A MULTI-AGENT SYSTEM TO SUPPORT DECISION MAKING IN ELECTRICITY MARKETS

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Abstract – Throughout the world, the electricity industry is undergoing enormous changes in the structure of its markets and their regulations. The electricity industry is evolving into a distributed and competitive industry in which market forces drive the price of electricity. Changes are towards a competitive framework and a market environment is replacing the traditional centralized operation approach. As electricity markets evolve there is a need for new modelling approaches that simulate how electric power markets could evolve over time and how participants in these markets may act and react to the changing economic, financial and regulatory environment in which they operate.

In this paper we present a Multi-Agent simulator to give decision support in Competitive Electricity Markets combining bilateral trading with power exchange mechanisms. This Multi-Agent environment includes several heterogeneous and autonomous intelligent agents, which are endowed with historical information about the market and have strategic behaviour to negotiate. This paper focuses on the different negotiation mechanisms supported by the simulator, and on agents' strategic behaviour to face them. A special attention is devoted to the structure of market players, Seller and Buyer agents, particularly in what concerns their decision analysis process to face the challenging market.

Keywords: Simulation, Decision-making, Intelligent Agents, Electricity Markets.

I. INTRODUCTION

The power industry is facing several transformations. Competition, open access, and the break-up of the traditional vertically integrated utility structure will result in a radically different industry. The transformation is being carefully managed to minimize disruption to various participants, from consumers to existing utilities, which must deal with the challenge and try to take advantage of the opportunities that are being presented, for achieving higher efficiency. Therefore, there is a prevailing need for tools to understand, predict and even design electricity markets.

Agents are autonomous or semi-autonomous entities that can perform tasks in complex and dynamically changing environments. Agent technology seems to be an appropriate paradigm for use in modelling individual participants of electricity markets since they exhibit some relevant capabilities like autonomy, adaptability and ability to interact with others.

A Multi-Agent System (MAS) consists of a group of agents that combine their specific competencies and cooperate in order to achieve a common goal [1]. Efficient cooperation as well as coordination procedures between agents endows a MAS with a capability higher than the sum of the individual agent capabilities.

Therefore we propose a Multi-Agent system to simulate Competitive Electricity Markets. This Multi-Agent Simulator includes several heterogeneous and autonomous intelligent agents representing the different independent entities in Electricity Markets. The Multi-Agent Simulator is intended as a Decision Support Tool, so it includes several types of negotiation mechanisms usually found in Electricity Markets, such as Bilateral Contracts, Pools, Symmetric and Asymmetric, and Mixed Markets (bilateral contracting simultaneously with a Pool), to let the user test them and obtain sensibility about the best way to negotiate in each one. These ideas originate the development of a prototype of the proposed Multi-Agent Simulator [2].

The architecture is flexible, the user defines completely the model she/he wants to simulate: how many agents are in the model, the type and strategies of each one and the type of market. To obtain an efficient decision support, agents have the capability of using an algorithm that analyses different bids under several scenarios. We call a pair bid-scenario a *play*. The analysis of several *plays* permits the construction of a matrix with possible results, and then, after a decision method is applied, the agent can select the bid to propose, having an idea of the expected payoff. This will increase its performance and improve their negotiation capabilities.

Some other approaches to agent-based simulation are more targeted and limited than our simulator. PowerWeb [3] considers single uniform auctions with fixed demand. The Auction Agents for the Electric Power Industry project [4] implements a Dutch auction. SEPIA (Simulator for Electric Power Industry Agents) studies just bilateral contracts [5].

The works of John Bower and Derek Bunn [6], Monclar and Quatrain [7] and James Nicolaisen, Valentin Petrov, and Leigh Tesfatsion [8] are relevant to our research in agent-based simulation; however, they discuss only the market in England and Wales. Jorge Villar and Hugh Rudnick present another important simulation application [9] focusing particularly on hydroelectric power station parameters. Javier Contreras and his colleagues present an interesting lab experience that shows the practical utility of electricity market simulators[10]. On the other hand our work is intended as a Decision Support Tool for the analysis and comparison of the negotiation mechanisms most used in Competitive Electricity Markets.

In this paper we start by giving an overview of the Multi-Agent model, its types of agents and their characteristics, focusing specially the Seller and Buyer agents. The negotiation mechanisms and the interaction between agents are detailed in another section. A special highlight is given to Seller and Buyer agent' strategies and decision analysis processes.

II. MULTI-AGENT MODEL

There are different types of agents in our model: Market Facilitator Agent, Seller Agents, Buyer Agents, Market Operator Agent and Network Operator Agent. In this section we will describe their roles, functionalities and the interactions between them.

The Market Facilitator plays the role of market coordinator of the Electricity Market and its main goal is the correct functioning of the market. The most important players in this type of markets are Seller and Buyer agents. The structure of these agents will be analysed in detail, particularly their strategic behaviour and decision-making algorithm. The Market Operator depends directly from the Market Agent and is responsible for the Pool mechanism. The Network Operator Agent is specific to the application domain, i.e. Electricity Markets, representing the transmission grid and all the involved technical constraints.

A. Market Facilitator

This agent is the market coordinator. In the application domain, it represents the electricity market regulation entity. It knows the identities of all the agents present in the market, regulates the negotiation process and assures the market is functioning according to the established rules. Agents before entering the market must perform first the registration in the Market Facilitator, specifying their market role and services.

B. Seller and Buyer Agents

Seller and Buyer agents are the two key players in the market, so a special attention is devoted to them, and particularly to their objectives and strategies they can use to reach them. These agents have similar structure and a kind of symmetrical (due to their antagonistic objectives) behaviour, for this reason they are both treated in this section, however, whenever necessary the differences between them will be pointed out.

The structure of these types of agents comprises two functional modules: *Events Handler* and *Strategic Decision Making*, plus one knowledge-based module: *Market & Individual Knowledge* module. Figure 1 illustrates the several modules of Seller and Buyer agents structure.

Figure 1- Seller and Buyer agents structure.

The *Events Handler* module is responsible for all processes related with messages 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 piece of information. Agents use ICL – Interagent Communication Language (see section V) – to exchange messages between themselves.

The *Market & Individual Knowledge* module contains information about the organisational and operational rules of the market, as well as other agent commitments and capabilities, and about the agent itself: agent own capabilities, current availability, past experiences and strategies. Through the analysis of historical market results, the profile of each agent in the market is constructed.

The *Strategic Decision Making* module is a module that analysis previous results and determines how to quote bids and which strategy to use. This module contains an algorithm that analyses several scenarios and applies a decision method to select the most appropriate bid to propose. A detailed description is presented in section IV.

The number of Seller and Buyer Agents in each scenario is completely defined by the user, who must also specify their intrinsic and strategic characteristics. By intrinsic characteristics we mean the *Individual Knowledge* related to reservation and preferred prices, and also to the available capacity (or power needs if it is a Buyer agent). By strategic characteristics we mean the type of strategies the agents will employ to reach the objective of selling the available capacity at the best price, if the agent is a Seller, or to buy the needed power if the agent is a Buyer.

Seller Agents will compete with each other, since they are all interested in selling all their available capacity and in obtaining the highest possible market quote. On the other hand Seller Agents will cooperate with Buyer Agents while trying to establish some agreement that is profitable for both. This is a rich domain where it is possible to develop and test several algorithms and negotiation mechanisms for both cooperation and competition.

C. Market Operator Agent

This agent is only present in simulations of Pool or mixed markets, and is the responsible for the functioning of the Pool. It will send a request for proposals, organise the received bids, determine the market price and select the accepted and rejected bids. After the processing of all bids, and market price settled on, the results are communicated to each Pool participant. Bids matching process is done with the technical approval of the Network Operator Agent.

In Pool markets the most common type of negotiation is a standard uniform auction [11]. If only the suppliers are able to compete in the Pool, it is called an Asymmetric Market. If both suppliers and buyers are able to compete it is called a Symmetric Market, also known as Double auction in the auction theory. Both of these types of Pool mechanisms are included in our simulator.

D. Network Operator Agent

One Network Operator Agent is present in every simulation; its objective is to simulate the constraints and technical feasibility in transmission lines. So, the Network Operator must technically approve all negotiations. In Pool Markets the Market Operator is the agent responsible for dealing with the Network Operator, in order to obtain technical approval for the bids matching process. In a bilateral contract, the Seller Agent must be sure of the technical possibility of delivering energy to the Buyer Agent localisation, so it is responsible for talking with the Network Operator, before an agreement is reached.

III. NEGOTIATION MECHANISMS

The process of negotiation can be of many different forms, such as auctions, protocols in the style of the contract net, and argumentation. Our simulator focuses on the mechanisms found in Electricity Markets, so it includes the possibility of negotiate through bilateral contracts, through auctions, single and double uniform auctions, and through a mixed market, where the agent must decide whether to negotiate in the auction and/or establish a bilateral agreement. This is an important characteristic giving to the simulator a high degree of flexibility and usefulness, since the same scenario can be analysed through different negotiation mechanisms.

In this section we will describe the negotiation mechanisms included in the simulator, particularly the interaction between the Seller and Buyer Agents.

A. Bilateral Contracts

Figure 2 illustrate the steps for establishing bilateral contracts. The process of negotiation through bilateral contracts starts by the Buyers, who send a *call_for_proposals* to all agents capable of supplying power.

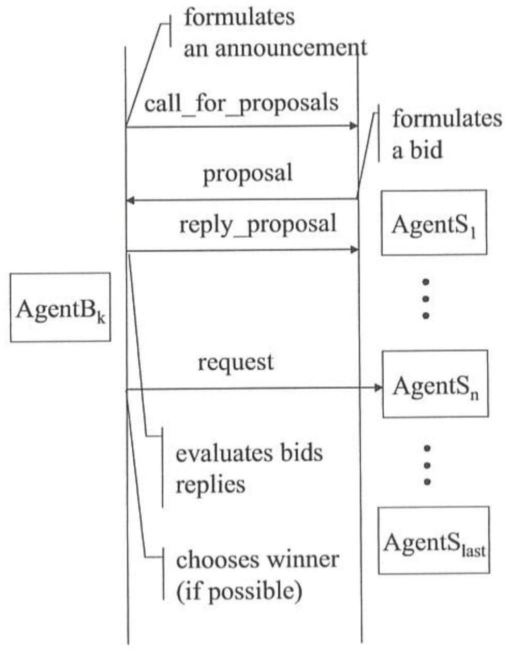

Figure 2- Negotiation mechanism for Bilateral Contracts.

call_for_proposals (AgentId, Params)

AgentId: Agent identification.

Params: List of parameters specifying the agent needs, such as power needed, localization and time period for the contract, and the reply parameters expected, such as price and technical feasibility.

The *call_for_proposals* message triggers the negotiation process and is delivered to all Seller agents existing in the simulated market. In response to a *call_for_proposals* message, a Seller Agent analyses its own capabilities, current availability, past experience and Network Operator Agent feedback. Then, formulates a bid, if it is able to make an offer to the requested parameters, and sends a message to the source Buyer Agent, specifying for each requested parameter the value of its proposal.

proposal (AgentId, PId, Params)

AgentId: Agent identification.

PId: proposal identification.

Params: List of parameters values.

The Buyer Agent evaluates all the received proposals and selects the Seller Agent that presents the most valuable bid, sending it a request message if the bid is satisfactory.

request(AgentId, PId)

Other agents are informed that their bids were not accepted, by sending them the following message:

reply_proposal(AgentId, PId, not_accepted, Reason)

Moreover, this message also includes the reason why this particular bid was not chosen.

B. Pool

The process starts at the Market Operator, who sends a request for participation in the Pool to all agents in the market.

call_for_participation (PoolTp, Params)

PoolTp: Type of Pool.

Params: List of parameters the agents must contemplate on the bid to be submitted.

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.

bid (AgentId, BId, Params)

AgentId: Agent identification.

BId: Bid identification.

Params: List of parameters values.

The process of formulating bids, by Buyer and Seller agents, is addressed in detail in section IV, and is related to agent strategies. The Market Operator evaluates all the received bids, analyses them through the Pool auction mechanism and Network Operator Agent feedback, and defines the market price and accepted bids. Then a *reply_bid* message is sent to all Pool participants, specifying the settled market price, if the bid was or not accepted and why.

reply_bid(AgentId, BId, Mprice, [accepted / not_accepted], Reason)

Figures 3 illustrate the steps involved in a market mechanism based on a Pool, regulated by an auction mechanism.

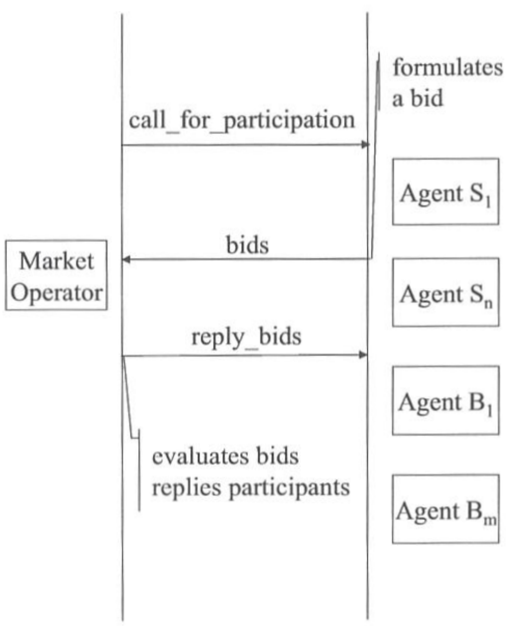

Figure 3- Negotiation mechanism for Pool markets.

C. Mixed Markets

In a mixed market, the two negotiation processes are developed simultaneously and the decision of biding, and what to bid, in a Pool and of accepting, or not, a bilateral contract, is totally made by Seller and Buyer agents, and depends on their strategic behaviour. Agents may still decide to participate only in the Pool, or only to establish bilateral agreements, however sometimes they can combine the two situations and take advantage of it, for example to establish an agreement where they can sell some of the capacity not accepted in the Pool.

IV. STRATEGIC DECISION MAKING FOR NEGOTIATION

The market simulator is organised in several negotiation periods and both Seller and Buyer Agents have strategic behaviour to define their desired price. These agents have time-dependent strategies: strategies to change the price according to the remaining time until the end of the negotiation period; and behaviour-dependent strategies to define the next period price according to the results obtained in the previous ones. To assure an efficient Decision Support, agents have the capability of analysing different scenarios to obtain knowledge to be used in future decisions. That is important for them to help on questions like "what to bid in the Pool?", "should a bilateral contract be accepted?" or "what strategy to use in a mixed market?". The strategic behaviour of agents and their mechanism of analysing different scenarios to support decision-making, which are the core of the Strategic Decision Making Module of Seller and Buyer Agents, will be detailed in this section.

A. Agent Strategies

Strategies to change the price under a negotiation period, also referred as time-dependent strategies, are called: *Determined*, *Anxious*, *Moderate* and *Gluttonous*. The difference between these strategies is the time instant at which the agent starts to modify the price and the amount it changes. Determined agents will maintain their prices constant during the negotiation period. Anxious agents will start modifying the prices early in the negotiation period but by small amounts. Moderate agents will start changing the prices in the middle of the period by a small amount, and Gluttonous agents will only start changing the prices at the end of the negotiation period but by major amounts.

To adjust price between negotiation periods, also referred as behaviour-dependent strategies, two different strategies were implemented: one called *Composed Goal Directed* and another called *Adapted Derivative Following*.

The *Composed Goal Directed* strategy is based on two consecutive objectives, the first one is selling (or buying) all the available capacity (power needed) and then increase the profit (reduce the payoff). Agents that use this strategy will decrease price if in the previous period the available capacity, the first objective, was not completely sold and will increase price when all the available capacity was sold in the previous period, trying to maintain satisfied the first objective while trying to obtain a higher profit. For Buyer agents the strategy is symmetrical: a Buyer will increase price if in the previous period the power needed was not completely bought and will decrease price when all the power needed was obtained, trying to maintain satisfied the first objective while trying to decrease market price in order to spent less money.

The *Adapted Derivative Following* strategy is based on a *Derivative Following* strategy proposed by Greenwald [12]. The *Adapted Derivative-Following* strategy adjusts its price by looking to 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 a different price change.

The price adjustment is based on the same calculation for both strategies and takes into account the difference between the desired results and the obtained results in the previous period. The calculation will be exemplified for a Seller, however for Buyer agents the calculations are identical but with different parameters, regarding Buyers objective of buying all the needed power at the lower expensive price. The price for the next period will be the previous period price adjusted by some amount, that will increase or decrease the previous price according to the strategy used.

$$price_{i+1} = price_i \pm amount_{i+1}$$

$$amount_{i+1} = price_i * \left(\beta + \frac{\Delta_i}{Capacity\_available_i * \alpha} \right)$$

$$\Delta_i = Capacity\_available_i - Energy\_sold_i$$

Instead of adjusting the price each day by a fixed percentage (like β), the change is scaled by a ratio based on the objective of selling all the available capacity. The amount price changes increases with the difference between the power intended to sell and the power actually sold. β and α are just scaling factors.

Details and examples about the behaviour of these strategies can be found in [13].

B. *Scenario Analysis Algorithm*

This algorithm is particularly suitable in Pool or hybrid markets, not only to support agents' decisions for proposing bids to the Pool but also their decisions to accept or reject bilateral agreements.

Agents can use the algorithm to analyse different scenarios and evaluate the expected returns. Seller and Buyer agents are like players in a game, and this algorithm analyses the possible scenarios resulting from other agents' reactions. Then, it will apply a decision method to decide what to bid in the Pool and whether to accept a bilateral contract. Every period includes the same steps, but the results of the analyses from each period update the agent's market knowledge. Figure 4 illustrates the algorithm steps.

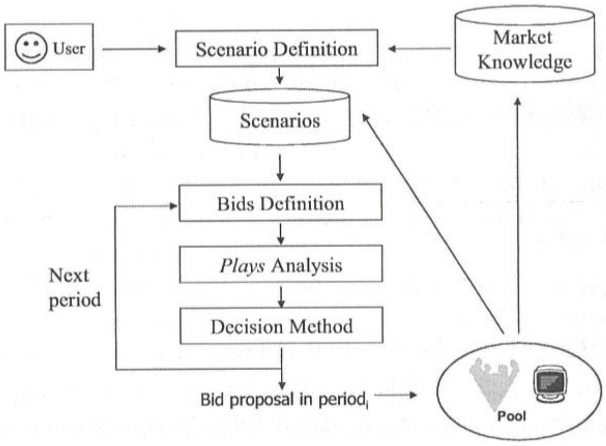

Figure 4- The Scenario Analysis Algorithm.

1) *Scenarios and Bid Definition*

Agents have historical information about the other agents in their market knowledge module. They can build a profile of other agents with the expected proposed prices, limit prices, and capacities. With this information, the agent constructs several scenarios and analyses them to determine the best way to deal with competitors and how to bid to get a good—or the most reliable—payoff.

To get warrantable data, each agent uses techniques based on statistical analysis and knowledge discovery tools, which search historical data. Usually, after a confidential period, markets disclose information about past transactions. For example, such information from the Spanish electricity market [14] is available online.

Each market player has two prices. *limit_price* is the minimum price if the player is a Seller and maximum price if the player is a Buyer. *expected_price* is the previewed bid price. The number of scenarios, which result from the different combinations possible considering the two prices for each agent, is 2^n, where n is the number of other agents in the model.

It's necessary to define which bids or move an agent or player should analyse. The agent should analyse the incomes that result from bidding its limit, desired prices, and competitive prices—those that are just slightly lower (or higher, in the Buyer's case) than its competitors' prices.

Consider how a Seller applies the algorithm. Let j be the Seller agent doing the analysis, cap_j its available capacity, $limit\_price_j$ its minimum acceptable price, and $desired\_price_j$ its expected desired price. (A Buyer applies the algorithm similarly, except the limit price is a maximum price instead of a minimum and the objective is to buy all the energy it needs at the lowest price instead of to sell at the highest price.) Let P denote the set of all players—Sellers and Buyers—in the market. Let ε be the smallest positive number allowed as a bidding increment.

The bids that agent j must analyse are:

$$\begin{cases} bid(limit\_price_j, cap_j) \\ bid(desired\_price_j, cap_j) \\ bid(limit\_price_i - \varepsilon, cap_j) \\ bid(expected\_price_i - \varepsilon, cap_j) \end{cases}, \forall\, i \in P, i \neq j,$$

subject to

$$limit\_price_i - \varepsilon > limit\_price_j$$

and

$$expected\_price_i - \varepsilon > limit\_price_j.$$

The number of bids to analyse is $2 \times n + 2$. This number hits the maximum when *limit_price*$_j$ is smaller than the other agents expected or the limit price. We will call a *play* to a pair bid – scenario, then, the total number of *plays* to analyse is number_of_bids × number_of_scenarios, and the maximum value it can achieve is $(2 \times n + 2)2^n$.

So far we've considered only when agents bid their limit or expected prices. However, an agent might bid between its limit and the expected price, or even above it. So, if we say that each agent might bid *np* prices, the number of scenarios becomes np^n, and the number of plays to analyse is $(np \times n + 2)np^n$.

Even in a model with few players, the number of plays can be high. For example, with four players and three different prices for each, the agent must analyse a maximum of 1,134 plays!

Furthermore, because the market is organised in several periods, an agent could increase, decrease, or maintain its bid—three possible actions—after each negotiation period, increasing the number of scenarios to analyse. So, after k periods, considering the possible bid updates, the number of plays to analyse becomes $(np \times n + 2)np^n \times 3^{(k-1)n}$.

In a model with four players and three prices, after three negotiation periods, an agent must analyse 7,440,174 plays, which is a huge number, even for a distributed execution of the model. However, must agents analyse every possible scenario?

Because our simulator is a decision support tool, the user should have the flexibility to decide which and how many scenarios to analyse. To do so, the user must define the scenarios to simulate by specifying the price that agents will propose:

$$Price_i = \lambda \times Probable\_Price_i + \varphi \times Limit\_Price_i,$$

where λ and φ are scaling factors that can differ for each agent.

Suppose that the user selects $\lambda = 0$ and $\varphi = 1$ for every Seller and $\lambda = 1$ and $\varphi = 0$ for every Buyer. This means she/he is interested in analysing a pessimistic scenario (from the Seller's viewpoint). But, if the user selects $\lambda = 1$ and $\varphi = 0$ for every agent, he or she is interested in analysing the most probable scenario.

With this formula, the user can define each agent's proposed prices for every scenario she/he wants to consider. If the user defines nc scenarios, the number of plays to analyse is $(nc \times n + 2)nc$.

After the agents analyse all the plays, the algorithm will construct a matrix, obtain the results, and apply a decision method to decide which bid to propose.

2) *Decision Method*

The matrix analysis with the simulated plays' results is inspired by the game theory concepts for a pure-strategy two-player game [15][16], assuming each player seeks to minimize the maximum possible loss or maximize the minimum possible gain.

A Seller—like an offensive player—will try to maximize the minimum possible gain by using the MaxiMin decision method. A Buyer—like a defensive player—will select the strategy with the smallest maximum payoff by using the MiniMax decision method. In Buyers' matrix analyses, they select only situations in which they can fulfil all their consumption needs. They avoid situations in which agents will accept reduced payoff but can't satisfy their consumption needs completely.

After applying the decision method, the agent selects one bid that it will propose on the Pool, unless it reaches an agreement for a bilateral contract that's more profitable than the previewed Pool results.

This analysis not only provides the agent with decision support about the bid to propose in a Pool but also helps improve the negotiation mechanism for establishing bilateral contracts. With this information, the agent can evaluate a bilateral contract's potential benefits, compare them to the benefits expected in a Pool, and make counterproposals.

3) *Scenario Actualisation*

As we stated earlier, 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 they might increase, decrease, or maintain their bid, agents use knowledge rules that restrict modifications on the basis of other agents' expected behavior. The following are some sample rules to update Sellers' behaviour:

- If a Seller bid is higher than the market price and higher than its limit price, the agent will decrease its bid.
- If a Seller bid is higher than the market price and equal to its limit price, the agent will maintain its bid.

Because a Seller probably won't increase its bid if it couldn't sell in the previous period, if it couldn't sell and is already bidding its limit price, it will most likely keep its bid at the limit price.

The following are some sample rules to update Buyers' behavior:

- If a Buyer bid is lower than the market price and lower than its limit price, the agent will increase its bid.
- If a Buyer bid is lower than the market price and equal to its limit price, the agent will maintain its bid.

Because a Buyer probably won't decrease its bid if it couldn't buy in the previous period, if it couldn't buy but is already bidding its limit price, it will most likely keep its bid at the limit price.

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 analysing market results—that it incorrectly evaluated other agents' behaviour, it will fix other agents' profiles on the basis of the calculated deviation from the real results.

V. IMPLEMENTATION

The implementation of the proposed architecture is already done. Some results about the behaviour of agent strategies, presented in section IV-A, were obtained and some conclusions established [2]. The prototype was developed in Open Agent Architecture (OAA) and in Java was developed.

OAA, developed at SRI International [17], 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.

VI. CONCLUSIONS

This paper describes the use of an agent-based simulation approach to understand a complex system. The multiagent technology allied to an object-oriented implementation enables easy future improvements and model enlargement. The electric power industry provides a very rich domain for illustration, but there are many other areas where these ideas could also be fruitfully applied.

The simulator presents some interesting features, like the possibility of simulating several different types of markets, and the strategic behaviour of both Seller and Buyer agents. The agents' strategies were analysed and detailed, particularly the Decision Support Algorithm for game analysis and bid selection. This algorithm seems to be very promising and is now being implemented. In the meanwhile some scenarios are prepared to test it.

The process of negotiation through bilateral contracts is being updated with the possibility of counter-proposals being presented. In the future the agents will be improved to have learning capabilities, with some kind of reinforcement-learning algorithm, like the Q-learning algorithm.

The simulator probes the possible effects of market rules and conditions by simulating the strategic behaviour of participants.

REFERENCES

[1] G. Weiss, Multiagent Systems, MIT Press, 1999.

[2] I. Praça, C. Ramos, Z. Vale and M. Cordeiro, "MASCEM: A Multiagent System that Simulates Competitive Electricity Markets", in *IEEE Intelligent Systems*, vol.18, nº 6, pp.54-60, Nov/Dec 2003.

[3] PowerWeb-URL. http://stealth.ee.cornell.edu/powerweb/.

[4] EPRI-(Electric Power Research Institute), "Using Intelligent Agents to Implement an Electronic Auction for Buying and Selling Electric Power". Available: http://www.agentbuilder.com/Documentation/EPRI/.

[5] S.A. Harp, S. Brignone and B.F. Wollenberg, "SEPIA: Simulator for Electric Power Industry Agents", in *IEEE Control Systems*, vol.20, nº4, pp.53-69, August 2000.

[6] J. Bower and D. Bunn, "Agent-based Simulation – An Application to the New Electricity Trading Arrangements of England and Wales", in *IEEE Transactions on Evolutionary Computation*, vol.5, nº5, pp. 493-503, Oct. 2001.

[7] F.R.Monclar and R. Quatrain,"Simulation of Electricity Markets: A Multi-Agent Approach", in Proc. of the 2001 International Conference on Intelligent Systems Application to Power Systems, pp. 207-212.

[8] J. Nicolaisen, V. Petrov and L. Tesfatsion, "Market Power and Efficiency in a Computational Electricity Market with Discriminatory Double-Auction Pricing", in *IEEE Transactions on Evolutionary Computation*, vol.5, nº5, pp.504-523, Oct. 2001.

[9] J. Villar and F. Rudnick, "Hydrothermal Market Simulator Using Game Theory: Assessment of

Market Power," in *IEEE Trans. Power Systems*, vol. 18, nº 1, pp. 91–98, Feb. 2003

[10]J. Contreras et al., "Power Engineering Lab: Electricity Market Simulator," in *IEEE Trans. Power Systems*, vol. 17, no. 2, pp. 223–228, May 2002.

[11]G. Sheblé, Computational Auction Mechanisms for Restructured Power Industry Operation, Kluwer Academic Publishers, 1999.

[12]A.Greenwald, J.Kephart and G.Tesauro, "Strategic Pricebots Dynamics", in Proc. of the First ACM Conference on Electronic Commerce, pp. 58-67. Available: www.cs.brown.edu/people/amygreen/.

[13]I. Praça, C. Ramos, Z. Vale and M. Cordeiro, "Intelligent Agents for the Simulation of Competitive Electricity Markets", in *International Journal of Modelling and Simulation*, vol.24, nº 2, 2004 (to appear).

[14]OMEL-URL. www.omel.es/.

[15]J. Von Neumann and O. Morgenstern, Theory of Games and Economic Behaviour, 1947.

[16]D. Fudenberg and J. Tirole, Game Theory, MIT Press, 1991.

[17]OAA-URL. www.ai.sri.com/~oaa/.