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Agent Based Approaches for Smart Charging Strategy for Electric Vehicles

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ABSTRACT: This paper presents an agent process simulation to control and monitor the Electric Vehicle charging process, using existing power distribution limitations and microgeneration capacity. The goal is to simulate the consumers' 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 an agent-based simulation platform where stochastic process is adopted to perform unexpected user behavior. This simulation tool can be used to determine the capability of the actual electrical distribution network for supply energy to the final consumers and for charge the bank of batteries of electrical vehicles, which can occur simultaneously.

KEY WORDS: Electric Vehicle, Charging Process, Agent, Simulation, Tracking System, Micro-grid.

1. Introduction

Transportation related industry is reaching a turning point during this period, as it begins the gradual transition away from the internal combustion engine towards Electric Vehicle (EV). This transition will provide 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 on this process, but the electrical network distribution could not be prepared for this high consumer demand. Also EV home charging process should be coordinated with local consumptions because there are power limitations. Electrical distribution will gradually be transformed from a centralized service to a distributed service with the realities of EV, Microgeneration and the integration of renewable energy sources. These 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, 4, 5), information retrieval systems (6), decision support systems (7), supply chain (8), transportation (9), communication systems (10) and many more (11, 12, 13). Most of these simulation tools use agent-based approaches on top of multi-agent system. A multi-agent system is a collection of software entities (i.e. agents) working together in pursuit of specified tasks. It can be defined as: a combination of several agents working in collaboration in pursuit of accomplishing their assigned tasks, resulting in the achievement of overall goal of the system.

So our main proposed idea is to model the EV driver behavior by an autonomous agent, where there are simulated 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 arrive, departure and distance), power limitation (home user and distribution), and EV type.

The main approach is defined according to several components, such as suggested in Fig. 1: A) Electric-distribution network in a geo-reference graph (see section 2); B) User information about home electrical equipment (time that they are connected); C) User behavior (time to go home) (see section 3); D) EV type; and E) Power limitation of user home contract and associated distribution network.

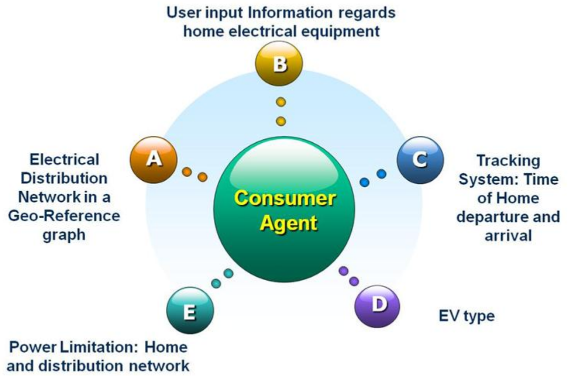

Fig. 1. Main approach based on five different areas.

This consumer agent can be configured also to incorporate microgeneration, which production can be tuned based on weather conditions (e.g., wind direction and speed, temperature and solar radiation incidence).

2. 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 (Fig. 2), where we add geographic information and power limitation between the nodes. In Fig. 2 are showed 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, the information about 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, is summarized in Table 1. This detailed 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.

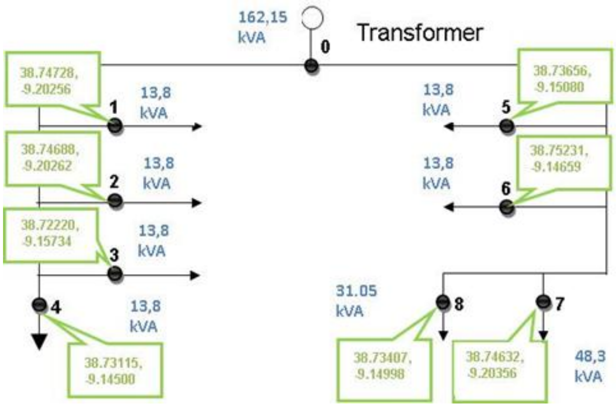

Fig. 2. Geo-reference electrical distribution network with power limitations.

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

Relatively 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 define also their usual routine (arrival time and departure time). Tracking system data can tune arrival and departure times. Every consumer has its own behavior, and changes or unexpected behavior are randomly generated at the beginning of the experiment, using an array of integers. Each consumer is represented by an agent who knows contractual power limitation and also the distribution.

3. Tracking System in 'Offline' Mode Drive

User profile plays and important role in the V2G (Vehicle-to-Grid) or G2V (Grid-to-Vehicle) 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. Our project was performed in an end year project at ISEL, described at (13), and its high level vision is showed in Fig. 3. This tracking application mainly stores time, GPS coordinates and user identification. 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.

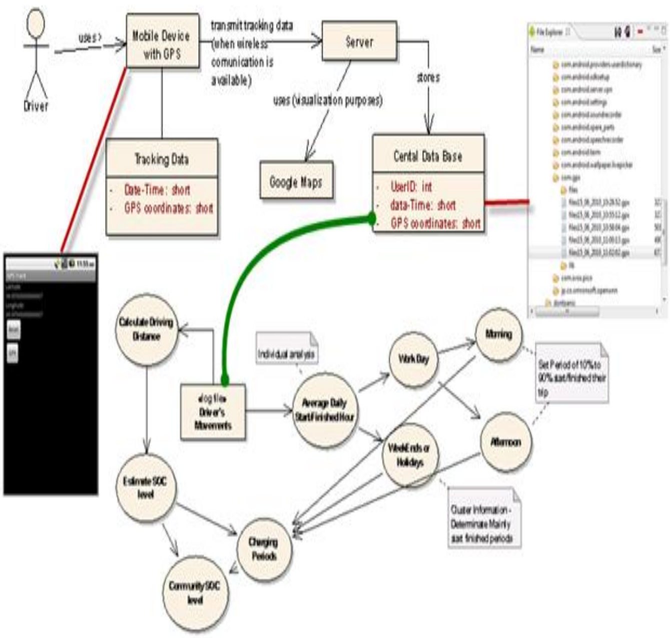

Fig. 3. Main module of driver's tracking system in a mobile device with GPS, and information created from Drivers Movements database.

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, which have the operating system Android 1.6 or higher. 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.

The system allows seeing statistics on the route taken, including: (1) travel duration time; (2) total distance traveled; (3) average speed; and (4) 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 of all the statistical data corresponding to journeys made by the system user and owner of an EV, so to be able to graphically view each journey made. 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 application GPS Tracker allows the user to see the GPS data on its position, direction, and speed, as showed in Fig. 4. This information is placed on the screen of the mobile device using the method DisplayLocationInfo () in class GPS.

Fig. 4. Main menu of the application GPS Tracker.

4. Simulation Tool - Netlogo

An agent based simulation attempts to simulate an abstract model of a particular system. Simulations can be used to explore and gain new insights into new technology, and to estimate the performance of systems too complex for analytical solutions. This approach has already been applied for Electrical Market (EM) (14, 15, 16), creating a simulation environment for market prices determination based on consumers demand, and for production capacity of producers. Our main idea is to simulate consumers consumption taking also into account unexpected user behavior, using past experience (consumption log files), and then, represent the information in an electrical network distribution graph.

There are several tools that can be used for this purpose, from which NetLogo tool has been chosen. NetLogo is a free agent-based simulation environment that uses a modified version of the Logo programming language, providing a graphical environment to create programs that control graphic “turtles” that reside in a world of “patches,” which are monitored by an “observer”. NetLogo also includes an innovative feature called HubNet, which allows groups of people to interactively engage in simulation runs alongside of computational agents. 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 at every 15 minutes (this time interval is configurable). 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. 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 Fig 5 (on last page). Relatively 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 (Fig. 6).

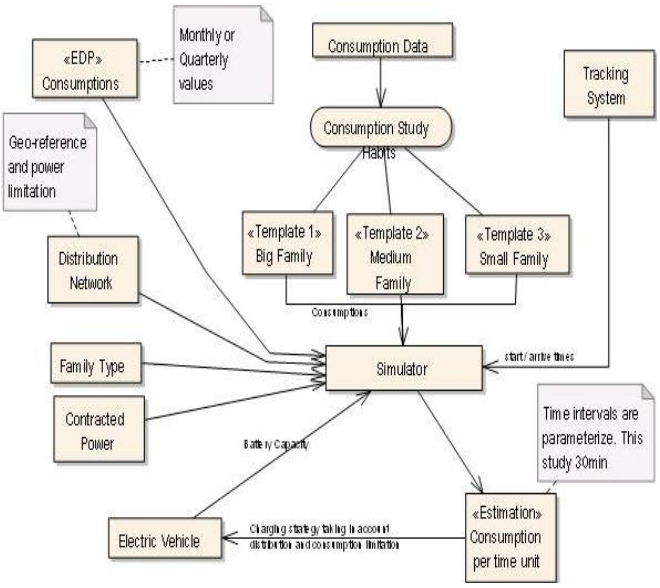

Fig. 6. Simulation Approach Methodology.

5. Model for Collecting Consumption Data

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) (17). 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 of table 3, which was obtained from questionnaires answered by users (18). 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.

From the tracking system we take information about the time drivers arrive / leave home, and the distance taken. These values are stored and a mean value and a standard deviation are used to feed simulation environment on Netlog. Agents representing drivers and average time are used to start actions. 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.

Table 2: Users questionnaires 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																								

Also weather information is used to increase or decrease overall power consumption. This simulation process uses distribution network information taken from the geo-reference graph.

6. Smart Charging Strategy

The Smart Charging system, to achieve the goals identified in Fig. 9, i.e. taking into account home consumption and distribution network limitations, has to identify a smart charging strategy. This system is based on a central information repository that can store and manage historical data on electricity consumption and production. From this 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). This central repository will be later, in a Smart Grid (SG) environment, a fundamental module to store all kind of SG data and to solve the problems of different data format diversity.

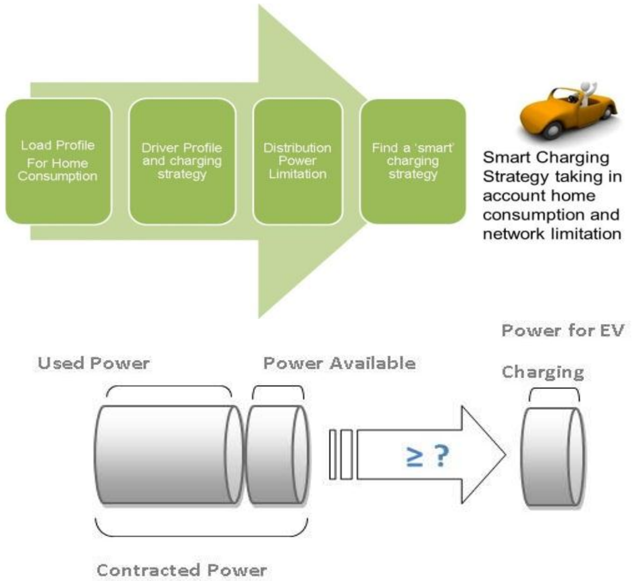

Fig. 7. Smart Charging approach and goals.

Main Output information is the visualization of electrical distribution network on a graph with the indication of power limits, as already seen in Fig. 5. 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. Table 3 presents data used and taken from the simulation of families, as well as the type of EV (we have assumed one per family), and the average distance traveled daily.

Main results are presented in Fig. 9 and Fig. 10; for more details of results, please see (18). 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 Fig. 9(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 Fig. 9(b). All range of results can be seen in the final year project at ISEL (18). 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.

Table 3: Data used and produced in Netlog Simulation.

	Family type		EV Type	EV Range(km)	Daily Km	Power Available (kW)	Power Needed for EV Charging (kW)
Building1	T2	Small Family	Nissan Leaf	160	10	56,67	120
	T2	Small Family	Volvo C30	150	30	56,67	120
	T2	Small Family	Nissan Leaf	160	40	56,67	120
	T2	Small Family	Toyota Prius	48	50	56,67	120
	T2	Small Family	Volvo C30	150	30	56,67	120
	T2	Small Family	Toyota Prius	48	20	169,11	120
Building2	T4	Big Family	Volvo C30	150	20	132,75	120
	T3	Medium Family	Nissan Leaf	160	40	169,11	150
House 1	T4	Big Family	Chevrolet Volt	64	50	169,11	120
House 2	T4	Big Family	Toyota Prius	48	40	169,11	120
House 3	T4	Big Family	Nissan Leaf	160	50	169,11	150
House 4	T4	Big Family	Chevrolet Volt	64	100	169,11	120
House 5	T4	Big Family	Volvo C30	150	20	169,11	120
House 6	T4	Big Family	Nissan Leaf	160	40	**1656,54**	**1740,00**

7. Repository of Information, Weather Information and Data Mining

In this section we describe our approach to integrate Micro Grid (MG) production. 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 (18), and Fig. 8 shows examples of information for wind and temperature. 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 4.

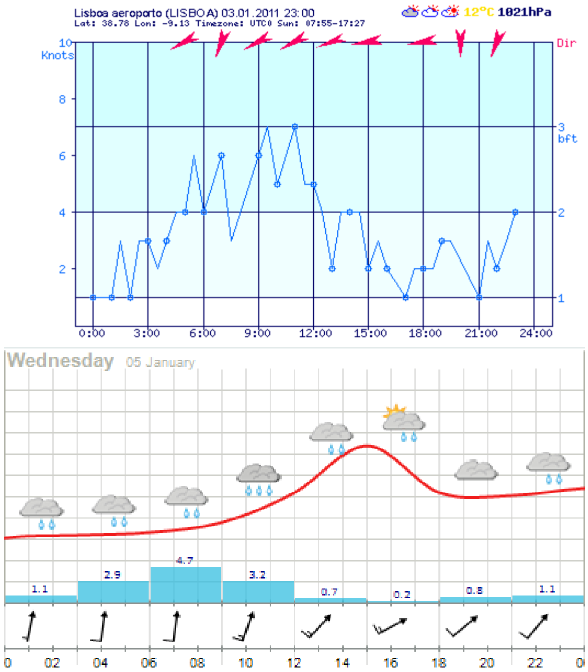

Fig 8. Weather information (wind and temperature) taken from weather sites for Lisbon, Portugal.

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 4 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 see (18). 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.

Table 4: 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)

8. CONCLUSION

This paper presents an agent-based electricity consumption simulator that allows determining the best EV charging process taking into account home and distribution power limitation. It was made a study for different types of residential consumptions with the goal to analyze the introduction of the Electric Vehicle (EV). Taken into account the 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 were found the ideal intervals along the days for EV charging. Also, the developed platform can be used for the simulation of real testing environments of EV charging, being adaptable to different countries specificities. Also electric distribution companies can use this tool for future planning, simulation and decision support. Consequently, 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 Electric Vehicles, which can occur simultaneously.

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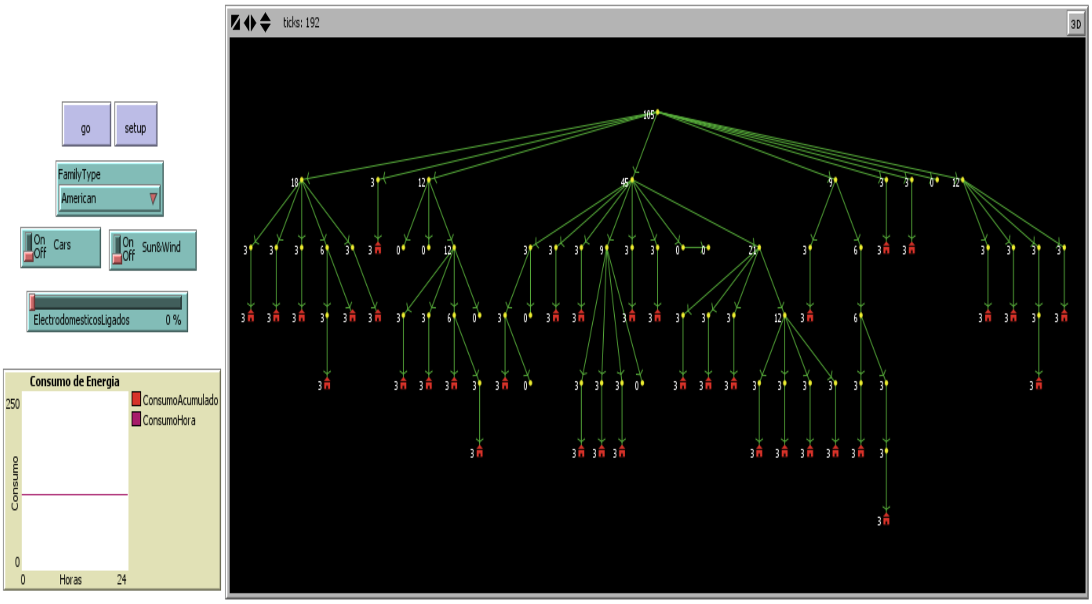

Fig. 5. Simulation application on Netlog.

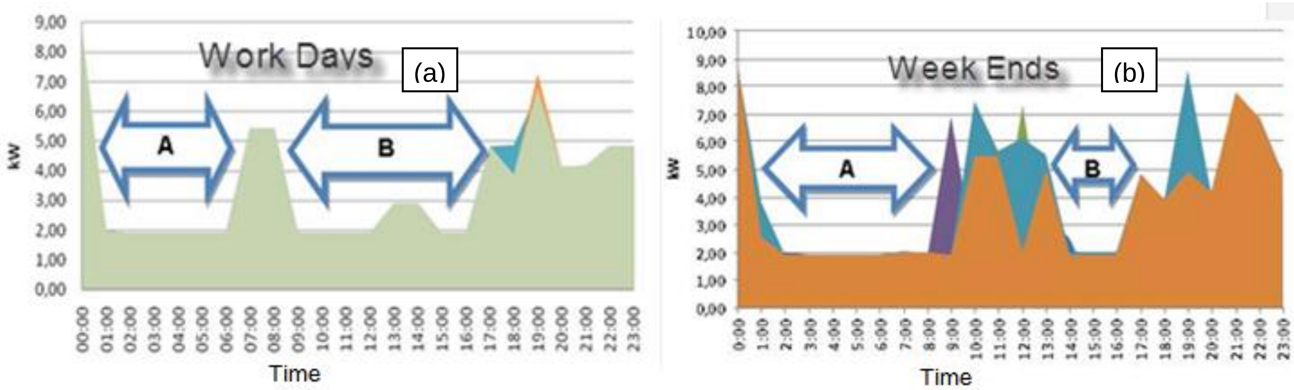

Fig. 9. Power Consumption Distribution (for all types of family).

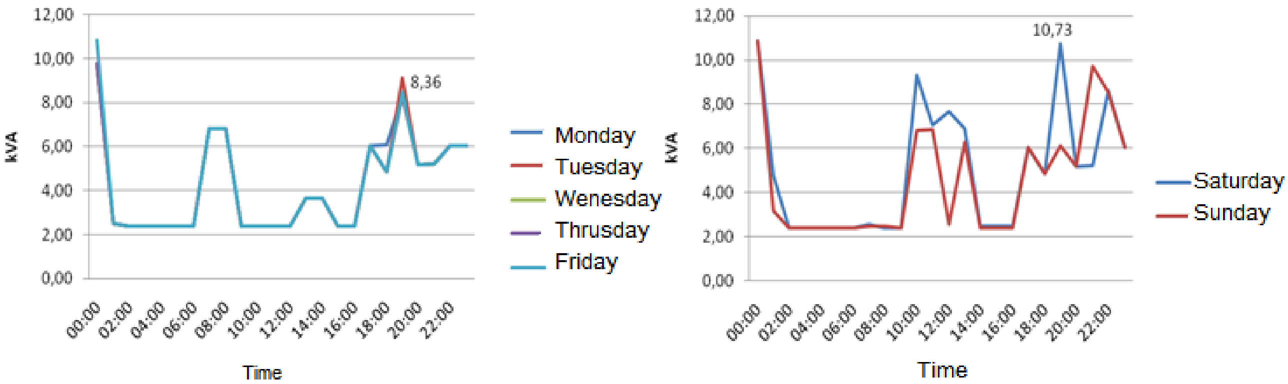

Fig 10. Big Family Consumption Simulation Results.