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An Agent-based System for Service-Oriented Smart Grids

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Abstract The power grid is undergoing a major change due mainly to the increase penetration of renewables and novel digital instruments in the hands of the end users that help to monitor and shift their loads. Such transformation is only possible with the coupling of an ICT (Information and Communication Technology) infrastructure to the existing power distribution grid. Given the scale and the interoperability requirements of such future system, Service-Oriented Architectures (SOAs) are seen as one of the reference models and are considered already in many of the proposed standards for the smart grid (e.g., IEC-62325 and OASIS eMIX). Beyond the technical issues of what the service-oriented architectures of the smart grid will look like, there is a pressing question about what the added value for the end-user could be. Clearly, the operators need to guarantee availability and security of supply, but why should the end users care?

In this paper, we explore a scenario in which the end-users can both consume and produce small quantities of energy and can trade these quantities in an open and deregulated market. For the trading they delegate software agents that can fully interoperate and interact with one another thus taking advantage of the SOA. In particular, the agents have strategies, inspired from game theory, to take advantage of a service-oriented smart grid market and give profit to their delegators, while implicitly helping balancing the power grid. The proposal is implemented with simulated agents and interaction with existing web services. To show the advantage of the agent with strategies, we compare our approach with the "base" agent one by means of simulations, highlighting the advantages of the proposal.

Keywords Agents · Smart Grid · Energy Market

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1 Introduction

The way in which electricity is produced and distributed appears to be rapidly changing. If in the past the production was centralized and the distribution was hierarchical, with the advent of renewable generation facilities at all scales, thus also for small scale, one notices a trend towards decentralization of production and multidirectional power flows. Potentially, anybody connected to the smart grid can *produce* and *consume* energy. Two major aspects make this situation appealing for the end users: one, being able to save electricity costs and gain an *economic* benefit from installing production facilities; two, the feeling of being *sustainable*. The first of these two aspects will be realized if the users are able to operate in a free market where they can choose to purchase energy from *several energy providers*, not necessarily large utility companies and if they are at the same time able to participate in such a market as sellers. The feasibility of creating such a market relies on a rich digital infrastructure capable of measuring and controlling energy flows, which are central points of the current shift towards the concept of a *Smart Energy Grid*.

The creation of open energy markets at the level of the end-users poses compelling technological challenges. In fact, the scenario is very *decentralized*, since each house holder could produce, negotiate and use energy in an autonomous way. Moreover, it is highly *dynamic*, since the price and the availability of the energy can change even every hour or more frequently, for instance depending on weather conditions. Finally, it will be *large-scale* or even *extreme-scale*, since energy companies can serve a wide geographical area with a large number of users and the power grid is becoming a wide international infrastructure. All these expected high level requirement hint at service-orientation as the enabling ICT pattern for the infrastructure and indeed the current standardization effort are going in the direction of service orientation, as we have overviewed in [35]. Service-oriented systems couple nicely with agent modeling. One is concerned with the interoperability while the other allows to take advantage of the autonomy to build loosely coupled scalable systems, such as smart grids [41].

1.1 A changing energy landscape: the Smart Grid

The term Smart Grid is a new concept that has not a final and unique definition yet, rather the various actors of the energy panorama (e.g., power producers, end users, energy distributors, and energy markets) have their own definition of the Smart Grid and each sees the challenges and the benefits of this new electricity system [31]. Although there is no clear and single definition, some aspects and benefits of the future electricity systems can be envisioned following the view of the U.S. Department of Energy (cf. [32] and [33]). The new Grid will be able to diagnose itself and take appropriate action in case of faults, therefore it will become more resistant to willing and unwilling attacks and disasters. Another key feature will be the ability of the Grid to accommodate more renewable-based sources of power. This last aspect is particularly challenging since renewable sources introduce substantial variability and unpredictability in the energy system, and it puts the system under stress. Last but not least, the end user: he will have an electrical system that has the same or even improved power quality and reliability meeting his needs and expectations; in addition, the user expects, of course, to have cheaper energy bills in a grid that is smarter.

One of the key issues of the whole power system is the necessity to keep the whole energy system in balance. With the term *balance* we mean that there should always be a null balance in the energy injected in the Grid and the energy withdrawn from it (considering losses too); otherwise imbalances provoke failure in the equipment and lead to blackout cascading effects [14]. In a future energy scenario, with an energy mix characterized by an higher penetration of renewable sources the balancing issues related to the Grid are even more worrying. One of the ideas to help in shaping the demand according to the energy availability is dynamic pricing [19]. The concept of dynamic pricing is that the price of electricity will vary considerably during the day, thus influencing the users to use more (or less) their electric devices.

Another pillar of the future Smart Grid is the distributed generation of energy. Energy will not be generated only in multi-megawatt power plants (as it has been done since the early days of Edison and Insull), but with more affordable and cheaper small-scale generating resources (e.g., photovoltaic panels, small wind turbines) the end user becomes a producer of energy too. To define this new figure on the energy scenario that is no more a passive customer, but who is also a small producer, the term *prosumer* (small producer and consumer at the same time) has been created. It is not hard to imagine that the prosumer will be able to feed the surplus of energy into the Grid (that is already possible nowadays) and to participate in an auction market where energy is traded in a manner similar to commodities on the stock market. Actually, the tendencies in the energy market that enable more competitiveness in the sector (i.e., unbundling [39]) might lead to totally free energy market where every consumer, prosumer and traditional generating company will be allowed to participate [48].

1.2 Smart Grid frameworks

Several frameworks to illustrate the stakeholders and components of the future Smart Grid have been proposed. There is not a unique standard, though a number of these have emerged among others, such as the GTM (Green Tech Media) [27] and the NIST (National Institute of Standards and Technology) ones [34]. The

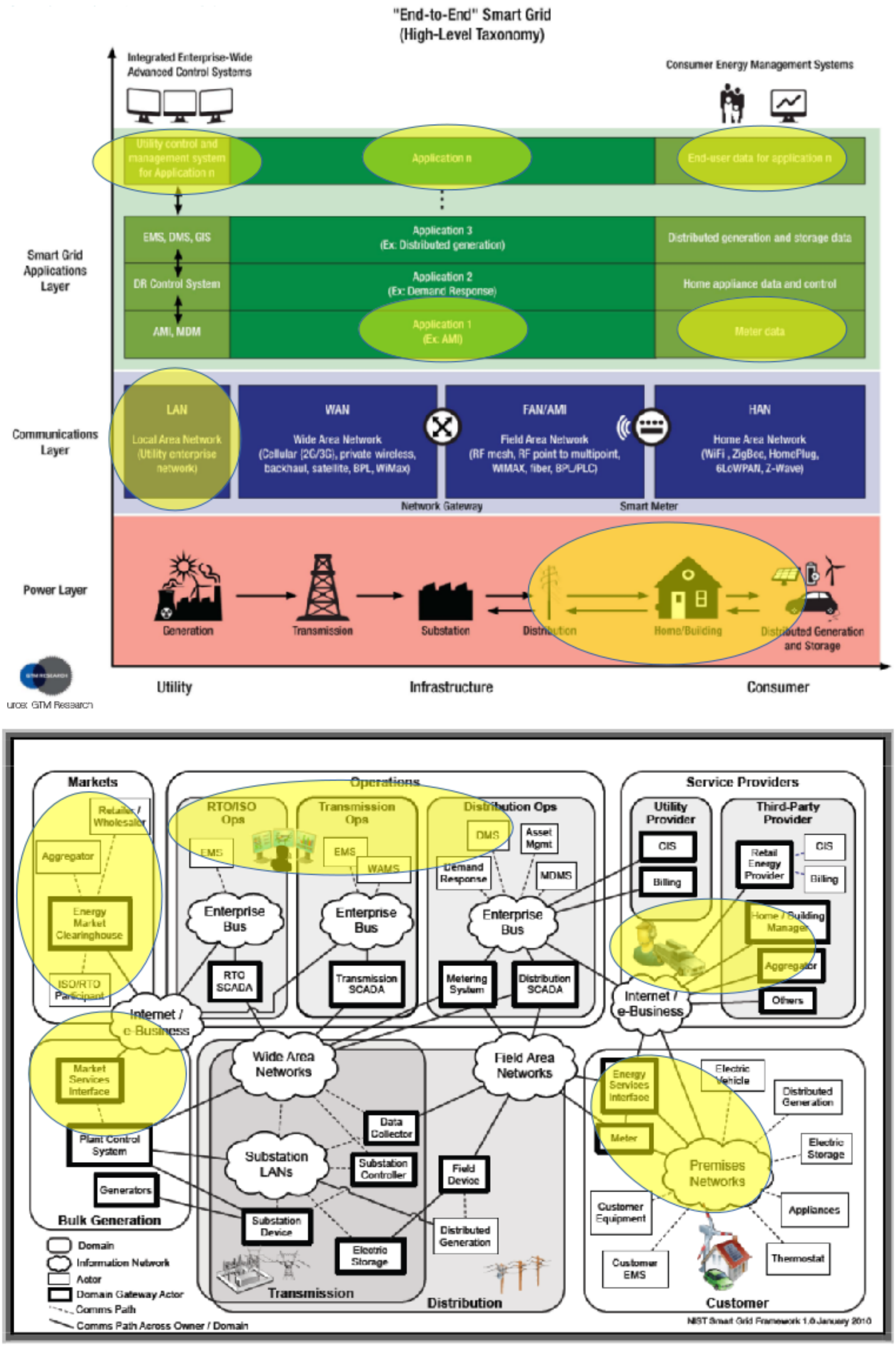

Fig. 1 GTM (above) and NIST (below) Smart Grid conceptual frameworks. Yellow ovals highlight where the present work fits in.

Smart Grid vision and proposal that we set out here fit with the key findings of [27]. In fact, our application covers five aspects of the twentyfive elements essential in the realization of the Smart Grid in the whole power domain as outlined by the GTM framework. In particular, our application goes in the direction of reducing the costs for producing and consuming energy for producers and prosumers/consumers. Further, the architecture and the application realized are tangible examples of how it is possible to develop new services and business cases by using the new smart grid use-cases and the well-known and flexible software approach of SOAs. This last aspect is perfectly in line with the finding of Leeds [27]: "Many of the advanced applications of Smart Grid are expected to develop in an evolutionary manner based on current technologies available and the needs of the market." Further, our application interacts with a real smart meter device to gather real consumption, therefore ready to a real industrial context and exploring the scenario close to dynamic pricing of energy for the end user. Our application targets mainly the consumer side of the power layer interacting with smart metering technologies. As communication layer, we take advantage of TCP/IP protocol over LAN for the inter-agent communication; an ad-hoc protocol converter that translates from the NTA8130 Dutch standard into TCP/IP has been used for the interaction with the smart meter. Therefore, at the application level, we satisfy the use cases concerning the smart meter reading and the realization of a distributed energy trading between energy utilities, prosumers, and consumers. We cover therefore in different ways the whole stack presented by GTM.

Considering the NIST framework [34], we also cover several parts of the information flow and application domain proposed cf. Figure 1. The solution here presented covers aspects of the user domain and the metering of his consumption together with the interfacing to energy services that in our specific case is energy trading. We cover the whole market stack of services/communication interacting also with traditional energy producers and a simplified form of operation controller that monitors the stability aspects of the network.

Figure 1 shows the high levels Smart Grid market taxonomy of GTM and the reference diagram of NIST information flows in the Smart Grid context, respectively. The yellow oval shades represent which areas are covered from the application presented in this paper.

1.3 Contribution and organization

Given the complexity of the future smart grid scenario, appropriate approaches are required. Multi-Agent Systems have appropriate features to face it and can take advantage of decentralized software architectures such as service-oriented ones [38]. However, even if agents can show some sort of *adaptivity*, the complexity of the scenario requires an *explicit* design of the system adaptation [52]. This can lead not only to a better adaptation feature, but also to results that better suit the expectations of the involved actors.

The contribution of this paper is to present a service-oriented agent-based system to manage deregulated energy markets. We show that the adoption of an adaptive strategy in such open environments can lead to meet the prices expected by involved actors better than the situation where agents have the bare autonomy feature. In addition, our approach turns out to pay more attention to the *environment*, since renewable sources of energy are better exploited than in an non-adaptive situation. We have implemented the proposed system using Jade, a wide-spread agent platform [3]. In JADE, agents register their capabilities as "services" available to other agents.

Moreover, the proposed system can be inserted in an "ecosystem" of services (see Fig.2), where agents provide services but at the same time exploit other services in order to take more grounded decisions; as an illustrative example, our system exploits weather forecast web services to know the future weather and infer how it will influence the production of energy. Then, we have compared our adaptive approach with the "basic" behavior of a system of autonomous software components without our proposed adaptive strategy. The results show that the prices of the energy in our approach better suit the price expected by the actors involved in the average case. The presented SOA architecture relies on an ecosystem of services in which agents are situated and able to interact with their surrounding context: the agents are able to obtain relevant information (such as weather conditions) and indirectly influence the same ecosystem by dynamically changing their role in the energy e-market. These changes are triggered according to their energy consumption needs or small scale energy production (in case of Prosumer agents). Non-trivial interactions between agents and their surrounding environment have already been subject of investigation on the point of view of formal modeling [20].

The paper substantially extends and systematizes our previous workshop and conference contributions [10, 9]. In comparison with the conference versions, in this paper we introduced the work with more details, pro-

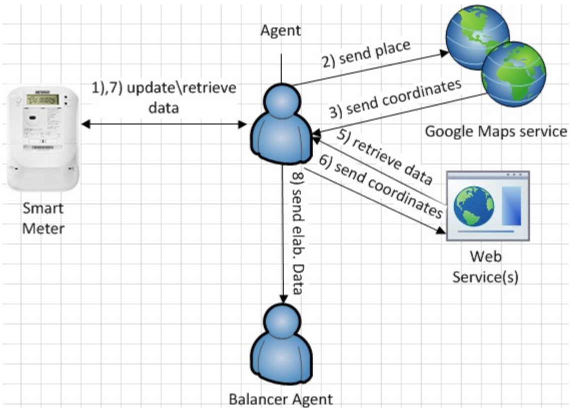

Fig. 2 Ecosystem of services

viding deeper motivations; from the content point of view, we focus on the exploitation of Service Oriented Architectures in this multi-agent system application; moreover, we discarded technological issues to focus on the strategies and advantages of the proposal; we significantly expanded the related work discussion, to provide more background for our work.

The rest of the paper is organized as follows. First, we describe the software components of the proposed system, along with their roles and their behaviors (Section 2). Then, we present the adaptive trading strategy that is based on game theory, detailing the adaptive behavior of the whole system (Section 3). In Section 4 we sketch the implementation of our system. We exploited this implementation to simulate real cases of deregulated energy market; the comparison between a base behavior of agents and the application of our strategy is presented in Section 5. Finally, after presenting some related work (Section 6), Section 7 concludes the paper.

2 Software Components Modeling

Several software components, or agents, are involved in the considered energy trading scenario; in this section, we describe them and we point out a clear distinction between how an agent is supposed to act in a real environment and what it actually performs in the simulation software, in order to achieve a better understanding of the problem. The agents involved in our application play different roles. The main and auxiliary agents are explained in Subsection 2.1, while balancing issues are discussed in Subsection 2.2.

2.1 Agents

Buyers represent energy consumers and their number is usually larger than the one of 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 have an estimation about how much energy they will need in 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 [16] 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 following two actions:

1. Attending an auction handled by *prosumers*, consisting of an iterative process of sending sealed bids.
2. Contacting a big energy producer (*Genco*, energy *Gen*erator *co*mpany) in order to obtain the cheapest short-term contract before the Genco reaches a congestion threshold of its production lines.

Prosumers represent actors that both *produce* and *consume* energy; prosumers are supposed to be more than Gencos, but they produce a smaller quantity of electricity compared to traditional supplier. Their production relies on the use of solar panels or wind turbines; when the amount of produced energy is higher than their domestic needs, they can sell the surplus of electricity to other buyers, in particular neighbors. *Prosumers* can exploit information about weather conditions (for instance, by querying existing web services) in order to make a forecast on the amount of energy that will be produced.

In our scenario, a buyer can stipulate a contract with a *prosumer* after winning an auction round, based on sealed bids. Any positive amount derived by selling energy can contribute to *prosumer*'s investment return, once the investment in a small-scale energy production plant based on renewables is realized. In order to be attractive, *prosumers'* starting prices must be lower than *Gencos'* initial contract prices. So, *prosumers* communicate to buyers an initial starting price that takes into account the contract costs of Distribution System Operators/Transmission System Operators (DSOs/TSOs) and a specific 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 represent big energy generating companies. In principle, they can supply an infinite amount of energy, but they sell energy at a fixed price, so there is no negotiation with buyers and every contract can be stipulated much faster compared to the *prosumers*' auction system.

The drawback is that their prices are higher than *prosumers*' starting price and they depend not only on DSO/TSO contracts, but also on 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 aspects and communicates the final price back to the buyer.

Usually, energy companies can produce a given amount of energy; but if the demand is higher than this amount, they have to buy the missing quantity on the market (e.g., a foreign and more expensive market) or to switch to more expensive and polluting production units. Thus we assume that every *Genco* has a supply *threshold*, and once reached, its production is "under stress" and it has to buy energy abroad. So the energy cost can be calculated as follows:

$$C_u = \begin{cases} Cost_{energy} & \text{if below supply threshold} \\ Cost_{energy} + (EC \times A) & \text{otherwise} \end{cases} \quad (1)$$

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.

We remark that exceeding the threshold, besides being expensive, can also be harmful for the environment since more polluting plants must be started (e.g., oil based). Asking the *Genco* for contracts when this threshold is already exceeded leads to more expensive contract prices for consumers. The more energy demand is beyond the threshold, the more prices rise. This particular pricing strategy already introduced in [11] is perfectly compliant with the findings of other researches: from the already cited [40] and [50] to older studies led by Brazier *et al.* [4]. 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.

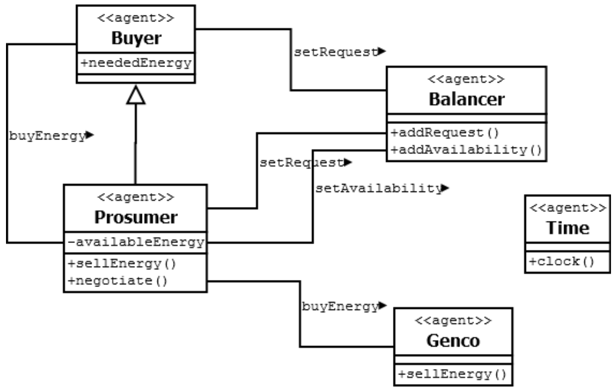

Fig. 3 Agent model

The **Balancer** and the **Time** agents are introduced as *auxiliary* agents, not directly involved in the negotiation process but useful to support the system activities. The *Time* agent has the only duty of providing a time reference for synchronizing processes, while the *Balancer* agent is in charge of 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*. Fig. 3 reports a simplified model of the agents, exploiting the AUML notation.

2.2 Balancing

A clear understanding of the balancing needs of the grid is a crucial aspect. Recent studies show how the nationwide energy dispatch will react to the introduction of renewable sources [5]; in particular, the energy production derived from traditional sources will decrease: in the U.S.A a future projection of four summer days in year 2030 is depicted in Fig. 4 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 PhotoVoltaic and Concentrating Solar Power plants) will cause decreasing in production by all the traditional suppliers.

The data in Fig. 4 refers to GridView[1] 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

[1] http://www.abb.com/industries/

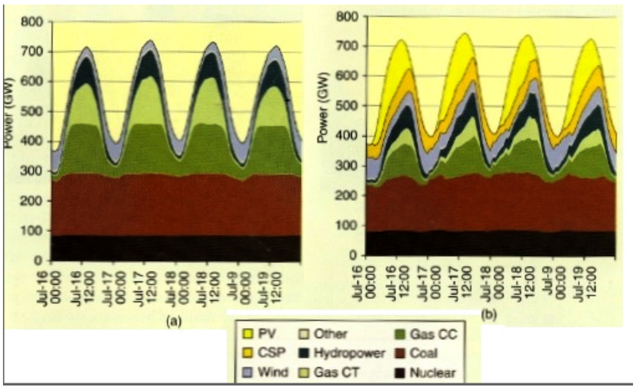

Fig. 4 U.S. Nationwide energy dispatch without (a) and with (b) renewable contributions. Source [5]

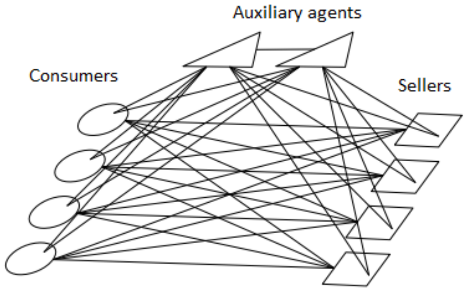

Fig. 5 Message topology between peers. Source [26,7]

out that, in Fig. 4, solar plants have production peaks during central hours of the examined days.

In our model we are dealing with situation (b) when it comes to balancing issues. Several mathematical models have been proposed, but most of them are simply ways to set to zero the algebrical sum between demand on one side and supply to the other side [47], which appears to be insufficient for taking into account the rising number of renewable installations.

We provide a model which captures the salient features of the energy paradigm of the near future. Consider:

Gc_x as Genco X with S_{Gc_x} being the supplies provided by that specific Genco
N_g number of Gencos
Pr_y as Prosumer y with S_{Pr_y} being the supplies provided by that specific Prosumer
M_p number of Prosumers
D_t total demand of the observed Area and Time Interval with $D_{C_{t_k}}$ the demand of the K^{th} buyer
T_i time interval i
C_t number of consumers in the observed Area and Time Interval

Consider also that the capability 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. That is because we are trying to deal with the short term market paradigm in order to avoid overloading electric lines as a result of bad long term forecasting or unoptimized distribution.

Obviously D is just the sum of all the demands (at a certain time) needed for all the consumers in the area. The balance relationship in equation 2 has to be satisfied:

$$\sum_{i=1}^{Ng} S_{G}c_i + \sum_{j=1}^{Mp} S_{P}r_j = \sum_{k=1}^{Ct} D_{C}t_k \tag{2}$$

Equation 2 does not take into account unavoidable leaks and calculation 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 2 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.

2.3 Components' behavior

Consumers, prosumers, gencos and auxiliary agents can be easily distributed among several areas and their messaging topology is represented in Fig. 5: we can see that consumers and sellers do not communicate with each other, but they can exchange messages with all other agents belonging the other categories. In Fig. 6 an example message topology is shown.

Other agents used for simulation purposes are represented by an Agent Creator which is able to dispatch the other agents in the corresponding areas [7] and an exception handler agent used to increase performances, which has been implemented during scalability and reliability tests [26].

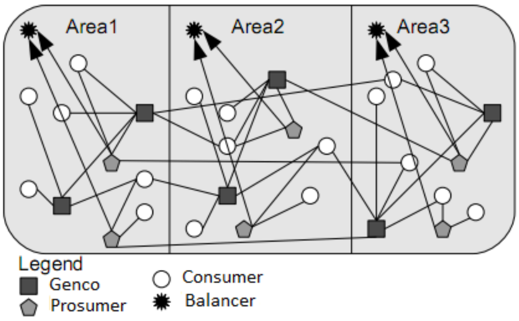

Fig. 6 Example of contract and messaging net between agents scattered in a distributed environment. Source [26]

In Fig. 7, we will present an overview of the behaviour that agents exhibit during a single negotiating round, in order to provide a clearer picture on how the contract negotiation and the adaptation to the energy market has been modelled.

The time line shown in Fig. 7 completely describes 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. Registration in the DF is done just once in the initializing method for balancers and consumers, while the search and discovery is done in every negotiating interval as the prosumer agent decides to register itself as a seller or buyer according to its prediction of energy production. 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, both at the level of numbers and roles.

The first step is to retrieve information by means of web services for both consumers and sellers.

The goal of the former ones is to obtain the local temperature to know in advance if an air conditioning system will be active: the function that relates temperature with consumption can be roughly described as a V-shaped function: to lower and higher temperatures (represented in the X-axis) correspond to higher energy consumption measures (represented on the Y-axis), while for average temperatures (19 to 21 celsius degrees) the energy consumption is minimized (see Fig. 8).

An agent can retrieve temperature values using appropriate web services (e.g., NOAA weather web service or OpenWeatherMap) 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). More details regarding these topics will be provided in Section 2.4.

A buyer can also retrieve information about previous consumptions and on-going tariffs by interacting with the services provided by a Smart Meter (a new generation electric energy consumption reader), in the starting steps. This has been previously and successfully tested with the presented implementation in [11].

Concerning the buyer's market strategy and adaptation to the dynamics of the short term electricity contracts, in Fig. 7, we can see how the agents' decisions are taken in several steps: as soon as they have received the notification from the balancer to start the negotiation, they have to first decide to contact either a prosumer or a Genco. This is done by using a *minority game* derived algorithm (see Section 3.2), 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 Fig. 9.

2.4 External Web Services

As mentioned, different kinds of agents need different kinds of *services*. The consumer agent can take better decisions if it knows the future consumption. The energy profile is built taking into consideration different parameters; the external temperature has been pointed out as one of the important factor when dealing with demand forecast [30,17]. The producers need accurate forecasting of wind (in case of WT owner) or solar irradiance (in case of PV unit).

Table 1 shows the existing web services investigated for our case scenario (wunderground[2], HC3vX[3] and NWX[4]). As can be seen, web services differ from type of input, services provided and granularity of data. Due to the scarce granularity of the NWX web service, we used the data provided by the first two.

In the following we sketch the mathematical and physical relationships between the external factors (obtained via web services) and the constructional char-

[2] www.wunderground.com/history/
[3] www.soda-is.com
[4] www.navlost.eu

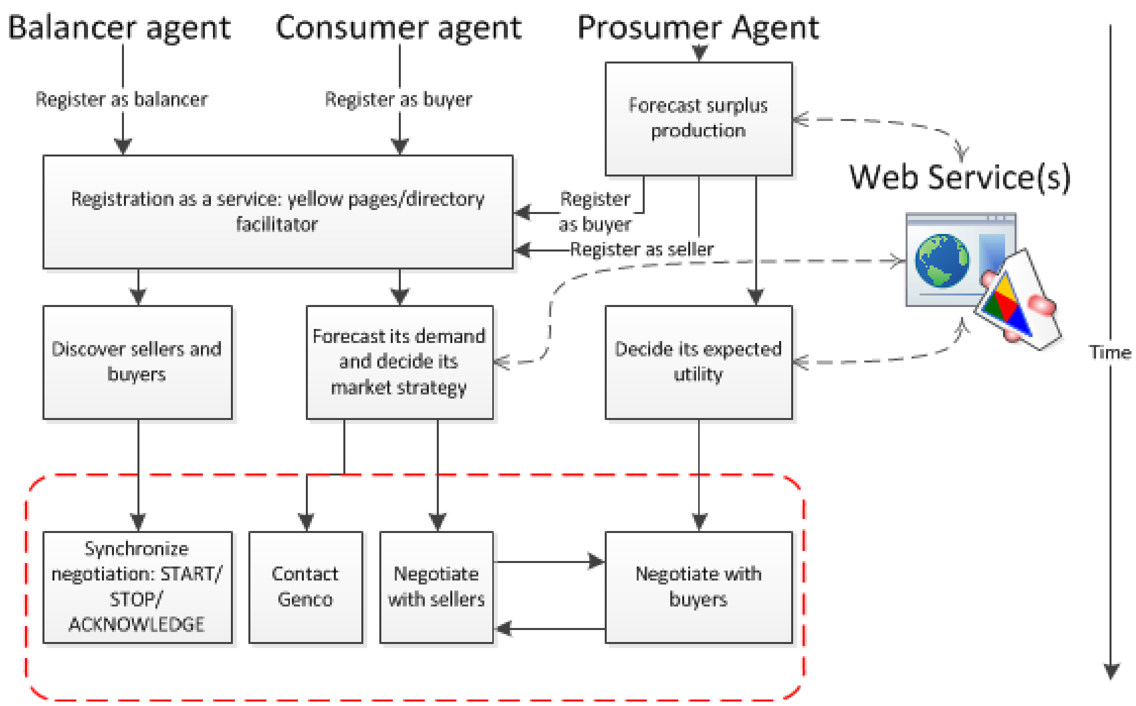

Fig. 7 Steps in the behavior of the main agents involved in the negotiation and balancing aspects.

Table 1 Investigated web services

Service name	Ser. provided	Intervals	Input
wunderground	Wind speed and direction; temperature	hourly	Location
HC3vX	Solar irradiance	hourly	Location or coordinates
NWX	Wind speed and direction; temperature	six hours	Coordinates

acterization of producers' renewable energy production devices, since they have specific constructional parameters. In a hypothetical applied scenario, these parameters can be soft coded in the smart meter (or in a middleware device situated between the agent platform and the consumption reader): it is important that this information is known in advance and is compliant to any changes of the devices installation.

2.4.1 Wind Power Production

The production of electrical power through wind turbines depends on the interaction between the rotor blades and the wind speed; in particular, the electric power generated by a wind turbine (P_e), expressed in watt, can be determined through the eq. 3:

$$P_e = \eta_e \times \eta_m \times C_p \times \frac{1}{2} \times \rho \times A \times Ws^3 \qquad (3)$$

Where: η_e is the efficiency of the electric generator, η_m the efficiency of the mechanical components, C_p is the power coefficient, A the area swept by the rotor $[m^2]$, ρ is the air density $[kg/m^2]$ and Ws is the wind speed $[m/s]$.

The Ws is the wind speed and this is a parameter obtained by requesting a Web service, providing the location of the place where the wind turbines are installed.

$C_{p,max} = 0.59$ is commonly called *Betz* Limit and expresses the following basic idea: "The maximum power that can be theoretically extracted, considering an air flow and an ideal wind turbine, may not exceed the 59% of the available power of the incident wind". In practice, there are in fact three effects that are able to decrease the maximum power coefficient:

- Rotation of wake behind the rotor;
- Finite number of blades;
- Aerodynamic resistance.

With modern turbines, however, reaching a $C_p \cong 0.5$ value represents a good approximation for the theoretical Betz Limit.

In our model, the C_p of different producers are randomly selected with values ranging from 0.3 to 0.5 in order to simulate the characteristics of the various wind turbines present in the market. The C_p so determined does not only represents the fraction of power that the wind transmits to the rotor, but, for sake of simplicity, also includes other factors that influence the operation of the wind turbine such as, for example, the roughness of the ground or the installation height [1]. The air density depends on the temperature and the altitude of the place of installation, which can be easily obtained from a meteorological Web service; the performance parameters are constructional features of the turbine. The last parameter represents the speed of the wind, which is known thanks to the web service exploitation.

2.4.2 Solar Power Production

To calculate the energy that can be produced by the whole PV system, based on the data of average irradiance in the considered time slot (3 hours), we exploit the eq. 4, which refers to a single PV module. We sum the single contributions of each installed module to obtain the whole energy production of the installation.

$$E_g = P_0 \times G \times K \times \eta_{PV} \times \eta_{INV} \tag{4}$$

Where: P_o is the module peak power $[Wp]$, G the solar irradiation $[W/m^2]$, K the shading factor, η_{PV} for the PV generator efficiency, η_{INV} is the inverter efficiency.

The solar irradiation $[W/m^2]$ is obtained by the Web service, again providing the location/coordinates of the place where the modules are installed.

The inverter efficiency range is between 0.88 and 0.94, while the efficiency of the photovoltaic generator has a range from 0.70 to 0.86 and depends on several factors such as the ambient temperature: a higher temperature could decrease the module efficiency. In [21] K represents a parameter (usually $K < 1$) that takes into account the phenomena of power reduction for aging, panels' inclination, shadowing and foliage due to nearby trees. For our level of abstraction, K is chosen with a randomized values varying from 0.8 to 0.95 in order to better represent the analyzed scenario. P_o is a characteristic parameter of the modules, so also in this case, the variation of the electricity production will depend on the weather conditions: solar irradiance is one of the parameter retrieved from the Web services.

2.4.3 Consumers' demand trend over time

The consumption of electricity is affected by different factors such as day of the week or holidays, climatic variables, seasonality and economic activity. When trying to predict the energy consumption in the short term we can consider most of these factors known via user profiling. In this model, they are treated as random variables in a plausible range according to typical trends.

In order to obtain some typical values regarding daily energy consumption, we took inspiration from previously stored data (source: www.terna.it). This information is then integrated with our model for bounding consumption and temperature (will be explained later in this section), creating a consumer model that takes into account both the energy profiling and the temperature impact.

The influence of external temperature is crucial because sudden changes in temperature will cause significant changes in consumption in the short term, while the other profile-related factors are supposed to follow a more static trend.

The relationship between temperature and consumption is non-linear and dynamic: we adopt an approach taken from the literature [6] and explained later; other approaches propose similar functions with different temperature thresholds.

The temperature versus consumption function is described by the followings:

- The relationship is a combination of linear functions, with knots (key values) in 8°C, 18°C, 22°C and 32°C. There is an interval of temperatures between 18°C and 22°C, where the temperature does not affect consumption; the temperatures below 20°C shape the cold zone (use of air conditioning) and temperatures above 24°C the heat zone (use of electric heating). Those areas are shown in Fig. 8 and they cause maximum consumption values;
- The cold zone can be approximated via two linear decreasing functions. The first one presents temperature values between 8°C and 18°C. To temperatures below 8°C the slope of the function decreases in absolute value, still maintaining the linear trend. Further attempt to cool down the environment are supposed to be inefficient;
- In the heat zone there is a similar relationship. There is a linear response function between 22°C and 32°C; above 32°C the slope presents a smaller value, so that the marginal effect of temperatures above 32°C is lower than temperatures between 22°C and 32°C. Just as in the cold zone, this last slope change is forced by the electric heating device used.

Again, the external temperature is achieved by means of a Web service.

2.5 Agents meet SOA in the Smart Grid

In [36], we defined the characteristics that the new Smart Grid environments demand in terms of service orientation to fully implement the features that the Smart Grid

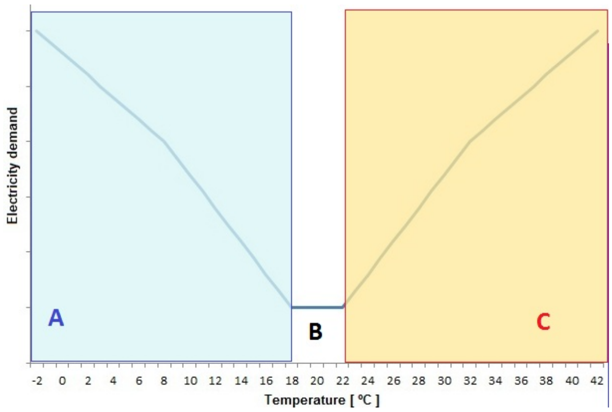

Fig. 8 Temperature vs. consumption: A: cold zone, B: no effect on consumption and C: heat zone

will enable. These are interoperability, scalability, discovery, mobility, resilience to failure and trust, service integration and composition, topology, smart metering, and real-time. To position the current work, we look at the same characteristics from an agent-oriented perspective and report the fitting in Table 2. The table shows the features of SOA and agents considered in the application presented here.

3 Energy Trading Strategies

When dealing with a fairly complex market model like the one described in the previous sections, the requirement of autonomicity of the entire system imposes the need of designing algorithms for agents so to enable them to maximize the probability of reaching certain goals. The complexity and dynamism of the market model proposed, however, forces the consumer agents to deal with a certain degree of uncertainty and unpredictability regarding other agents decisions.

A common trend in dealing with such uncertainties is to adopt a game theoretic approach for modeling the processes and mechanisms.

As pointed out in the survey by *Fadlullah et al.* about several game theoretic approaches to the smart grid, the notion of Nash equilibrium is constantly involved in these models: finding a Nash Equilibrium means finding a particular strategy, if it exists, that each agent has no interest in changing, independently of which strategies other agents choose [15]. By no means this is a violation of the *rationale* of the agent: if we think about the famous prisoners dilemma [42], we realize how the Nash equilibrium is not the right strategy to follow in order to let a single agent (or limited number of agents) win the specific round by letting the others (loser agents) paying the consequences, but it is a strategy aimed to loss minimization in the worst cases.

Table 2 SOA and agent technology for the Smart Grid

Feature	Description
Interoperation	Web service technologies are used to achieve interoperation between different elements of the proposed solution. Environmental conditions of the locations where the energy trading operated are obtained through Web services; the smart meter provides too a web based service (thanks to an ad-hoc realized hardware gateway); agents interact with Web service to provide their position for geo-location purposes.
Scalability	The agent technology and the enabling platform (JADE) allows natively the scalability of the solution. More experimental details are given in Section 5.
Discovery	Both the involved Web services used and the agent platform have discovery services that ease the implementation.
Mobility	In the use case of this application we do not consider the mobility of the agents, but JADE allows agents to migrate from one context to another. Such functionality might be useful for scenarios such as mobile prosumers (e.g., electric vehicles).
Resilience to failure, trust and security	In this paper the trust and security problem is not directly addressed, however we exploit the related features of JADE-S (a security extension to JADE platform) as explained in [7]. The resilience to failure of the solution is tested in the additional test cases available in [26].
Service integration and composition	The solution itself provide integration of different services (weather, location, energy trading).
Topology	The topology issue is not taken into account by the present solution however the costs of transporting electricity take into account this aspect to a certain extent.
Smart meters	The solution fully integrates the interaction to a smart meter following the Dutch standard NTA 8130.
Real-time	The solution is not real-time, however the auction mechanism operates in near real-time.

In [15], the authors show how classes of games can be applied to a number of aspects of the smart grid, while earlier works mainly focused on energy demand estimation and load balancing. Other contributions deal with adaptive micro-storage management, so to have agents able to decide whether it is convenient for them to store electric energy for later consumption as opposed to constantly participating in the electric energy e-market [50]. We are mostly interested in the aspects regarding demand side pricing strategies: to this end, we present our game theoretic approach to the smart grid, which relies on the notion of *minority game* (Section 3.1). The aim is, therefore, to study how agents can autonomously decide the way they will address the market so as to minimize the cost per obtained energy unit. This is a similar approach to the one presented in the work of *Mohsenian-Rad et al.* [29], in which the considered smart grid allows the presence of a unique Genco, while in our approach we consider a plurality of Gencos, which is a more accurate model for future smart grids. The difficulties in comparing the performances of these different game-related approaches arise from the fact that there is no unified tariffs model to be adopted by smart grids: each work relies on different, yet reasonable assumptions.

As far as classes of minority games are concerned, minority or congestion games have been mainly studied as approaches to prevent net overloading: in [22] an approach similar to the one we are presenting is proposed, but no pricing or tariffs models are involved. In our contribution, the minority game is used to provide the agents with adaptive strategies for minimizing a cost per energy unit that follow a pricing model that relies on a SOA for updating prices and availability for the different sellers during the negotiating rounds in which we ideally split the market day.The iterated negotiating rounds can therefore be expressed in terms of a *repeated game* as known from the game theoretic literature. In particular, each round or stage of the game ends by assigning a reward to the participants. Seeing the negotiation problem as a *game* implies translating each goal for each category of agents into an *utility*: from the consumer point of view, the utility function (for each round related to the previous round) is minimizing the difference between an expected price and the obtained price per single energy unit, while from the producer point of view the goal of maximizing the profits translates as minimizing the difference between an expected profit and the price which they manage to sold a single energy unit they produced. The amount of such differences discriminates between winning and losing situations. Once goals and utilities are defined, the following step is to design algorithms and decisional models for the agents involved, thus to define strategies (as set of actions) for agents to perform in order to satisfy the previously mentioned goals.

The relation between a minority or congestion game and its related Nash equilibrium is extensively studied in game theoretic literature [53,45], so in the following sections we will exploit a common game and its equilibria to then adapt this solution to our specific case study by mapping all the variables of the examined game to their respective counterparts in our Multi-Agent System.

The minority game which best fits the smart grid agent negotiation process is the *El Farol Bar* game.A recent variation of the El Farol Bar problem, called the *Kolkata Paise restaurant problem* [12] was proposed in order to study minority games characterized by a macroscopically large number of possible strategies for the participating agents: in our case, a future smart grid will have a large number of agents involved, but each agent will have a restricted amount of choices that are related to either trying to stipulate a contract with a prosumer or a Genco. Therefore, the traditional version of the El Farol Bar game better suits our reference model.

3.1 A Game for the energy negotiation problem

The “El Farol Bar” minority game [53] has important similarities to the delocalized energy auction problem. Here is an informal description of the game. The El Farol Bar is a really existing bar situated in Santa Fe, New Mexico (USA). Every Thursday night it delivers Irish parties with discounted beer prices, becoming really appetizing for the local potential costumers. So every person living near that bar, wants to go there in that particular night. Formally, given a N population of the nearby area, and a threshold T of people attending the Irish night event, the night at the bar is considered as enjoyable if the number n ($\leq N$) of people attending it during a particular Thursday is below the threshold T (win situation), otherwise it would have been better for the single person to have stayed at home (lose situation, the pub is too crowded). This game belongs to the so called *minority game* class of games: each agent has the same set of actions to perform in each round and the agents who choose the actions or set of actions taken by the minority of the participants are likely to expect higher rewards. In the specific El Farol case, in Table 3 the payoff matrix for this game is shown.

The similarity with our problem are shown in this two-paths way of thinking: if every agent would sign an agreement with Gencos, it will result in overloading the production lines of these big energy producers causing them to supply in more expensive markets with higher 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 small number of participants could get a good deal, due to the fact that *prosumers* can deliver variable percentages of energy and usually the total amount of this production is extremely unlikely to cover the 100% of the total demand [8]. Moreover relating to the bar game, participants are competitive and they are not able to communicate among them, so they cannot organize in order to create shifts, in which they can split and chose (for a fraction of them) not to go on this Thursday, but instead go to the next one. Exactly like the El Farol Bar game, in our energy negotiation problem, bidding agents do not exchange information, so they have to guess how other buyers are going to act.

In the bar dilemma, there are degrees of benefits and penalties according to the result of each game round: a participant gets the highest score by going to the bar and he discovers that it is not crowded. He gets a medium amount of points if he chooses to stay home, and he gets a penalty (or the minimum score) in case he chooses to attend the Irish night and finds it crowded. In our problem, this score system can be replaced by the difference between what a single agent was expecting to spend and what he actually spends at the end of the negotiation interval.

3.2 From El Farol to energy negotiation

For the bar game, plenty of studies have been conducted in order to find a point of equilibrium; for the sake of simplicity, we first analyze the most intuitive one (the stage game solution) [53].

There is a unique symmetrical mixed strategy solution:

$$\frac{M-L}{H-L} = \sum_{m=0}^{T-1} \binom{N-1}{m} p^m [1-p]^{N-1-m} \qquad (5)$$

Where p is the probability to go at the bar and M,L and H the payoffs as shown in Table 3.

Different studies such as [53] and [18] have shown other solutions as well. Especially, in [18], these approaches are reviewed according to metrics related fairness and efficiency.

In the solution shown in Eq. (5), fairness expectations are met, but according to [18], the efficiency ratio is low (around 50%). Other solutions proposed by the just cited authors, suggest the use of fictitious plays in order to propose a more efficient outcome over a sacrificed fairness. An approach that satisfies both fairness and efficiency requirements is represented by a Q-Learning strategy in which a central authority (e.g., a major) introduces entrance fees for bar attending costumers to be distributed to the players who are staying at home.

Table 4 Initial state 1

Action	P. has supplies	P. has no supplies
Contact Pros.	See tab3 (+2 Ip)	See tab2 (0 Ip)
Contact *Genco*	See tab4 (+1 Ip)	See tab4 (+1 Ip)

Table 5 Initial state 2

Action	P. has supplies	P. has no supplies
Contact other P.	See tab3 (+2 Ip)	See tab2 (0 Ip)
Contact *Genco*	See tab4 (+1 Ip)	See tab4 (+1 Ip)

Table 6 Final state 3

Action	Pros. accepts	Pros. refuses
Place bid	**H**	Stay in tab3 (-1 Ip)
Abort negotiation	-	See tab2 (0 Ip)

Table 7 Final state 4

Action	*Genco* above T.	*Genco* below T.
Accept offer	**L**	**M**
Refuse offer	Table 2(-1 Ip)	Table 2(-1 Ip)

Focusing again on the energy problem, we have to assign higher priorities to the fairness metric: our goal is to define a peer to peer architecture in which, by definition, there is no space for discrimination between peer agents. In addiction to that, the third (i.e. the centralized Q-Learning) solution provides a fair and efficient way to approach the bar dilemma, but it increases complexity with the concept of a central authority and introducing fees that have no correspondence to our case.

Using Eq. (5), we can see that for each participant we have a certain probability that can be used to determine whenever it is advisable to attend the Irish night. Iterating the game stages we can see how 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 this solution to our problem, we map some variables: T is the amount energy produced by a prosumer, N is the total consumers' demand and M, H and L are the intervals defined according to the actual money spent by a consumer. The obtained probability p becomes the basis for the buyer agents decisions, that is, identifying whether it is convenient to start contracting with a Genco or with a prosumer. In addition, we also model the possible actions (thus to define strategies) that the consumer agent can chose to perform when the bids are refused or the contacted prosumer does not have enough supplies to the respect of the requested demand. The latter consideration implies the need to see the game as divided in several stages, thus to have four payoff matrices instead of one (Tables 4, 5, 6 and 7).

Table 3 El Farol Bar payoff matrix. With payoff score $H > M > L$, with M unconditioned.

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

Tables 4 and 5 are called *initial state tables* while tables 6 and 7 can be defined as *final state tables*. The difference is that only tables 6 and 7 show an ending of the negotiation that is symbolized with letters H, M or L as the payoff entity inside those cells, while the first two matrices show Intermediate Payoffs (Ips). Therefore, we have:

- A multitude of agents representing a set of players $\mathfrak{I}$;
- Players move through different tables shaping the *finite state space* $\mathcal{M} = \{$TAB1, TAB2, TAB3, TAB4$\}$;
- Each player (agent) $i \in \mathfrak{I}$ is provided by an action set $\mathcal{S}^i(TAB_x) = \{$Contact *Genco*, Contact Prosumer, Accept Offer, Refuse offer, Place Bid$\}$;
- The risk accumulation when traveling from current state A to next state (TAB_x) using the action profile $s \in S^i$, is described in Tables 4, 5, 6 and 7 with their assigned payoff chains.

Every buyer starts by taking a decision in the first table (as element of the state space $\mathcal{M}$) . The balancer agent is the entity that knows how much energy can be produced by all the *prosumers* and by using this information it can calculate a quantity that represents how many buyers 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 *consumer* probability to chose to contact *prosumers* instead of a *Genco* in this early stage of the negotiation (quite similar on 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 assign to those initial tables, a certain amount of fictional points that we call "intermediate payoffs". These Ips represent the chain of payoffs for this multiple stages 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. Risk aware in auction bidding systems have already been studied [43], although the concept of risk is not elaborated in a multi-stage game, it has to be specified that a risk aware agents better simulates how a human user could act. On the other side, higher Ips increase the chance to have a satisfactory game result (H or M as 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 (e.g: 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 deliver. 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 traveling around several tables for such a long time and chances to find a suitable seller or even a *Genco* that has not overtaken his threshold will be scarce. That is because in the ending tables negative Ips values are present. When the Ip value is largely below zero then the agent is forced to get a contract with a *Genco* in order to avoid wasting other time (and likely more money).

At the end of each round each buyer agent evaluates the outcome of the previous round: this latter step has to be done in order to foster adaptivity towards the dynamic market variations. If a buyer agent ends a round in a H final payoff but still the difference between his expected price to spend per energy unit and what he actually paid at the end of the negotiation is a large negative value, this means that the agent was expecting to spend an unrealistically low price, that is completely unbounded to the real market trends (i.e: raw material prices, peak production values, and so on). The agent has then to rise his expected money to spend in order to adapt to these market variations. The rising of the expectation prices is proportional to the value of the above mentioned difference: the larger is the difference, the stronger will be the agent reaction. Obviously, the same but specular actions are taken in the opposite case in which a consumer ends with a L final payoff, but still his price expectation are met: this means that the agent was expecting to spend much more than the average real market price, therefore a decrease in these expectations has to be operated.

Another possible buyer agents' reaction is to vary the amount of the single bid in case of bid refusals: small increases in buyer's bids could translate in longer negotiations with prosumers, so to increase the probability

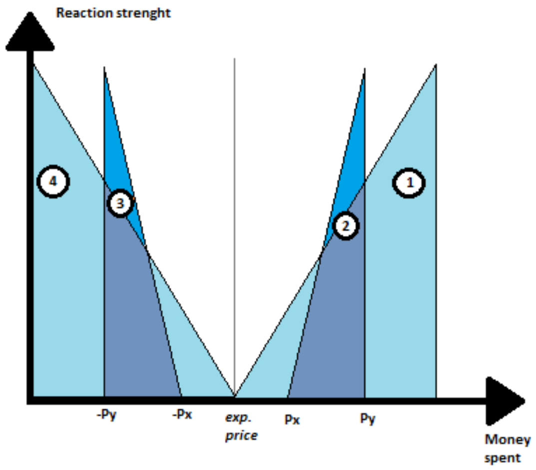

Fig. 9 Fuzzy logic styled diagram for controlling bids. Buyer's side. 1) Increase expected money to spend 2) Rise stakes/bids 3) Decrease Rise stakes/bid 4) Decrease expected money to spend

that other buyers could reach an agreement with the seller, while bigger increases will lead to faster agreements, but at potentially higher prices. An additional fuzzy styled block is shown in Fig. 9, helps the consumer agent to find a balance between these two specular reactions. The graph is centered in the expected money to spend. If the money spent is surpassing the right interval, then the system reacts by slowly rising the stake of every single bid and increasing the spending expectations. On the other side, if the value for money spent is located in the left side of the graph, the reactions will be the contrary compared to the last situation: this is done in order to adjust expectations in the case of lowering of market's prices for electricity.

4 Implementation

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 more price scales using agents. The restricted number of agents, does not compromise the purpose of the test: this is because the kind of market modeled 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.

To test the scalability of the system, we perform additional experimentaiton with several JADE platforms running and communicting concurrently. These simulations go closer to a real implementation of the system on distributed platforms. A representation of the distributed configuration is provided in Figure 10. One sees that the unifying layer is the JADE platform that can run distributed once the network layer is available. The only difference between the agents residing in the platform is the presence in one machine of the Exception Handling (EH) agent that has the task of handling exception conditions and eventually restart agents. For this purpose a set of identical HP DC7800 host machines have been used with the following characteristics. The hardware is based on Intel Core2 Duo E6550 @ 2.33GHz, with 2GB of RAM, 160GB of HDD and gigabit ethernet. The operating system is Debian GNU/Linux 6.0, kernel 2.6.32-5-686, and further software is Eclipse version 3.5.2 Java EE IDE for Web Developers, JADE version 4.1, and JRE version 1.6.0.24 with just-in-time compiler enabled.

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).

5 Evaluation via Simulation

In order to have a clearer idea of the efficiency and precision of the strategy, we show the difference between

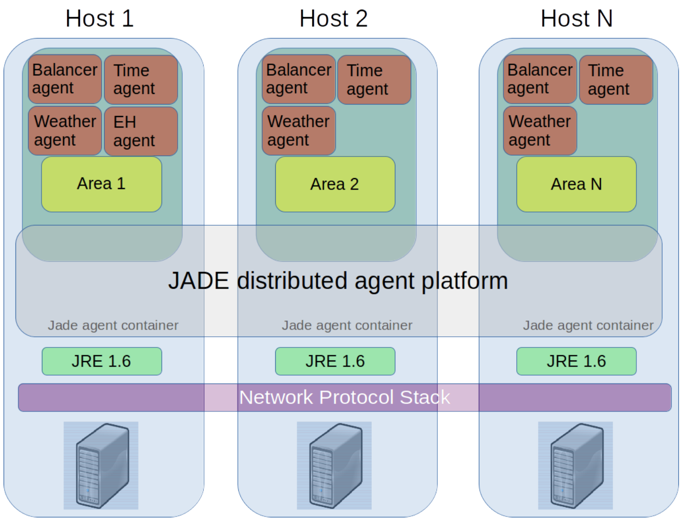

Fig. 10 Distributed realization of the energy interaction platform.

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 Fig. 11, 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 Fig. 11, 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. Proving the effectiveness of the described game is a challenging open question that we tried to answer with this simulation test.

In the simulation, the expected price starts from 0 in the first round, and the convergence between the expected price and the paid price starts in the range of 11^{th}-21^{st} round. 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 is guaranteed compared to agents that always choose the strategy that immediately appears as the most convenient (Fig. 11).

As shown in the graph in Fig. 11, the gap between the two situations (i.e., agents following the adaptive strategy and agents always contacting cheaper sellers first) 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 equilibrium in the amount that represents the cheapest alternative in almost all the examined negotiation rounds. The prices obtained with the proposed strategy follow really close that value. Opportunistic agents that always try to win *prosumers'* auction may have some chance to win during the initial rounds, but still the algorithm provided tries to establish a Nash equilibrium nonetheless; once the prices are balanced, chances to obtain the best bargain are going to be sporadic for those agents.

In the simulation, the expected price starts from 0 in the first round, reaching a convergence during the 8^{th} round. Starting from that point, it becomes visible how expected and obtained prices of agents that follows the multi-stage minority game approach (represented by

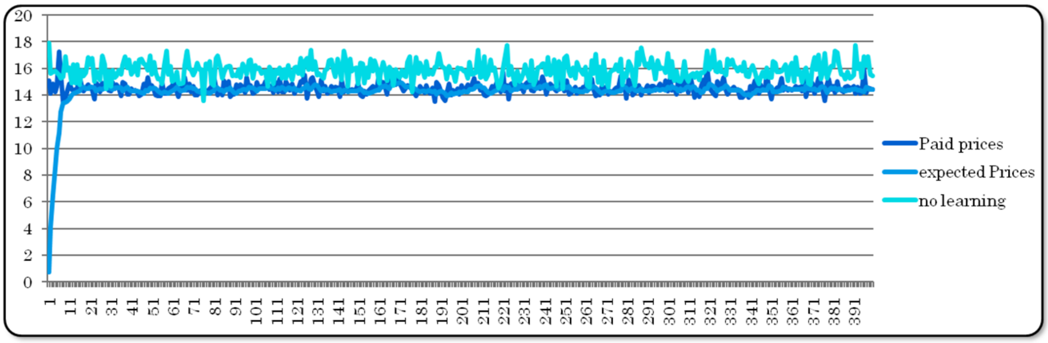

Fig. 11 Three functions showing the difference between no learning prices and the chasing of expected prices with obtained average deals when using the explained strategy, considering 400 rounds.

the two continuous lines in Fig. 11), 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 behavior (Fig. 11, 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. In a more complex scenario in which sellers adopt strategies according to the economic background, the presence of market competitors will determine an additional factor that needs to be further investigated in order to provide a more realistic model.

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 5, buyer agents just have to solve an iterated amount of conditional instruction and comparing variables (e.g: if the current Ip 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.

Distributed environment

To test the scalability of the system in terms of the obtainable performance compared to an environment with just one machine and one agent container, we distribute the agent platform over several machines.

Table 8 Scalability of the system till proper functioning.

Measured metric	**Distributed case**	**Standalone case**
Number of hosts	6	1
Number of agents	818(600c, 140p, 60g, 6b, 6t, 6w)	243(180c, 42p, 18g, 1b, 1t, 1w)
Average number of messages transferred	2865639	65439
Average time to reach convergence	519800 ms	1879993 ms
Average CPU and memory usage	46%, 566MB	39%, 667MB
Average CPU and memory usage by JADE	13%, 230MB	40%, 100MB

Table 8 shows the property of scalability of the distributed system versus a standalone system in their maximal load configuration. The number of agents that can be created on the two platforms grows a bit less than linearly while maintaining similar performances. For a number of agents that is more than triplicated between the distributed and the standalone case, we see an increase of the number of exchanged messages that is more than one order of magnitude larger. This high increase of the required communication is due to the dynamics of the auction system. However, the distributed solution achieves a convergence of the system almost three time faster than the standalone one.

Scalability of the distributed versus a standalone system having the same number of agents participating in the trading is reported in Table 9. One can see that the time to reach completion is more or less the same in the first case, while for the distributed solution the increase is sublinear, the standalone version experiences a sharp increase in the time to reach completion of the auction process. This aspect is also reflected

Table 10 Scalability of the system with increase of the host resources.

Measured metric	Test 1	Test 2	Test 3
Number of hosts	1	3	6
Number of agents	99(60c, 14p, 6g, 6b, 6t, 6w 1e)		
Average number of messages transferred	7851	5058	5470
Average time to reach convergence	17562 ms	10569 ms	17113 ms
Average CPU and memory usage	55%, 323MB	50%, 263MB	40%, 148MB
Average CPU and memory usage by JADE	22%, 111MB	32%, 118MB	39%, 115MB

in the amount of resources required in terms of CPU and RAM. The performance of the distributed solution is definitely a consistent improvement and proves that the system has to be distributed in a solution similar to real cases in terms of the parties involved.

The last scalability test deals with a solution where we keep constant the number of agents involved and we increase the available resources from 1 to 3 and finally to 6 hosting machines. We see that the best results in terms of required messages and time to reach convergence of the problem is achieved with the platform with 3 hosts. The additional effort of a solution with 6 machines is due to the resources required by JADE to keep the platform running in a consistent manner. One notices that the use of the CPU is mostly dedicated to the agent platform.

In general, the results of the scalability tests show that having more platforms does provide for faster convergence. However, as shown in Test 3, the optimum does not always mean that the maximum number of hosts have to be used. The over-distribution of the load requires additional synchronization and consistency messages to be exchanged in the agent platform that have an impact on the performance of the whole application. Additional tests concerning the failure and recovery of the application and its components in a distributed domain are reported in [26]. Finally, we remark as this is just a way of test scalability. Our approach has been that of simulating communities of agents (e.g. related to micrograds) interacting. An alternative approach is to test agents living in individual containers. We leave such an approach for future research.

6 Related Work

Several topics contribute to the state of the art on which the present work on service-orientation and the smart grid is based on. Solutions that apply agents, game theory, adaptation in the Smart Grid context are limited so far. Usually, works focus on just one specific aspect of the topic without taking in consideration all the aspects arising in a prosumer-based energy landscape.

The Smart Grid is a very good example of an application domain for SOAs. Although the Smart Grid is not yet implemented, and the standardization process is underway, several scientists advocate for SOAs as the approach to deal with the complexity of the Smart Grid environment. In [37] we outline the service requirements for the future applications of the Smart Grid . We emphasize the use of services for weather, energy market prices, and production of energy of small renewable-based production units. The paper also shows how to realize a simulation of the Smart Grid today with focus on the aspects of the Smart Grid essential for the end user. The proposed implementation uses some online services provided on the Internet. The broader panorama of the service approach to the Smart Grid is analyzed in [35]. The paper shows how services are required to cover the many aspects and actors present in the new approach to the electrical grid. The interoperation between many systems, lots of them with a legacy heritage, is possible through the adaptation of the systems in a service-oriented way. The paper also clearly explains the additional challenges that a service-oriented architecture in the power domain poses compared to the traditional business process-oriented world. Cox and Considine [13] stress how collaboration is the essential characteristic of the Smart Grid. The interaction among the many actors involved in the Smart Grid requires transparency, composition, extensibility and loose coupling. The authors also identify the standards for information exchange to be used in the Smart Grid for some aspects such as scheduling and time functions, weather information, device discovery and market interactions. All these elements fit in a SOA framework. Collaboration between future Smart Grid objects, appliances and devices in order to achieve better energy management and efficiency is the idea of [23]. The author envisions a collaboration between different entities such as energy resources, energy marketplaces, enterprises and energy providers through Web services, since they enable flexible integration without the problems due to implementation details. In Karnouskos's vision device of the Smart Grid will be *SOA-ready* exposing in a standard way the services it can provide.

Looking more specifically at Smart Grid , many works have the goal of realizing simulation software taking into account the scenarios that the future Grid will enable. In [46], the authors simulate the effects of combining households loads and electric vehicles to play the buffer role in balancing a Grid mainly powered by solar resources. The result is a reduction in the required

Table 9 Scalability of the distributed vs. standalone system.

Measured metric	**Distributed case 1**	**Standalone case 1**	**Distributed case 2**	**Standalone case 2**	**Distributed case 3**	**Standalone case 3**
Number of hosts	6	1	6	1	6	1
Number of agents	58(30c, 7p, 3g, 6b, 6t, 6w)	43(30c, 7p, 3g, 1b, 1t, 1w)	98(60c, 14p, 6g, 6b, 6t, 6w)	98(60c, 14p, 6g, 1b, 1t, 1w)	178(120c, 28p, 12g, 6b, 6t, 6w)	163(120c, 28p, 12g, 1b, 1t, 1w)
Average number of messages transferred	4578	7124	7408	54578	28189	531730
Average time to reach convergence	10871 ms	10486 ms	12148 ms	38076 ms	22583 ms	696450 ms
Average CPU and memory usage	42%, 190MB	51%, 234MB	46%, 143MB	55%, 306MB	42%, 244MB	72%, 606MB
Average CPU and memory usage by JADE	36%, 100MB	25%, 71MB	32%, 113MB	27%, 77MB	25%, 132MB	18%, 95MB

spinning reserves (i.e., on-line extra generating capacity) and the benefits in terms of reduction of CO_2 emissions. Another simulation tool for Smart Grid in general with focus on the Demand-Response is provided in [51]. The presented system is basically a MATLAB simulation that addresses mainly the electrical problems of the Smart Grid and to a smaller extent the ICT and communication aspects. An investigation that exploits the principles of agents considering the wholesale electricity market and its prices is provided in [28]. The main contribution of the paper is to simulate a market with multiple participants with their own strategies that have to take into account power line constraints and generator constraints. Another simulation environment with the Smart Grid flavor is proposed in [44]. The paper focuses on a simulation of the residential environment energy management, therefore the effects inside the house of the Smart Grid. The main features of the simulation are demand response with several devices and scenarios considered (dishwasher, dryer, electric vehicle, refrigerator, etc.). From an economic point there is no mention of tariff differentiation or energy negotiation, but the only aspect considered is a return on investment analysis considering the cost of residential energy management system and the savings in energy costs obtained by the home intelligent equipment.

Software architectures in the picture of the future Smart Grid is the focus of several researchers. The importance of services and related architectures that can handle such a scenario in the future Smart Grid is emphasized by Karnouskos in his vision paper [24]. The author believes that services are the right choice in the Smart Grid panorama give the heterogeneity and flexibility required by the many actors involved. Also on the architecture level of the future Smart Grid is the work of Strobbe *et al.* . From a technical perspective the work uses a java-based platform and protocols. Although the platform is well described and sound, the services proposed are mainly used to increase the level of awareness of the users and stimulate them to save energy by providing price signals. Such a mechanism is a form of demand shape through prices that can help in shaving the peaks and have a better user of renewable sources. Another example of architecture for the Smart Grid is proposed by Verschueren *et al.* [49]. The most interesting aspect of the proposed architecture is the generality in the purposes that it has by the ease in the addition of new services. In the description proposed it can interact and control Smart Grid-enabled devices; moreover, the architecture can act also as a integration point for other services provided by service-providers related to energy such as real-time energy pricing and remote device control. Although this architecture is valuable and enables a good simulation in the large of the Smart Grid, it lacks in considering the prosumer interactions that are a key ingredient for the future Smart Grid; for this purpose we consider an agent-based system better suited. Web services are the key components envisioned in the Smart Grid as suggested in [25] and [2]. However, these works are mainly a test related to web service interaction and simulation of web services communication for instance representing appliances and sensors. There is no mention of agents and markets dynamics in such works. A brief overview on the integration of Web services and agents in the Smart Grid is presented in [54], in which a generic overview on such integrated architectures is presented, without detailing negotiations and market aspects.

7 Conclusions

People will perceive the true benefits of the smart grid only when the digitalization of the infrastructure will deliver added valued services to them. Being able to participate in an open deregulated energy markets has the potential of being one of such services. To enable it though there are a number of technical challenges that need to be addressed. Service-orientation and agent based modeling promise to be the solution for the job. In the present work, we proposed such an architecture and we introduce an adaptive strategy at the system level, based on minority games. Our strategy considers aspects of balancing and pricing, focusing in particular on negotiation and adaptation to deregulated energy market conditions.

To show the feasibility and soundness of the approach, we have implemented and tested the proposed system. The results of the simulations show that the gap between the two approaches (i.e., agents following the proposed adaptive strategy and agents following a baseline behavior) is remarkable when certain conditions are satisfied. These conditions relates to remarkable differences between Genco's prices (and related price penalties) and Prosumers' starting prices, but also to slow oscillations of raw material prices among different negotiation rounds, and proper tuning of all the parameters involved in the simulation. In general, the average price of our approach better suits the expected price than the base approach. We remark also that expected prices, starting from very low (and impossible to obtain) values, tend to reach a balanced amount that represents the cheapest alternative in almost all the examined negotiation rounds. Additional tests should be executed in a larger scale, involving real world data, and actually deployed service-oriented smart grids. However the easiness by which agents can be dynamically added to a service-oriented architecture promises to for scalable solutions.

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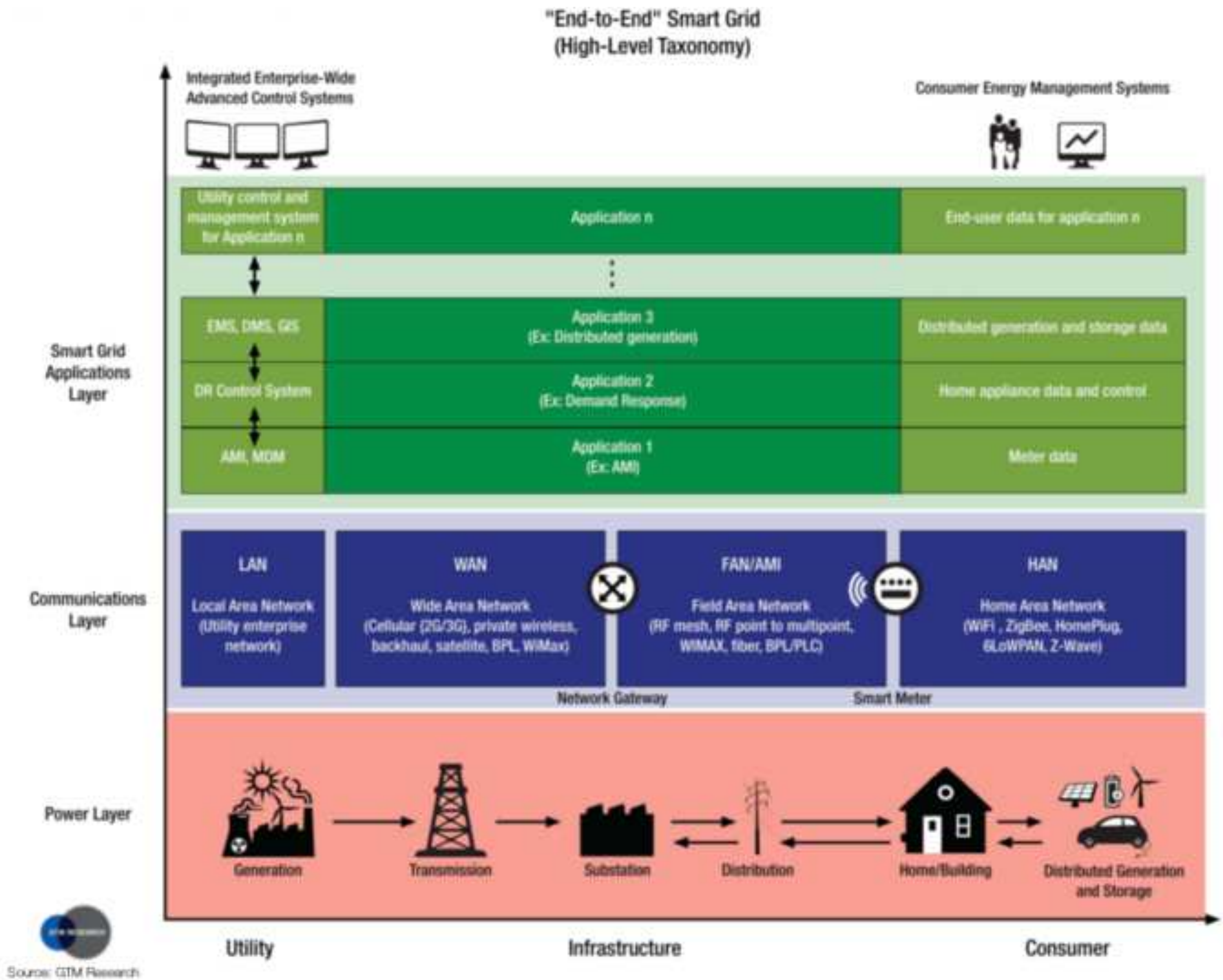

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