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SPECIAL ISSUE PAPER

Context-awareness in the deregulated electric energy market: an agent-based approach

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SUMMARY

Multiagent systems are commonly used for simulation of new paradigms of energy distribution. Especially when considering Smart Grids, the autonomicity deployed by goal-driven agents implies the need for being aware of multiple aspects connected to the energy distribution context. With 'context', we refer to the outside world variables such as weather, stock market trends, location of the users, government actions, and so on; therefore, an architecture highly context-aware is needed. We propose a model in which every important factor concerning the electric energy distribution is presented by modeling context-aware agents able to identify the impact of these factors. Moreover, some tests have been performed regarding the web service integration in which agents contracting energy will automatically retrieve data to be used in adaptive and collaborative aspects; an explicative example is represented by the retrieval of weather forecasting that provides input on ongoing demand and data for the predicted availability (in case of photovoltaic or wind powered environments). Copyright © 2013 John Wiley & Sons, Ltd.

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1. INTRODUCTION

The Smart Grid is a new generation of electric energy distribution that acts on the base of information about the behavior of all participants thus involving balancing between energy *consumers* and *producers* in a liberalized market. This is obtained by shaping a peer-to-peer (P2P) network between consumers and producers of electricity in a short-term approach [1] for stipulating contracts among different parties. This allows more participants to enter the energy exchanging (therefore negotiating) market, shaping a whole new scenario that features more actors compared with the traditional (i.e. centralized) approach.

In particular, the novelty lies not only in opening a dynamic market to other traditional energy suppliers (mostly producing energy using fossil fuels, hydropower, nuclear, or others) but also in involving smaller competitors (likely to be private domestic environments) that have solar panels or wind turbines installed in their property, making them able to contract for incoming as well as outgoing electric energy. This scenario is leading to open challenges, and balancing is likely to be the most critical one: the total amount of energy supplied by producing peers should be ideally equal to the consumers' demand. Failing to satisfy these requirements will lead to wastes in energy distribution, thus leading to more *expensive* contract prices, resource *waste* and further environment *pollution* problems. Moreover, such complex scenario requires integration with multiple sources to

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autonomously deploy the fittest pricing strategy and to be compliant to current governing laws. The balancing equation is heavily influenced by the weather: the consumer of electricity has to know and communicate in advance how much energy she is going to need for following negotiation intervals. This implies being aware of weather forecasting to know if heating or air-conditioning is needed, and be aware also of specific issues related to appliances usage over time. This latter factor is the base for shaping the user profile of the specific consumer, a very important issue when coming to energy consumption prediction. The producer has to retrieve data from weather forecasting too and be aware of the design and installation aspects of his or her photovoltaic (PV) panels and/or wind turbines (WTs): in our proposed model, combining these data will provide the important information of how much renewable penetration will be expected by the grid. The short-term approach for stipulating contracts will force this calculation and data retrieval to be executed several times per day: this is complaint with the unpredictability of wind for WTs and solar irradiance (SI) for PV panels; whereas meteorological stations can forecast temperature with several days in advance with acceptable errors, and SI and wind strength have to be analyzed with considerably less advance [2].

Our contribution lies in showing all the factors that can influence the balancing equation between demand and offer (defined as *context*), by providing an overview on all the most important factors connected to the energy distribution. Moreover, this paper will deeply investigate how a web service interaction can be used for supporting a multiagent system (MAS) to correctly cooperate in reaching the energy balancing in a prenegotiation step of this highly dynamic scenario.

The paper is organized as follows: in Section 2, we provide a view on the related work on the energy problem. In Section 3, the main agents and the short-term approach are presented, whereas the most important factors in energy distribution are analyzed in Section 4. In Section 5, we present the model we used for the web service integration, as well as detailed discussions about services and approximations used in our specific case. After presenting the simulation aspects in Section 6, we discuss results and propose future investigations in the conclusive Section 7.

2. RELATED WORK

Multiagent systems are a common choice for simulating situations where different kinds of actors have to be modeled according to the goal of their respective counterpart in the real environment [3]. In this very scenario, an agent represents a peer inside an electricity distribution net in which producers and consumers are the main components of the market. Previous work about Smart Grids and the energy distribution problems have been commonly addressed with agents [4]. Most of the previously published articles are dealing with the negotiation step (e.g. [5, 6]). As for load balancing aspects, Rumley *et al.* proposed in [7] an algorithm in which two kinds of agents (feeder and load) have to balance the electrical load in the involved distribution lines taking into account the possible links overload. More than avoiding these overloads, our solution tries to establish collaboration between different kinds of sellers for avoiding useless over production of electricity by balancing the correct penetration of PV and wind energy in the electricity market. Also, before any kind of attempt for balancing as well as negotiation, a correct estimation of the amount of electricity that a producer (with PVs or WTs) can provide is needed. We therefore choose to contact appropriate and existing web services for correctly provide this data. Web services and SOA are not new in the field of Smart Grids or, more general smart computing: whereas in [8], we have an example on how to use and create web services to share common data in smart house environments, the energy exchanging problem per se can be seen as an SOA in which consumers and producers of electricity are registered and able to be exploited in a distributed architecture [9]. Our solution will use existing web services/sources of information; thus, we have performed a small survey of the existing market: the retrieved data will be then processed to correctly estimate the renewable energy penetration for the grid. More references and related work on context awareness are presented in Section 4.

3. AGENTS' FEATURES

Different elements of the context influence different kind of agents in the Smart Grid. In an application for enabling a P2P energy exchange in an MAS, we need to stress what are the most

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important agents that are present in the architecture and how basic interactions are performed among them.

In the presented scenario, the most important actors are represented by consumers and producers of electric energy. The formers present an energy demand that refers to the upcoming negotiating interval: according to the short-term approach for energy contract stipulation, in a deregulated market in which peers are connected to each other in the Smart Grid, there is no longer space for long-lasting contracts. This will force buyers of electricity to contact the producers in an hourly basis. Producers that exploit devices producing renewable energy (henceforth, *prosumers*) have to follow a similar, yet specular procedure: still referring to a particular time interval, each of them have to provide to the grid an estimation of the amount of energy that they are capable to produce and a pricing strategy according to the combination of internal and external factors. A complete summary of all of these factors is provided in the following Section 4. The producer of energy with traditional sources (*Genco*) is also characterized and influenced by some of those factors.

The short-term approach requires data acquisition and elaboration; in fact, the architecture as a whole has to be complaint to the actual possibilities of nowadays meteorological stations: in [2], we can clearly see, for instance, how accuracy in wind forecast increases as we narrow down the forecast time. Even if in this paper we are not dealing with the following step of negotiation, the collaborative adaptation strategy of producers is introduced when we realize that the penetration of renewable energy will not satisfy the totality of the consumers' demand: the deficit energy asked by the consumers has to be satisfied by Gencos. The correct estimation of the renewable penetration should be used by the traditional suppliers for varying their production according to the real needs of the market. In Figure 1, a class diagram with the important agents is shown and summarizes the agent characterization so far introduced.

The *adaptive collaboration* strategy involves the formulation in Equation (1):

$$\sum_{i=1}^{N_c} D_i(t+1) - \sum_{j=1}^{N_p} P_j(t+1) = E_D(t+1) \tag{1}$$

In Equation (1), N_c (N_p) is the total number of consumers (producers), whereas D_i (P_j) is the demand (predicted availability) of the single ith consumer (jth producer). By subtracting the first two terms, we can estimate the amount of production that remains to produce by traditional suppliers. E_D is therefore the total energy demand not satisfied by renewable penetration: this information can be further used for setting in advance the production thresholds for traditional producers [5]. Every calculation shown in that equation is performed every time interval according to the chosen granularity; therefore, Equation (1) is calculated at a generic time interval t, being $t + 1$ the following (therefore future) time interval for the forecast. It should be taken into account that the formulation in 1 does not consider losses in transmission lines; however, this simplification is mandatory for creating an initial model to study in an MAS.

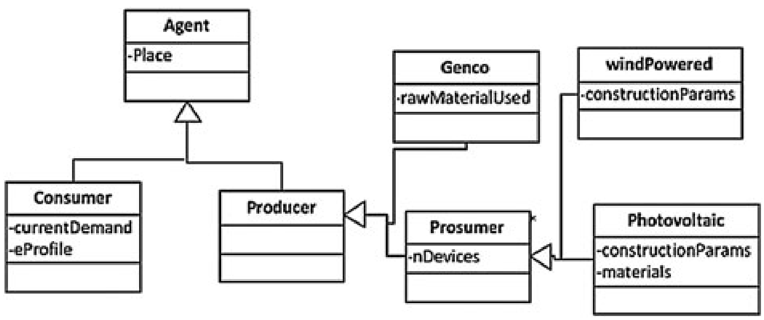

Figure 1. Agent class diagram

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4. CONTEXT DEFINITION

Before actually going into the details of how we modeled the problem and all the related simulations, it is crucial to provide a more formal definition of *context* when talking about agents in the Smart Grid. With 'context', we refer to all the important variables, requirements, and external conditions that need to be taken into account when designing an MAS for energy market applications. If we summarize all of them using the term *factors*, then we can identify *internal*, *external*, and *user-related* factors. In Figure 2, readers can see how the concept of market is located in the very center; this concept is heavily influenced by government operators because laws and regulation can be exploited for boundary shaping this new market approach. The legislation is therefore an external factor, as well as the weather (for this latter one, refer to Section 5.2). Internal factors relate to user profiling of consumers (and therefore prosumers too), such as appliances detection and usage. Prosumers have to deal with hardware features of their renewable devices. Gencos have to constantly be in touch with stock market prices for determining their pricing strategy. User-related factors are preferences of the user, which agents have to take into account when the actual negotiation starts (see Section 4.2).

4.1. Government impact

Because of the size of the problem and to the fact that this whole new concept of producing and distributing energy among a P2P net touches several aspects of our everyday life, the legislation about this matter is huge. Switching from a centralized paradigm to the new system implies law-related aspects that are linked to the different legislation present in different countries: the effort each country has to make to prepare itself (legally and economically wise) to this radical change are extremely diverse, and therefore almost every country should be studied as a separate scenario. Even if all of this is not properly treated in this paper, we can therefore study and have to understand more about this by reading some common legislation for European Union (EU) zone countries.

The European parliament, taking into account that the most recent economic crisis made all our governments perfectly conscious of our strong dependency from old and not renewable energy sources coming from eastern countries, emanated different regulations for suggesting to the EU members how to act to change the monopolistic current structure of energy distribution in something more environmental-care related. For this purpose, the Regulation European Community(EC) No 663/2009 of the European Parliament and of the Council of 13th July 2009 for establishing a program to aid economic recovery by granting community financial assistance to projects in the field of energy distribution has been issued and published in the official journal of EU parliament

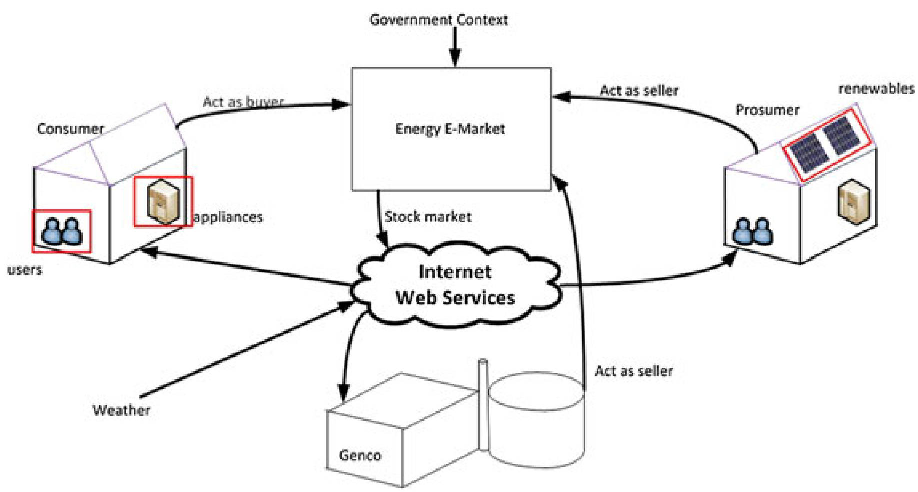

Figure 2. General context map.

emanations under the issue *Official Journal L 200, 31/07/2009 P. 0031 - 0045*‡. In that regulation, also distribution of gas and coal capture is treated. Other discussions and comments about these new regulations can be obtained here [10].

Obviously, Europe is not the only area in which this transformation is beginning to be discussed and investigated: an equivalent of the previous legislation paper in a worldwide perspective can be found here: [11].

Basically, the most important points discussed in all of these references refer to the following:

- 1) Control and minimization of polluting emission;
- 2) Back up guarantees;
- 3) Fair market rules under the deregulation.

With regard to 1), this point is strictly related to provide tax incentives or other economical aids both to consumers and to the industry to help them with the initial investment for the installation of PV modules and/or WTs, so to become active distributors of the Smart Grid. Being aware of these conditions will play an important role of their pricing strategy. Point 2) refers to the fact that still today, in a mostly centralized approach, producers have to provide guarantees when selling electricity: these guarantees may translate into providing assistance or monetary compensation in case of long-lasting blackouts (as impossibility to provide electricity to the agreed buyer). Newer participants (as sellers) of the energy market need to take into account the risk of fault in their renewable devices: insurances and back up plans have been thought in advance. In 3) with fair market rules, we imply the necessity of every single seller to provide the same offer conditions to the all the buyers; in [12], we can see how this point is taken into account by Brazier *et al.* in the Swedish case. It is trivial to understand that these regulations shape the generic behavior of every agent involved.

4.2. Consumers and prosumers factors

The consumer of electricity has to provide in advance an estimation of how much energy will be needed for the upcoming negotiation round. Because the prosumer is basically a consumer that can become a producer node just in case of surplus electricity production, we can consider these two entities as very similar when characterizing their user profiling. There is much work related to characterize each dwelling house, taking into account their consumption load and plausible contribution to the active grid, but most of them deal with constructing a model for Smart House integration, so domotics and intelligent user-aware environments. Our goal to detect the internal factors for agents in the Smart Grid, still being connected with these concepts, can find useful results in experiments in those fields. In [13], the context is elaborated through a model that Ha *et al.* address as *5W1H*: *Who, Where, What, When, Why,* and *How*. *Who* refers to the single user inside the dwelling: the importance lies in characterizing the presence of people inside the house, so to anticipate who will be using appliances in the home according to their work, school, or other habits in the weekly calendar, and thus to provide a more correct estimation for future consumption. *What* refers to understanding which kind of appliances is used: in [14], a recognition algorithm based on appliances' signatures of consumption (by considering power consumption [kw] values over time [m]) is presented. It is crucial to create a profile in which information about user operating particular appliances or devices can be used for understanding patterns of consumption, because each appliance consumption can sensibly vary and this can create mismatch while forecasting future electricity needs. *When* refers to the time interval and time of activation of those devices: understanding its importance is trivial, whereas lesser important internal factors for our context are *Why, Where,* and *How*, because they are too specific to the domotic case study.

A less fine-grained classification of the consumer can be performed by identifying it as a domestic household, an hospital, or a building with government-related functions. This becomes important when thinking about down times of electricity provisioning. The law forces providers to guarantee special assets and times for restoring in case of power failures in critical nodes such as hospitals and

‡http://eur-lex.europa.eu

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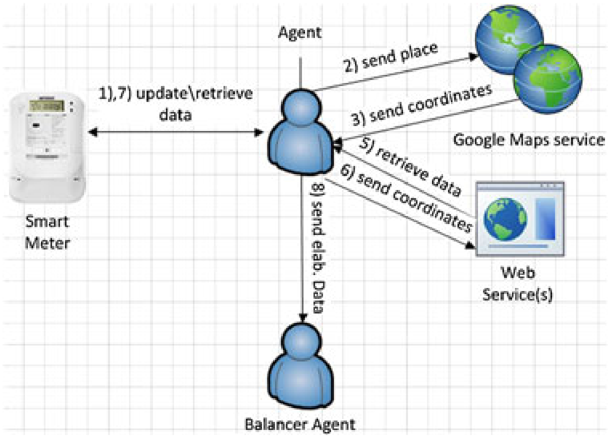

Figure 3. Interaction scheme.

similar ones; however, in a deregulated market, we can think about having a buyer agent with specific preferences that goes beyond the mere pricing of the energy unit. A domestic environment, a big company, or a research center may want to be represented by an agent that takes into account these preferences, thus will search to stipulate a contract at a slightly higher price per energy unit, but with more remunerative guarantees for down times. The owner of a dwelling house could also consider spending more money for the single energy unit, provided that the source of this electricity is a certified nonpolluting generation line. An interesting US survey on this matter has been published [15], and this implies a pricing model for the single energy unit that has to match with this and the previous considerations.

To summarize, an MAS that is aware of the user, also means designing agents with the same desires as the user they are representing in the architecture. As for the external factors, web services can be used for retrieving most of these data, even if the dynamism of these variables and the sources of data can be very diverse. From the following section, we present in details the integration between weather forecasting and the balancing Equation (1) shown earlier in Section 3.

5. WEB SERVICE INTEGRATION FOR WEATHER FORECASTS

An important schematic for agents, services, and entities involved in the model and their typical interaction scheme can be found in Figure 3. We can see that the generic agent is directly connected to its smart meter for retrieving information about incoming/outgoing electric energy, pricing, tariffs, and present and past consumption measures. The versatility and easiness of interfacing a smart meter to software agents [16], adds the possibility to define other constants to be used for our model: we can think about saving in the smart meter the construction and setting parameters of a generic renewable producer wind (or solar) device. As we will see in Section 5.1, most of the existing web services for weather forecasting require an input expressed in absolute geographical coordinates (latitude, longitude): a generic agent, before contacting those web services, has to know those coordinates in advance. In case this agent has a position expressed in location (place) instead of coordinates, the conversion is used via a hypertext transfer protocol request to the Google Maps service[§]. This service will respond via a keyhole markup language-formatted response, from which the agent extracts the requested coordinates. The agent now can easily request the web service interaction, that will be explained in detail in Section 5.1. The elaborated data is then sent to a balancer agent, able to calculate Equation (1), to then suggest the E_D value to the remaining traditional suppliers.

[§]http://maps.google.com/

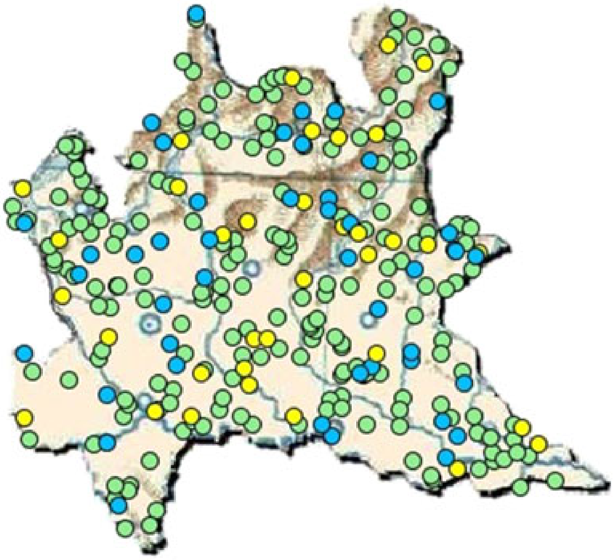

Figure 4. Peer topology for the examined scenario: consumers are green, wind-powered producers are blue, in yellow the photovoltaic suppliers.

5.1. Proposed scenario and services

The proposed scenario involves 200 consumers and 80 prosumers, with the latter ones able to produce energy either via PV or WTs. We investigated what happens in a regular working day (1st of April 2005) in all the 12 provinces of Lombardia region (North-West Italy). A node topology in the chosen territory is shown in Figure 4. Time granularity for the examined day is 3 h, starting from 00:00.

We have already mentioned that different kinds of agents need different kinds of *services*: in particular, the consumer is defined by an energy profiling that provides the system with useful information about its future consumption. In our simulation test bed, the energy profiling for the demand forecast follows a trend that resembles the national average[¶]. This trend is then randomly adjusted to provide different needs for different consumers: in a real scenario, those random parameters for trend changes are predicted thanks to energy profiles that refer to particular households (details in Section 4). However, different studies show that external temperature is one of the most important factors when dealing with demand forecast [17, 18].

As far as the producers are concerned, they will need accurate forecasting of wind (in case of WT owner) or SI (in case of PV unit). In all these cases, in Sections 5.2 and 5.3, we will provide the details of the bound between external temperature and demand variations as well as the wind or solar impact for renewable energy providers. Table I shows the existing web services investigated for our case scenario (wunderground[‖], HC3vX[**] and NWX[††]).

As seen in Table I, web services differ from type of input, services provided, and granularity of data. All of them present limitations if the user is not registered (fees apply). Because of the scarce granularity of the NWX web service, we therefore used the data provided by the first two.

5.2. From data to production of electrical power

In this section, we provide the mathematical and physical relationships that shape the link between the external factors (obtained via web services) and the constructional characterization of producers'

[¶]data sources: www.terna.it, TERNA the biggest Italian Transmission system operator
[‖]www.wunderground.com/history/
[**]www.soda-is.com
[††]www.navlost.eu

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Table I. Investigated web services

Service name	Service provided	Intervals	Input
wunderground	Wind speed and direction; temperature	hourly	Location
HC3vX	Solar irradiance	hourly	Location or coordinates
NWX	Wind speed and direction; temperature	6 h	Coordinates

renewable devices, because these devices (that can be either solar panels or WTs) 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 does not really matter where these parameters are stored, provided that this information is known in advance and is complaint to any changes of the devices installation.

In the rest of this section, we formalize the energy produced by the different kinds of prosumers, whereas the formalization of the consumers' needs is treated in Section 5.3, where we provide an overview of our model of consumption during the simulation day.

5.2.1. Wind power. The production of electrical power through WTs depends on the interaction between the rotor blades and wind speed; in particular, the electric power generated by a WT (P_e), expressed in watt, can be determined through Equation (2) as follows:

$$P_e = \eta_e \times \eta_m \times C_p \times \frac{1}{2} \times \rho \times A \times Ws^3, \tag{2}$$

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

$C_{p,\max} = 0.59$ is commonly called *Betz* Limit and expresses the following basic idea: 'The maximum power that can be theoretically extracted, considering an air current and an ideal WT, 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 as follows:

- 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 particular, in this model, the C_ps of different producers are randomly selected with values ranging from 0.3 to 0.5 to simulate the characteristics of the various WTs present in the market. The C_p so determined not only expresses 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 WT such as the roughness of the ground or the installation height [19]. The air density depends on the temperature and the altitude of the place of installation, so it is easily calculable; 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 described in Section 5.1.

5.2.2. Solar power. To calculate the producible energy by the whole PV system, on the basis of the data of average irradiance in the considered time slot (3 h), we used Equation (3). Equation (3) refers to a single PV module; therefore, multimodules environments have to sum the single contributions of the installed modules.

$$E_g = P_0 \times G \times K \times \eta_{\mathrm{PV}} \times \eta_{\mathrm{INV}}, \tag{3}$$

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

The inverter efficiency range is between 0.88 and 0.94, whereas the efficiency of the PV generator has a range from 0.70 to 0.86 and depends on several factors such as the temperature outside the modules: a higher temperature could decrease the module efficiency. In [20], K represents a parameter (usually $K < 1$) that takes into account the phenomena of power reduction for aging, panels' inclination, shadowing, and foliage because of nearby trees. For our level of abstraction, K is chosen with a randomized values varying from 0.8 to 0.95 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: SI is one of the parameter retrieved from the web services.

5.3. *Consumers' demand trend over time*

The consumption of electricity is affected by different factors such as workability (calendar effect, see Section 4), 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.

For obtaining 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 of the sudden changes in temperature that will cause significant changes in consumption in the short term, whereas the other profile related factors are supposed to follow a more static trend.

The relationship between temperature and consumption is nonlinear and dynamic: previous literature (e.g. [21]) proposes same trends with different key values.

Our temperature versus consumption function is described by the following:

- 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 and temperatures above 24°C the heat zone. Those areas are shown in the Figure 5, and they cause maximum consumption values;

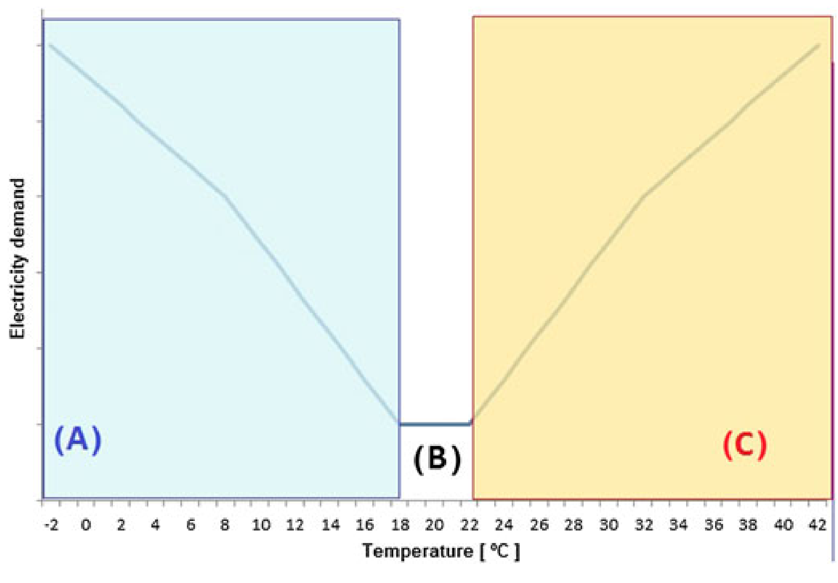

Figure 5. Temperature versus consumption: (A) cold zone, (B) no effect on consumption, and (C) heat zone.

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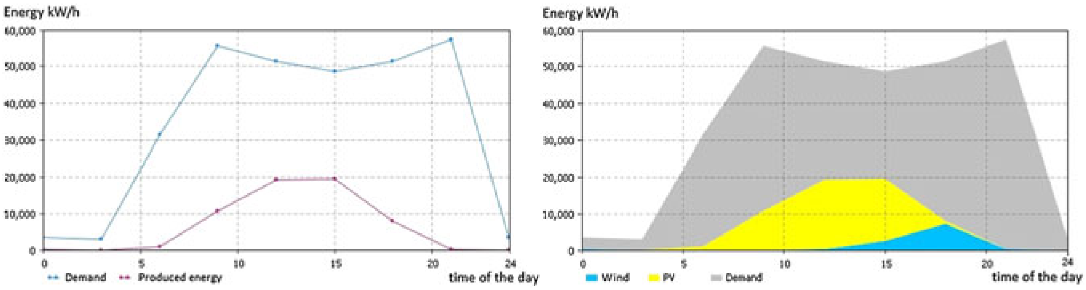

Figure 6. Simulation output for the examined scenario. PV, photovoltaic.

- 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.

6. SIMULATION

The simulation involved the same model presented in Section 5. The simulation test bed was implemented using the AnyLogic[‡‡] software agent platform: being a general-purpose platform for simulations and trend plotting, it is widely used to model a very wide range of problems [22]. The purpose of this simulation is to see how a multitude of consumer agents can generate different demand values to be then satisfied by the producers. However, the producers present in the simulation, because they represent a diverse variety of PVs or WTs energy generator in household environments, can only satisfy a fraction of the total demand: the remaining demand have to be covered by traditional suppliers. This is the main idea behind the concept of adaptation and collaboration: the *adaptation* lies in all the aspect that are able to vary the consumers' demand according to their habits (as seen in Section 5.3), but also how different devices react to the changing weather parameters previously obtained via the web service integration. The architecture should therefore prove to be *aware* of the context (energy profiling, weather, location, and so on). The *collaboration* aspect refers to the different kinds of producers: because we can assume that domestic environments that feature renewable energy producing devices will be able to sell their surplus energy directly to other consumers at a lower price compared with the bigger (traditional) energy companies [5], these latter ones should take into account that every time interval a fraction of the requested energy is already covered and reintroduced in the grid. Ignoring this information will cause a not convenient surplus of production of electricity.

In Figure 6, the output of the simulation is shown. The demand follows the predicted trend in which we have peaks during certain hours of the day. In the first graph, we see the sum between the wind and solar penetration, whereas in the second one, we can clearly see the difference between these two plots facilitating the reading of these two different contributions. During the central hours of the day, the renewable energy penetration reaches its maximum values: that is a straightforward consequence of the presence of hour of sunlight. As for the wind speed, in this case, its peak is reached around later hours (between 3:00 PM to 6:00 PM). In the second graph, the gray area represents the E_D value of Equation (1) and will influence the production request for the traditional producers. Our model, therefore, makes the assumption that the totality of renewable energy produced will be sold during the appropriate time interval: this is justified by thinking that

[‡‡]www.xjtek.com, St. Petersburg, Russian Federation

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if a small producer does not manage to sell its production to a neighboring consumer, then the energy will, nonetheless, be reintroduced in the grid. From a negotiating point of view, this means that this kind of energy without a direct buyer will be obtained by other traditional suppliers or transmission services.

7. CONCLUSION AND FUTURE WORK

In this paper, we have presented an MAS in which each agent acts on behalf of energy producers and consumers, and it is situated in particular location and therefore influenced by external factors related to the energy market context. After providing an exhausting list and explanation of all the factors involved, we have then proposed an implemented simulation through web services. Web service integration is a useful approach for getting information to be used as input for the awareness of our architecture; therefore, a small set of existing web services were investigated and thus used for simulation purposes. By combining these external factors to the different models for approximating the future production of energy via renewable electricity producing devices, we were able to construct a realistic model of a North-Western region of Italy. The simulation showed that the agents adapt to the ever changing weather conditions and consumers' habits. This is an essential initial step to be performed before the actual energy negotiating procedure, because balancing between PV and wind penetration over the totality of the energy demand for the considered area is the most crucial factor. It is interesting to note that our model clearly resembles other studies that illustrate that the renewable penetration will change the existing energy production and market models [23].

Future work will involve the further step represented by the negotiation among the described parties. Also, the equations used for predicting the penetration of renewable energy can be further characterized taking into account more complex models [24]. As for the context, following work will go deeply in how to automatize the retrieval of government factors in the pricing models, as well as investigating further model for privacy management in delicate scenario such as user preferences and characterization [25]. Moreover, because most of the work related to Smart Grid is perfectly complaint with newer trends about home automation, a future investigation on the details of a multipurpose architecture is needed [8].

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