A Mixed-integer Linear Programming Model for Optimal Management of Residential Electrical Loads under Dynamic Tariffs

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***Abstract*—This paper presents a mixed-integer linear programming model to automate energy decisions of residential consumers regarding the operation of shiftable, interruptible and thermostatic loads under dynamic tariffs. The cost objective function includes energy costs and a discomfort cost associated with the deviation of indoor temperature with respect to a comfort range. The model has been solved using GAMS/Cplex for a 24-hour planning period considering a 15-minute time discretization anddifferent consumer comfort profiles.**

***Keywords*—Mixed-integer linear programming, Demand response, Energy management**

I. Context and Motivation

Residential electricity consumers will be able to have a more active role in the management of the grid with potential economic benefits for households, as the process of evolution to smart grids advances. The deployment of smart meters, leading to further and more frequent information available, offers the technological basis for residential consumers to contribute to a more efficient balance between electrical energy supply and demand. From the perspective of the grid, the management of the flexibility of residential end-users regarding the time and settings of operation of some loads, by effective reduction and shifting of consumption to off-peak periods, will enable to release network congestion and decrease losses. These load management activities have a positive impact on postponing network reinforcement investments due to better peak management, as well as on peak generation capacity expansion [1]. Decreasing load during more critical peak periods reduces the need to use thermal power plants with higher variable costs thus diminishing energy marginal prices. Moreover, renewable energy sources can be used at a larger extent since better demand management enables to adjust the demand profile to their intermittent nature with impact on generation availability (i.e., adopting load follows supply strategies). In addition, since this surplus generation often happens in periods of lower demand, consumption profiles more aligned with the renewable generation capacity imply a lower need to export electrical energy generated by renewable sources at very low prices [2].

Currently, even where competition exists in retail electricity markets, tariff schemes do not provide, in general, the necessary stimulus for changing consumers' habitual energy behaviors [1] by making the most of their flexibility in the usage of loads (which provide energy services such as laundry, hot water, air conditioning, electric vehicle charging, etc.). Dynamic tariffs, i.e. energy prices varying possibly with significant magnitude in short periods of time, have the potential to convey the incentives leading to the modulation of demand thus contributing to improve the overall system efficiency while offering economic benefits to consumers [3]. It is expected that consumers adhering to dynamic tariff schemes and able to exploit their demand flexibility, namely by shifting demand to off-peak periods and redefining thermostat settings without jeopardizing comfort, will benefit from lower average prices [4].

Dynamic tariff schemes offered by electricity retailers (also accounting for variable network access prices) are already being implemented in some countries and several pilot projects are underway or planned. The active integrated optimization of residential energy resources (grid, local generation, storage systems, shiftable, interruptible and thermostatically controlled loads) in face of dynamic tariffs, as well asend-users' preferences and comfort requirements, can be made operational by means of home energy management systems (HEMS) [5].

These HEMS receive price (and possibly emergency) signals from the grid, can be parameterized with the end-user's preference information and send instructions to devices (for instance, using the zigbee communication protocol). After receiving price information some time in advance (e.g., one day), the consumer's HEMS is able to respond by scheduling the operation of laundry machines, electric vehicle charging, etc., or re-parameterizing thermostat settings [6]. HEMS should be affordable for a wide acceptance and deployment, typically running on low cost processors with mild computational requisites. In this setting, computational intelligence residing in HEMS should be able to run locally to generate solutions to be communicated through appropriate control signals to devices associated with the energy resources, e.g. on/off signals to be sent to shiftable loads or increase/decrease room temperature comfort thresholds (thermostat dead-band).

In this context, this paper presents a comprehensive mixed-integer linear programming (MILP) model to optimize the energy decisions of a residential consumer regarding the operation of shiftable, interruptible and thermostatic loads. The new model proposed herein includes the physical characterization of the operation cycles of non-interruptible shiftable appliances (e.g. dishwasher), interruptible appliances (e.g. electric water heater) and thermostatic loads (air conditioning). It is further considered that some interruptible and thermostatic loads can be operated at different power levels. The overall cost objective function to be minimized includes energy costs and a discomfort cost associated with the deviation of indoor temperature with respect to a comfort range. The model is solved using a general solver (Cplex), considering different values of the coefficient penalizing temperature deviation and the difficulty of its resolution is analyzed.

The MILP model is comprehensively described in section II. Illustrative results are presented in section III. Conclusions are drawn in section IV.

II. Model and Methods

The MILP model considers a planning period (e.g., one day) in which time-differentiated tariffs are known in advance (e.g., day-ahead). According to the type of control, the loads being managed are categorized in: shiftable, interruptible and thermostatic-controlled loads. Shiftable loads includelaundry, dishwasher and cloth dryer. Interruptible loads includeelectric water heater (EWH) and electric vehicle (EV). The thermostatic-controlled load is an air conditioning appliance (AC). Moreover, the EV and the AC (inverter type) can be supplied at different power levels, while the EWH is supplied at constant power. Constraints refer to contracted power to supply all types of loads, feasible time slots for operation of shiftable and interruptibleloads, amount of energy to be supplied to interruptible loads (as a surrogate for water temperature in EWH and EV battery state-of-charge), and comfort temperature range for the thermostatically-controlled load, according to the consumer'spreferences.

The model, which builds on [7-10], has been solved using GAMS/Cplex with different time discretization (15, 5 and 1 minute) of the planning period $\mathrm{T} = \{1, \dots, T\}$ and consumer profiles (more or less willing to trade-off cost vs. comfort). A dynamic tariff scheme is considered, with time-differentiated energy prices π_i (€/kWh) being applied in each sub-period P_i, $i \in \{1, \dots, I\}$ of the whole planning period.

The cost objective function (1) encompasses the energy cost of the base load (which is not controllable) and the operation of shiftable, interruptible and thermostatic loads plus a term monetizing the discomfort resulting from the deviation of indoor temperature θ_t^{in}, $t = 1, \dots, T$, outside the comfort range $[\theta_t^{min}, \theta_t^{max}]$. For this purpose, a monetary penalty coefficient per degree of deviation ρ (€/ºC) is considered [11].

For shiftable load $j = 1, \dots, J$, the following information is required: the comfort time slots $T_j = \left[T_{1_j}, T_{2_j}\right]$ allowed for its operation according to the consumer's preferences; the characterization of the operation cycle with duration d_j, being f_{jr} the power requested at stage r. Variable $w_{jrt} = 1$ if shiftable appliance j is "on" at time $t \in T_j$ and stage r of its operation cycle. Constraints (2)-(9) model the operation of shiftable appliances.

Interruptible loads can be supplied at constant power, $k = 1, \dots, K$, or at different power levels, $m = 1, \dots, M$. For both types of interruptible loads, the comfort time slots $T_k = \left[T_{1_k}, T_{2_k}\right]$ and $T_m = \left[T_{1_m}, T_{2_m}\right]$ allowed for operation of loads k and m should be specified according to the consumer's preferences. It should also be set the constantpower Q_k or the different levels of power Q_m^1, $Q_m^2, \dots, Q_m^S$ necessary to operate the interruptible load for a total energy E_k or G_m to be supplied. Variables $u_{kt} = 1$ if interruptible appliance k supplied at constant power Q_k is "on" at time $t \in T_k$. Variables $x_{mt}^s = 1$ if interruptible appliance m is supplied at power level Q_m^s, $s = 1, \dots, S$ at time $t \in T_m$. Constraints (10)-(14) model the operation of interruptible appliances supplied at constant power. Constraints (15)-(20) model the operation of interruptible appliances that can be supplied at different power levels.

The thermostatic load is an inverter type AC system, which can be "off" or operated at 20-40-60-80-100% of the nominal power P_{nom}^{AC}. The user should specify the indoor temperature comfort range $[\theta_t^{min}, \theta_t^{max}]$ at instant t (this may be constant for the whole planning period, i.e. $[\theta^{min}$, $\theta^{max}]$ for all t. Decision variables δ_t^s=1 if the AC is operating at load level s=1,…,5, corresponding to the levels 20-40-60-80-100%, respectively, at time $t \in \mathrm{T}$. v_t is the temperature deviation of θ_t^{in} (indoor temperature) below θ_t^{min} or above θ_t^{max} at time t. Constraints (21)-(26) model the operation of the AC. Constraint (21) is obtained from the thermal balance of a building unit being heated by an AC. Parameters α, β, and γ result from the building characteristics and the AC coefficient of performance (COP). α=1-β, and $\beta = UA.\Delta t / C$ are non-dimensional and γ is expressed in ºC/W. U is the global heat transfer coefficient of the building envelope (expressed in kW/(m^2.ºC)), C is the global thermal capacity of indoor air (kJ/ºC), A is the area of the surface envelope (m^2), $U.A$ is the thermal conductance of the building envelope (kW/ºC) and Δt is the time interval; θ_t^{ext} is the outdoor temperature. Powers are expressed in kW and energy in kWh regardless of the time discretization of the planning period.

A base load b_t not suitable for control is considered, which accounts for utilizations such as oven, entertainment, etc.

Constraint (27) imposes an upper bound P_t^{cont} on the power requested from the grid, which is generallyestablished in the contract with the energy retailer.

$$\min f = \sum_{i=1}^{I} \sum_{t \in P_i} \pi_i \big(b_t + \sum_{j=1}^{J} p_{jt} + \sum_{k=1}^{K} q_{kt} + \sum_{m=1}^{M} y_{mt} + p_t^{AC}\big) + \sum_{t \in T} \rho v_t \tag{1}$$

s. t.

$$p_{jt} = \sum_{r=1}^{d_j} f_{jr} w_{jrt}, \; j = 1, \dots, J, t = T_{1_j}, \dots, T_{2_j} \tag{2}$$

$$p_{jt} = 0, \; j = 1, \dots, J, t < T_{1_j} \vee t > T_{2_j} \tag{3}$$

$$\sum_{r=1}^{d_j} w_{jrt} \leq 1\ ,\ j = 1, \dots, J\ , t = T_{1_j}, \dots, T_{2_j} \quad (4)$$

$$w_{j(r+1)(t+1)} \geq w_{jrt}\ ,\quad j = 1, \dots, J\ ,\ \ r = 1, \dots, (d_j - 1)\ ,$$
$$t = T_{1_j}, \dots, (T_{2_j} - 1) \quad (5)$$

$$\sum_{t=T_{1_j}}^{T_{2_j}} w_{jrt} = 1\ ,\ j = 1, \dots, J\ , r = 1, \dots, d_j \quad (6)$$

$$\sum_{t=T_{1_j}}^{T_{2_j}-d_j+1} w_{j1t} \geq 1\ ,\ j = 1, \dots, J \quad (7)$$

$$w_{jrt} \in \{0,1\}\ , j = 1, \dots, J\ , r = 1, \dots, d_j\ , t = T_{1_j}, \dots, T_{2_j} \quad (8)$$

$$p_{jt} \geq 0\ ,\ j = 1, \dots, J\ , t = 1, \dots, T \quad (9)$$

$$q_{kt} = u_{kt} Q_k\ ,\ k = 1, \dots, K\ , t = T_{1_k}, \dots, T_{2_k} \quad (10)$$

$$q_{kt} = 0\ ,\ k = 1, \dots, K\ , t < T_{1_k} \vee t > T_{2_k} \quad (11)$$

$$\sum_{t=T_{1_k}}^{T_{2_k}} q_{kt} = E_k\ ,\ k = 1, \dots, K \quad (12)$$

$$u_{kt} \in \{0,1\}\ , \quad k = 1, \dots, K,\ t = T_{1_k}, \dots, T_{2_k} \quad (13)$$

$$q_{kt} \geq 0\ ,\ k = 1, \dots, K\ ,\ t = 1, \dots, T \quad (14)$$

$$y_{mt} = \sum_{s=1}^{S} x_{mt}^s Q_m^s,\ ,\ m = 1, \dots, M\ ,\ t = T_{1_m}, \dots, T_{2_m} \quad (15)$$

$$\sum_{s=1}^{S} x_{mt}^s \leq 1,\ ,\ m = 1, \dots, M\ ,\ t = T_{1_m}, \dots, T_{2_m} \quad (16)$$

$$\sum_{t=T_{1_m}}^{T_{2_m}} y_{mt} = G_m\ ,\ m = 1, \dots, M \quad (17)$$

$$y_{mt}^s = 0\ ,\ s = 1, \dots, S,\ m = 1, \dots, M\ ,\ t < T_{1_m} \vee t > T_{2_m} \quad (18)$$

$$x_{mt}^s \in \{0,1\}\ ,\ s = 1, \dots, S,\ \ m = 1, \dots, M,\ t = T_{1_m}, \dots, T_{2_m} \quad (19)$$

$$y_{mt} \geq 0\ ,\ m = 1, \dots, M\ ,\ t = 1, \dots, T \quad (20)$$

$$\theta_t^{in} = \alpha \theta_{t-1}^{in} + \beta \theta_{t-1}^{ext} + \gamma P_t^{AC}\ , \quad t = 1, \dots, T \quad (21)$$

$$p_t^{AC} = (0.2\delta_t^1 + 0.4\delta_t^2 + 0.6\delta_t^3 + 0.8\delta_t^4 + \delta_t^5)\, P_{nom}^{AC}\ \ ,\ t = 1, \dots, T \quad (22)$$

$$\delta_t^1 + \delta_t^2 + \delta_t^3 + \delta_t^4 + \delta_t^5 \leq 1 \qquad ,\ t = 1, \dots, T \quad (23)$$

$$v_t\ \geq\ \theta_t^{min} - \theta_t^{in} \qquad ,\ t = 1, \dots, T \quad (24)$$

$$v_t\ \geq\ \theta_t^{in} - \theta_t^{max} \qquad ,\ t = 1, \dots, T \quad (25)$$

$$v_t\ \geq 0 \qquad ,\ t = 1, \dots, T \quad (26)$$

$$b_t + \sum_{j=1}^{J} p_{jt} + \sum_{k=1}^{K} q_{kt} + \sum_{m=1}^{M} y_{mt} + P_t^{AC} \leq P_t^{cont}\ ,\ t = 1, \dots, T \quad (27)$$

III. RESULTS

This section reports the computational results obtained with the MILP model presented in the previous section with 15-minute discretization of the planning period (i.e., 96 time steps in 24 hours) and different values of the coefficient penalizing temperature deviation with respect to comfort range. Results have been obtained for the data instantiation mentioned below. The model was coded in GAMS and solutions were obtained using the Cplex solver. A MIP gap of 0.5% was set to avoid an excessive computational burden.

Figure1 displays dynamic tariff prices. Figure 2 presents the base load, which is not deemed for control. The operation cycles of shiftable loads (dishwasher, laundry machine and clothes dryer) are displayed in Figure 3. Each shiftable load requires a specific amount of power at each stage of its operation cycle. Experiments have been carried out for three consumer profiles, with different willingness to trade-off cost vs. comfort.

The time slots allowed for operation of shiftable loads, with 15-minute discretization are: Base comfort profile - dishwasher [t1-t36], laundry [t32-t60], cloth dryer [t76-t96]; Restricted comfort profile - dishwasher [t1-t34], laundry [t32-t50], cloth dryer [t70-t82]; Extended comfort profile - dishwasher [t1-t44], laundry [t28-t65], cloth dryer [t70-t96].

The EWH is operated as an interruptible load supplied at fixed power level $Q_1 = 1.5$ kW and the energy required during the planning period is $E_1 = 7.5$ kWh. The time slots allowed for the EWH operation are: Base comfort profile – [t24-t40]; Restricted comfort profile – [t24-t36]; Extended comfort profile – [t24-t45].

The EV is operated as an interruptible load that can be supplied at three power levels: $Q_1^1 = 1.38$, $Q_1^2 = 2.3$, and $Q_1^3 = 3.68$ kW. The total energy required for the EV is $G_1 = 20.7$ kWh (state-of-charge 100%). The time slots allowed for the EV operation are: Base comfort profile – [t1-t48]; Restricted comfort profile – [t1-t45]; Extended comfort profile – [t1-t48].

The AC is operating in heating mode. The temperature data recorded in Coimbra on 01-01-2012 is considered as the outdoor temperature in (21). The initial indoor temperature is $\theta_0^{in} = 18$ °C. α, β and γ are equal to 0.8569, 0.1431 and 0.002775 °C/W respectively (for the 15-min. time discretization). The comfort range for the indoor temperature is $[\theta^{min}, \theta^{max}]$=[20°C, 24°C] and the nominal power of the AC is $P_{nom}^{AC} = 1.5$ kW.

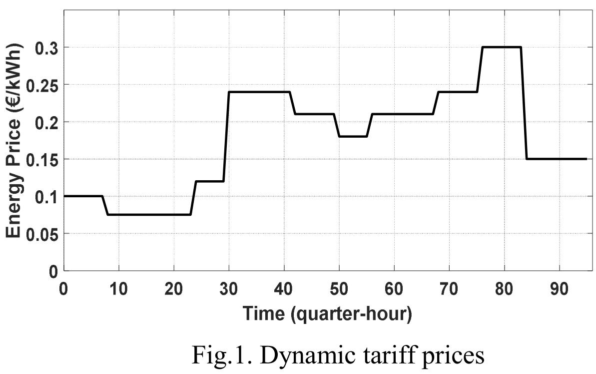

Fig.1. Dynamic tariff prices

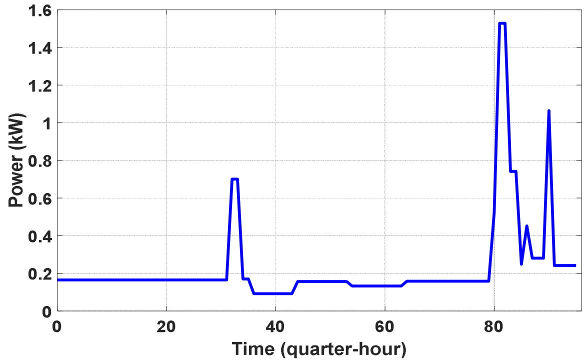

Fig.2. Base load profile

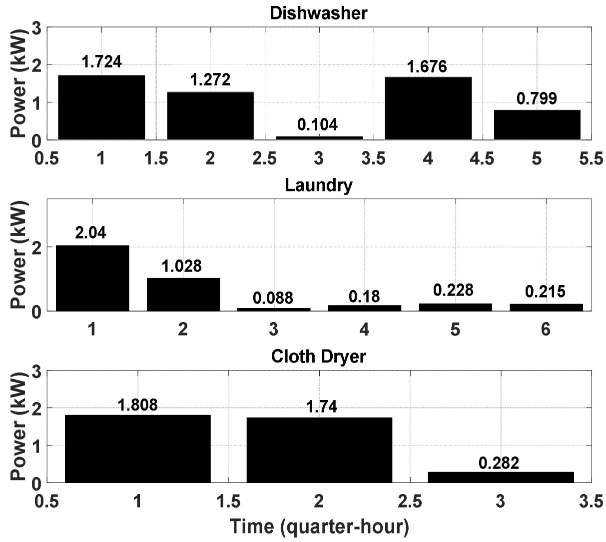

Fig.3. Operation cycle patterns of shiftable loads

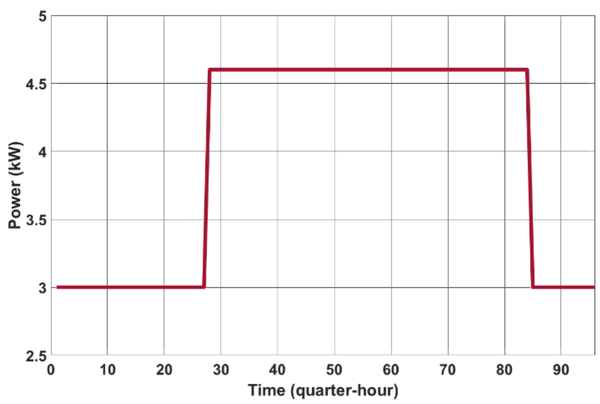

Fig.4. Contracted power

Two very distinct values of the temperature deviation penalty coefficient ρ were considered for illustrative purposes: 0.2 €/ºC and 20 €/ºC.

The contracted power limitation throughout the planning period is displayed in Figure 4.

The results for 15-min. discretization for the three consumer (base, restricted and extended) profiles are presented in Tables 1-3. The number of continuous and binary variables in the model are 768 and 2208, respectively. The number of constraints considered for base, restricted and extended profiles is 1643,1545 and 1751, respectively.

The higher penalty coefficient ρ=20 €/ºC considerably decreases the computational time and avoids temperature deviation in all comfort profiles, although the electricity bill increases, thus evidencing the cost vs. comfort trade-off.

The corresponding schedule of the shiftable loads is detailed in Table 4. For each temperature deviation penalty coefficient, wider time slots allowed for load operation give more freedom to shiftable loads to operate when electricity is cheaper. For instance, in the restricted comfort profile, laundry is operated in the time slot [t45-t50] while in the base and extended comfort profiles it is operated in the time slot [t51-t56], which includes lower prices according to Figure 1.

The scheduling of the two interruptible loads, EWH and EV, is presented in Figures 5-8, for ρ=0.2 €/ºC and ρ=20 €/ºC. For the extended comfort profile, the EWH is allowed to operate in time slot [t24-t45], which includes lower prices compared to the other comfort profiles, thus leading to a lower electricity bill. The same pattern is seen for the EV. For example, during the time period [t31-t42]a local peak price of 0.24 €/kWh happens. The EV shouldbe charged in this period in the restricted comfort profile, while this is avoided in the operation under base and extended profiles.

The scheduling of the AC is presented in Figures 9 and 10, for ρ=0.2 €/ºC and ρ=20 €/ºC, respectively. With the lower temperature deviation penalty coefficient, the indoor temperature is kept close to 20 ºC to avoid extra AC consumption. However, with the higher penalty coefficient, the indoor temperature has some peaks close to the upper limit of the comfort range (24 ºC), which leads to a higher electricity bill.

Table 1- Results for 15-min. discretization, base profile

Time discretization	15 minute	
Comfort profile	Base	
ρ (€/ºC)	0.2	20
Cplex time (s)	325.88	5.19
Min f (€)	6.68343	6.822651
Electricity bill (€)	6.67623	6.822651
Penalty term (€)	0.0072	0
Relative gap	0.47 %	0.48 %
Temperature deviation (ºC)	t96: 0.036	0

Table 2- Results for 15-min. discretization, restricted profile

Time discretization	15 minute	
Comfort profile	Restricted	
ρ (€/ºC)	0.2	20
Cplex time (s)	329.47	2.42
Min f (€)	6.903374	7.036994
Electricity bill (€)	6.899974	7.036994
Penalty term (€)	0.0034	0
Relative gap	0.46 %	0.49 %
Temperature deviation (ºC)	t28: 0.017	0

Table 3- Results for 15-min. discretization, extended profile

Time discretization	15 minute	
Comfort profile	Extended	
ρ (€/ºC)	0.2	20
Cplex time (s)	2322.77	3.86
Min f (€)	6.693351	6.812326
Electricity bill (€)	6.693351	6.812326
Penalty term (€)	0	0
Relative gap	0.47 %	0.46 %
Temperature deviation (ºC)	0	0

Table 4- Schedule of shiftable loads, 15-min. discretization

Time discretization	15 minute		
Shiftable load	Dishwasher	Laundry	Cloth dryer
ρ / Comfort profile	0.2€/ºC		
Base	[t11-t15]	[t51-t56]	[t92-t94]
Restricted	[t8-t12]	[t45-t50]	[t74-t76]
Extended	[t11-t15]	[t51-t56]	[t94-t96]
ρ / Comfort profile	20 €/ºC		
Base	[t18-t22]	[t51-t56]	[t93-t95]
Restricted	[t18-t22]	[t45-t50]	[t74-t76]
Extended	[t5-t9]	[t51-t56]	[t94-t96]

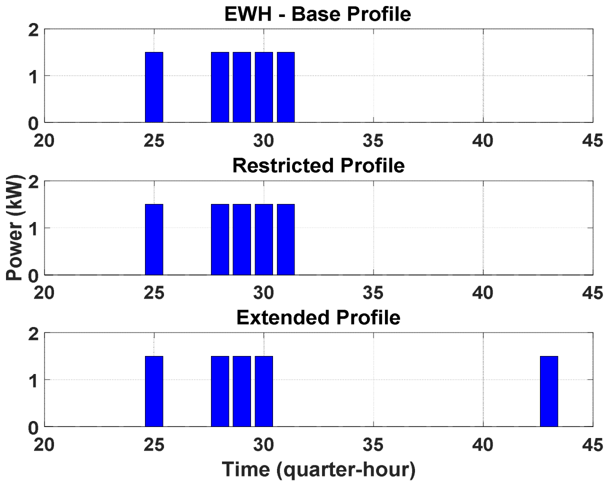

Fig. 5. Scheduling of EWH for ρ=0.2 €/ºC and 15-min. time discretization

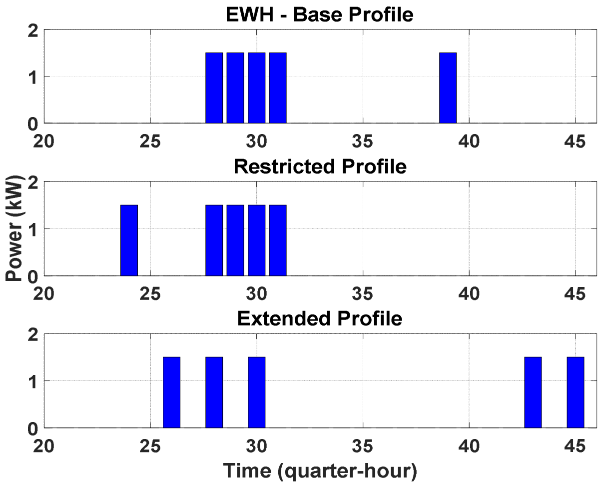

Fig. 6. Scheduling of EWH for ρ=20 €/ºC and 15-min. time discretization

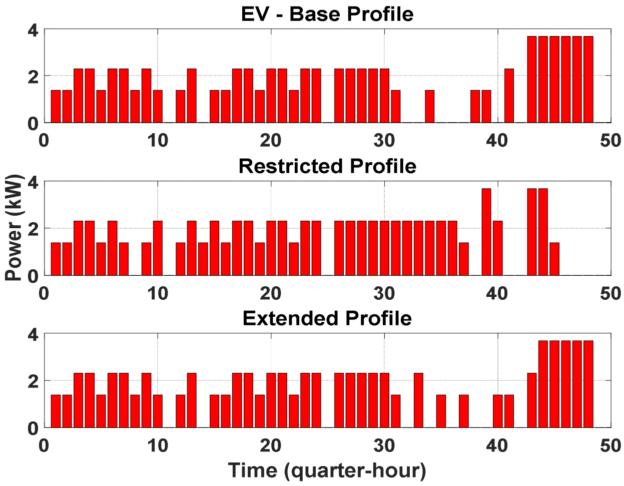

Fig. 7. Scheduling of EV for ρ=0.2 €/ºC and 15-min. time discretization

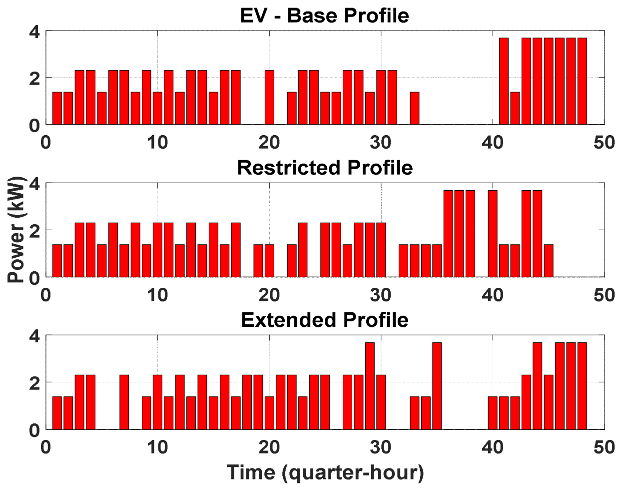

Fig. 8. Scheduling of EV for ρ=20 €/ºC and 15-min. time discretization

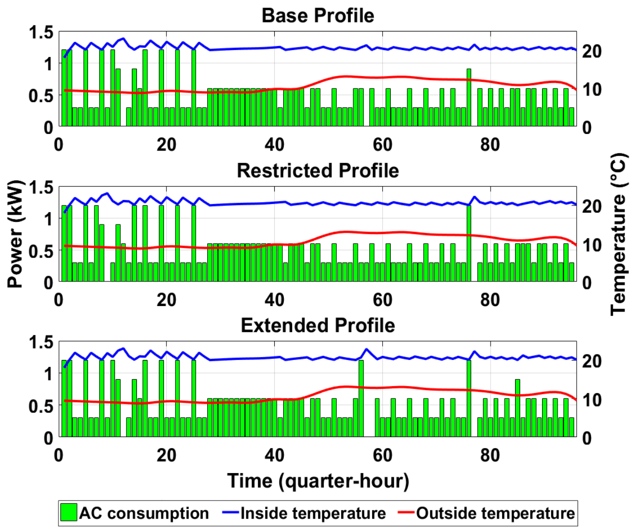

Fig. 9. Scheduling of AC for ρ=0.2 €/ºC and 15-min. time discretization

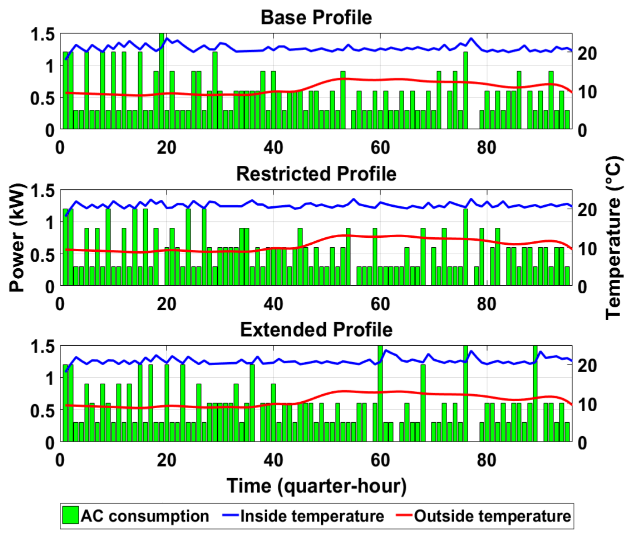

Fig. 10. Scheduling of AC for ρ=20 €/ºC and 15-min. time discretization

IV. CONCLUSIONS

Results unveil that residential consumers may achieve important savings by exploiting their flexibility in the usage of loads (shiftable, interruptible and thermostatic loads), while dependent on comfort preferences and degree of willingness to accept automated HEMS control.

The exact solution of the MILP model may involve a significant computational effort, which may become impractical for finer time discretization. Therefore, customized meta-heuristic approachesmay be advantageous from the computational effort point of view, also having in mind being embedded in HEMS.

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REFERENCES

[1] V. Venizelou, N. Philippou, M. Hadjipanayi, G. Makrides, V. Efthymiou, and G. E. Georghiou, “Development of a novel time-of-use tariff algorithm for residential prosumer price-based demand side management,” Energy, vol. 142, pp. 633-646, January 2018.

[2] S. Stelt, T. AlSkaif, and W. Sark, “Techno-economic analysis of household and community energy storage for residential prosumers with smart appliances,” Applied Energy, vol. 209, pp. 266-276, January 2018.

[3] P. Layer, S. Feurer, and P. Jochem, “Perceived price complexity of dynamic energy tariffs: An investigation of antecedents and consequences,” Energy Policy, vol. 106, pp. 244-254, July 2017.

[4] E. A. M. Klaassen, C. B. A. Kobus, J. Frunt, and J. G. Slootweg, “Responsiveness of residential electricity demand to dynamic tariffs: Experiences from a large field test in the Netherlands,” Applied Energy, vol. 183, pp. 1065-1074, December 2016.

[5] M. Shakeri et al., “Implementation of a novel home energy management system (HEMS) architecture with solar photovoltaic system as supplementary source,” Renewable Energy, vol. 125, pp. 108-120, September 2018.

[6] T. Sattarpour, D. Nazarpour, and S. Golshannavaz, “A multi-objective HEM strategy for smart home energy scheduling: A collaborative approach to support microgrid operation,” Sustainable Cities and Society, vol. 37, pp. 26-33, February 2018.

[7] M. J. Alves, and C. H. Antunes, “A semivectorial bilevel programming approach to optimize electricity dynamic time-of-use retail pricing,”Computers & Operations Research, vol. 92, pp. 130-144, 2018.

[8] M. J. Alves, C. H. Antunes, and P. Carrasqueira, “A hybrid genetic algorithm for the interaction of electricity retailers with demand response,” Applications of Evolutionary Computation, vol. 9597, pp. 459-474, 2016.

[9] P. Carrasqueira, M. J. Alves, and C. H. Antunes, “Bi-level particle swarm optimization and evolutionary algorithm approaches for residential demand response with different user profiles,” Information Sciences,vol. 418-419, pp. 405-420, 2017.

[10] A. Soares, Á. Gomes, and C. H. Antunes,“Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions,” Renewable and Sustainable Energy Reviews, vol. 30, pp. 490-503, 2014.

[11] M. Zugno, J. M. Morales, P. Pinson, and H. Madsen,“A bilevel model for electricity retailers' participation in a demand response market environment,” Energy Economics, vol. 36, pp. 182-197, 2013.