AN AGENT-BASED APPROACH TO SUPPORT DECISIONS ON ELECTRONIC MARKETPLACES

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Abstract – With the increasing importance of Electronic Commerce across the Internet the need for software agents to support both customers and suppliers in buying and selling goods/services is growing rapidly. It is becoming increasingly evident that in a few years the Internet will host a large number of interacting software agents. Most of them will be economically motivated, and will negotiate a variety of goods and services. It is therefore important to consider the economic incentives and behaviours of economic software agents, and to use all available means to anticipate their collective interactions. This paper addresses this concern by presenting a Market Simulator designed for analysing agent market strategies based on a complete understanding of buyer and seller behaviours, preference models and pricing algorithms. The system includes agents that are capable of increasing their performance with their own experience, by adapting to the market conditions. The results of the negotiations between agents will be analysed by Data mining tools in order to extract rules that will give the agents feedback to improve their strategies. We will describe the characteristics and technologies involved in the architecture we are specifying and developing.

Keywords: Intelligent agents, Electronic Marketplaces, Dynamic agent strategies, Decision-Making, Recommender systems.

I. INTRODUCTION

As the result of technological developments Electronic Commerce is emerging as the new way of doing business. We believe that, over the course of the next decade, the global economy and the Internet will merge into a global market with billions of autonomous software agents that exchange goods and services with humans and other agents. Agents will represent, and be, consumers, producers, and intermediaries.

The transition to the global economy is an evolutionary step. The tremendous pressures that have fuelled the rapid growth of Electronic Commerce in the last few years will continue to drive automation, and some of this automation will be encapsulated in the form of software agents. As they grow in sophistication and variety, software agents will begin to interact, not just with humans, but with each other too. Interactions among agents will be supported by a number of efforts that are already under way, including standardisation of agent communication languages, protocols, and infrastructures by organisations such as FIPA [1] and OMG [2], and numerous attempts to establish standards in ontology's for numerous domains.

When interactions among agents become sufficiently rich, a crucial qualitative change will occur. New classes of agents will be designed specially to serve the needs of the other agents.

The agents we are envisaging will not be just assistants to business process. They will be economic software agents: independent, self-motivated economic players, endowed with algorithms for maximizing utility and profit on behalf of their human owners. They will add value to their activities by, synthesising, filtering, translating, and mining.

However, it would be dangerous to assume that theories and intuitions based on centuries of experience with human economic agents will be directly applicable to understand, anticipate, and controller the behaviour of markets in which software agents participates.

With these issues, as underlying motivation for our work, we will present a multi-agent market simulator, ISEM (Intelligent System for Electronic MarketPlaces), based on the model proposed by us in [3,4,5], designed for analysing agent strategies for a market based on a complete understanding of buyer behaviour, preference model and pricing algorithms. This simulator has been selected to be included in a book about the application of agents in Electronic Commerce in Europe [6]. The main objectives will be described as follows.

First, the ISEM addresses the complexities of online buyer behaviour by providing a rich set of behaviour parameter. Second, the ISEM provides available market information, which allows seller agents make assumptions about buyer behaviours and preference models. On the other hand, buyer agents make assumptions too, about their owners preference models and seller agent behaviours. Third, the different agents customise their behaviours adaptively, by learning each users preference model and business strategies.

The learning agent capacity is achieved through Data mining techniques applied on-line during the market sessions.

We will describe the characteristics of the ISEM simulator that we are specifying and developing, focusing specially on the performance of the seller and buyer agents. The negotiation model and the interaction between agents are also detailed in another section. A special highlight is given to seller and buyer agent's strategies, decision algorithms and Data mining techniques used.

II. The ISEM Concept

ISEM is a multi-agent market simulator designed for analysing agent strategies. The underlying structure of ISEM is that a simulation-based approach can model more diverse and complex scenarios, rather than the general case. By using a simulator prior to conducting marketing experiments, sellers and buyers can develop an intuitive understanding of the theoretical findings and use this knowledge to develop a more sophisticated strategy implementation.

The economic motivation for agent-based simulators is also important in other fields. For example, MASCEM is an agent-based simulator for the new electricity markets. This system was developed in our group and was recently selected as a worldwide case study of the conjunction between agents and markets [7].

We propose a simulator designed for analysing agent strategies for a market that has finite resources and capabilities. Furthermore, seller agents make assumptions about buyer behaviours and preference models based on available market information. Moreover, in most cases, agent actions typically mutually affect one another.

Different kinds of marketing strategies require different types of market information. The market stores all information about transactions, user profiles and other relevant information like users behaviour in a database that will be analysed with Data mining techniques in order to extract knowledge that give agents feedback to improve their strategies.

The benefit of our simulator is its ability to model diverse and complex scenarios, rather than only simplified cases. By producing tangible, numerical results, the ISEM has enabled us to explore the possibilities and potential for dynamic agent market strategies within these complex markets.

These ideas seem very promising and innovative, when compared to other approaches that study dynamic market strategies for finite markets, such as the work of Gallego and van Ryzin [8], Biller et al. [9], and J. M. DiMico et al. [10].

Gallego and van Ryzin, addressed the challenges of dynamic pricing in markets with a finite time horizon and inventory, but from a theoretical standpoint. They examined a deterministic version of the problem by making the assumption that consumer's demand curves do not change over time. They conclude that the optimal pricing strategy is "jittery" and requires constant price adjustments. For them a fixed-price strategy works "surprisingly well" when the demand curve is known, but what our analysis of pricing strategies emphasises is that we cannot assume perfect knowledge of the demand curve.

In a recent analysis of the automotive industry, Biller et al., designed a theoretical model for applying dynamic pricing to a marketplace with unknown changing demand levels, they demonstrate that under fluctuating demand there is always a dynamic pricing strategy which is more successful than a fixed-price strategy; but their model does not account for constraints in inventory.

Very relevant is the work of J. M. DiMico et al., with the Learning Curve Simulator, a market simulator designed for analysing agent pricing strategies in a market under finite time horizons and fluctuation demand. This perspective on dynamic pricing focuses on how a seller can take advantage of the fluctuations in cumulative buyer demand over time; however they are interested in analysing only agent pricing strategies for sellers.

The results obtained with these approaches can be duplicated in ISEM. On the other hand our simulator works as a tool for buyers and sellers analysing dynamic agent market strategies, enriched by the inclusion of Data mining techniques for discovering new knowledge resulting from the last negotiations.

III. ISEM Marketplace Model

ISEM works like an open market where buyer and seller agents meet in the marketplace. There are different types of agents in our model: market facilitator, sellers, buyers and market knowledge.

The market facilitator agent plays the role of a market coordinator and its main goal is the correct functioning of the market. It knows the identities of all the agents present in the market, regulates the negotiation process and assures that the market is functioning according to the established rules. Before entering the market, agents must first register with the market facilitator, specifying what kind of role they will play: *players* $\in$ *{buyer, seller, market knowledge}*, and what specific services they are prepared to do:

services $\in$ *{request for proposal, proposal, buy, sell, request for market information, provide market information}*

Seller and buyer agents are the two key players in the market, so we devote special attention to them, particularly to their business objectives and strategies to reach them. In order to be competitive in today's economic markets, buyer and seller do not need only to be efficient in their business field, but also to be able to quickly react and adapt to new environments as well as to interact with other available entities. The control architecture adopted for the design of those agents should meet these requirements, having a similar structure but with a kind of symmetrical behaviour (due to their antagonistic business objectives), figure 1 describes our proposed buyer/seller agent structure.

The structure comprises four functional modules: communication, individual knowledge, decision making & coordination, and execution.

The communication module is responsible for all processes related with message handling. Incoming messages are ordered by degree of importance and time of arrival. Outcoming messages are sent only to those agents that are known to be possibly interested in that particular service. Agents use ICL – Interagent Communication Language (see section 6 for details), to exchange messages between themselves.

The individual knowledge module contains information about the agent itself: own capabilities, current availability, past experiences and strategies. Through the analysis of historical market results, this module constructs the profile of each agent in the market, particularly in what concerns their capabilities, business objectives, risk preference, reservation prices, expected prices, last proposes and results obtained. Agents have different historical information regarding the acceptance and rejection of their own previous experiences.

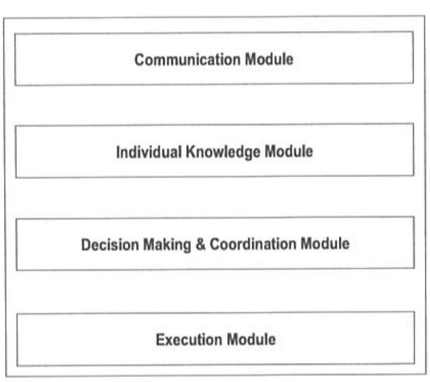

Figure 1- Seller and buyer agents structure

The decision making & coordination module is the most complex one. This is the module that determines the agent's behaviour: On the seller side, how to formulate a proposal (PP) in response to a request for proposal (RFP) and which strategy to use; on the buyer side, how to formulate an RFP, select a strategy to use, and evaluate and choose a PP. This module is being improved with an algorithm that analyses several possibilities and applies a decision method to select the best strategy to follow. A detailed description is presented in the section 5.

The execution module warrants the effective carry out of the local tasks that agents are responsible.

The number of seller and buyer agents in each scenario is completely defined by the user, who can define the model to be simulated, how many sellers, how many buyers, which products and their description, which strategy each one will use and how many negotiation periods will be simulated. The different agents negotiate autonomously, in order to reach agreements about product transactions.

The market knowledge agent is a special agent included in ISEM, which plays the role of "power" agent. This agent has access to market knowledge, which contains information about the organisational and operational rules of the market, as well as information about all different running agents, their capabilities, historical information and also market. The market previsions and agent behaviour models are achieved with Data mining techniques applied through data resulting from agent negotiations and information about all agents. The market knowledge agent is a kind of information provider; moreover the other agents can request their services.

The ISEM facilitates agent meeting and matching, besides supporting the negotiation model. In order to have results and feedback to improve the negotiation models and consequently the behaviour of user agents, ISEM simulates a marketplace for a fixed period of time, and it considers that this limit is composed by a regular number of periods, which can represent one day, for example. At a particular day, each agent has an objective that specifies its intention to buy or sell a particular product and on what conditions.

A. Market Strategies

It is well understood that some buyers will pay more than others for a product because they attach great value to the benefits it offers or it can occur that some buyers will be ready to buy any product from a certain category of products. But in the real world, companies have trouble tailoring products/prices to customer segments, particularly retail segments, either because those companies cannot identify which customers to target before a purchase or because it is difficult to customise offerings.

On-line companies can quickly segment their customers by drawing upon multiple sources of information, from click stream data on the current on-line session to customer buying histories tracked in databases.

Once a retailer can identify an on-line customer segment, that retailer can immediately offer a segment-specific price or product. However, this unfortunately causes the explosive growth of data, which requires a more efficient way to extract useful knowledge.

One the other hand, people have gradually noticed that Data mining not only can offer very meaningful knowledge about customer shopping behaviours by analysing the transaction data in the past, but also can improve the efficiency and quality of managerial decision making.

The ISEM simulator has the advantage that all agent interactions are logged at a transaction level of detail, which provides a rich source of business insight that can help to customise the business offerings to the needs of the individual agent buyers.

Data from multiple agent negotiations are manipulated to create "basket" records showing product purchases with also data behaviour of each buyer agent. This data is combined and manipulated with À priori algorithm [11] to discover associations between buyer details and purchases. The best association rules, those with a strong support and confidence, are extracted and transferred to the market knowledge agent. With this kind of knowledge it is possible to provide insight to the sellers agents about the profiles of buyer agents with certain purchase propensities, showing associations between price, style, etc.

ISEM also allows sellers agents to define targeted marketing strategies. This entails systematic analysis of agent buyer behaviour. For that a Two-Step clustering algorithm [12] designed to handle very large data sets, with both continuous and categorical attributes, is used to target buyer agents with similar characteristics in the same agent group. After agent clustering a rule-based modelling technique, C4.5 algorithm [13], is used to analyse those clusters and to obtain descriptions based on a set of attributes collected in the individual knowledge module. These models offer a set of market information: preferred sellers, preferred marks, favourite products and reference prices about each buyer agent.

Only players with more sophisticated strategies will take advantage of this new knowledge by requesting the services provided by the market knowledge agent.

IV. Negotiation Model

The negotiation model used in ISEM is bilateral contracting where the buyers are looking for sellers that can provide them desired products at the best price. ISEM simulates bilateral contracts through a series of Requested for Proposals (RFP) that are initiated by the buyers.

The buyer formulates a request for proposal for each product. As shown in figure 2, the market facilitator agent sends these RFP's to all available sellers.

The sellers analyse RFP's and formulates proposals (PP), and send these PP's to the buyers directly. The PP includes products and attributes.

The buyer evaluates the PP's received and either accepted or rejected, based on the user profile (see section *Buyer Performance* for details).

Seller can formulate two types of proposals: a Proposal for the product requested by the buyer or a Proposal for a related product, according to the buyer preferences model (see section *Seller Performance* for details).

On the basis of the bilateral agreements made among market players and lessons learned from previous bid rounds, both buyer and seller agents revise their strategies for the next negotiation rounds and update their individual knowledge module.

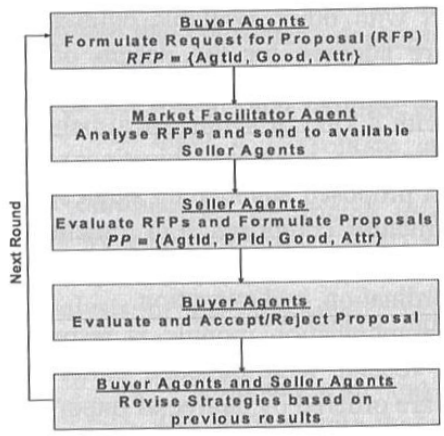

Figure 2- Sequence of bilateral contracts

V. Agents Strategic Behaviour Model

The Market simulator is organised in several negotiation days and both seller and buyer agents have strategic behaviour to define their business actions. These agents have *time-dependent strategies* to change the price during a negotiation period; and *behaviour-dependent strategies* to define the next period parameters according to the results obtained in the previous ones. Buyers and sellers develop their behaviours and strategies based on a combination of public information (available by requesting the services provided by the market knowledge agent) and private information (available only to the specific agent at their individual knowledge module).

It is expected that each agent develops the individual knowledge module with historical information, since they have different behaviours and consequently different results. On the basis of results from ISEM simulations, the agents update their price expectations and strategies. The maintenance of an individual knowledge module is extremely important since the negotiation model used at ISEM is bilateral contracting; the results of the bilateral transaction are not public.

On the other hand the possibility to request for market knowledge also provides a great support for agents that have more sophisticate behaviours. Agents that want to follow their business objectives without compromise the main one, to sell/buy, needs to be more up to date, since they must be informed with the real demand/offer. Those agents usually have better results and frequently have power to influence the market.

The strategic behaviour of agents and their mechanisms of analysing different possibilities to support decision-making will be detailed in this section.

A. Buyer Performance

The user defines the behaviour of the buyer agents in the market, both in terms of their behaviour over time and their behaviour on a per day basis.

Each buyer has a set of products that it wants to buy. For each product the buyer has information about attributes and products alternatives if any. Buyers will analyse the sellers Proposals and two types of proposals are possible: a Proposal for the requested product or a Proposal for related products. First it sorts the Proposals for the requested product by price and selects the best price, which will be compared to its own values. If it finds a seller Proposal satisfactory then it will contact directly the seller agent in question, otherwise if the buyer agent has a preferred "seller" then it can increase the reserve price (e.g. plus 10%). Otherwise the buyer will analyse the Proposals for related products and compare with its preferences, if it finds a proposal for an alternative product, accordingly to the user preference model, then it will start a similar analysis for the alternative products.

Buyer agents always try to buy for the best price even if the best offer does not satisfy all the units required.

Over the course of the market, the collective behaviour of buyer agents is defined by three variables: the lifetime, the maximum price, and its strategy. The lifetime parameter indicates how many days they are disposed to wait in the market, continuously looking for the best deal. Indirectly, the lifetime of buyer agents determines the number of buyers in the market each day. Pre-existing buyer agents return if they were unable to purchase in the previous days and their specified lifetime has not expired.

The buyer agents can use *time-dependent* to change the price under a negotiation day, which determines how agents average reservation prices, or valuations, change over the time, according to the time they have to negotiate and limit their parameters, such as the maximum price they can support. *Determined*, *anxious*, *moderate* and *gluttonous* strategies are supported [3]. The first one is a fixed-price strategy, and the others differ depending on both the point in time when the agent starts to modify the price and the amount it changes.

To adjust negotiation parameters between periods, also referred as *behaviour-dependent* strategies, two different strategies were implemented: one called *modified goal directed for buyers* (MGDB) [5] and another called *fragmented demand* (FD) [3].

The MGDB strategy is based on two consecutive objectives; buying all the units required for a given product and then reducing payoff. Following this strategy, buyers will raise their price if, in the previous day, they didn't meet their consumption needs and decrease the price if they succeeded in meeting their needs.

The FD strategy calculation, shown in (1), (2) and (3), adjusts the demand per day by attempting to reach the goal of buying its entire needs by the last day of the market, and not before, this strategy paces its purchases over the market, with the goal of buying all the units needed but with less cost.

$$\text{(1)} \quad UnitstoBuy_i = ExpGoodstoBuy_i - TotalUnitsBought_{i-1}$$

$$\text{(2)} \quad TotalUnitsBought_{i-1} = \sum_{n=1}^{i-1} UnitsBought_n$$

$$\text{(3)} \quad ExpGoodstoBuy_i = i * \left(\frac{QtInitial}{DaysInMarket} \right)$$

The results obtained with FD strategy show that allow buyers to save money; however, sometimes they are not capable of buying all the needed units, because while waiting to buy till the last day of market buyers may loose the chance of buying.

B. Seller Performance

The user defines the behaviour of the sellers in the market, both in terms of their behaviour over time and their behaviour on a per day basis. Every day each seller agent has a set of products that it wants to sell.

The sellers will analyse the Requested for proposals sent by the market facilitator agent and formulate proposals, and send them to the buyer agents directly. Each PP includes product and attributes.

Seller agents can formulate two kinds of Proposals: when the seller agent has the product requested then it formulates a Proposal for this product; when the seller agent does not sell the product requested it is expected that it can be pro-active, by asking for the services provided by the market knowledge agent to suggest a feasible alternative Proposal.

The seller agents formulate an alternative Proposal supported by an overall utility function, which reflect the business objectives of the user that it represents. In practice the seller agents that are capable of using this market functionality, request the services provided by the market knowledge agent in order to obtain information about product associations; then the seller agents will analyse the provided list in order to find one or more products that it sells. The choice between possibilities is based in an expected utility function and agent risk characterisation (see section *Agent Risk Preference* for details). The price to propose for an alternative product is obtained with the strategy, *alternative price* (AP): which calculates the price to propose based on: the sell price of the alternative product, weighted by the value of the strength of its association and supported by the individual agent knowledge module.

It is expected that agents with more sophisticated behaviours use this module to improve future proposals. Each seller agent has a set of business objectives and an agent risk characterisation, which will determine how the sellers will behave.

Seller agents can also use the same *time-dependent* strategies and two *behaviour-dependent* strategies: the *modified goal directed for sellers* (MGDS) [5] that adjusts its price by attempting to reach the goal of selling the entire inventory by the last day of the market, by lowering prices when sales in the previous day are low and raising prices when the sales are high in the previous negotiation day, and the *derivative following* (DF) strategy that can be weighted by seller *satisfaction* (DFWS) or by the *previewed demand* for a specific good (DFWPD) [3,5]. This strategy adjusts its price by looking to the amount of revenue earned on the previous day as a result of the previous day price change. If in the previous day, the price change produced more revenue, then the strategy makes a similar change in price. If the previous change produced less revenue, then the strategy makes an opposite price change. This strategy calculation, shown in (4), (5) and (6), is based on a derivative-following strategy proposed by Amy Greenwald, Jeffrey Kephart, and Gerald Tesauro [14]. The working principle is the same; however, we have adapted the calculations.

The DF strategy considers the revenue the seller earned in the last period as a result of the previous price change and based on the percentage of buyers that we expect to satisfy (*% Satisf*) or the value for previewed demand (*Demand*) which allows to do changes that will be done accordingly to buyer loyalty and to demand expected for a given product.

Seller agents can obtain these values by requesting the services provided by the market knowledge agent and/or at their individual knowledge module.

(4) $$Price_{i+1} = Price_i + Change_{i+1}$$

(5)
$$Change_{i+1} = Price_i * \left(\frac{UnitsSold_i - ExpGoodsSdd_i}{ExpGoodsSdd_i * \alpha}\right) * \left(\frac{1}{(\%Satisf \,/\, Demand) + \beta}\right)$$

(6) $$ExpGoodsSold_i = i * \left(\frac{InitialInventory}{DaysInMarket}\right)$$

Instead of adjusting the price each day by a fixed percentage, the formula scales the change by a ratio to sell the entire inventory. The amount of change increases with the difference between the amount of units the seller wanted to sell and the amount it actually sold. β and α are scaling factors.

We implemented these strategies and have already obtained some results [3,5]. The following example illustrates some differences in how behaviour-dependent strategies performed.

Let us consider a simple scenario with few sellers and few buyers using time-dependent and behaviour-dependent strategies. In every trial we present, the market has 10 days, each seller has 200 units and each buyer wants 150 units of the same good (ex: mobile phone). We test the strategies under a comparison-shopping and with preferences for certain sellers over others. All sellers start with the same price and each buyer are able to pay different prices. All of the traders have the last day of functioning of market as deadline to do their transactions. We pretend to analyse which behaviour-dependent strategy is appropriate under these specific conditions.

In a competitive market, the adaptive pricing strategies react to the others strategies in the Market in addition to the buyers demand. As we can see in figure 3 all the sellers achieve their goal, to sell almost everything.

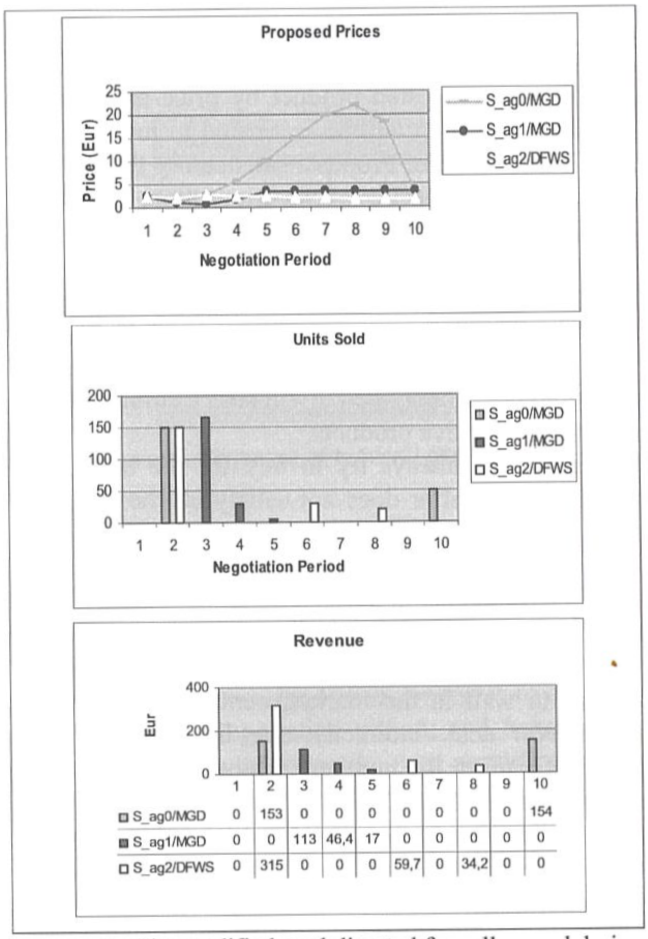

Figure 3- The modified goal directed for sellers and derivative following weighted by satisfaction strategies

After carefully analysing the results, we can observe that the DFWS strategy produces a high amount of revenue and often sells more units than the others seller agents using MGDS strategy.

The success of a DFWS depends on the starting price it chooses, and the percentage of buyers satisfied. When DFWS sells approximately the same amount of inventory as MGDS, usually produces more revenue than the MGDS strategy, and frequently occurs that, even DFWS sells less amount of inventory, it usually produces more revenue than MGDS, since this one makes dramatic price changes. This occurs because the MGDS strategy spreads out its sales, including selling on the last days when prices approaches minimum. Another important issue is that MGDS does not take into account the percentage of buyers that are satisfied when making price changes. Moreover, we can conclude that when the demand is less than the most competitive seller's available capacity, the seller will lose money when using the MGDS. The seller will decrease the price and try to sell more, which won't be possible because of insufficient demand. However, MGDS strategy can be valuable, particularly to increase market share when two or more sellers are competing directly because of similar proposed prices.

In general DFWPD has the same behaviour as DFWS; nevertheless some times projections for demand are subject to uncertainty. This uncertainty arises from such factors as weather forecast errors, inaccurate projections of type and number of future customers.

It would be interesting to develop another strategy that combines the two seller described strategies. This way, an agent could select the most suitable strategy for each negotiation period on the basis of market conditions and business objectives: if a seller concludes that the demand is lower than its available capacity and it pretends increase profit, it will use DFWS/P, otherwise, if it pretends increase market share, it will use MGDS; Moreover, if it concludes that a competitor has similar prices, and it pretends increase market share, it will use the MGDS, otherwise it will use DFWS/P.

Buyers using time-dependent strategies always try to buy all units as soon as possible what is equivalent to have more expenses. On the other hand, when buyers choose the FD strategy, frequently, bought the requested units, with les costs.

Although these strategies are computationally straightforward, they are surprisingly robust under extremely different market conditions.

C. Agent Risk Preference

Agent risk preferences are broadly classified into risk-avoidance, risk-indifference and risk-looking. The risk preference is modelled by using a von Neumann-Morgenstern expected multi-objective utility function. On the other hand each agent has a set of business objectives, like: minimizing inventory, maximizing profits or maximizing revenue, increasing market share. Different agents may have different types of objectives. Moreover, individual agent objectives may conflict with each other, since the achievement of one objective may negate the achievement of other objectives.

Each objective of an agent is represented by a minimum expected value (X_{min}), a maximum expected value (X_{max}), and a risk preference (RP). A scaling factor (k) for each objective is used to compute the overall expected utility as the sum of all single-objective expected utilities weighted by k.

We will illustrate these concepts with a simple example: Consider two seller agents, seller A, using risk-avoidance, and seller B, using risk-looking, which will formulate a proposal for an alternative product. First they need to request the services provided by the market knowledge agent to obtain information about product associations; then the seller agents will analyse the information sent by the market knowledge agent and suppose that they find four associations that they are available to propose. It is expected that the agents choose the first one to formulate an alternative proposal (the strongest associated), but the seller agents have to follow their business objectives. Suppose that they have just the same, maximizing revenue, they need first to calculate the respective utility function for all possible alternatives, and then they will be able to choose the best one that guarantees their business objective.

For example, for the first one alternative product ABC: price 100€, 1 unit required and 80€ for revenue, the utility of the seller A, risk-avoidance, is higher than that of the seller B, risk-looking agent, as shown in the following figure.

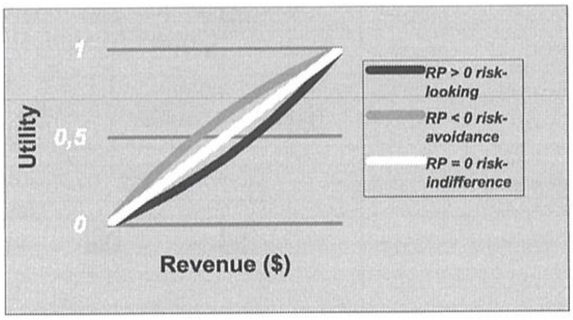

Figure 4- Example of an increasing utility function with risk preference, considering the revenue

Risk-preference choice will lead to different behaviours, the risk-avoidance agent may prefer respect the suggestion made by Data mining tool while the risk-looking agent may not be satisfied with the low utility and will try to increase this utility by choosing another suggested alternative product, even with a weak relationship.

VI. IMPLEMENTATION

We developed the ISEM in the Open Agent Architecture (OAA) and Java. OAA, developed at SRI International [15], is a framework for integrating a community of heterogeneous software agents in a distributed environment. It is structured to minimise the effort involved in creating new agents, written in various languages and operating platforms; to encourage the reuse of existing agents; and to allow the creation of dynamic and flexible agent communities. The OAA Interagent Communication Language is the Interface and communication language that all agents share, no matter which machine they are running on or language they are programming in. Because the OAA framework isn't specifically devoted to developing simulations, we made it suitable by extensions; for example, we included a clock to introduce the simulations time evolution mechanism.

Even in our initial exploration of a simulation-based approach with the ISEM, where simulation speed was not a primary goal, we had already incorporated the multi-threading concept. Each agent is implemented in Java, as a Java Thread. The model can be distributed over a network of computers, which is a very important advantage to increase simulation runs for scenarios with a huge amount of agents. The speed of each simulation run depends on the number of buyer agents and the respectively number of different products to buy, as more buyer agents with a large number of different products are added to the simulator, the simulation time increases linearly.

Figure 5 shows the prototype interface for a simple scenario with two seller agents and two buyer agents.

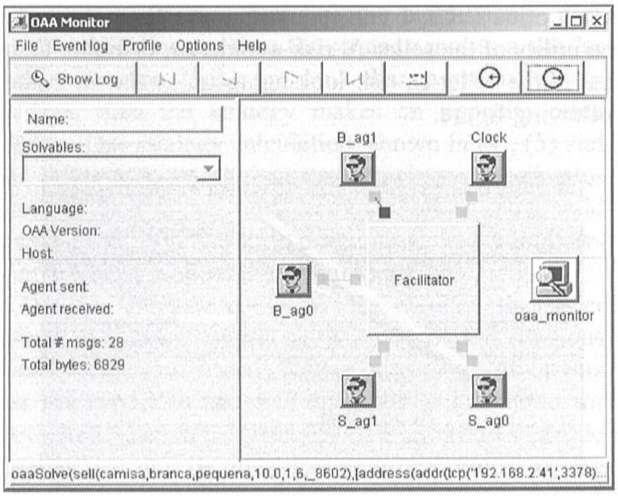

Figure 5- OAA prototype interface

VII. CONCLUSION

In the near future, agent market strategies will be a common competitive manoeuvre for electronic marketplaces. Different kinds of marketing strategies require different types of market information. The availability of such information will be vital for supporting marketing and sales. Also important is the development of agent-based tools that will help retailers in understanding what kinds of electronic market strategies are appropriate.

This paper proposes an approach for the problem by suggesting the use of a multi-agent simulator, ISEM, designed for analysing agent strategies for a market, based on a complete understanding of buyer and seller behaviours, preference model and pricing algorithms. In this context, the inclusion of Data mining functionalities in our simulator is a new important improvement, to deal with aspects like client clustering, forecasting, etc. ISEM works as a platform for evaluation, enriched with the ability to segment the buyer population into different sub-groups that behave independently. This allows the modelling of mixed populations such as a group of brand loyal customers combined with a group of committed comparison customers. This will determine what seller adaptive strategies are adequate to focus on each subgroup. Another important particularity of ISEM simulator is the inclusion of a buyer behaviour-dependent strategy, able to adapt based on observed market changes. We believe that by using a simulator sellers and buyers could develop an intuitive understanding of the theoretical findings and use this knowledge to develop a more sophisticated strategy implementation in real-world markets.

Directions of our future work include evaluating additional dynamic market strategies; based on different *value-added* services, for sellers and more sophisticate behaviour-dependent strategies for buyers.

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