A MULTI-AGENT SIMULATOR FOR TESTING AGENT MARKET STRATEGIES

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ABSTRACT

We envision a future in which the global economy and 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 multi-agent market simulator designed for analysing market strategies based on a complete understanding of buyer and seller behaviours, preference models and pricing algorithms. 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.

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 a large amount of autonomous software agents that exchange goods and services with humans and other agents. Agents will represent or support consumers, producers, and intermediaries. 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 the business process. 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 human experience in business processes will be directly applicable to understand, anticipate, and control the behaviour of markets in which software agents participate.

To study electronic markets behaviour and evolution, we developed ISEM (Viamonte et al., 2004) (Viamonte et al., 2003), a multi-agent market simulator, designed for analysing agent market strategies. This simulator has been selected to be in-cluded in a book about the application of agents in electronic commerce in Europe (Viamonte and Ramos, 2001) and was recently selected as a worldwide case study in simulation of negotiation agents (Viamonte et al., 2006). ISEM ideas are also currently being applied under the scope of the project Agent&Markets (POSI/EIA/56260/2004) supported by the Portuguese Agency for Scientific Research (FCT). The main objectives of ISEM are: first, the ISEM system addresses the complexity of on-line buyer's behaviour by providing a rich set of behaviour parameters; second, the ISEM system provides available market information allowing sellers to make assumptions about buyer's behaviour and preference models; third, the different agents customise their behaviour adaptively, by learning user's preference models and business strategies. The agent learning ability is achieved through data mining techniques applied on-line during the market sessions of ISEM simulator.

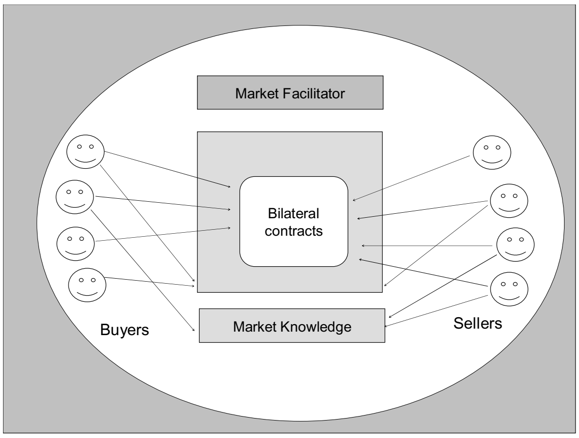
ISEM CONCEPT

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, suppliers and consumers can develop an intuitive understanding of the theoretical findings and use this knowledge to develop a more sophisticated strategy implementation. Our investigation of agent-mediated electronic commerce focuses specially on agent market strategies for an extremely common type of market: a market with finite time horizon, seller inventory, and buyer population, such as airline tickets, hotel rooms and seasonal retail. Also inherent to the finite nature of these markets is an increased importance of fluctuations in consumer demand. In order to take advantage of these demand changes we are interested in investigate dynamic agent market strategies. Our strategy algorithms make assumptions about the behaviour of the buyers or the type of buyers, based on available market information that is obtained with data mining tools. Our approach opens some interesting research directions to study user modelling with knowledge discovery tools.

As decision support tool, we developed a market simulator that creates real-life bargain situations and is based on the model proposed by Fatima et al. (Fatima et al., 2004). Seller and buyer agents negotiate over the price of a good or service in order to established bilateral contracts and in addition to attempting to obtain the best price, agents need to ensure that negotiations ends before a certain deadline; moreover, agents make assumptions about buyers behaviour and preference models based on available market information. The simulator probes the conditions and the effects of market rules, by simulating the participant's strategic behaviour; moreover, agents can adapt their strategies as the simulation proceeds on the basis of previous efforts successes or failures. ISEM is flexible since the user completely defines the model he or she wants to simulate, including the number of agents, each agent's type and strategies.

ISEM MARKETPLACE MODEL

ISEM works like an open market where buyer and seller agents meet in the marketplace. It includes these types of agents: a market facilitator, sellers, buyers and market knowledge, figure 1.



Figures 1: Multiple Agents in ISEM

The market facilitator agent coordinates the simulated market and ensures that it functions correctly. It knows the identities of all the agents in the market, regulates negotiation, and assures that the market operates according to established rules. Before entering the market, agents must first register with the market facilitator, specifying their role and services.

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 agents need not 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). The structure comprises four functional modules: communication; individual knowledge; decision making & coordination; and execution.

The user completely defines the number of seller and buyer agents in each scenario and must specify their intrinsic and strategic characteristics. "Intrinsic characteristics" refer to the agents' individual knowledge related to product list, limit prices, preferred prices, profile and available capacity or consumption needs. "Strategic characteristics" refer to the strategies the agent will use to reach the objective of selling the available inventory at the best price (seller) or buying the needed items with less costs (buyer). Sellers will compete with each other because they are all interested in selling their inventory at the highest possible values. On the other hand, sellers will cooperate with buyers to establish an agreement that is profitable for both. This is a rich domain for which it is possible to develop and test several decision algorithms and strategies for cooperation and competition.

The market knowledge agent is a special agent included in the ISEM system, 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 and historical information. The market previsions and agent behaviour models are obtained through data mining algorithms, using data resulting from agent negotiations that support agents' market strategies. In practice, usually, after a confidential negotiation period, the market facilitator agent discloses information about past transactions and agents' characteristics (if possible); all agent interactions are logged at a transaction level of detail, which provide a rich source of business insight that can help to customise the business offerings to the needs of the individual buyers. With this functionality it is possible to discover sub-groups that behave independently and associations between products. For that, ISEM uses clustering, classification and association operations.

To carry out the clustering operation a Two-Step clustering algorithm (Zhang et al., 1996) is used to target buyers with similar characteristics in the same agent group. Then, to obtain more relevant information that describes the consumption patterns of each cluster population, a rule-based modelling technique, using

C5.0 classification algorithm, an evolution of C4.5 algorithm (Quinlan, 1993), is used to analyse those clusters and to obtain descriptions based on a set of attributes, collected in the individual agents' knowledge module. These models are transferred to the market knowledge agent and offer a set of market information, such as: preferred sellers; preferred marks; favourite products and reference prices, which support the process of agents' strategy implementation. To discover associations between buyer details and purchases, data from multiple agent negotiations are manipulated to create "basket" records showing product purchases. This permits the observation of the behaviour of each buyer agent. This data is combined and manipulated by the "Apriori algorithm" (Agrawal et al., 1996), 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 into the sellers' agents about the profiles of buyer agents with certain purchase pro-pensities, showing associations between products, prices, style, etc.

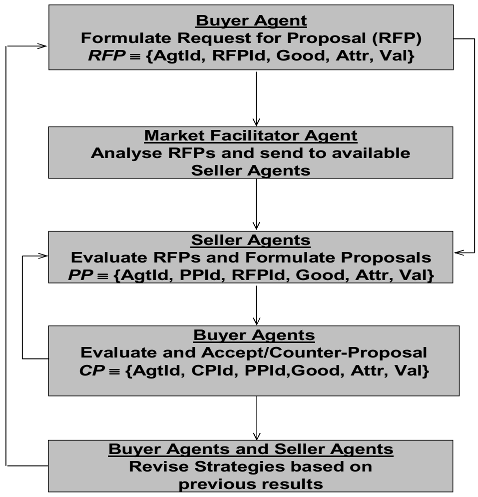
After these operations, to get confident data, agents can request the services provided by the market knowledge agent, in order to support their strategic behaviour. Only players with more sophisticated behaviour will take advantage of this new knowledge; since the user can determine which seller agents have access to this facility. The user can also determine if the agents' information will be private or public; public information is available to market analysis with the data mining functionality. However the market can get knowledge about an agents' behaviour even if they are set as a private information agent. This situation occurs, by the simple fact of being on the market.

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 series of negotiation periods, $D = \{1,2,...,n\}$ where each negotiation period is composed by a fixed interval of time $T = \{0,1,...,m\}$. Moreover, each agent has a deadline $D_{\max}^{Agt} \in D$ to achieve its business objectives. At a particular negotiation period, each agent has an objective that specifies its intention to buy or sell a particular good or service and on what conditions.

Negotiation Model

The negotiation model used in ISEM is bilateral contracting where buyer agents are looking for sellers that can provide them the desired products at the best price. We adopt what is basically an alternating protocol (Fatima et al., 2004) (Gallego and Ryzin, 1994). Let $Agtb$ denote the buyer agent, $Agts$ the seller agent and let $[Pi_{\min}, Pi_{\max}]$ denote the range of values for price that are acceptable for agents. A seller agent has the range $[Psi_{\min}, Psi_{\max}]$, which denotes the scale of values that are comprises by the minimum value that the seller is disposed to sell to the optimal value. A buyer agent has the range $[Pbi_{\min}, Pbi_{\max}]$, which denotes the scale of values that are comprises by the optimal value to buy to the maximum value.

Negotiation starts when a buyer agent sends a request for proposal (RFP), figure 2. In response, a seller agent analyses its own capabilities, current availability, and past experiences and formulates a proposal (PP). Sellers can formulate two kinds of proposals: a proposal for the product requested or a proposal for a related product, according to the buyer preference model (see section Seller Behaviour for details).



Figures 2: Sequence of Bilateral Contracts

$PPg_{i\,Agts \to Agtb}^{DT}$ represents the proposal offered by the seller agent $Agts$ to the buyer agent $Agtb$ at time T, at the negotiation period D for the $good_i$. The buyer agent evaluates the proposals received with an algorithm that calculates de utility for each one, U_{PPgi}^{Agtb} (see section Buyer Behaviour for details); if the value of U_{PPgi}^{Agtb} for $PPg_{i\,Agts \to Agtb}^{DT}$ at time T is greater than the value of the counter-proposal (CP) that buyer agent will formulate for the next time T, in the same negotiation period D, then the buyer agent accepts the offer and negotiation ends successfully in an agreement; otherwise a counter-proposal $CPg_{i\,Agtb \to Agts}^{DT}$ is made by the buyer agent to the next time T. The seller agent will accept a buyer counter-proposal if the value of U_{CPgi}^{Agts} is greater than the value of the counter-proposal (CP) that seller agent will formulate for the next time T; otherwise seller agent rejects. On the basis of the bilateral agreements made among market players and lessons learned from previous bid rounds, both agents revise their strategies for the next negotiation rounds and update their individual knowledge module.

AGENTS STRATEGIC BAHAVIOUR MODEL

Agents use time-dependent strategies to change their price during a negotiation period: offers and counter-offers are generated by lineal combinations of simple functions, for simple criteria, the time; at this work, we have also used the time-dependent strategies to model different attitudes towards time, during a negotiation period; an agent that gains utility, with the time, and has the incentive to reach a late agreement (within the remaining time until the end of a negotiation period) is considered a strong or patient player; an agent that loses utility with time and that tries to reach an early agreement is considered a weak or impatient player. Agents use behaviour-dependent strategies to adjust parameters (price, demand) for the next negotiation period according to the results obtained in the previous ones.

Buyers and seller agents develop their behaviour and strategies based on a combination of public information, available through requesting for market knowledge agent services; 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 can build a profile of the other agents with expected proposed prices, limit prices, needs and capabilities. On the other hand, requests for market knowledge agent services also provide a great support for agents that have more sophisticate behaviour.

Buyer Behaviour

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 buyers determines the number of buyers in the market each day. Pre-existing buyers return if they were unable to purchase in the previous days and their specified lifetime has not expired. Each buyer has a set of products that it wants to buy, and for each one it has information about attributes and products alternatives, if any. Buyers will analyse the seller's proposals with an advanced algorithm which analyses the different proposals, evaluates the expected returns and then apply a decision method (decision buyer algorithm) to decide when accept a bilateral contract. The advanced algorithm, first sorts the proposals for the requested product by price and selects the best one, which will be compared to its own values. If it finds a seller proposal satisfactory then the buyer will contact directly the seller in question; otherwise if the buyer has a preferred "seller" then it can increases the reserve price (e.g. plus 10%); finally it will analyse the proposals for related products, if it finds proposals for alternative products accordingly to the user preference model, then it will start a similar analysis. Buyer agents can choose from four different time-dependent tactics: Determined, Anxious, Moderate and Gluttonous (Viamonte et al., 2003): these strategies depending on both the point in time when the agent starts to modify the price and the amount it changes; and can use two complementary behaviour-dependent tactics: the Modified Goal Directed for Buyers (MGDB) and the Fragmented Demand (FD). The MGDB strategy (Viamonte et al., 2003) is based on two consecutive objectives; the first one is buying the consumption needs and then reducing payoff. Following this strategy, buyers will offer a higher price if they didn't meet their consumption needs in the previous period and offer less if they succeeded in meeting their needs. The FD strategy (Viamonte et al., 2003), 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 costs. This strategy allow buyers to save money, however, some times buyers are not capable of buying all the needed units, because while waiting to buy till the last day of market they lose the chance of buying.

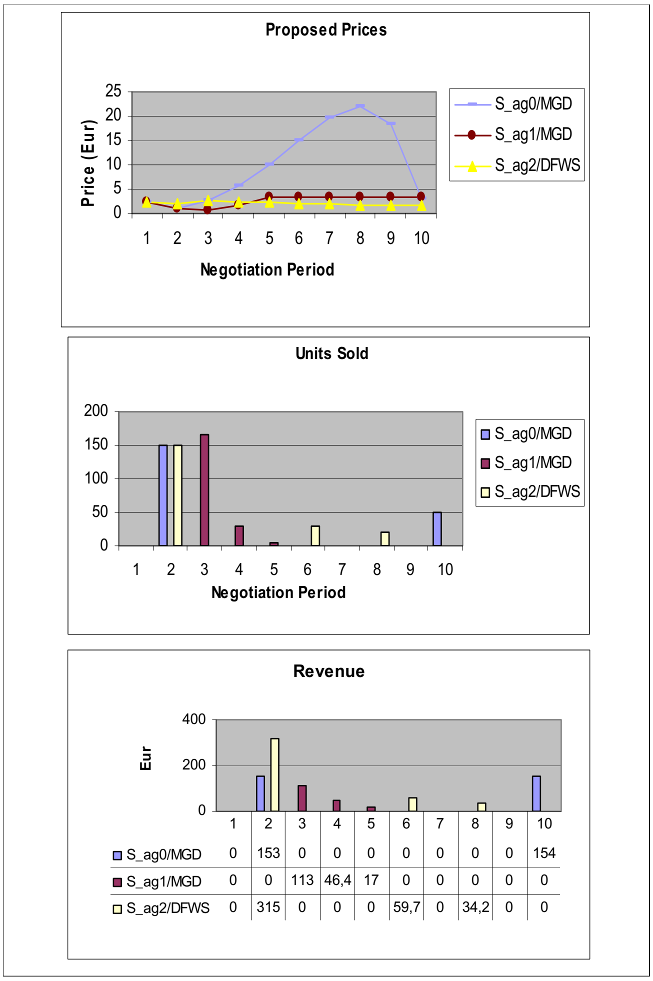
Seller Behaviour

The user defines the behaviour of the sellers in the market, both in terms of their behaviour over time (business objectives and agent risk characterisation), and their behaviour on a per day basis (negotiation strategies). Every day each seller has a set of products that it wants to sell. The seller will analyse the request for proposals received and formulates a proposal with an advanced algorithm. Two kinds of proposals are possible: a proposal for the requested product, if the seller has the requested product or a proposal for a related product. It is expected that seller agents be pro-active, by asking for the services provided by the market knowledge agent to suggest a feasible alternative product. A seller formulates an alternative proposal supported by an overall utility function, which reflect the business objectives of the user that it represents and agent risk characterization (Viamonte et al., 2003), which will determine how the sellers will behave. To define the next period parameters according to the results obtained in the previous ones sellers choose between two different behaviour-dependent strategies: the Modified Goal Directed for Sellers (MGDS) (Viamonte et al., 2003), 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; and the Derivative Following (DF) strategy (Viamonte et al., 2003) that can be weighted by Seller Satisfaction (DFWS) or by the Previewed Demand for a specific product (DFWPD), 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, otherwise the strategy makes an opposite price change. This strategy calculation is an adjustment of the Derivative Following strategy analysed in (Greenwald et al., 1999). We modified the DF strategy for a finite market by attempting to reach the goal of selling its entire inventory by the last day of the market, instead of adjusting the price each day, the change is scaled by a ratio based on the progress through the market and can be based on the percentage of Buyers that we expect to satisfy (% Satisf) or based in the value for Previewed Demand. Seller agents can obtain these values through requesting for market knowledge agent support; and permits to do changes that will be done accordingly to buyer loyalty and to demand expected for a given product.

DYNAMIC STRATEGIES ANALYSE

We use the above referred strategies, which are already implemented, to present the following example, which illustrates some differences in how behaviour-dependent strategies performed. 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 these 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. Moreover, all of the agents 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, figure 3, all the sellers achieve their goal, to sell almost everything. 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 other seller agents using the MGDS. 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, it usually produces more revenue than the MGDS strategy, and frequently occurs that, even when DFWS sells a smaller amount of inventory, it usually produces more revenue than MGDS, since this one makes a dramatic price change; this occurs because the MGDS strategy spreads out its sales, including selling on the last days when prices approach the minimum. Another important issue is that MGDS does not take into account the percentage of buyers that are satisfied when making price changes. Furthermore, we can conclude that when the demand is less than the most competitive sellers' available capacity, the seller will lose money when using the MGDS; the seller will decrease the price and try to sell more, which may not 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. Buyers using the FD strategy frequently buy the requested units, with fewer costs. Although these strategies are computationally straightforward, they are surprisingly robust under extremely different market conditions.



Figures 3: The Modified Goal Directed for Sellers and Derivative Following Weighted by Satisfaction Strategies

CONCLUSIONS

ISEM seems to be a valuable framework for studying market evolution. The multi-agent technology allied to an objected-oriented implementation enables easy future improvements and model enlargement. Market participant's strategic behaviour is very significant in the context of competition. In addition, the availability of new market knowledge obtained with data mining algorithms is vital for supporting marketing and sales. ISEM works as a platform for evaluation, enriched with the ability to segment the buyer population into different sub-groups that behave independently. Another important particularity of ISEM simulator is the inclu-sion of a buyer behaviour-dependent strategy, able to adapt based on observed market changes. Although we implemented some valuable and promising strategies, we must increase and improve the portfolio of agents' strategies and behaviours. 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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