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A MILP framework for electricity tariff-choosing decision process in smart homes considering ‘Happy Hours’ tariffs

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ABSTRACT

Nowadays, electricity end users can choose among a huge variety of different electricity plans on a deregulated energy market. The wide variety of tariffs besides the advent of novel agents like smart consumers and prosumers, are becoming the tariff-choosing process more complex. This paper proposes a MILP optimization framework which aims at facilitating this task. More precisely, the main endings of the developed framework are: (i) determine the most suitable tariff for smart consumers and prosumers based on historical consumption data, (ii) determine the optimal hours to be hired for a so-called ‘Happy hours’ tariff plan. In addition, other useful results can be directly obtained from the developed tool. The developed approach carries out a MILP optimization framework for optimal scheduling a series of flexible appliances through various characteristic days obtained from clustering historical collected data. This process is repeatedly executed for the different tariff options and, finally, the most attractive one is selected. A case study on the Spanish retail market for a benchmark prosumer environment is used for showing the capabilities of the developed framework.

1. Introduction

Deregulation of retail electricity markets has enabled free competition among retail companies. Under the umbrella of this paradigm, many companies have emerged in order to increase the competency of electricity markets. Thus, retailer companies compete each other in an open market environment to get customers [1]. In this context, many companies are developing multiple original electricity tariffs and economic plans in order to become themselves more attractive for consumers. Consequently, electricity users can choose among a wide offer of electricity plans with much different particularities provided by a plethora of retailer companies. To cite just some examples, in Spain an end user from the community of Andalucía can choose among the plans offered by more than 50 companies [2]. Other remarkable example is the “Power-to-Choose” platform [3] promoted by the Public Utility of Commission of Texas (US). In this web site, more than 1000 electricity plans of different electricity retailers are available for review and selection.

Typically, electricity retailers charge the energy consumption by fixed or variable tariffs [4], which can be incentive or penalized by a series of terms which depend on the peak power or the total energy consumed through a month [5]. Fig. 1 pictorially represents the basic principles of the most typical tariffs, which are explained in the following points:

- *Fixed tariffs*: in this case, electricity consumption is charged by a price which is kept constant over the whole day. Similarly, the pre-paid tariffs charge a prefixed price regardless the energy consumed by the user. An evolution of this kind of tariffs is currently offered in some countries. It consists on posing a fixed tariff in which some hours of the day (known as ‘happy hours’) are not charged at all (see Fig. 1 and [6]).
- *Time-variable tariffs*: the electricity price is different each hour of the day. Typically, two time slots are distinguished during a day (peak and off-peak hours). The most typical examples are the time-of-use and real time pricing tariffs. In the former, the electricity retailer set a different price for the peak and off-peak hours while in the former, the pricing varies during a day according to market signals.
- *Others*: other kind of charges find to incentivize or penalize some behaviors. Examples are the stepwise tariffs described in [7] and [8], whereby the electricity bill is charged proportionally to the observed peak power or total energy consumed through a month.

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Nomenclature

Acronyms

MILP	Mixed-Integer linear programming
PV	Photovoltaic
WM	Washing machine
DW	Dishwasher
SD	Spin dryer
EV	Electric vehicle

Indices and sets

t	Subscript for time slots
s	Subscript for representative days
i	Superscript for controllable appliances
T	Set of time slots over a time horizon
H	Set of o'clock hour slots over a time horizon
S	Set of representative days
Ω^s	Cluster of the representative days

Parameters

$\Delta\tau$	Time step (h)
ω^s	Weight of the representative days
M	Large possitive number
$\overline{p}^{G}$	Maximum power that can flow from/to the utility grid (kW)
P^{PV}	Rated power of the PV array (kW)
I	Solar irradiation (kW/m^2)
θ	Ambient temperature (°C)
η^{PV}	Efficiency of the PV array (pu)
$\hat{p}^{PV}$	Forecasted PV power (kW)
ξ	Nominal capacity of the battery storage system (kWh)
λ	Energy-to-power ratio (h)
DOD	Depth of discharge (pu)
η^{B}	Efficiency of the batteries (pu)
D	Home demand due to non-controllable appliances (kW)
P^i	Rated power of the controllable appliance i (kW)
LB^i	Lower band of allowable operation time slot of the controllable appliance$i$
UB^i	Upper band of allowable operation time slot of the controllable appliance$i$
δ^i	Operation time slots of the controllable appliance$i$
$\pi^{€}$	Cost of energy (€/kWh)
μ	Factor that determines the selling energy price (pu)
ϑ	Total number of happy hours

Decision variables

p^{GH}	Power purchased from the grid (kW)
p^{HG}	Power sold to the grid (kW)
p^{PV}	Power given by the PV array (kW)
$p^{B,dch}$	Batteries discharging power (kW)
$p^{B,ch}$	Batteries charging power (kW)
e^{B}	Energy stored in batteries (kWh)
u	Binary decision variable which indicates the commitment status of an appliance (1 = ON, 0 = OFF)
$\overline{u}$ / u_{-}	Binary decision variable which marks the switch on/off transition of a controllable appliance (1 = OFF-ON/ON-OFF)
$\nu^{€}$	Binary decision variable which is equal to 0 if a happy hour is hired at time t, and 1 otherwise
$\overline{\nu}^{€}$, $\nu_{-}^{€}$	Auxiliary variables for continuity of the happy hours tariff
y, z	Dummy variables

Functions

$\phi(\cdot):(\cdot)^n\rightarrow\mathbb{N}$	Returns the number of elements of a set/cluster

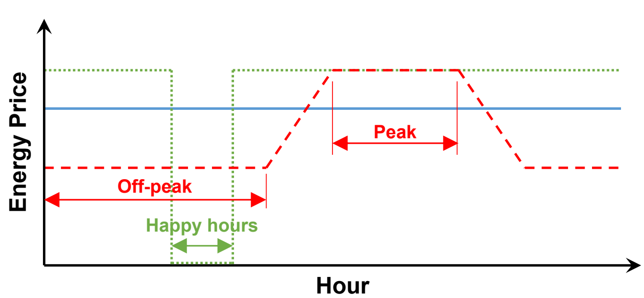

Fig. 1. Principles of some typical electricity tariffs. Fixed (blue), time-of-use (red) and happy hours (green).

Nowadays, electricity retailers and distribution companies are more concerned to encourage demand response from the users [9]. This end can be achieved through home energy management control schemes over the home appliances in order to reduce the electricity bill. This fact enables the active participation of end users in the electricity market as another agent which is customary called smart consumer/prosumer [10]. While a smart consumer is conceived as a pure load, a smart prosumer has the capability of producing a surplus energy by means of own resources (PV or batteries), which can be sold to the grid in order to obtain a revenue [11]. With the former pure-passive home paradigm, load curve of dwellings could be easily guessing since the peak and valley loads typically occurred at same hours, and there was not possibility to sell back energy to the grid. However, the current prosumer environment makes this behaviour hardly predictable due to higher versatility and stochastic features of renewable-based generators. This evidence along the growing diversity and complexity observed in current electricity rates, are provoking that the tariff-choosing decision process is no longer a trivial task [12].

In this context, home users may still choose their energy tariffs on the basis of their experience, personal recommendations or even heuristically. However, monetary expenditures may notably vary by choosing one or another tariff. Hence, tariff-choosing decision task should not be only entrusted to human decisions. In this regard, support decision tools capable of determining the optimal energy plan for a smart user are reaching a high level of importance within the retail electricity market. Despite its apparent importance, this kind of tools are not widely developed and most of them are simply comparator datasets [13]. On the other hand, many works are rather focused on the optimal tariff design instead (e.g. see [14]). These facts make evident the necessity of further developing tariff-choosing tools, adapted to the modern electricity retail market paradigm. Indeed, to the best of our knowledge, the reference [12] supposes the unique exception to this trend. In this work, the authors developed a personalized recommender tool based on information filtering systems. The developed approach collects a series of temporally electricity consumptions through advanced metering infrastructure. On the basis of the collected information, this system infers the preference of individual users on each tariff plan. As final stage, a collaborative filtering algorithm is carried out, which is able to recommend the most suitable tariff plans to an arbitrary target user.

This work aims at contributing to the narrow pool of decision support tools for tariff-choosing of smart users. More precisely, this paper develops a MILP framework which, based on historical consumption profiles and shiftable capabilities of home appliances, determines the most

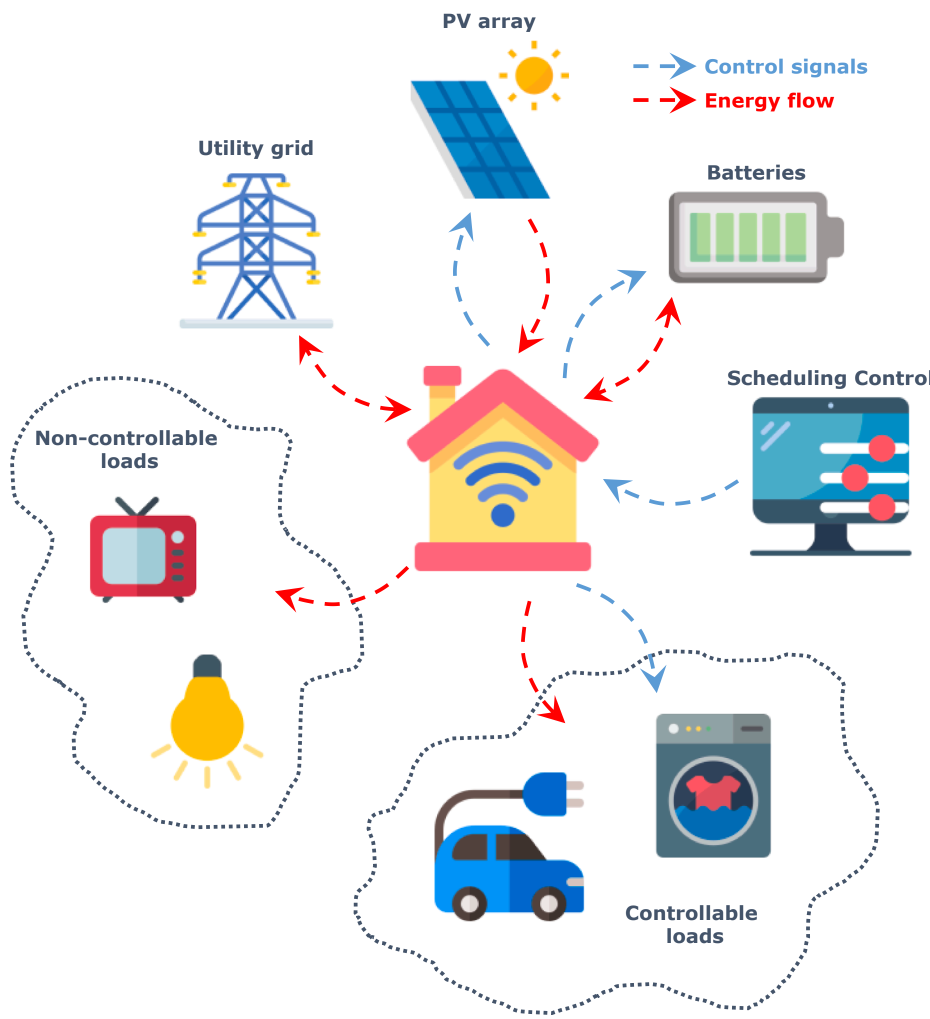

Fig. 2. Schematic representation of main elements of consumer/prosumer paradigm.

suitable tariff plan for a smart user (consumer or prosumer). In addition, other useful results can be directly obtained from the developed framework. The most salient features of our proposal which suppose its main contributions with respect the reference [12] are as follows. 1) It is applicable to both smart consumers and prosumers. 2) Some useful results can be obtained as byproduct, among them, the optimal hours to be hired for a happy hours tariff plan. These results may be also helpful for other kind of decision processes. 3) The novel framework does not require information of other residential users. A case study on the Spanish retail market for a benchmark prosumer environment is used for showing the capabilities of the developed framework.

Remainder of this paper is organized as follows. Section 2 describes the smart prosumer paradigm, which supposes the basis for the developed tool. Section 3 introduces the mathematical formulation of the developed MILP framework for optimal tariff-choosing tasks, considering three benchmark tariffs. Section 4 presents various numerical results on a benchmark prosumer environment in order to show the capabilities of the developed framework. Finally, this paper is concluded with Section 5.

2. Overview of smart consumer/prosumer paradigm

Fig. 2 pictorially shows the main elements and energy and control flows on a generic smart consumer/prosumer paradigm. As seen, it is considered that the home can purchase energy directly from the grid or from own resources (a PV array in this case). This energy can be directly consumed by a set of controllable and non-controllable loads or stored in batteries. While the operation of non-controllable loads is governed by user decisions, the controllable loads can be scheduled during different hours of the day in order to reduce the electricity bill. This decision framework is carried out on a home energy management scheme which, on the basis of price signals of electricity tariffs and forecasted PV generation, determines the scheduling program of controllable loads along the PV-batteries system. If the described home system has the capability of producing a surplus energy from own resources (PV and batteries), it can be sold to the utility grid in order to obtain a revenue (smart prosumer [15]).

3. Developed MILP framework for optimal tariff-choosing

The main contribution of this paper is to develop a MILP framework for tariff-choosing decision of smart consumers and prosumers. Fig. 3 is the flowchart of the developed support tool. It starts from a set of metering data, which should encompass the consumption profiles due to non-controllable appliances, ambient temperature and solar irradiation through a year. The proposed framework has the advantage that necessary data uniquely correspond with the study home, and extra information from other users is not required. Then, the available data is temporal represented by means of representative days, in order to make easier its treatment. The treated data along the necessary information of electricity tariffs pool serve as inputs of a developed MILP optimization problem, which has to be run for the different tariffs compared. Through

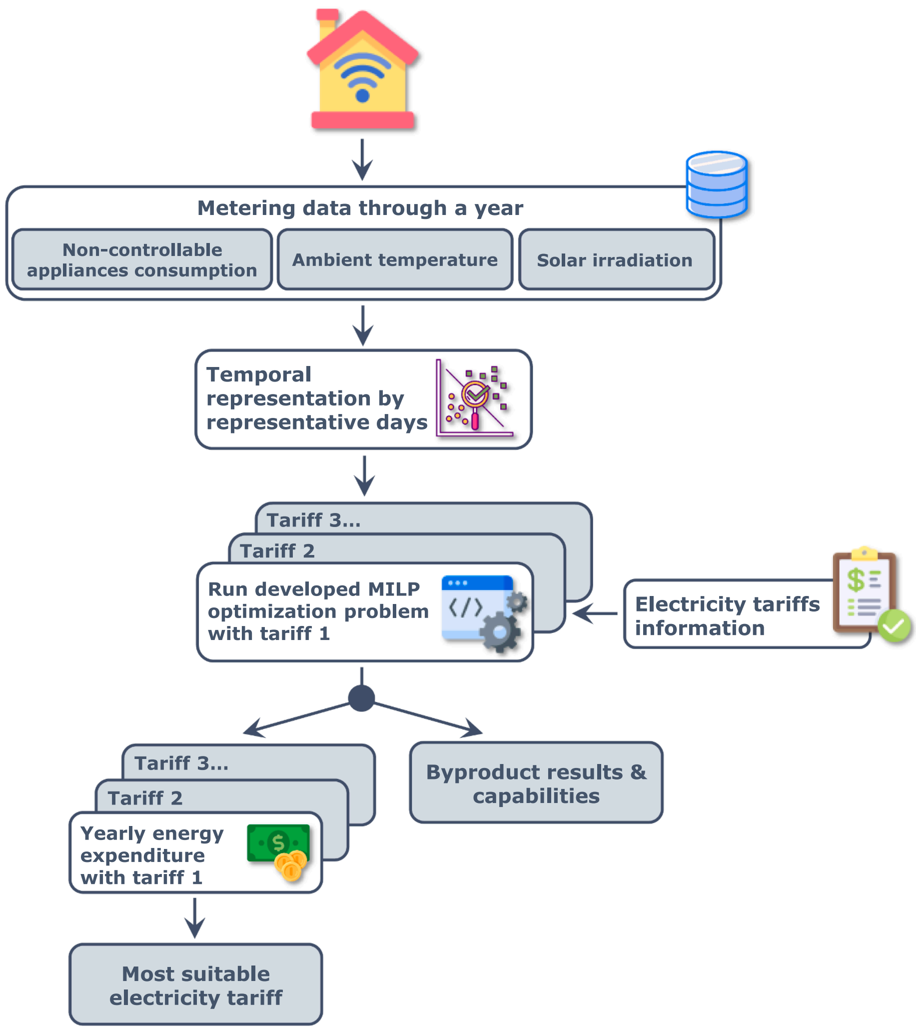

Fig. 3. Flowchart of the developed tariff-choosing decision framework.

this MILP problem, the yearly energy expenditure (which also serves to determine the most suitable tariff plan) along other relevant results are obtained. The following sections are devoted on further explaining each stage involved within the developed framework.

3.1. Representative days

The raw information which serves as starting point of the developed framework span a huge amount of data (1095 profiles with up to 1-min time resolution). This amount of information might be difficulty tractable computationally. A popular technique to reduce these computational requirements consists on only taking into account those profiles that can be considered sufficiently representative of the remainder data. This process is known as temporal representation by representative days [16]. To reduce the available data to only those representative days, the k-medoids clustering method is often considered a good choice [17]. This technique gathers the most similar profile within clusters. Then, each cluster is represented by its medoid, which is assumed a good representation of all the members of its cluster. In our proposal, the different medoids are the representative days which serve as input of the MILP optimization problem. The total number of clusters has to be determined heuristically, attending to some support indicators like the Davies-Bouldin index [18].

3.2. MILP optimization problem

The developed MILP optimization problem corresponds with the home energy management of the prosumer paradigm described in Fig. 2. Mathematically, this problem is established as follows:

$$\min_{\boldsymbol{x}} \sum_{s \in S} \omega^s \sum_{t \in T} \left\{ c_{st}^{\mathrm{GH}} - c_{st}^{\mathrm{HG}} \right\} \qquad (1)$$
$$\mathrm{s.t.}(3) - (18)$$

where $\boldsymbol{x}$ is the vector of decision variables (see Nomenclature) and c_{st}^{GH} and c_{st}^{HG} are factors that vary depending on the electrical tariff considered (see Section 3.3). The objective function (1) aims at minimizing the electricity bill of home users through a year. In this equation, the weight of each representative day is simply calculated as the number of elements within each cluster.

$$\omega^s = \phi(\Omega^s); \forall s \in S \qquad (2)$$

While the constraints (3)–(18) are stated below.

$$p_{st}^{\mathrm{GH}} + p_{st}^{\mathrm{PV}} + p_{st}^{\mathrm{B,dch}} = p_{st}^{\mathrm{HG}} + p_{st}^{\mathrm{B,ch}} + D_{st} + \sum_{i \in \{\mathrm{WM,DW,SD,EV}\}} u_{st}^{i} P^{i}; \forall s \in S, \forall t \in T \qquad (3)$$

$$0 \le p_{st}^{\mathrm{GH}} \le u_{st}^{\mathrm{GH}} \overline{p}^{\mathrm{G}}; \forall s \in S, \forall t \in T \qquad (4)$$

$$0 \le p_{st}^{\mathrm{HG}} \le u_{st}^{\mathrm{HG}} \overline{p}^{\mathrm{G}}; \forall s \in S, \forall t \in T \qquad (5)$$

$$u_{st}^{\mathrm{GH}} + u_{st}^{\mathrm{HG}} \leq 1; \forall s \in S, \forall t \in T \tag{6}$$

$$0 \leq p_{st}^{\mathrm{B,dch}} \leq u_{st}^{\mathrm{B,dch}} \frac{\xi}{\lambda}; \forall s \in S, \forall t \in T \tag{7}$$

$$0 \leq p_{st}^{\mathrm{B,ch}} \leq u_{st}^{\mathrm{B,ch}} \frac{\xi}{\lambda}; \forall s \in S, \forall t \in T \tag{8}$$

$$u_{st}^{\mathrm{B,dch}} + u_{st}^{\mathrm{B,ch}} \leq 1; \forall s \in S, \forall t \in T \tag{9}$$

$$e_{st}^{\mathrm{B}} = e_{st-1}^{\mathrm{B}} + \Delta\tau \left(p_{st-1}^{\mathrm{B,ch}} \eta^{\mathrm{B}} - \frac{p_{st-1}^{\mathrm{B,dch}}}{\eta^{\mathrm{B}}} \right); \forall s \in S, \forall t \in T \backslash t > 1 \tag{10}$$

$$(1 - DOD)\xi \leq e_{st}^{\mathrm{B}} \leq \xi; \forall s \in S, \forall t \in T \tag{11}$$

$$e_{s1}^{\mathrm{B}} = \xi; \forall s \in S \tag{12}$$

$$e_{sT}^{\mathrm{B}} = \xi; \forall s \in S \tag{13}$$

$$0 \leq p_{st}^{\mathrm{PV}} \leq \hat{p}_{st}^{\mathrm{PV}}; \forall s \in S, \forall t \in T \tag{14}$$

$$\sum_{t=LB^i}^{t=UB^i} u_{st}^i = \delta^i; \forall s \in S, \forall i \in \{\mathrm{WM, DW, SD, EV}\} \tag{15}$$

$$\overline{u}_{st}^i - \underline{u}_{st}^i = u_{st}^i - u_{st-1}^i; \forall s \in S, \forall t \in T \backslash t > 1, \forall i \in \{\mathrm{WM, DW, SD}\} \tag{16}$$

$$\sum_{\forall t \in T} \overline{u}_{st}^i = 1; \forall s \in S, \forall i \in \{\mathrm{WM, DW, SD}\} \tag{17}$$

$$u_{st}^{\mathrm{GH}}, u_{st}^{\mathrm{HG}}, u_{st}^{\mathrm{B,dch}}, u_{st}^{\mathrm{B,ch}}, u_{st}^i, \overline{u}_{st}^i, \underline{u}_{st}^i \in \{0,1\}; \forall s \in S, \forall t \in T, \forall i \in \{\mathrm{WM, DW, SD, EV}\} \tag{18}$$

The constraint (3) is the home balance, by which the home demand has to be fully satisfied any moment. The constraints (4) and (5) impose limits over the amount of power that can be purchased and sold from/to the utility grid, respectively. The smart home cannot purchase and sell energy to the grid at the same time, as forced by the constraint (6). The constraints (7) and (8) impose limits on the charging and discharging processes of the batteries. Also, these both processes are complementary, as modelled by the constraint (9). The constraint (10) models the state of charge of the batteries, which is limited by the capacity and depth of discharge of these devices, as forced by the constraint (11). It is assumed that the batteries are fully charged at the beginning and the end of the studied time horizon, as imposed by constraints (12) and (13), respectively. The amount of energy that can be generated by the PV array by unit of time is upper bounded by the forecasted value $\hat{p}_{st}^{\mathrm{PV}}$, as modelled with (14). The controllable loads have to be operated a predefined number of hours within their allowable time windows, as forced by the constraint (15). In addition, some controllable loads have to be continuously operated and just can be activated once over a time horizon, as imposed by the constraints (16) and (17), respectively. It is worth noting that (16) and (17) are not imposed on the EV, since it is assumed that this appliance has just to be fully charged at the end of its allowable time window, and discontinuous scheduling is allowed. Finally, constraint (18) imposes integrality on some variables.

The equation (14) bounds the power that the PV array can give any instant as a function of the forecasted PV generation. This forecasted value is typically obtained as a function of weather parameters. One of the salient features of the developed MILP optimization framework is the usage of historical information in order to yield realistic and accurate results adapted to each case. Apart from historical consumption of the home system under study, other weather parameters can be obtained from public database in order to further develop the model. Thus, the instantaneous power that a PV array can give any instant can be derived from solar irradiance and ambient temperature. To that end, any available solar panel model can be considered. In this paper, that described in [19] has been used, which yields the maximum PV generation as function of ambient temperature and solar irradiation as follows.

$$\hat{p}_{st}^{\mathrm{PV}} = P^{PV} I_{st} \{ 0.8 + 0.024 (\theta_{st} + I_{st} [33.8 - 37.5\eta^{\mathrm{PV}}] - 25) \}; \forall t \in T, \forall s \in S \tag{19}$$

However, the value yielded by the equation (19) supposes an upper bound for the variable p_{st}^{PV} and, in practice, solar inverters may set it at a lower value if required.

3.3. Objective function for different tariffs

The objective function (1) is determined by the cost of purchasing energy minus the revenues obtained by selling energy to the utility grid. The way in which these two concepts are charged varies with the tariff considered. In this paper, the three most conventional tariffs (which are outlined in Fig. 1), have been considered and explained in the following sections.

3.3.1. Fixed tariff

By this tariff, the concepts involved in the objective function are charged by a fixed rate. Thus, they can be calculated as follows.

$$c_{st}^{\mathrm{GH}} = \pi^{\epsilon} \Delta\tau p_{st}^{\mathrm{GH}}; \forall s \in S, \forall t \in T \tag{20}$$

$$c_{st}^{\mathrm{HG}} = \mu\pi^{\epsilon} \Delta\tau p_{st}^{\mathrm{HG}}; \forall s \in S, \forall t \in T \tag{21}$$

In this paper, the selling price is taken as a percentage of the purchasing price (μ), which is customary ≤ 1 [20].

3.3.2. Time-variable tariffs

The users subjected to this tariff are charged in a similar way to a fixed tariff but, in this case, the energy price varies each hour of the day. Thus, the objective function is in this case given by.

$$c_{st}^{\mathrm{GH}} = \pi_t^{\epsilon} \Delta\tau p_{st}^{\mathrm{GH}}; \forall s \in S, \forall t \in T \tag{22}$$

$$c_{st}^{\mathrm{HG}} = \mu\pi_t^{\epsilon} \Delta\tau p_{st}^{\mathrm{HG}}; \forall s \in S, \forall t \in T \tag{23}$$

The equations (22) and (23) can be straightforward applied to the two most conventional variable tariffs namely time-of-use and real time pricing [3].

3.3.3. Happy hours tariff

In this case, energy consumption is charged by a fixed tariff, however, during a number of hours through a day (ϑ) energy consumption is not charged at all. These hours are colloquially called 'happy hours' and they can be often selected by the users. This fact adds a new variable to the problem since the objective function may notably vary depending on which time slots are selected as happy hours. Indeed, the objective function is in this case given by.

$$c_{st}^{\mathrm{GH}} = \pi^{\epsilon} \Delta\tau y_{st}; \forall s \in S, \forall t \in T \tag{24}$$

$$c_{st}^{\mathrm{HG}} = \mu\pi^{\epsilon} \Delta\tau z_{st}; \forall s \in S, \forall t \in T \tag{25}$$

where the dummy variables are defined as follows.

$$y_{st} = \nu_t^{\epsilon} p_{st}^{\mathrm{GH}}; \forall s \in S, \forall t \in T \tag{26}$$

$$z_{st} = \nu_t^{\epsilon} p_{st}^{\mathrm{HG}}; \forall s \in S, \forall t \in T \tag{27}$$

The developed framework should also provide the most suitable time slots to be hired as 'happy hours'. Hence, ν_t^{ϵ} is considered a decision variable of the problem in this case. This provokes that (26) and (27) becomes bilinear terms, which can be converted to linear ones by imposing the constraints (28)–(31) [21].

$$p_{st}^{\mathrm{GH}} - M(1 - \nu_t^{\epsilon}) \leq y_{st} \leq p_{st}^{\mathrm{GH}} + M(1 - \nu_t^{\epsilon}); \forall s \in S, \forall t \in T \tag{28}$$

Table 1
Characteristics of the different tariffs considered in simulations.

Tariff	Energy price ($\pi^{\epsilon}/\pi_t^{\epsilon}$)	Happy hours (ϑ)
1	0.12 €/kWh	–
2	0.08 €/kWh (22:00–12:00 h) 0.16 €/kWh (13:00–21:00 h)	–
3	0.16 €/kWh	2 h/day

$$p_{st}^{\mathrm{HG}} - M\left(1-\nu_t^{\epsilon}\right) \leq z_{st} \leq p_{st}^{\mathrm{HG}} + M\left(1-\nu_t^{\epsilon}\right); \forall s \in S, \forall t \in T \tag{29}$$

$$-M\nu_t^{\epsilon} \leq y_{st} \leq M\nu_t^{\epsilon} \tag{30}$$

$$-M\nu_t^{\epsilon} \leq z_{st} \leq M\nu_t^{\epsilon} \tag{31}$$

Besides of (26)–(31), the developed MILP optimization problem is subjected to other additional constraints in the case of happy hours tariffs. Firstly, the total number of happy hours that can be hired is limited, as imposed the constraint (32).

$$\sum_{\forall t \in T} \nu_t^{\epsilon} = \left(\phi(T) - \frac{\vartheta}{\Delta\tau}\right) \tag{32}$$

Frequently, the happy hours have to be consecutive, as forced by the constraint (33).

$$\nu_{-t}^{\epsilon} - \overline{\nu}_t^{\epsilon} = \nu_t^{\epsilon} - \nu_{t-1}^{\epsilon}; \forall t \in T \backslash t > 1 \tag{33}$$

The zero-cost period has to begin at o'clock hours (i.e. 0:00 h, 1:00 h, …). However, the time step taken in simulations may be set shorter than an hour. This provokes that not all time slots are allowed to be set as starting point for happy hours. This restriction is satisfied by the pair of constraints (34) and (35).

$$\sum_{\forall t \in H} \overline{\nu}_t^{\epsilon} = 1 \tag{34}$$

$$\sum_{\forall t \notin H} \overline{\nu}_t^{\epsilon} = 0 \tag{35}$$

Finally, it is required to impose integrality on some variables, as follows.

$$\nu_t^{\epsilon}, \overline{\nu}_t^{\epsilon}, \nu_{-t}^{\epsilon} \in \{0,1\}; \forall t \in T \tag{36}$$

Typically, consumers are encouraged to keep the same two happy hours through a year (e.g. see [6]). Also, a real electricity consumer is not normally willing to vary the hired happy hours each day or even each month, which may provoke demand response fatigue [22]. Due to these reasons, we have preferred to keep the developed model as realistic as possible. Thus, some variables (e.g. $\nu_t^{\epsilon}, \overline{\nu}_t^{\epsilon}, \nu_{-t}^{\epsilon}$) are just defined for time slots and they do not vary depending on the representative day. Nevertheless, the developed MILP model could be straightforward adapted to any other situation.

4. Case study

In order to show the capabilities of the developed tool, it has been run on a benchmark case study. Specifically, the Spanish retail market has been considered. More precisely, the company Endesa has been taken as benchmark. Currently, this retailer offers (among others) three tariffs that are described in Table 1 [23]. Indeed, the tariff 1 corresponds with a fixed tariff, the tariff 2 can be assimilated to a time-of-use tariff while the tariff 3 corresponds with a happy hours plan. This case study is considered suitable to illustrate the capabilities of the developed tool, since this retail offers the three kind of tariffs modelled in the present paper. In addition, including more tariffs may be unsuitable as it may difficult the analysis of the results obtained as most of the tariffs offered through the world only differ in the energy price and its mechanism and conditions are similar. The selling price is assumed to be 0.9 times the purchasing price (i.e. $\mu = 0.9$) [20]. It is assumed that, during happy hours, the selling price is set to zero in order to avoid unrealistic energy transactions between the home and the grid during those hours.

Table 2
Relevant characteristics of the prosumer system under study.

Parameter	Value	Parameter	Value
$\overline{p}^{G}$	10 kW	λ	4 h
P^{PV}	0.5 kW	DOD	0.6
η^{PV}	0.17	η^{B}	0.98
ξ	5 kWh		

Table 3
Characteristics of controllable loads.

Load (i)	P^i(kW)	δ^i	LB^i	UB^i
WM	3	3	16	23
DW	2.5	4	15	33
SD	2.5	2	25	35
EV	3.5	6	3	14

A benchmark smart prosumer system has been considered for simulations. The main characteristics of the system under study are listed in Table 2. This home system counts with a series of controllable appliances, whose most relevant features are collected in Table 3 [8].

The simulations have been run over a 1-day time horizon with a time step of 30 min (i.e. $\Delta\tau = 1/2$). To build the different scenarios considered (representative days), we have taken the data available in various database. More precisely, the ambient temperature and solar irradiance were taken from [24], and correspond with measurements collected at Madrid (Spain) during the year 2016. On the other hand, the home demand due to non-controllable loads has been taken from [25]. In this case, the demand corresponding to the DW has been neglected as it is considered a controllable appliance.

Once the data corresponding to ambient temperature, solar irradiation and non-controllable loads demand have been collected, the resulting profiles are reduced by using the k-medoids technique to only consider the most representative ones. The total number of clusters has been selected on the basis of the Davies Bouldin index and the total sum of distances, so a compromise solution between these two indicators is taken. Fig. 4 shows the value of the two considered indexes. The compromise solution between the Davies Bouldin Index and the total sum of distances has to be addressed by direct inspection of the value of both indexes. For the case study, one can clearly check that the total sum of distances is not further improved beyond 14 clusters. So, let us only consider clustering numbers beyond 14. Then, one can check the value of the Davies Bouldin index for more than 14 clusters. As observed, the lowest Davies Bouldin value is clearly obtained with 15 clusters, which has been the value selected for simulations. Fig. 5 plots the profiles corresponding to the 15 representative days considered in simulations. These profiles serve to calculate the value of $\widehat{p}_{st}^{\mathrm{PV}}$ by using (19) and as input of the developed MILP optimization problem described in Section 3, which serves to determine the most suitable tariff for the home system under study.

4.1. Tariff-choosing result

Table 4 reports the yearly energy expenditure for the three tariffs considered besides the total solution time required by an Intel® Core™ i5-9400F 2.90 GHz 8.00 GB RAM personal computer under Matlab R2019a environment. For further illustrating how the total number of clusters (representative days) affects the results provided by the developed tool, the analysis has been extended for 1, 5 and 15 clusters. The authors also carry out a simulation without clustering the available data (i.e. 365 representative days), however, resulting size of the problem

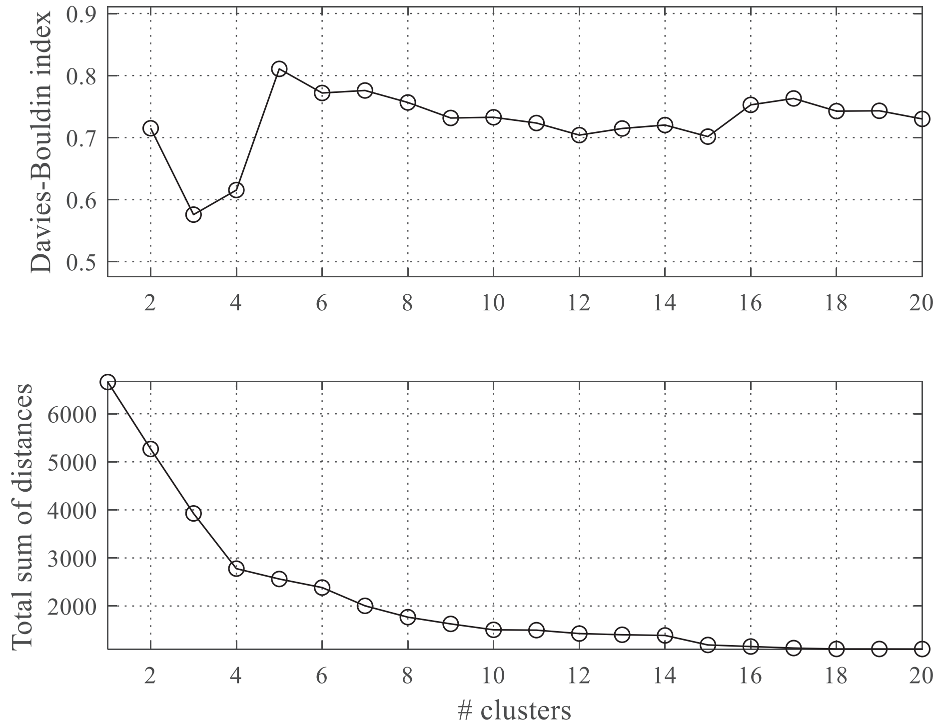

Fig. 4. Value of the metrics used for evaluating different clustering numbers.

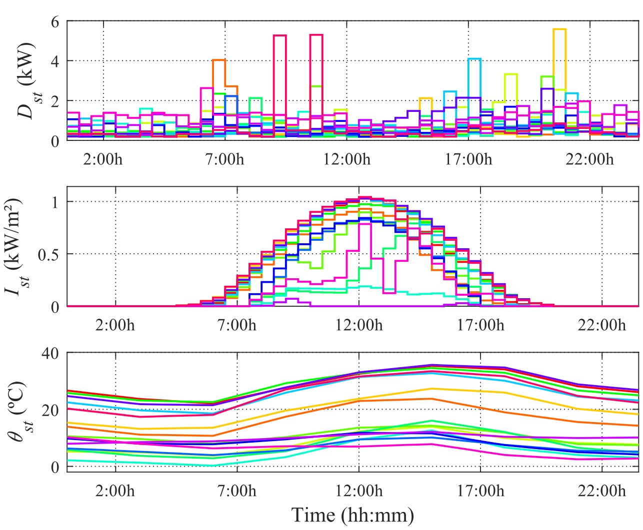

Fig. 5. profiles of the 15 representative days considered in simulations.

was unaffordable and the used software yielded an error, remarking the importance of reducing the available data.

For the system under study, the tariff 2 resulted the most attractive one attending to the yearly energy expenditure for the users. For the tariff 3, 7:00–8:00 h was determined to be the most suitable period to be hired as happy hours. The final decision yielded by the developed tool was the same regardless the total number of clusters considered, however, the yearly energy expenditure was clearly underestimated if few clusters are considered. This is due to some days with low PV production are ignored if few representative days are taken into account. These days suppose the most unfavourable situation for home energy consumption as much energy has to be purchased from the utility grid.

As expected, solution time grows as the number of clusters is increased. However, even with 15 clusters, computational burden can be considered acceptable. One should note that the tariff choosing-decision process is normally carried out over a planning time horizon (days). In this context, solution time is not as important as in operational tools [25]. These results also serve to validate the applicability of the developed tool to other retail markets with thousand of tariff options. Considering that most of available electricity tariffs only differ on the energy price, solution time can be considered as a linear function of the total number of tariffs included in the analysis. Keeping this on mind, the presumable time consumed by the developed application on a potential retail market with over 1,000 different tariffs would be approximately 10 h, which seems reasonable in this context. It is also worth noting that parallel processing strategies can be easily implemented in the developed tool. Thus, the developed MILP optimization framework could be simultaneously carried out for the different tariffs considered, reducing the solution time notably.

In order to show the coherency of the results calculated by the developed framework, Fig. 6 plots the total home demand (controllable and non-controllable loads) along the PV generation for the three tariffs

Table 4
Results provided by the developed MILP optimization problem for the three tariffs considered.

Tariff	1 cluster			5 clusters			15 clusters		
	Yearly energy expenditure [€]	Most suitable happy hours	Solution time [s]	Yearly energy expenditure [€]	Most suitable happy hours	Solution time [s]	Yearly energy expenditure [€]	Most suitable happy hours	Solution time [s]
1	1,239.4	–	43.55	1,332.5	–	101.24	1,406.3	–	155.28
2	834.0	–		943.5	–		1,006.8	–	
3	931.2	7:00–8:00 h		1,055.7	7:00–8:00 h		1,131.4	7:00–8:00 h	

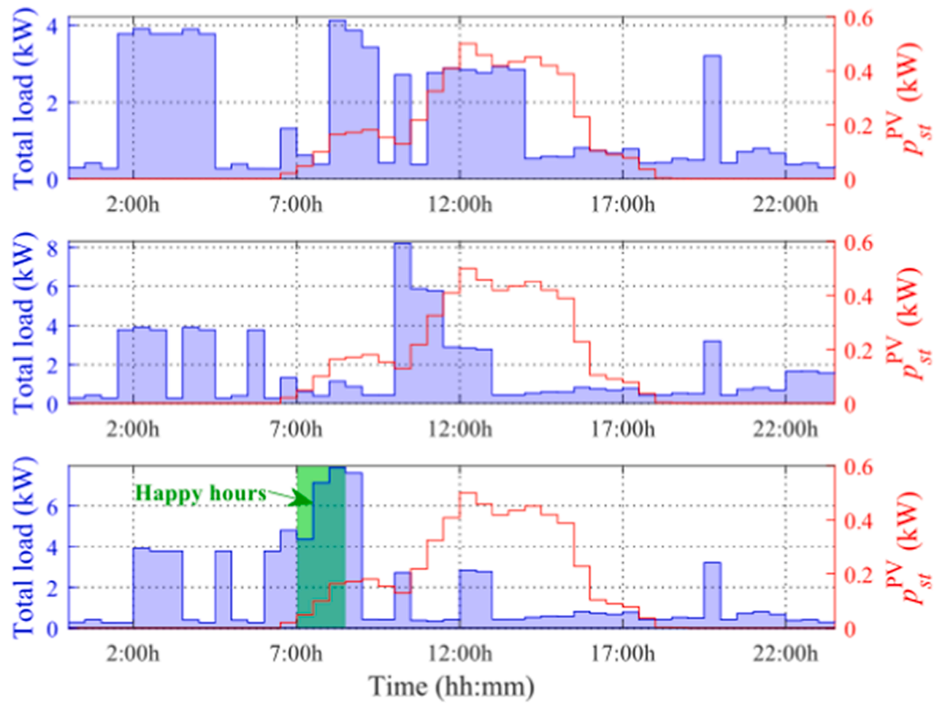

Fig. 6. Total home demand and PV generation resulted for the tariff 1 (upper), tariff 2 (middle) and tariff 3 (bottom) at a typical day.

Table 5
Total expected energy transactions between the utility grid and home through a year.

Tariff	E^{GH}	E^{HG}
1	11.7 MWh	–
2	11.9 MWh	0.13 MWh
3	11.9 MWh	–

Table 6
Monetary incomes through a year.

Tariff	Q^{GH}	Q^{HG}
1	1,406.3 €	–
2	1,025.5 €	18.7 €
3	1,131.4 €	–

considered at a typical day considering 15 representative days. As seen, most load was scheduled during those hours with high PV penetration in tariff 1. In the case of tariff 2, most of the load was scheduled at midday, when energy price is still low and PV production begin to be high. In the case of tariff 3, most of load was consumed during happy hours.

4.2. Other capabilities

As commented, the developed framework is capable of offering other relevant capabilities and results as byproduct. Let us illustrate how some of them can be obtained in this section. Onwards, only results with 15 clusters will be showed.

4.2.1. Energy exchanged with the utility grid

Firstly, the total expected energy purchased and sold from/to the grid can be respectively calculated as follows.

$$E^{GH} = \sum_{s \in S} \Delta\tau \omega^s \sum_{t \in T} \{p_{st}^{GH}\} \tag{37}$$

$$E^{HG} = \sum_{s \in S} \Delta\tau \omega^s \sum_{t \in T} \{p_{st}^{HG}\} \tag{38}$$

The value (37) and (38) can be used for multiple endings, for example, they may be useful to decide if results profitable to oversize the PV-batteries system in order to increase the revenues obtained from selling energy to the grid, to hire buying-selling contracts with the distribution company or to undertake some important investments like bidirectional power meters. Table 5 reports the value of (37) and (38) obtained for the tariffs analysed. As observed, the total energy purchased is expected to be similar regardless the tariff considered. On the other hand, while zero energy is expected to be sold to the grid in the case of tariffs 1 and 3, the developed MILP framework determines that a certain amount of energy is expected to be delivered to the utility grid if the tariff 2 is hired.

4.2.2. Further monetary expenditures analysis

Similarly, the total cost of purchasing energy along the expected revenues obtained from selling energy to the grid can be estimated by using the equations (39) and (40), respectively.

$$Q^{GH} = \sum_{s \in S} \omega^s \sum_{t \in T} \{c_{st}^{GH}\} \tag{39}$$

$$Q^{HG} = \sum_{s \in S} \omega^s \sum_{t \in T} \{c_{st}^{HG}\} \tag{40}$$

Table 6 reports the value of (39) and (40) for the three tariffs considered. As expected, the value of (39) corresponds with the total

Table 7
Total charging-discharging battery cycles through a year.

Tariff	χ
1	8.9
2	181.4
3	228.3

yearly energy expenditure reported in Table 4 for the tariffs 1 and 3, since zero energy is expected to be sold to the grid in these cases. On the other hand, according to the results reported in Table 5, only few monetary revenues from home-to-grid energy transactions is expected in the case of tariff 2.

4.2.3. Further analysis of the battery system

Finally, the total charging-discharging cycles in which the batteries incur through a year can be estimated as follows.

$$\chi = \sum_{s\in S}\frac{\omega^s \Delta\tau}{2\xi}\sum_{t\in T}\{p_{st}^{\mathrm{B,dch}} + p_{st}^{\mathrm{B,ch}}\} \quad (41)$$

The value of (41) is especially relevant as it has a direct impact on the expected lifetime of batteries [26]. Table 7 reports the value of (41) for the tariffs analyzed. As observed, the batteries are practically useless for tariff 1. On the other hand, the batteries are expected to be quite used with a tariff 3.

This result evidences the importance of deploying a storage system if a happy hours plan is hired. To illustrate this last conclusion, let us observe the Fig. 7, where the batteries scheduling result at a typical day is plotted. As seen, the batteries were very few exploited in the case of tariff 1. With tariff 2, the system only takes advantage of storage facilities at last hours of the day, when a transition between peak and off-peak hours occurs; thus, batteries tend to be discharged during peak hours, partially covering the home demand, to later recover its state of charge at off-peak hours. In the case of tariff 3, it is clearly observed how the happy hours are intensively exploited to fully charge the batteries, which were devoted on partially covering the home demand during the first hours of the day.

The total charging-discharging cycles through a year can be also used for determining a suitable depth of discharge strategy in order to maximize the batteries lifetime as the electricity bill is reduced. As reported in [26], the expected lifetime of a battery system directly depends on the depth of discharge strategy.

5. Conclusions

This work has presented a support tool for tariff-choosing decision in deregulated electricity markets. The new proposal is based on an MILP optimization problem, which is capable to determine the most suitable tariff for a smart consumer/prosumer along the optimal hours to be hired on a happy hours plan. In addition, various useful results can be directly extracted from the stated problem as byproduct.

A benchmark studied case in the Spanish retailer market on a prosumer environment has served to show the capabilities of the developed tool. In this example, fixed, time-variable and happy hours tariff plans have been considered. The developed framework determined that the considered time-variable tariff was the most attractive plan for the home under study. For a happy hours tariff, the period 7:00–8:00 h was determined to be the most suitable to be set as happy hours. In addition, this example has served to show how other useful results can be directly obtained from the proposed scheme. These results may be invaluable for related decision-making tasks.

Future projects will be focused on further developing similar tools with more capabilities.

Fig. 7. Batteries scheduling result for the tariff 1 (upper), tariff 2 (middle) and tariff 3 (bottom) at a typical day.

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.

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