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A MILP model to relieve the occurrence of new demand peaks by improving the load factor in smart homes

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ABSTRACT

Demand response (DR) programs based on pricing options allow residential customers to achieve a financial reduction in their energy bill due to changes in their consumption patterns, especially during peak periods. However, when a large number of consumers adopt this energy management program, the demand shifted to periods with low energy prices can generate new demand peaks. As a result, the quality of the power supply service may be compromised. To address this concern, this paper proposes a mixed-integer linear programming (MILP) model that aims to improve the load factor (LF) related to the demand profile of customers. To achieve this goal, an intelligent scheduling strategy for household appliances that considers flexibility in customer comfort, here called customer hourly preferences, is developed. Based on these preferences, the strategy seeks the efficient daily usage of smart appliances, mainly those with higher average power, to avoid its coincident consumption in periods with lower energy rates, thus mitigating the appearance of new peaks. In the proposed model, the operating expenses of both customers and the electricity company (ECO) are minimized. A set of technical and operational constraints such as the average power, number of times utilized, and average time of usage of home appliances, as well as the charging rate, average time for charging, and initial state-of-charge (SoC) of the plug-in electric vehicle (PEV) battery, are considered. Uncertainties related to the periods of the day when a given appliance (including PEV) is turned-on for consumption are modeled using a Monte Carlo Method (MCM). The MILP model is solved using a commercial solver CPLEX that makes use of classical optimization techniques to ensure the optimal solution to this problem. The performance of the MILP model was tested through two case studies. Case study 1 considers a group of consumers with the same income, while case study 2 triples the number of consumers in the previous case considering different incomes. The results show the importance of the proposed tool for analyzing and evaluating prospective scenarios that guarantee the efficient usage of electric energy with the lowest financial expense for both consumers and the ECO.

1. Introduction

1.1. Context

Information and communication technologies (ICTs) are the backbone of *Smart Grids* (SGs). They allow the bi-directional flow of information between consumers' homes and electricity companies (ECOs). Through these technologies, ECOs can know the behavior patterns of their consumers when turning on a given set of appliances in the day. Thus, energy needs of residential customers can be met efficiently, safely, and reliably (Ekanayake, Liyanage, Wu, Yokoyama, & Jenkins, 2012; Sioshansi, 2012).

In the SG environment, smart domestic homes are equipped with control, measurement, and sensing systems to reach a certain level of automation. In these smart homes, smart household appliances exchange information with the smart meter. In turn, the meter communicates information related to the customer's demand profile to the ECO operation center. Communication networks, such as home area network (HAN), neighborhood area network (NAN), and wide area network (WAN), are used to support this flow of information (Bem Dhaou, 2019; Obushevs, Oleinikova, & Mutule, 2016; Saleem, Crespi, Rehmani, & Copeland, 2019). Based on this data flow, electric power companies can devise efficient strategies on the demand side to manage electricity usage in each domestic unit, considering the operational limits of the power grid. To do this, a promising alternative is in the implementation

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Nomenclature

A. Functions

F Objective function
Ω_1 Cost function related to customers energy bill
Ω_2 Cost function related to the usage of appliances with higher average power
Ω_3 Cost function related to ECO's financial gains
$|.|$ Cardinal of a set

B. Sets and indexes

u Index for customers
a Index for smart appliances
t Index for periods
y Index for discrete blocks
$\mathbb{U}$ Set of home customers u
$\mathbb{A}$ Set of smart appliances a
$\mathbb{T}$ Set of periods t
$\mathbb{Y}$ Set of discrete blocks y

C. Parameters

ζ_t Hourly tariff ($/kWh)
B_u PEV battery capacity related to customer u (kWh)
β_a Indicates the type of appliances a (−1: PEV; 0: appliances with working hours less than 1 h; 1: appliances with working hours greater than or equal to 1 h)
$\beta_a^{'}$ Binary parameter that adopts 1 for higher average power appliances; otherwise 0
$\mathscr{D}_{a,t}$ Probability distribution related to the consumption of household appliances a at period t
$\widehat{\mathscr{D}}_{a,t}$ Accumulated probability distribution related to the consumption of household appliances a at period t
$\mathscr{H}^{cp}_{u,a,t}$ Habitual consumption profile (kWh). Indicates the energy consumed by the customer u when turn-on appliance a at period t
$\mathscr{M}$ Big value used in the linearization process
P_a Average power of appliance a (kW)
P^{ev} Charging rate of the PEV battery (kW)
q_a Number of time that appliance a is turned-on for less than 1 h
$\underline{q}_a/\overline{q}_a$ Minimum and maximum number of times that the appliance a is turned on throughout the day
$\underline{q}^{ch}_u/\overline{q}^{ch}_u$ Minimum and maximum number of times that the PEV battery related to the customer u can be charged
SoC^0_u Initial state-of-charge of the PEV battery related to user u (kWh)
s Accumulator
Δt Duration of each period t (h)
$\theta^c_{u,a,t}$ Customer hourly preference. Indicates the periods t of flexibility in which an appliance a can be connected for consumption without affecting customer u comfort
t^{av}_a Average time that an appliance a is turned-on for power consumption (h)
$\left[\underline{t}_a, \overline{t}_a\right]$ Time variation interval within the period t in which the appliance a is turned on (h)
$\left[\underline{t}^{ev}_u, \overline{t}^{ev}_u\right]$ Time variation interval of the variable $\tau^{ev}_{u,t}$ (h)
$\mathscr{X}^{hu}_{u,a,t}$ Binary value related to $\mathscr{H}^{cp}_{u,a,t}$. Indicates the status of a given appliance a (1: the customer u has turned on the appliance a at period t; 0: otherwise)
ξ Represents the final state-of-charge of the PEV battery in percentage
η Charging efficiency of the PEV battery
$\mu^{'}, \mu^{''}, \mu^{'''}$ Weights related to Ω_1, Ω_2, and Ω_3, respectively
$\Pi_{t,y}$ Inclination value related to the discrete block y at period t (equal to $[2y-1] \times \overline{\Delta}_t$)
$\overline{\Delta}_t$ Upper limit related to the variable $\Delta\Gamma_{t,y}$

D. Variables

$\mathscr{X}^{ou}_{u,a,t}$ Binary value related to $\mathscr{O}^{cp}_{u,a,t}$. Indicates the status of a given appliance a (1: the customer u has connected the appliance a at period t; 0: otherwise)
$\theta^{'}_{u,t}$ Coincidence factor. Represents for each customer u the number of appliances that are turned-on for consumption at the same period t
$\mathscr{O}^{cp}_{u,a,t}$ Optimal consumption profile (kWh). Indicates the energy to be consumed by the customer u when turn on the appliance a at period t
$\tau^{us}_{u,a,t}$ Continuous variable that represents for each customer u the time that the appliance a is turned on in the period t (h)
$\mathscr{G}^{ev}_{u,t}$ Continuous variable that represents for each customer u the energy stored in the PEV battery at period t (kWh)
$\tau^{ev}_{u,t}$ Continuous variable that represents to the customer u the charging time of the PEV battery at period t (h)
$\mathscr{G}^{s}_{u}$ Continuous variable that represents for each customer u the total energy stored by PEV battery (kWh)
P^{eu}_t Continuous variable that represents the power supplied by the ECO in each period t (kW)
$\overline{P}^{eu}$ Average value related to the variable P^{eu}_t (kW)
$\Delta\tau^{us}_{u,a,t}$ Represents the product $\tau^{us}_{u,a,t} \times \mathscr{X}^{ou}_{u,a,t}$ to be linearized
$\Delta\tau^{pev}_{u,a,t}$ Represents the product $\tau^{pev}_{u,t} \times \mathscr{X}^{ou}_{u,a,t}$ to be linearized
Γ_t Represents the difference between P^{eu}_t and $\overline{P}^{eu}$ at period t
$\Delta\Gamma_{t,y}$ Auxiliary variable to be used in the square of Γ_t discretization process
Γ^+_t/Γ^-_t Auxiliary variables to be used in the objective function discretization process

of demand response (DR) programs. Through these DR programs, the minimization of operating costs related to both customers and ECO can be reached (Shawkat Ali, 2013).

Basically, DR programs are based on financial incentives, demand bids, or price options (Shareef, Ahmed, Mohamed, & Hassan, 2018). Financial incentives programs involve strategies, such as direct load control, load shedding, and demand reward, which aim to reduce customer demand at a certain time of day (Hussain & Gao, 2018; Shareef et al., 2018). By demand bids programs, ECOs seek the participation of customers in periods of heavy load or with the risk of damage to the power grid. During these periods, consumers can indicate their demand available to be reduced in exchange for financial benefits (Hussain & Gao, 2018). Both programs, previously mentioned, are implemented for critical periods of the electrical system. Unlike these programs, pricing options programs are suitable for residential consumers to manage their demand voluntarily throughout the day. And in this way to guarantee the financial reduction of energy consumption expenditures (Di Santo, Kanashiro, Di Santo, & Saidel, 2015; Shareef et al., 2018). Several pricing schemes are established by ECOs to change users' consumption patterns. Among them, time-of-use (TOU) price, critical peak pricing (CPP), and real-time pricing (RTP) can be adopted by consumers participating in the DR program (Ponce-Jara et al., 2017). According to each tariff scheme, consumers can turn on their home appliances for consumption, including the plug-in electric vehicles (PEV) for battery charging, at times of the day with a cheaper fare (Marah & Hibaoui, 2018). However, the adoption of this type of DR program by a large number of consumers can lead to the appearance of high consumption peaks. Due to the low energy prices in off-peak periods, the appearance of peak consumption during these periods is evident once the coincident consumption of household appliances, especially those of higher average power, occurs (Shakouri & Kazemi, 2017). Consequently, congestion in the energy distribution system can happen, affecting the quality of the supply service to domestic customers (Ghorashi, Rastegar, Senemmar, & Seifi, 2020).

According to the U. S. Energy Information Administration (IEA), in its annual report *Annual Energy Outlook 2019 with projections to 2050*, the annual use of electricity in each residential home will decrease by 22 % from 2018 to 2050 as a result of using more efficient appliances and the alternative sources (US Energy Information Administration, 2019). To guarantee this projection, changes in the customers' habitual consumption behavior must happen considering its impact on both consumption profile and the performance of the electricity network. In this scenario, the DR programs to be implemented must go beyond merely reducing peak demand. This reduction should consider the hourly preferences of customers as a basis for determining the effective strategy for managing consumption, thus avoiding excess energy consumption during off-peak periods that compromise the quality of supply. In this work, the hourly preferences relate to how many periods consumers are willing to anticipate or postponed the usage of a given appliance (i.e., flexibility in the hours of appliances usage) to obtain a financial benefit on the energy bill without harming their comfort level (Anvari-Moghaddam, Monsef, & Rahimi-Kian, 2016; Chupong & Plangklang, 2017). Based on this flexibility of consumption periods, the efficient scheduling of home appliances can contribute to obtaining a reshaped demand profile with the mitigation of demand peak in periods with a more economical tariff.

One way to reshape the demand profile towards a homogeneous distribution of consumption is by improving the load factor (LF), which in turn indicates the efficient usage of electricity. The LF is equal to the ratio between average demand and maximum demand for a given period (day, week, month, etc.). In addition, the LF value varies between zero and one (Nuchprayoon, 2016). When its value is close to one, the demand profile will show a homogeneous distribution of consumption throughout the day. In this case, the average and maximum demand are very close. If its value is close to zero, the consumption profile will present a heterogeneous distribution with the presence of peaks and valleys (Nuchprayoon, 2016; Saikia, Manas, & Baruah, 2015). The concerns reported above are the main source of motivation for this research. In this way, this study has developed an intelligent tool for scheduling home appliances for residential customers, reducing peak demand, according to the consumption preferences of each customer, without the occurrence of new peak consumption during off-peak periods, which in turn, contributes to the improvement of the LF and the reduction of overloads in feeders and transformers, postponing future investments in grid maintenance.

1.2. Related works

In the vast majority of studies, DR programs aiming to minimize expenditures related to the customers' energy bills through the shaving of peak demand. Thus, reference (Shakouri & Kazemi, 2017) proposed a multiobjective mixed-integer linear programming (MILP) model to schedule a set of home appliances. The model aims to minimize the energy bill taking into account the daily energy needs as well as consumption preferences. References (Yahia & Pradhan, 2018) and (Yahia & Pradhan, 2020) addressed the problem of scheduling home appliances. In both studies, the objectives to be minimized were related to the reduction of peak load, energy bill, as well as the inconvenience of scheduling appliances according to consumption preferences. In (Yahia & Pradhan, 2018) the experimental analysis considered a single consumer, while (Yahia & Pradhan, 2020) evaluated the performance of the proposal for a group of consumers. The performance of the applied strategies was corroborated with data from the literature. These strategies have been effective in minimizing the objectives taking into account the management of inconveniences in the appliances usage. In (Ghorashi et al., 2020), the authors implemented a DR program that considered the economic rewards and penalties for consumers. These incentives were a function of the electricity company's requirements and the domestic demand available to be reduced to mitigate congestion during power supply. The work of (Khalid et al., 2018) developed a methodology for efficient scheduling of smart home appliances. A tariff scheme, as well as hourly preferences and consumption patterns of customers, were considered in reducing peak demand. Similarly, in (Croce et al., 2017), via a DR program, an automatic load control architecture was implemented in a community of residential and industrial customers to reduce peak demand. (Wang, Lin, Liu, Sun, & Wennersten, 2018) developed an efficient energy management scheme to reduce expenses on the energy bill of a multi-occupant residence. Domestic loads were considered to be shiftable and sheddable loads. The results showed a reduction in electricity consumption without interrupting the occupants' comfort. Fuzzy logic techniques were used by (Farham, Mohammadian, Alipour, & Pouladi, 2019) to allocate the demand of large number of consumers at certain times of the day. Considering a time-varying tariff scheme, this investigation aims to minimize the expenses on customers' electricity bills. References (Setlhaolo and Xia, 2015) and (Setlhaolo & Xia, 2016) addressed the problem of optimal scheduling of appliances. In (Setlhaolo and Xia, 2015), the scheduling considered a battery as a storage device as well as a strategy to coordinate its operation with the power grid. In (Setlhaolo & Xia, 2016), in addition to a storage system, the presence of a PV source was also considered. In both references, economic and technical constraints ensured the efficient operation of household appliances at minimal cost. An efficient management scheme based on smart plugs was proposed by (Heo, Park, & Lee, 2017). In addition to turning on/off domestic loads, these devices provide customer consumption information, and, in case of insufficient supply, these plugs disconnect non-priority loads, thus minimizing energy waste. An energy management system was used by (Keerthisinghe, Verbic, & Chapman, 2018) to reduce the coincident usage of appliances with higher average power. Technical and operational restrictions related to household appliances were taken into account to achieve energy savings. Another domestic energy management system was proposed by (Anzar et al., 2018). In this work, a knapsack algorithm to find the optimal scheme for managing schedule and non-schedule appliances with minimal expense was used. In (Sehar, Pipattanasomporn, & Rahman, 2017), the authors proposed an efficient control of cooling and lighting loads in commercial buildings. The control strategy considers the behavior of the occupants to minimize energy consumption during peak hours. Automatic systems aiming to reduce peak demand were developed by Alquthami & Meliopoulos (2018), Chakraborty, Mondal, & Mondal (2020) and Farrokhifar, Momayyezi, Sadoogi, & Safari (2018) and. Reference Farrokhifar et al. (2018) proposed a linear integer programming model (LIP) to optimize the level of automation home. The authors Chakraborty et al. (2020) used the G-MinPeak and LevelMatch algorithms to establish the efficient scheduling of residential loads, while Alquthami & Meliopoulos (2018) scheduled domestic loads in the presence of EVs charging. In these last surveys, the peak reduction contributed to avoiding overloading the distribution system. Based on the predicted percentage of dissatisfaction (PPD) model, a home energy automation strategy was proposed by Ma, Yu, Yang, & Yang (2019). The strategy reduces electricity costs through the optimal control of thermal equipment. The automatic adjustment of this equipment is a function of the variable tariffs. In Ahmed, Levorato, & Li (2018), the authors modeled customers' daily consumption using Markov techniques. Besides, hourly preferences were also considered in order to establish demand reduction policies in hours with higher energy costs. Following this same objective, the authors Basit, Sidhu, Mahmood, & Gao (2017) implemented an autonomous system for scheduling home appliances based on the Dijkstra algorithm. The work Aduda, Labeodan, Zeiler, & Boxem (2017) proposed an automation system for controlling thermal loads of a group of domestic consumers. The proposed system aimed to minimize the electricity bill based on the demand available to be reduced during heavy load times. Fuzzy logic techniques were applied by the authors Al-Mousa & Faza (2019) and Hosseinnia, Nazarpour, & Talavat (2018) and, aiming to change the consumption profile of customers. Reference Hosseinnia et al. (2018) used fuzzy rules to study several patterns related to residential consumption profiles considering the presence or not of electric vehicles (EVs). The model developed by Al-Mousa & Faza (2019) considered the flexibility of customers to change the consumption periods of their appliances. A methodology that aims to determine the best DR strategy that consumers can adopt was developed by Yu et al. (2020). By reducing the distance peaks and valleys in the consumption profile, this methodology minimizes peak consumption.

Other studies have addressed the improvement of LF related to a set of consumers considering the integration of distributed sources and EVs in the power grid. For example, Villalobos et al. (2017) increased the LF value through the minimization of the losses of active power in the electrical grid. This minimization has considered the level of insertion of renewable sources and EVs. Similarly, Trongwanichnam, Thitapars, & Leeprechanon (2019) improved the LF value through the optimal coordination of both power generation sources and battery charging of EVs. Also, improving LF through energy management was addressed in the following surveys. In Ali, Hasanuzzaman, & Rahim (2018), the authors through the implementation of energy waste reduction programs aim to increase the LF of a university building. The reference Surai & Surapatana (2014) implemented an optimal scheme for domestic equipment in order to reduce peak demand, which consequently minimizes consumption expenses and improves LF. A DR strategy that aims to meet the energy requirements of customers and the electricity grid was developed by Chiu, Hsieh, & Chen (2020). Through the use of an evolutionary algorithm and the analysis of the Pareto Frontier, the strategy minimized consumption costs in periods of the day with heavy demand, thus increasing the LF. The reference Saikia et al. (2015) developed a load management strategy in the distribution network. In this strategy, the minimization of losses allowed the improvement of the LF. To improve the LF of a set of commercial buildings, the authors Fardan, Gahtani, & Asif (2017) developed a strategy for reducing electricity consumption that considers a variable tariff during the day together with the control and monitoring of electrical equipment. Despite the different approaches aforementioned, there are still gaps with regard to the improvement of the LF while the occurrence of new peaks in periods with an economic energy tariff is being mitigated. Therefore, this research tries to fill this knowledge gap in the search for mutual financial benefits for both customers and ECOs. Table 1 highlights the features that are included (✓) and not included (×) in each work mentioned above in comparison to the present approach, which includes all of them. To this end, the features that are taken into account are: mitigation of new consumption peaks by improving the LF (F1); reduction in the coincident consumption of household appliances with higher average power (F2); scheduling household appliances considering consumer preferences (F3); and minimizing peak load and electricity costs (F4).

Table 1
Analysis of related works in the existing literature.

References	Features			
	F1	F2	F3	F4
Ahmed et al. (2018), Al-Mousa and Faza (2019), Basit et al. (2017), Heo et al. (2017), Sehar et al. (2017), Setlhaolo and Xia (2015, 2016), Shakouri and Kazemi (2017), Yahia and Pradhan (2018, 2020)	×	×	✓	✓
Ghorashi et al. (2020)	✓	×	×	✓
Aduda et al. (2017), Alquthami and Meliopoulos (2018), Anzar et al. (2018), Chakraborty et al. (2020), Croce et al. (2017), Farham et al. (2019), Farrokhifar et al. (2018), Hosseinnia et al. (2018), Khalid et al. (2018), Keerthisinghe et al. (2018), Ma et al. (2019), Wang et al. (2018) and Yu et al. (2020)	×	×	×	✓
Ali et al. (2018), Trongwanichnam et al. (2019) and Villalobos et al. (2017)	✓	×	×	×
Chiu et al. (2020), Fardan et al. (2017), Surai and Surapatana (2014) and Saikia et al. (2015)	✓	×	×	✓
Proposed MILP Model	✓	✓	✓	✓

1.3. Contributions

In this paper, a MILP model to mitigate the occurrence of new peak demand at times with lower energy tariffs is proposed. Mitigation is achieved by the intelligent scheduling of home appliances, especially those with higher average power, avoiding coincident consumption at certain off-peak times. An hourly tariff scheme, as well as consumer preferences differentiated by each home appliances, are used to direct the efficient usage of household appliances (including EV) in each smart home. The objective function of the MILP model aims to minimize the financial expenses of both customers and ECOs while taking into account technical and operational restrictions related to household appliances and the EV battery. The Monte Carlo Method (MCM) is used to simulate the uncertainties related to the customers' habitual consumption patterns. The commercial solver CPLEX is used to found the optimal solution to this problem. In the analysis of two case studies, the results showed the efficient performance of the proposed model to obtain financial and operational benefits for users and ECOs without compromising the quality of power supply. In summary, the key contributions of this paper are as follows:

1) Proposing a computationally efficient MILP model to improve the LF value while the peak demand in periods with low tariffs is mitigated.
2) Establishing scheduling schemes based on customers hourly preferences to avoid the coincident consumption of household appliances (mainly those with higher average power) as well as PEVs battery charging aiming to reduce congestion during the energy supply.
3) From a sustainable point of view, the application of this intelligent tool by ECOs in a SG environment in order to reduce the dependence on fossil fuel to meet the energy needs of the domestic customers.

1.4. Paper organization

The remainder of this work is organized as follows. The main hypotheses and stochastic simulations are explained in Section 2. Section 3 formulates the MILP model and explains the linearization process. Section 4 presents the discussion of the results related to the two case studies, as well as the sensitivity analysis of the weights. Finally, the conclusions, limitations, and the proposals related to the future extension of this work are given in Section 5.

2. Simulation setup

In this section, the main assumptions related to household appliances, PEV batteries, and hourly tariff schemes, are mentioned (Di Santo et al., 2015). Moreover, explanations related to the consumer's hourly preferences are also considered. Due to the difficulty of obtaining information about residential consumption patterns, consumer behavior related to uncertainties in the usage of home appliances (Christopher & Wang, 2014) was simulated using the MCM (Robert & Casella, 2004).

2.1. Assumptions

The key premises that guide this work are mentioned below. This research is carried out considering the advanced monitoring and measurement environment depicted in Fig. 1. The problem is studied for a

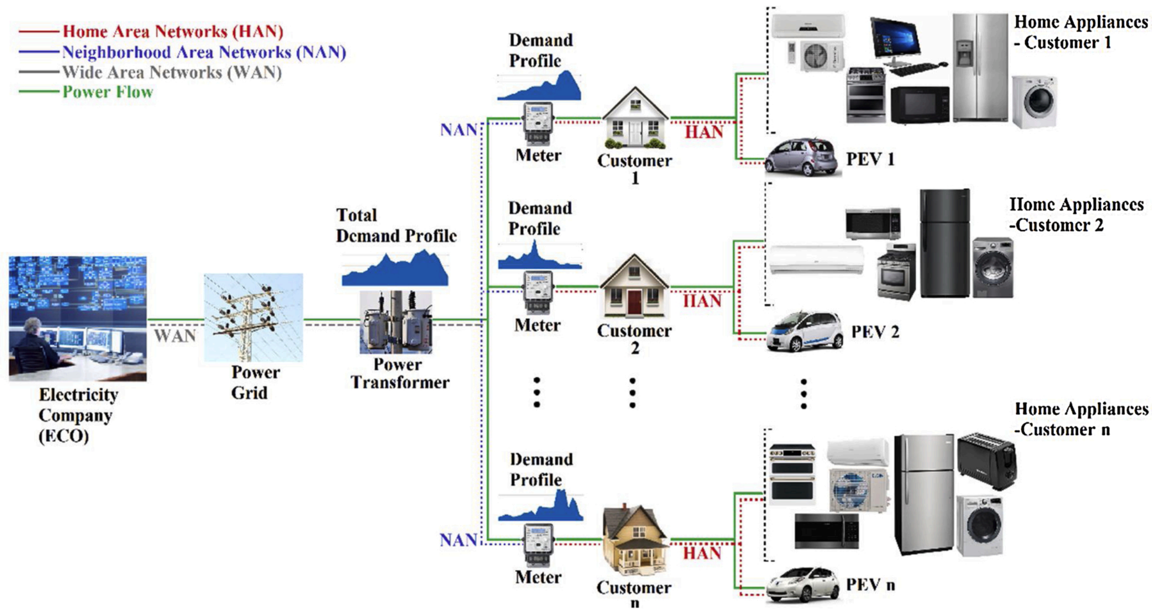

Fig. 1. SG environment.

time horizon of one day that is discretized in periods t of one hour. Consumer groups are analyzed considering a smaller number of customers with the same number of appliances, as well as a greater number of customers, but with different appliances present in each home. This assumption is related to the consumer's household income. According to DEA Technical Note 14/10 (2010), IBGE – Brazilian Institute of Geography & Statistics (2019) and Residential Class Brazil Report (2007), the possession of household appliances in a home is related to family income. When the income is higher, the purchase of home appliances also increases, which in turn causes a greater consumption of electricity; otherwise, the number of appliances is lower, which does not generate significant expenses on the energy bill. It is assumed that, for each smart home, all appliances have an independent operating regime, e.g., the clothes dryer and washing machine can be used without considering the sequential logic. Furthermore, the set of appliances and the EV are differentiated through β_a. For the EV, the value of β_a is -1. In the case of appliances present in the smart home, β_a adopts two values, 1 and 0. $\beta_a = 1$ indicates the appliances with an operating regime greater than or equal to 1 h. $\beta_a = 0$ value represents appliances with an operating regime of less than 1 h. The differentiation of household appliances by the operating regime is motivated by the fact that they can be used one or more times a day and depending on the customer's usage habits, in short, or long periods. For example, an electric shower can be used for 10 min in a given period t. The microwave, for heating the food, for a time of approximately 20 min also within a given period t. Both cases represent the appliances used for short periods in the day. On the other hand, TVs, with an average usage time of 5 h, (see Table 2) can have a usage regime of 2 h in the morning (two periods t), 1 h in the afternoon (one period t) and the remaining 2 h during the night (two periods t), thus completing 5 h. The efficient scheduling of these household appliances is performs based on the technical data presented in Table 2 (Anzar et al., 2018; Cerna, Pourakbari-Kasmaei & Gallego, 2018). It is worth noting that, in Table 2, each PEV battery is differentiated by its capacity, B_u. A tariff scheme that considers three hourly levels, as reported in Table 3 (ANEEL, 2016), is used to lead the scheduling of consumption periods of household appliances.

Table 2
Technical data to each smart appliance.

a	Appliances	P_a	β_a	t_a^{av}	$\underline{q}_a$	$\underline{t}_a$	q_a	$\beta_a^{'}$
1	Air Conditioner	4.00	1	2	2	0.25	–	1
2	Freezer	0.40	1	10	10	0.50	–	0
3	Clothes Dryer	3.50	1	1	1	0.50	–	1
4	Computer	0.25	1	2	2	0.50	–	0
5	Incand. Light	0.10	1	5	5	0.25	–	0
6	TV	0.09	1	5	5	0.50	–	0
7	Electric Iron	1.00	1	1	1	0.25	–	1
8	Fan	0.10	1	4	4	0.50	–	0
9	DVD Player	0.025	1	2	2	0.25	–	0
10	Stereo	0.020	1	2	2	0.25	–	0
11	Electric Faucet	3.50	0	0.50	1	–	1	1
12	Dishwasher	1.50	0	0.75	1	–	1	1
13	Coffe Maker	1.00	0	0.50	1	–	1	0
14	Resistance Oven	1.50	0	0.50	1	–	1	0
15	Electric Shower	3.50	0	0.15	1	–	1	1
16	Microwave	1.30	0	0.33	1	–	1	0
17	Washing Machine	1.50	0	0.50	1	–	1	0
18	Vacuum Cleaner	1.00	0	0.33	1	–	1	0
19	Hair Dryer	0.70	0	0.50	1	–	1	0
20	Toaster	0.80	0	0.16	1	–	1	0
a	Appliances	P^{pev}	β_a	B_u		t_u^{ev}	$\underline{q}_u^{ch}$	$\beta_a^{'}$
21	PEV 1	4.00	−1	20.0		0.50	5.00	1
	PEV 2			28.0			7.00	
	PEV 3			32.0			8.00	
	PEV 4			24.0			6.00	

Table 3
Electricity price levels.

Levels	Periods (h)	Tariff ($/kWh)
Off-peak	0 h–17 h; 22 h–24 h	0.22419
Intermediate	17 h–18 h; 21 h–22 h	0.32629
Peak	18 h–21 h	0.51792

2.2. . Consumer hourly preferences

Due to the different energy consumption priorities of customers, defining a level of flexibility (postponed or anticipate) of the periods of usage of each appliance is complicated. A high level of flexibility can compromise the satisfaction of customers' needs. Unlike, when this flexibility is low or restricted to short periods of the day, the consumption of household appliances can coincide, thus resulting in an economically inefficient scheme. Therefore, flexibility in the hourly preferences of each appliance is a key factor to ensure efficient scheduling of appliances as well as the optimal operation of the supply network. This work assumes four types (e.g., type 1, 2, 3, and 4) of consumer hourly preferences and are defined and shown in Fig. 2 (Rahman, Arefi, Shafiullah, & Hettiwatte, 2018; Yahia & Pradhan, 2020).

Fig. 2 shows the types of hourly preferences to be considered for domestic customers. Each type of preference depicted in this figure is the result of adding the hourly preferences of each appliance present in the smart home. In addition, each type of preference, i.e., type 1, 2, 3, and 4, presents for each period t the number of household appliances connected for consumption. Fig. 3 shows the types of hourly preferences related only to household appliances such as air conditioning (figures on the left) and PEV (figures on the right). For air conditioning, i.e., Fig. 3(a), (c), (e), and (g), each type of preference related to a given consumer shows the time intervals in which this appliance can be connected for energy consumption without affecting the comfort of these customers. As mentioned earlier, each smart home has a unique PEV. Thus, Fig. 3 (b), (d), (f), and (h) show the respective hourly preferences in which each customer could connect the battery of their PEV for charging without compromising the use of this vehicle in daily activities. Note that although most PEVs can be connected from early evening until dawn, there are also hourly preferences in which the flexibility of the periods can take into account the afternoon and evening periods. Hourly preferences are represented by $\theta^{c}_{u,a,t}$ in Eqs. (2) and (3) within the proposed MILP model. In the SG environment (i.e., with advanced communication infrastructure, as illustrated in Fig. 1), hourly preferences can be inserted into the smart meters of each smart home and thus programmed by customers according to the desired level of comfort in the usage of each appliance.

2.3. Uncertainties in domestic consumption behavior

The behavior of residential customers regarding energy consumption varies during the day. This variation occurs according to the needs of each domestic customer. This means that the household appliance usage within each smart home can be represented by a probability (or uncertainty) value for each period of the day. To make the proposed model more realistic, these uncertainties in each home are simulated using the MCM depicted in Fig. 4.

The scheme is run considering the information related to P_a, $\mathscr{D}_{a,t}$, $\underline{q}_a$, q_a, $\underline{q}^{ch}_u$, and Δt, which are the average power of appliance a, the distribution of the probability of using the appliance a at each period t (US Department of Energy, 2019), the number of times and the minimum number of times that an appliance a is turned on for consumption, as well as the minimum number of times that the PEV is turned on to charge its battery, and the duration of each period t, respectively. Moreover, each parameter described above is related to sets $\mathbb{U}$, $\mathbb{A}$, and $\mathbb{T}$ through their respective indexes u, a, and t. Next, the values of $\mathscr{D}_{a,t}$, $\mathscr{X}^{hu}_{u,a,t}$ and $\mathscr{Q}_{u,a}$ are initialized. Thus, $\mathscr{D}_{a,t}$ and $\mathscr{X}^{hu}_{u,a,t}$ are set to zero. Note that the value of $\mathscr{Q}_{u,a}$ depends on β_a. When $\beta_a = 1$, then $\mathscr{Q}_{u,a}$ adopts the value of $\underline{q}_a$. For the value of $\beta_a = 0$, then $\mathscr{Q}_{u,a}$ assumes the value of q_a. For β_a = -1 (case of PEV) the value adopted by $\mathscr{Q}_{u,a}$ is $\underline{q}^{ch}_u$. It is worth to mention that all the parameters highlighted above correspond to the input data of the scheme that aims to simulate the uncertainties related to the energy consumption of the participating customers. Then, an iterative process related to each appliance a is executed, and for each iteration, the accumulator s is set to zero. Thereafter, another iterative process for the periods t is done, in which $\mathscr{D}_{a,t}$ is added to each current value of the accumulator s, obtaining a new value of s to be assigned to $\widehat{\mathscr{D}}_{a,t}$. Both iterative processes end when the respective indexes t and a reach the values of $|\mathbb{T}|$ and $|\mathbb{A}|$. Hereafter, an iterative process related to the set of domestic customers u is carried out. Then, a new iterative process for appliances a is done. Within this iterative process, for each appliance a, an infinite loop is performed, and in each iteration, a random number α is generated for values between 0 and 100. Next, block 1 receives the values of α via input (1) and returns the information via outputs (2) and (3). The data flow within block 1 is shown in detail in the same Fig. 4 on the right side. In block 1, the α value is evaluated under condition $\widehat{\mathscr{D}}_{a,t-1} \le \alpha \le \widehat{\mathscr{D}}_{a,t}$ within the iterative process related to set of periods t. When this condition is checked, then a unity value is assigned to $\mathscr{X}^{hu}_{u,a,t}$, otherwise the zero value remains. After completing the iterative process for all periods t (i.e., when the condition $t = |\mathbb{T}|$), another condition $\sum_{t=1}^{|\mathbb{T}|} \mathscr{X}^{hu}_{u,a,t} = \mathscr{Q}_{u,a}$ is evaluated. When this condition is not met, then, through the output (3) of block 1, the flow is directed to continue executing the infinite loop; otherwise, if this condition is checked, then another iterative process for all periods t is performed and in each period t the value of $\mathscr{H}^{cp}_{u,a,t}$ is calculated as the product of P_a, $\mathscr{X}^{hu}_{u,a,t}$, and Δt. Once the condition $t = |\mathbb{T}|$ is met, the infinite loop is broken and, through the output (2) of block 1, condition $a = |\mathbb{A}|$ is evaluated. If this condition is not met, the iterative process continues to be performed for each appliance a; otherwise, condition $u = |\mathbb{U}|$ related to the iterative process of customers u is evaluated. Likewise, iterations are performed until the condition is met. In this case, the execution of the scheme ended thus obtaining the values $\mathscr{X}^{hu}_{u,a,t}$ and $\mathscr{H}^{cp}_{u,a,t}$ as outputs. Finally, the habitual profile $\mathscr{H}^{cp}_{u,a,t}$ is part of the input data for the proposed MILP model, specifically is used in Eq. (17).

3. The proposed model

This section provides details of the mathematical formulation related to the problem of mitigating the occurrence of new demand peaks in the domestic consumption profile by the improvement of the LF.

3.1. MINLP model

Initially, the problem is formulated as a mixed-integer nonlinear programming (MINLP) model expressed by (1) − (20).

3.1.1. Objective function

$$\min F \tag{1}$$

In (1), F is the objective function that has as components functions Ω_1, Ω_2, and Ω_3 shown below.

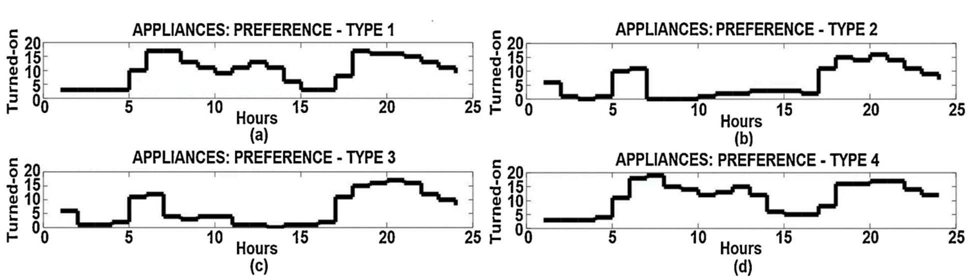

Fig. 2. Hourly preferences for total appliances.

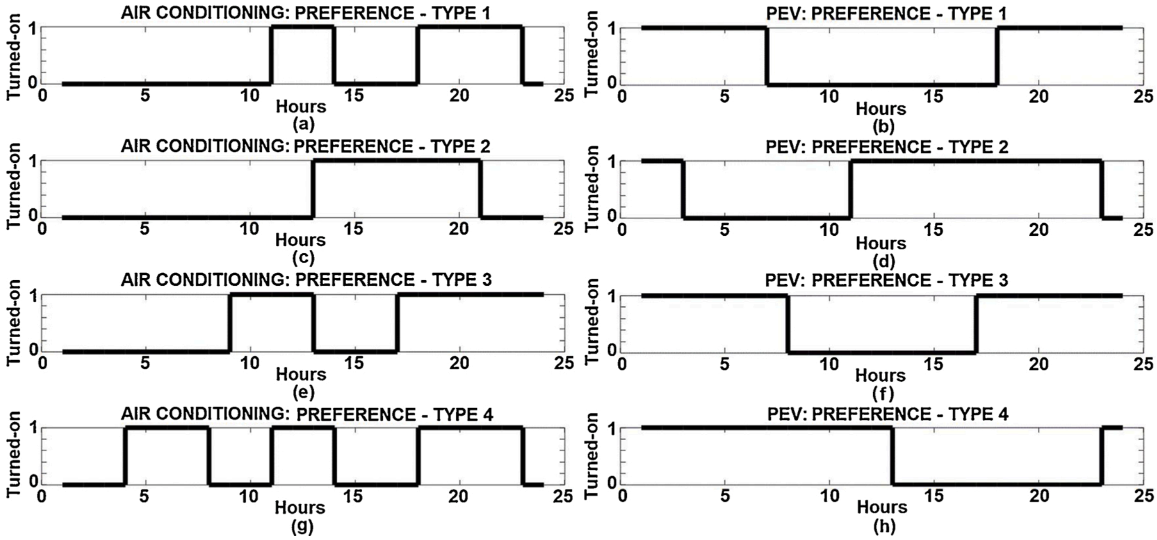

Fig. 3. Hourly preferences for air conditioning and PEV.

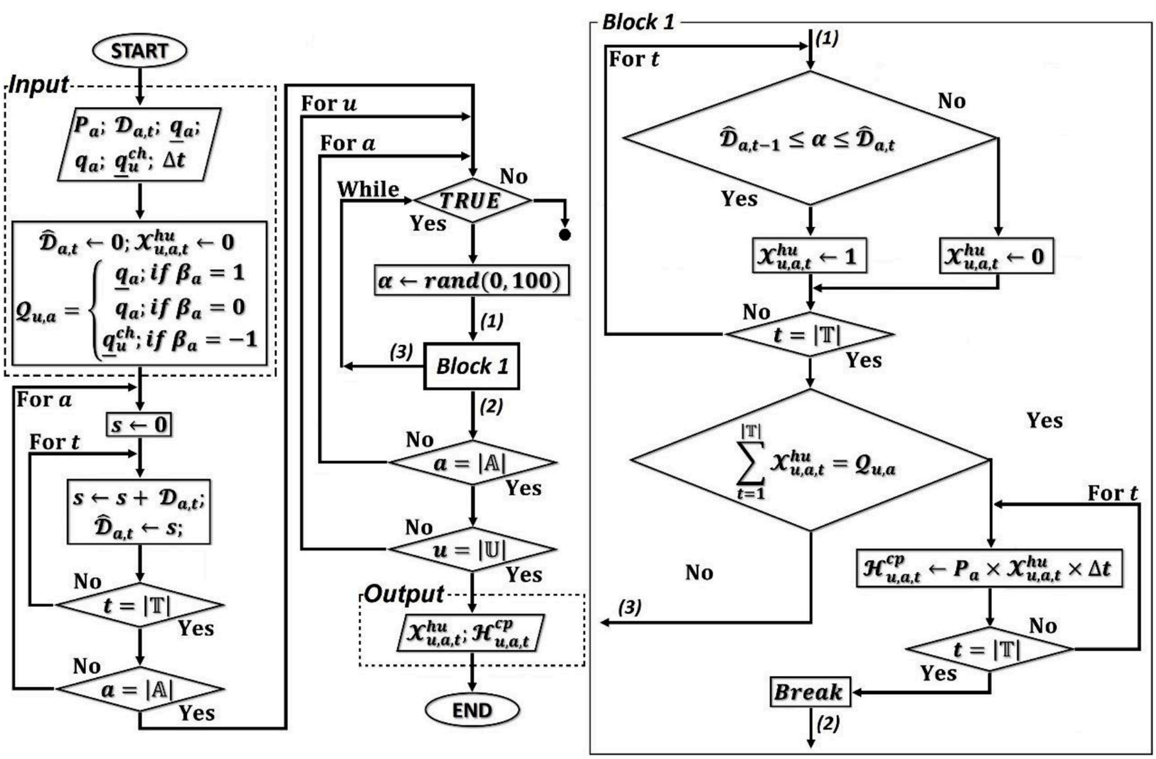

Fig. 4. Scheme to simulate uncertainties in the behavior of energy consumption.

$$\Omega_1 = \mu^{'} \times \left[\sum_{\forall t \in \mathbb{T}} \sum_{\forall a \in \mathbb{A}} \sum_{\forall u \in \mathbb{U}} \zeta_t \times \mathscr{C}^{cp}_{u,a,t} \right]$$

$$\Omega_2 = \mu^{''} \times \left[\sum_{\forall u \in \mathbb{U}} \sum_{\forall t \in \mathbb{T}} \theta^{'}_{u,t} \right]$$

$$\Omega_3 = \mu^{'''} \times \left[\sum_{\forall t \in \mathbb{T}} \left(P^{eu}_t - \overline{P}^{eu} \right)^2 \right]$$

Function Ω_1 is related to minimizing the monetary expenses of energy consumption, $\mathscr{C}^{cp}_{u,a,t}$, for all domestic customers. Function Ω_2 is related to the coincident factor, $\theta^{'}_{u,t}$, which represents for each customer u the number of appliances with higher average power that are connected in a given period t. In this way, Ω_2 minimizes the coincident usage of this type of appliance. It is worth mentioning that the minimization of functions Ω_1 and Ω_2 represent, per customer, the financial gains obtained through a reduction in the energy bill. The ECO's financial gain is represented by function Ω_3. As previously discussed, the improvement of the LF guarantees the efficient usage of energy in the ECO supply grid. Thus, the maximization of the LF can be achieved when the square of the difference between P^{eu}_t and $\overline{P}^{eu}$ is minimized. Please note that in the solution of the problem, each function Ω_1, Ω_2, and Ω_3 will have a given level of influence according to the values to be adopted by the respective weights $\mu^{'}$, $\mu^{''}$, and $\mu^{'''}$. Based on the already mentioned, to guarantee mutual gains, function F in (1) should be minimized taking into account the set of constraints detailed below.

3.1.2. Operational constraints

Constraints related to the consumption of smart household appliances are mathematically formulated as follows:

$$\mathscr{X}^{ou}_{u,a,t} = 0,\ \forall u \in U, \forall a \in A, \forall t \in T\ :\ \theta^{c}_{u,a,t} = 0 \tag{2}$$

$$\mathscr{X}^{ou}_{u,a,t} \leq 1,\ \forall u \in U, \forall a \in A, \forall t \in T\ :\ \theta^{c}_{u,a,t} = 1 \tag{3}$$

$$\theta^{'}_{u,t} = \sum_{\forall a \in A} \mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t} \times \beta^{'}_{a},\ \forall u \in U, \forall t \in T \tag{4}$$

$$\sum_{\forall t \in T} \mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t} = q_a,\ \forall u \in U,\ \forall a \in A\ :\ \beta_a = 0 \tag{5}$$

$$\mathscr{O}^{cp}_{u,a,t} = P_a \times \mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t} \times t^{av}_{a},\ \forall u \in U,\ \forall a \in A,\ \forall t \in T\ :\ \beta_a = 0 \tag{6}$$

$$\underline{q}_a \leq \sum_{\forall t \in T} \mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t} \leq \overline{q}_a,\ \forall u \in U,\ \forall a \in A\ :\ \beta_a = 1 \tag{7}$$

$$\underline{t}_a \leq \tau^{us}_{u,a,t} \leq \overline{t}_a, \forall u \in U,\ \forall a \in A,\ \forall t \in T\ :\ \beta_a = 1 \tag{8}$$

$$\mathscr{O}^{cp}_{u,a,t} = P_a \times \left(\mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t}\right) \times \left(\tau^{us}_{u,a,t}\right),\ \forall u \in U,\ \forall a \in A,\ \forall t \in T\ :\ \beta_a = 1 \tag{9}$$

$$t^{av}_{a} = \sum_{\forall t \in T} \left(\mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t}\right) \times \left(\tau^{us}_{u,a,t}\right),\ \forall u \in U,\ \forall a \in A\ :\ \beta_a = 1 \tag{10}$$

$$\mathscr{G}^{ev}_{u,t} = P^{ev} \times \mathscr{X}^{ou}_{u,a,t} \times \tau^{ev}_{u,t},\ \forall u \in U,\ \forall a \in A,\ \forall t \in T\ :\ \beta_a = -1 \tag{11}$$

$$\underline{t}^{ev}_{u} \leq \tau^{ev}_{u,t} \leq \overline{t}^{ev}_{u}, \forall u \in U,\ \forall t \in T \tag{12}$$

$$\underline{q}^{ch}_{u} \leq \sum_{\forall t \in T} \mathscr{X}^{ou}_{u,a,t} \leq \overline{q}^{ch}_{u}, \forall u \in U,\ \forall a \in A\ :\ \beta_a = -1 \tag{13}$$

$$\mathscr{O}^{cp}_{u,a,t} = \mathscr{G}^{ev}_{u,t}, \forall u \in U,\ \forall a \in A,\ \forall t \in T\ :\ \beta_a = -1 \tag{14}$$

$$\mathscr{G}^{s}_{u} = SoC^{0}_{u} + \sum_{\forall t \in T} \mathscr{G}^{ev}_{u,t}, \forall u \in U \tag{15}$$

$$\mathscr{G}^{s}_{u} = \xi \times B_u, \forall u \in U \tag{16}$$

$$\sum_{\forall a \in A} \mathscr{O}^{cp}_{u,a,t} \leq MAX_{\forall t \in T}\left\{\sum_{\forall a \in A} \mathscr{H}^{cp}_{u,a,t}\right\}, \forall u \in U,\ \forall t \in T \tag{17}$$

$$P^{eu}_{t} = \sum_{\forall u \in U}\left(\sum_{\substack{\forall a \in A\\ :\beta_a \geq 0}} P_a \times \mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t} + \sum_{\substack{\forall a \in A\\ :\beta_a < 0}} P^{ev} \times \mathscr{X}^{ou}_{u,a,t} \times \theta^{c}_{u,a,t}\right),\ \forall t \in T \tag{18}$$

$$\overline{P}^{eu} = \frac{1}{|T|}\sum_{\forall t \in T} P^{eu}_{t} \tag{19}$$

In Eqs. (2) and (3), the state (turned -on/-off) of smart appliances a at each period t is represented through variable $\mathscr{X}^{ou}_{u,a,t}$. In both equations, the hourly preferences related to each customer u, $\theta^{c}_{u,a,t}$, are considered. Eq. (2) ensures that scheduling should not be done at periods t without customer preferences ($\theta^{c}_{u,a,t} = 0$). In contrast, Eq. (3) establishes that scheduling must be done (or not) at periods t with hourly preferences ($\theta^{c}_{u,a,t} = 1$) already established for electricity consumption. In Eq. (4), the coincidence factor, $\theta^{'}_{u,t}$, related to each customer u is calculated as the number of smart appliances a (with $\beta^{'}_{a} = 1$) that are turned on at each period t.

Constraints related to the appliances a with consumption hours less than one hour ($\beta_a = 0$) are established by Eqs. (5) and (6). The number of times during the day that customer u turned on a given appliance a for energy consumption is guaranteed in Eq. (5). In addition, the energy required at each period t when a customer u turns on the appliance a is calculated using Eq. (6).

Eqs. (7) – (10) are related to the appliances a with consumption hours greater than or equal to one hour ($\beta_a = 1$). In Eq. (7), the number of times that the appliances a can be turned on for power consumption is bounded by $\underline{q}_a$ and $\overline{q}_a$. Similarly, in Eq. (8), values $\underline{t}_a$ and $\overline{t}_a$ are used to establish the lower and upper bounds related to the energy consumption time of each appliance a in each period t. It is worth mentioning that the upper limit $\overline{t}_a$ is less than or equal to one hour. The energy consumed by a given smart appliance a with $\beta_a = 1$ at the period t is calculated by Eq. (9). Furthermore, Eq. (10) allows to determine the t^{av}_{a} value.

The charging of PEV batteries ($\beta_a = -1$) is modeled considering the Eqs. (11) – (16). For a given customer u, the energy stored in his PEV battery at period t is calculated according to Eq. (11). In Eq. (12), the variation interval related to the charging time of the PEV battery is defined between limits $\underline{t}^{ev}_{u}$ and $\overline{t}^{ev}_{u}$. Likewise, in Eq. (13), the interval $\left[\underline{q}^{ch}_{u}, \overline{q}^{ch}_{u}\right]$ determines the number of recharges that can be made by the PEV battery. In Eq. (14), the value of $\mathscr{G}^{ev}_{u,t}$ is assigned to $\mathscr{O}^{cp}_{u,a,t}$. The total energy of the PEV's battery, $\mathscr{G}^{s}_{u}$, is calculated, in Eq. (15), considers the initial state-of-charge SoC^{0}_{u} as well as the value of $\mathscr{G}^{ev}_{u,t}$ previously calculated. Eq. (16) sets the final energy state to a value equal to a percentage ξ multiplied by the capacity of the PEV battery, B_u.

Eq. (17) establishes that, for customer u, the optimal consumption $\mathscr{O}^{cp}_{u,a,t}$ in a given period t must be less than or equal to the maximum peak related to the habitual consumption $\mathscr{H}^{cp}_{u,a,t}$. Eqs. (18) and (19) are related to the power supplied by the ECO to residential customers. This power supplied for all smart appliances, including PEVs, in each period t is calculated in Eq. (18). Using Eq. (19), the average value of P^{eu}_{t} is also calculated.

3.2. Linearization

In order to ensure the global solution of the proposed MINLP model, the function Ω_2, as well as the Eqs. (9)–(11) must be linearized. Therefore, a set of linearization techniques to recast these nonlinear terms is applied.

The following equations are the result of linearizing the function Ω_3 based on (Borges, Franco, & Rider, 2014; Gonçalves, Alves, Franco, & Rider, 2013). Thus, $\Omega^{'}_{3}$ aims to replace the quadratic function Ω_3. At the same time, Eqs. (20) – (25) are considered in the proposed model.

$$\Omega^{'}_{3} = \mu^{'''} \times \left[\sum_{\forall t \in T}\sum_{y=1}^{|Y|} \Pi_{t,y} \Delta\Gamma_{t,y}\right]$$

$$\Gamma_t = P^{eu}_{t} - \overline{P}^{eu},\ \forall t \in \mathbb{T} \tag{20}$$

$$\Gamma^{+}_{t} - \Gamma^{-}_{t} = \Gamma_t,\ \forall t \in \mathbb{T} \tag{21}$$

$$\Gamma^{+}_{t} - \Gamma^{-}_{t} = \sum_{y=1}^{|\mathbb{Y}|} \Delta\Gamma_{t,y},\ \forall t \in \mathbb{T} \tag{22}$$

$$0 \leq \Delta\Gamma_{t,y} \leq \overline{\Delta}_t,\ \forall t \in \mathbb{T},\ \forall y \in\ 1..|\mathbb{Y}| \tag{23}$$

$$0 \leq \Gamma^{+}_{t},\ \forall t \in \mathbb{T} \tag{24}$$

$$0 \leq \Gamma^{-}_{t},\ \forall t \in \mathbb{T} \tag{25}$$

To linearize Eqs. (9)–(11), the Big-M method applied by (Cerna, Pourakbari-Kasmaei, & Gallego, 2018; Cerna, Pourakbari-Kasmaei, Romero, & Rider, 2018) is used. Thus, Eqs. (9) and (10) are replaced by the respective Eqs. (26) and (27), while Eqs. (28) and (29) are also considered.

$$\mathscr{O}^{cp}_{u,a,t} = P_a \times \theta^c_{u,a,t} \times \left(\Delta\tau^{us}_{u,a,t}\right), \ \forall u \in U, \ \forall a \in A, \ \forall t \in T \ : \ \beta_a = 1 \tag{26}$$

$$t^{av}_a = \sum_{\forall t \in T} \theta^c_{u,a,t} \times \left(\Delta\tau^{us}_{u,a,t}\right), \ \forall u \in U, \ \forall a \in A \ : \ \beta_a = 1 \tag{27}$$

$$0 \leq -\Delta\tau^{us}_{u,a,t} + \tau^{us}_{u,a,t} \leq \mathscr{M} \times \left(1 - \mathscr{X}^{ou}_{u,a,t}\right), \ \forall u \in U, \ \forall a \in A, \forall t \in T \tag{28}$$

$$0 \leq \Delta\tau^{us}_{u,a,t} \leq \mathscr{M} \times \mathscr{X}^{ou}_{u,a,t}, \ \forall u \in \mathbb{U}, \ \forall a \in \mathbb{A}, \forall t \in \mathbb{T} \tag{29}$$

Similarly, Eq. (11) is replaced by linearized Eqs. (30) – (32) shown below:

$$\mathscr{G}^{ev}_{u,t} = P^{ev} \times \mathscr{X}^{ou}_{u,a,t} \times \tau^{ev}_{u,t}, \ \forall u \in \mathbb{U}, \ \forall a \in \mathbb{A}, \ \forall t \in \mathbb{T} \ : \ \beta_a = -1 \tag{30}$$

$$0 \leq -\Delta\tau^{ev}_{u,a,t} + \tau^{ev}_{u,a,t} \leq \mathscr{M} \times \left(1 - \mathscr{X}^{ou}_{u,a,t}\right), \ \forall u \in \mathbb{U}, \ \forall a \in \mathbb{A}, \forall t \in \mathbb{T} \tag{31}$$

$$0 \leq \Delta\tau^{ev}_{u,a,t} \leq \mathscr{M} \times \mathscr{X}^{ou}_{u,a,t}, \ \forall u \in \mathbb{U}, \ \forall a \in \mathbb{A}, \forall t \in \mathbb{T} \tag{32}$$

3.3. *The MILP model*

The linearized model is obtained considering the equations listed below.

$$\min(1)$$
$$\text{s.t.} : (2)\text{–}(8); (12)\text{–}(19); (20)\text{–}(25); (26)\text{–}(29), (30) - (32)$$

4. Case studies and results

The two case studies depicted in Fig. 5 are used to assess the performance of the proposed model. In each case, the four types of hourly preferences, $\theta^c_{u,a,t}$, (see Fig. 3) explained above are considered. Case study 1 considers a group of 4 consumers ($|\mathbb{U}| = 4$), all with the same household income, whereas case study 2 considers 12 customers ($|\mathbb{U}| = 12$), with differentiated domestic income. Also, in case 1, all customer have different consumption patterns, $\mathscr{H}^{cp}_{u,a,t}$. In case 2, there are customers with similar consumption patterns. As can be seen in Fig. 5, in both cases, each consumer u has a certain type of hourly preference $\theta^c_{u,a,t}$. Therefore, each case calculates the financial gains of customers and ECO when the preferences of consumers are diversified.

The general information used in both case studies is described below. Twenty-one ($|\mathbb{A}| = 21$) smart home appliances are considered for each customer u, including PEV. The operational characteristics of each appliance are detailed in Table 2. It is worth mentioning that for each appliance with $\beta_a = 1$, in Table 2, the value of $\bar{t}_a$ is equal to 1. Note that each PEV is related to a given type of hourly preference $\theta^c_{u,a,t}$. Thus, type 1 is related to PEV 1; type 2 is related to PEV 2, and so on. To assess efficient charging from an initial state to full capacity, B_u, PEVs batteries are initialized completely discharging, i.e., $SoC^0_u = 0$. Moreover, scheduling strategy considers a hourly tariff (Table 3) for one day that is divided into 24 hourly periods ($|\mathbb{T}| = 24$). Because the weight coefficients $\mu^{'}$, $\mu^{''}$, and $\mu^{'''}$ can adopt different values, in this research, the values attributed to these weights are based on the powers of 10 (e.g., 10^{-1}, 10°, 10^1, etc.). Thus, the level of influence of each cost function Ω_1, Ω_2, and Ω_3, in the solution of the problem is given by their respective weights, $\mu^{'}$ and $\mu^{''}$, and $\mu^{'''}$, whose values are 10^{-1} (0.1), 10^1 (10), and 10° (1), respectively. Note that function Ω_2 has the highest level of influence, while the lowest level of influence is related to function Ω_1. Thus, the problem solution should consider reducing the energy bill by strongly avoiding the coincident usage of appliances with higher average power in given periods of the day. The values of the constants $\mathscr{M}$ and θ, and the number of discretization blocks $|\mathbb{Y}|$, introduced in the linearization process, are set to 1000, 10, and 15, respectively. Also, the $\overline{\Delta}_t$ value is considered fixed for each t and is obtained as $10/|\mathbb{Y}|$ (Cerna, Pourakbari-Kasmaei et al., 2018; Borges et al., 2014; Cerna, Pourakbari-Kasmaei, Romero et al., 2018). Furthermore, the habitual consumption profile, $\mathscr{H}^{cp}_{u,a,t}$, obtained via the scheme shown in Fig. 4 is used to represent customers' consumption patterns. It is worth mentioning that this scheme is run before the proposed model. The habitual consumption profile $\mathscr{H}^{cp}_{u,a,t}$ is used by the MILP model to determine the optimal consumption profile $\mathscr{O}^{cp}_{u,a,t}$ while the occurrence of peak demand in off-peak hours is mitigated. This proposed model is coded in AMPL (Fourer, Gay, & Kernighan, 2003) and solved using the CPLEX solver (IBM ILOG CPLEX V 12.1, 2009). Moreover, a 2.67-GHz computer with 3GB of RAM and CPU time of about 40.6 s, is used to approach this problem.

4.1. *Case study 1*

As mentioned above, this case study analyzes the gains obtained by customers and ECOs when consumers have different hourly preferences $\theta^c_{u,a,t}$ but with the same household income. Figs. 6 and 7 illustrate the profiles of $\mathscr{H}^{cp}_{u,a,t}$ (dashed line) and $\mathscr{O}^{cp}_{u,a,t}$ (continuous line) consumption related to air conditioning and PEV, respectively, which belong to the set of home appliances with higher average power ($\beta^{'}_a = 1$, see Table 2).

According to Fig. 6, domestic customers have the habit of turning on the air conditioning during the peak period or in hours surrounding it. Note that customer 2 turns on his air conditioning only during peak period, as shown in Fig. 6(b). Additionally, the air conditioning of customers 1, 3, and 4 also consume energy within the same peak period, thus contributing to the emergence of the well-known peak demand. For the $\mathscr{O}^{cp}_{u,a,t}$ profile, the figure reveals a wide distribution of the air conditioning consumption periods t along off-peak hourly (low electricity tariff). Note that the distribution of consumption is carried out based on each type of hourly preference $\theta^c_{u,a,t}$ related to one consumer u, avoiding the coincident consumption of these appliances, i.e., minimizing the $\theta^{'}_{u,t}$

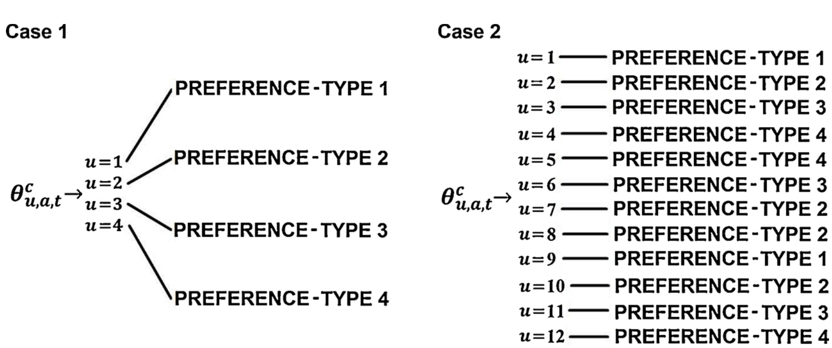

Fig. 5. Case studies.

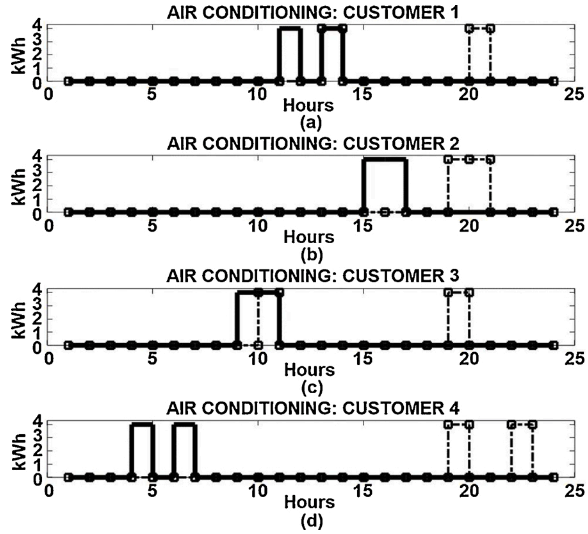

Fig. 6. Habitual and optimal consumption profile of air conditioning.

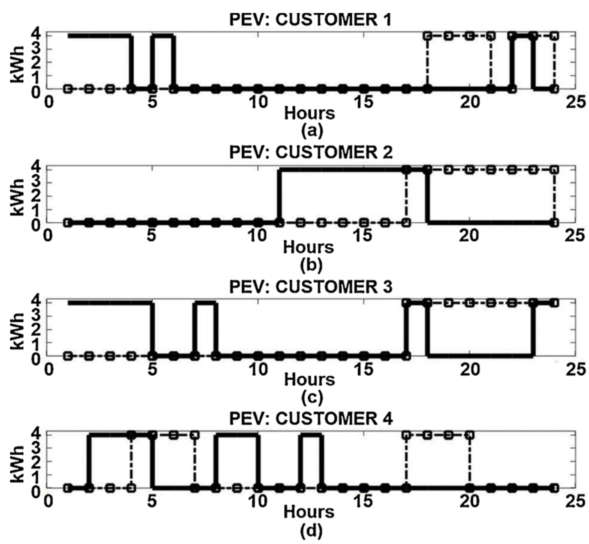

Fig. 7. Habitual and optimal consumption profile of PEV.

value. In Fig. 6(a), the consumption of the air conditioning, related to customer 1, is shifted from 20 h – 21 h ($\mathscr{H}^{cp}_{u,a,t}$ profile) to 11 h – 12 h ($\mathscr{O}^{cp}_{u,a,t}$ profile). Besides, the usage of air conditioning in the period 13 h – 14 h ($\mathscr{O}^{cp}_{u,a,t}$ profile) remains the same in comparison to $\mathscr{H}^{cp}_{u,a,t}$ profile. Note that to mitigate the appearance of new peaks, the proposed model should schedule the air conditioning consumption of customers 2, 3, and 4 for the rest of the hours within the off-peak period considering the respective hourly preferences $\theta^{c}_{u,a,t}$. Based on this, the efficient scheduling ($\mathscr{O}^{cp}_{u,a,t}$ profile) of air conditioning related to customers 2 and 3 in Fig. 6(b) and (c), is done for the periods 15 h–17 h and 9 h–11 h, respectively. These periods are after and before the consumption hours of the air conditioner related to the customer 1. For customer 4, Fig. 6 (d), the air conditioning consumption periods are shifted from 19 h to 20 h and 22 h to 23 h ($\mathscr{H}^{cp}_{u,a,t}$ profile) to the beginning of the morning, i. e., 4 h–5 h and 6 h–7 h ($\mathscr{O}^{cp}_{u,a,t}$ profile). Please note that the scheduling of air conditioning consumption periods, for each customer, is made considering the corresponding hourly preferences for this type of appliance, as shown in Fig. 3(a), (c), (e), and (g).

Another smart appliance with higher average power is PEV, whose hourly preference types are shown in Fig. 3(b), (d), (f), and (h). Fig. 7 shows, for each customer, the $\mathscr{H}^{cp}_{u,a,t}$ (dashed line) and $\mathscr{O}^{cp}_{u,a,t}$ (continuous line) profiles related to the full battery charging of each PEV. Habitually, customers 1, 2, and 3 charge the battery of their PEVs during night periods including the peak period. Customer 4, in addition to charging the battery of his PEV during the night 17 h – 20 h, also performs the charging in the early morning 4 h–7 h. The charging of PEVs batteries coincidentally at certain times of the day, especially during the peak period, can contribute to creating bottlenecks in the supply network. For this reason, it is necessary to ensure efficient scheme for charging this electric mobility. To this end, the proposed model establishes an optimal scheme that allows the PEV battery charging to be adapted to hourly preferences of customers and thus smooth the operation of the electrical network. Thus, Fig. 7(a) shows the $\mathscr{O}^{cp}_{u,a,t}$ profile established for charging the PEV 1 (with B_u equal to 20 kW h) during the dawn periods 1 h–4 h and 5 h–6 h, as well as at night 22 h – 23 h. The optimal battery charge of the PEV 2, with a B_u capacity of 28 kW h, is shown in Fig. 7(b). Note that the battery charge is shifted from the 17 h – 24 h period in the $\mathscr{H}^{cp}_{u,a,t}$ profile to the 11 h–18 h period in the $\mathscr{O}^{cp}_{u,a,t}$ profile avoiding the consumption of electricity within the peak period. Likewise, Fig. 7(c) illustrates the optimal PEV 3 recharge (B_u equal to 32 kW h). Note that the greatest number of hours for charging the battery is scheduled for periods 1 h–5 h (dawn) and 7 h–8 h (morning). The total battery capacity is fully filled within the 17 h–18 h and 23 h–24 h periods (close to the peak period). Finally, the battery charging of the PEV 4 (with B_u of 24 kW h) shown in Fig. 7(d) is shifted from 17 h–20 h ($\mathscr{H}^{cp}_{u,a,t}$ profile) for the periods of 8 h–10 h and 12 h–13 h ($\mathscr{O}^{cp}_{u,a,t}$ profile). It is worth noting that the efficient charging of PEVs batteries is carried out considering a wide distribution of energy consumption within the off-peak period, contributing to the improvement of the LF.

The reduction in the coincident energy consumption of appliances with higher average power ($\beta^{'}_{a} = 1$, see Table 2) can be better appreciated in Fig. 8. This figure illustrates the $\mathscr{H}^{cp}_{u,a,t}$ profile, in dashed line, as well as the $\mathscr{O}^{cp}_{u,a,t}$ profile, in continuous line, related to the number of appliances with $\beta^{'}_{a} = 1$ that are connected for energy consumption in each period *t*. In Fig. 8(a) related to customer 1, the maximum number of appliances connected for energy consumption in the $\mathscr{H}^{cp}_{u,a,t}$ profile is equal to 4. Being connected within the peak period. In the case of the $\mathscr{O}^{cp}_{u,a,t}$ profile, this number of appliances is reduced to 2, with the rest of the appliances scheduled in periods with low energy tariffs. For the rest of the customers related to Fig. 8(b)–(d), the maximum number of appliances connected for consumption in a given period *t* is reduced from 3 (in each $\mathscr{H}^{cp}_{u,a,t}$ profile) to 2 (in each $\mathscr{O}^{cp}_{u,a,t}$ profile). It is worth mentioning that all customers show a reduction in the number of household appliances connected in the peak period. Note that the maximum number of household appliances scheduled for consumption in the off-peak period reaches a value of 2 for each customer.

Fig. 9 shows, in dashed and continuous lines, the profile of $\mathscr{H}^{cp}_{u,a,t}$ and $\mathscr{O}^{cp}_{u,a,t}$ consumption, respectively, when the 21 appliances (including PEV) reported in Table 2 are considered for each customer. In the $\mathscr{H}^{cp}_{u,a,t}$ consumption profile, each domestic customer has a consumption of 17.055 kW h; 27.044 kW h; 23.024 kW h; and 15.044 kW h within the peak period, i.e., 18 h–21 h. In the $\mathscr{O}^{cp}_{u,a,t}$ consumption profile, the energy to be consumed within the same period is equal to 18.74 % (customer 1); 9.31 % (customer 2); 11.65 % (customer 3), and 8.75 % (customer 4) of the energy consumed in the $\mathscr{H}^{cp}_{u,a,t}$ profile during the period 18 h–21 h. This fact reveals that approximately 80 % of the energy consumed during the peak period related to the $\mathscr{H}^{cp}_{u,a,t}$ profile is scheduled efficiently within the off-peak period related to the $\mathscr{O}^{cp}_{u,a,t}$ profile. Fig. 9(a) shows the maximum consumption values for each $\mathscr{H}^{cp}_{u,a,t}$ (9 kW h at period 20 h–21 h) and $\mathscr{O}^{cp}_{u,a,t}$ (5 kW h at period 13 h–14 h) profile related to customer 1. In the case of domestic customers 2, 3, and 4 related to Fig. 9(b)–(d), the maximum consumption values ($\mathscr{O}^{cp}_{u,a,t}$ profile) are close

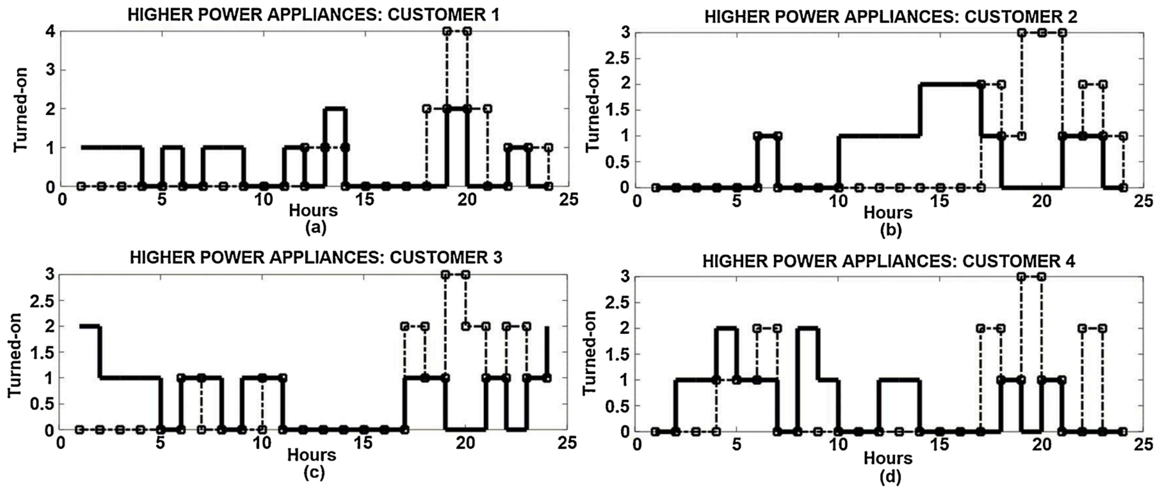

Fig. 8. Number of appliances ($\beta_a^{'} = 1$) turned on for consumption.

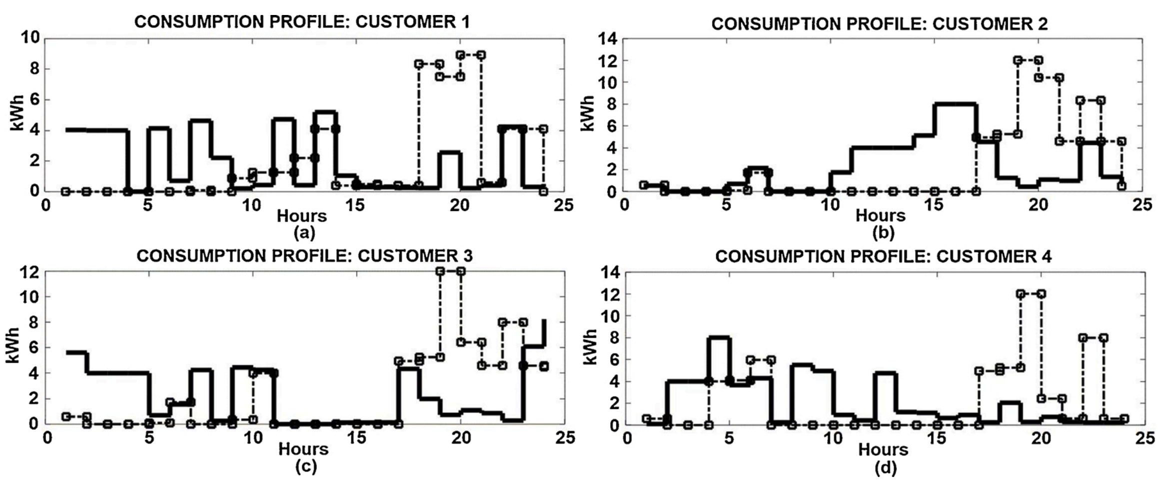

Fig. 9. Habitual and optimal consumption profile for the 4 customers.

to 8 kW h for the periods 15 h–17 h, 0 h–1 h, and 4 h–5 h, respectively. Note that the maximum consumption values of customers are allocated in different periods, mitigating the appearance of high consumption peaks, which in turn contributes to the increase in the LF value.

Fig. 10 shows the profile of $\mathscr{H}^{cp}_{u,a,t}$ and $\mathscr{O}^{cp}_{u,a,t}$ consumption of the total number of customers shown in Fig. 9. Fig. 10 also illustrates in black and white bars, the LF values related to both consumption profiles. Fig. 10(a) shows the $\mathscr{H}^{cp}_{u,a,t}$ profile (dashed line) with a heterogeneous distribution of consumption during the day, with an LF value around 0.195. Note that this value is close to zero, which indicates an inefficient energy usage. In addition, there is high level of congestion during power supply within the peak period, compromising the reliability of the system. In the $\mathscr{O}^{cp}_{u,a,t}$ profile (continuous line) obtained by applying the proposed model, the energy consumed within the peak period is approximately equal to 20 % of the consumption related to the $\mathscr{H}^{cp}_{u,a,t}$ profile (dashed line) within the same period. Note that the distribution of consumption in this $\mathscr{O}^{cp}_{u,a,t}$ profile is strongly homogeneous, i.e., a higher LF value equal to 0.709. This means that the efficient usage of electricity in this profile is guarantee considering the customers' hourly preferences $\theta^{c}_{u,a,t}$. Fig. 10(b) shows the LF values related to the $\mathscr{H}^{cp}_{u,a,t}$ (black bars) and $\mathscr{O}^{cp}_{u,a,t}$ (white bars) consumption profile of each customer and the total number of customers. For each domestic customer, the LF increase is approximately 0.10, while for the total number of customers, the LF value increased significantly from 0.195 to 0.709. Note that the homogeneous distribution of the total $\mathscr{O}^{cp}_{u,a,t}$ consumption profile (high LF value) is the

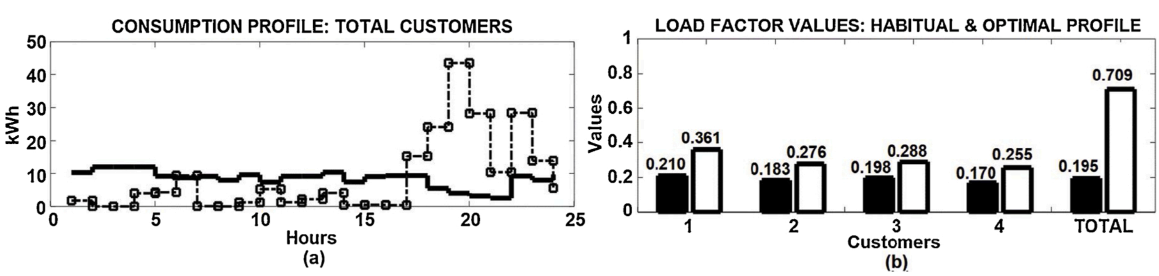

Fig. 10. Consumption profile and LF values for the 4 customers.

result of adding the $\mathscr{O}^{cp}_{u,a,t}$ consumption profile of each customer (low LF value), which presents a heterogeneous distribution in energy consumption over the off-peak period.

Fig. 11 shows the daily expenses related to both the $\mathscr{H}^{cp}_{u,a,t}$ (black bars) and $\mathscr{O}^{cp}_{u,a,t}$ (white bars) profile of each customer and for all of them. Table 4 summarizes in numerical values the results presented in the previous figures. Note that for each consumer, expenses related to the $\mathscr{O}^{cp}_{u,a,t}$ consumption profile represent 70.19 %, 62.26 %, 66.06 %, 69.29 % of expenses related to the $\mathscr{H}^{cp}_{u,a,t}$ consumption profile. For all consumers, total spending is reduced to 33.38 % (from the $\mathscr{H}^{cp}_{u,a,t}$ profile with \$ 75.302, to the $\mathscr{O}^{cp}_{u,a,t}$ profile with \$ 50.160), thus ensuring financial savings. Therefore, this case study showed how the different hourly preferences of each customer within the consumer group can contribute to the optimal scheduling of appliances, ensuring efficient usage of energy, i.e., improving the LF. In this way, maintenance investments by ECO can be postponed while saving on each customer's energy bill.

4.2. Case study 2

In this case, the number of customers is three times the previous case. As can be seen in Fig. 5, each consumer adopts a certain type of hourly preference $\theta^{c}_{u,a,t}$ (see Fig. 2). Moreover, the same type of hourly preference can be adopted by different customers, e.g., customers 1 and 9 adopt the same type 1; customers 2, 7, 8, and 10 adopt type 2; and so on. In order to represent a group of consumers with different family incomes, this case study considers that most customers have different number of appliances present in the home. Table 5 shows the appliances present in each customer's home. For example, in the home of customer 10, there are appliances 2, 5, 6, 7, 8, 10, 15, 16, and 17, which, based on Table 2, correspond to freezer, incand. light, TV, electric iron, fan, stereo, electric shower, microwave, and washing machine, respectively. Note that customers 1, 3, 6, 9 and 11 have PEVs. Air conditioning is not present in the homes of customers 2, 3, 6, 7, 8, 10, and 11. Additionally, the number of appliances with $\beta^{'}_{a} = 1$ is 7 for customer 1; 2 for customer 2; 3 for customer 3; 3 for customer 4; 3 for customer 5; 2 for customer 6; 1 for customer 7; 2 for customer 8; 7 for customer 9; 2 for customer 10; 3 for customer 11; and 3 for customer 12.

Fig. 12 depicts the $\mathscr{H}^{cp}_{u,a,t}$ (dashed line) and $\mathscr{O}^{cp}_{u,a,t}$ (continuous line) profiles for each consumer reported in Table 5. Note that the vast majority of consumers (i.e., 1, 3, 4, 5, 6, 9, 11, and 12) experience a reduction in peak demand. Also note that although there are customers with similar consumption habits, $\mathscr{H}^{cp}_{u,a,t}$, their $\mathscr{O}^{cp}_{u,a,t}$ profiles are different. For example, customers 1 and 9, (Fig. 12(a)) and (i)), respectively, both with peak consumption close to 10 kW h (in profile $\mathscr{H}^{cp}_{u,a,t}$). However, during peak hours, customer 9 achieved a lower reduction in electricity consumption compared to customer 1. Another case can be seen with customers 4 (Fig. 12(d)), 5 (Fig. 12(e)), and 12 (Fig. 12(l)), also with similar $\mathscr{H}^{cp}_{u,a,t}$ profiles. Here, although the $\mathscr{O}^{cp}_{u,a,t}$ profile for consumers 4 and 5 shows a concentration of consumption in periods close to 12 h–13 h, consumer 12 has very low consumption (less than 1 kW h) within that same period. Also, in all cases the peak consumption related

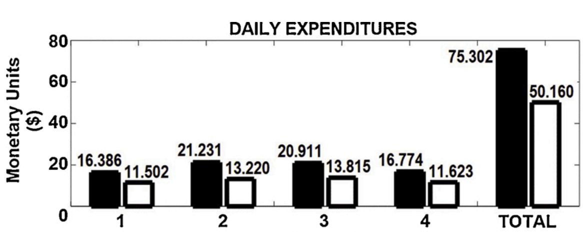

Fig. 11. Daily expenses for the 4 customers.

Table 4
Expenses related to the habitual and optimal consumption profile of the 4 customers.

Type of Preferences	Customers	Habitual Profile		Optimal Profile	
		Expenses (\$)	Load Factor	Expenses (\$)	Load Factor
1	1	16.386	0.210	11.502	0.361
2	2	21.231	0.184	13.220	0.276
3	3	20.911	0.198	13.815	0.289
4	4	16.774	0.170	11.623	0.256
–	Total	75.302	0.195	50.160	0.709

Table 5
Customers and their home appliances.

Customer	Appliances at the home	Customer	Appliances at the home
1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21	7	2, 5, 6, 8, 10, 15, 16, 17
2	2, 5, 6, 7, 8, 10, 15, 16, 17	8	2, 5, 6, 7, 10, 15, 16, 17
3	2, 4, 5, 6, 7, 8, 12, 16, 17, 18, 20, 21	9	1, 2, 3, 4, 5, 6, 7, 8,9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21
4	1, 2, 5, 6, 7, 11, 13, 16, 17, 18, 19	10	2, 5, 6, 7, 8, 10, 15, 16, 17
5	1, 2, 5, 6, 7, 11, 13, 16, 17, 19	11	2, 4, 5, 6, 7, 8, 12, 16, 17, 18, 20, 21
6	2, 4, 5, 6, 8, 12, 16, 17, 18, 20, 21	12	1, 2, 5, 6, 7, 11, 13, 16, 17, 18,19

to the $\mathscr{O}^{cp}_{u,a,t}$ profile is less than the peak consumption of the $\mathscr{H}^{cp}_{u,a,t}$ profile by 3 kW h. Also in Fig. 12, note that cases with a new peak of consumption greater than or equal to the habitual peak of consumption are related to customers 2 (Fig. 12(b)), 7 (Fig. 12(g)), 8 (Fig.12(h)), and 10 (Fig. 12(j)). For customer 8, the difference between the new peak consumption (in profile $\mathscr{O}^{cp}_{u,a,t}$) and the habitual peak consumption (in profile $\mathscr{H}^{cp}_{u,a,t}$) is close to 1 kW h. It is also worth noting that consumers with a large number of home appliances have a wide distribution of consumption throughout the day, while those with a smaller number of home appliances, the distribution of their consumption turns out to be heterogeneous. Thus, the sum of each individual profile $\mathscr{O}^{cp}_{u,a,t}$ results in the profile $\mathscr{O}^{cp}_{u,a,t}$ of all customers, which, in turn, shows the homogeneous distribution of consumption during the day, without presence of new consumption peaks at off-peak hours, as can be seen in Fig. 13(a).

Fig. 13(a) shows the $\mathscr{H}^{cp}_{u,a,t}$ and $\mathscr{O}^{cp}_{u,a,t}$ profiles for all customers in Table 5. Note that the $\mathscr{H}^{cp}_{u,a,t}$ profile, in dashed line, the highest peak consumption of 57.61 kW h is reached in the period of 19 h – 20 h. In the same period, the $\mathscr{O}^{cp}_{u,a,t}$ profile, in continuous line, shows a reduction in consumption by 85.36 % of this peak of habitual consumption. Note that the electricity consumption shifted to off-peak periods is widely distributed with a valley between 15 h–16 h. Also note that, within that time, the energy consumption remains close to 16 kW h. This represents approximately the third part of the peak consumption in the $\mathscr{H}^{cp}_{u,a,t}$ profile. Therefore, the proposed model also presents an efficient performance for a greater number of consumers with differentiated family income.

Fig. 13(b) depicts, for both consumption profiles, the LF values of each customer as well as for all 12 customers. Note how the LF value related to the $\mathscr{H}^{cp}_{u,a,t}$ profile (in black bars) of each customer, including the LF of all customers, adopts values below 0.3, that is, close to 0. By applying the MIPQC model, the $\mathscr{O}^{cp}_{u,a,t}$ profile (in white bars) of most customers shows an improvement in LF with values ranging between 0.13 and 0.45. However, this increase in the LF values of each customer, although low, has a greater effect on the value of the LF related to all customers, which turns out to be 0.72. This fact reinforces the

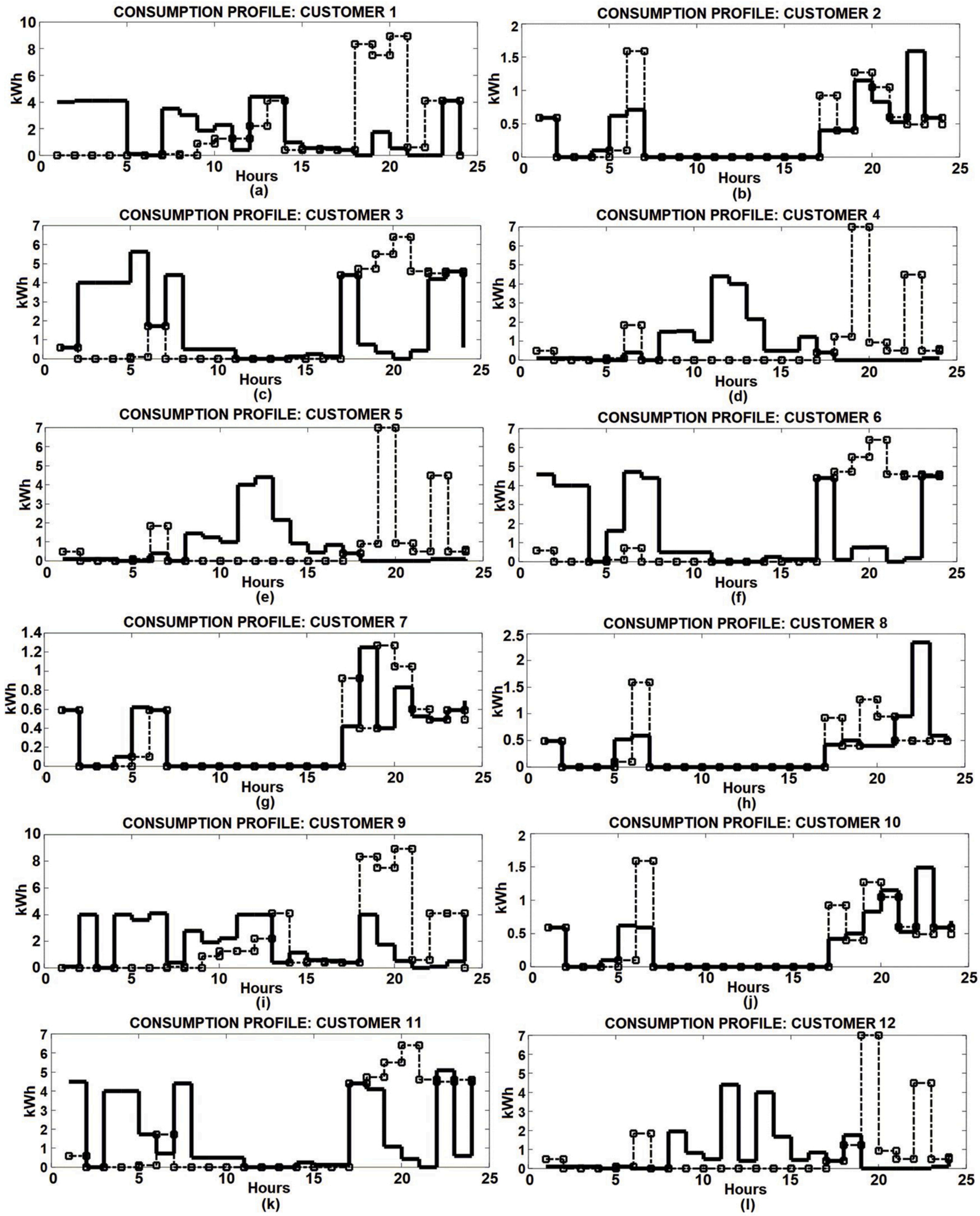

Fig. 12. Habitual and optimal consumption profile for the 12 customers.

importance of the proposed tool that allows to schedule the consumption of each consumer, in order to reduce the coincident usage of appliances with higher average power in periods with low energy tariffs which, consequently, guarantees the rational use of electricity minimizing the expense unnecessary energy.

Fig. 14 shows the daily expenses associated with each customer as well as for all of them. The black and white bars show these expenses for the $\mathscr{H}^{cp}_{u,a,t}$ and $\mathscr{O}^{cp}_{u,a,t}$ profiles, respectively. Table 6 details the values shown in Figs. 13(b) and 14 . These values are different for each consumer and for the total number of consumers, for both consumption profiles. In addition, Table 6 shows the hourly preferences $\theta^{c}_{u,a,t}$ adopted by each consumer. Note that, among all customers, customer 8 does not show an improvement in LF. In this case, the value of LF in the consumption profile was reduced from 0.2016 (in profile $\mathscr{H}^{cp}_{u,a,t}$) to 0.1370 (in profile $\mathscr{O}^{cp}_{u,a,t}$). Thus, this consumer, in his profile $\mathscr{O}^{cp}_{u,a,t}$, presents a high peak consumption during off-peak hours, as seen in Fig. 12(h). Even with this occurrence, note that the expenditure for energy consumption related to the $\mathscr{O}^{cp}_{u,a,t}$ profile (of 2.530 \$) is less than the expenditure for the $\mathscr{H}^{cp}_{u,a,t}$ profile (of 2.614 \$) due to the consumption being concentrated during off-peak hours. Moreover, consumers with higher household income, i.e., higher energy consumption, as are 1, 3, 6, 9, and 11, achieved a reduction of 35.25 %, 33.48 %, 35.69 %, 31.69 %,

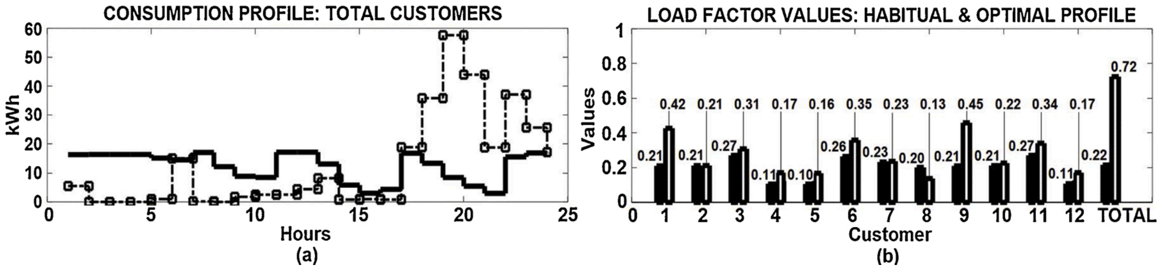

Fig. 13. Consumption profile and LF values for the 12 customers.

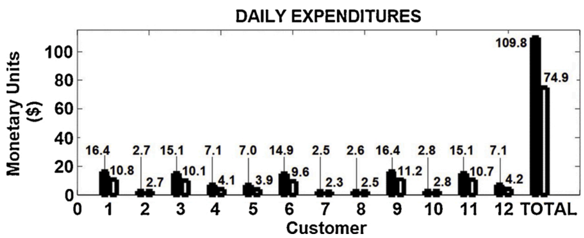

Fig. 14. Daily expenses for the 12 customers.

Table 6
Expenses related to the habitual and optimal consumption profile of the 12 customers.

Type of Preferences	Customers	Habitual Profile		Optimal Profile	
		Expenses ($)	Load Factor	Expenses ($)	Load Factor
1	1	16.386	0.2100	10.774	0.4268
2	2	2.763	0.2121	2.753	0.2121
3	3	15.118	0.2707	10.056	0.3082
4	4	7.109	0.1074	4.049	0.1710
4	5	7.001	0.1055	3.985	0.1678
3	6	14.894	0.2642	9.578	0.3586
2	7	2.539	0.2327	2.283	0.2364
2	8	2.614	0.2016	2.530	0.1370
1	9	16.386	0.2100	11.193	0.4580
2	10	2.763	0.2121	2.753	0.2263
3	11	15.118	0.2707	10.711	0.3406
4	12	7.109	0.1074	4.227	0.1710
–	Total	109.8	0.2161	74.892	0.7238

and 29.15 %, respectively, in spending for habitual consumption. For low-income customers, with spending on habitual consumption of around 2.7 $, the savings in the energy bill was practically zero. For all consumers, energy consumption expenditures are reduced by 34.908 $ with the consequent improvement in LF with a value greater than triple by 0.2161. Therefore, the proposed tool, besides guaranteeing an efficient scheme at a minimum cost, also increases the reliability of the supply service.

4.3. Sensitivity analysis of μ', μ'', and μ'''

In this subsection an analysis of the values of the weights μ', μ'', and μ''' related to the objective function (1) of the proposed MIPQC model is done for case study 2, since it has the largest number of customers with different family income. As mentioned before, weights μ', μ'', and μ''' are associated with cost functions Ω_1, Ω_2, and Ω_3 related to customers' energy bills, coincident usage of appliances with higher average power and financial gains from ECO, respectively.

Table 7 reports the combination of values 10^{-1} (0.1), 10° (1), and 10^{1} (10) to be considered for each weight μ', μ'', and μ'''. Thus, for each combination, a given value of the objective function is obtained. Taking into account the organization of the values of the objective function, e.g., from the lowest value of 15.542 to the highest value of 1556.44, the combinations are ordered from 1 to 9 in this table. In addition, the two columns on the right side of Table 7 show, for each combination, the LF values as well as the costs per energy consumption of all customers. Fig. 15 depicts the graph related to all combinations attributed to μ', μ'', and μ'''. Also, in Table 7, combination 7 corresponds to the values of the weights used in the case studies analyzed above. This combination has an LF value and total costs equal to 0.7238 and 74.802 $, respectively. Similar values of the LF and total costs can be seen in combinations 1, 4, 8, and 9. Note that, for each of the combinations 1, 4, and 9 all weights are equal, i.e., for combination 1 all weights are equal to 10^{-1}, for combination 4 are equal to 10°, and for combination 9 are equal to 10^{1}. In combination 8, all weights are different, with the largest weight attributed to the Ω_2 cost function, related to the coincident use of higher power appliances. These combinations demonstrate other alternative values that can be used in the analysis of the case studies. On the other hand, the weight values related to combinations 2, 5, and 6 are not very attractive when the objective is to increase the LF only. However, these combinations show the biggest reduction in customers' energy consumption expenses. Combination 5 shows the maximum cost reduction, 68.863 $, but the low LF of 0.5892 can compromise the ECO's operating

Table 7
Weight values.

Order N°	Weights			Obj. Function Values	Total Costs ($)	Load Factor Values
	μ'	μ''	μ'''			
1	10^{-1}	10^{-1}	10^{-1}	15.542	74.003	0.7238
2	10°	10^{-1}	10^{1}	80.741	70.040	0.6194
3	10^{-1}	10°	10^{1}	92.989	75.559	0.7451
4	10°	10°	10°	155.407	74.349	0.7324
5	10^{1}	10^{-1}	10°	700.027	68.863	0.5892
6	10^{1}	10°	10^{-1}	790.613	69.285	0.6094
7*	10^{-1}	10^{1}	10°	800.729	74.919	0.7238
8	10°	10^{1}	10^{-1}	814.815	74.802	0.7268
9	10^{1}	10^{1}	10^{1}	1556.44	74.135	0.7281

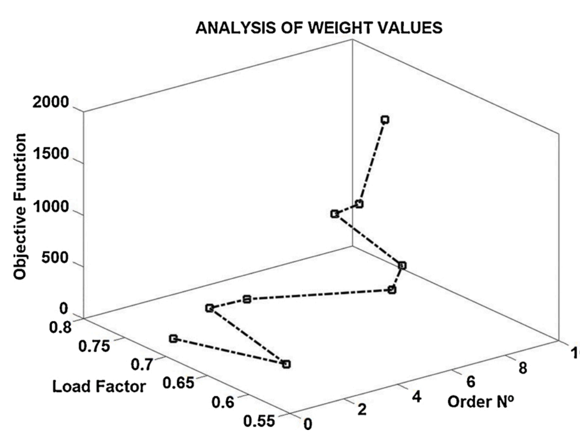

Fig. 15. Values of the objective function related to the weights μ', μ'', and μ'''.

costs. Unlike this combination, combination 7 turns out to be advantageous when it comes to reducing energy waste due to the high LF value, 0.7451. However, this same combination shows a higher cost per consumption of 75.559 $ compared to combination 5, resulting financially unfavorable for consumers. On the user's side, combination 5 would be the most appropriate financially. While on the ECO's side, the most economically appropriate alternative is combination 3. Therefore, based on the combinations presented in Table 7, our criterion adopted in the choice of weights related to combination 7 aims to meet the financial and operational aspects of both customers and the ECO.

5. Conclusions

In this paper, a MILP model has been proposed to mitigate the occurrence of new demand peaks during periods with lower energy prices. This mitigation was achieved by improving the LF related to the consumption profile of a group of domestic customers. In this work, the LF value has been improved by avoiding the coincident consumption of smart home appliances, mainly of the smart appliances with higher average power, taking into account flexibility in consumers' hourly preferences. In the proposed model, the economic expenditures related to customers and ECO are minimized, while the technical and operational constraints of home appliances, including the battery charging of the PEV, are being considered. Uncertainties in customers' habitual consumption patterns are modeled using an MCM. The results shown in the case studies reveal the potential of the proposed tool in reducing the monthly bill of customers through the efficient management of smart home appliances, as well as the efficient usage of energy in the electricity distribution network. Consequently, financial impacts will be perceived by ECO in the long term. Among them is the postponement of investments in maintenance or installation of new distribution transformers, feeders, protection devices, etc., due to efficient demand management.

Although the proposed model has shown its effectiveness in reducing expenses for both customers and ECOs, limitations must still be overcome in order to obtain a more realistic model. To overcome the limitations present in the current stage of the proposed model, the following factors should be considered: i) inclusion of operational constraints that guarantee the logical sequence in the household appliances usage, as in the case of using the clothes dryer after using the washing machine, among others; ii) the operational regime of thermal loads, in view of the effect of temperature variation inside and outside the house; iii) the kilometers traveled by EVs as an influential factor in the time when battery charging starts, which can impact the domestic consumption profile; iv) the insertion of either generation or storage sources, individual or shared, that will allow to meet the peaks of demand, reducing the electric grid stresses, as well as the uncertainties related to the intermittent energy generation and the price scheme for the sale. Based on these limitations, different approaches can be considered in future works, among them:

1 Investigate how the levels of thermal and electrical comfort in homes impact the formation of a more economical consumption profile once the number of appliances is considered to be variable and dependent on the domestic income of each consumer;
2 Address the improvement of the LF when demand response programs based on incentives and prices are adopted within the community;
3 Consider the variation of the LF due to the presence of shared intermittent generation and how the new peaks in demand are mitigated for a time horizon of one week.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aduda, K. O., Labeodan, T., Zeiler, W., & Boxem, G. (2017). Demand side flexibility coordination in office buildings: A framework and case study application. *Sustainable Cities and Society, 29*, 139–158.

Ahmed, N., Levorato, M., & Li, G. P. (2018). Residential consumer-centric demand side management. *IEEE Transactions on Smart Grid, 9*(5), 4513–4524.

Ali, S. B. M., Hasanuzzaman, M., & Rahim, N. A. (2018). Investigation on the load factor performance at wisma R&D University Malaya building. *5th IET International Conference on Clean Energy and Technology (CEAT2018)*, 1–6.

Al-Mousa, A., & Faza, A. (2019). A fuzzy-based customer response prediction model for a day-ahead dynamic pricing system. *Sustainable Cities and Society, 44*, 265–274.

Alquthami, T., & Meliopoulos, P. S. (2018). Smart house management and control without customer inconvenience. *IEEE Transactions on Smart Grid, 9*(4), 2553–2562.

ANEEL. (2016). *Normative resolution 733*, 6 September 2016. National Agency of Electrical Energy http://www2.aneel.gov.br/cedoc/ren2016733.pdf.

Anvari-Moghaddam, A., Monsef, H., & Rahimi-Kian, A. (2016). Optimal smart home energy management considering energy saving and a comfortable lifestyle. *IEEE Power and Energy Society General Meeting (PESGM)*, 1.

Anzar, M., Iqra, R., Kousar, A., Ejaz, S., Alvarez-Alvarado, M. S., & Zafar, A. K. (2018). Optimization of home energy management system in smart grid for effective demand side management. *International Renewable and Sustainable Energy Conference (IRSEC)*, 1–6.

Basit, A., Sidhu, G. A. S., Mahmood, A., & Gao, F. (2017). Efficient and autonomous energy management techniques for the future smart homes. *IEEE Transactions on Smart Grid, 8*(2), 917–926.

Bem Dhaou, I. (2019). Smart plug design for demand side management program. *19th International Conference on Power Electronics and Their Applications (ICPEA)*, 1–5.

Borges, M. C. O., Franco, J. F., & Rider, M. J. (2014). Optimal reconfiguration of electrical distribution systems using mathematical programming. *Journal of Control Automation and Electrical Systems, 25*, 103–111.

Cerna, F. V., Pourakbari-Kasmaei, M., & Gallego, L. A. (2018). Evaluation of the performance of HEV technologies using a MILP model to minimize pollutant emissions. *IEEE International Conference on Industry Applications (INDUSCON)*, 446–452.

Cerna, F. V., Pourakbari-Kasmaei, M., Romero, R. A., & Rider, M. J. (2018). Optimal delivery scheduling and charging of EVs in the navigation of a city map. *IEEE Transactions on Smart Grid, 9*(5), 4815–4827.

Chakraborty, N., Mondal, A., & Mondal, S. (2020). Efficient load control based demand side management schemes towards a smart energy grid system. *Sustainable Cities and Society, 59*. Article 102175.

Chiu, W. Y., Hsieh, J. T., & Chen, C. M. (2020). Pareto optimal demand response based on energy costs and load factor in smart grid. *IEEE Transactions on Industrial Informatics, 16*(3), 1811–1822.

Christopher, O. A., & Wang, L. (2014). Autonomous appliance scheduling for household energy management. *IEEE Transactions on Smart Grid, 5*(2), 673–682.

Chupong, C., & Plangklang, B. (2017). Electricity bill forecasting application by home energy monitoring system. *International Electrical Engineering Congress (iEECON)*, 1–4.

Croce, D., Giuliano, F., Tinnirello, I., Galatioto, A., Bonomolo, M., Beccali, M., et al. (2017). Overgrid: A fully distributed demand response architecture based on overlay networks. *IEEE Transactions on Automation Science and Engeneering, 14*(2), 471–481.

DEA Technical Note 14/10. (2010). *Evaluation of energy efficiency in industry and residences in the decennial horizon (2010 - 2019)*. https://www.epe.gov.br/sites-pt/publicacoes-dados-abertos/publicacoes/PublicacoesArquivos/publicacao-245/topico-270/20100809_4[1].pdf.

Di Santo, K. G., Kanashiro, E., Di Santo, S. G., & Saidel, M. A. (2015). A review on smart grids and experiences in Brazil. *Renewable and Sustainable Energy Reviews, 54*, 1072–1082.

Ekanayake, J., Liyanage, K., Wu, J., Yokoyama, A., & Jenkins, N. (2012). *Smart grid technology and applications*. UK: John Wiley&Sons.

Fardan, A. S. A., Gahtani, K. S. A., & Asif, M. (2017). Demand side management solution through new tariff structure to minimize excessive load growth and improve system load factor by improving commercial building energy performance in Saudi Arabia. *IEEE International Conference on Smart Energy Grid Engineering (SEGE)*, 320. -308.

Farham, H., Mohammadian, L., Alipour, H., & Pouladi, J. (2019). Energy procurement of large industrial consumer via interval optimization approach considering peak demand management. *Sustainable Cities and Society, 46*. Article 101421.

Farrokhifar, M., Momayyezi, F., Sadoogi, N., & Safari, A. (2018). Real-time based approach for intelligent building energy management using dynamic price policies. *Sustainable Cities and Society, 37*, 85–92.

Fourer, R., Gay, D. M., & Kernighan, B. W. (2003). *AMPL: A modeling language for mathematical programming'* (2nd ed). Pacific Grove: Brooks/Cole-Thomson Learning.

Ghorashi, S. M., Rastegar, M., Senemmar, S., & Seifi, A. R. (2020). Optimal design of reward-penalty demand response programs in smart power grids. *Sustainable Cities and Society, 60*. Article 102150.

Gonçalves, R. R., Alves, R. P., Franco, J. F., & Rider, M. J. (2013). Operation planning of electrical distribution systems using a mixed integer linear model. *Journal of Control Automation and Electrical Systems, 24*, 668–679.

Heo, S., Park, W. K., & Lee, I. (2017). Energy management based on communication of smart plugs and inverter for smart home systems. *International Conference on Information and Communication Technology Convergence (ICTC)*, 810–812.

Hosseinnia, H., Nazarpour, D., & Talavat, V. (2018). Benefit maximization of demand side management operator (DSMO) and private investor in a distribution network. *Sustainable Cities and Society, 40*, 625–637.

Hussain, M., & Gao, Y. (2018). A Review of demand response in an efficient smart grid environment. *The Electricity Journal, 84*(5), 55–63.
IBGE – Brazilian Institute of Geography and Statistics. (2019). *Family budget survey*. https://biblioteca.ibge.gov.br/visualizacao/livros/liv101670.pdf.
IBM ILOG CPLEX V 12. 1. (2009). *User's manual for CPLEX*. Incline Village, NV, USA: CPLEX Division, ILOG Inc.
Keerthisinghe, C., Verbic, G., & Chapman, A. C. (2018). A fast technique for smart home management: ADP with temporal difference learning. *IEEE Transactions on Smart Grid, 9*(4), 3291–3303.
Khalid, A., Javaid, N., Guizani, M., Alhussein, M., Aurangzeb, K., & Ilahi, M. (2018). Towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings. *IEEE Access : Practical Innovations, Open Solutions, 6*, 19509–19529.
Ma, K., Yu, Y., Yang, B., & Yang, J. (2019). Demand-side energy management considering price oscillations for residential building heating and ventilation systems. *IEEE Transactions on Industrial Informatics, 15*(8), 4742–4752.
Marah, R., & Hibaoui, A. E. (2018). Algorithms for smart grid management. *Sustainable Cities and Society, 38*, 627–635.
Nuchprayoon, S. (2016). Calculation and allocation of load losses in distribution system using load research data and load factor method. *6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, 85–90.
Obushevs, A., Oleinikova, I., & Mutule, A. (2016). Demand side management plataform for HAN flexibility estimation with agent control. *13th International Conference on the European Energy Market (EEM)*, 1–5.
Ponce-Jara, M. A., Ruiz, E., Gil, R., Sancristóbal, E., Pérez-Molina, C., & Castro, M. (2017). Smart grid: Assessment of the past and present in developed and developing countries. *Energy Strategy Reviews, 18*, 38–52.
Rahman, M. M., Arefi, A., Shafiullah, G. M., & Hettiwatte, S. (2018). A new approach to voltage management in unbalanced low voltage network using demand response and OLTC considering consumer preference. *International Journal of Electrical Power & Energy Systems, 99*, 11–27.
Residential Class Brazil Report – Procel/Eletrobrás. (2007). *Survey of possession of equipment and habits of use – Base year 2005*. file:///C:/Users/SAMSUNG/Dropbox/My%20PC%20(DESKTOP-G480JG7)/Downloads/Classe_Residencial_Relatorio_Brasil.pdf.
Robert, P. C., & Casella, G. (2004). *Monte Carlo statistical methods*. New York: Springer Science+Business Media.
Saikia, B. J., Manas, M., & Baruah, D. C. (2015). Distribution loss reduction in a university of north east India through load factor improvement. *International Conference on Energy Systems and Applications*, 203–208.
Saleem, Y., Crespi, N., Rehmani, M. H., & Copeland, R. (2019). Internet of things-aided smart grid: Technologies, architecture, applications, prototypes, and future research directions. *IEEE Access : Practical Innovations, Open Solutions, 7*, 62962–63003.
Sehar, F., Pipattanasomporn, M., & Rahman, S. (2017). Integrated automation for optimal demand management in commercial buildings considering occupant comfort. *Sustainable Cities and Society, 28*, 16–29.
Setlhaolo, D., & Xia, X. (2016). Combined residential demand side management strategies with coordination and economic analysis. *International Journal of Electrical Power & Energy Systems, 79*, 150–160.
Setlhaolo, D., & Xia, X. (2015). Optimal scheduling of household appliances with a battery storage system and coordination. *Energy and Buildings, 94*, 61–70.
Shakouri, G., & Kazemi, A. (2017). Multi-objective cost-load optimization for demand side management of a residential area in smart grids. *Sustainable Cities and Society, 32*, 171–180.
Shareef, H., Ahmed, M. S., Mohamed, A., & Hassan, E. A. (2018). Review on home energy management system considering demand responses, smart technologies, and intelligent controllers. *IEEE Access : Practical Innovations, Open Solutions, 6*, 24498–24509.
Shawkat Ali, A. B. M. (2013). *Smart grids opportunities, development, and trends*. London: Springer-Verlag.
Sioshansi, F. P. (2012). *Smart grid integrating renewable, distributed & efficiency energy*. Elsevier Inc.
Surai, J., & Surapatana, V. (2014). Load factor improvement in industrial sector load duration curves. *International Electrical Engineering Congress (iEECON)*, 1–4.
Trongwanichnam, K., Thitapars, S., & Leeprechanon, N. (2019). Impact of plug-in electric vehicles load planning to load factor and total generation cost in a power system. *IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia)*, 599–604.
US Department of Energy. (2019). *Appliance & equipment Standards/Standards and test procedures*. https://www.energy.gov/eere/buildings/standards-and-test-procedures.
US Energy Information Administration. (2019). *Annual energy outlook 2019 with projections to 2050*. https://www.eia.gov/outlooks/aeo/pdf/aeo2019.pdf.
Villalobos, J. G., Zamora, I., Eguia, P., Torres, E., Etxegarai, A., & San Martin, J. I. (2017). Optimization of load factor in distribution networks with high share of plug-in electric vehicles and photovoltaic generation. *52nd International Universities Power Engineering Conference (UPEC)*, 1–6.
Wang, Y., Lin, H., Liu, Y., Sun, Q., & Wennersten, R. (2018). Management of household electricity consumption under price-based demand response scheme. *Journal of Cleaner Production, 204*, 926–938.
Yahia, Z., & Pradhan, A. (2018). Optimal load scheduling of household appliances considering consumer preferences: An experimental analysis. *Energy, 163*, 15–26.
Yahia, Z., & Pradhan, A. (2020). Multi-objective optimization of household appliance scheduling problem considering consumer preference and peak load reduction. *Sustainable Cities and Society, 55*. Article 102058.
Yu, D., Xu, X., Dong, M., Nojavan, S., Jermsittiparsert, K., Abdollahi, A., et al. (2020). Modeling and prioritizing dynamic demand response programs in the electricity markets. *Sustainable Cities and Society, 53*. Article 101921.