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Published in:
IEEE Computer Software and Applications Conference (COMPSAC 2012)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2012

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):
Capodieci, N., Cabri, G., Pagani, G. A., & Aiello, M. (2012). An Agent-based Application to Enable Deregulated Energy Markets. In IEEE Computer Software and Applications Conference (COMPSAC 2012) IEEE (The Institute of Electrical and Electronics Engineers).

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An Agent-based Application to Enable Deregulated Energy Markets

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Abstract—Private houses are more and more enabled with devices that can produce renewable energy, and the not so remote chance of selling the surplus energy makes them new players in the energy market. This market is likely to become deregulated since each energy home-producer can negotiate the energy price with consumers, typically by means of an auction; on the other hand, consumers can always rely on energy companies, even if their energy is more expensive. This scenario could lead to advantages for users, but it is certainly complex and dynamic, and needs an appropriate management. To this purpose, in this paper we propose an agent-based application to deal with the negotiation among different parties producing and consuming energy. Software agents, thanks to their autonomy in taking decisions, well suit the requirements of the proposed scenario. For our application, we adopt a strategy derived from game theory, in order to optimize energy production and supply costs by means of negotiation and learning. The effectiveness of our approach is proved by simulation results of a situation involving energy buyers, energy producers using renewable micro-generation facilities and large-scale traditional electricity companies.

Keywords—Energy; Market; Agents; Game theory;

I. INTRODUCTION

The evolution of the energy market started when the centralized approach, that is characterized by a monopolistic scenario of energy providers strictly regulated by the governments, opened towards the introduction of new players. However, the real evolution towards a completely new paradigm is accomplished by the growing diffusion of solar panels and wind turbines (also inserted in domestic environments): first, the user could produce clean energy using renewable sources and decide to feed surplus energy to the electricity grid for obtaining bill discounts from the service providers as reward. In a second and still ongoing step of this deregulation, Transmission and Distribution System Operators (TSOs and DSOs) are also undergoing a liberalization process. They might extend their services to domestic users who rely on renewable energy devices in order to let them participate as consumers and at the same time producers, forming a completely new form of actor (the *prosumer*). The new kind of player introduces new paradigms of tariff profiles [1] as well as new negotiation procedures (e.g: the auction [2]). All these changes are

perfectly compliant to the introduction of the *Smart Grid*, giving the possibility to ordinary consumers to retrieve their needed energy from the neighbouring *prosumers* that can supply both those domestic environments, creating a new kind of decentralized distribution net involving several kinds of sellers with added dynamism and an higher time granularity for contracts' stipulation. The novelty introduced in this paper is to propose a specific agent oriented architecture in which different software agents could act like different type of users: from the ordinary energy consumer represented by a buyer agent, to the specific designed *prosumer* agent, but also considering agents acting on behalf of traditional big energy producers. This choice of agents refers to the short-term paradigm for contracts' stipulation: taken into account that the introduction of the Smart Grid will require autonomous systems able to deal with the negotiation aspect on behalf of the end user. Obviously, such an architecture needs appropriate design choice to deal with system heterogeneity, reliability, scalability and security issues. To achieve these challenges we have used JADE¹ as agent platform to perform our tests. Such tests have to deal with all the most important aspects of the energy problem: balancing electricity demand, forecasting supplies and also negotiation with specific market adaptation strategies. Since the autonomous agents have to decide how to obtain the cheapest energy contract, the class of minority game adapted to this project, will help the market participants to find the best strategy in the short-term energy market, making them able to take decisions regarding contacting the most convenient sellers. Sellers can be represented by two categories (the *prosumer* and the *Genco*, with the latter one being the big traditional energy supplier). The Multi Agent System (MAS) designed represents a very interesting application in the field to model this future energy exchange scenario. The real application of such project in an environment should feature a constant monitoring of thousands of domestic nodes; this will result obvious difficulties in realization: however as far as the metering aspect is concerned, an hybrid scenario with a real domestic environment with multiple other agent simulated nodes have been previously provided [3]. As for all the other

¹<http://jade.tilab.com/>

aspects, a MAS simulation will be presented in this work.

After reviewing the related literature (Section II), this paper presents an overview of the models and agents used (Section III) followed by technical considerations regarding the platform related issues (Section IV). In Section V the market adaptation algorithm will be presented, showing simulations and results in Section VI. Final remarks and future work possibilities end the paper in Section VII.

II. RELATED WORK

For implementation purposes we used JADE, therefore using several reports for reference (e.g: [4], [5]). Nonetheless, agents are not the only solution proposed by researchers in this field: an alternative architecture featuring web based approach in a Java powered framework with extensive usage of JSP/Servlet pages as resources have been previously investigated [6]. Further discussions on using different technologies can be found in Section IV. Interesting applications featuring agents in the energy market can be found in [7]. In this latter work, Ramchurn *et al.* describe a decentralized agent approach for avoiding energy consumption peaks, achieving less polluting emissions and average lower contract prices using all the features a Smart Meter can offer. Vytelingum *et al.* in [8] used the game theoretic approach in order to find the Nash equilibrium to determine whenever an agent inserted in a Smart Grid is supposed to use a previously stored amount of energy or obtain electricity from the grid. We have to specify that our approach relies on the fact the buffering and/or storing electric energy is difficult and expensive to achieve and hardly fits the short-term approach to the market that (especially for wind power) is proven to be more effective [9]. Definitions and notations for the game theoretic concepts commonly used later in this work can be found in Layton-Brown and Shoham work [10] and [14]. For deeper knowledge investigations on repeated games, see for instance [11], while the reference example of minority game used in solving the presented problem has been already investigated in [12], [13]. The minority game features several specifications and example scenarios, however the scenario presented by the previously cited authors is the one that we refer with the term "minority game".

III. MODELLING OF AGENTS APPLICATION

In this section we give a complete overview of the agents set required in the energy trading scenario proposed: in particular we describe the kind of agents involved in the energy market with a in depth explanation of the most important steps of their behaviors.

Buyers are energy consumers and they usually outnumber the sellers; they do not produce energy so they are searching for obtaining their electricity demand supplied by stipulating contracts related to a specific time interval. Each market day is divided into several time intervals and for each one every

buyer has to decide in advance who is going to be its energy supplier for the next time interval. In the developed software, a *balancer agent* controls the amount of energy exchanged in the negotiation process (the details are explained later in this section). Buyers can predict how much energy they need for the following time interval. This can be obtained by reading previous electric measurement and by applying an energy consumption forecasting algorithm. It is important to perform this forecast before any negotiation, so that the buyer can choose the most suitable seller according to the energy availability of the suppliers. A really effective forecasting algorithm that fits our short-term paradigm is thoroughly described in [15] and it is based on an adaptive two-stage hybrid network with a Self-Organized Map (SOM). Every buyer is in competition with other buyers: each consumer has the goal to stipulate the cheapest contracts by deciding to attend an auction handled by *prosumers* (constituted by an iterative process of sending sealed bids) or by contacting a big energy producer (*Genco*) for obtaining the cheapest short-term contract before the Genco reaches a congestion threshold of its production lines.

Prosumers produce and consume energy; even if there are more prosumers than gencos, they produce a smaller quantity of electricity compared to traditional suppliers. Their production derives from the use of solar panels or wind turbines and if the amount of produced energy is higher than their domestic needs, they may decide to sell the surplus of electricity to other neighbors (buyers). *Prosumers* have also information about weather conditions in order to have a forecast on the amount of energy that will be produced (an example on how to automatically retrieve weather forecasting information is by using existing web services).

A buyer can stipulate a contract with a *prosumer* after winning an auction round, based on sealed bids. For a *prosumer* once the investment in a small-scale energy production plant based on renewables is realized, any positive amount derived by selling energy contributes to the investment return. Therefore in order to be attractive, *prosumers'* starting prices can be considered substantially lower than *Gencos'* initial contract prices. *Prosumers* communicate to buyers an initial starting price that is influenced by contracts with DSOs/TSOs and a random cost due to the devices used to produce electricity (e.g., maintenance costs). The energy produced by a *prosumer* has to be sold and cannot be stored or buffered. Every *prosumer* is in direct competition with other sellers: they have to propose an appealing starting price and make an intelligent use of refusing bids in order to rise the price and, at the same time, avoid pushing buyers in contacting other sellers.

Gencos are big energy generating companies. They have

a theoretically infinite amount of energy supplies, but sold at a fixed price, so there is no auction negotiation and every contract can be stipulated much faster compared to the *prosumers*' auction system.

However their prices are higher than *prosumers*' starting price and they depend on TSO/DSO contracts, raw material prices and (most important in our scenario) threshold exceeding costs. This aspect is thoroughly explained in the following paragraph and represents a modeling choice to prevent overloading production lines as well as avoiding concentrating a huge number of consumers for a single big producer. A *Genco* receives a request from a buyer; then it just calculates the price according to the above-explained variables and communicates the final price back to the buyer.

Gencos' threshold system. A key point is how much energy a generating company can produce without having to buy a quantity on the market (e.g., a foreign and more expensive market) or switching to more polluting production lines. Thus we assume that every *Genco* has a supply *threshold*, and once reached, the *Genco* has to buy energy abroad (the energy production of that seller is under stress). So the energy cost can be calculated as follows:

$$C_u = \begin{cases} Cost_{energy} & \text{if below supply threshold} \\ Cost_{energy} + (EC \times A) & \text{if above supply threshold} \end{cases}$$

where C_u is a single energy unit cost, $EC > 1$ is an external cost constant and $A > 0$ is the number of energy units above the threshold.

In addition, surpassing the threshold might also be harmful for the environment since more polluting plants might be started (e.g., oil based). Asking the *Genco* for contracts when this threshold is already surpassed leads to more expensive contract prices. Those prices rise as we get further from the specified threshold. This particular pricing strategy already introduced in [3] is perfectly compliant with the findings of other researches: from the already cited [7] and [8] to older studies led by Brazier *et al.* [16]. These researches do not provide the same formulation, however the common conclusion is that satisfying large number of demands will stress energy production lines introducing additional costs for the final user.

A. Balancing aspects

Other auxiliary agents, not directly involved in the negotiation process are represented by the **Balancer** and the **Time** agents. While the latter's only duty is to provide a time reference for synchronizing processes, the **Balancer** agent is responsible for the demand/supply balancing aspects: it acts in the very first step of the negotiation round by retrieving the single demand of every consumer and the production forecasts of the *prosumers*.

Having a clear understanding of the balancing needs of the grid is essential. In fact, recent studies [17] have shown how the nationwide energy dispatch will react to the introduction of renewable sources; in particular, the energy production

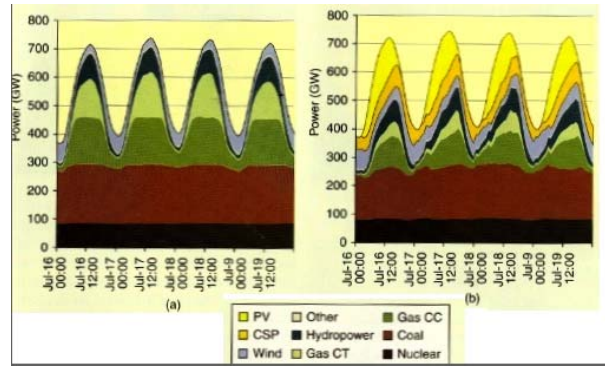


Figure 1. U.S. Nationwide energy dispatch without (a) and with (b) renewable contributions. Source [17]

derived from traditional sources will decrease: in the U.S.A a future projection of four summer days in year 2030 is depicted in Figure 1 and shows two scenarios, with and without solar penetration and how their percentage of produced energy compares to traditional sources. The demand satisfied by the total production from all sources remains constant in these two scenarios; however, in (b) we can see that the introduction of PV and CSPs (respectively PhotoVolaic and Concentrating Solar Power plants) will cause decreasing in production by all the traditional suppliers.

The data in Figure 1 refers to GridView² production cost model, with hourly load, solar and wind projections for 2030 based on 2006 information to maintain data correlation. On a separate note, it is important to point out that, in Figure 1, solar plants have production peaks during central hours of the examined days.

In our model we are clearly dealing with the (b) situation when it comes to balancing issues. Several mathematical models are presented, but most of them are different way to set to zero the algebraical sum between demand on one side and supply to the other side [18], taking into account that rising of renewables will be balanced by a decreasing of the traditional energy production. Here follows a simplified mathematical approach that considers all the aspects already explained in this section.

Given:

G_{C_x} as *Genco num.x* with S_{GC_x} being the supplies provided by that specific *Genco*

N_g number of *Gencos*

Pr_y as *Prosumer num.y* with S_{Pr_y} being the supplies provided by that specific *Prosumer*

M_p number of *Prosumers*

D total demand of the observed Area and Time Interval with D_{Ct_k} the demand of the K^{th} buyer

T_i time interval(s)

²<http://www.abb.com/industries/>

C_t number of consumers in the observed Area and Time Interval

The ability of producing an amount of energy is influenced mostly by the market of raw materials for the Genco production line, while the prosumers have to deal with local weather.

Producing more than the quantity that they are supposed to supply is risky for the sellers since we assume the absence of buffering or storing of surplus energy. Moreover, we have to take into account all the previous considerations regarding traditional suppliers versus PVs and CSPs.

Demand D is calculated by a specific algorithm of demand forecasting, but no matter which kind of statistics we are going to use in order to solve that, we have to specify that the demand refers to a pre-determined interval of time.

Obviously D is just the sum of all the demands (at a certain time) needed for all the consumers in the area. It has to satisfy the balance relationship in equation 1:

$$\sum_{i=1}^{N_g} S_{Gc_i} + \sum_{j=1}^{M_p} S_{Pr_j} = \sum_{k=1}^{C_t} D_{Ct_k} \quad (1)$$

Equation 1 does not take into account unavoidable leaks and calculating errors. On the other side, if the supply and demand forecasting are efficient and precise enough, we can rely on an easy implementation model for simulations. Equation 1 is quite straightforward in its meaning: the sum between the two production sources (Gencos and prosumers) should be equal to the total consumer demand. Also, from previous sections, we know that dealing with a fixed demand will cause the other two elements to change accordingly and it is more likely to see in the future an increment on the prosumers' supplies that will be balanced by a decrease of gencos' production.

B. Agent and message interactions

Consumers, different kinds of sellers and auxiliary agents can be easily distributed among several areas and their messaging topology is represented in Figure2: we can see how consumers and sellers do not communicate with each other, but they can exchange messages with all other agents belonging in the other categories. In Figure3 an example message topology is shown.

C. Agents behaviour

Other agents used for simulation purposes are represented by an Agent Creator who is able to dispatch the other agents in the respective areas [20] and an exception handler agent used to increase performances, which has been implemented during scalability and reliability tests [19].

In order to provide a clearer picture on how the contract negotiation and the adaptation to the energy market has been

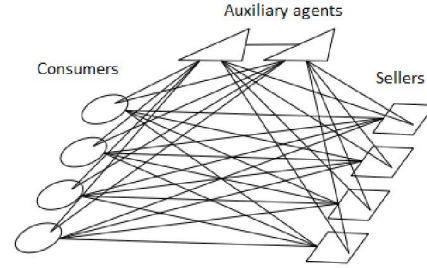


Figure 2. Message topology between peers. Source [19], [20]

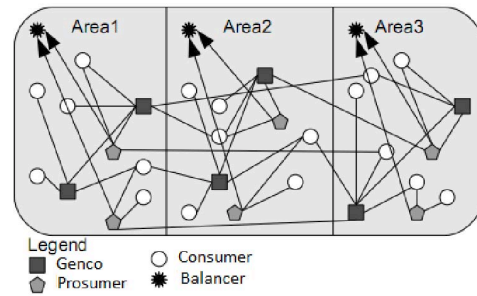


Figure 3. Example of contract and messaging net between different agents scattered in a distributed environment. Source [19]

modelled for our test simulations, this section presents an overview of the behavior that agents are following during a single negotiating round. Some auxiliary agents have been left out, due to their simple tasks that does not require further explanations, while the Balancer and Prosumer's behavioural steps are shown in Figure4. Also the Genco has been left out due to the simplicity of its behavior compared to buyers/prosumers auction system and due to the fact that its threshold pricing model has already been thoroughly explained.

The steps in figure 4 provide a complete picture on what happens during a single negotiating round. Some behaviors are common, such as the discovery of agents according to the role they have: this is obtained using a feature of the chosen agent platform. In fact, JADE has a distributed Directory Facilitator (DF) in which any agent can register itself to be then found by other agents distributed elsewhere, therefore the DF acts as a yellow pages service. The registration itself is not shown in Figure4, since just the steps in the JADE main behavioural method (i.e: *action()*) is shown. Registration in the DF is done just once in the initializing method, while the search and discovery is done in every negotiating interval. This latter choice obviously introduces more computational load, however it is completely justified for having a dynamic architecture in which the number of total peers is constantly changing. An introduction of a new seller, for instance, will be known to the other agents starting

Type of Agent	Step 0	Step 1	Step 2	Step 3
Balancer	Discovers Time agent	Discovers Seller, and sends them a synch message. Waits for forecasting of production	Same as step 1, but with buyers. Waits for forecasting of their demands	Calculate balancing and suggests threshold for Gencos. Gives every peer A synch message to begin/end negotiation. step 4 is executed at the end of the negotiations.
Buyer	Discovers weather forecasts and previous consumption	Discovers balancers and sends him its data: demand, position and id.	Defines its preferred Genco according to a "nearest supplier" criteria	Having received a signal for starting the negotiation, it decides to contact a prosumer or a Genco according to the strategy adopted
Prosumer	Discovers weather forecasts and calculates future production	Discovers balancers and sends him its data: forecasted supplies, position and id.	Waits for synch signals and buyers' proposals. It moves in the next steps until enough bids are received or according a deadline	Refuses all the bids except the highest. If this latter one is high enough it accepts, otherwise it refuses and goes back to step 3. In case of acceptance it goes in step 4.
Type of Agent	Step 4	Step 5	Step 6	Step 7
Balancer	If at the end of negotiating interval not all buyers have a contract, will send a message to force those buyers to contact the nearest genco.	-	-	-
Buyer	If prosumers have been chosen, it starts by receiving their starting prices and sends bids. If offers are refused, it will rise the bids according to its decided strategy. In case of no contract have been stipulated, Gencos will be contacted	Contacts Gencos and stipulate contract with the cheapest one.	Informs the balancer that it has reached an agreement with a seller	Evaluates if its budget has been respected and updates its market strategy.
Prosumer	Communicates to the winning buyer the contract stipulation.	-	-	-

Figure 4. Steps in the behavior of the main agents involved in the negotiation and balancing aspects.

from the following time interval. These and others technical aspects will be explained in Section IV.

Initial steps indicate the retrieving of web services for both consumers and sellers. The goal of the former is to obtain the local temperature to know in advance if an air conditioning system will be active: thinking about a function for describing the bound between temperature and the consequent energy consumption, we can roughly describe a V shaped function in which to the lowest amount of energy used corresponds to average temperature from 19 to 21 degrees, while we have consumptions peak as far as we move from this point (meaning that is either too hot or too cold). An agent can retrieve temperature values using appropriate web services and a prosumer does the same for obtaining weather information for forecasting its production (e.g: wind direction and strength in case it has a micro generation through wind turbine). Still regarding the buyer's initial steps, a buyer can retrieve informations about previous consumptions and also on going tariffs by interacting with a Smart Meter (a new generation electric energy consumption reader). This has been previously and successfully tested with this presented implementation [3].

Concerning the buyer's market strategy and adaptation to the dynamics of the short term electricity contracts, in

Figure4, we can see how the agents' decisions are taken in different steps: as soon as they have received the notification from the balancer to start the negotiation, they have to first decide to contact a prosumer or a Genco. This is done by using a *minority game* derived algorithm (see Section V), taking into account the limited prosumers supplies compared to the traditional Gencos. In case of the choice of contacting a prosumer, also the amount of stakes and maximum number of sent bids follow the adaptation algorithm: the goal is to avoid wasting time in sending multiple bids while Gencos are exceeding their production threshold. The market adaptation deals with the last step: every consumer has to evaluate if his budget expectations have been respected, changing how to rise their bids accordingly to the previous negotiation outcomes. This latter step is obtained by an added fuzzy logic block.

IV. TECHNOLOGIES AND PLATFORMS

While in the previous section we provided an exhaustive overview of the agents involved, here we present the used platform. We justify how an agent approach can perfectly fit the need of an energy market system, especially compared to traditional (centralized) approaches that involve a central web server handling all the necessary information [6].

Several past researches (e.g: the PELLUCID related project [21]) elected JADE (Java Agent Development Environment) [4] as the best or one of the best agent platforms for general purpose uses. It features the FIPA³ standard messaging protocol, as well as an ontology support in an open source highly customizable environment. The continuous development of extensions adds further possibilities for the designer while still maintaining a quite good efficiency [22]. The use of JADE to solve and simulate our problem pointed out several advantages compared to the traditional web applications for centralized management: issues like mobility and security [23] can be easily taken into account in a transparent way still obtaining the same results. The JADE-LEAP extension allows the designer to load a JADE agent in devices with limited computational capabilities with no modifications to the code. In our context, this aspect is useful when thinking about embedding in a Smart Meter (a new generation household energy consumption reader) or on board computing devices in hybrid cars. The same transparency has been found in conducting tests for securing exchanged data [23], [20] using JADE-S (JADE Security extension): security issues are a critical concern in this kind of applications since sensitive data is passed through different agents (therefore hosts). Traditional approaches obtain the same degree of security by further software implementation for encrypting messages, authorization and authentication, without the transparency featured by JADE-S.

While a centralized approach features a single point of failure architecture, our JADE architecture for the energy problem can easily run in a distributed environment strongly decreasing chances of failures for the auxiliary agents. Agent replication and mobility (also fully supported by JADE) give us other ways to increase the safety of our architecture, and that is important due to the criticality of having fault in an energy provisioning service.

During a single negotiation round each buyer agent can contact multiple sellers (both prosumers and Gencos), switching from one to the other according on the negotiation outcome or insisting in auctions by rising the bids several times. This implies a necessary large volume of exchanged FIPA complaint messages that introduces limits while testing the architecture with a large number of agents. However, the tests done with a 1000 MBPS Ethernet network between six machines having an Intel Core2 Duo E6650 @ 2.33 GHz with 2Gbyte RAM, running on Debian GNU/Linux 6.0 (Kernel 2.6.32-5-686) with JADE version 4.1 and JRE 1.6.0.24 (just-in-time compiler enabled) show that the simulation runs at a limit of 818 total agents with an average of 2865639 exchanged messages during an hypothetical division of six time intervals [19]. On a single host, the number of agents we can test being sure of trustful results decreases to

³<http://www.fipa.org/>

243. These numbers represent a sufficient sample for our purposes still being sensibly larger than the number of agents that would be present in case of an implementation in a real scenario. In fact, these limits are set by the memory availability and CPU usage of the host and not by the amount of message exchanged. In addition, since a single host represents a single end user, it is very unlikely to have more than 3 or 4 agents per host. The whole distributed architecture however, will handle thousands of peers. The computational load will be actually balanced in thousands of heterogeneous hosts.

In section III-C we pointed out how an agent features one or more behaviours that are divided in several steps: according to [5], the scheduling of behaviours in an agent is not *pre-emptive* (as for Java threads) but *cooperative*. This means that is up to the programmer to define whenever an agent switches from the execution of a behavior to the execution of the next one. Even if all of this implies the necessity of further programming efforts, it forces the architecture to handle a single Java thread per agent, but on the other side it provides better performances since behaviour switch is extremely faster than Java thread switch. Other advantages compared to a standard Java programming lies in the elimination of all synchronization issues between concurrent behaviours accessing the same resources (with an obvious performance increase).

V. MODELLING OF AGENT STRATEGIES

As already introduced, the buyer agents in our architecture are supposed to chose between contacting a Genco or a prosumer when they first receive a notification for beginning the negotiation. This two path approach has to lead to the cheapest energy contract possible for the buyer that acts on behalf of an human user and therefore has to simulate his/her rationality. Having a restricted set of actions as initial choices and a final outcome to be evaluated suggests us to seek in the game theoretic literature for a similar scenario that we can apply for solving our problem. In particular in the class of minority games we can think about a scenario in which two actions are initially possible and the outcome of this game depends on the actions of the other players, provided that each participant does not know in advance how his competitors will act. In these games, the players who have chosen the action taken by the minority of the total participants are rewarded with higher payoffs. Furthermore, since the energy market model proposed repeats itself in several negotiating round we should also take into account the game theoretic notion of repeated game. We are now presenting an already solved basic game scenario and on a second step we will show how to extend it to provide our buyer agents with an adapting strategy for the presented market model. This model is also described in a previous work [24], however, the simulations featured in that work, did not involve JADE software agents.

Table I
EL FAROL BAR PAYOFF MATRIX

Action	Crowded Bar	not Crowded Bar
Attend	L	H
Do not Attend	M	M

With payoff score $H > M > L$, with M unconditioned.

A. El Farol Bar game

“El Farol Bar” is an existing bar situated in New Mexico (USA). Every Thursday night it delivers discounted drink prices, becoming really appetizing for the local potential costumers, making obvious why every person living near the bar, wants to go there on that particular night. The bar has been used to model the El Farol Bar minority game [12], [13]. Given N as the population in the nearby area, and a threshold T representing the bar capacity for hosting people, for a participant point of view the night can considered as enjoyable if the number n ($\leq N$) of participants during a particular Thursday is below the threshold T (win situation). Otherwise, it is better for the single person to remain at home (lose situation, the pub is too crowded). The payoff matrix of the above scenario is presented in Table I: an high(low) payoff is retrieved if the player goes to bar with a number of people below(above) the threshold, while it is supposed an unconditioned average payoff in case he decide to stay at home.

Switching back to our problem, the two possible initial choices of action are still present in our energy related scenario: if every agent contacts a *Genco*, it will result in overloading the production lines of these big energy producers, causing them to provision in more expensive markets with high prices for the end-user and environmental issues too. Likewise, if every agent contacts (or tries to do so) the same restricted set of *prosumers*, only a few number of participant gets a nice deal, due to the fact that a *prosumer* can deliver a little amount of energy, especially compared to a *Genco*.

In our problem, we can adapt the different degrees of payoff of the bar scenario with the difference between what a single agent expected to spend and what it actually spends at the end of the negotiation interval (budget evaluation).

B. Solutions for the minority game approach

A simple way to find an equilibrium for the El Farol Bar game has been proposed originally in [12]. We begin by illustrating this first intuitive approach.

According to the demonstration in [12] there is a unique symmetrical mixed strategy solution:

$$\frac{M - L}{H - L} = \sum_{m=0}^{T-1} \binom{N-1}{m} p^m [1-p]^{N-1-m} \quad (2)$$

Where p is the probability to go at the bar and M , L and H the payoffs as shown in Table I.

Table II
INITIAL STATE 1 (TAB₁)

Action	P. has supplies	P. has no supplies
Contact Pros.	See TAB ₃ (+2 Ip)	See TAB ₂ (0 Ip)
Contact <i>Genco</i>	See TAB ₄ (+1 Ip)	See TAB ₄ (+1 Ip)

Table III
INITIAL STATE 2 (TAB₂)

Action	P. has supplies	P. has no supplies
Contact other P.	See TAB ₃ (+2 Ip)	See TAB ₂ (0 Ip)
Contact <i>Genco</i>	See TAB ₄ (+1 Ip)	See TAB ₄ (+1 Ip)

Using equation 2, we can see that for each participant we have a given probability that can be used to decide whether it is advisable to attend the discounted price night. Repeating the game we can see that every agent sooner or later will attend the bar and that most of the times, the pub will not be so crowded.

When trying to apply the solution shown in the equation 2 to our energy problem, we map some variables as follows:

T for the ratio between the amounts of energy produced by *Prosumers* over the total production, N is the total number of buyer agents and M , H and L are intervals defined according to the expected/actual money spent. A difference between the bar game and our energy market is that in the bar game if a number m of people are attending the bar with $m > T$ then m players are losing. In our problem just $T - m$ people are actually going to retrieve a low payoff.

This initial model still lacks of influential variables like time constraints and limited *prosumers*' supplies, implying the necessity of adding further stages to our game. We now present an approach in which several tables represent different payoff matrices for all the stages forming the game. This *new* methodology that mixes the minority game approach with a stochastic game (every payoff table refers to a specific participant's state) is used in order to model the complexity of the energy problem.

The main idea behind the adaptation of the game we propose is presented more formally in Figure 5. It is an infinite game split into finite rounds. The decision each agent takes at every state is compactly represented in the following payoff tables.

Tables II and III are called *initial state tables* while Tables IV and V are defined as *final state tables*. The difference is that only Tables IV and V show an ending of the negotiation, represented by the letters H , M or L as the payoff entity inside those cells.

Every buyer starts by taking a decision in the first table (referring to an element of the state space \mathcal{M}). The balancer

Let \mathcal{J} be a set of agents representing the consumers;
 \mathfrak{P} be the set of prosumers, while \mathfrak{G} represents the Gencos;
 Players $\in \mathcal{J}$ move through different tables shaping the *finite state space* $\mathcal{M} = \{m_0, m_1, m_2, m_3\}$.
 m_0 : initial state in which the agent $i \in \mathcal{J}$ decides who is going to first contact. It can be a Genco or a specific Prosumer $P_0 \in \mathfrak{P}$.
 m_1 : second state in which i decides who will be contacted next, provided that $D(i) > S(P_0)$ with D being the consumer demand and S is the seller's supply capacity.
 m_2 : here i decides if it is convenient to place a bid to a previously contacted prosumer $P_x \in \mathfrak{P}$ or abort the negotiation, provided that $D(i) \leq S(P_0)$.
 m_3 : i decides to accept or not the offer of a specified Genco $G_x \in \mathfrak{G}$.
 Therefore each player (agent) $i \in \mathcal{J}$ can perform an action inside the set(s):
 $\mathcal{A}^i(m_0) = \mathcal{A}^i(m_1) = \{\text{Contact Genco, Contact Prosumer}\}$;
 $\mathcal{A}^i(m_2) = \{\text{Place bid, Abort Negotiation}\}$;
 $\mathcal{A}^i(m_3) = \{\text{Accept offer, Refuse offer}\}$.
 The probability P to move from the current state m_x to next state (m_y) after performing a specific action $a \in \mathcal{A}$, written $P(m_x, a, m_y)$ is described in Tables II, III, IV and V with their assigned payoff chains.

Figure 5. Game formalization.

Table IV
 FINAL STATE 3 (TAB₃)

Action	Pros. accepts	Pros. refuses
Place bid	H	Stay in TAB ₃ (-1 Ip)
Abort negotiation	See TAB ₂	See TAB ₂ (0 Ip)

agent is the entity that knows how much energy can be produced by all the *prosumers* and by using this information it can calculate the number of buyers that could be served by *prosumers*; this number can be related to the threshold T in the El Farol game. According to that threshold we can calculate the probability to contact *prosumers* instead of a *Genco* in this stage of the negotiation (quite similar to how it was possible to solve the “El Farol Bar” dilemma using the unique mixed strategy solution). However, at this moment we do not have a clear vision of future payoffs, but we can

Table V
 FINAL STATE 4 (TAB₄)

Action	Genco above T.	Genco below T.
Accept genco's offer	M	L
Refuse genco's offer	See TAB ₂ (-1 Ip)	See TAB ₂ (-1 Ip)

assign to those initial tables a certain amount of fictional points that we call “Intermediate points” (Ips). Those Ips represent the chain of payoffs for the stochastic game approach: assuming that every action taken by a participant agent is time consuming, decreasing Ips simulates time flow as well as a risk increase that the participating agent should be aware of. On the other side, higher Ips increase the chance to have a satisfactory game result (H or M final payoff). In this way the buyer is redirected to other tables until it reaches a final cell: doing so the number of Ips can increase in case it is a lucky choice (contacting a *prosumer* that for sure has enough supplies) or decrease in the opposite scenario. In the *initial state tables* the buyer is redirected to other tables according to a previously calculated value that is related to the amount of energy all *prosumers* can produce. In the *final state tables* the algorithm is different: in order to simulate the importance of the time variable, lower Ip values mean that the buyer has been travelling around different tables for such a long time and chances to find a suitable seller or even a *Genco* that has not overtaken its threshold will be scarce. That is because in the ending tables negative values are present. When the Ip value is very small ($\ll 0$) then the agent is forced to get a contract with a *Genco* in order to avoid wasting other time (and consequently other money).

At the end of each round, each buyer agent evaluates its outcome. Above we said that the difference between the expected money spent and the actual money spent can point out who are the winners and who are the losers, however ending a negotiation in a H(L) payoff cell of a matrix not always ensure a win(lose) situation: that is because the market dynamics (being bounded by swinging prices of raw energy production materials) leads to constant changes in energy minimum prices. Therefore obtaining an higher contract price compared to the pre-determined budget can happen even if the agent ended its cycle with an H payoff: in this case it just means that the agent was expecting an unrealistically low contract price. The same considerations have to be done in the opposite scenario of having an L payoff for a cheap contract. This implies the addition of a fuzzy logic block able to adjust the expected budget and the amount for the single bids (in case of a prosumer auction). The further we are from the centre of the fuzzy logic function, the stronger will be the reaction of the agent (either to increase or decrease stakes and/or expected budget), following simple and linear trends.

VI. SIMULATION

In such complex and dynamic scenario, a simulation is needed to prove if the designed strategy could be used by agents to negotiate in the market, thus obtaining cheaper contract prices. In particular, we use 5 consumers, 3 *prosumers* and 2 *Gencos* within a 10 round negotiation runs to test the JADE agents implementation. This simpler scenario allows us to evaluate the game based algorithm with different

price scales using agents. The restricted number of agents, does not compromise the purpose of the test: this is because the kind of market modelled is more heavily influenced by the ratio between total demand and prosumers' supplies rather than the number of agents *per se*. The simulation setup uses a computer featuring an Intel Core 2 duo processor (2.2 Ghz, 800 Mhz FSB) with 4 GB of RAM. We used Windows 7 64 bit OS running JAVA SE 6 Update 21, using JADE agent platform v. 4.0.1.

Several parameters can be adjusted influencing the agent decision, namely: (1) number of Ips used as threshold in order to redirect the participant from one final table to the other; (2) difference between starting prices for the two kinds of sellers; (3) threshold switching values in the fuzzy logic block; (4) best way to assign values to *H*, *M* and *L* final payoffs; (5) price dynamics from one round to the other; (6) *Gencos'* price penalties for exceeding thresholds; (7) probability for a *prosumer* to become more expensive than a *Genco*; and (8) accuracy about energy supply and demand forecasting that might not be 100% correct.

The best way to give a precise value to these parameters is to study an analytical formulation in which we can combine all the other known values (e.g., number of participants and amount of demands and supplies) in order to retrieve the unknown constants. However, due to the complexity and dynamics of the proposed model, we decided to use a numerical approach by trying several value combinations of every input variables of the algorithm.

At the end of each round, the buyer agent calculates the average expecting budget and the average money spent, assigning to each round number those other two values (e.g., round #, Paid Price, Expected Price).

In order to have a clearer idea of the efficiency and precision of the strategy, we show the difference between applying the presented algorithm or use a baseline set of actions. In the latter scenario, every buyer will contact a *prosumer* straightaway, since their starting prices are lower, becoming more appetizing to a rational agent. In addition, after signing a contract, the participant does not adjust any strategy parameter.

We obtain the results shown in Figure 6, under the following conditions: (1) intersection between average starting prices of the sellers should not exceed 33%; (2) slow and not exaggerated price swings between each round; (3) significant price penalties for exceeding *Gencos'* threshold; (4) the higher the error percentage between the forecast demand values and the actual requested values (negative error), the better becomes the improvement between using the presented algorithm compared to the baseline scenario; positive errors may worsen participant performances; and (5) very fast reaction to follow the expected price. The conditions (1) and (3) force the gap between the prices to be wide enough to justify the minority game approach, while (2) and (5) deal with the difficulty of the algorithm

in finding equilibria in exaggerate dynamic scenarios. While (4) is straightforward.

The results of the simulation, as depicted in Figure 6, show that expected prices follow the previous peak of paid prices. It is important to highlight that we are also trying to simulate the impact of swinging prices due to raw material prices fluctuations and/or payback costs for solar panels or wind turbines for *prosumers*. Even if those swings are not exaggerated due to high granularity for stipulating contracts, they are indeed an additional challenge to further prove the reaching of certain equilibrium scenarios.

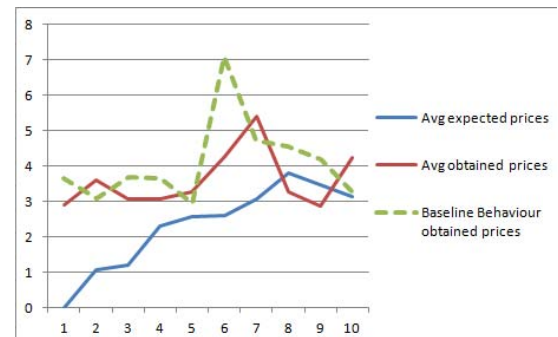


Figure 6. Prices varying during 10 rounds with and without the presented algorithm (JADE output). Prices have to be intended as price per energy unit.

In the simulation, the expected price starts from 0 in the first round, reaching a convergence during the 8th round. Starting from that point, it becomes visible how expected and obtained prices of agents that follows the minority and stochastic approach (represented by the two continuous lines in figure 6), will constantly chase each other. Economically speaking, it means that in earlier rounds a buyer agent adopting the algorithm with the described strategies is likely to pay equally or slightly more than an agent following other strategies. However, if we consider a sufficiently large number of rounds, the saving compared to agents following the baseline behaviour (Figure 6, the dotted line) is obtained more frequently, with significant lowest peaks during the most expensive period for buying energy.

The test was executed having a constant numbers of agents, although sellers' supply capacity was subject to randomized swings from one round to the other. Therefore, changing sellers' number does not drastically affect the presented results, provided that this number does not exaggeratedly and unrealistically change in a short period of time.

Computationally wise, the complexity of the presented algorithm is variable but does not appear to represent a problem. While the balancer agent has the duty to solve equation 2, buyer agents just have to solve an iterated amount of conditional instruction and comparing variables

(e.g: if current I_p value is greater than the threshold value then execute action A, otherwise jump to action B). The fuzzy logic block is just composed of a mixed set of linear functions and it is executed just once at the end of the negotiating round.

VII. CONCLUSIONS AND FUTURE WORK

In this paper we have presented an agent-based application for deregulated energy market taking into account all the major issues involving the electric energy exchange. Aspects like balancing, pricing but especially negotiation and adaptation in the energy market have been discussed, modeled and successfully implemented. On the base of a previous experience with physical Smart Meters connected to user homes [3], we then presented a simulation environment, that, using the negotiating rules we modeled, has enabled us to perform complex negotiations with different kind of sellers perfectly compliant with the introduction of the Smart Grid. Moreover, when dealing with negotiation and market adaptation strategies we adapted the concept of *minority game* to provide a better distribution of the available resources, and we used a *stochastic game* design to simulate time flow and risk variation through an accurate intermediate payoff accumulation during the same negotiating round. All of this has been simulated with a JADE implementation. The results presented in Figure 6 show that the gap between the two situations (i.e., agents following the adaptive strategy and agents following a baseline behavior) is remarkable when certain conditions are satisfied. In addition to that, we can see how expected prices, starting from very low (and impossible to obtain) values tend to reach an equilibrated amount that represents the cheapest alternative in almost all the examined negotiation rounds.

Due to the complexity of the presented scenario further investigations and mathematical proofs are needed. Also testing the same implementation with other possible market scenario as well as implementing more accurate balancing strategies will be necessary, especially when more agents are present. However, the modular implementation realized on top of JADE platform, combined to its efficiency in large distributed environment won't make it a difficult task.

ACKNOWLEDGMENT

The work is partially supported by the ASCENS project (EU FP7-FET, Contract No. 257414)

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