GRASP Model for Smart Home Electrical Loads Scheduling

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***Abstract*—Controllable load scheduling is an important topic of study in smart homes which intends to use intelligent distributed resources, especially those which provide renewable energy in order to minimize cost of power supplied by the distribution network. This paper develops a model for controllable load scheduling in a smart home using GRASP. The developed model seeks to maximize the available energy from distributed resources in order to use less power supplied by the distribution network. Thus, the Home Energy Management System can make decisions about the most appropriate periods to turn on controllable loads based on the model developed in this work. A typical residential user in the area of Sao Paulo (Brazil) which has strong solar radiation and a significant contribution of wind speed was established as study case. The charging and discharging batteries profile presented an interesting performance, showing the capabilities of such system to reduce peak loading on the distribution network. The development of a simplified model for scheduling the most appropriate moments for turning on a controllable load is the original contribution of this work.**

Keywords— Smart Homes, Controllable Load Scheduling, Grasp, Home Energy Management, Demand Response.

I. INTRODUCTION

Different kinds of system components including hardware elements, software algorithms, network connections, and sensors are required to cooperate with each other to provide various services in smart home. With the development of smart grid providing a two-way communication infrastructure, residents have the opportunity to schedule their electricity usage pattern to reduce their electricity cost [1]. Since electricity is economically non-storable, wholesale prices (i.e., the prices set by competing generators to regional electricity retailers) vary from day to day and usually fluctuate by an order of magnitude between low-demand night-time hours to high-demand afternoons. The main idea about a controllable load scheduling (CLS) is twofold: first, allowing retail prices to reflect fluctuating wholesale prices to the end users so that they pay what the electricity is worth at different times of the day; second, encouraging users to shift high-load household appliances to off peak hours to not only reduce their electricity costs but also to help to reduce the peak-to-average ratio (PAR) in load demand [2]. In addition, with an introduction of electric vehicles in residential markets, CLS can be performed within a home to avoid any potential distribution transformer overloading problems. Therefore, it is necessary to develop a methodology for a CLS in smart home. This methodology can be treated by searching algorithms for obtaining efficient solutions. This paper presents the GRASP heuristic approach applied to maximize the available energy from distributed resources in order to use less power supplied by the distribution network. In section II a brief description of the smart Home Energy Management (HEM) system is presented. In section III, papers in the literature focused in different CLS algorithms and models are briefly mentioned. In section IV, the proposed model is exposed. In section V, a case study is exposed. In section VI the conclusions are described. Lastly, in section VII future developments are presented.

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II. SMART HOME ENERGY MANAGEMENT SYSTEMS

In the context of a residential home, three types of CLS automation levels exist: a) manual CLS; b) semi-automated CLS; and c) fully automated CLS. The fully automated CLS is the most popular automation type that can be achieved by a HEM System [3]. An HEM system is responsible for monitoring and managing the operation of in-home appliances, and providing load shifting and shedding according to a specified set of requirements. An HEM system is an integral part of a smart grid that can potentially enable demand response applications for residential customers. The key functions of such systems are to monitor, control, and optimize the flow and use of energy. Depending on renewable energy sources (RES) installed, load characteristics, power quality constrains and the market strategies, the control and management of a smart house can be significantly different from the ones typically applied to conventional power systems; mainly because the steady-state and dynamic characteristic of RES, especially electronically coupled units, are different from those control strategies applied to large centralized units [4]. Based on this, the HEM final configuration needs to be envisioned based on the adopted distributed energy resources (DER) technologies, load requirements and the expected operational scenarios. HEM has the end-goals as to conserve energy, reduce cost and improve comfort. On other hand, HEM offers five key services: monitoring, logging, control, management and alarms. To provide an optimal CLS, the HEM requires information about load consumption, RES forecast, price of electricity, environmental regulations, etc. This will allow the smarthouse to be properly operated in order to guarantee benefits such as enhancement of power quality and reliability of supply to the customers, and efficiency increase [5]. As input information, an HEM requires information such as forecasting of non-dispatchable generation, forecasting of electrical consumption, forecast of energy price, State-of-Charge (SOC) of the Energy Storage Devices, operational limits, security and reliability constraints, all used to estimate and provide operational set points and load management to the micro-source controllers (MSs), load controllers (LC), etc. Once all input information is collected, an optimization algorithm can be executed to obtain the optimal scheduling by solving a CLS problem.

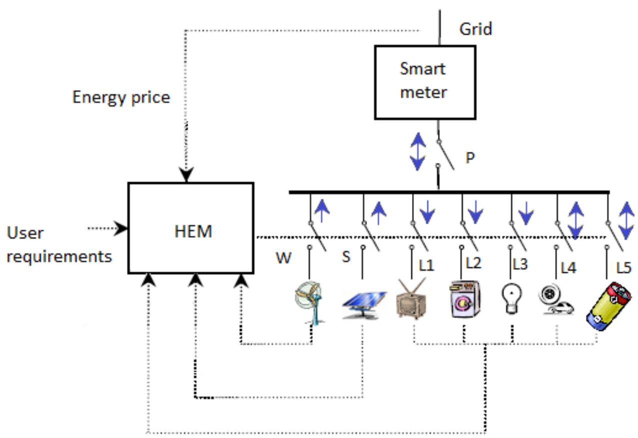

Fig. 1 Home energy management

III. ENERGY CONSUMPTION SCHEDULING MODELS

Different algorithms and models can be used in the CLS problem, depending on different factors: user requirements, user comfort constraints, social and environmental factors etc. The work in [1] describes an extensive survey about the problem of smart scheduling from the consumer's point of view or side mainly. Various HEM hardware applications are proposed in [6] and [7]. Several papers in the literature focused in energy resources programming through linear and nonlinear techniques optimization [7]-[11]. Several studies illustrate energy resources programming methods through meta-heuristics which mostly with highly complex development [3], [12], [13]. Many works consider cost reduction in energy consumption and dynamic prices in the network [5], [11], [14], [15]. Several papers consider user requirements, user comfort and external variables as environmental and social factors [12],[16]. However, the meta-heuristics methods are often complex. Instead, the GRASP method allows the development of a simple model, increasing computational efficiency. This paper presents the GRASP heuristic approach applied to the CLS problem. A GRASP is an iterative process that has two phases associated with each iteration: a construction phase, where a feasible solution is built by a random sampling technique; and a local search phase, which starts from the construction phase solution and seeks a local optimum in a given neighborhood. The best overall solution is chosen as a result [17]. This overview does not include all works related with CLS. However, the most important contributions were reported.

IV. OUTLINE OF THE METHODOLOGY

The problem applied to maximize the available energy from distributed resources in order to minimize cost of power supplied by the distribution network is stated as follows:

Minimize

$$\text{Min} \sum_{t\in\Omega t} \Delta C_t P_t^{grid} \qquad (1)$$

Subject to

$$P_t^{sun} + P_t^{wind} + P_t^{grid} + P_t^{bi} = P_t^{ncl} + \sum_{j\in\Omega cl} P_j^{cl} + P_t^{br} \quad (2)$$

Where:

P_t^{sun} = active solar power - $\forall t \in \Omega_t$ [kW]

P_t^{wind} = active wind power - $\forall t \in \Omega_t$ [kW]

P_t^{ncl} = active not controllable load power (ncl) - $\forall t \in \Omega_t$ [kW]

P_j^{cl}= active controllable load power - $\forall j \in \Omega_{cl}$ [kW]

C_t= Cost of utility power - $\forall t \in \Omega_t$ [\$/kWh]

P_t^{br} = rechargeable active home battery power- $\forall t \in \Omega_t$ [kW]

P_t^{bi}= supply active home battery power - $\forall t \in \Omega_t$ [kW]

P_t^{grid}= active power supplied from the grid- $\forall t \in \Omega_t$

Δ : Discretization time

Ωt : Discretization time set

Ωcl : controllable load set

The model shown above is the classic approach to this type of problem. The original contribution of this work is to focus on defining additional restrictions related to the requirements of controllable loads. Each controllable load has a special feature that determines the best time to turn it on. In addition, it is considered a criteria about whether it´s load can or cannot turn off during its operation cycle. These special operational requirements are described as follows:

a) In the case of a washing machine, which can be turn on at any time of the day, its most important criterion is not to be turn off during its wash cycle, since doing so, it could result in damage to the machine and to the clothing.

b) In the case of the dryer, it can be turned on at any time of the day, provided it is done after the working cycle of the washing machine; the equipment cannot be switch off during working cycle.

c) In the case of an electric rice cooker, it is to be turned on during the morning and before 12:00 PM, and thus have the rice ready for lunch; this equipment cannot be switched off during its cycle.

d) In the case of a dishwasher, it can be connected to any hour at night (after use daily) and not be turn off during its operating cycle.

e) In the case of the electric vehicle battery (EVB), it must be recharged before the time set for use and in that time, it must be fully charged; the battery connection and disconnection during the charging process is possible. In this work, the battery is used only as a load (recharging state), in other words, it does not supply power to the house.

f) A rechargeable device like a cell phone can be disconnected during the recharge process, but it must be fully charged at the expected hour to use it, especially in the case of the cellphones, because generally users are used to leaving home in the morning and returning at night. These special characteristics of controllable loads are presented in Table I.

TABLE I. HOUSEHOLD APPLIANCES REQUIREMENTS.

Load	Power (kW)	Time of use (minutes)	Operation specification
Washing machine	1,5	45	Not disconnect during operation cycle
Dryer machine	2	15	Not disconnect during operation cycle. Turn on after washing machine
Dishwasher	1	10	Not disconnect during operation cycle
Rice cooker	1	30	Not disconnect during operation cycle. Turn on before at 12:00 P.M.
Electric oven	1	25	Not disconnect during operation cycle
Rechargeable equipment (Cell phone, etc.)	0,3	30	It must be fully charged at the time specified, for example 07:00 A.M.
Home Battery	0,8	120	Keep the minimum energy
EVB	0,8	120	It must be fully charged at the time specified, for example 07:00 A.M.

One alternative to solve the problem illustrated above is to employ heuristic methods to find a good and feasible solution, but not necessarily optimal. The effectiveness of such methods is related to their adaptability, avoiding local minima and exploring the basic structure of each particular problem. GRASP is a heuristic iterative sampling technique composed by two phases, a construction phase and a local search phase [17]. The construction phase solutions are not guaranteed to be locally optimal in a given neighborhood, because they are the result of additions made with a myopic criterion. Hence, it is a good idea to apply a local search procedure to try to improve each construction phase solution. In general terms, the local search algorithm works replacing the current solution by a better one in the neighborhood of the current solution. It stops when no better solution exists in the neighborhood.

GRASP Construction Phase: As referred in [17], the construction phase of GRASP defines an initial pattern, in which a local search will start. In this work, we connect each of the controllable loads in each of the time periods. Figure 2 presents the GRASP construction phase.

GRASP Local Search: This phase starts from the feasible solution of construction phase, and tries to reach for better solutions within a given neighborhood. Before continuing, we need to introduce the concept of a neighborhood. In accordance to the problem adopted in this work, it consists on selecting the moments closest to the times set in the construction phase. This selection of neighborhood must be carefully considered for each type of load, according to the conditions set out in Table I.

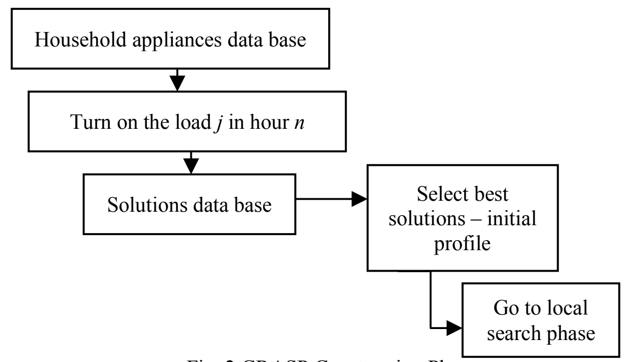

Fig. 2 GRASP Construction Phase

To select a specific neighborhood for a controllable load it is necessary to verify its cycle time as well as the period of time where each load can be turns on. Figure 3 illustrates the neighborhood effect for some cases. For the controllable load CL1 there are two nearest neighborhoods: Δt1 and Δt3. It means that the GRASP model developed in this study evaluates the objective function shown in equation (1) when CL1 is turn on in Δt1, Δt2 and Δt3, selecting the most economical option. For CL2 (which must be turn on after CL1 is turned off) there are two nearby neighborhoods: Δt3 and Δt5. Finally to CL3 there are two nearby neighborhoods: Δt2 and Δt4.

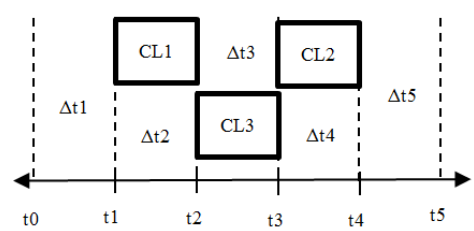

Fig. 3 Concept of a neighborhood.

Starting from an initial profile established in the construction phase, one initial solution is iteratively defined. Thanks to the initial profile, this new solution can be close to the best solution. New solutions are produced through random numbers generated with a normal distribution (given by Matlab tool), where the average corresponds to the solution defined in the initial construction phase. This search is not far from the area of better solutions. The local solution is performed with the criteria described above and illustrated in Figure 2. For each solution found, the feasibility is estimated. In this work, the feasibility is achieved if the energy in storage devices correspond within the technical capabilities of the respective devices. Thus, the possible solutions that do not meet the technical criteria are discarded. The general model developed in this study is illustrated in Figure 4.

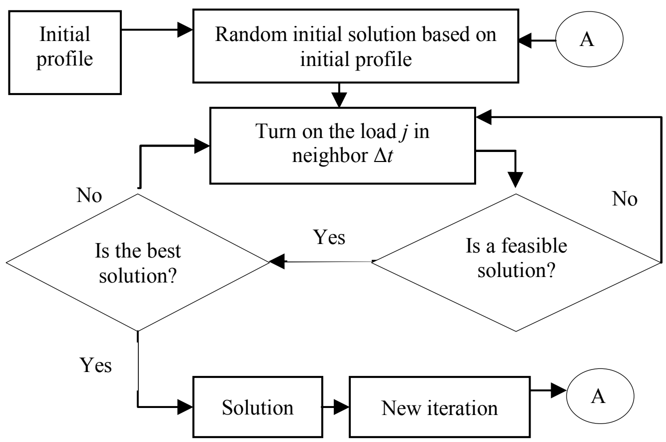

Fig. 4 HEM GRASP Model.

V. CASE STUDY

Two cases are studied in this section: In the first case, we used one typical load profile corresponding to one residential average user, which was obtained from the database GRIDLAB-D. In the second case, we used data obtained directly from a user's home located in the city of Campinas, state of São Paulo, Brazil.

In the case 1, for the weather data, a typical meteorological year (2005) for the state of São Paulo was used, considering a schedule horizon of 24 hours ahead in time-steps of 1 hour. In this paper, it is assumed that the Photovoltaic (PV) system always operates at the maximum power point, as we done in one previous work and showed in [18]. We used the methodology showed in the work above to model the PV generation according to the available irradiance and module temperature. To model the wind system generation a piecewise power curve model is used to give the output power as a function of the wind velocity, as is shown in the above work.

In Brazil, ANEEL (National Regulatory Agency) has recently established a time-of-use pricing scheme, where the price of electricity is tied to specific time periods, aiming to reduce the energy consumption in the peak hours and to encourage the demand side management. According to ANEEL's resolution [19], three different periods can be identified: peak, intermediary and off-peak. The used cost of energy corresponds to the price defined by one of the Sao Paulo's utilities (CPFL-Paulista). In Figure 5, the power profile of the PV, the power wind turbine systems profile, typical load profile and price of electricity is shown. Generally, batteries are the most common choice for short-term energy storage in smart homes. In this paper, the electrical storage system (ESS) is composed of a bank of lead-acid batteries. The main function of the ESS is to reduce the variability of the RES and storage energy to use it in periods when the energy has a higher cost. All the values used in this work for the battery model are listed in [18].

For the two cases studied in this paper, we used the EVB parameters shown in Table II. The simulation results are illustrated in Figure 6. In Table III, the moments to be turn on the controllable loads are described. Switching times correspond to the times where the cost of utility power is lower. In this case, the CL3 (dryer) is connected after turning off CL1 (washing machine), satisfying its operational requirements shown in Table I. In this case, the uncontrollable loads consume the PV generation. This energy also used to maintain the house battery fully charged. Between 18 and 22 hours, the cost of utility power is higher; therefore, in this period the stored energy of the home battery is extracted to supply the loads. The house battery is charged in periods where the cost of utility power is lower. In Figure 7 the home battery stored energy and the EVB stored energy are illustrated. In addition Figure 8 the home battery state of charge (SOC) and the EVB SOC are illustrated. Therefore, Figure 7 and Figure 8 shows the feasibility of the simulated results.

TABLE II. EVB PARAMETERS.

Maximum capacity of stored energy	100 kWh
Maximum power injection	10 kW
Maximum power recharge	10 kW
Injection efficiency	95%
Recharging efficiency	95%
Self-discharge rate	2,1%

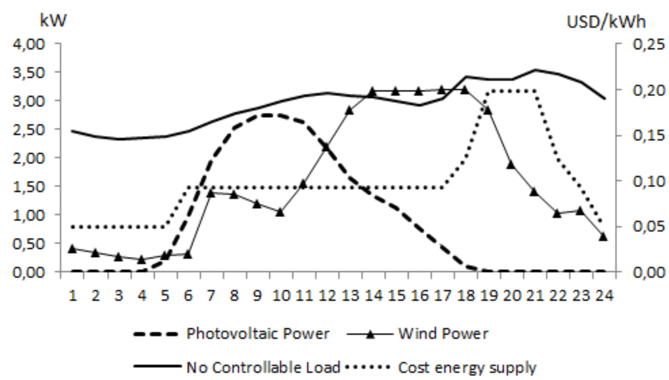

Fig. 5 Input data – Case 1.

In case 2, the meteorological data for the year 2015 in the state of São Paulo was used, considering a schedule horizon of 24 hours ahead in time-steps of 1 hour. In this case, we used the same methodology applied in the first case to obtain: PV generation, wind power, cost of energy supply, house battery model and EVB data. We used data obtained directly from a user's home located in the city of Campinas, where the periods of greatest consumption were taken, therefore, the load profile in this case differs from the case 1.

Figure 9 shows the power profile of the PV, the power profile of the wind turbine, user load profile and price of electricity are shown. In this case, we used one photovoltaic panel system which has an area of 50 square meters (panels installed on the house roof), therefore the photovoltaic system in this case is bigger than in the case 1. Figure 10 shows the simulation results for case 2. In Figure 11 and Figure 12 the home battery energy and SOC and the EVB energy and SOC are illustrated respectively.

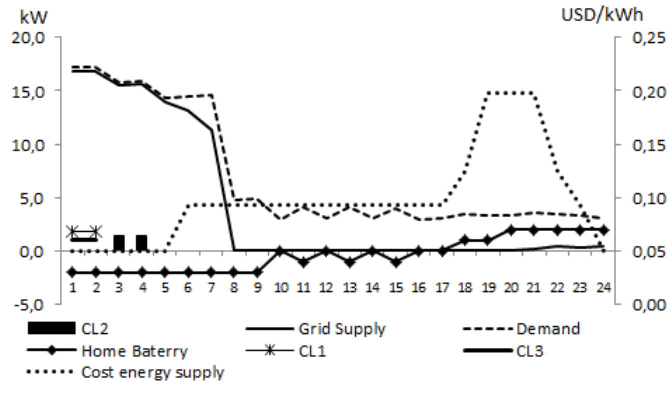

Fig. 6 Output data – Case 1.

TABLE III. CONTROLLABLES LOADS SCHEDULING

Load	Time
CL1	01:00
CL2	03:00
CL3	01:00

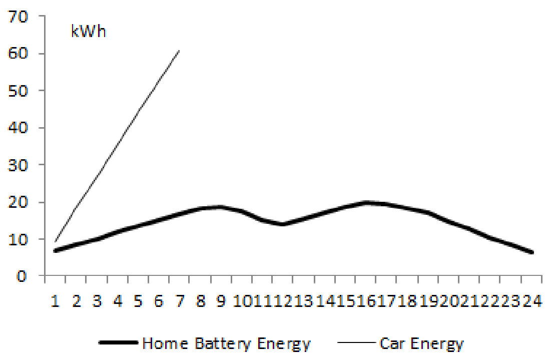

Fig. 7 Batteries Energy – Case 1.

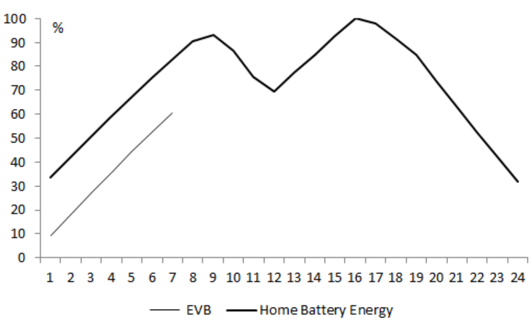

Fig. 8 SOC Batteries– Case 1.

The results of CLS are the same set times obtained in case 1 (as in Table III). The difference between case 2 and the case 1 is the charge and discharge profile of the home battery. With high presence of photovoltaic panels, more photovoltaics energy is used to charge the home battery.

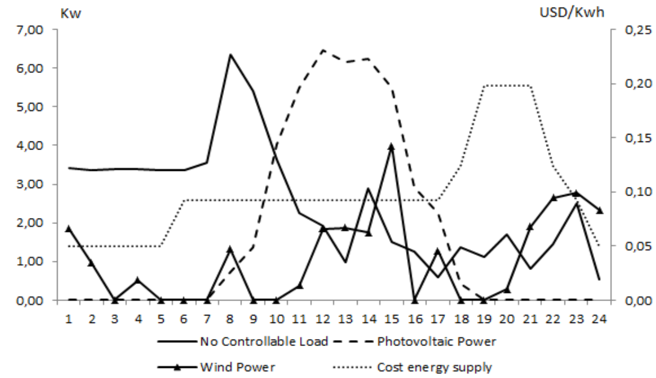

Fig. 9 Input data – Case 2.

For the simulated cases, the EVB is the larger load equipment, because in the scheduled time to use the car (in this case at 07:00 AM) the energy stored in the battery, must be as far as possible the maximum capacity. Therefore, the HEM takes the maximum power of the electrical grid (according to the maximum EVB power recharge) hours before the scheduled time to use the electric car. Maximum values of electrical grid consumption for the two simulated cases are around 17 kW, which translates into: a) increased capacity of the house electrical system, b) high demand from the network hours before to use the electric car (according to the number of users who own electric vehicles), c) excess photovoltaic energy is wasted when the electric vehicle is away from home in the hours where there is more solar radiation. The same situation also occurs for the wind, where its potential is wasted when the EVB is not connected in recharge mode during strong winds.

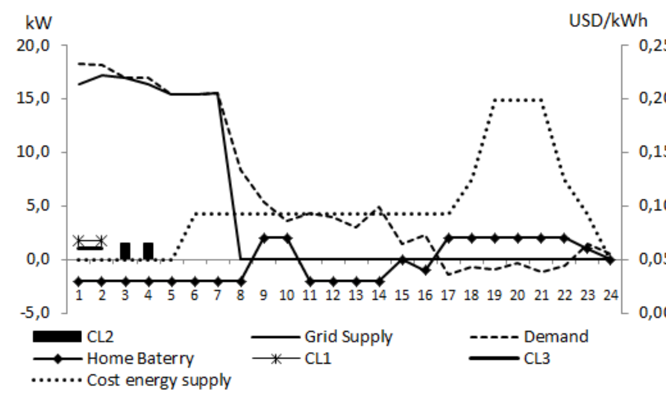

Fig. 10 Output data – Case 2.

VI. CONCLUSION

The GRASP model developed in this work meets the objective. The energy consumption of the electric network is minimized and the use of renewable energy is maximized. Although, the GRASP model found feasible solutions, this simulation take extensive computation time, since several scenarios of charging and discharging of home battery must be evaluated.

Controllable loads can be easily programmed with methodologies such as that developed in this work, when the potential of renewable energy available in the analyzed period is estimated. The success of the scheduling depends on the errors in the renewable generation forecasting.

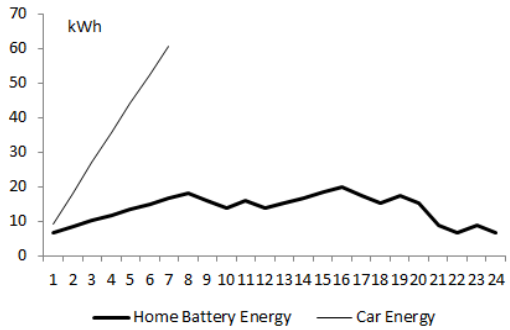

Fig. 11 Batteries Energy – Case 2.

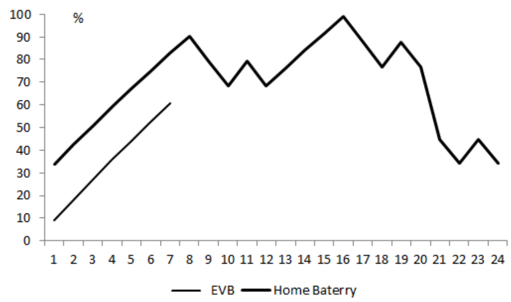

Fig. 12 SOC Batteries– Case 2.

Simulations in this study showed that renewable energy in excess must be used for example to supply neighboring users or to sell it to the electrical grid.

The use of electric cars, which batteries are recharged using the home´s electrical system, may demand reinforcement of the circuits. Simulations showed that the high penetration of electric vehicles requires large consumption of power from the electrical grid, in this way, the problem of peak power may move to another period. Therefore, to make better use of distributed renewable resources, recharging EVBs, must be done in the moments in places where the potential for greatest of these resources are available. Thus, battery charging stations for electrical vehicles must be installed in offices, banks, car parks, factories, etc.

VII. FUTURE WORKS OF FUTURE DEVELOPMENTS

We propose to develop the following works:

a) Compare the model developed in this work with other models developed with other meta-heuristics methodologies related to computing times.

b) To simulate cases where the electrical vehicle is connected to the HEM in times of increased solar radiation.

c) Simulate cases for workplaces (offices, shopping centers, car parks, etc.) where the vehicle can be connected in periods of increased solar radiation.

d) To develop a mathematical model for the problem shown in this work, which is not implemented with meta-heuristic methods, instead, implement it with classical optimization methods which allow to find the optimal solution.

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