end, either with success or failure.

The simulation will assume the existence of two agents, a buyer and a seller. Their mental attributes of Price, Commitment and Time will be specified by the user running the simulation and will allow values between 0 and 1. These values will indicate the importance of every mental attribute for the agent, where 0 means that the attribute is of little importance and 1 means that the attribute is of prime importance. The user will also have to include the public maximum and minimum values for the item being negotiated as publicly available prices for the item in the marketplace. The public prices will be available for both agents, as is the case in the DALIA virtual marketplace where agents would be able to retrieve the item public values from the marketplace's ontology.

I used the Java programming language to the write the code for the agents. In our model the buyer and the seller would be two different objects, interacting with each other. Every agent calculates its own private values that include the private minimum, private maximum and the step. The agent then starts the negotiation, making offers, accepting offers form their opponents, readjusting their internal values, recalculating a next offer price and restating another offer. The process will repeat itself until the negotiation's end with either success, when agents agree to a price and conclude the deal, or with failure, when agents fail to agree on a certain price.

3.2 The Initial Work

As part of the DALIA environment, some functions were designed and proposed as basis for the agents' behavior. These functions take into consideration the agents' mental attributes and use them to calculate their private values in order to negotiate accordingly.

The following is a table containing the different proposed functions to be used by the different agents:

	Buyer	Seller
Private Minimum 1	pubMin+T*(pubMax-pubMin)/10	pubMin+(pubMin)*P*(1-C)/10
Private Minimum 2	-	pubMin+(pubMin)*P*(1-C)
Private Maximum 1	pubMax-(pubMax)*P*(1-C)/10	privMaxS=pubMax-T*(pubMax-pubMin)/10
Private Maximum 2	pubMax-(pubMax)*P*(1-C)	-
Step 1	(PublicMaximum-PublicMinimum)/100	
Step 2	(PublicMaximum+PublicMinimum)/100	
Step 3	(PrivateMaximum-PrivateMinimum)/100	

Table 2: Original Agent Negotiation Functions

For the buyer, the proposed functions were the following:
To calculate the buyer's private minimum:
privMinB= pubMin+T*(pubMax-pubMin)/10

As for the buyer's private maximum, two functions were proposed in different publications:
privMaxB1=pubMax-(pubMax)*P*(1-C)/10

privMaxB2=pubMax-(pubMax)*P*(1-C)

As for the seller, the proposed functions were the following:
To calculate the seller's private minimum, two functions were proposed in different publications:
privMinS1=pubMin+(pubMin)*P*(1-C)/10

privMinS2=pubMin+(pubMin)*P*(1-C)

As for the seller's private maximum:
privMaxS=pubMax-T*(pubMax-pubMin)/10

Where:
privMinB is the buyer's calculated private minimum.
privMaxB1 is the buyer's calculate private maximum according to function 1.
privMaxB2 is the buyer's calculate private maximum according to function 2.
privMinS1 is the buyer's calculated private minimum according to function 1.

privMinS2 is the buyer's calculated private minimum according to function 2.
privMaxS is the buyer's calculate private maximum.
pubMin is the marketplace's publicly available item specific minimum price.
pubMax is the marketplace's publicly available item specific maximum price.
P is the agent's specific price importance attribute.
C is the agent's specific commitment importance attribute.
T is the agent's specific time importance attribute.

And finally, when it comes to calculating the agents' step, which is the value that the agent would be adding or subtracting when it comes to counter offering the opponent agent. The agents' step was defined to be adaptive and dependent on the agent's mental attributes. But in no DALIA specifications paper was the step defined with a "mental attributes" dependant formula. Some step formulas were provided, in particular, the following two formulas, which seem to be agent independent:

Step1=(PublicMaximum-PublicMinimum)/100

Step2=(PublicMaximum+PublicMinimum)/100

3.2.1 Discarding the Un-Needed Functions:

Unfortunately, when used in the simulation, these functions proved to be of little use and did not behave as expected and thus did not provide the expected functionality.

For example, privMaxB2, that is the buyer's second formula for calculating the agent's private maximum price, can be easily discarded as unrealistic.

Given the circumstances where the agent's personal mental attributes are of the following configuration:

Price =1; Commitment=0; the Time attribute can be of any value;
The Public Maximum can be of any value;
The Public Minimum can be of any value strictly larger than 0;

Applying the formula to get the buyer agent's private minimum results in a value strictly larger than 0:

privMinB= pubMin+T*(pubMax-pubMin)/10

The least number this formula can generate is pubMin. This value can be generated when T, the importance of time, is equal to 0; And since the public maximum is larger than 0, then the final value of the private minimum will also be larger than 0.

When it comes to calculating the buyer agent's private maximum using the second formula, the "to be discarded" formula, and under the highlighted circumstances, we get a value less than the private minimum, thus creating a logical inconsistency which leads to ignoring the given formula:

privMaxB2=pubMax-(pubMax)*P*(1-C)

This variable, and under the given circumstances where the Price is equal to 1 and the Commitment is equal to 0, will lead to the following: privMaxB2=pubMax-(pubMax)*1*(1-0)

thus privMaxB2=pubMax-(pubMax)
and finally we get privMaxB2=0;

Since the privMinB is strictly larger than 0, and privMaxB2 is equal to 0, then privMinB is larger than privMaxB2 and thus we have a contradiction which leads us to discard the formula calculating privMaxB2. The same approach will be applied to discard privMaxS2. Given the circumstances where the agent's personal mental attributes are of the following configuration:

Price =1; Commitment=0; the Time attribute can be of any value;
The Public Maximum can be of any value;
The Public Minimum can be of any value strictly larger than 0;

Applying the formula to get the seller agent's private maximum results in a value that is at most equal to public maximum:

privMaxS=pubMax-T*(pubMax-pubMin)/10

When T is 0, privMaxS=pubMax-0 and the seller agent's private maximum becomes equal to the marketplace's Public Maximum.

When calculating the seller agent's private minimum using the second formula and under the indicated circumstances, we get the following:

privMinS2=pubMin+(pubMin)*1*(1-0), thus
privMinS2=pubMin+pubMin
privMinS2=2*pubMin;

In the case where pubMax<2*pubMin, that is when the maximum is not twice as large as the minimum, we will have:

privMinS2 = 2*pubMin>pubMax
pubMax = privMaxS
finally privMinS2 > privMaxS

This creates another contradiction, forcing us to drop the function privMinS2.

And finally, when evaluating the Step2 formula:

Step2 = (PublicMaximum+PublicMinimum)/100

One can easily imagine a scenario where the difference between the public prices can easily lead to a scenario where the first offer by either agent would lead to an offer that is outside the public price range.

For example, given the following scenario:
Public Maximum Price = 10000
Public Minimum Price = 9900
The difference between the Public Maximum Minimum is equal to 100
The step according to step 2 is Step2 = (10000+9900)/100
Thus Step2 = 199

And so Step2 is much larger than the difference, and thus the any increment by either agent would lead to an offer outside of the publicly known range. For this reason the Step2 formula needs to be discarded.

The formula generating Step1 is not perfect too... Since it relies on the Public Maximum and Minimum, the Step will be the same for both agents, and so the final deal will always be according to the current formulas the average between the seller's maximum and the buyer's minimum. And since the buyer's maximum and the seller's minimum are localized is a certain, rather limited, range then the final deal will also always be in a certain minimal range. And so there will be very little difference between the different dealing agents' combinations.

Thus an alternate Step formula needs to be used in order to create a more dynamic experience. For the first set of tests, we propose the following Step:

Step3=(PrivateMaximum-PrivateMinimum)/100

This formula makes up for many shortcomings of the first proposed formula: The use of Private Minimum and Maximum will ensure that the step will be personalized for every agent. Since the agent's private range is calculated according to his personal mental preferences, then the step will be affected indirectly by these mental attributes, thus making it closer to DALIA's initial design. And finally, this new Step formula will ensure that the final negotiation outcome will be dependant on the agents' different mental attributes. Thus the final negotiation outcome range should be wider than the initial range, and so the different negotiating agents' mental attributes combinations will have a more significant impact on the final negotiation outcome.

3.2.2 The Simulation:

Now that no more extra formulas are available, the proposed simulation can be run using the existing formulas, with the exception of the step, that will be using the slightly modified formula that we introduced, Step3.

The simulation will first start by creating the buyer and seller agent according to their mental attributes. Then a draw is made to decide which agent will start the negotiation and will get the chance to present the first offer. The other agent will take the offer and evaluate it, if is less than his next offer, then he will accept it, otherwise, he will adjust his personal maximum or minimum according to his step, then present the new offer to the other agent. The process will repeat itself until both agents agree on a price, or until one of the agents reaches his limit and then the negotiation will end in failure.

Many tests are run for every simulation to ensure the test's integrity. But five major cases will be given more importance and analyzed more thoroughly:

- Rash buyer, conservative seller
- Conservative buyer, rash seller
- Rash buyer, rash seller
- Conservative buyer, conservative seller
- Average buyer, average seller

Where:

- The Rash buyer and seller have their mental attributes of the following configuration: Price = 0, Commitment = 1, Time = 1
- The Conservative buyer and seller have their mental attributes of the following configuration: Price = 1, Commitment = 0, Time = 0
- The average buyer and seller have their mental attributes of the following configuration: Price = 0.5, Commitment = 0.5, Time = 0.5

The rash agent is an agent who wants to conclude a deal as fast as possible and is dying to conclude it.

The conservative agent is an agent looking for a deal of opportunity, willing to take all the required time in order to get the best possible deal.

The average agent is an agent with moderate mental attributes, looking to make a deal in a reasonable amount of time and he is interested at the same time in a fair price.

All simulations will be run with Maximum Public Price = 5000 and Minimum Public Price = 3500.

Of the five scenarios suggested above, the following two will only be displayed:

- Rash buyer, conservative seller
- Average buyer, average seller

3.2.2.1 Rash Buyer, Conservative Seller:

<u>The Buyer attributes are:</u>
The Price attribute is: 0.0
The Commitment attribute is: 1.0
The Time attribute is: 1.0

The Private max is: 5000.0
The Private min is: 3650.0
The Step is: 13.5

<u>The Seller attributes are:</u>
The Price attribute is: 1.0
The Commitment attribute is: 0.0
The Time attribute is: 0.0

The Private max is: 5000.0
The Private min attribute is: 3850.0
The Step is: 11.5

The negotiation was successful with the final value of: 4379.0
The negotiation was completed in 56 proposals and counter proposals

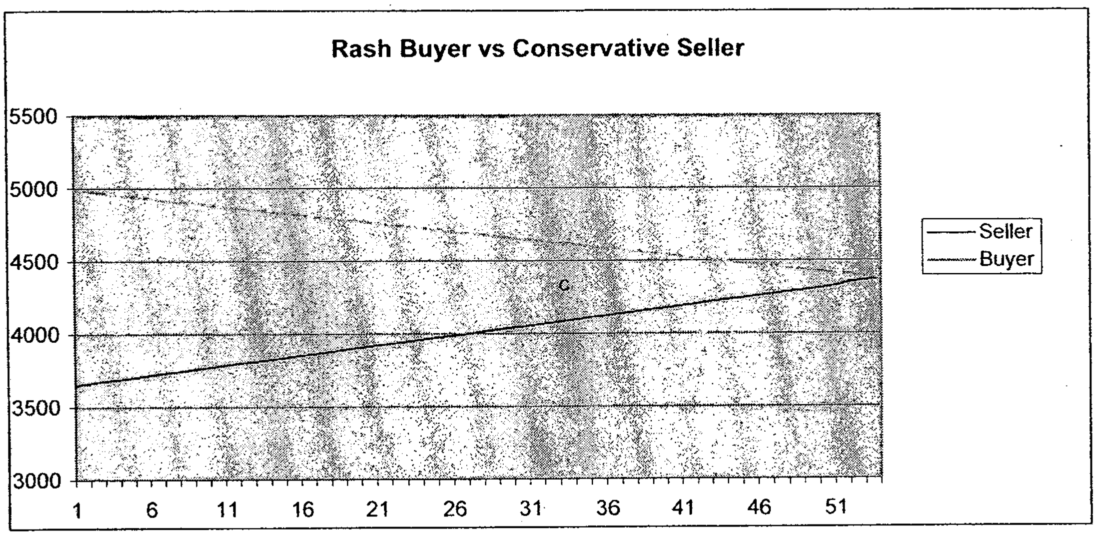

Figure 6: Simulation 1 – Rash Buyer vs Conservative Seller

3.2.2.2 Average buyer, average seller:

<u>The Buyer attributes are:</u>

The Price attribute is: 0.5
The Commitment attribute is: 0.5
The Time attribute is: 0.5

The Private max is: 4875.0
The Private min is: 3575.0
The Step is: 13

<u>The Seller attributes are:</u>

The Price attribute is: 0.5
The Commitment attribute is: 0.5
The Time attribute is: 0.5

The Private max is: 4925.0
The Private min attribute is: 3587.5
The Step is: 13.375

The negotiation was successful with the final value: 4238.0
The negotiation was completed in 53 proposals and counter proposals

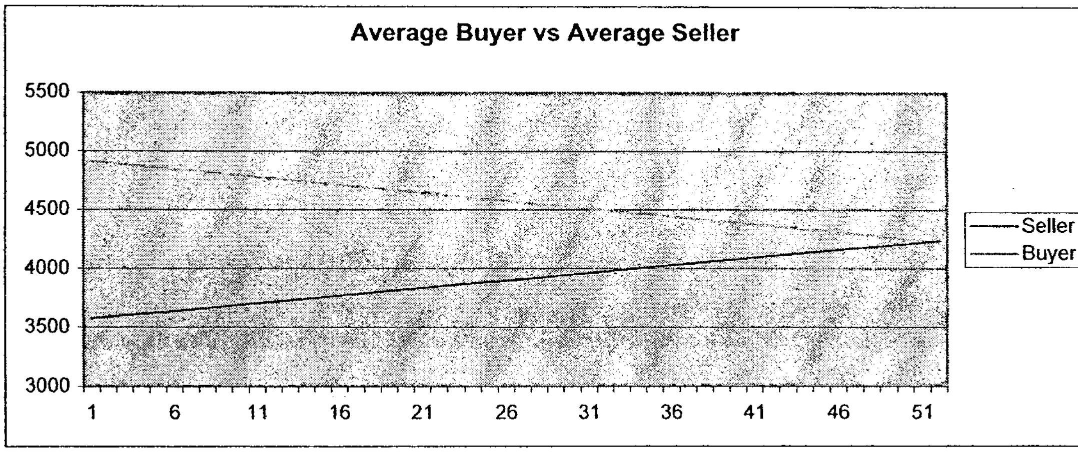

Figure 7: Simulation 1 – Average Buyer vs Average Seller

3.2.2.3 Analyzing the Simulation Results:

All these simulations' analysis leads to the same conclusion, independently from the different negotiation scenarios. In itself, this indicates that the used formulas for the mental states had very little impact on the negotiations' outcome. And so it can be concluded that the mental states had very little impact on the negotiation's outcome.

Given that the halfway point between the two public values, 5000 and 3500, is 4250 we can notice that all the negotiated values were very close to this number. The two numbers that were furthest away from the average were 4070 and 4379 that are away from the average by 180 and 129 respectively.

Assuming that the average would be the fair deal, then the most the agents were able to gain were a mere 4.2% and a 3% in the circumstances were a conservative buyer was negotiating with a rash seller, and when a rash seller was negotiating with a conservative buyer. This, and by far, is not a dramatic result, given the dramatic circumstances of the different agents.

When you couple this result with the fact that the agents' offers were linear, we can conclude that the step, the way offers are evaluated and then new offers are generated needs to be revised.

A final look at the private minimum and maximum agents' formulas, show many weaknesses in these formulas:

For instance in both the buyer's personal maximum and seller's minimum formulas:

$$privMaxB1=pubMax-(pubMax)*P*(1-C)/10$$

$$privMinS1=pubMin+(pubMin)*P*(1-C)/10$$

Whenever the price factor is 0, the commitment factor becomes useless and won't affect the outcome of the formula anymore. And vice versa, whenever, the commitment factor is equal to 1, the price factor loses its importance.

The buyer's minimum and seller's maximum are only affected by the time factor, and so these values need to be adjusted to reflect the relative importance of the time factor, as opposed to other functions that are affected by two mental attributes.

And finally, these functions rely on absolute values; that is they do not take into consideration the difference between the minimum and maximum. In other words, and under certain circumstances, the personal minimum value can have a value larger than the private maximum and even the public maximum.

For instance, when the public maximum is 5000 and the public minimum is 4550, and when both agents have the same mental attitude: Price = 1, Commitment = 0 and Time =1; the agents' private values will be the following:

The buyer's private maximum would be equal to 4500;
The buyer's private minimum would be equal to 4595;

The seller's private maximum would be equal to 4955;
The seller's private minimum would be equal to 5005;

As it can be observed, both minimums under the current circumstances are larger than their respective maximums, and even more, the seller's maximum is even larger than the public maximum.

Thus comes the need to modify these functions to make them more reliable, and realistic. Both private minimum functions and private maximum functions need revision in order to make them more robust. And finally, the step needs to be modified in order for the agent's mental states attributes to have a more dramatic impact.

3.3 The New Functions

In order to be able to introduce new functions, the need arises to go back to the drawing board and analyze how each and every mental attribute can affect the agent's behavior. Even more, the mental attributes need to affect the agent's behavioral model each according to its own weight. And finally, the new functions need to be robust enough in order to make sure that they offer no inconsistencies that can jeopardize the reliability of the agents, and that no special attribute value can affect the importance of other mental attributes.

3.3.1 The Buyer's Behavioral Analysis:

The analysis of the buyer's behavior goes as follows:

- The Time factor: if the time factor is high, then the user must be in a hurry to get the item he desires. This should come at the expense of the price. That is in order to make sure he gets the deal quickly, he must be willing to spend more money. Alternatively, when the time factor is small, then the agent would adopt a more conservative approach that would ensure that he gets an adequate price for the deal.
- The Price factor: the higher the price factor, the less the agent is willing to spend. When the price factor is small, then the agent has no problem paying as much as it takes to get the desired item.
- The Commitment factor: the higher the commitment factor, the more the agent is willing to do to get the desired item. In this case, the more money he is willing to spend to get the item. The lower the commitment, the less the agent is willing to spend, whether it is time or money.

The time factor can only affect the private minimum factor and the step. The higher the private minimum, the less time it takes for the negotiation to reach an end.

It has no effect on the private maximum, as it would not matter how much or how little the agent pays when he is in a hurry.

As for the step, it is obvious that the higher the time, the more the agent is in a hurry, and thus the more the agent is wiling to spend to get the deal done. Thus the higher the time factor, the larger the step.

The price factor does not affect the private minimum, as it does not matter how much or how little the agent pays.

Alternatively, it affects the private maximum as it allows it to extend the amount the agent and user are willing to pay to get the desired item. Thus the higher the price factor, the higher should be the agent's private maximum.

If the price is of high importance, meaning that if the agent is not willing to pay a lot of money, and then he should have smaller increments. This finally means that the higher the importance of time, the smaller the agent's step.

Finally the commitment attribute only affects the private maximum as it would indicate how much the user and agent are willing to pay in order to get the desired item. Thus the higher the commitment the higher the agent must be ready to pay.

Alternatively, the agent should have no problem getting the item he desires for a low price and thus the commitment attribute does not affect the agent's private minimum.

When it comes to the step, the higher the commitment level the more the agent is willing to spend to get the item, and thus the large the increments he will have to conclude the deal. So, the higher the commitment level, the larger the step should be.

The new private minimum and private maximum functions should be designed in such a way to depend on the difference between the public maximum and the public minimum. Following this line of thought, the functions will be designed according to the schema specified hereafter:

- The private maximum value should vary between the public maximum, and 20% off the difference between the Public Maximum and Public Minimum deducted from the Public Maximum. That is:
  PublicMaximum >= PrivateMaximum >=
  PublicMaximum – (PublicMaximum-PublicMimum)*20/100
- The private minimum should vary between the public minimum, and 20% off the difference between the Public Maximum and Public Minimum added to the Public Minimum. That is:
  PublicMinimum <= PrivateMinium <=
  PublicMinimum+(PublicMaximum-PublicMimum)*20/100

Thus, the attributes affecting the private minimum and the private maximum values should re-arranged in such a way to ensure that private minimum and maximum values behave according to design specified above.

3.3.2 The Buyer's Private Maximum:

The buyer's private maximum is proportional to the agent's commitment attribute value. Meaning that whenever the agent's commitment is small, the public maximum should also be small, and as the commitment value rises, the private maximum value should grow with it.

The buyer's private maximum is inversely proportional to the agent's price attribute value. Meaning that whenever the agent's price mental attribute has a small value, the buyer's private maximum would have a rather large value, and whenever the price attribute value starts to rise, the buyer's private maximum would become smaller and smaller.

The buyer's private maximum would be equal to the public maximum when the price mental attribute is 0 and the commitment mental attribute is 1. This combination of attributes' values indicates that the agent is dying to get the item whatever it takes.

The buyer's private maximum would reach its minimal value when the price mental attribute is 1 and the commitment mental attribute is 0. This combination of attributes' values indicates that the agent has little interest in the deal.

When both price and commitment mental attributes are equal to each other, the private maximum's value would be half the difference between private maximum's highest and lowest values. The reason behind this approach is that these two attributes are balancing towards each other and thus whenever they are equal, they cancel each other out and the agent cannot decide which is more important.

Keeping in mind the other formulas' requirements, such as the fact that no attribute should cancel any other attribute for any value it takes, or the domain range limit imposed on the buyer's private maximum values, the following formula is proposed:

BuyerPriateMaximum = PublicMaximum - (PublicMaximum-PublicMinimum) * (1+Price-Commitment)/10

3.3.3 The Buyer's Private Minimum:

In order to design the buyer's private minimum formula, the same approach that was used to design the buyer's private maximum will be adopted.

The function should be proportional to the time mental attribute. Meaning that whenever the time attribute has a small value, the private minimum should be small, and as the time attribute grows, the private minimum should grow with it.

Thus the buyer's private minimum would be equal to the public minimum when the time mental attribute is 0. The reason behind this, is the fact that the agent is rather relaxed and isn't in a rush to concluding a deal.

The buyer's private minimum would reach it maximal value when the time mental attribute is 1 indicating that time is of prime importance for the agent. Starting with a high minimum would reduce the time needed to conclude the deal.

Following the same guidelines used when designing the buyer's private maximum formula, the following is suggested as the agent's private minimum formula:

BuyerPrivateMinimum = PublicMinimum + (Time * (PublicMaximum-PublicMinimum)) /5

3.3.4 The Seller's Behavioral Analysis:

The seller's behavior is exactly the opposite of the buyer's. Ironically they both share the same understanding of the concept of time, price and commitment. But when it comes to putting these concepts into practice, they apply them in two completely opposite directions.

For instance:

- The Time factor: if the time factor is high, then the user must be in a hurry to sell the item he has. A quick sale can not guarantee a perfect selling price, thus a quick sale must happen at the expense of price. Alternatively, for the buyer to grab a better price for his item, he must be willing to spend more time negotiating. Thus a smaller time factor would have the seller agent adopting a more conservative approach that would ensure a more adequate price for the sale.
- The Price factor: the higher the price factor, the more the agent is interested in a good deal. Where a good deal means that the agent isn't ready to sell unless the offered price is more than adequate. When the price factor is small, then the agent has no problem selling his item for any price the potential buyer might offer.
- The Commitment factor: the higher the commitment factor, the more the agent is willing to do to sell the desired item. In this case, the more money he is willing to let go in order to make sure that a sale would take place. The lower the commitment, the more the agent acts in a "laisser aller" attitude, as if he doesn't really care if the deal takes place or not. In practice, this means that the agent would only sell if the price is very generous.

The time factor can only affect the private maximum factor and the step. The lower the private maximum, the less time it takes for the negotiation to reach an end.

It has no effect on the private minimum, as it would not matter how much or how little the agent gets for the item when he is in a hurry.

As for the step, it is obvious that the higher the time, the more the agent is in a hurry, and thus the more the agent is wiling to let go in order to get the deal done. Thus the higher the time factor, the larger the step.

The price factor does not affect the private maximum, as it does not matter whether the agent gets his desired maximum or not.

Alternatively, it affects the private minimum as it allows the agent what is the minimum price he is willing to accept in order to conclude the deal. Thus the higher the price factor, the higher should be the agent's private minimum.

If the price is of high importance, meaning that if the agent is not willing to sell but for lot of money, thus meaning that he should adopt small decrements in order to achieve his goal. This finally means that the higher the importance of time, the smaller the agent's step.

Finally the commitment attribute only affects the private minimum as it would indicate how much the user and agent are willing to accept in order to conclude a deal for the negotiated item. Thus the higher the commitment the less the agent must be ready to accept.

Alternatively, the agent should have no problem accepting a deal if his opponent is willing to offer a generous offer, and thus the commitment attribute does not affect the agent's private maximum.

When it comes to the step, the higher the commitment level the more the agent is willing to let go in order to sell the item, and thus the large the increments he will have to conclude the deal. So, the higher the commitment level, the larger the step should be.

The new private minimum and private maximum functions should be designed in such a way to depend on the difference between the public maximum and the public minimum. Just the same way the buyer's functions were designed. Following this line of thought, the functions will be designed according to the schema specified hereafter:

- The private maximum value should vary between the public maximum, and 20% off the difference between the Public Maximum and Public Minimum deducted from the Public Maximum. That is:
  PublicMaximum >= PrivateMaximum >=
  PublicMaximum - (PublicMaximum-PublicMimum)*20/100
- The private minimum should vary between the public minimum, and 20% off the difference between the Public Maximum and Public Minimum added to the Public Minimum. That is:
  PublicMinimum <= PrivateMinium <=
  PublicMinimum+(PublicMaximum-PublicMimum)*20/100

Thus, the attributes affecting the private minimum and the private maximum values should re-arranged in such a way to ensure that private minimum and maximum values behave according to design specified above.

3.3.5 The Seller's Private Maximum:

In order to design the seller's private maximum formula, the same approach that was used to design the buyer's functions will be adopted.

The function should be inversely proportional to the time mental attribute. Meaning that whenever the time attribute has a small value, the private maximum should be large, and as the time attribute grows, the private maximum should decrease until it reaches its minimum.

Thus the seller's private maximum would be equal to the public maximum when the time mental attribute is 0. The reason behind this, is the fact that the agent is rather relaxed and isn't in a rush to concluding a deal.

The seller's private maximum would reach its minimal value when the time mental attribute is 1 indicating that time is of prime importance for the agent. Starting with a low maximum would reduce the time needed to conclude the deal.

Following the same guidelines used when designing the buyer's private minimum formula, the following is proposed as the agent's private maximum formula:

SellerPrivateMaximum = PublicMaximum –
(Time * (PublicMaximum-PublicMinimum)) /5

3.3.6 The Seller's Private Minimum:

The seller's private minimum is inversely proportional to the agent's commitment attribute value. Meaning that whenever the agent's commitment is small, the public minimum should be high, and as the commitment value rises, the private maximum value should become gradually smaller.

The seller's private minimum is proportional to the agent's price attribute value. Meaning that whenever the agent's price mental attribute has a small value, the buyer's private minimum would also have a small value, and whenever the price attribute value starts to rise, the seller's private minimum would grow with it.

The seller's private minimum would be equal to the public minimum when the price mental attribute is 1 and the commitment mental attribute is 0. This combination of attributes' values indicates that the agent is waiting for a very good price to conclude a deal.

The seller's private minimum would reach its maximum value when the price mental attribute is 0 and the commitment mental attribute is 1. This combination of attributes' values indicates that the agent dying to reach a deal.

When both price and commitment mental attributes are equal to each other, the private minimum's value would be half the difference between private maximum's highest and lowest values. The reason behind this approach is that these two attributes are balancing towards each other and thus whenever they are equal, they cancel each other out and the agent can not decide which is more important.

While abiding by the rules and requirements specified before, the following formula is suggested:

SellerPriateMinimum = PublicMinimum +
(PublicMaximum-PublicMinimum) * (1+Price-Commitment)/10

3.3.7 The Step:

Since both buyer and seller agents' step behaves the same way, it was decided to have them both share the same formula. In other words, the mental attributes of price, commitment and time affect the step the same way regardless of the agent type.

For instance, when considering the time attribute with the step, it becomes obvious that the higher the time importance, the more the agent is in a hurry. Thus to be able to conclude a deal quickly, he must have a large step. Thus the higher the time factor, the larger the step. The opposite is also true, if the price factor is small, then the agent is in no hurry to conclude the deal, and so his step should b small. Thus the time attribute and the step are proportional.

If the price is of high importance, then the agent is conservative about the deal, thus meaning that he should adopt a small step in order to show his uncertainty.

This finally means that the higher the importance of time, the smaller the agent's step. The opposite is also true. If the agent doesn't care about the price, then he wouldn't mind spending as much as it takes in order to conclude the deal, thus indicating a larger step. Thus the price and step are inversely proportional.

Finally the higher the commitment attribute value the higher the step. Since the user is very committed to the deal, and thus in order to make sure the deal is successful, it is in the agent's interest to adopt a rather large step. Inversely, if the commitment is small, then it would not be in the agent's interest use a large step approach and it would be more beneficial if he uses a smaller step, thus he would only be interested in an opportunistic deal and thus a more conservative step. Thus the commitment and step are proportional.

The step, in order for it not to violate any minimum and maximum values, also needs to depend on the difference between the private maximum and minimum of the agent. Given that the agent's private minimum and maximum are included in the public minimum and maximum range, then the step should not face any logical problems.

As a condition, the step will be made to vary between 2.5*x/100 and 0.5*x/100 where x is (PrivateMaximum-PrivateMinimum). When the circumstances are most favorable, meaning when the price's value is 0 and the time and commitment values both are 1, then the step will be at its peak. On the other hand, when the time and commitment values are 0 and the time's value is 1 then the step will be at the lowest value it can take.

So, the following formula is proposed to be applied for the price, as it satisfies all the conditions described before:

Step= (PrivateMaximum-PrivateMinimum) * (1.5+Commit+Time-Price)/100

3.3.8 Simulating the New and Revised Functions:

After revising the existing functions, and integrating them in the simulation, another round of simulation is tested in order to check the whether the different agents' mental attributes have any significant effect on the negotiation outcome.

To this end, the same simulation procedure described before will also be adopted. Thus once more, the buyer and seller agents will first be created according to their mental attributes. Except that this time, the agent's private maximum, minimum and step will be calculated according to the new functions. And then, in turn, the agents will propose each other offers. In turn the agents will evaluate their opponent's offer, and then accordingly, they will either accept them or counter offer them, or, if need be, reject them and forfeit the negotiation. And thus the negotiation will end with either success when both agents agree on a certain price or with failure when one of the agents reaches his negotiation limit without agreeing on a price.

Once more, five cases will be presented and analyzed:
- Rash buyer, conservative seller
- Conservative buyer, Rash Seller
- Rash buyer, rash seller
- Conservative buyer, conservative seller
- Average buyer, average seller

Where:
- The Rash buyer and seller have their mental attributes of the following configuration: Price = 0, Commitment = 1, Time = 1
- The Conservative buyer and seller have their mental attributes of the following configuration: Price = 1, Commitment = 0, Time = 0
- The average buyer and seller have their mental attributes of the following configuration: Price = 0.5, Commitment = 0.5, Time = 0.5

The rash agent is an agent who wants to conclude a deal as fast as possible and is dying to conclude it.

The conservative agent is an agent looking for a deal of opportunity, willing to take all the required time in order to get the best possible deal.

The average agent is an agent with moderate mental attributes, looking to make a deal in a reasonable amount of time and he is interested at the same time in a fair price.

All simulations will be run with Maximum Public Price = 5000 and Minimum Public Price = 3500.

Of the five suggested scenarios, only the following two will be displayed:
- Rash buyer, conservative seller
- Average buyer, average seller

3.3.8.1 Rash Buyer vs. Conservative Seller

The Buyer attributes are:
The Price attribute is: 0.0
The Commitment attribute is: 1.0
The Time attribute is: 1.0

The Private max is: 5000.0
The Private min is: 3800.0
The step is: 42.0

The Seller attributes are:
The Price attribute is: 1.0
The Commitment attribute is: 0.0
The Time attribute is: 0.0

The Private max is: 5000.0
The Private min attribute is: 3500.0
The step is: 7.5

The negotiation was successful with the final value: 4820.0
The negotiation was completed in 26 proposals and counter proposals

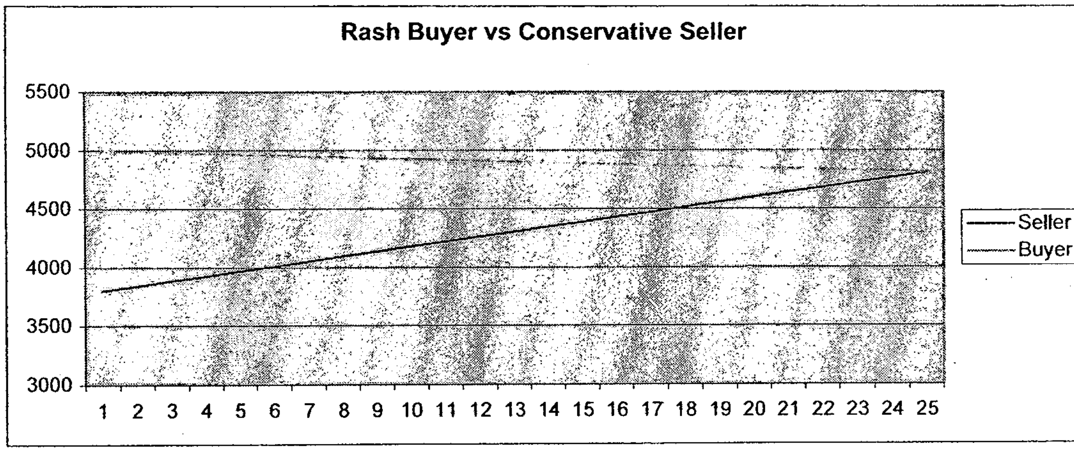

Figure 8: Simulation 2 – Rash Buyer vs. Conservative Seller

3.3.8.2 Average Buyer vs. Average Seller

The Buyer attributes are:
The Price attribute is: 0.5
The Commitment attribute is: 0.5
The Time attribute is: 0.5
The Private max is: 4850.0
The Private min is: 3650.0
The step is: 24.0

The Seller attributes are:
The Price attribute is: 0.5
The Commitment attribute is: 0.5
The Time attribute is: 0.5
The Private max is: 4850.0
The Private min attribute is: 3650.0
The step is: 24.0

The negotiation was successful with the final value: 4250.0
The negotiation was completed in 27 proposals and counter proposals

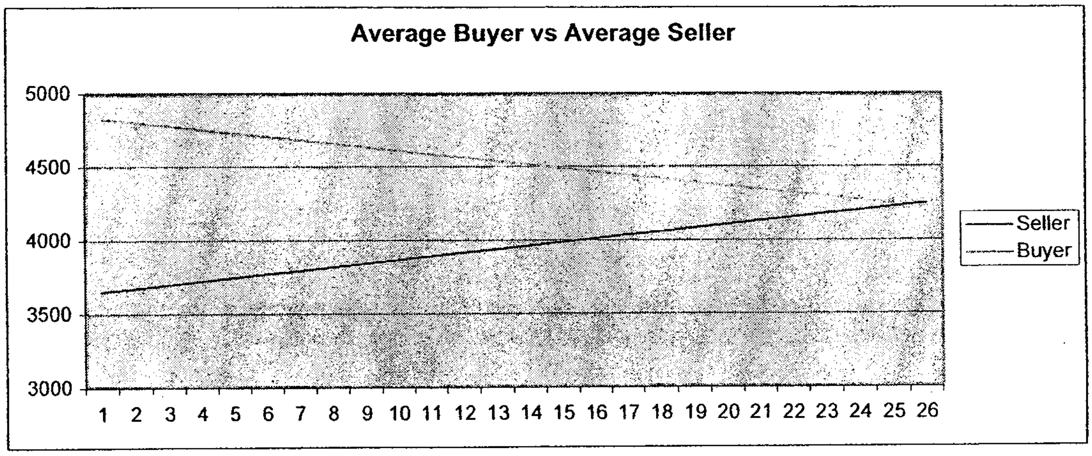

Figure 9: Simulation 2 – Average Buyer vs. Average Seller

3.3.8.3 Analyzing the Simulation Results:

A quick look at the new negotiation charts show an improvement over the previous simulation results: This is very apparent when considering the final negotiation outcome as it varies dramatically with the different agents' combinations, and the varying number of turns that also reflects much clearer now the different agents' mentalities and priorities.

Of course this is due to the more adequate mental state translation functions operating in the background. These functions better reflect the mental states of the agent, and thus give more realistic private attributes such as the agent's private maximum, minimum and step. These better attributes, that operate in the background, lead to better and more realistic negotiation results.

First of all, the new mental attributes functions now effectively affect the negotiation outcome: thus a conservative agent acts, like he should, starting with offers very close to the public minimum for the buyer or to the public maximum for the seller. Even more, their offer increments are also shy, better reflecting their mental states. For example, a conservative buyer's private minimum is equal to the public minimum, and has step of 6, which is very conservative and given that it is 4% the difference between the public maximum and the public minimum.

Alternatively, a rash agent has a very bold attitude starting the negotiations with very large offers and increasing his offers by very large values. For instance, a rash buyer's private minimum is of 3800, a full 300 above the public minimum, and when coupled with a step of 42, which is around 30% of the difference between the public maximum and the public minimum, you are guaranteed a quick negotiation. In only a few turns, the rash agent can cover the difference with any other agent.

As for the negotiation results, some dramatic differences can be noticed with the different combinations of agents, especially the most extreme of combinations. For instance, when posing a rash buyer with a conservative seller, the final negotiation ends successfully with the final price of 4820, meaning that the rash agent almost paid the public maximum in order to get the deal going. The final result is around 90% more than the average that an agent is supposed to pay under normal circumstances, given that the average is half the sum of the public maximum and the public minimum.

Alternatively, when opposing a conservative buyer to a rash seller, even though the agents fail to agree on a final price, the final offer had a value of 3680, which is also around 85% less than the average that an agent is supposed to pay under normal circumstances. This shows the desperation of the seller to get the deal done; even though he failed to get a deal, the seller gave a very good price for the opposing agent before finally giving up on the negotiation as he deemed it to be unprofitable.

And finally, the number of turns, and thus the time, that every negotiation requires to reach its conclusion, also varies dramatically depending on the agent combination at hand. In the previous simulation, almost all negotiations consumed the same time to reach their conclusion. Under the new conditions, the negotiation time varied according to the mental attributes of the negotiating agents. For instance, two rash agents negotiating only needed 14 proposals to reach an agreement whereas two conservative agents required 113 offers and counter offers in order to agree in a price.

A weak point still not covered by these revised functions and agents is the linearity of the proposals. Both agents keep offering the same step from beginning to end, thus making them very predictable, and so very vulnerable. Thus the way agents consider new offers still needs some adjustments in order for them to be abele to cope with the different circumstances and changes that occur during the negotiation process.

3.4 Enhancing the Step

3.4.1 The Art of War:

As pointed out in the sections before, the only remaining weak point in the current agent model is the linear offers algorithm implemented into the agents. In order to help the agents become more adaptable the introduction of a multiplier for the step is proposed, thus making the agent's step variable and adaptable.

In order to optimize the agent performance by modifying the step, "The Art of War", the famous Chinese book written by general Sun-tzu, will be used as a source for inspiration. "The Art of War" is a well renowned book on which lies the foundation of many military, business and relationship models. The suggested model will be improved according to advices purged from "The Art of War".

Chapter 3 titled "Strategic Offensive" presents some strategies to be followed in order to ensure victory. Finally the chapter is concluded by the following:

"Hence the saying
'Know the enemy,
Know yourself,
And victory
Is never in doubt,
Not in a hundred battles.'

He who knows self

But not the enemy
Will suffer one defeat
For every victory.

He who knows
Neither self
Nor enemy
Will fail
In every battle."

From this, we conclude that our agent needs to know first himself, then this opponent in order to be able to achieve a good negotiation result. Thus some sort of technique needs to be put in place so that the agent can monitor his opponent to get the upper hand in the negotiation.

Moving back to chapter 1, titled "Making of Plans", we quote the following:
"The Way of War is
A Way of Deception.

When able,
Feign Inability;

When deploying troops,
Appear not to be;

When near,
Appear far;

When far,
Appear near."

And the chapter resumes with:
"If the enemy is full,
Be prepared,
If strong,
Avoid him.

If he is angry,
Disconcert him.

If he is weak,
Stir him to pride.

If he is relaxed,
Harry him;"

Thus when dealing with the opponent agent, it is not enough for agent not to make a mistake, he also has to deceive his opponent in order to make him assume wrong information about the agent's circumstances and preferences. Even more, the agent has also to deceive his opponent in order to make force him into making a mistake.

And finally in chapter 6, "Empty and Full", Master Sun suggests that in order to gain an advantage over your enemy, you have to discover his plans while making sure that yours stay hidden from him:

"Scrutinize him,
Know the flaws
In his plans.

Rouse him,
Discover the springs
Of his actions.

Make his for visible,
Discover his grounds,
Of death and life.

Probe him,
Know his strengths
And weaknesses."

Thus in order for an agent to gain an advantage over his opponent in a negotiation, he would have to better know his opponents desires and thus he would be able to better adapt with the situation.

Master Sun resumes by talking about how an agent should adapt to the varying circumstances of the war, in order to make the most out of the circumstances themselves:

"The highest skill
In forming dispositions
Is to be without form;
Formlessness
Is proof against the prying
Of the subtlest spy
And the machinations
Of the wisest brain.

Exploit the enemy dispositions
To attain victory;
This the common man
Can not know."

"Victorious campaigns
Are unrepeatable.
They take form in response

To the infinite varieties
Of circumstance.

Military dispositions
Take form like water.
Water shuns the high
And hastens to the low.
War shuns the strong
And attacks the weak.

Water shapes its current
From the lie of the land.
The warrior shapes his victory
From the dynamic of the enemy.

War has no
Constant dynamic;
Water has no
Constant form.

Supreme military skill lies
In deriving victory
From the changing circumstances
Of the enemy."

Thus, an agent cannot make any significant gain by adopting a strategy independently from his opponent's actions but will rather have to create his strategy from his opponent's strategy and actions. In short, the agent's opponent needs to be analyzed, and then the agent would have to react to this accordingly, by adopting a strategy that depends on the different circumstances and on the opponent agent himself.

3.4.2 Applying the "Art of War" strategies for the agents

Starting from Master Sun's stratagem, the following four key factors will be taken into consideration when computing the agent's step and thus his next offer:

- A time limit: it would be introduced to create an actual time limit for the agent's negotiation time. The time limit would depend on the agent's mental attributes and a cumulative negotiation consumption time average. The agent's time limit would be represented by the number of offers an agent is allowed to make during a certain negotiation. Thus an agent would have to conclude a deal before he reaches his time limit; otherwise he would have to forfeit the negotiation. This also serves as a precaution system: the longer the negotiation takes, the more an agent would be giving up to be able to conclude a deal, thus a longer negotiation indicates a large preferences mismatch between the two competing agents thus putting one agent at disadvantage towards the other agent.

- A time factor: the time factor will affect the agent's step. As the agent starts running out of time, he would have to increase his step in order to strike a deal before running out of time. Thus this factor starts very small and becomes larger as the agent starts running out of time.

- A step comparator: The agent would have to compare his step to his opponent's step and react accordingly. If an agent's step is larger than his opponent's, than he would decrease his step for the following offer in order to try and stay on par with his opponent and not be the only one sacrificing the winning margin in order to conclude the deal.

- A pattern identifier: the agent would have to memorize his opponent's previous two offers. He would then check these patterns, if any significant change is detected in the opponent's offers, the agent would immediately counter react with inverse ratios to his opponent's making sure that he decreases his step until the situation clarifies.

Thus the new agents would know themselves, by knowing their preferences, their step and their time limits. They would know their enemy by constantly monitoring his offers.

When the opponent agent tries increases or decreases his offers significantly, the agent would instantly react, and protect himself thus making sure he deals well with agents with better circumstances, while at the same time rousing intimidated agents so that they give up more than they wanted initially.

By adapting his offers according to his opponent's, an agent would be probing his opponent and waiting for him to show what he wants before making an adequate move.

Finally by having all his offers adapted to his opponent's and according to the circumstances of the negotiation, and agent would be formless like the water, thus allowing him to negotiate better and achieve better deals...

3.4.3 Calculating the Time Limit:

The time limit depends on the agent's mental attributes as well as a certain average time value.

Thus to be able to get the average negotiation time, 300 simulation runs were performed with random mental attributes for the buyer and seller, while fixing the item's public price range.

As a result, the average negotiation time was determined to be 27.6. For practicality reasons, the average's ceiling will be considered as the average value. Thus, a negotiation under normal circumstances should be done in around 28 offers and counteroffers.

The most rapid negotiation was finished in 14 offers and counter offers.

The longest negotiation took 130 steps to complete.

Thus the time limit range should vary between 14 and 130 with the average being at 28.

The mental states attributes as stated before affect the time limit:

- The price: the higher the importance of price, the longer the agent should affect the negotiation to last in order to ensure that he gets a satisfactory deal. Thus the higher the importance of time, the higher the time limit. The opposite is true, the lower the importance of price, the lower the time limit. The time factor can only increase the time limit, but a low time limit cannot take the agent's time limit below the average time limit. Thus a price attribute with value 0 does not affect the time limit, whereas a time limit of 1 would significantly increase the time limit.

- The commitment: the higher the commitment, the harder the agent will try to get the deal and thus the higher the time limit. In short, a high commitment indicates a high time limit. The opposite is also true, the lower the commitment, the lower the time limit. Keeping I mind that the commitment attribute can only increase the time limit and cannot decrease it below the average limit. Thus a commitment of 0 won't affect the time limit, whereas a commitment of 1 would dramatically increase it.

- The time: the higher the importance of time, the lower the time limit, as the agent would be in a rush to concluding a deal and thus he would not need a high limit cap. A low time attribute would alternatively increase the time limit, but not beyond the average. Thus a time attribute of 0 would not affect the time limit at all whereas a time attribute of 1 would significantly decrease the time limit taking it close to its minimum.

In order for the time limit to reach the maximum of 130, the agent needs to have both the price and commitment attributes set to 1 and his time attribute set to 0.

In order for the time limit to reach the minimum of 14, the agent needs to have time attribute set to 1 and both the price and commitment attributes set to 0.

Thus the time factor should affect the time limit twice as much as the other two attributes since it is the only attribute reducing the time limit value.

Following the guidelines stated above, the following formula to calculate the agent's time limit is proposed:

AgentTimeLimit = AVG + (AVG*Price/4) + (AVG*Commitment/4) - (AVG*Time/2)

Where AVG is the average time limit value.

The formula above would produce symmetric time limit values where the average is half way through. A postern function is then applied to ensure that the function respects the range indicated above of 14 to 130 while keeping the 28 as average.

As the agent learns from experience and as he undergoes more and more negotiations, he would constantly keep updating his average time limit, and would thus use the updated value for the future negotiations. Unfortunately this feature won't be implemented in the current agents build as no history is available yet.

3.4.4 The Time Factor:

The time factor is a multiplier that will be applied to the step in order to affect it, the step, by the time limit. It is designed to increase as the agent's negotiation time reaches 0, meaning that, as the agent's time runs out he will be increasing his step to make sure he reaches a deal.

The time factor will vary between 1 and 3. When the negotiation starts, time is not a factor, and thus the agent is not particularly in a hurry to conclude a deal. This the time factor will take a value of 1 and thus won't be affecting the step. As the agent runs out of time, the time factor will steadily increase until it reaches the value of 3 thus indicating that the step will be multiplied by 3 as a last attempt to conclude a deal.

At every turn, the time factor is incremented by a certain value that was calculated earlier. The incremented value depends on the number of offers an agent is allowed to present, and will adapt accordingly to make sure that the time factor starts as 1 and finishes as 3 when the agent is running out of time.

3.4.5 The Step Comparator:

At every turn, the past step is compared to the opponent agent's step. If the agent's step is smaller than his opponent's then he has nothing to do and the comparing factor will take the value of 1 thus not affecting the step.

Whenever the agent's step is larger than his opponent's that the agent would have to deal with the situation and decrease his step in order to keep it close to his opponent so that the final negotiation outcome isn't unfavorable. In other words, if an agent's step is larger than his opponent's, then the final negotiation outcome would definitely be unfavorable for the agent. So, and in order to fight back this discrepancy, the agent would monitor both steps, and try to reduce his, whenever it is deemed to be unfavorable in order to compensate the difference against the other agent.

Thus, in the case when the agent's step is larger than his opponent's the comparing factor would take the following value:

stepCompare = opponentStep/MyStep

According to this function, the further away the two steps are from each other, the intense will be the effect of the step comparator on the step, in order to make up for the difference between the two agents. Conversely, whenever the two steps are closer, the step comparator will only have a minor effect on the step.

This factor would only decrease the agent's step as a precaution measure, and it would not increase it. The least value it can take is very close to 0 and the highest value would be 1.

Finally, this attribute relates to Master Sun's teachings in the sense that the agent would be relying on his enemy, and not only on himself, in order to create a dynamic strategy that would help him get a better result from the negotiation. This would also compensate for the agent's mental attributes and creates a balancing factor that is purged from the dynamic of the negotiation.

3.4.6 The Pattern Identifier:

The pattern identifier keeps monitoring the opponent's previous steps. Whenever a significant change is detected in the opponent's behavior, a similar effect will be applied by the agent.

For instance, if the opponent agent is running out of time, then his step would tend to increase significantly. Whenever such an increase is detected, the agent would respond by lowering step, thus profiting from the circumstances that his opponent is forced to use a high step to make some extra profit margin.

If on the other hand the opponent is reducing significantly his step, indicating that he's conditions are better than the agent's, then it becomes the agent's responsibility to protect itself by lowering its step in its turn by a value relevant to the opponent's variation.

Thus, whenever a change is detected in the opponent's strategy, the agent would counter-react accordingly in order to make sure that he will not be at a disadvantage come the end of the negotiation.

Once more, the agent would be using the opponent himself and the dynamic of the negotiation in order to better his final outcome of the situation, as mentioned in Master Sun's teachings. This factor will also have a throttling effect that would compensate for the agent's initial mental attributes, and shape a negotiation dependant strategy.

This factor is calculated according to the following:

If a dramatic increase in the opponent's step is detected, then the agent would decrease his own step relatively to this decrease, as it would be more beneficial for him to leave the other agent increase his step on his own and in the mean time the current agent would be profiting from the circumstances to gain an advantage when the negotiation ends:

If CurrentStep significantly larger than PreviousStep

Factor = PreviousStep/CurrentStep

If a dramatic decrease in the opponent's step is detected, then the agent would also decrease his step as a precaution measure in order not to be at a disadvantage when the negotiation reaches its closing stages:

If CurrentStep significantly smaller than PreviousStep

Factor = CurrentStep/PreviousStep

This factor can only decrease the agent's step as a precaution measure, and would not increase it. The lowest value is can take is very close to 0 and its maximum value would be 1.

3.4.7 The Step Multiplier:

Having finished introducing the new attributes that will be introduced to the agents, it is time to talk about how these factors will be implemented and how they will be integrated with the step.

The new step as indicated earlier will be dynamically affected by the time factor, the step comparator factor and the step pattern factor. That is by the agent's own preferences and circumstances as well as his opponent's offers.

Using the opponent's offers as a basis for counter offering the opponent, and not other techniques has a major reason behind it. Since the agents are competing over the price, it makes more sense to analyze the opponent agent's price offers rather than try and predict his mental attributes. Predicting an agent's mental attributes while ignoring his behavior during the negotiation will be like judging a person according to what he thinks rather than to what he does. Even more, in the case of heterogeneous agents negotiations, the opposing agent might be using a different approach that determines his behavior that cannot be mapped to system used by the current agent, and thus putting the agent in a situation where he is not able to predict his opponent. For these two reasons, the adoption of a technique that reacts according to the opponent agent's offer would be of more benefit to the agent.

Thus, at every turn, the step will be recalculated so that the time factor, comparator factor and the pattern factor will be recalculated and reintegrated with the step. To this end, the following multiplier function is proposed as integration for all of the step attributes into one multiplier.

Multiplier = TimeFactor * CompareFactor * PatternFactor

At its lowest, the multiplier will take a value very close to 0. This will be the case when both CompareFactor and the PatternFactor have values close to 0 and the time factor has a rather low value. The highest value the multiplier can take is equal to highest value the TimeFactor can take. According to the current design, the TimeFactor can at most be equal to 3 and thus 3 is the maximum value that the multiplier can take. It will happen when the Timefactor reaches it maximum value while having the CompareFactor and the PaternFactor with values equal to 1.

Once the multiplier calculated, it would have to be integrated with the step. To this end, the following is suggested:

Step = Step * Multiplier

Having the step affected by the multiplier will result in a more dynamic step that will ensure that the agent approaches every negotiation situation accordingly. And as the negotiation circumstances change, so will the step to reflect the priorities of the agent and the way he is approaching the current situation. By using the formula specified above, the step will vary between a value close to and up to 3 times the initial step. This variance is directly affected by the multiplier, and the variance of the multiplier was described and analyzed earlier, and so the same that applies to the multiplier value also applies for the step.

3.4.7 Running the Final Simulation:

A final simulation run will be executed and analyzed. The same cases specified earlier will also be simulated again.

The goal of the last simulation is to check the effect that the multiplier factor has had on the outcome of the negotiation and most importantly is to verify whether the agents' offers are still linear or whether they are more dynamic and "curved".

The buyer and seller agents will be created as before according to their mental attributes and will contribute to the negotiation by presenting in turn their offers and counter offers. The negotiation ends with either success or failure. Success means that the two agents were able to agree on a price. Failure indicates that the agents required more time to achieve an agreement.

One last time, five cases will be presented and analyzed:

- Rash buyer, conservative seller
- Conservative buyer, rash seller
- Rash buyer, rash seller
- Conservative buyer, conservative seller
- Average buyer, average seller

Where:

- The Rash buyer and seller have their mental attributes of the following configuration: Price = 0, Commitment = 1, Time = 1
- The Conservative buyer and seller have their mental attributes of the following configuration: Price = 1, Commitment = 0, Time = 0
- The average buyer and seller have their mental attributes of the following configuration: Price = 0.5, Commitment = 0.5, Time = 0.5

The rash agent is an agent who wants to conclude a deal as fast as possible and is dying to conclude it.

The conservative agent is an agent looking for a deal of opportunity, willing to take all the required time in order to get the best possible deal.

The average agent is an agent with moderate mental attributes, looking to make a deal in a reasonable amount of time and he is interested at the same time in a fair price.

All simulations will be run with Maximum Public Price = 5000 and Minimum Public Price = 3500.

The agent time limit factor will only be used to monitor the progress of the agents and will not be used as an actual negotiation-ending factor. This will allow for monitoring of the development of the simulation till its closing stages without causing any premature ending. But at the same time, the time limit can always be used added to the analysis and it will help determine what deals were to end in failure had it been implemented.

Of the five suggested scenarios, only the following two will be displayed:

- Rash buyer, conservative seller
- Average buyer, average seller

3.4.7.1 Rash Buyer vs. Conservative Seller

The Buyer attributes are:
The Price attribute is: 0.0
The Commitment attribute is: 1.0
The Time attribute is: 1.0

The Private max is: 5000.0
The Private min is: 3800.0
The step is: 42.0
The time limit is: 21.0

The Seller attributes are:
The Price attribute is: 1.0
The Commitment attribute is: 0.0
The Time attribute is: 0.0

The Private max is: 5000.0
The Private min attribute is: 3500.0
The step is: 7.5
The time limit is: 79.0

The negotiation was successful with the final value: 4755.411468896812
The negotiation was completed in 44 proposals and counter proposals

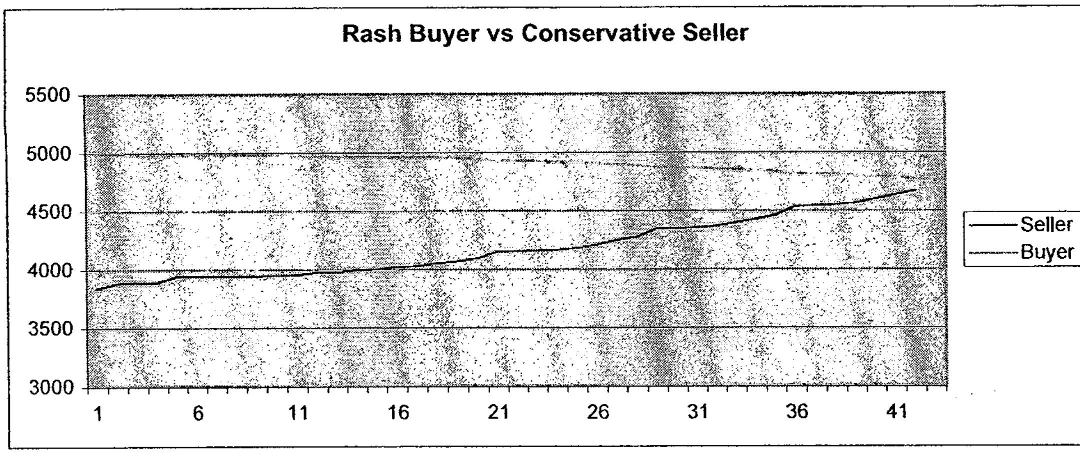

Figure 10: Simulation 3 – Rash Buyer vs. Conservative Seller

3.4.7.2 Average Buyer vs. Average Seller

The Buyer attributes are:
The Price attribute is: 0.5
The Commitment attribute is: 0.5
The Time attribute is: 0.5

The Private max is: 4850.0
The Private min is: 3650.0
The step is: 24.0
The time limit is: 28.0

The Seller attributes are:
The Price attribute is: 0.5
The Commitment attribute is: 0.5
The Time attribute is: 0.5

The Private max is: 4850.0
The Private min attribute is: 3650.0
The step is: 24.0
The time limit is: 28.0

The negotiation was successful with the final value: 4228.66666666667
The negotiation was completed in 18 proposals and counter proposals

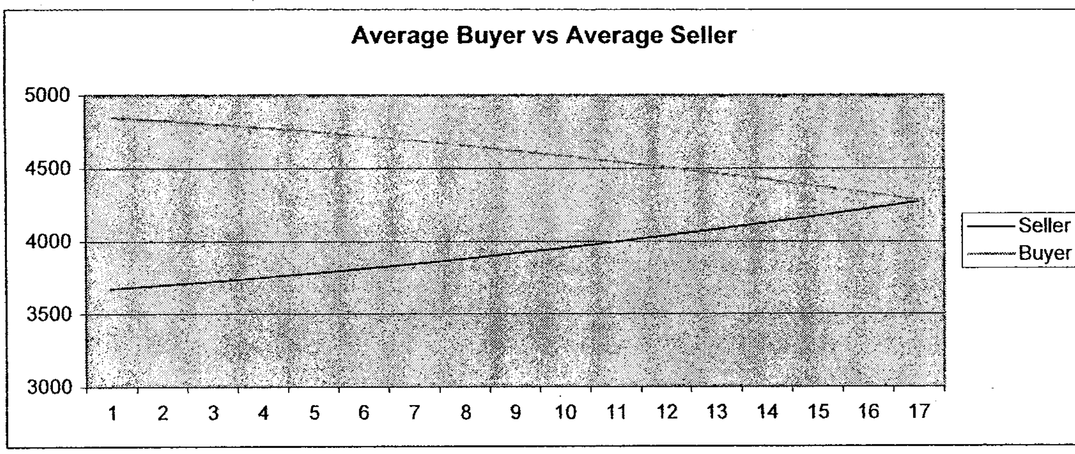

Figure 11: Simulation 3 – Average Buyer vs. Average Seller

3.4.7.3 Simulation Analysis:

The final negotiation results are close enough to the previous run. This is because the major functions governing the behavior of the agents are still in place. Functions like the private minimum and maximum calculation are still in place and still play a major role in the behavior of the agents. For instance, the rash buyer/conservative seller negotiation concluded with the values 4820 and 4755 in the revised and final versions respectively, with the difference between the conclusions of both deals being mere 65. Even more, the rash buyer/rash seller negotiations ended with just 3 as the difference between both negotiations types, with the respective values of 4304 and 4271 for the old and the new systems.

This is due to the fact that both agents are constantly reacting to each other's changes and using the same model in order to counter offer each other. This is why no significant change in the final negotiation value was found.

Alternatively, the time that is required in order to achieve a negotiation is where the major improvement happened. With the new technique, it becomes more obvious when we have a case of agent cooperation and agent competition. In the cases where the agents were competing against each other and had opposing priorities, the negotiation took significantly more time to complete. Whereas in the case when agents had common mental attributes values and priorities, the negotiations took significantly less time to complete.

For instance, in the case where we oppose a rash buyer to a conservative seller, the steps required to reach an agreement jumped 44% from 26 for the old simulation to 44 in the new simulation. Whereas the case when opposing two conservative agents, the negotiation ended in 60% less steps moving the required time from 133 for the old simulation to just 67 steps for the new system.

But most important of all is the agent behavior during the negotiations. Whereas the previous agents used to submit offers with constant increments without taking into consideration the negotiation's circumstances, the new agents on the other hand react dynamically to the different circumstances that happen during the negotiation making them more adaptable to the varying circumstances of the negotiation.

These dynamic agents' reactions lead to more dynamic negotiation experiences, where the agents dynamically change their offer types, making them sometimes stubborn and refusing to cooperate with the other negotiator, and sometimes very cooperative where they generously offer up to 3 times their initial step.

This has a direct effect on the agents' offer curves making them sometimes linear, sometimes rather flat, and sometimes with exponential like slops. These different negotiation attitudes are dynamic to the agent's own preferences and to the circumstances of the negotiation. Meaning that even if an agent is in a hurry, if his opponent is even more rash, then the agent would end up with a rather linear offers curve when compared to the other agent's curve.

When comparing this result to Kasbah's, many advantages can be instantly noticed. For instance, in Kasbah the user has to pre-select 1 of 3 negotiation curves, and the agent would adopt this curve in his negotiation regardless of the circumstances of the negotiation and of the other agent. For instance, if two users select exponential functions with different slopes, both agents would stick to the requirement rather than adapt to the situation. Such behavior would be non existent with the proposed agents as they would adapt with the situation and circumstances and their offers will vary according to the user's needs and opponent's offers.

Even more, an average user who is not very familiar with curves and how they operate would find the process of choosing a negotiation curve a not very friendly process. On the other hand, it would be very easy for a user to determine his mental preferences and the agent from then on would calculate the relevant attributes in order to meet the user's needs. And then, the agent would dynamically determine during the negotiation and according to the user's preferences and opponent's offers the adequate curve that would fit best the negotiation.

And finally, the time limitations would help determine whether a deal is favorable and worth proceeding with, meaning that if the agent is in an unfavorable position during a negotiation, then he would most certainly reach his time limit before reaching a deal. Agents usually find themselves at the bad end of a deal when there is a large difference between their priorities and their opponent's. But in this case, when agents strongly disagree with each other, the negotiation would last longer as both agents would try to impose their rules on each other, thus making the negotiation process even longer. In such a case, where an agent would have to make unnecessary compromises in order to reach a deal, the agent's time out value would be reached before making a deal and thus ending, earlier than expected, an unfruitful negotiation.

For instance, consider the case of the rash buyer/conservative seller. This combination of agents represents a strong disagreement. Because of this it takes a long time to finish, forcing the agent with the larger step, the rash buyer, to give up more than he needs to. If it wasn't for the time limit, the negotiation would require 44 offers and counter offers to complete, and the buyer had to pay 4755, which is almost the public maximum, to conclude the deal. But the buyer who is in a hurry has a time limit of 21. Thus if no deal is made within 21 offers and counter offers, the buyer would forfeit the negotiation. This is because the circumstances of the negotiation will be determined to be unfavorable for the buyer; ironically they are very favorable for the seller. Thus when faced odds against him the buyer would forfeit the negotiation with the conservative seller in favor of a seller that he would be able to agree with more...

Chapter 4: Conclusions

4.1 Summary of Main Results

Verifying and validating the DALIA negotiation paradigm was the main target of this thesis.

In a first phase, the current negotiation model was implemented, tested and validated.

The initial functions defined for the negotiation model proved to be less than perfect: More than a function were already defined for the same variables, two for the calculation of the buyer's private maximum and two for the seller's private minimum. These functions had to be tested first to validate the best and use them. Two of these functions proved to offer conflicting values, the buyer's private maximum and the seller's private minimum. For instance the buyer's private maximum value range can vary to include values that are less than the buyer's private minimum, thus leaving us with a private minimum that would be larger than the private maximum. The same also applies to the seller's private minimum.

After eliminating the unnecessary functions, the complete system was put to the test for the validation of the buyer and seller's private functions calculation as well as the step used by each of the agents. Varying the agents' attitudes from one extreme to the other, while using the initially provided functions, did not affect the negotiation outcome significantly.

The observation above was due to following facts:
The value range for the public maximum and minimum for both the buyer and seller was very minimal. And thus the highest and smallest values that the buyer's private maximum could take were very close to each other and to the public maximum. And thus the varying mental attitudes' attributes had little effect on the buyer's private maximum. The same applies to the rest of the private variables, buyer's private minimum, seller's private maximum and minimum.

In addition, the agents' step or the value by which they increase or decrease their offers was constant, and was initially dependant on the public maximum and minimum which are similar to both agents regardless of their attitudes. Thus the initial step was the same to both agents regardless of their mental attributes. Even modifying the step to make it dependant of the agent's own private maximum and minimum didn't introduce enough difference between the agents and didn't reflect the change in their mental attributes. This was due to the minimal range of values that could be taken by the agents' private maximum and minimum and to the facts were too close to the public maximum and minimum, thus making the agents' step too similar to one another even with different mental attributes.

Having similar private values and similar steps meant that the negotiation outcome was always very close to the median value of the public maximum and minimum, or the private maximum and minimum: (Private_Max+Private_Min)/2

The first enhancement introduced to the agents' functions was to make sure that the private maximum and minimum had non intersecting ranges that would reflect the actual changes in the agent's attitude. And that the different attributes values did not affect and eliminate one another but rather combined to positively affect the agent's private values.
To this end it was suggested that the private maximum would have a range varying from public maximum and would go down for as much as 30% the difference between the public maximum and minimum:
Private_Maximum=Public_Maximum-(Public_Maximum-Public_Minimum)/3

The same would also apply to the private minimum:
Private_Minimum=Public_Minimum+(Public_Maximum-Public_Minimum)/3

The step would also be modified to become more affected by the agent's attitude. Thus the Price, Commitment and Time attributes would be integrated in the agent's own step calculation, in addition to the private maximum and minimum, thus making the step more customized and more agent specific:
Step= (PrivateMaximum-PrivateMinimum) * (1.5+Commit+Time-Price)/100

Running the simulation with functions specified above showed a dramatic improvement over the initial results with final negotiation outcome being affected by the agents' mental attributes and swing of moods.

Further enhancements were introduced to the agents to ensure their adaptability to the varying circumstances of every negotiation.

To this end, 3 factors are taken into consideration that would affect the step: the time factor, the compare factor and the pattern factor.

The time factor is the actual time indicator of the agent. It indicates how much negotiation time the agent has, and thus urges him to increase his offers to conclude a deal as the agent's time runs out.

The compare factor is the ration comparing the agent's step to his opponent's. If the agent's values are less than his opponents he wouldn't change his negotiation strategies. If, on the other hand, his opponent step is smaller than his, then it would in his own benefit to reduce his offers so that he doesn't give away more than his opponent did.

The pattern factor is the monitoring of the opponent's step. If the opponent agent has an increasing step tendency, then this is an indication of his urgency to conclude the deal and thus it would in the agent's benefit to decrease his step to make sure he benefits as much as possible from his opponent's circumstances.

These factors would then be incorporated with the step making it variable and thus adaptable, as opposed to the constant and rigid approach experimented earlier.

The final simulation test incorporating all these factors shows a more lifelike agent behavior with the different agent attitudes being reflected into negotiation process and most importantly in the final negotiation outcome.

The agents with relaxed attitudes would have offers negotiation curves that look like logarithmic curves whereas more hurried agents' offers negotiation curves would look similar to exponential curves, reflecting real negotiation strategies adopted by people depending on their mental states.

4.2 Main Contributions of the Thesis

The thesis's main objective was to verify the current negotiation strategy adopted by the DALIA agents, and enhance that in any way possible.

The strategies initially used by the DALIA agents were showed to be inefficient and unrealistic.

Under special circumstances, the proposed negotiation and private data calculation formulas would fail resulting in having the private minimum with a larger value than that of the private maximum.

Thus, a more scientific basis was introduced as a starting point to create the agents' private values and negotiation function strategies.

To this end the private minimum and maximum were redefined each with their own private uninteresting existence ranges.

Some additional care was added in order to make sure that these formulas depended on all their attributes and that no one attribute could make any other attributes redundant.

Then the step formula was refined to make sure it reflects the agents' personal private attitudes and priorities.

And as a final enhancement, rules were introduced to enhance the agents' behavior making sure they can better read their environment and detect the changes occurring with the environment and with their opponent agents. Thus the agent would now compare his own step to his opponent's and react accordingly. Even more, he would adapt with the time factor which was concretized as a part of the negotiation and that would give some sense of urgency to the agents forcing them to do everything possible to conclude a deal before their negotiation time expires. And finally, the agent would track his opponent's bidding trend and make the best of the situation and adapt to his bidding style accordingly so that he makes the most out of the situation.

All the factors described above resulted in more lifelike agent behavior, with the agents reacting to offers and counteroffers and adapting to the situation. The agents' mental attributes' interference with the negotiation's progress and outcome can be clearly observed. Even more, the agents' negotiation functions and variable and adaptable step lead to more realistic offers that reflect the agents' attitude. The agent's offer curve would vary from logarithmic to exponential depending on the agent's attitude and whether it is a conservative approach or whether the agent is in a hurry to concluding the deal.

The dynamic agent negotiation paradigm also means that the agents are more user-friendly and practical and less mathematical than other agents. The user would only need to specify his priorities, and the agent would dynamically decide the best approach to be taken when dealing with the specific negotiation circumstances. The user would not need to specify before hand the agent's negotiation approach and would also not need to know about the different mathematical curves and how they would affect negotiations.

The dynamic, offer dependant agents also means that the agents would not need to be using the same negotiation paradigm. Thus the proposed agents will be able to deal with any other agent regardless of his design paradigm and negotiation priorities and is not restricted to dealing only with other DALIA agents. Since the agents only require other agents' offers as an interface for dealing with them and adapting to their changing behaviors, they would be able to deal with them under all circumstances and with all his functionality just by receiving their offers.

In short, the agents negotiating in the DALIA environment abiding by the introduced negotiation functions and standards display more realistic and human like attributes. They exhibit smarter behavior which can be observed by better analysis and adaptability to the different and changing negotiation circumstances. The agents feel more bound to the negotiation and with a deeper sense of commitment towards the conclusion of a deal and getting the item of desire. This is reflected with the variation of betting as the time passes by and as the agent feels the urgency to conclude a deal. This urgency is the mark of a human behavior, indicating that the agents also exhibit some human behavioral signs. As part of the agent's human behavior, the agents are not fault free, and when they become pressurized by time to conclude a deal, they would spend more money than an agent acting on optimal rules and not on behavioral attitudes. This would result sometimes in mistakes leading to conclusion of deals that are not exactly in the benefit of the agent, but that rather validate his human behavior.

4.3 Possible Extensions and Future Work

The world of agents and agent negotiation hold a lot of promise and potential. The work described above can be extended in many ways.

A direct addition the negotiation paradigm described in this thesis is the addition of random factor that would boost or hinder the agents' bidding strategy making them more unpredictable and more error prone. In short, more human like.

By introducing more business oriented negotiation schemas with an enhanced knowledge in advanced economics, the agents can become tougher at negotiation. The introduction of advanced business and negotiation rules can allow the agent to optimize his bidding strategies and even adapt his priorities to ensure he gets the best possible deal without compromising too much the user's priorities.

Implementing the case based model for past experience learning would be a great improvement and would go some way in bettering the agents' behavior. By making the agents learn from their past negotiations, they would be able to better assess the different situations and thus better approach them and consequently get better negotiation results.

Introducing some psychological knowledge to the agent would allow him to better assess and understand his opponent's priorities. By better understanding his opponent, the agent would have a better idea about his foe's limits. This would the a agent a huge advantage allowing him to re-plan and re-assess his strategies according to the assessment he made of his opponent, allowing him to make the most out of the situation and get the best possible deal form his opponent.

The introduction of psychological assessment to the equation would also allow the agent to use bluffs and tricks on his opponent, acting in a way to make him think that he wants to achieve a certain goal whereas the agent would actually be manipulating his adversary and tricking him to do and offer exactly what the agent wants him to do. In short the agent would bluff, fake and manipulate his opponent in order to make sure he gets the best possible deal.

In his research to create the DALIA environment, Saba introduced a paradigm for the processing and analysis of natural languages. The extension of this work and realizing it, then coupling it with internet mobile and capable agents, would ensure that the agents would be able to surf the internet and analyze and understand its content without further adaptation for the net. This would allow the agents to search the internet for potential deals that might be of interest to the user, negotiate directly with its respective agent and then bring the final deal for the user for final evaluation. This would eliminate lots of tedious tasks from the user's perspective including searching and negotiating in order to get the best possible deal.

A better knowledge in natural language would also allow the agent to better understand the specs of the product he's looking for. Understanding the product specs would allow them to make compromises or suggest better alternatives that might better suit the user's needs. The agent would be able to make compromises on the fly regarding price versus specs allowing him to offer the user better value for money products.

Bibliography

1 – Albers, Jonker, Karami, Treur, 2004, Agent Models and Different User Ontologies for an Electronic Market Place, Knowledge and Information Systems Journal, p1-41

2 – Albers, Jonker, Karami, Treur, 1999, An Electronic Market Place: Generic Agent Models, Ontologies and Knowledge, Practical Application of Intelligent Agents and Multi-Agent Technology, PAAM'99

3 – Bates, 1994, The role of emotion in believable agents, Communications of the ACM, 37(7):122-125

4 – Brustoloni, 1991, Autonomous Agents: Characterization and Requirements, Carnegie Mellon Technical Report CMU-CS-91-204, Pittsburgh: Carnegie Mellon University

5 – Chavez, Maes, 1996, KASBAH: An Agent Marketplace for Buying and Selling Goods, MIT Media Lab, First International Conference on the Practical Application of Intelligent Agents and Multi-Agent Technology (PAAM'96)

6 – Coen, 1994, SodaBot: A Software Agent Environment and Construction System, MIT AI Lab Technical Report 1493, Proceedings of the 12th National Conference on Artificial Intelligence AAAI 1994

7 – Cunningham, Nangle, 1996, Distributed Agent technology: an Overview, IAG REPORTS / PAPERS, https://www.cs.tcd.ie/research_groups/aig/iag/pubreview/chap4/chap4.html

8 – Farhat and Saba, 2004, DALIA: Towards Distributed, Artificial and Linguistically Competent Intelligent Agents, European Conference on Combinatorial Optimization (ECCO XVII) - New Opportunities for Management Sciences & Information Technologies

9 – Fatima, Wooldridge, Jennings, 2002, Multi-Issue Negotiation under Time Constraints, First International Joint Conference On Autonomous Agents and Multi-Agent Systems

10 – Fatima, Wooldridge, Jennings, 2001,Optimal Negotiation Strategies for Agents with Incomplete Information, Pre-proceedings of the Eighth International Workshop on Agent Theories, Architectures, and Languages (ATAL-2001)

11 – Gilbert, et al, 1995, The role of intelligent agents in the information infrastructure, IBM

12 – Gruber, 1993, A Translation Approach to Portable Ontology Specifications, Knowledge Acquisition, 5(2), 1993, pp. 199-220

13 – Gruber, 1993, Toward principles for the design of ontologies used for knowledge sharing, International Workshop on Formal Ontology 1993

14 – Guttman and Maes, 1998, Agent-mediated Integrative Negotiation for Retail Electronic Commerce, First International Workshop on Agent Mediated Electronic Trading on Agent Mediated Electronic Commerce, AMET-98

15 – Hayes-Roth, 1995, Agents on Stage: Advancing the State of the Art of AI, Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence (IJCAI-95)

16 – Franklin and Graesser, 1996.,Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents, Proceedings of the Third International Workshop on Agent Theories, Architectures, and Languages, Springer-Verlag, 1996.

17 – Jennings et al, 1993, Transforming standalone expert systems into a community of cooperating agents, International Journal of Engineering Applications of Artificial Intelligence, 6(4):317-331

18 – Jennings, 1995, Agent Software, Proceedings of the UNICOM Seminar on Agent Software

19 – Jennings et al, 1995, Archon: A Distributed Artificial Intelligence System For Industrial Applications, Foundations of Distributed Artificial Intelligence

20 – Jennings, Wooldridge, 1998, Applying Agent Technology, Agent Technology: Foundations, Applications, and Markets, Applied Artificial Intelligence

21 – Jennings, Wooldridge, Kinny, 2000, The Gaia Methodology for agent-oriented analysis and design, Journal of Autonomous Agents and Multi-Agent Systems 3 (3) 285-312

22 – Jonker, Robu, 2004, Automated Multi-Attribute Negotiation with Efficient Use of Incomplete Preference Information, Technical Report, Vrije Universiteit, Amsterdam, Department of Artificial Intelligence

23 – Kersten and Lo, 2003, Aspire: an integrated negotiation support system and software agents for e-business negotiation, International Journal of Internet and Enterprise Management 2003 - Vol. 1, No.3 pp. 293 - 315

24 – Maes, 1994, Modeling Adaptive Autonomous Agents, Artificial Life, I,MIT Media-Laboratory

25 – Nwana and Ndumu, 1999,A Perspective on Software Agents Research, The Knowledge Engineering Review, Volume 14 , Issue 2 (September 1999), Pages: 125 – 142, Cambridge University Press New York, NY, USA

26 – Paurobally, Turner, Jennings, 2003, Automating Negotiation for M-Services, IEEE Transactions on Systems, Man, and Cybernetics (Part A: Systems and Humans), Special issue on M-services. 33(6) 709-724

27 – Russell, S. and Norvig, P., 1995, Artificial Intelligence: A Modern Approach, Englewood Cliffs, NJ: Prentice-Hall., page 33

28 – Saba, 2001, Negotiating with an Attitude in a Virtual Marketplace, Intelligent Agent Technology - Research and Development, pp. 444-453, World Scientific Publishers
N. Zhong, J. Liu, S. Ohsuga, and J. Bradshaw (Eds.)

29 – Saba, 2002, Mental States of Autonomous Agents in Competitive and Cooperative Settings, Developments in Applied Artificial Intelligence: 15th International Conference on Industrial and Engineering. Applications of Artificial Intelligence and Expert Systems, IEA/AIE 2002, Cairns, Australia, p373

30 – Saba, Sathi, 2001, Agent Negotiation in Virtual Marketplace, The IAT-2001 and WI-2001 Joint Conference

31 – Thibodeau P., 2004, Agents of change: Autonomous agents could one day play a key role in everything from setting market prices to creating more resilient networks, Computer World,
http://www.computerworld.com/softwaretopics/software/story/0,10801,95672,00.htm
l

32 – Tsvetovatyy, Gini, 1996, Toward a virtual marketplace: architectures and strategies. In: Proceedings of the First International Conference on the Practical Application of Intelligent Agent and Multi-agent Technology (PAAM'96)

33 – Tsvetovatyy, Gini, Mobasher, Wieckowski, 1997, MAGMA: An Agent Based Virtual Marketplace for Electronic Commerce, University of Minnesota, International Journal of Applied Artificial Intelligence, 11:501-523

34 – Virdhagriswaran, 1996, S. Mobile unstructured Business ObjecT (MuBot) technology

35 – Wavish and Graham, 1995, A situated action approach to implementing characters in computer games. Applied AI Journal

36 – Weld and Ying Sun, 1995, Automated bargaining Agents (Preliminary Results), Department of Computer Science and Engineering, FR-35 University of Washington Seattle