Agent-based Simulation of Electronic MarketPlaces with Decision Support
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ABSTRACT
This paper presents a Multi-Agent Market simulator designed for analyzing agent market strategies based on a complete understanding of buyer and seller behaviors, preference models and pricing algorithms, considering user risk preferences and game theory for scenario analysis. The system includes agents that are capable of improving their performance with their own experience, by adapting to the market conditions, and capable of considering other agents reactions.

Categories and Subject Descriptors

General Terms
Design, Economics.

Keywords
Intelligent Agents, Simulation, Negotiation, Decision-Making.

1. INTRODUCTION
Unlike traditional tools, agent based simulation does not postulate a single decision maker with a single objective for the entire system. Rather, agents, representing the different independent entities in electronic markets, are allowed to establish their own objectives and decision rules. Moreover, as the simulation progresses, agents can adapt their strategies, based on the success or failure of previous efforts.

We present a multi-agent market simulator designed for analyzing agent market strategies based on a complete understanding of buyer and seller behaviors, preference models and pricing algorithms, considering user risk preferences and game theory for scenario analysis. Each market participant has its own business objectives, and decision model. The results of the negotiations between agents are analyzed by data mining algorithms in order to extract knowledge that gives agents feedback to improve their strategies. The extracted knowledge will be used to set up probable scenarios, analyzed by means of simulation and game theory decision criteria.

We intend to apply this platform to different market types, taking into account some previous work of our research group, where two different simulation platforms have already been developed, namely ISEM – Intelligent System for Electronic MarketPlaces [10], and MASCEM – Multi-Agent Simulator for Competitive Electricity Markets[8].

ISEM focuses specially on markets with finite time horizon. This simulator was recently selected as a worldwide case study in simulation of negotiation agents [11], while MASCEM focus specially on market mechanisms usually found in liberalized electricity markets and was selected as a worldwide case study of agents technology applied to markets [7].

Our proposal is a Market Simulator that will act as a kind of What-if tool, trying to analyze what may occur if some decision is taken. However, some additional intelligence need to be placed in the system, otherwise we will have a kind of combinatorial explosion, since many scenarios need to be analyzed. Moreover, the Market Simulator will be used as the engine of a Market Participant (Seller or Client) in order to suggest him/her about the actions to have in the market.

Entities from real markets can use our tool to test several different negotiation mechanisms, different behaviors, strategies and risk preferences, and to analyze the future market evolution and other entities expected reactions.

2. MULTI-AGENT MODEL
Our Simulator 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, we simulate a series of negotiation periods, $D = \{1,2,\ldots,n\}$, where each one is composed by a fixed interval of time $T = \{0,1,\ldots,m\}$. Furthermore, each agent has a deadline $D_{\text{max}} \in D$ 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.
The available agents can establish their own objectives and decision rules. Moreover, they can adapt their strategies as the simulation progresses on the basis of previous effort’s successes or failures. The simulator probes the conditions and the effects of market rules, by simulating the participant’s strategic behaviour.

The simulator was developed based on “A Model for Developing a MarketPlace with Software Agents (MoDeMA)” [11]. The following steps compose MoDeMA:

- Marketplace model definition, that permits doing transactions according to the Consumer Buying Behaviour Model;
- Identification of the different participants, and the possible interactions between them;
- Ontology specification, that identifies and represents items on transaction;
- Agents architecture specification, and information flows between each agents module;
- Knowledge Acquisition, defining the process that guarantees the agent the knowledge to act on pursuit of its role;
- Negotiation Model, defining the negotiation mechanisms to be used;
- Negotiation Protocol, specification of each negotiation mechanism rules;
- Negotiation Strategies, specification and development of several negotiation strategies;
- Knowledge Discovery, identification and gathering of market knowledge to support agents’ strategic behaviour.

Multi-agent model includes a market administrator, buyers, sellers, traders and a market operator.

The market administrator agent has two main functions: coordinator and knowledge provider. On one hand it coordinates the simulated market and ensures that it functions correctly, according to market mechanisms and established rules. On the other hand, it plays the role of “power” agent, since it 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.

Since we intend to cover several negotiation mechanisms, our model also includes a market operator agent, responsible to support negotiations based on an auction mechanism.

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 meet these requirements, having a similar structure but with a kind of symmetrical behavior (due to their antagonistic business objectives).

3. NEGOTIATION MECHANISMS

As a decision support tool, our simulator includes several types of negotiation mechanisms to let the user test them and learn the best way to negotiate in each one. So, we include bilateral contracts and a Pool, centralized mechanism based on an auction, and regulated by a market operator. Both types of negotiation may exist at the same time: Mixed Market. These implies each agent must decide whether to, and how to, participate in each market type.

Let Agtb denote the buyer agent, Agts the seller agent and let \([P_{i_{\text{min}}}, P_{i_{\text{max}}}]\) denote the range of values for price that are acceptable for agents.

A seller agent has the range \([P_{i_{\text{min}}}, P_{i_{\text{max}}}]\) which denotes the scale of values that are comprised of the minimum value that the seller is disposed to sell to the optimal value.

A buyer agent has the range \([P_{b_{\text{min}}}, P_{b_{\text{max}}}]\), which denotes the scale of values that are comprised of the optimal value to buy to the maximum value.

3.1 Bilateral Contracts

In bilateral contracting 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 [2].

Negotiation starts when a buyer agent sends a request for proposal. In response, a seller agent analyses its own capabilities, current availability, and past experiences and formulates a proposal.

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.

\[PP_{Agts \rightarrow Agtb}^{DT}\] represents the proposal offered by the seller agent Agts to the buyer agent Agtb at time T, at the negotiation period D for a specific product.

The buyer agent evaluates the proposals received with an algorithm that calculates the utility for each one, \(U_{PPg}^{Agtb}\) ; if the value of \(U_{PPg}^{Agtb}\) for \(PP_{Agts \rightarrow Agtb}^{DT}\) at time T is greater than the value of the counter-proposal that the 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 \(CP_{Agtb \rightarrow Agts}^{DT}\) is made by the buyer agent to the next time T.

The seller agent will accept a buyer counter-proposal if the value \(U_{CPg}^{Agts}\) is greater than the value of the counter-proposal that the seller agent will formulate for the next time T; otherwise the seller agent rejects the counter-proposal.

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.

3.2 Pool
In our simulator, agents also have the possibility of negotiating through a Pool, which is a centralized mechanism that functions according to an auction mechanism, and is regulated by a market operator. We have two different auction mechanisms: a double and a single uniform auction.

The process starts at the market operator, who sends a request for participation. The call_for_participation message triggers the negotiation process and is delivered to all agents in the simulated market. If the agent is interested, or capable, of participating in the Pool, it will formulate a bid and send it to the market operator, specifying for each requested parameter the value of its proposal. The process of formulating bids, by buyer and seller agents, is related to agent strategies, addressed in detail in section 6. The market operator evaluates all the received bids, analyses them through the pool auction mechanism, defines the market price and accepted bids. Then a reply_bid message is sent to all pool participants, specifying the settled market price and if the bid was accepted and why.

3.3 Mixed Markets
The Mixed model combines features of Pools and Bilateral Contracts. In this model, a Pool isn’t mandatory, and customers can either negotiate an agreement directly with sellers, at the pool market price or both. Agents must decide whether to try or not the Pool, whether to keep bilateral negotiations simultaneously with Pool negotiations or just after Pool results if bids were not accepted. For that agents use their past experiences, market knowledge and agents own negotiation strategies to support their decisions.

4. DATA MINING
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 administrator 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, our market simulator uses clustering, classification and association operations.

To carry out the clustering operation a Two-Step clustering algorithm [12] 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 [9], 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 administrator 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” [1], 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 administrator 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 propensities, showing associations between products, prices, style, etc.

After these operations, to get confident data, agents can request the services provided by the market administrator agent, in order to support their strategic behavior. Only players with more sophisticated behavior 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’ behavior even if they are set as a private information agent. This situation occurs, by the simple fact of being on the market.

5. STRATEGIC BEHAVIOR
5.1 Time-dependent Strategies
Agents use four time-dependent strategies to change their price during a negotiation period: Determined, Anxious, Moderate and Gluttonous, these strategies depending on both the point in time when the agent starts to modify the price and the amount it changes.

Although time-dependent strategies are simple to understand and implement [6], they are very important since they allow the simulation of important issues such as: emotional aspects and different risk behaviors. For example, 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.

5.2 Behavior-dependent Strategies
In this work, we have also used the time-dependent strategies, based on the model proposed by S. Fatima [3], to model different attitudes towards time, during a negotiation period.

Agents use behaviour-dependent strategies to adjust parameters 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 from market administrator services; and private information, available only to the specific agent at their individual knowledge module.

For Pool Negotiations we define two different behaviour-dependent strategies: one called Composed Goal Directed (CGD)
and another called Adapted Derivative Following (ADF). The CGD strategy is based on two consecutive objectives, the first one is selling (or buying) all the available (or needed) units, and then increase the profit (reduce the payoff). The ADF strategy is based on the Derivative Following strategy proposed by Greenwald [5]. The ADF strategy adjusts its price by looking at the amount of revenue earned in the previous period as a result of the previous period’s price change. If the last period’s price change produced more revenue per good than the previous period, then the strategy makes a similar change in price. If the previous change produced less revenue per good, then the strategy makes an opposite price change.

For Bilateral Contracts Negotiations we also have several behaviour-dependent strategies. Buyer agents can use two complementary behaviour-dependent strategies: the Modified Goal Directed for Buyers (MGDB) and the Fragmented Demand (FD). The MGDB strategy is an adaptation of CGD for bilateral contracts. The FD strategy, 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. Seller agents can also choose from two different behaviour-dependent strategies: the Modified Goal Directed for Sellers (MGDS), 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 weighted by Seller Satisfaction (DFWS) or by the Previewed Demand for a specific product (DFWPD). The DFWS/PD is based on the ADF behaviour weighted by the referred issues. Seller agents can obtain these values through requesting for market administrator agent support.

5.3 Scenario Analysis Algorithm
To obtain an efficient decision support, seller and buyer agents also have the capability of using the Scenario Analysis Algorithm. This algorithm provides a more complex support to develop and implement dynamic pricing strategies since each agent analyses and develops a strategic bid, for the next period, taking into account not only its previous results but also other players possible results and expected future reactions. It is particularly suitable for markets based on a Pool or for Mixed Markets, to support sellers and buyers decisions for proposing bids to the Pool and accepting or not a bilateral agreement. The algorithm is based on analysing several bids under different scenarios, constructing a matrix with the simulated results and applying a decision method to select the bid to propose.

Each agent uses historical information about market behaviour and about other agents’ characteristics and behaviour, and information provided by the market administrator, by means of Data Mining techniques. With the information gathered agents can build a profile of other agents based on their expected proposed prices, limit prices, and capacities. With these profiles, and based on the agent own objectives and user risk preference, several scenarios, and the possible advantageous bids for each one, are defined.

We call a play to a pair bid-scenario. After defining all the scenarios and bids, market simulation is applied to build a matrix with the expected results for each play. The matrix analysis with the simulated plays’ results is inspired by the Game Theory concepts for a pure-strategy two-player game, assuming each player seeks to minimize the maximum possible loss or maximize the minimum possible gain [4]. Several decision methods are available, for example: a Seller trying to maximize the minimum possible gain may use the MaxiMin decision method; a Buyer trying to obtain the smallest maximum payoff may use the MiniMax decision method.

The analysis of each period’s results will update the agent’s market knowledge and the scenarios to study. After each negotiation period, instead of considering how other agents might increase, decrease, or maintain their bid, agents use knowledge rules that restrict modifications on the basis of other agents’ expected behavior. The knowledge rules update agents’ bids in each scenario, but the number of scenarios remains the same. If at the end of a negotiation period the agent concludes—by analyzing market results—that it incorrectly evaluated other agents’ behavior, it will fix other agents’ profiles on the basis of the calculated deviation from real results and will also update the knowledge rules.

6. IMPLEMENTATION
A prototype was developed in Open Agent Architecture (OAA) and in Java. Figure 1 illustrates the main interface of the MarketPlace.
OAA (http://www.ai.sri.com/~oaa/) is a framework for integrating a community of heterogeneous software agents in a distributed environment. It is structured to minimize 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’s Interagent Communication Language is the interface and communication language shared by all agents, no matter which machine they are running on or which programming language they are programmed in. OAA is not a framework specifically devoted to develop simulations; some extensions were made to make it more suitable, such as the inclusion of a clock to introduce the time evolution mechanism of the simulation.

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.

7. CONCLUSIONS
In the near future, agent market strategies will be a common competitive manoeuvre for Electronic Markets. 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. Also important is the development of agent-based tools that will help in understanding what kinds of electronic market strategies are appropriate. Very relevant is the availability of a Scenario Analysis Algorithm which is a promising algorithm to improve agents bidding process and counter-proposals definition. This analysis gives the agent not only decision support about the best bid to propose in a Pool but also makes possible the improvement of the negotiation mechanism for establishing bilateral contracts.

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9. REFERENCES


