João C. Ferreira, Paulo Trigo, Alberto Silva, Helder Coelho, João L. Afonso, "Simulation of Electrical Distributed Energy Resources for Electrical Vehicles Charging Process Strategy", Published by IEEE Computer Magazine - dedicated to the Second Brazilian Workshop on Social Simulation (BWSS 2010), 24-25 Oct. 2010, São Bernardo do Campo, São Paulo, Brazil, pp. 82-89, ISBN: 978-1-4577-0895-4, DOI: 10.1109/BWSS.2010.15

Simulation of Electrical Distributed Energy Resources for Electrical Vehicles Charging Process Strategy

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Abstract—**This paper presents a simulation platform for control and monitor the Electric Vehicle charging process, based on existing power distribution limitations and Microgeneration capacity. The goal of this research is to simulate the energy consumption and their unexpected behavior, using past experience and taking into account distribution network and home power limitation to find an intelligent charging pattern. This paper proposes a novel approach for this problem based on a simulation platform where stochastic process is adopted to perform unexpected user behavior. This simulation platform can be used to determine the capability of the actual electrical distribution network for supplying energy to the final consumers and for charging the bank of batteries of electrical vehicles, which can occur simultaneously.**

Keywords: **Electric Vehicle, Charging Process, Simulation, Tracking System, Micro-Grid, Micro generation**

I. INTRODUCTION

Transportation industry is reaching a turning point as it begins the gradual transition away from vehicle based on the internal combustion engine towards Electric Vehicle (EV). This transition challengers new business opportunities in the creation of charging infrastructures, with charging equipment ranging from residential equipment to public, private and workplace associated charging stations. Market studies forecast that a total of 1 million of EV and 4.7 million such charging points will be installed worldwide for the period 2010 - 2015 [1]. Niche vendors (such as AeroVironment, Better Place, Coulomb Technologies, and ECOtality), heavyweight technology players (such as GE, Panasonic, Samsung, and Siemens) are now making bold moves into this area. New open Electric Market (EM) will play an important role in this process, but the electrical network distribution could not be prepared for this high consumer demand.

In spite these new business opportunities, there are significant concerns with the electricity distribution, because EV charging process require high charging rates usually more than the maximum current demand of a typical home. This new reality could in peak time overload electrical distribution networks and street level transformers serving between 20-200 homes may became significant bottlenecks with the introduction of EV [2]. To avoid this distribution bottleneck electrical companies tend to introduce time-of-use prices to dissuade owner of charging their EV at peak times, but usually fails on local distribution constraints because there is no intelligent distribution that can monitor this process and take these constraints of limit use. So, EV charging process should be controlled by an intelligent process that taking into account users' needs, proprieties of EV usage (e.g. departure and arrival timing, driven distance), electrical home consumption and power limitation on local contracts and local distribution network.

Still, associated with this problem (EV charging without violating the network distribution technical restrictions) the Microgeneration (MG) can play an important role, when local production excess could be stored locally by EV without charging the network. This is part of a Distributed Energy Resources (DER), small-scale power generating technologies close to energy loads, are expected to become an important part of the future power system. MG and EV will play an important role in this process and nearby community will use this power because the network distribution allows it. Since distributed energy resources are installed near the loads, they are likely to be installed on low-voltage below 25 kV distribution systems. The distribution systems also account for the higher percentage of system losses compared with the higher voltage transmission systems, causing an improvement of the overall efficiency of the system. DERs have the problem of variability (changes in load), uncertainty (supply contingencies) and unpredictability (renewable generation). Main important fact is that EV can store local MG production excess and users' can tune their consumer behavior in part based on MG production, i.e. they can develop a collaborative process based on energy production they can start/stop washing machines and other equipment's that don't have time constrains. This reality brings new investigation problems where simulation process plays an important role, since there is not available and intelligent distribution network that can know and control user consumption. Also the distributed resources present a substantial change in the way the electricity infrastructure is managed and controlled [2]. In this complex system, it is difficult to perform real tests on a controlled environment, so the main solution is the use of simulation processes. Simulation tools have been applied with success to several areas, such as military systems [3], information retrieval systems [4], energy market [5], social analysis [6], crime [7], decision support systems [8], supply chain [9] and many more domains [10, 11, 12].

The key contribution of this research our main proposed idea is to model the EV charging process, based on EV type and users driving needs, simultaneous home user consumptions based on pre-defined data, user data taken from a tracking device installed on a mobile device with GPS capacity (time of home arrival, departure and distance), power limitation (home user and distribution), and Microgeneration (MG) production capacity based on weather forecast, as illustrated in Figure 1. The main approach of this research involves the integration of the following issues: electrical distribution network in a geo-reference graph (section 2); tracking user behavior (section 3); simulation of residential consumptions (section 4); DER model with MG integration (section 5); smart charging strategy (section 6).

II. Geo-Reference Graph for the Electric Distribution Network

One important approach introduced in this work is the Geo-Reference Graph for the electrical distribution network. This allows computational data manipulation, such as distance calculation, identification of power limitation, and identification of user communities. The area with the distribution of the electrical network is manually transformed in a graph (Figure 2), where we add geographic information and power constraint between the nodes. Figure 2 shows different nodes with different apparent power capabilities (these nodes represent six T4 houses and two buildings with two and three floors). The main node (node zero) represents the power transformer responsible to supply the others eight nodes. For our case study, Table 1 summarizes, the information of distribution network for these nodes, taking into account the different nodes, the description and type of each house, the apparent power of the elevator and of the common services (when available), and the apparent power available. This information is very important because it allows determining the apparent power available for each different node in the distribution network. This is a slow process where we expect in a near future to introduce some automation. Regarding to the consumer's behavior several assumptions were considered: (1) consumers define their house and family (number of house divisions and number of persons); (2) they define the number and type of electrical appliances from a pre-defined list; and (3) they also define their usual routine (e.g. arrival and departure times). Every consumer has its own behavior, and changes or unexpected behavior are randomly generated at the beginning of the experiment.. Each consumer is represented by an agent who knows contractual power limitation and also the distribution.

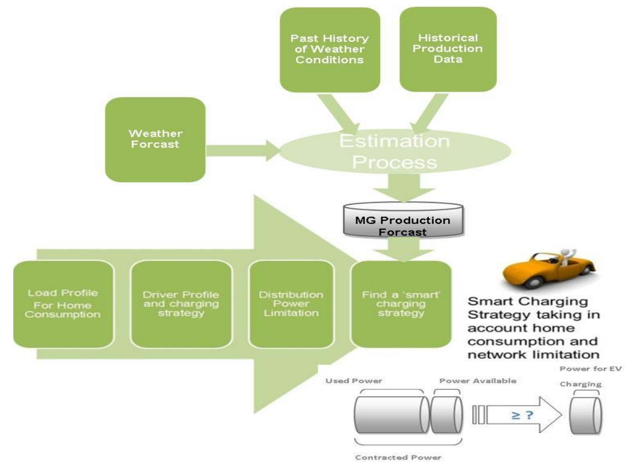

Fig. 1. Main objectives of this research work, involving the integration of the following issues: simulation of residential energy consumption; forecast of MG production based on past data and weather information; and based on distribution network and residential power limitation to find a smart charging strategy for EV.

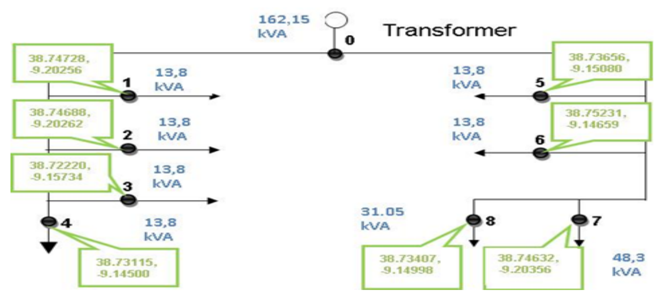

Fig. 2. Geo-reference electrical distribution network.

Table 1: Information about distribution network, used for our case study.

node	DESCRIPTION	TYPE	ELEVATOR	COMMON SERVICES	SIMULTANEOUS COEFFICIENT	Power Available
1	House 1	1 x T4	0	0	1	13.8
2	House 2	1 x T4	0	0	1	13.8
3	House 3	1 x T4	0	0	1	13.8
4	House 4	1 x T4	0	0	1	13.8
5	House 5	1 x T4	0	0	1	13.8
6	House 6	1 x T4	0	0	1	13.8
7	Building 1 3 Floors	6 x T2	20.7	6.9	0.75*	40.83**
8	Building 2 2 Floors	1 x T4 1 x T3	0	6.9	1	31.05***

* 6 installations
** 48,3=(6x4,6x0,75) +6,9+20,7
*** 31,05=13,8+10,35+6,9

III. TRACKING SYSTEM IN 'OFFLINE' MODE DRIVE

V2G (Vehicle-to-Grid) or G2V (Grid-to-Vehicle) process are process that controls the charging of a EV (G2V) or discharging process of a EV (V2G. User profile plays and important role on both V2G and G2V process. Also to study drivers' habits and profile update we have developed a tracking application to run in an offline mode (to avoid communication costs) in a mobile device with GPS device. This project was developed in an academic final year project at ISEL, described at [13], and its high level vision is showed in Figure 3. This tracking application mainly stores times, GPS coordinates and user identifications. From the GPS coordinates it is easy to calculate travel distances. Using Google Maps API we can represent the drive route and obtain the travel distance. From the travelled distance and the EV efficiency we can estimate the remaining energy stored in the batteries of each EV (SOC – State-of-Charge level), as well as the community SOC level (sum of all individual community SOC levels). The studied population (from the city of Lisbon area), with 50 cases, contains a mixture of university students and their parents, and takes into account the first EV introduced in Portugal: the Nissan Leaf (with a 24 kWh lithium ion battery pack, a 3.3 kW onboard charger, with a fast charger that can charge 80% of the batteries capacity in about 30 minutes, and with an autonomy of 160 km obtained with a careful driving). The application designated as GPS Tracker was developed to be used in mobile devices, like PDA, on top of Android. The purpose of this application is to create GPX files with the recording of the GPS data (namely: latitude, longitude and instantaneous speed) related to the travels of the user. The user has yet the possibility of observing, in real time, the collected data.

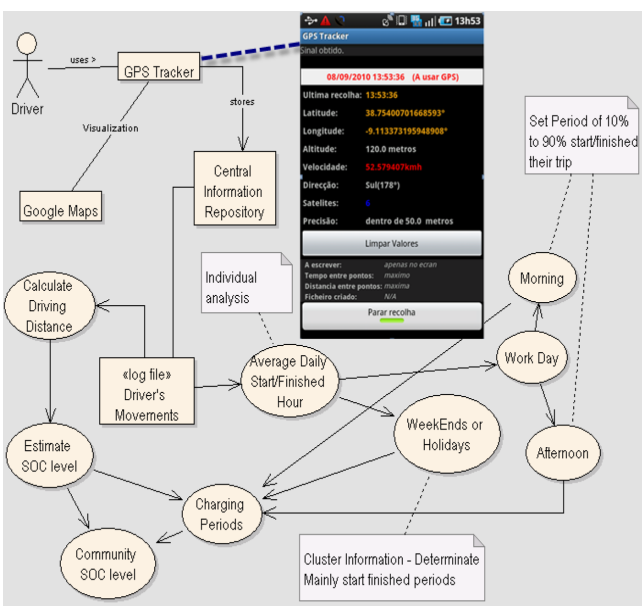

Fig. 3. GPS Tracking Application and main functionalities.

The system allows seeing statistics on the route taken, including: travel duration time; total distance traveled; average speed; and others that can be obtain by data manipulation (e.g., trip cost).The system can also provide all the above parameters for all the paths of the user, thus obtaining the total average values. The presentation of statistical results for one route or for all the paths of the user is done via GPS ReportView. The purpose of this application is to allow viewing all the statistical data corresponding to journeys made by the user (and owner). This application provides a list of all journeys made to the user menus and two more with statistics and a course with the average values of all paths. The GPS Tracker allows the user to see the GPS data on its position, direction, and speed, as showed in Fig. 3.

IV. SIMULATION OF RESIDENTIAL CONSUMPTIONS

Consumption patterns are studied based on three factors: (1) what equipment is used by consumers; (2) power used by this equipment; and (3) time interval in which they are used. In order to know how much each device consumes, we have used data from ERSE (Energy Services Regulatory Authority, in Portugal) [www.erse.pt]. Since there are no devices installed in the homes of consumers to collect this information automatically, the data collection was done manually. Representative consumers were chosen (around 50 families in Lisbon area were asked to report suspected daily use of equipment in their home - details of this study can be found at www.deetc.isel.ipl.pt/matemtatica/jf/inq_cons.pdf). Table 2 presents a list of possible equipment to be used, ordered to fill this table with the amount of equipment for every hour. The study of consumer habits was based on an analysis of the data obtained from surveys answered by users [14]. The set of connected devices and related values of power per hour provide the total consumption per hour per family. We combine the study of these three sets to get the templates: (1) template 1: big family; (2) template 2: medium family; and (3) template 3: small family, these templates are available in [14]. From the tracking system we take information about the time drivers arrive / leave home, and the distance taken. These values are stored and the mean value and a standard deviation are used to feed simulation environment on Netlog. A stochastic environment is created by random functions (change start times) that can change mean values to maximum deviations taking into account a probabilistic function.

Also weather information (temperature) is used to increase or decrease overall power consumption, since there is a correlation between consumption and temperature [15]. This simulation process uses distribution network information taken from the geo-reference graph. On the simulation tool (Netlog) we follow a bottom-up approach where we estimate consumption based on consumer profile and historical consumption data. Weather information (temperature) is used as a percentage increase factor on usual consumption. Each consumer is represented by an agent that is based on historical data, profile and temperature information, based on a random function for energy consumption, which is estimated regularly. Each agent has a utility function, but the agent is not optimizing it because this process is too expensive under many aspects: in terms of information retrieval cost, in terms of information processing costs from a computational point of view, and in terms of cognitive effort in searching alternatives. We decide to model each consumer as a node on a network distribution graph. Simulation takes into account house power limitation contract and electrical energy distribution limitations.

Table 2: User survey about home energy consumption.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Home Appliances																								
Washing Machine																								
Tumble Dryer																								
Dishwasher																								
Oven																					1			
Cooktop																								
Microwave																				1				
Broiler																								
Exhaust																								
Toaster								1																
Aspirator																								
Iron																							1	1
Fridge	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Freezer	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Hairdryer								1																
Fryer																								
Leisure																								
TV (convencional)	1	1																			1	1	1	1
TV (plasma)																								
Stereo sound								1																
DVD																								
Computer	1																					1		
Lighting																								
Incandescent Lights																								
Halogen Lights																								
Fluorescent Lights								1																
LFC (Economics lights)	3	1	1					1													4	4	3	3
Home Temperature																								
Air Conditioning																								
Oil Radiator																								
Heater																								
Water Heater																								
Heat accumulator																								
W.C. Heater																								

Our simulation platform is: (1) Dynamic: updating each entity (agent) at each occurring event; (2) Stochastic: based on conditional probabilities; and (3) Discrete: changes in the state of the system occur instantaneously at random points in time as a result of the occurrence of discrete events. Main Output information is the visualization of electrical distribution network on a graph with the indication of power limits. Red color means above power capacity, which indicates that EV charging should be processed in intelligent interactive process; green color means that we can charge EV batteries on full power. We can estimate consumption and use this information for a smart EV charging, without measuring devices and real time information. The main application screen of the consumption simulation is illustrated on Figure 4 (next page). Relatively to EM functions, we can aggregate energy production and consumption data, and based on this simulation estimate prices and then determine the best charging or discharging periods Figure 5.

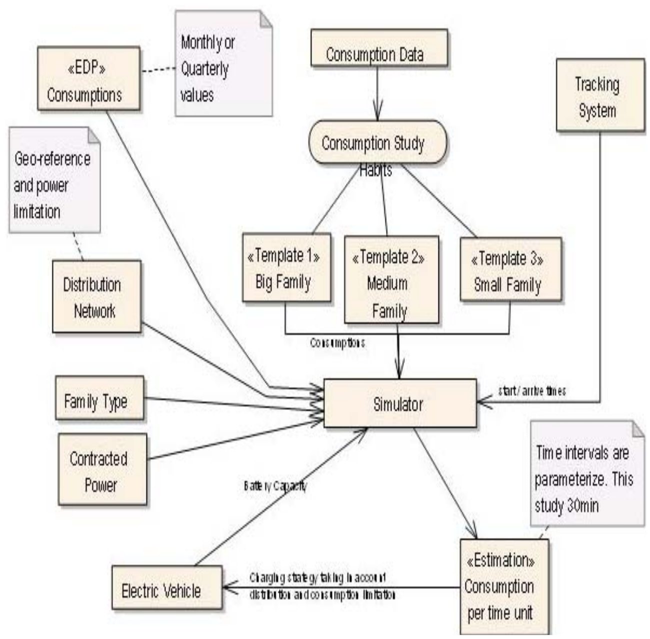

Fig. 5. Simulation Approach Methodology.

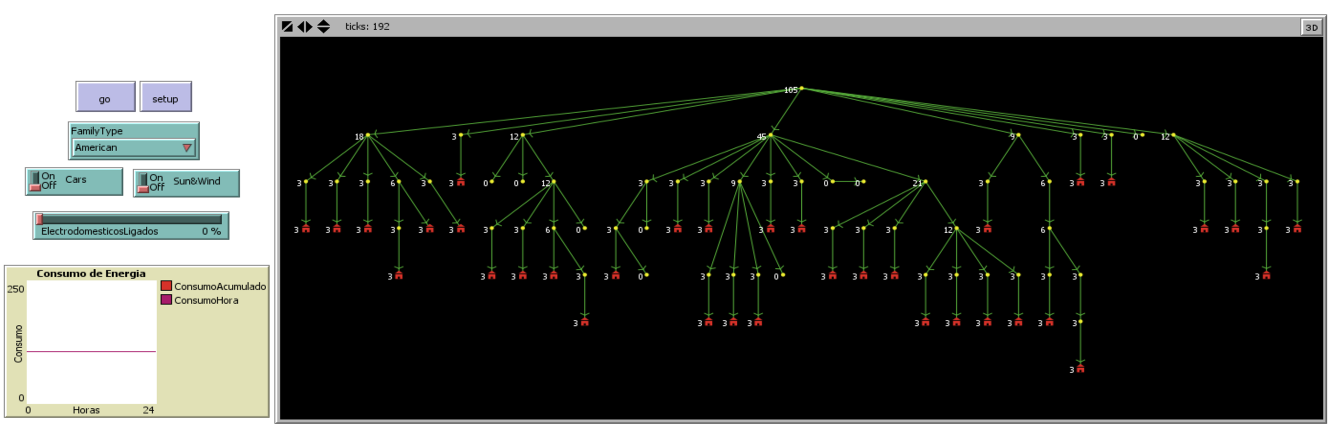

Fig. 4. Simulation application on Netlog. Red color means overloading, implying that a slower EV charging process is required.

V. COLLABORATIVE APPROACH FOR DER - DISTRIBUTED ENERGY RESOURCES

Our work proposes the creation of a collaborative broker system to handle EV and MG integration on EM, supported by users collaborative process, transaction data integration and central information repository knowledge, where we can store past experience to help on solving problems such as: (1) The excess of energy produced by microgeneration should be distributed along the MG to the EV or to consumers, minimizing the use of the distribution network. Each EV can be part of an Energy Storage Systems (ESS), which can store the excess of energy produced by MG, and deliver this energy when it is necessary.

The main modules of the proposed system illustrated on Figure 6, are: (1) Central Repository - stores information about: (a) user energy consumption (amount and time); (b) energy production with available information of power; (c) energy supplier and source (e.g., hydropower, wind power, photovoltaic, etc); (d) energy prices; and (e) weather information (temperature, wind direction and speed, rain amount, solar radiation, etc). A proper interface is created for user profile, creation and manipulation. This information data is worked under Data mining approach for consumption data analyses. An example of this is the Naïve Bayes (NB) showed. We implemented a weather crawler, based on a web robot to pick weather information from pre-defined sites and store this information on this information repository. Community creation is based on clustering available user profiles, based mainly on geographical position (distance is calculated based on the distribution network) and electrical transactions performed from MG to EV; (2) Information Communication Tools (ICT) - mainly are: communication networks for information exchange; and high-speed digital monitoring, to take care of energy transactions; (3) Simulation Tool (section IV); (4) Georeference Graph based on electricity distribution network (section III); and (5) Collaboration Software Tool - has as goal to help the people involved in a common task. In this collaboration, the distribution network uses the shortest path (less impedance) to deliver production excess and EV, if available, can store this local production excess. If MG generation doesn't have a local EV, the network can deliver to the nearest EV neighbor establishing a collaborative process. Also if EV SOC (state of charge) is about drivers' requirements, neighbors can take EV energy. Non critical equipment (e.g. washing machine and others) can be started when there is a local production excess. This collaboration is controlled by the collaboration software, for accounting purposes and the price is established between the local production and local demand. The system will work always above big producers' prices and will always try to minimize energy transitions outside the community. A community is established based on geographic location on the distribution network and MG and EV transactions. This community created by 'near-by' EV owner and MG producers can together represent a load or a resource of a size appropriate to exploit economic opportunities in the electricity markets. The size of the community is indeed a key to ensuring its effective role (100 EV of 24 kWh can store 2.4 MWh, and around 300 EV of 10 kWh can reach 7.2 MWh. In terms of load, a community of EVs represents the total consumption of all vehicles an amount in Megawatts that constitutes a significant size and allows each EV to benefit from the buying power of a large industrial/commercial customer. There are additional economic benefits that grow as a result of the economies of scale. The aggregated collection behaves as a single player that can undertake transactions with considerably lower transaction costs than would be incurred by the individual EV owners. In the longer term, the aggregation of V2G resources will allow them to be integrated more readily into the existing ancillary services command and contracting framework, since the grid system operator need only to communicate directly with the Community. This collaboration will establish an important local energy flux from MG to EV using only a local structure of the distribution network.

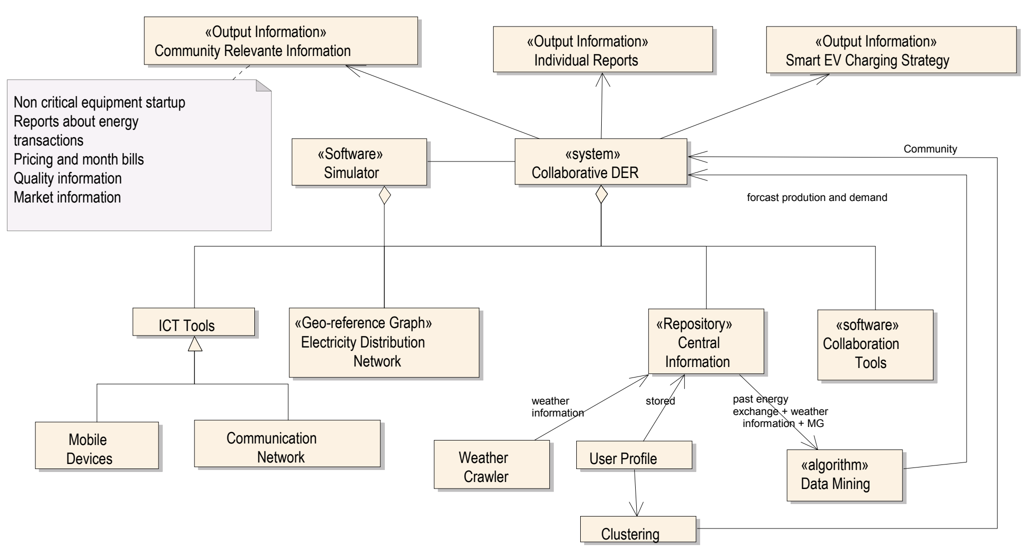

Fig. 6: Main system modules.

Collaboration Tool, User Profile and Community

User profiles are based on: (1) The EV type, including the technology of the batteries (as Lead-Acid, Nickel or Lithium), and the capacity of batteries in kWh; (2) Driver's travel habits: time and date of the travels, and the distance in km planned to be covered; and (3) Data related with market participation: minimum SOC (State of Charge) that allows participation on energy market, prices at which drivers want to sell and buy energy.

The main stakeholders of the collaborative process are the electrical power grid, EVs (Electric Vehicles), MG (Microgeneration), and the EM (Electric Market). In this collaboration, the distribution network uses the shortest path (less impedance) to deliver energy production excess, and EVs, if available, can store this local production excess. If MG generation doesn't have local EVs, the network can deliver to the nearest EVs at neighborhood, establishing a collaborative process. Also, if EVs SOC (State of Charge) are above drivers' requirements, neighbors can take energy from EVs. Non critical equipment (e.g., washing machines and others) can be started when there is a local production excess. This collaboration is controlled by the central broker, who manages energy flux transactions for accounting purposes, and the price is established according to the local production and the local demand. The system will always work bellow large producers' prices and will always try to minimize energy transitions outside the Community. The Community is mainly defined by the network distribution topology that can be defined and controlled by a collaborative broker, and the energy can flow in different ways. This collaboration is useful in many aspects, mainly when the local MG has capability to produce energy and the Electrical Power Grid does not need to receive energy. In this scenario, with the collaboration within the different parts in the SG (Smart Grid), the energy produced by MG can be distributed to the EVs or to the consumers. This distribution of energy should take into account the production and sale costs. Prices should change based on production capacity and energy needs. So the prices of electricity vary in time, and for that it is necessary energy measurement capability at the consumers. This function is accomplished with the use of energy meter devices, which have their cost as an inconvenience. If the price difference between time periods is significant, customers can respond to the price structure with significant changes in energy use. Consequently, consumers are able to reduce their electricity bills if they adjust the timing of their electricity usage to take advantage of lower-priced periods and/or to avoid consuming when prices are higher.

VI. Smart Charging Strategy

The Smart Charging strategy takes into account home consumption, distribution network limitations, MG available and energy price. EV charging strategy is modeled by: user time and driving distances, energy price and also available power. From our central repository it is possible the development of tools to extract knowledge from past electricity exchange log files, EM prices, renewable energy availability, home energy consumption (if EV is connected at home), and electrical distribution network constraints. Also, the weather information can be used for the forecast of energy production from renewable energy sources, and the EV users arrival and departure times from home (obtained from a tracking device) can be used for consumption timing optimization (e.g., users can change their behavior, and thus historical data needs to be fitted).

A deterministic approach to forecast MG production is complex, because wind power depends on the type of turbine, location (urban vs. rural), height, orientation and wind speed. In solar generation the power generation depends on the environmental factors, mainly the irradiation, and on the cell temperature. Each individual case should be analyzed, and this should raise a complex scenario. To avoid this and since we aren't looking for an accurate prediction, we propose a novel approach based on data mining. The idea is to store past energy production data with main weather factors that influences MG production, such as wind speed and direction, temperature and weather condition. For that, a flexible structure used to store and retrieve different data was created. For this task a database is used to store all data transactions (EV charging and discharging, and also MG production), weather information, and user profile information. Several approaches using data mining algorithms can be used for knowledge extraction: past transaction data can be used to try to identify, with clustering approaches, main periods of consumption and production, trends with the identification of the main behavior. We implemented a Weather Crawler, based on a web robot, to pick weather information from pre-defined sites (in our case, Portuguese weather site). Details on this can be found at [14]. Also by manipulating available data we can perform several reports, like: home energy consumptions; weekly, monthly and annual energy expenses; price variation of electricity; and charging periods, among others. Naïve Bayes (NB) can be used to relate consumption and MG production to weather information (temperature, wind speed and direction, and also humidity, with raining information). A small example is shown in Table 3. Production capacity is divided in n classes. In our implementation $n = 10$ and classes are defined based on percentage of production capacity: class 0 is zero production; class 1 is performed from 0 to 10% of production; and class 10 is used if we reach maximum production. Wind and temperature were also discretized in a pre-defined class. Time is also a discrete variable. In our example we simulate one day that have only one class, but in a real case more classes should be added (for example 24 x 4 = 96). Wind speed and directions is correlated to pre-defined classes that characterize local Eolic production, and temperature is dived in interval classes. Table 3 shows a small example on how NB algorithm works, showing the probability of occurrence of an event. In this case we want to know the energy production prediction taking into account current weather forecast (solar radiation, temperature, and wind in class 2). Based on historical data (in the case of ten events) NB shows the probability for p1 to p10. For more details, please see [14].

Table 3: Renewable production forecast taking into account NB approach applied over weather conditions (small example).

Day	Weather	Temperature	Wind	Production
1	Sun	2	3	3
2	Cloudy	1	5	4
3	rain	4	1	2
4	Sun	5	4	9
5	Sun	3	2	4
6	rain	1	2	1
7	Cloudy	3	2	2
8	Cloudy	4	6	5
9	rain	3	3	3
10	sun	3	2	4
11	sun	2	2	???

P(production)=0.1 (10 classes)
P(sun|p3)=1/2 (appears one in two examples of P3)
P(sun|p4)=2/3 (appears 2 in 3 examples of P4)
the same four others examples
P(p1|sun+T2+W2)=P(p1)xP(sol|p1)xP(T2|p1)xP(W2|p1)
P(p2|sun+T2+W2)=P(p2)xP(sol|p2)xP(T2|p2)xP(W2|p2)
…
P(p10|sun+T2+W2)=P(p10)xP(sol|p10)xP(T2|p10)xP(W2|p10)

From this particular example we have a production capacity based on a probability approach. Since we aren't looking for an accurate prediction, and most results follow a certain pattern, the obtained results tend to be fairly correct. In this case, p3 and p4 have the highest probabilities, which mean that, if we have an installed capacity of 3 kW, under these conditions we are able to generate around 1 kW of electrical power. Home consumption is lower on night period (from 0 to 6 hours, in average) but in this time most of EVs are plugged in, so they can take easy production excess. Main Output information is the visualization of electrical distribution network on a graph with the indication of power limits, as already seen in Figure 4. The first step is to estimate the electrical power consumed per household, and given the contracted power, to determine the available electrical power for charging EVs. It was considered a power limit for the electrical distribution system of 80% of the nominal power of the transformer that feeds a set of consumers of each particular zone of the low voltage electrical network. So, depending on the percentage of existing EVs, we may have additional limitations.

Main results are presented in Figure 7 and Figure 8 (for more details of these results, please see [15]). These studies were oriented to simulate domestic consumption, and distances traveled determine the most appropriate forms for charging the EV. Regarding the time of day where there is a greater amount of energy to be used were compiled values of consumption per hour, and it was found that the ideal intervals during the week for charging EVs would be between one and six o'clock in the morning (range A), or between nine and the sixteen hours (range B), as shown in Figure 7(a). During the weekend, the ideal period to charge EVs would be between one and eight hours (range A) or between fourteen and sixteen hours (range B), as presented in Figure 7(b). All range of results can be seen in the final year project at ISEL [14]. Relatively to Electrical Market (EM) functions, we can aggregate energy production and consumption data, and based on this simulation estimate prices and then determine the best periods for charging or discharging the batteries of EVs. In Figure 7 is also marked the maximum MG production and the production estimation based on weather information and past production achieved.

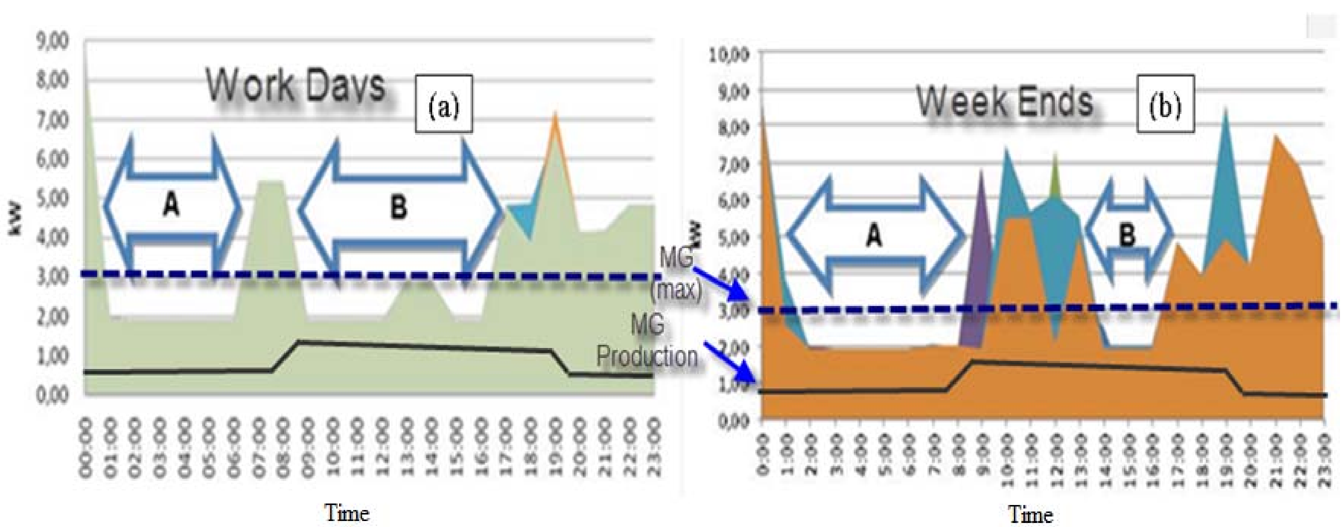

Fig. 7. Power Consumption Distribution (for all types of families).

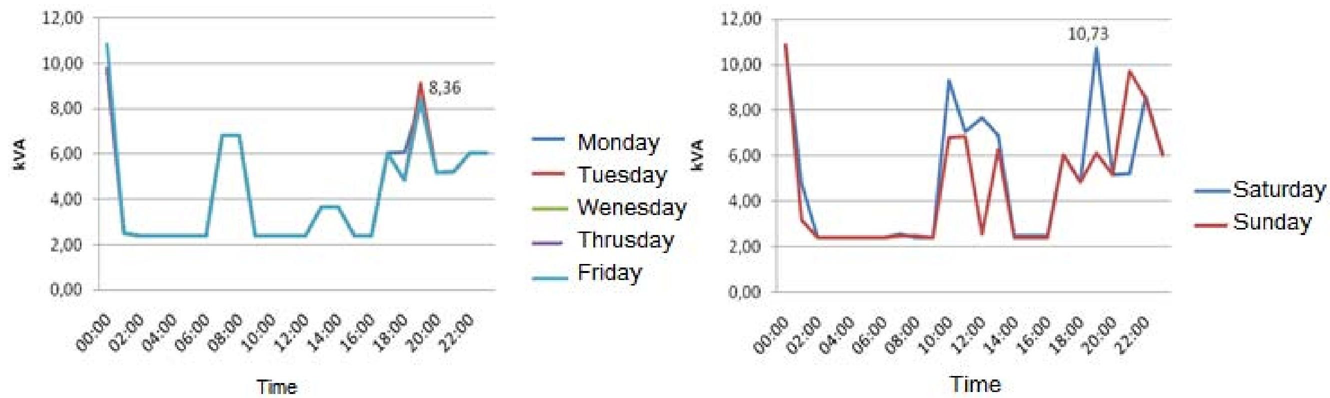

Fig 8. Big Family Consumption Simulation Results.

VII. Conclusion

This paper proposes an agent-based electricity consumption pattern simulator that allows determining the best EV charging process taking into account electrical home consumption and distribution power constraints. It is made a study for different types of residential consumptions with the goal to analyze the introduction of the EV. Taken into account different profiles of families (with different power consumptions and traveled distances), and assuming one EV per family, it was determined the most appropriate forms to charging the EV. Thus, it was determined the time of day where there is a great amount of energy to be used, and, consequently, compiling the values of consumption per hour was found the ideal intervals along the days for EV charging. Still, the developed platform can be used for simulation testing scenarios of EV charging. Electric distribution companies can use this tool for future planning, simulation and decision support. Finally, this information can be used to determine the capability of the actual electrical distribution network for supplying energy to the final consumers, and also for charging the banks of batteries of the EVs, which can occur simultaneously.

Acknowledgement

The authors are grateful to FCT (*Fundação para a Ciência e a Tecnologia*) and MIT-Portugal Program, for funding the Project MIT-PT/EDAM-SMS/0030/2008.

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