Model For Smart Building Electrical Loads Scheduling

Francisco D. Moya Ch., framoya@dsee.fee.unicamp.br
Luiz C. P. da Silva, lui@dsee.fee.unicamp.br
Juan C. Lopez A., jclopeza@dsee.fee.unicamp.br
School of Electrical and Computing Engineering - University of Campinas (Unicamp), Campinas/Brazil

***Abstract*— In this paper, a novel mathematical optimization model for the optimal load scheduling in smart buildings is presented. The proposed building energy management system uses the optimization model to make a quick and optimal load scheduling. Analysis of the results shows the stability of the propose model when solving the problem in residential smart buildings. Minimization of the use of the grid's power was achieved, which also led to a reduction in the electricity bill up to 26% for one specific user. Demand peaks were avoided and the demand curve was flattered at the end of the scheduling process. Moreover, the propose optimization model considers a fair payment constraint of the electrical bill for all users.**

Keywords— Smart Building, Controllable Electrical Load Scheduling, Building Energy Management Systems, Demand Response.

ACRONYMS-NOMENCLATURE

The abbreviations and notation used in this paper are presented below.

Acronyms:	
CEL	Controllable electrical loads
MCELS	Model for controlled electrical loads scheduling
BEMS	Building energy management system
EMS	Energy management system
EV	Electrical vehicle
Symbols:	
Ω_{cel}	Set of controllable electrical load
Δ	Discretization time t
P_t^{sun}	Active power from photovoltaic system
P_t^{wind}	Active power from wind turbines
P_t^{ncel}	Active power from non-controllable load
P_j^{cel}	Active power from controllable load
C_t	Cost of utility electricity
Cre_t	Cost of renewable energy
T_{cli}	The right time to connect cel_j
T_{clf}	The right time to disconnect cel_j
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
$celn$	First controllable electrical load
P_t^{grid}	Active power consumed from the grid
P_t^{br}	Rechargeable active power from home battery
P_t^{bi}	Supply of active power from home battery
P_t^{evb}	Rechargeable active power from electric vehicle battery
Eev_{Tf}	Stored energy from electric vehicle [kwh]
$x_{j,t}$	Defines the status of the cel_j at the time period t
α_j	Cel_j connection state
β_j	Cel_j disconnection state

I. INTRODUCTION

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]. Utility companies have been adopting different price of electricity at each time slot of a day [2]. The prices are usually higher during peak hours by nightfall when residents turn on the house lights. In Brazil it was established a time-of-use pricing scheme, categorized three different periods: peak, intermediary, and off-peak. The rationale behind this is to shift the electricity demand away from the time of peak load, expecting a consumer-side reaction according to the change of prices.

The role of residential smart buildings became crucial: from the one hand, thanks to their smartness, i.e. thanks to automation (domotic) systems, they can gather important information about their energy consumption and occupants habits; on the other hand, they can also expose digital interfaces that enable an automatic and dynamic interaction with the smart grid, and the possibility of shaving their energy consumption with respect to the needs of the energy provider [3].

As residential smart buildings would be equipped with renewable energy sources such as solar panels or a windmill power generator, there are alternative energy sources that can be provided. The scheduler also needs to consider this alternative source of electricity during scheduling [4]. Fig. 1 describes a basic arquitecture in a residential smart building.

To achieve the full economic benefit of dynamic pricing, it is imperative that electric devices be equipped with an automatic price-aware scheduling mechanism that requires minimal action from the consumers. In this regard, smart sockets have been developed [6]. A smart socket is placed between an appliance and an electricity outlet, and monitors the electricity usage information of the appliance; it also has an ability to communicate with smart meters, and controls the electricity state of the appliance.

This study aims to develop a MCELS, with the aforementioned characteristics for smart home applications in a residential building. Accordingly, it is developed a model using a mathematical optimization approach that delivers a single optimal solution, which is based on linear modeling.

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, in section 5 analysis of results is illustrated, and in section 6 presents the conclusions of this work.

978-1-5090-2320-2/16/$31.00

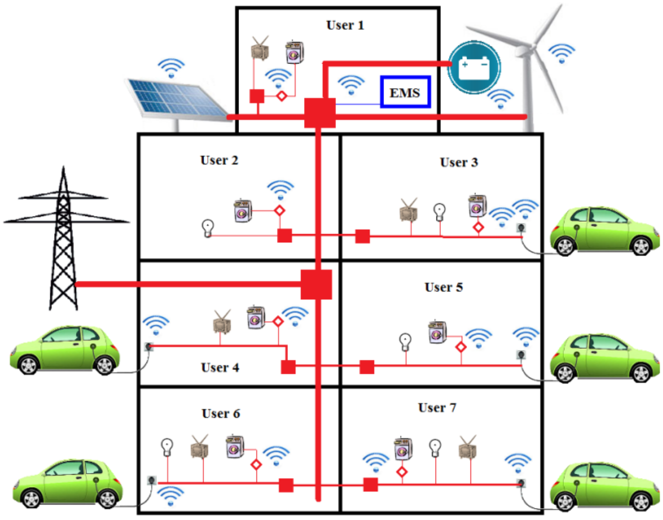

Figure 1. Smart building architecture.

II. ELECTRICAL LOADS SCHEDULING

Modern residential buildings 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 residential buildings 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 residential smart buildings which are operated by Building Energy Management System (BEMS) are illustrated in [7] and [8]. A state of the art Energy Management System (EMS) 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 small power generation and storage systems. The work presented in [9] provides a background of smart EMS technologies, and highlights its major components. A comparative analysis of several approaches is provided. A EMS mainly comprises advanced metering infrastructure, home gateway, energy management controller, and in-home display devices. The entire architecture of EMS assisted by wireless home area network is shown in [8].

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 EMS applications are proposed in [10]-[11]. The work in [12] focused on energy resources programming through linear and nonlinear optimization techniques. Works in [13]-[14] consider cost reduction in energy consumption and dynamic prices in the grid. The paper in [15] 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 [16] 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 BEMS uses the MCELS to make a quick and optimal CEL scheduling.

III. OUTLINE OF THE METHODOLOGY

As done in [8], 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 residential smart building 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

$$\mathrm{Min}[\textstyle\sum_t \Delta C_t * P_t^{grid} + \sum_t \Delta Cre_t * P_t^{re}] \qquad (1)$$

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

Subject to:

a) $$P_t^{sun} + P_t^{wind} + P_t^{grid} + P_t^{bi} = P_t^{ncel} + \sum P_{j,t}^{cel} + P_t^{br} + P_t^{evb} \qquad \forall t,\ j \in \Omega_{cel} \qquad (3)$$

b) Constraints shown in Equations 4 to 10.

Equation 2 defines the power of renewable energy sources available in the residential smart building. 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) a methodology to mitigate the demand peak problem; and c) EV batteries that have large storage capacity. These contributions are explained as follows.

A. Solving 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 [19]. 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. 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 CEL_j must be connected (turned on) at that time; on the other hand, $x_{j,t}$ with a value of zero (0) indicates that the CEL_j 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 CEL_j. 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.

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 a 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. These special operational requirements are described in Table I.

The programming of the CEL_j should determine the optimal period to connect it, evaluating each period t, as done in [8]. The right time to connect CEL_j is T_{cli}, and accordingly, the right time to disconnect it is T_{clf}. Thus, completion of the CEL_j operation cycle is required to occur between T_{cli} and T_{clf} periods. In order to model the toggle characteristics of each CEL illustrated in Table I, this work used the binary variable α_j to store the CEL_j connection status, where $\alpha_j = 0$ when CEL_j has not yet been connected, and $\alpha_j = 1$ when CEL_j has been connected. This work also used the binary variable β_j to store the CEL_j disconnection state, where $\beta_j = 0$ when CEL_j has not been disconnected, and $\beta_j = 1$ when the CEL_j has been disconnected. Therefore, Equation 4 models the connection and disconnection of CEL_j, and Equation 5 models the initial state when $t = 0$. Equations 4-5 ensure that CEL_j is not disconnected during its operation cycle. Equations 6 and 7 ensure that there is only one time for the shifting the states α_j and β_j. Equation 8 ensures that CEL_j fulfills its entire operation period. Equation 9 ensures that the variable x is zero during periods when the CEL_j 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.

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

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

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

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

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

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

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

B. 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 [8]. 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 $x_j = 1$, for which the Equation 11 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 12.

TABLE I. HOUSEHOLD APPLIANCES REQUIREMENTS

Load	Power (W)	Time of use (minutes)	Operation specification
Washing machine	1000	60	Do not disconnect during operation cycle
Clothes Dryer	800	60	Do not disconnect during operation cycle. Turn on after washing machine
Dishwasher	600	60	Do not disconnect during operation cycle
Rice cooker	500	30	Do not disconnect during operation cycle. Turn on before at 12:00 P.M.
Electric oven	1200	30	Do not disconnect during operation cycle
Electric pool pump	1000	240	Turn on between 06:00 A.M. and 8:00 P.M. avoiding noise at night
Electric kettle	800	15	Do not disconnect during operation cycle
Rechargeable equipment (Cell phone, etc.)	300	45	It must be fully charged at the time specified, for example 07:00 A.M.
Home Battery	800	120	Keep the minimum energy
EV	800	120	It must be fully charged at the time specified, for example 07:00 A.M.

$$\sum_{j=cel1}^{j=celn} x_{j,t} \leq \lambda \qquad \forall j \in \Omega_{cel} \quad (11)$$

$$\sum_{j=cel1}^{j=celn} x_{j,t} \cdot P_{j,t}^{cel} \leq \gamma \quad \forall j \in \Omega_{cel} \quad (12)$$

C. Fair cost when scheduling CEL:

A big challenge when programming loads in an smart building environment is to schedule the CEL for each user in an equitable, fair way; i.e., each CEL should be connected so that the average electricity bill of one user is fair, if compared with the others. In order to perform this task, this paper proposes a constraint that compares the costs of scheduling all the CELs from one with the others, and setting a limit for the difference between the electricity bills. If the limit value is small, then most users will pay a similar amount of money at the end of the day. This methodology is described in Equation 13, where φ defined the limit value.

$$\left| \sum_t \sum_{cel} x_{i,t} \cdot P_{i,t}^{cel} * C_t - \sum_t \sum_{cel} x_{j,t} \cdot P_{j,t}^{cel} \cdot C_t \right| \leq \varphi \quad \forall j \in \Omega_{cel} \quad (13)$$

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), and solved via commercial solver tool (CPLEX), where all equations used were linear.

IV. CASE STUDY

In this case study we used data obtained from the load profile from seven users 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 m^2 (7.5 kW, panels installed on the building roof). We used the same methodology as presented in our previous works showed in [20]-[21] 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 [22] 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 2, all input data for May 11th of 2015 are shown, including the power profile of the PV, the power profile from wind turbine, and price of electricity. The load profile from seven users is shown in Figure 3.

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 [21].

The first seven CELs in Table I were used for all users in each case. We have simulated only the CELs listed in Table I for two reasons: a) they are controllable loads, in other words, they can be automatically connected whether of the user is at home, or not; b) those loads are operated in on/off fashion, thus they are easy to model using the control variable $x_{j,t}$. We have considered that other appliances are adjustable equipment that can be automated for the user's comfort (e.g., heating and air conditioner). In addition, it was established that only the first five users have electric vehicles.

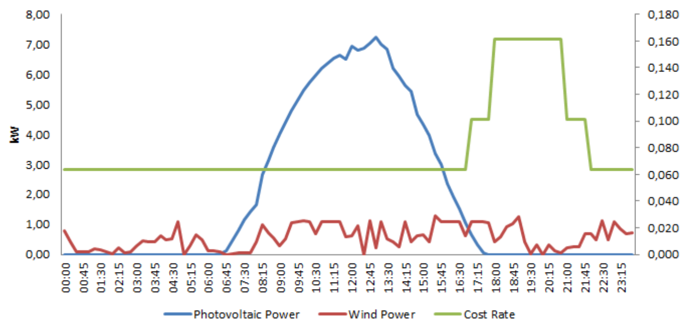

Figure 2. Case study input data in May 11th of 2015.

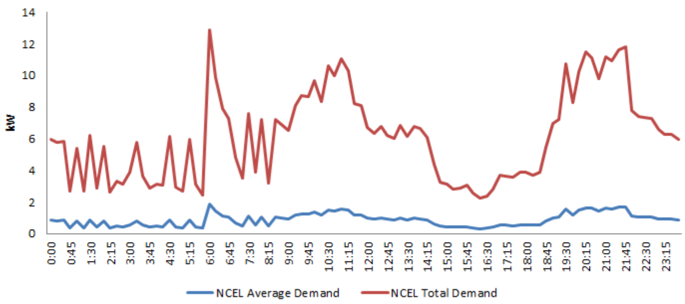

Figure 3. Demand profile - case study input data in May 11th of 2015.

V. ANALYSIS OF RESULTS

In Figure 4, sum of demand CEL curves for May 11th of 2015 are shown before and after the application of the proposed optimization process. The base case, where users freely connected seven CELs along the day, can be observed along with the optimized case in which the MCELS solved the problem. In Figure 5, the consumption from the grid is illustrated. In these figures, 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. Figure 5 compares the consumption from the grid considering the base case and the solution provided by MCELS, where a decreased consumption of 3% can be observed. As shown in Figure 5, the early hours have high energy consumption due to the recharging of five electric vehicles.

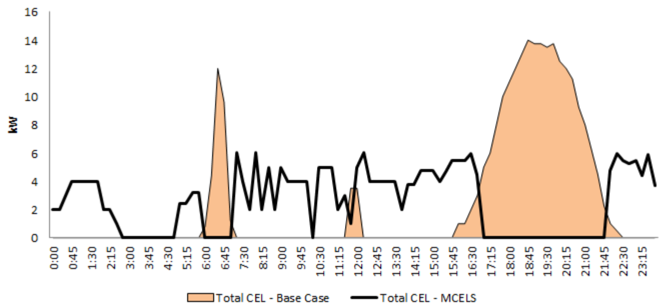

Figure 4. Demand CEL curves for May 11th of 2015

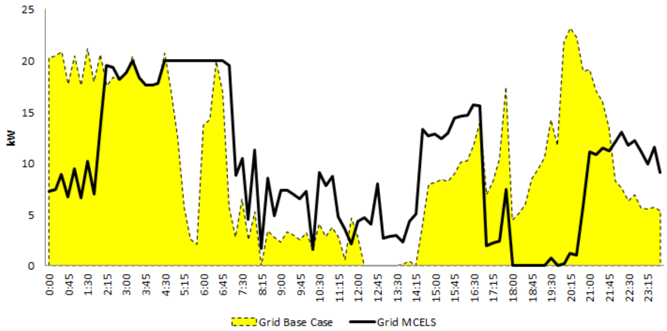

Figure 5. Consumption from the grid for May 11th of 2015

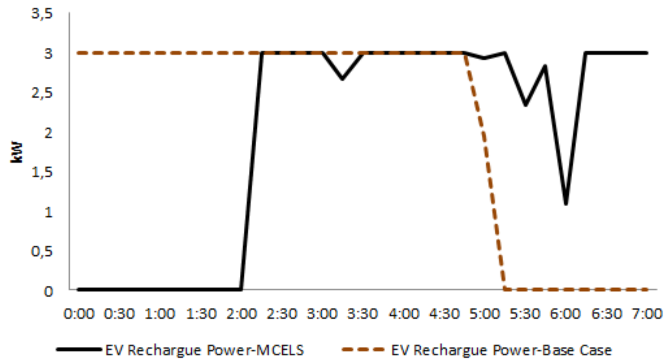

Figure 8. Operation of EV battery for May 11th of 2015

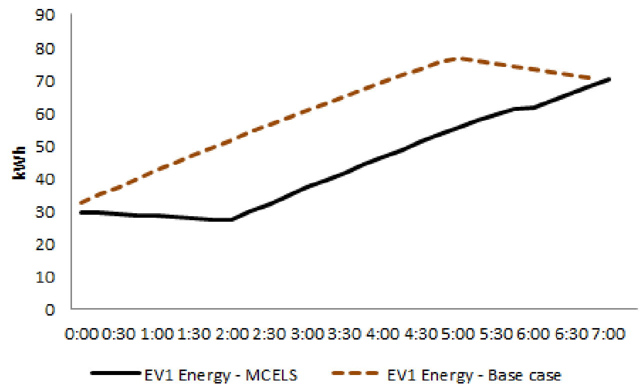

Figure 9. Energy of EV battery for May 11th of 2015

Figure 6 and Figure 7 show a comparison of operation and the energy stored respectively in the batteries for the base case and for the optimized scenario using MCELS. Figure 8 and Figure 9 show the recharging process and the energy stored, respectively, for the EV battery of one user. Figures 6, 7, 8, and 9 illustrate the optimized operation of the batteries for both, the base case and for the MCELS case, confirming the feasibility of each simulated scenario.

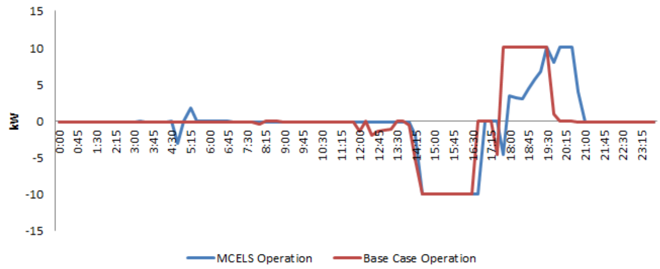

Figure 6. Operation of building battery for May 11th of 2015

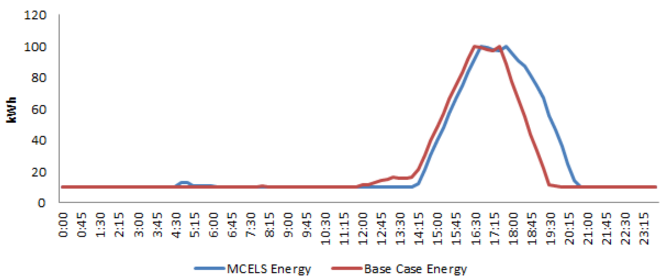

Figure 7. Building battery energy for May 11th of 2015

Electricity bills for each user in the base case are shown in column A of Table II. The first five users have a higher value because they have EVs.The cost of the CEL's, excluding the EV, are indicated in column B from Table II. Note that the costs of the seven users are all differents in spite of the fact that all users have the same CELs. C column indicates the reduction in the electricity bills when using the MCELS model, with a total reduction of 13.96% for the user 2, and 26% for the user 7 as illustrated in column E. Finally, column D shows the application of equation 13, where the proposed MCELS model schedules the CELs so that users pay the same bill, which is also illustrated in Figure 10.

TABLE II. COMPARING OPTIMIZATION RESULTS

	A	B	C	D	E
	Total Bill value/per day ($) Base Case	CEL - Base case - without EV ($USD)	Total Bill value/per day ($) MCELS	CEL-MCELS - without EV ($USD)	Bill Reduction (%)
User 1	3,85	1,18	3,13	0,5501	18,53
User 2	4,85	1,15	4,17	0,550	13,96
User 3	4,15	1,13	3,49	0,5501	15,68
User 4	3,57	1,13	2,96	0,5501	17,00
User 5	3,41	1,06	2,81	0,5501	17,29
User 6	2,92	1,16	2,30	0,5501	21,03
User 7	2,33	1,16	1,71	0,5501	26,27

I. CONCLUSION

Analysis of the results shows the stability of the MCELS when solving the CEL scheduling problem in residential smart buildings. Scheduling the connection of CELs was performed in compliance with each of the objectives for each user.

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.

Demand peaks were avoided by using the methodologies described in this paper, flattening the demand curve, and consequently leading to less effort from the electrical grid to supply the demand.

The proposed MCELS do not only make possible to reduce the electricity bill for each user but also, it established a fair payment policy when scheduling the CELs.

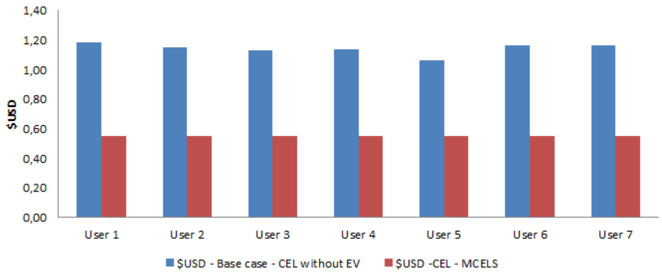

Figure 10. Comparing optimization results

ACKNOWLEDGMENT

This work was supported by Coordination for the Improvement of Higher Education Personnel Foundation (CAPES), Brazil - 2016.

REFERENCES

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

[2] E. Lee, A. Arbor, H. Bahn, “A Genetic Algorithm Based Power Consumption Scheduling in Smart Grid Buildings”, in The International Conference on Information Networking 2014 (ICOIN2014), pp.469-474, 10-12 Feb. 2014

[3] G. Bettinazzi, A. Nacci, and D. Sciuto, “Methods and Algorithms for the Interaction of Residential Smart Buildings with Smart Grids”, in 2015 IEEE 13th International Conference on Embedded and Ubiquitous Computing, pp.469-474, 10-12 Feb. 2014

[4] T. Wei, Q. Zhu, and N. Yu, “Proactive Demand Participation of Smart Buildings in Smart Grid”, in IEEE Transactions on Computers, Volume:65, Issue:5, 27 Outubro 2015

[5] M. Fanti, A. Mangini, and M. Roccotelli, “A Petri Net Model for a Building Energy Management System Based on a Demand Response Approach”, in 2014 22nd Mediterranean Conference on Control and Automation (MED), pp.816-821, June 16-19, 2014

[6] Y. Tajika, T. Saito, K. Teramoto, N. Oosaka, and M. Isshiki, “Networked home appliance system using Bluetooth technology integrating appliance control/monitoring with Internet service”, in IEEE Trans. Consumer Electron., vol.49, no.4, Nov. 2003, pp.1043-1048.

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

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

[9] L.I. Jeong, C. Chang-Sic, P. Wan-Ki, H. Jin-Soo and L. Il-Woo, “A study on the use cases of the smart grid home energy management system”, in ICT Convergence (ICTC) 2011 International Conference on, pp.746-750, 28-30 Sept. 2011

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

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

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

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

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

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

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

[17] S. Squartini, "Optimization algorithms for home energy resource scheduling in presence of data uncertainty", in 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”, in 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”, in IEEE Transactions on Smart Grid, Vol. 1, No. 2, September 2010

[20] 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", in 2015 IEEE Power and Energy Society General Meeting, pp.1-5, 26-30 July 2015.

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

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