Multi-energy Retail Market Simulation with Intelligent Agents

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Abstract—**This paper presents an overview of a simulation platform for studying the behavior of energy retail markets where multiple energies enter in competition. This platform is based on autonomous agent techniques. The simulations include agents representing Residential, Commercial and Industrial Consumer Groups, Electricity, Gas, Heat Retail Suppliers and Energy Deliverers, Regulators, Market Operators, Economy and Information Environment. Each pursues its own interests and from their interaction a complex collective behavior emerges. Agents formulate their strategies namely by inner complex simulation process that try to guess other agent moves and define optimum decisions in energy purchasing, price fixing, market share wining, investing and capturing new consumers, among other. The process works on a FIPA complying platform being able to run in a parallel cluster machines. The paper shows the results of experiments illustrating that consumer awareness and rapid response are important to have a real market while lack of timely response allows retailers to take advantage of them.**

Index Terms—**Energy Markets, Autonomous Agents, Regulation, Simulation**

I. Introduction

REGULATED markets are now a major form of organization of power systems worldwide, even if in many countries vertical sector arrangements are still the norm. The introduction of competition redefines objectives and attitudes of actors in the power business, and new actors have gained their place. The social concerns of power delivery have been transferred from utilities to regulatory entities and companies now focus on profit and economic efficiency (this statement is made regardless of the definition of a social role to enterprises in a market environment). The actions of regulators are the means to translate in economic terms the concerns of the society on quality, environment, fairness, low prices, competition or transparency.

Technological progress has meanwhile multiplied the means of energy conversion. If end use energy consumption is heat, one may traditionally obtain it from electricity, gas or even from district heating services, in some countries. However, with the progress of micro-turbine technology and fuel cells, a user may now also purchase electricity from a power supplier or from a gas supplier – one only requires energy conversion equipment. Energy conversion is no longer confined to sources; it may happen all along the chain of supply down to the user.

It is not surprising therefore that electric power companies have in many countries made moves into the gas business. Regulatory bodies have increasingly acquired competence on gas markets as well.

This is the movement we are now witnessing in the constitution of MIBEL, the Iberian Electricity Market, joining together Portugal and Spain, which started by considering only electric power and now things have evolved such that, at political level, the parallel creation of an Iberian Gas market is under discussion and the extension of regulatory powers of the existing Regulatory Entities in both countries in on the table.

In fact, especially at distribution level, we may now witness a renewed kind of competition among parallel distribution networks that develop side by side in the attempt to gain consumers. What has been thought of as unlikely (power networks belonging to different entities developing in geographical competition) and led to the concept of natural monopoly in electricity distribution, is now a reality if we consider electricity, gas and heat networks and how they spread in the territory [1].

Economists have attempted for a long time to analyze the structure, efficiency and evolution of markets. The traditional approach uses mathematical models such as game theory to find the steady state solution of the dynamic economic system. Although such models have yielded significant research in simple market structures, they clearly lack the ability to analyze the micro-interaction among market actors of complex markets [2].

This paper is presenting the development of a simulation platform for markets with competing energies. The interest in this development is threefold:

a) The development is based on JADE, Java Agent Development Framework, a FIPA compliant platform for intelligent autonomous agent technology. This option allows portability, independent development of agents, standardization of the development process, modularity and benefits from all knowledge acquired that led to FIPA specifications and the successes of its application in other areas such as communications (FIPA – Foundation for Intelligent Physical Agents – http://www.fipa.org/).

b) Agents representing entities in the market are developed independently of one another and may be made as complex as required. Each agent has its own objectives, internal processes of decision and form of communication with other agents. It is from the interaction of individual agents that a complex behavior emerges [3], and this collective behavior mirrors the market behavior even in conditions difficult to define by mathematical models. The plug-in capacity of agent technology

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allows one to simulate a diversity of agents and to insert them in the platform with a minimum of effort.

c) The emerging complex behavior allows one to experiment a diversity of market conditions. A typical example is to test market behavior under different regulatory conditions, and try to detect perverse effects from what, at first, seemed to be sound policy.

In fact, we will show that consumer awareness and rapid response to retailer moves are necessary conditions to establish a real market. Otherwise, retailers may in practice take advantage of slow consumer response to make extra profit and keep market shares while steadily raising prices in a combined way (even if no provision for such arrangement exists in the definition of retailer agents).

II. TERRITORY

The paper reports experiments developed in a market simulated in a territory that may be represented in a GIS platform (Geographic Information System). The land is divided in squares or blocks, each block having a number of consumers of different types (typically, residential, commercial and industrial). Crossing the territory there are networks serving the clients that buy different types of energy: electricity, gas or heat.

Fig. 1 represents such a territory with a power network serving it. Other grids develop in the same territory, competing for clients. There are areas already developed and areas under development, not yet served by one or all the networks. There is, therefore, room for network expansion and conquer of new clients.

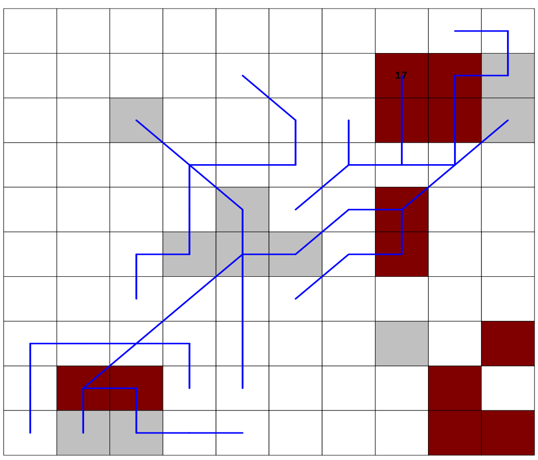

Fig. 1. Territory divided in cells or blocks. Dark grey cells: industrial clients dominant. Light grey cells: commercial clients dominant. White cells: mainly residential. A power grid is serving existing clients buying electricity. There is room for network expansion.

III. AGENT TYPES

The paper reports results from the interaction of nineteen market agents engaging in energy market simulation; among them, we find Residential, Commercial and Industrial consumer groups, Retail One and Retail Two involved in electricity retailing, Retail Three and Retail Four involved in gas retailing, Retail Five involved in heat retailing, Electricity Delivery, Gas Delivery, Heat Delivery, Electricity Market Operator, Gas Market Operator, Heat Market Operator, Electricity Regulator, Gas Regulator, Heat Regulator, Economy and Information Environment.

Interaction among market actors is introduced with indirect communication through Environment, as a way in which interactions between Environment and individual market actors take place as hybrid of sequential and parallel. Less complex set of market actors such as Economy, Regulator and Market Operator perform simple duties such as a) requesting information from the Environment, b) performing their typical duty and c) returning new information back to the Environment. But the process is more complicated when evaluation and optimization tasks are added for complex set of actors such as Consumer, Delivery and Retailer, who must analyze information for better understanding of other actors´ motives and goals, forecast future market behavior, make decisions based on predictions and learn and evolve from experience.

The basic functions in each fundamental set of agents are:

A – Economy – This agent translates into energy demand variables basic data such as economic drive, season of the year, weather conditions. These demand values are passed to the Information Environment Agent.

B – Consumer – Agents of this type represent not individual consumers, but rather classes or groups of consumers such as residential, commercial or industrial. Each agent purchases a mix of energies and changes market shares of these energies according to prices, needs, elasticity of demand and adjustment delays to price changes. Energy efficiency is also taken in account as well as costs of capacity increments do increase purchases of a given type of energy.

C – Information Environment – This agent acts as a blackboard where all available information from market players displayed and exchanged. It can be seen as an intermediate in which market actors post information regarding their current actions and request information for evaluating new actions. Apart from communication purposes, it also performs compilation on the data obtained from market participants, providing more clear and transparent information.

D – Energy retailer – Every agent of this type has internal functions a) monitoring its performance in terms of profitability as well as market share movement, b) finding optimal decision combinations for performance improvement, and c) improving management efficiency. Among various duties, achieving maximum profit while providing reliable service to consumer is the ultimate goal for a profit-oriented energy retail supplier. However, the level of reliability may, in some implementations, depend on the actions of the regulator and reactions of clients.

One important function inside a Retail agent is strategic planning. Therefore, these agents are equipped with an inner capacity for simulating the market and guessing other actor moves. This is a “simulation inside the simulation” process, based on the best knowledge an agent has of the behavior of others. An agent of this kind uses, in our model, neural networks to predict consumptions and prices and uses evolutionary computing simulation to plan ahead and derive an optimal strategy both for expansion of the business and for price determination.

E – Delivery – Such agents perform duties such as extending networks over the territory to supply new consumers, under request from the Retail agents. Network expansion is performed using functions optimizing paths and profits, which are also available in GIS platforms. An agent of this type has logic of its own and also seeks to maximize profit while guaranteeing contracts of supply. The action of these agents puts energies in competition, because they allow consumers to have choices.

F – Regulator – In the simulation to be reported, the regulatory agent imposes simple restrictions such as limiting duration between successive product price movements and imposing price-cap over price of energy products. More complex actions are under observation.

G – Market Operator – This agent acts as the replacement of wholesale market, issuing energy prices of day-ahead wholesale market.

During a cycle of simulation, each market actor performs the tasks mentioned above rotationally and the cycle ends when every market actors finishes performing its duties.

IV. AGENT MODELS

The following paragraphs present an explanation and mathematical models inside the complex market entities, used in the simulations. Because of the agent approach, any model may be replaced by another model in the simulation platform. The models below have been developed to give a flavor of reality to the simulations and do not intend to actually represent it faithfully. This description cannot be too detailed due to the lack of space and only the main features are mentioned.

A. Economy market actor

The energy demand of a particular block in the territory is calculated with following equation

$$ {}_{n}ED_{d} = \left[WEEK_{d} + \left(1 + TIME_{d}\right)\frac{EGR_{y}}{2} + \left(wf_{C} \times WEATHER_{d}\right)\right]\frac{{}_{n}BASE_{y}}{DE_{d}} \quad (1) $$

where,

${}_{n}ED_{d}$ = Energy demand of block n at day d

EGR_{y} = Regional economic growth rate

$TIME_{d}$ = Normalized duration to particular day d

wf_{C} = Weather depend factor of consumer type c

$WEATHER_{d}$ = Weather condition of day d

${}_{n}BASE_{y}$ = Reference energy demand of block n

$WEEK_{d}$ = Demand factor of block at weekend of year y

DE_{d} = Demand elasticity at day d

B. Consumer agent

Microeconomic theory suggests that consumers of energy commodities will increase their demand to the point where the marginal benefit they derive is equal to the price they have to pay [4]. The demand will virtually go down when the price is higher suggesting that movement of market share of a commodity is inversely related to the movement of its price in general. The following mathematical formulation is used for adjusting consumer consumption to the movement of commodity prices, giving new market shares:

$$ {}_{C}S_{p}^{d} = {}_{C}S^{d} \times \frac{\left(CP_{p}^{d}\right)^{-k}}{\sum_{i=1}^{n}\left(CP_{i}^{d}\right)^{-k}} \quad (2) $$

where

${}_{C}S_{p}^{d}$ = Share of commodity p in consumer type c at day d

${}_{C}S^{d}$ = Share of consumer type c at day d

CP_{p}^{d} = Converted price of commodity p at day d

CP_{i}^{d} = Converted price of commodity i at day d

k = Attitude factor of consumer type c on commodities

To incorporate time delay on consumption adjustment to commodity price changes, the following formula has been used so that the shares of commodities are gradually changed during the delay span

$$ {}_{C}S_{p}^{d} = LS_{p}^{i} \pm \frac{SC_{p}}{\pi}\left[ArcTan\left(\frac{t \times C}{t_{m}^{2} - t^{2}}\right)\right] \quad \text{if} \left[\begin{array}{l} i = lower, \pm become + \\ i = upper, \pm become - \end{array}\right] \quad (3) $$

where,

LS_{p}^{i} = Limit to share change for commodity p in condition i

SC_{p} = Share change of commodity p due to price change

t_{m} = Mid-point of delay time

t = Time interval between commodity price change and present time

C = Coefficient factor of share changing

C. Retailer

The profit of a Retailer, which is a profit oriented market player, is developed as follows

$$ {}_{p}PF_{y}^{d} = UEP_{y}^{d} \times P_{p}^{d} - \left|FC_{p} + {}_{p}UC_{y}^{d} \times UEP_{y}^{d}\right| \quad (4) $$

where

${}_{p}PF_{y}^{d}$ = Profit received by retail p at day d

UEP_{y}^{d} = Consumption of commodity at day d

FC_{p} = Fixed cost of retail p

${}_{p}UC_{y}^{d}$ = Production cost of commodity p at day d

P_{p}^{d} = Price of commodity p at day d

The decisions made by the Retailer Agents are generated with an Evolutionary Particle Swarm Optimization (EPSO) [5][6] model, which performs a simulation of the market in the future, assuming a certain behavior of competitors and clients and optimizes immediate decisions, which have influence on profit. The fitness function, used to measure the quality of the each decision set, is created based on the objective function of the problem and is mainly used as the criterion for selection of decisions to the next stage. The objective function used in this EPSO can be formulated as follow:

$$ \text{Maximize:} \quad Obj = \sum_{i=1}^{n}\left[\left(Coe_{p} \times P_{i} + Coe_{m} \times M_{i}\right) - Pen\right] \quad (5) $$

subject to: $P_i \rangle P_{LIMIT}$, $M_i \rangle M_{LIMIT}$

where

P_i = Profit available at day i

M_i = Market share at day i

Pen = Penalty applied when violation occurred

D. Delivery

In the Delivery agent, the network expansion is performed using a minimum path algorithm determining the most profitable distance from one geographical block to the nearest source block. The expected profit of each block is calculated using the following equation

$$EP_b = PP_b - UC_b \tag{6}$$

where,

EP_b = Expected profit at block b

PP_b = Potential profit at block b

UC_b = Unit cost value for connecting block b

A unit cost that assigns a value in some uniform-unit measurement system depicting the cost involved in connecting to any particular block is developed from installation cost of blocks. The unit cost value is calculated using

$$UC_b = Coef \times \left[\frac{EC_a + EC_b}{2}\right] \begin{cases} Coef = 1.0 \text{ if blocks are not in diagonal} \\ Coef = 1.414 \text{ if blocks are in diagonal} \end{cases} \tag{7}$$

where

UC_b = Unit cost value for connecting block b

EP_b = Equipment installation cost at block b

EP_a = Equipment installation cost at block a, adjacent to block b

V. IMPLEMENTATION

The energy market simulation platform is developed on JADE (Java Agent DEvelopment Framework), which is a distributed multi-agent software framework based on the peer-to-peer communication architecture, fully implemented in Java. It simplifies the implementation of multi-agent systems through a middle-ware that complies with FIPA specifications and through a set of tools that supports the debugging and deployment phase. The intelligence, the initiative, the information, the resources and the control can be fully distributed on mobile terminals as well as on computers in the fixed network [7]. The scheduling of agents in the simulation platform is made with a hybrid of sequential and parallel ways. The sequential scheduling is done at entity or class level, in which it is necessary for the agents to wait for their turn to receive updated information. For an entity having multiple agents, the parallel scheduling approach is used for the agents inside it to take advantage of the parallel processing approach.

The 19 market actors are represented in Fig. 2, grouped in categories. The energy market simulation begins with the Economy agent producing a regional economic growth rate and meteorological information in the form of a weather index. Using the economic growth rate and the weather index, the potential energy demand of a particular block is calculated with (1). Potential energy demand of particular type of consumer is attained with summing up the energy demand of blocks, which have similar load pattern.

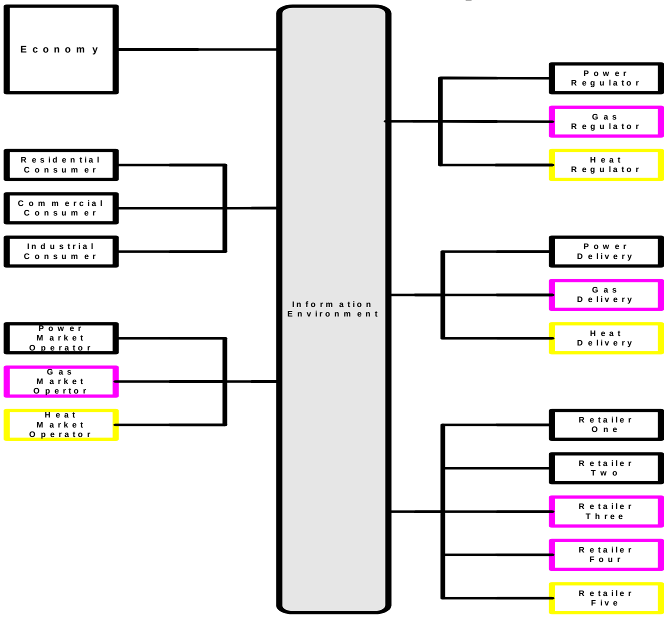

Fig. 2. Agent-based energy market simulation platform – agents grouped by categories and sharing information through the Information Environment

The Regulatory bodies make enforcements directing the market into more efficient and reliable operation. A minimum requirement for the duration between successive decisions on tariffs was set at one month, and ceiling and floor were assigned on the changing of energy prices and incentives.

Using (2), reference market shares of the energy commodities are calculated. The classification of consumers is done with the Consumer entity categorizing the consumers according to their level of access to available energy suppliers; a demand availability factor is determined as a function of the access to supply. With the reference market share of commodities and demand availability due to accessibility, the expected market share of energy commodities is determined, and the effect of reaction-delay in market share is taken in account using equation (3). The demand of each commodity is then calculated from the potential energy demand of particular consumer blocks and the expected market share of the energy commodity. An economic feasibility check is made when demand is greater than the existing capacity of the equipment, and energy consumption of the consumer block is determined using the recommendation from an economic feasibility check about new equipment installation.

The Energy Delivery entity begins its process by exploring the most potentially profitable consumer at present. Then, an investigation for finding the most profitable route to that consumer is done using a profit-distance function. A profit-distance grid is developed by calculating expected profits of blocks, with (6). Then, an accumulated-profit distance grid is produced by accumulating profit from connecting blocks adjacent an existing source into the existing system and converting them to sources iteratively until all blocks become source blocks. Simultaneously, a back link grid, which keeps track of connections made among blocks during the source converting process, is developed. The best path between new potential consumers and the existing network is then determined from the accumulated profit distance grid and back link grid. After planning the expansion, the construction process starts by connecting the blocks in the plan, nearest to the existing network, one by one until the final block in the expansion plan has been connected. A duration of two months has been taken as construction time for connecting two adjacent blocks.

The Market Operator entity acts as the wholesale energy market and produces the wholesale energy prices in day-ahead market basis. The Energy Retailer who requires more energy than the amount it has bought with contracts will be buying energy from wholesale market.

Each Energy Retailer entity monitors movements in market share and profitability, evaluates its economical performance, and defines its operational state, either profit-taking or share-taking, depending on whether dropping of profit or share is beyond an allowable limit, or normal state otherwise. Then, the decision process of manipulating influential variables such as energy prices, incentives, publicity, service, quality and management efficiency has at its core an Evolutionary Particle Swarm Optimization (EPSO) routine [5]. EPSO was selected for adjusting profit related variables because of its properties of flexibility as well as suitability in a complex environment. The number of decisions (individuals) in the population was set at 20 and each decision possesses ten variables. Each decision is assigned with random values at the initial stage and a gradual improvement is sought afterward.

The fitness function, the function used to measure the quality of the each decision, was created based on the objective function as in (5) and is mainly used as the criterion for selection of decisions to the next stage. This way, a market simulation is set up inside the objective function to foresee the performance of the given decision. Two months duration was taken as the length of the simulation inside the objective function. The selected decisions are then modified with logN distribution mutation. After this, the decisions are evaluated and selected according to their fitness value and the process is done for one generation. Details of EPSO and its mutation and reproduction process can be seen in [6].

The best decision is accepted as the decision to be taken for current situation. The decision-making duration, which was the delay time in decision-making process, was set at 14 days and candidate variables come to effect after that duration. The next optimization step is started when the consecutive price setting time limit is passed; a new population is created from the upper half of the decisions inherited from the previous optimization and randomly generated decisions, otherwise.

The Environment entity accepts the information from market actors when they wish to display it and releases it at market actors request. The market information is gradually updated with new data coming from the market players. Finally, one cycle of simulation is ended when every market participant finishes performing its duty.

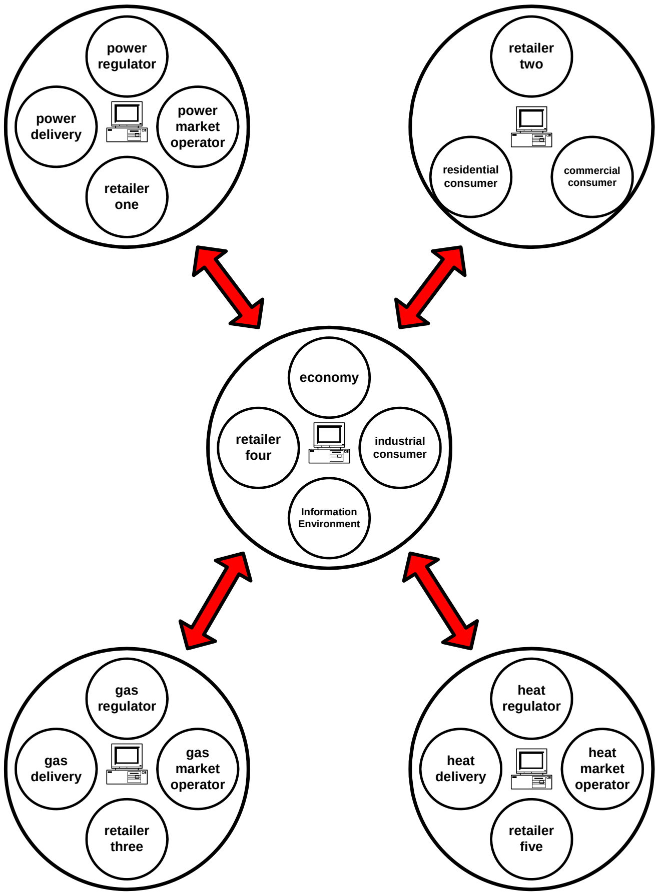

Fig. 3. Agents in a cluster of PC supporting the JADE platform

VI. RESULTS

The energy market simulation platform has been run on a cluster of PCs with 5 computers connected in parallel in a LAN. Agents are arranged such that no two parallel-scheduling agents under an entity exist on the same computer. Fig. 3 presents the arrangement used in the simulations reported.

The evolution of the market has been simulated for a period of 720 days. A number of experiments have been conducted but this paper will address only the following. *Scenario 1* emulates the situation where the energy market is in transition from a vertical structure to a competitive market; one assumes a low competitiveness of consumers due to the lack of awareness of opportunities as well as being too accustomed to existing under a vertical monopoly. *Scenario 2* is developed with consumers well alert to the competitive market, admitting that the regulators or the government provided pubic campaigns to educate the public about the new market structure and pros and cons of new level of freedom given to consumers, and create awareness of opportunities and threats. The observation was focused on how competitive the nature of market becomes, developed from the interaction among evolving agents in the two scenarios. The change in behavior of consumers was achieved by manipulating their attitude factor.

The results from *Scenario 1* are shown in Fig. 4-Fig. 6, in terms of energy prices offered by retailers of all types of energies to all types of consumers, and in Fig. 7, describing the evolution of market shares for all retailers.

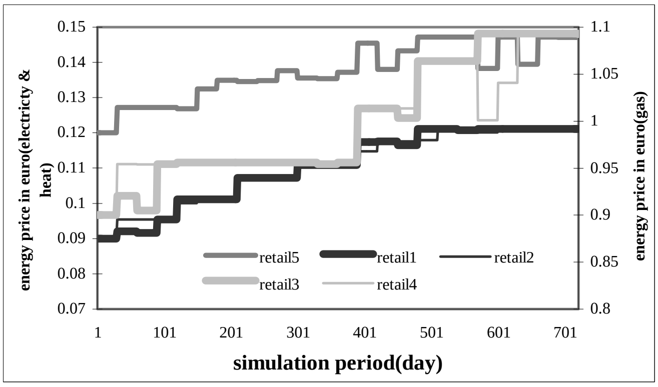

Fig. 4. Evolution of energy retail prices for residential consumers in *Scenario 1*

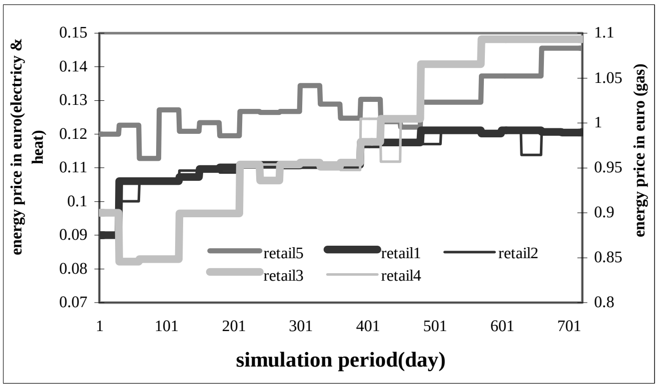

Fig. 5. Evolution of energy retail prices of commercial consumers in *Scenario 1*

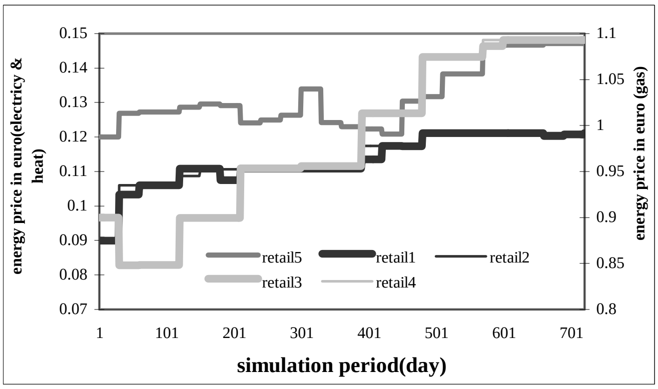

Fig. 6. Evolution of energy retail prices of industrial consumers in *Scenario 1*

The consumers did not have fast reactions and the responses to retailer moves in prices were not strong enough to compel the retailers to compete against each other. The energy retailers developed a behavior exploiting consumer lack of response by gradually increasing prices in a combined way without losing a substantial amount of market share. This behavior is seen clearly in the figures, where the energy prices set by retailers are gradually raising for all consumer types, residential, commercial or industrial. Notice that the prices from retailers competing with the same product (Retailer 1 vs. Retailer 2 in electricity, Retailer 3 vs. Retailer 4 in gas) keep a very similar behavior. This must be explained also by the fact that, in this simulation, the retailers had a similar starting point and no distinctive traces of behavior have been assigned to either of them.

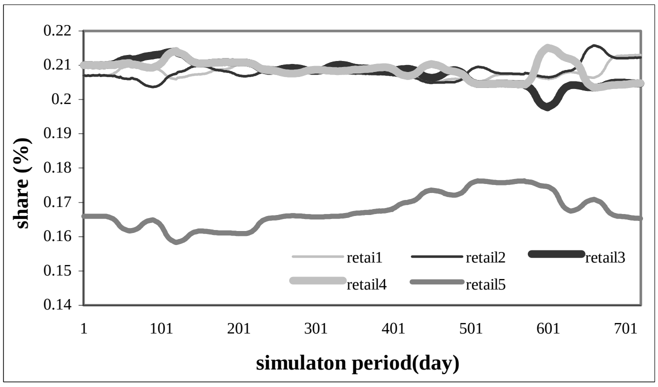

Fig. 7. Market share of retailers in *Scenario 1*

Although the energy prices have been gradually rising, check in Fig. 7 that the market share of energy retailers keeps stable with only minor fluctuations. The results from S*cenario 1* suggest a case where the retailers develop cooperative behavior (tending to oligopoly), because there is no regulation penalizing it and consumer reaction is very passive.

Instead, in *Scenario 2*, without forbidding oligopoly behavior, we have increased the capacity of consumers to react to retailer moves. This may happen following public awareness campaigns or education and training campaigns provided by the government or the regulatory bodies, leading to more access to information, more understanding of the economic consequences of decisions and a more aggressive attitude. This is achieved by manipulating coefficients k and C in (2) and (3).

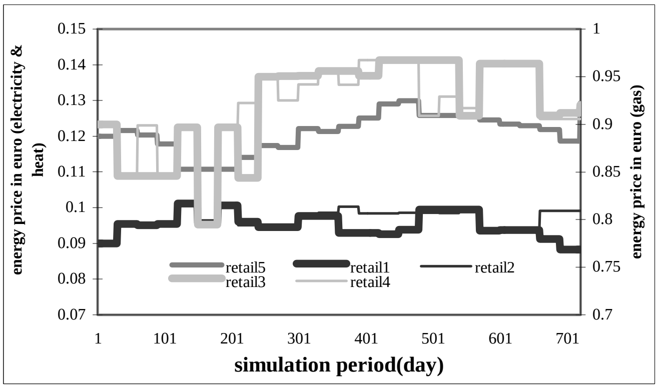

Fig. 8. Evolution of energy retail prices of residential consumer in *Scenario 2*

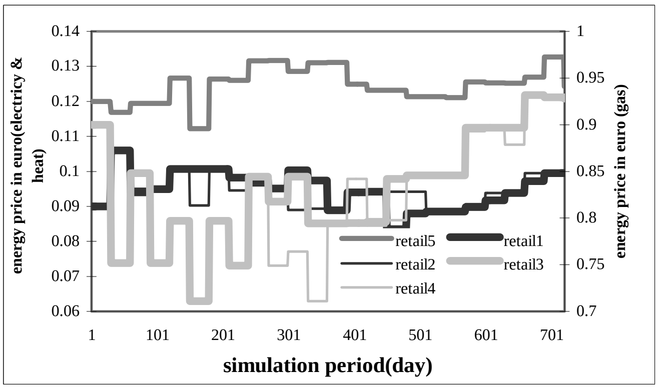

Fig. 9. Evolution of energy retail prices of commercial consumer in *Scenario 2*

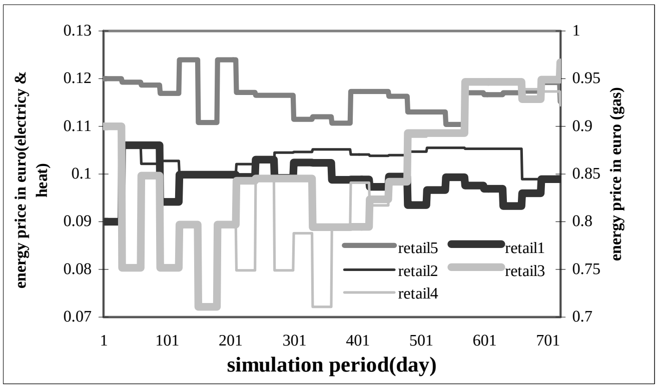

Fig. 10. Evolution of energy retail prices of industrial consumer in *Sc. 2*

The energy retailers are, then, unable to take advantage over consumers. Since consumers respond well to the advances of retailers, retailers have no choice except competing against each other to make profit. Since competition among retailers is fierce, the movement of energy prices is oscillating but on average does not grow, as shown in Fig. 8-10. The higher fluctuation of market share resulting from fierce competition among energy retailers can be seen in Fig. 11.

The results shown in Fig. 12 indicate that the retailers are more profitable in *Scenario 1*, when consumers are less informed about the competitive market and less reactive.

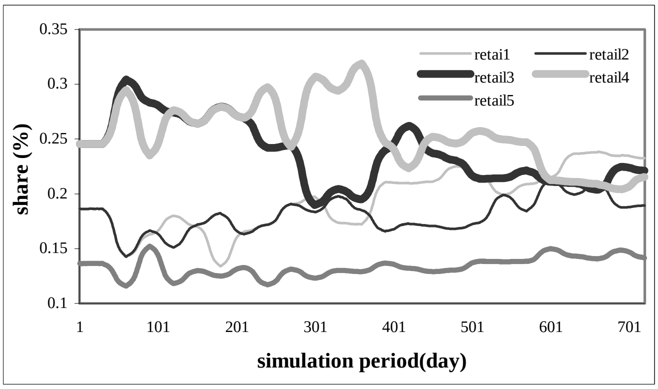

Fig. 11. Market share of retailers in S*cenario 2*

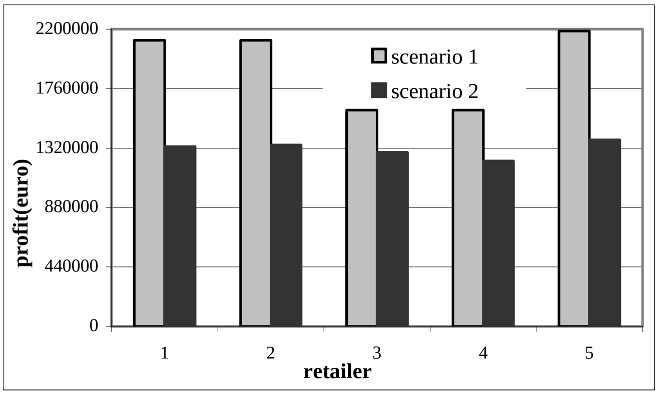

Fig. 12. Retailer profit in each Scenario

VII. CONCLUSION

The paper has presented an intelligent agent simulation platform for multi-energy market simulation, and results from a simulation experiment involving two scenarios. These simulation results are in agreement with the idea that the formation of a real market does not depend only on formal mechanisms, but also in regulator intervention in making the market more transparent and on consumer rapid reaction based on timely information and awareness of market conditions. The potential of the technique is completely demonstrated.

Of course, some of the internal models implemented in the agents were clearly fabricated and the simulation itself was also synthetic and not representing any real case. However, it is not only realistic enough, serving as a didactic tool, but also has the potential to test the consequences of many ways of regulating a multiple energy market. Because of the agent technology, it is also possible to make each agent evolve and to define each agent with distinct characteristics and internal models. One should not take the internal model descriptions in this paper as limitative. They are just examples complex enough to mimic reality.

The fact that extremely complex behavior emerges from the interaction of agents, without any explicit definition of such behavior, speaks in favor of the agent technology and the model developed. This work opens a fruitful path for research not only in the application of the technology to energy systems but also in the behavior of energy markets.

VIII. ACKNOWLEDGMENT

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X. BIOGRAPHIES

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