A Mathematical Model for the Optimal Scheduling of Smart Home Electrical Loads

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Abstract: - This study develops a mathematical model for the optimal scheduling of controllable electrical loads in a smart home - MCELS. The goal of the MCELS is to minimize the total cost of the energy consumed by the smart house while decreasing the power supplied by the distribution network, still respecting requirements stablished by the costumer. To verify the MCELS results, a GRASP algorithm was used to compare both methodologies. A typical residential user in the area of Sao Paulo (Brazil), which has strong solar radiation, is established as a case study. The results show that the GRASP algorithm reduces the energy purchased from the network in approximatively 4%. Meanwhile, the MCELS provides a reduction of 6% on the energy used from the grid. This work also includes simulations where an electrical vehicle equipped with batteries of high storage capacity is recharged. Analysis of the results showed a superior performance of the MCELS if comparison with the GRASP algorithm, in five major aspects: a) lower use of the grid, b) reduction of electricity bill, c) higher use of renewable sources, d) reduction of demand peaks, and e) lower computation time.

Key-Words: - Smart Homes, Controllable Load Scheduling, GRASP, Home Energy Management, Demand Response.

Acronyms

The abbreviations of common terms used in this paper are presented below.

CEL: Controllable electrical loads
MCELS: Model for controlled electrical loads scheduling
NICEL: Non-interruptible controllable electrical loads
ICEL: Interruptible controllable electrical loads
HEMS: Home energy management system
ANEEL: Agência Nacional de Energia Elétrica (Brazilian regulatory agency)
GRASP: Greedy randomized adaptive search procedure
EV: Electrical vehicles

Nomenclature

The notation used throughout this paper is reproduced below for quick reference.

Sets

Ωt set of time from analyzed period
Ωcel set of controllable electrical load
$Pcel_j$ set of active power from controllable electrical loads

Constants

Δ discretization time t
P_t^{sun} active power from photovoltaic system - $\forall t \in \Omega_t$ [kW]
P_t^{wind} active power from wind turbines - $\forall t \in \Omega_t$ [kW]
P_t^{ncl} active power from non-controllable load - $\forall t \in \Omega_t$ [kW]
P_j^{cl} active power from controllable load - $\forall j \in \Omega_{cel}$ [kW]
C_t cost of utility electricity - $\forall t \in \Omega_t$ [\$/kWh]
T_{cli} the right time to connect CELj
T_{clf} the right time to disconnect CELj

Δti initial time from period analyzed
Δtf end time from period analyzed
λ number of CELs that can be connected during the same period Δt
γ maximum load that can be connected via CELs [kW]
cel1 first controllable electrical load
celn last controllable electrical load
$P_{ev\ max}$ maximum power charging from electric vehicle in Δt
Eev_{max} maximum stored energy from electric vehicle [kWh]
ρ percentage of battery storage from electric vehicle [%]

Continuous variables
P_t^{grid} active power consumed from the grid- $\forall t \in \Omega_t$
P_t^{br} rechargeable active power from home battery - $\forall t \in \Omega_t$ [kW]
P_t^{bi} supply of active power from home battery - $\forall t \in \Omega_t$ [kW]
P_t^{clr} rechargeable active power from batteries [kW].
P_t^{evb} rechargeable active power from electric vehicle battery - $\forall t \in \Omega_t$ [kW]
Eev_{Tf} stored energy from electric vehicle [kWh]

Binary Variables
$x_{j,t}$ defines the status of the CELj at the time period t
αj CELj connection state
βj CELj disconnection state
δ auxiliary variable to store the state of precedence between CELi and CELj

1 Introduction
Demand management represents a hot topic in the area of smart grids, enabling automatic connection and disconnection of various appliances and other electrical devices installed in a house. Thanks to new technologies in household automation and optimization techniques, environment protection and energy efficiency are no longer exclusive concerns of governments and industries. Individual customers can program their appliances time-of-use in order to reduce their energy consumption and carbon footprints. The CEL scheduling can contribute in a simple manner not only in the improvement of environmental conditions on the planet but also bringing other benefits, such as savings on the energy bill. This topic has being rapidly developed over the last decade through many studies with different approaches, from basic operation in a smart home to those involving exogenous variables such as social and environmental conditions [1]-[4]. Moreover, new considerations can be taken into account, such as the increased use of renewable distributed resources, substantial use of EV [5], increasing capacity of energy storage systems, new communication systems [6], etc.

With the development of powerful tools for taking measurements, for collecting and processing data, it is currently possible to design systems involving complex variables working in tandem that can properly manage the CEL [7]. However, any system that develops heavy analysis tasks and data processing are exposed to problems, such as long processing times, miscalculations, among others. Therefore, it is necessary to develop models that employ concepts for gathering just useful data, be dependent on short computational processing times, deliver reduced error rates, and guarantee simplicity.

This study aims to develop a MCELS with the aforementioned characteristics for smart home applications. Accordingly, it is developed a model using a mathematical optimization approach that delivers a single optimal solution, which is based on linear modeling. The proposed MCELS is convex with binary variables and the optimal solution is guaranteed by the classical optimization techniques.

The MCELS takes into account ICEL's which, up to the authors knowledge, have not yet been considered in previous studies. In addition, the MCELS takes into account EV equipped with batteries of large storage capacity, which can cause demand peaks in the electrical system of the house and, consequently, in the grid. The work present here is a continuation of our approach report in [8].

In section 2, papers in the literature focused in different CEL scheduling algorithms and models are briefly mentioned. In section 3, the proposed model is described, in section 4, a case study is discussed, and in section 5 presents the conclusions of this work.

2 Electrical loads scheduling
Modern houses have started to incorporate digital control systems in order to enable users to take advantage of time of use tariffs by controlling each device that is generating, consuming or storing electricity within their circuits. Modern home control systems enable optimum start/stop of appliances, night purge ventilation, control of maximum load demand, supervisory functions for improving illumination system, sun-blind control

strategies, energy metering and disaggregation, and many other applications. Examples of control architectures for smart homes which are operated by HEMS are illustrated in [9] and [10]. A state of the art HEMS must be capable of providing optimal management and monitoring systems on the electricity consumed by home appliances. It should intelligently controls household loads in association of smart meters, smart appliances, electric vehicles, and home power generation and storage systems. The work presented in [3] provides a background of smart HEMS technologies, and highlights its major components. A comparative analysis of several approaches is provided. A HEMS mainly comprises advanced metering infrastructure, home gateway, energy management controller, and in-home display devices. The entire architecture of HEMS assisted by wireless home area network is shown in [10].

Different algorithms and models can be used to solve the CEL scheduling problem, depending on different factors such as user requirements, user comfort constraints, and social and environmental factors. Various HEMS applications are proposed in [11]-[12]. The work in [13] focused on energy resources programming through linear and nonlinear optimization techniques. Works in [14] – [15] consider cost reduction in energy consumption and dynamic prices in the grid. The paper in [16] considered user requirements, user comfort, and external variables, such as environmental and social factors. For better detailing of several developed models for CEL scheduling problem, the work in [2] describes an extensive survey used to address the problem of smart scheduling from the consumer's point of view. As an example, the paper in [17] illustrates energy resource programming methods via meta-heuristic techniques. In most cases, metaheuristic algorithms have a long and complex development process and results are difficult to replicate. Meta-heuristic methods are often complex in nature; instead, classical optimization techniques using linear modeling allows the development of simple models, thereby increasing computational efficiency. This paper presents the MCELS, which is developed using traditional optimization techniques. Hence, the proposed HEMS uses the MCELS to make a quick and optimal CEL scheduling.

3 Outline of the methodology

As done in [10], the proposed optimization model was adapted to consider various periods of time along a day. The challenge of the proposed methodology is to minimize the total cost of the energy consumed by the smart house in order to use less power supplied by the grid, as stated in Equation 1. The total energy cost is given by the sum of the energy purchased from the network plus the renewable generation cost.

Minimize

$$\mathrm{Min}[\textstyle\sum_{t\in\Omega t}\Delta C_t * P_t^{grid} + \sum_{t\in\Omega t}\Delta Cre_t * P_t^{re}] \quad (1)$$

Where: $$P_t^{re} = P_t^{sun} + P_t^{wind} \quad (2)$$

Subject to:

$$P_t^{sun} + P_t^{wind} + P_t^{grid} + P_t^{bi} = P_t^{ncl} + \sum P_{j,t}^{cl} + P_t^{br} + P_t^{evb} + P_t^{clr} \qquad \forall\, t, j \quad (3)$$

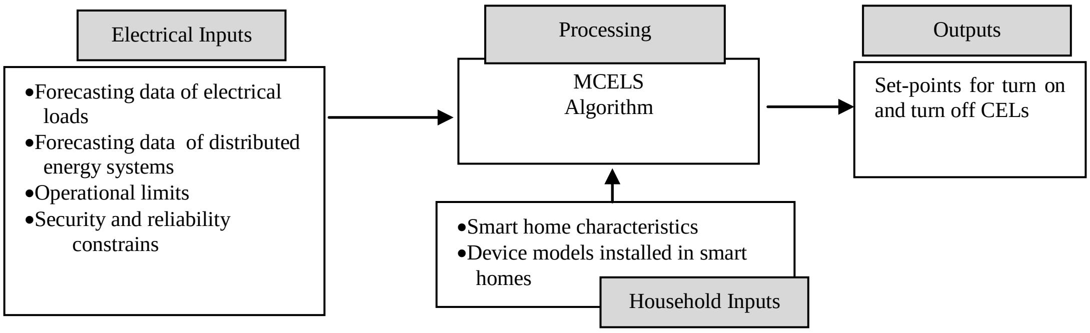
Constraints shown in 3.1 to 3.6

Equation 2 defines the power of renewable energy sources available in the smart house. Equation 3 provides the typical power balance. The model shown in Equations 1 to 3 represents the classic approach to this type of problem studied in many works, such as [18]. However, this paper provides the following set of original new considerations: a) a new approach to solve the problem, which is based on classical optimization tools; b) CEL priority; c) modeling of special CEL characteristics; d) a methodology to mitigate the demand peak problem; e) EV batteries that have large storage capacity; and f) use of commercial optimization solvers and mathematical programming languages. These contributions are explained as follows.

3.1 The methodology to solve the problem

The proposed CEL optimization software defines the appropriate time to connect a CEL in order to meet a specific objective. Works that have been developed on this topic, usually take a load profile of each appliance as a model input vector, as demonstrated by [9]. In this work, we do not use a input vector; instead, we use a decision variable x for each CEL j. This variable is also related to the time period, thus $x_{j,t}$ defines the status of the CEL load j at the time period t; if $x_{j,t} = 1$, then the CEL j will be ON at the time t; otherwise, if $x_{j,t} = 0$, it will be OFF that that time. As illustrated in Figure 1, the binary decision variable $x_{j,t}$ is defined as the output of the proposed optimization model. The model analyzes whether or not a certain CEL should be connected for each period t. Therefore, $x_{j,t}$ with a value of one (1) indicates that the CELj must be connected (turned on) at that time; on the other hand, $x_{j,t}$ with a value of zero (0) indicates that the

Fig. 1 Proposed model for the optimal electric loads scheduling (MCELS).



CELj must be disconnected (turned off). The model output has a vector, containing $x_{j,t}$ values for each period t, where a value of one (1) indicates the period of operation for each CELj. Since $x_{j,t}$ has two subscripts, it is already a binary matrix, e.g. $x_{1,t} = \{0,1,1,1,0\}$; $x_{2,t} = \{0,0,0,1,1\}$; etc, as illustrated in Figure 2.

$$x_{j,t} = \begin{bmatrix} 0 & 1 & 1 & \ldots & 0 \\ 1 & 1 & 0 & \ldots & 1 \\ 0 & 0 & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & 1 \end{bmatrix}$$

Fig. 2. Output matrix $x_{j,t}$

The development of an optimization model with binary variables requires a simple model that delivers solutions in a short time. Consequently, the constraints of the CEL scheduling problem can be defined using matrix $x_{j,t}$. We identified five main constraints that determine the operation of a CEL, which are represented in Equations 4 to 8. Each CEL has a set of parameters that determine its time-of-use characteristics (Table 1). In addition, a CEL can or not be turned off during its operation cycle, which differentiates a NICEL from an ICEL, as detailed in section 3.3. These special operational requirements are also described in Table 1.

The programming of the CELj should determine the optimal period to connect it, evaluating each period t, as done in [10]. The right time to connect CELj is T_{cli}, and accordingly, the right time to disconnect it is T_{clf}. Thus, completion of the CELj operation cycle is required to occur between T_{cli} and T_{clf} periods as illustrated in Figure 3a. In order to model the toggle characteristics of each CEL illustrated in Table 1, this work used the binary variable αj to store the CELj connection status, where αj = 0 when CELj has not yet been connected, and αj = 1 when CELj has been connected. This work also used the binary variable βj to store the CELj disconnection state, where βj = 0 when CELj has not been disconnected, and βj = 1 when the CELj has been disconnected, as illustrated in Figure 3(b). Therefore, Equation 4 models the connection and disconnection of CELj, and Equation 5 models the initial state when t = 0. Equations 4-5 ensure that CELj is not disconnected during its operation cycle. Equations 6 and 7 ensure that there is only one time for the shifting the states αj and βj. Equation 8 ensures that CELj fulfills its entire operation period. Equation 9 ensures that the variable x is zero during periods when the CELj is not connected (i.e., outside the T_{cli} and T_{clf} period). To simplify the modeling, Equations 4, 5, 6 and 7, are replaced with Equation 10.

Table 1 Household appliances requirements.

	Load	Power (W)	Time of use (minutes)	Operation specification	Type
CC1	Washing machine	1000	60	Do not disconnect during operation cycle	NICEL
CC2	Clothes Dryer	800	60	Do not disconnect during operation cycle. Turn on after washing machine	NICEL
CC3	Dishwasher	600	60	Do not disconnect during operation cycle	NICEL
CC4	Rice cooker	500	30	Do not disconnect during operation cycle. Turn on before at 12:00 P.M.	NICEL
CC5	Electric oven	1200	30	Do not disconnect during operation cycle	NICEL
CC6	Rechargeable equipment (Cell phone, etc.)	300	45	It must be fully charged at the time specified, for example 07:00 A.M.	ICEL
CC7	Electric pool pump	1000	240	Turn on between 06:00 A.M. and 8:00 P.M. avoiding noise at	ICEL

				night	
CC8	Electric kettle	800	15	Do not disconnect during operation cycle	NICEL
CC9	Home Battery	800	120	Keep the minimum energy	ICEL
CC10	EV	800	120	It must be fully charged at the time specified, for example 07:00 A.M.	ICEL

$$x_{j,t} - x_{j,t-1} = \alpha_{j,t} - \beta_{j,t} \quad \forall j, t \quad (4)$$

$$x_{j,1} - x_{j,0} = \alpha_{j,t} - \beta_{j,1} \quad \forall j \quad (5)$$

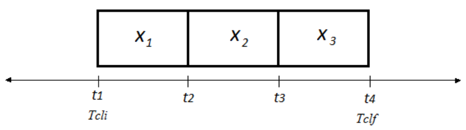
$$\sum_{t=Tcli}^{t=\Delta tf} \alpha_{j,t} = 1 \quad \forall j \quad (6)$$

$$\sum_{t=Tcli}^{t=\Delta tf} \beta_{j,t} = 1 \quad \forall j \quad (7)$$

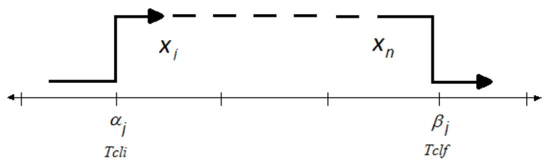
$$\sum_{t=Tcli}^{t=Tclf} x_{j,t} = \Delta t_j \quad \forall j \quad (8)$$

$$\sum_{t<\Delta ti \text{ or } t>\Delta tf} x_{j,t} = 0 \quad \forall j \quad (9)$$

$$\sum_{Tcli}^{Tclf} \left| x_{j,t} - x_{j,t-1} \right| = 2 \quad (10)$$



(a)



(b)

Fig. 3 Time-of-use curve of the CEL_j.

The operation cycle is required to occur between T_{cci} and T_{ccf} periods (a) Discretized curve using the binary decision variable $x_{j,t}$. (b) Toggle representation of the time-of-use curve switching variables α_j and β_j.

3.2 The methodology for CEL priority

Some CELs must be connected only after certain loads have completed their cycle, as in the case of the dryer, which may be turned on only after the washing machine cycle is completed. To model the above condition, we used the precedence matrix ϕ, which defined whether CELi was conditioned to CELj disconnection; therefore, a value of 1 is used in ϕ, as illustrated in Figure 4. We used the auxiliary binary variable δ to store the state of precedence between CELi and CELj; thus, δ = 0 when CELj has not yet completed its operating cycle, and δ = 1 once that CELj operating cycle is over.

$$\Phi = \begin{array}{c|cccc|} & CC_j & CC_{j+1} & & CC_{jn} \\ CC_i & 0 & 0 & \cdots & 0 \\ CC_{i+1} & 0 & 1 & \cdots & 0 \\ & \vdots & \vdots & & \vdots \\ CC_{in} & 0 & 1 & \cdots & 0 \end{array}$$

Fig. 4 The precedence matrix ϕ.

Equations 11 to 14 guarantee this condition as follows: Equation 11 defines δj =1 only when the variable xj = 1; Equation 12 ensures that δj = 1 only after βj,t is changed to a state of activation, that is βj,t = 1; Equation 13 guarantees that δj = 0 before βj,t = 1; Equation 14 ensures that δj = 1 only when CELj has precedence with CELi in matrix ϕ.

$$\delta_{j,t} <= 1 - x_{j,t} \quad (11)$$

$$\delta_{j,t} => \delta_{j,t-1} + \beta_{j,t} \quad (12)$$

$$\delta_{j,t+1} <= \delta_{j,t} + (1 - \beta_{j,t}) \quad (13)$$

$$\alpha_{j,t} <= \delta_{i,t} + (1 - \phi_{i,j}) \quad (14)$$

3.3 Modeling of special CEL characteristics

Within the category of ICEL, we take into account the pool pump (used to clean and filtering the water), which can be interrupted during its operating cycle as illustrated in Figure 5 and listed in Table 1. To model this ICEL we used Equations 5, 7 and 8. Equation 6 is excluded, allowing such loads to have several connection periods, separately. This model improves the optimization process, as it allows allocation of load connections at different times of the day, especially those where there is a high proportion of renewable sources, or periods when the cost of the grid electricity is cheaper, also leading to reduced demand peaks.

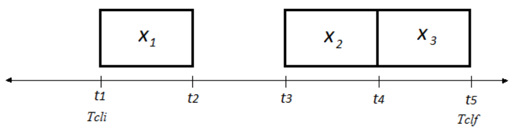


Fig. 5 Intermittent controlled electric loads.

3.4 The methodology to mitigate the demand peak problem

In this work, two methodologies were employed to minimize the impact of the demand peak that may appear when several CELs are connected at the same time, as described in [10]. The first methodology verified the amount of CELs connected for each row of the matrix $x_{j,t}$. Therefore, for each time t, there exists a limit of variables xj = 1, for which the Equation 15 defined λ values represents the number of CELs that can be connected during the same period t. Thus, λ assumes a value between 0 and the maximum quantity of CELs. In the second methodology, the limit used to control high demand peaks is set by the constant γ, which defines the maximum load that can be connected via CELs. This methodology is described in Equation 16.

$$\sum_{j=cel1}^{j=celn} x_{j,t} \leq \lambda \qquad \forall t \qquad (15)$$

$$\sum_{j=cel1}^{j=celn} x_{j,t} \cdot Pcel_j \leq \gamma \quad \forall t \qquad (16)$$

3.5 Electrical vehicles batteries with large storage capacity

With the increased use of EVs, it is currently necessary to analyze its impact on the smart house electric system [20]-[21]. This work included simulations where EV batteries were recharged, taking into account factors such as: 1) high capacity storage, 2) maximum power charging, 3) injection efficiency, 4) self-discharge rate, etc. To model the EV battery, the methodology proposed in [22] was used. In this work, we took into account additional factors to improve the real conditions in a smart house, such as: 1) hours available to recharge the car batteries according to a schedule when the vehicle would be at home; 2) use of maximum power charging to maximize recharge during time when the vehicle is at home (see Equation 17); and 3) maximized storage capacity of the battery. As established by Equation 18, in which ρ defines the percentage of battery storage for the end of the period, thus if ρ = 100, the algorithm must schedule the battery to be fully charged at end of period Tcf, because the EV will be used immediately following this period.

$$P_t^{evb} = P_{ev\,max} \qquad (17)$$

$$Eev_{Tf} \leq \rho \cdot Eev_{max} \qquad (18)$$

3.6 Use of classical optimization techniques which gives an optimal solution

One alternative to solving the CEL scheduling problem is to employ heuristic methods to find a good and feasible solution, but not necessarily optimal, as shown in [23]. In this work, we developed the model using classical convex optimization methods which guarantee the optimal solution. The model has been implemented using the mathematical programming language (AMPL) [24], and solved via a commercial solver (CPLEX) [25], where all equations used were linear.

4 Case study

In this case study we used data obtained from the load profile from a home located in the city of Campinas, State of São Paulo, Brazil. The weather data was obtained from Tanquinho 1MW PV power station located in the city of Campinas, considering a schedule horizon of 24 hours ahead in time-steps of 15 minutes. In this paper, it was assumed that the photovoltaic system always operates at maximum power tracking. In this case, we used a photovoltaic system with an area of 50 m2 (7.5 kW, panels installed on the house roof). We used the same methodology as presented in our previous works showed in [26]-[27] to model the photovoltaic generation, according to the available irradiance and module temperature. To model the wind system generation of 1,2 kW, a piece-wise power curve model was used to give the output power as a function of wind speed, as shown in the aforementioned papers.

In Brazil, the national regulatory agency (ANEEL) recently established a time-of-use pricing scheme, where the price of electricity corresponds to specific time periods, in an effort to reduce the energy consumption during peak hours and to encourage demand side management. ANEEL's resolution [28] categorized three different periods: 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 6, all input data for May 11th of 2015 are shown, including the power profile of the PV, the power profile from wind turbine, the user load profile, and price of electricity.

Generally, batteries are the most common choice for short-term energy storage systems in smart houses; in this work, the energy storage system was composed of a bank of lead-acid batteries. The main function of the energy storage system was to reduce the variability of the renewable resources and storage energy so that it could be used during periods when the energy supplied by the grid had a higher cost. All the values used for the battery model are listed in [27]. For the scenarios studied in this paper, we used the EV battery parameters shown in Table 2.

Table 2. Electrical vehicles battery 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%

4.1 Analysis of results:

In Figure 7, demand curves for May 11th of 2015 are shown before and after the application of the proposed optimization process. The base case, where the user freely connected seven CELs along the day, can be observed along with the optimized case in which the MCELS solved the problem. In this figure, it is possible to see that MCELS reduced the demand peaks, flattening the demand curve, and consequently leading to less effort from the electrical grid to supply the demand.

In Figure 8, the consumption from the grid for the first 8 hours of May 12th of 2015 is illustrated. The highest consumption occurred in this period because the EV battery was recharged to be ready for use at 7 A.M. Figure 8 compares the consumption from the grid considering the base case and the solution provided by MCELS, where a decreased consumption can be observed. In order to verify the results, we simulated seven days in May of 2015, corresponding to a full week, and evaluated the decrease in terms of total energy supplied by the grid. A reduction of 6% was observed, as illustrated in Figure 9 and Table 3.

By optimizing the scheduling of the CELs, energy of lower cost was purchased from the grid to meet the demand. In the present case study, the electricity bill was reduced in 16% for one week, as illustrated in Table 3. It is due to the fact that MCELS turn on the CELs in periods where consumption from the grid is cheaper, according to the time-of-use pricing scheme.

Figure 10 and Table 3 show a comparison of the energy stored in the home batteries for the base case and for the optimized scenario using MCELS, where lower energy storage was required. With the MCELS, the house would require a battery with a lower storage capacity, leading to smaller batteries, and ultimately lower costs.

4.2 Checking results using GRASP:

An alternative for solving the problem illustrated above was to employ heuristic methods to find a good and feasible solution, though 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 [29]. The construction phase solutions are not guaranteed to be locally optimal in a given neighborhood, because they are the result of additions made with heuristic approach. In general, the local search algorithm works to replace the current solution with a better one within the realm of the current solution. It stops when no better solution exists in that realm. To verify the MCELS results, a previously developed model was used [27]. Figure 8 shows the comparison between the base case, the case where the MCELS was used, and the optimization provided by the GRASP model. The GRASP model reduced the consumption of the grid; however the MCELS achieved better results. These results, along with the seven day simulation results, are also verified in Figure 9 and Table 3 where it can be seen that the GRASP model achieved lower consumption of the grid by more than 4%, and the MCELS achieved lower consumption by 6%.

4.3 Programming interruptible loads:

The MCELS accommodated schedules for both the ICELs as well as NICELs as is illustrated in

TABLE 3. COMPARING CEL OPTIMIZATION METHODOLOGIES.

	Energy used from the grid in one week (kWh)	Electric bill value R$()	Energy used from wind system (kWh)	Energy used from photovoltaic system (kWh)	Energy Stored by the battery (kWh)	Computational performance: average solution time (minutes)
Base Case	827,97	51,87	210,95	1128,35	246,49	-
GRASP	794,56	46,80	210,95	1128,40	245,12	16
MCELS	747,01	43,06	210,95	1128,60	243,62	0,14

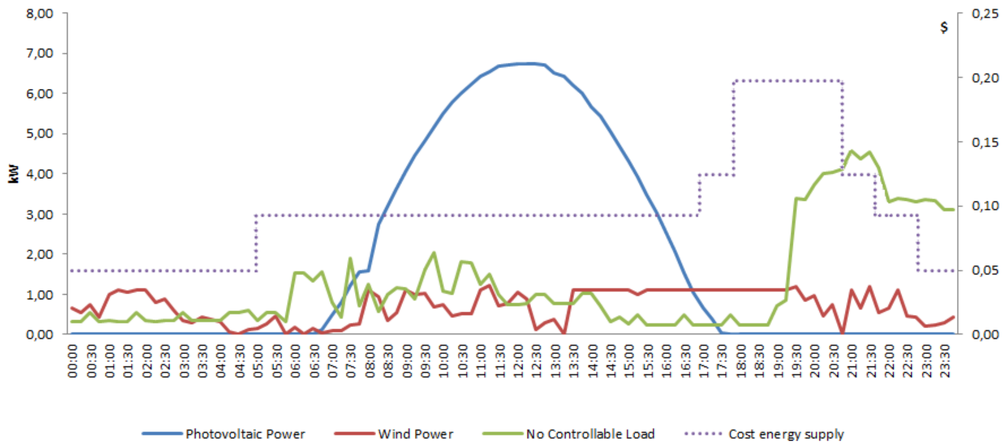


Fig. 6 Case study input data in May 11th of 2015.

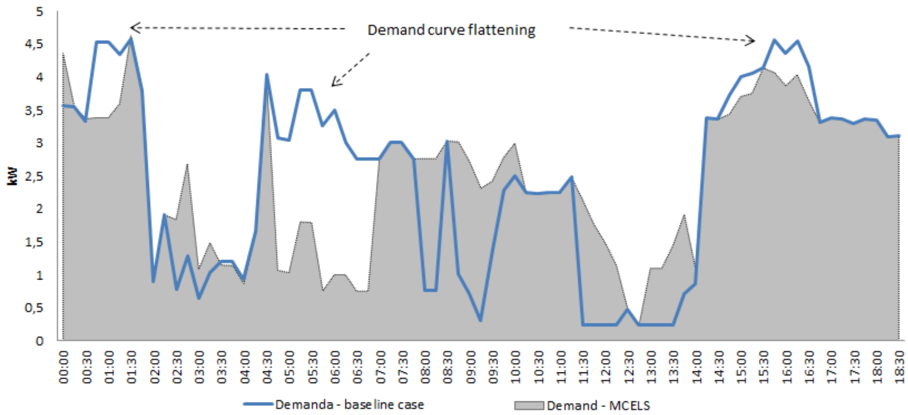


Fig. 7 Demand curve in May 11th of 2015.

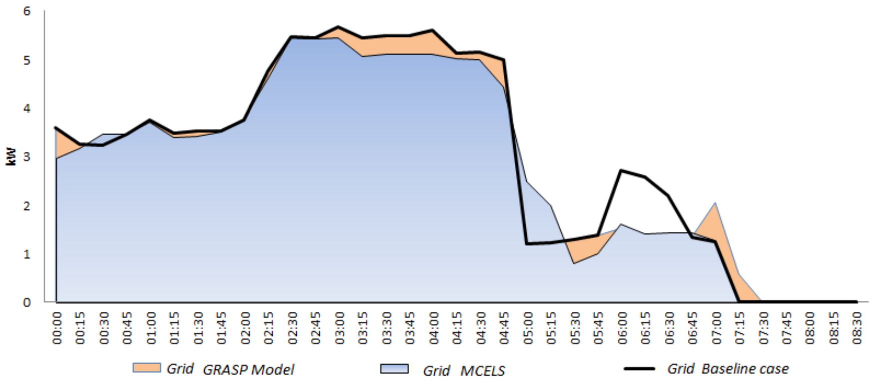


Fig. 8 Energy supplied from the grid for the first 8 hours of May 12th of 2015.

Figure 11, where two scenarios for the pool pump for May 11th of 2015 are shown. In the base case, the user determined a period for pool pump operation. For the scenario that is based on the MCELS the activation of the pump took place at different times, which maximizes the energy supplied by the PV and wind systems. In Figure 11, the power delivered by the home batteries in the optimal scenario was lower, confirming lower storage capacity of the home batteries when using the MCELS.

4.4 Control of demand peak:

Figure 12 illustrates a specific scenario where the MCELS does not make use of Equations 15 and 16. Therefore, the MCELS scheduled the network of CELs simultaneously, producing demand peaks around 23:15. Figure 12 also illustrates the scenario in which the MCELS uses Equation 16, where a maximum load limit (γ) to the connected CELs was defined. Hence, the connection of CELs was made at different times of the day, resulting in a flatted demand curve.

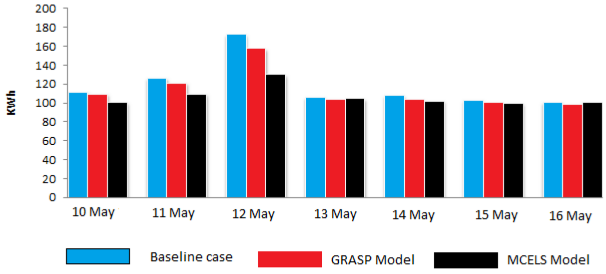


Fig. 9 Energy supplied from the grid for a week.

The MCELS successfully scheduled both NICELs and ICELs improving the optimization process, achieving all the objectives and surpassing current state of the art methodologies.

Demand peaks were avoided by using the methodologies described in this paper, highlighting the use of a simple model that provided better performance than current state of the art methodologies.

The MCELS was tested against the heuristic GRASP model. The simulated scenarios included the base case where the user determined the hours for connecting the CELs, the scenario using the MCELS, and scenarios where the GRASP model was used. The analysis of the results showed

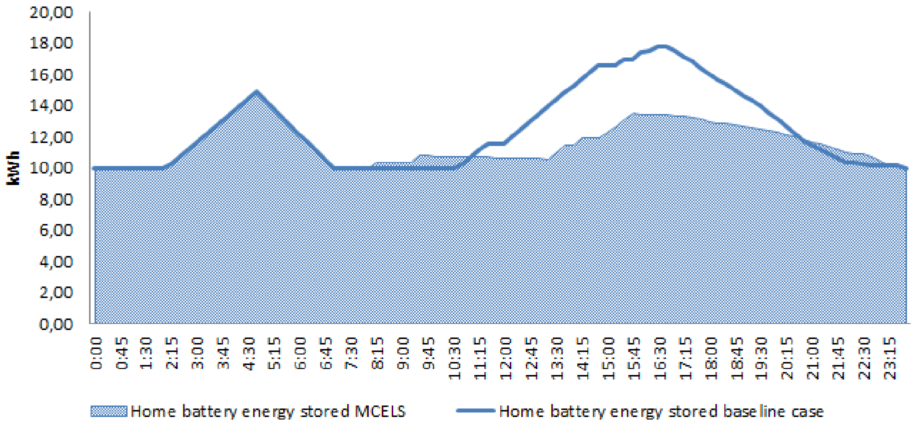


Fig. 10 Energy stored in the home batteries in May 15th of 2015.

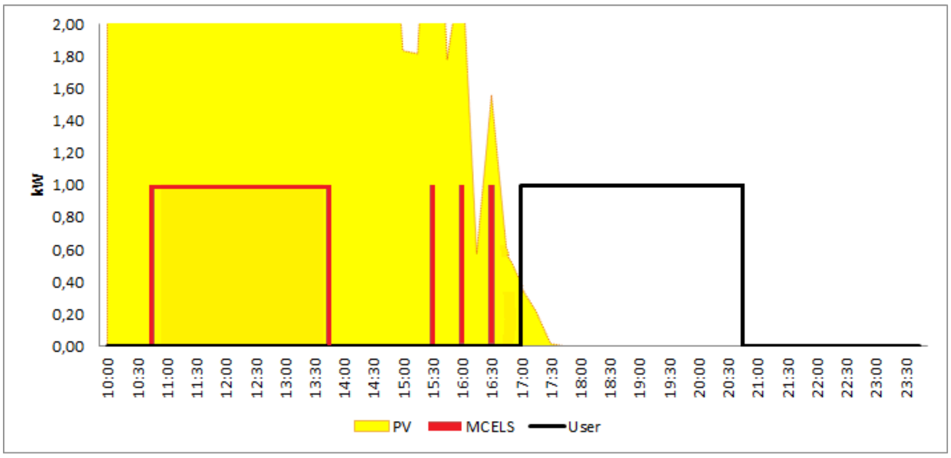


Fig. 11 Scenarios for the pool pump in May 15th of 2015.

5 Conclusion

Analysis of the results shows the stability of the MCELS when solving the CEL scheduling problem. Scheduling the connection of both NICELs and ICELs was performed in compliance with each of the objectives. Maximization of the use of renewable energy was achieved, as well as minimization of the use of the grid, which also led to a reduction in the electricity costs.

superior performance of the MCELS, surpassing the GRASP model by: a) less use of the grid, b) reduction of electricity bill, b) increased use of renewable sources, c) minimization of demand peaks, and d) lower computation time.

The MCELS demonstrated the advantages of using classical optimization techniques to solve this specific optimization problem compared with a heuristic method. The linear modeling was capable

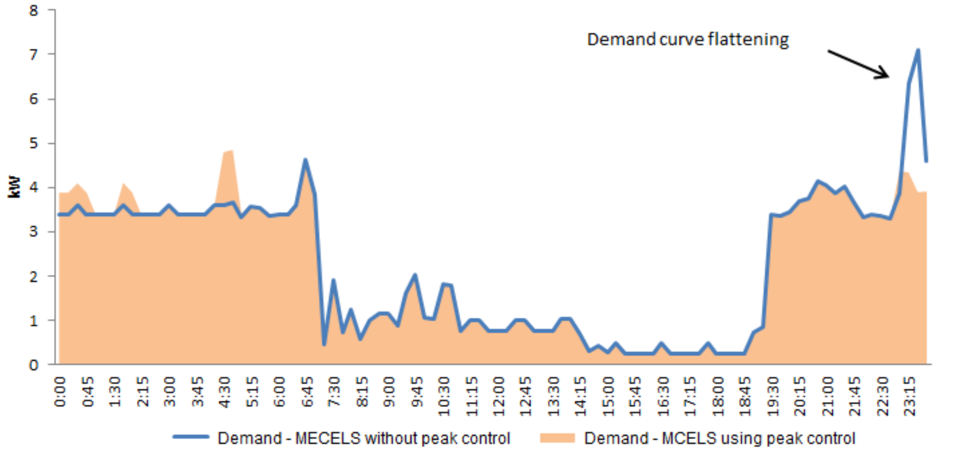


Fig. 12 Demand curve in May 11th of 2015.

of producing a simple algorithm with less code development and decreased computational effort.

The use of EVs results in recharging of high capacity batteries using the home´s electrical system. Simulations showed that EV requires large consumption of power from the grid, which could potentially transfer the problem of demand peak to another period of the day. Therefore, to make better use of distributed renewable resources, recharging of electrical vehicles battery must be done during times when these resources are most readily available. MCELS has proved to be very useful for accomplishing this objective. As future works the MCELS concept will be used in case studies associated to intelligent buildings and micro-grids.

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References:

[1] Cheah, E., Consumer energy portal and home energy management system for smart grid applications, *IPEC 2012 Conference on Power and Energy*, pp. 1-6. 407 - 411

[2] Amer, M., Naaman, A., M'Sirdi, A., and A. El-Zonkoly, Smart home energy management systems survey", *Renewable Energies for Developing Countries (REDEC), 2014 International Conference on*, 2014, pp.167-173, 26-27

[3] Jeong, L., Chang-Sic, C., Wan-Ki, P., Jin-Soo, H. and Il-Woo, L., A study on the use cases of the smart grid home energy management system, *ICT Convergence (ICTC) 2011 International Conference on*, 2011, pp.746-750

[4] Chen, C., Kyatsandra, N., Gang, X., Shalinee, K. and Lawrence, S., A communication-based appliance scheduling scheme for consumer-premise energy management systems, *Smart Grid IEEE Transactions on*, Volume 4, Issue 1, pp. 56 - 65

[5] Shao, S., Zhang, T., Pipattanasomporn, M. and Rahman, S., Impact of TOU rates on distribution load shapes in a smart grid with PHEV penetration, *Proc. IEEE Transm. Distrib. Conf. Expo.*, 2010, pp. 1-6

[6] Sagi, M. and Telvent DMS, Smart home automation, *Telecommunications Forum (TELFOR)*, 2012, pp. 1512 - 1515

[7] Qinran, H. and Fangxing, L., Hardware design of smart home energy management system with dynamic price response, *Smart Grid IEEE Transactions on*, Volume:4, Issue: 4, pp. 1878 - 1887

[8] Moya, F., da Silva, L., and Lopez, J., Model For Smart Building Electrical Loads Scheduling, *16 IEEE International Conference on Environment and Electrical Engineering*, Florence-Italy, (2016)

[9] M. Pipattanasomporn, M. Kuzlu and S. Rahman, An Algorithm for Intelligent Home Energy Management and Demand Response Analysis, *IEEE Transactions on Smart Grid*, Volume:3, Issue: 4, pp. 2166 - 2173, 13 Junho 2012

[10] Z. Zhao, W. Lee, Y. Shin, and K. Song, An Optimal Power Scheduling Method for Demand Response in Home Energy Management System, *IEEE Transactions On Smart Grid*, Vol. 4, No. 3, September 2013.

[11] E. Ozturk, An intelligent home energy management system to improve demand response, *Smart Grid IEEE Transactions on*, Volume:4, Issue: 2, pp. 694-701, June 2013.

[12] S. Kalogridis, PEHEMS: Privacy enabled hems and load balancing prototype, *Smart Grid Communications (SmartGridComm) 2012 IEEE Third International Conference on*, pp. 486-491, 5-8 Nov. 2012.

[13] F. De Angelis, Optimal home energy management under dynamic electrical and thermal constraints, *Industrial Informatics IEEE Transactions on*, Volume:9, Issue: 3, pp.1518-1527, Aug. 2013.

[14] E. Tsui, Demand response optimization for smart home scheduling under real-time pricing, *Smart Grid IEEE Transactions on*, Volume:3, Issue: 4, pp. 1812 - 1821, Dec. 2012.

[15] S. Chen, Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home, *Smart Grid IEEE Transactions on*, Volume:4, Issue: 2, pp. 932 - 941, June 2013.

[16] K. Xiao, Comfort-aware home energy management under market-based demand-response, *Network and service management (CNSM) 2012 8th international conference and 2012 workshop on systems virtualization management (SVM)*, pp. 10 - 18., 22-26 Oct. 2012.

[17] S. Squartini, Optimization algorithms for home energy resource scheduling in presence of data uncertainty, *Intelligent Control and Information Processing (ICICIP) 2013 Fourth International Conference on*, pp. 323-328, 9-11 June 2013.

[18] M.Bozchalui, S. AhsanHashmi, H. Hassen, C. Cañizares and K. Bhattacharya, Optimal Operation of Residential Energy Hubs in Smart Grids, *IEEE Transactions On Smart Grid*, Vol. 3, No. 4, pp. 1755 - 1766, December 2012

[19] M. Pedrasa, T. Spooner and I. MacGill, Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services, *IEEE Transactions on Smart Grid*, Vol. 1, No. 2, September 2010

[20] S. Squartini, Home energy resource scheduling algorithms and their dependency on the battery model, *Computational Intelligence Applications In Smart Grid (CIASG) 2013 IEEE Symposium on*, pp. 122 - 129, 16-19 April 2013.

[21] A. Yoza, K. Uchida, A. Yona and T. Senjyu, Optimal operation of controllable loads in dc smart house with EV, *Renewable Energy Research and Applications (ICRERA) 2012 International Conference on*, pp. 1 - 6, 11-14 Nov. 2012.

[22] L. Macedo, J. Franco, M. Rider and R. Romero, Optimal Operation of Distribution Networks Considering Energy Storage Devices, *Smart Grid, IEEE Transactions on*, Volume:6 , Issue: 6, pp. 2825 - 2836, 25 April 2015.

[23] F. Fernandes, T. Sousa, M. Silva, H. Morais, Z. Vale and P. Faria, Genetic Algorithm Methodology applied to Intelligent House Control, *Computational Intelligence Applications In Smart Grid (CIASG) 2011 IEEE Symposium on*, pp. 1-8, 11-15 April 2011.

[24] R. Fourer, D. M. E. Gay, and B. W. Kernighan, *AMPL: A Modeling Language for Mathematical Programming*, 2nd ed. Pacific Grove, CA, USA: Brooks/Cole-Thomson Learning, 2003.

[25] *CPLEX Optimization Subroutine Library Guide and Reference*, Version 11.0, CPLEX Division, ILOG Inc., Incline Village, NV, USA, 2008

[26] P. Vergara, R. Torquato and L.C.P. da Silva, Towards a real-time Energy Management System for a Microgrid using a Multi-Objective Genetic Algorithm, *2015 IEEE Power and Energy Society General Meeting*, pp.1-5, 26-30 July 2015.

[27] F. Moya, L. da Silva, J. Lopez and P. Vergara, GRASP Model for Smart Home Electrical Loads Scheduling, *Energy and Sustainability International Conference (IESC)*, pp.1-6, 12-13 Nov. 2015.

[28] Currenty *ANEEL Data Base in web site*, Available:http://www.aneel.gov.br/area.cfm?id Area=493, Last accessed: December 01, 2015.

[29] T. Feo and M. G. C. Resende, Greedy randomized adaptive search procedure, *Journal of Global Optimization*, Vol. 6, pp. 109-133, 1995.