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Large-scale optimization of households with photovoltaic-battery system and demand response

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Abstract: The adoption of distributed resources by households, e.g., storage units and renewables, open the possibility of self-consumption (on-site generation), sell energy to the grid as a small producer, or do both according to the context of operation. In this paper, a framework capturing the interactions between an aggregator and a large number of households is envisaged. We consider households equipped with distributed resources and simple smart technologies that look for the reduction of energy bills and can perform demand response actions. A mixed-integer linear programming formulation that provides optimal scheduling of household devices and minimal operation costs is developed. Results show that the model can be applied considering up to 10000 households. Moreover, households can reduce up to 20% of their energy bill on average using storage units and demand response. Besides, the aggregator can attain profits by offering the resulting flexibility to upper-level players of the energy chain, such as the distribution system operator.

Keywords: Energy storage, energy management systems, linear programming, optimization, renewable energy systems.

1. INTRODUCTION

The European Union is imposing strict targets to their members, mainly due to environmental concerns, expecting a penetration of 20% of renewables by 2020 and increasing that quantity up to 100% by 2050 according to the EU renewable energy directive (2009/28/EC). Such a target can only be reached throughout an elaborated and systematic electrical grid evolution Connolly et al. (2016).

In this scenario, end-users with generation capabilities (the so-called prosumer), equipped with photovoltaic (PV) panels and small-scale storage units, can provide additional flexibility to the system and themselves Abrishambaf et al. (2019); Soares et al. (2018). Upon on this, innovative forms of energy management, including demand response (DR) programs Siano (2014), promise several benefits, such as the reduction of energy bills and carbon-emission footprints, if effective management optimization approaches are developed.

Different approaches have been proposed in the literature to take the most advantage of the use of distributed resources and energy management. From the residential point of view, the benefits that small battery systems can provide have been showed in several studies Zheng et al. (2018); Angenendt et al. (2019). Results acknowledge the influence of combined operation strategies and optimization of components to take the most profit of resources. Despite the efforts made so far, it is expected a massive penetration of distributed resources at the local level, with its associated variability, into the electrical mix Lezama et al. (2019). This situation will pose a significant burden to the developed models, requiring efficient approaches that can be scaled to larger instances of the problem if needed. This work follows the line of research presented in Spínola et al. (2017), in which a methodology for the management of a PV-battery system and DR, analyzing the possible role of operating on-site generation and selling energy to the grid was proposed. In that work, a mixed-integer linear programming (MILP) model for a single residential house was developed and tested for the day-ahead scheduling of resources. The model was later refined in Faia et al. (2019), where an evolutionary computation approach was applied to find near-optimal solutions to the problem. However, no large-scale optimization, i.e. a large number of resources, was considered in those works.

In this paper, a MILP formulation is proposed for the coordination of hybrid PV-battery systems of residential houses. The optimization problem envisages a framework in which a central entity (i.e., an aggregator) needs to perform an optimization of a large variable number of households (aiming at large-scale instances of the problem). The problem is formulated first to benefit households

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(e.g., reducing energy costs) while aggregating DR capabilities to offer flexibility and avoid congestion or other related grid issues. Results show that the problem can be efficiently solved for up to 10000 households, reducing operational costs and obtaining the optimal scheduling of PV-battery operation and DR.

The contributions of this paper are as follows:

- An optimization framework for the coordination of households minimizing cost while increasing the flexibility provided by DR.
- A MILP formulation that can be applied to a large number of households.
- An assessment of the framework under four different cases studies with up to 10000 households with PV and storage units.

The paper is organized as follows: after the introduction in Sect. 1, the system architecture is presented in Sect. 2, the mathematical formulation is introduced in Sect. 3, the case study and results are provided in Sects. 4 and 5 respectively, to finalize with the conclusions in Sect. 6

2. SYSTEM ARCHITECTURE

This section describes the developed methodology regarding the aggregation model and energy management systems in the demand side. The main goal of the aggregator in this model is to aggregate all small and medium scale DR capacities of end-users and offer them as a unique resource to the distribution system operator (DSO). Fig. 1 illustrates the overall architecture of the proposed model.

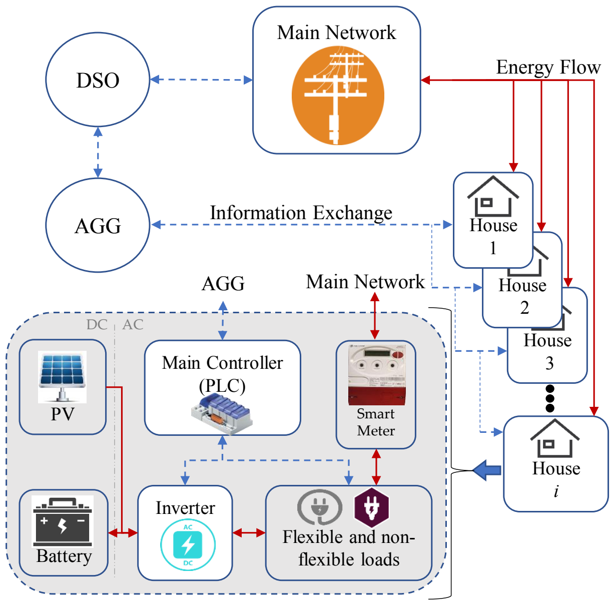

Fig. 1. Overall view of the proposed model (AGG stands for aggregator).

As Fig. 1 shows, the aggregator is a third-party entity between the upstream players of the network (i.e., the DSO in this model), and the demand side. In this model, the DSO is in charge of monitoring and controlling the distribution network, while the aggregator takes care of the distributed renewable energy resources and DR programs. Also, the aggregator can establish bidirectional contracts with the end-users for DR programs to manage consumption resources. This is clear also in Fig. 1, as the aggregator has information exchange with the main controller (e.g., Programmable Logic Controller - PLC) in the households. The PLC controller unit manages the consumption and generation resources in the houses according to the commands and orders received from the aggregator.

It is also considered that each household is a prosumer (a consumer able to produce electricity), equipped with a PV and an energy storage system. The PLC is in charge of managing the produced energy by the PV. In fact, the generated energy can be stored in a battery, consumed by the local loads, or directly injected to the main network. Furthermore, the PLC manages the flexible loads in the household according to DR signals received from the aggregator.

It is assumed that the DSO owns the smart meters in the demand side, and the aggregator manages consumption and generation behind the smart meter. Thus, the aggregator has no interference with the smart meters owned by the DSO (As Fig. 1 shows).

In the next section, it is presented the developed mathematical model employed by the aggregator to minimize the operational costs.

3. MATHEMATICAL FORMULATION

The mathematical formulation is divided into four subsections concerning the general objective function (Sect. 3.1) the households operational costs (Sect. 3.2), the aggregator operational costs (Sect. 3.3), and the constraints of the problem (Sect. 3.4).

3.1 Objective function

The objective function (1) aims at the minimization of operational costs, considering possible revenues for both, households and the aggregator:

$$min f = \sum_{i=1}^{I} OC_{House(i)} + OC_{Agg} \tag{1}$$

where $OC_{House(i)}$ represents the operational costs or energy bill of each agent i, I is the number of households, and OC_{AGG} represents the costs and profits that the aggregator obtains from the procurement and provision of flexibility through DR.

3.2 Household operational costs

To capture the costs/revenues that household i can obtain, the operational costs of each household i are represented by (2):

$$OC_{House(i)} = \sum_{t=1}^{T} \begin{pmatrix} P^{in}_{(i,t)} \times Price^{buy}_{(i,t)} - \\ P^{out}_{(i,t)} \times Price^{sell}_{(i,t)} - \\ P^{DR}_{(i,t)} \times Price^{DR}_{(i,t)} \end{pmatrix} \cdot \frac{1}{\Delta t}, \ \forall i \in I \tag{2}$$

where the first term is the cost of buying $P^{in}_{(i,t)}$ units of power (in kW) from the grid at a price $Price^{buy}_{(i,t)}$ (in EUR/kWh); the second term is the revenue for selling $P^{out}_{(i,t)}$ units of power (in kW) to the grid at a price $Price^{sell}_{(i,t)}$; and the third term is the revenue of DR, i.e., for reducing $P^{DR}_{(i,t)}$ power units at an incentive $Price^{DR}_{(i,t)}$ given by the aggregator. Δt is used to adjust the considered period of optimization (i.e., $\Delta t = 4$ in this work since 15 min periods are considered), and T represents the total horizon of time (i.e., one day consisting on 96 periods of 15 minutes each in this work).

3.3 Aggregator operational costs

Regarding the aggregator participation in the model, its operational costs are captured through equations (3):

$$OC_{AGG} = \sum_{t=1}^{T} \left(\begin{array}{l} \sum_{i=1}^{I} P^{DR}_{(i,t)} \times Price^{DR}_{(i,t)} - \\ \sum_{i=1}^{I} P^{DR}_{(i,t)} \cdot Price^{FlexDSO}_{(t)} + \\ \left(Flex^{DSO}_{(t)} - \sum_{i=1}^{I} P^{DR}_{(i,t)} \right) \times Price^{DSOPen}_{(t)} \end{array} \right) \cdot \frac{1}{\Delta t} \tag{3}$$

where the first term is the cost of paying an incentive of $Price^{DR}_{(i,t)}$ (in EUR/kWh) for each $P^{DR}_{(i,t)}$ units of DR reduction given by household i at period t; the second term are the revenues got by the aggregator due to the DSO payment of $Price^{FlexDSO}_{(t)}$ (in EUR/kWh) for the total of DR activated by households; and the third term is a penalty costs associated to flexibility imbalance, i.e., the difference between the amount of reduction required by the DSO ($Flex^{DSO}_{(t)}$) and the total procured by households ($\sum_{i=1}^{N_A} P^{DR}_{(i,t)}$), at each period t. It is assumed that the DSO payment is higher than the compensation given to households, but the aggregator is responsible for any deviation in the scheduling paying a penalty for it.

3.4 Constraints

The formulation is subject to different constraints captured in (4) - (15).

- Power balance constraint per household (4):

$$\begin{aligned} & P^{in}_{(i,t)} + P^{dch}_{(i,t)} + P^{PV}_{(i,t)} + P^{DR}_{(i,t)} = \\ & P^{out}_{(i,t)} + P^{ch}_{(i,t)} + \left(P^{Load}_{(i,t)} - \sum_{c=1}^{C} P^{cut}_{(c,i,t)} \right), \\ & \forall i \in I, \forall t \in T \end{aligned} \tag{4}$$

where the left side of the balance equation (generation) includes the energy bought from the grid $P^{in}_{(i,t)}$, the battery discharged energy $P^{dch}_{(i,t)}$, the PV generation $P^{PV}_{(i,t)}$, and the energy reduction $P^{DR}_{(i,t)}$ for DR; while the right side of the balance equation (i.e., consumption) includes the energy injected to the grid $P^{out}_{(i,t)}$, the battery charged energy $P^{ch}_{(i,t)}$, and the net load including the load $P^{Load}_{(i,t)}$ minus the total load shedding of controllable loads $P^{cut}_{(c,i,t)}$ by the inverter (Sect. 2); for each household i at each period t.

- Allowed limits of energy that households can buy and sell from the grid, (5) - (7):

$$0 \le P^{in}_{(i,t)} \le P^{Contract}_{(i)} \times X^{in}_{(i,t)}, \tag{5}$$

$$0 \le P^{out}_{(i,t)} \le \frac{P^{Contract}_{(i)}}{2} \times X^{out}_{(i,t)}, \tag{6}$$

$$X^{in}_{(i,t)} + X^{out}_{(i,t)} \le 1, \quad \forall i \in I, \forall t \in T \tag{7}$$

where $P^{Contract}_{(i)}$ is the contracted power of household (i.e., the maximum power available at the grid connection point); $\frac{P^{Contract}_{(i)}}{2}$ is the limit of energy that can be sold to the grid (due to Portuguese regulation Decreto Lei n.º 153/2014.); and $X^{in}_{(i,t)}$ and $X^{out}_{(i,t)}$ are two binary variables to avoid buying and selling energy in the same period t.

- Allowed limits of load shedding in the different loads connected to the relays of households (8):

$$P^{cut}_{(i,c,t)} = P^{cutMax}_{(c,i,t)} \cdot X^{cut}_{(c,i,t)}, \quad \forall c \in C, i \in N_A, t \in T \tag{8}$$

where $P^{cutMax}_{(c,i,t)}$ is the maximum power reduction of controllable load $c \in C$ connected to the inverter (see Sect. 2), and $X^{cut}_{(c,i,t)}$ is a binary variable to control the interruption of the loads. The users can also define preferences by for instance, setting $P^{cutMax}_{(c,i,t)} = 0$, allowing DR activation only in certain periods and loads of interest for them.

- Allowed limits of DR power reduction determined by the household, (9):

$$0 \le P^{DR}_{(i,t)} \le P^{DRmax}_{(i,t)}, \forall i \in I, t \in T \tag{9}$$

where $P^{DRmax}_{(i,t)}$ is the limit of power reduction allowed by household i for DR. We assume that households not participating in DR can set $P^{DRmax}_{(i,t)} = 0$, while the ones that have a contract with the aggregator set $P^{DRmax}_{(i,t)}$ to a given percentage of their total load. Notice that setting $P^{DRmax}_{(i,t)} = 0$ still allows household i to use the controllable loads $c \in C$ for their own benefice since $P^{cut}_{(c,i,t)}$ is still included in the balance equation (4).

- Allowed limits of DR power reduction determined by the aggregator, (10):

$$0 \le \sum_{i=1}^{I} P^{DR}_{(i,t)} \le Flex^{DSO}_{(t)}, \quad \forall t \in T \tag{10}$$

where $Flex^{DSO}_{(t)}$ is the limit of power reduction considered by the aggregator at each time t. Notice that when $Flex^{DSO}_{(t)} = 0$, the aggregator does not collect any flexibility to avoid imbalance.

- Constraints related to household batteries, (11) - (15):

$$E^{bat}_{(i,t)} = E^{bat}_{(i,t-1)} + P^{ch}_{(i,t)} - P^{dch}_{(i,t)}, \quad \forall i \in I, t \in T \quad (11)$$
$$0 \le E^{bat}_{(i,t)} \le E^{batmax}_{(i,t)}, \quad \forall i \in I, t \in T \quad (12)$$
$$0 \le P^{ch}_{(i,t)} \le P^{chmax}_{(i,t)} \times X^{Pch}_{(i,t)}, \quad \forall i \in I, t \in T \quad (13)$$
$$0 \le P^{dch}_{(i,t)} \le P^{dchmax}_{(i,t)} \times X^{Pdch}_{(i,t)}, \quad \forall i \in I, t \in T \quad (14)$$
$$X^{Pch}_{(i,t)} + X^{Pdch}_{(i,t)} \le 1, \quad \forall i \in I, t \in T \quad (15)$$

where $E^{bat}_{(i,t)}$ represents the battery state of charge at each period t, $E^{batmax}_{(i,t)}$ is the maximum battery capacity, and $P^{chmax}_{(i,t)}/P^{dchmax}_{(i,t)}$ is the maximum charging/discharging rate of the battery. $X^{Pch}_{(i,t)}$ and $X^{Pdch}_{(i,t)}$ are two binary variables to guarantee that only charge or discharge occurs in the same period t. This is applied to all households i at each time t.

4. CASE STUDY

In this section, we present the case study developed to evaluate our framework. We consider households representing Portuguese consumers complying with actual Portuguese legislation, which allows small producers (consumers with local generation) to use their energy to satisfy their own load needs, and inject excess of energy to the grid. We assume that all households are equipped with PV panels with a maximum power capacity of 7.5 kW. Households can also possess a battery unit with a maximum storage capacity of 1.2 kWh based on reference Xue et al. (2020), and a maximum charge/discharge rate of 0.15 kW per 15 min period (i.e., 0.6 kWh). Households equipped with controllable loads through an invertor can reduce 10% on average of their total consumption.

To generate power consumption and PV generation data of residential households, two sample power profiles, one for consumption and one for PV generation, were built using real open datasets available at PES ISS website (online at http://sites.ieee.org/pes-iss/data-sets/). With these profiles, 1000 households data was generated using a randomized function with a uniform distribution, ±25% around the standard profiles.

Fig. 2 shows the retail tariffs and PV generation of the base profiles. We assume that households have a power supply contract with a given retailer of 11 KVA characterized by three different periods: peak (0.33 EUR/kWh), intermediate (0.16 EUR/kWh), and off-peak (0.093 EUR/kWh). We also consider a feed-in tariff of 0.095 EUR/kWh and a DR compensation given by the aggregator following a percentage of the retailer tariff, i.e., 50% peak (0.16 EUR/kWh), 30% intermediate (0.05 EUR/kWh), and 25% off-peak (0.023 EUR/kWh). Tariffs are based on real values of a Portuguese retailer.

From the perspective of the aggregator, we assume a remuneration given by the DSO 5% higher than compensation paid to the households for DR reduction. However, an imbalance penalty cost 5 times higher than the DR tariff is applied to the aggregator for the flexibility reduction not provided Ødegaard Ottesen et al. (2016). This high imbalance price was set to represent extreme situations and force the aggregator to fulfill the flexibility commitments. The DSO request reduction was set intentionally to

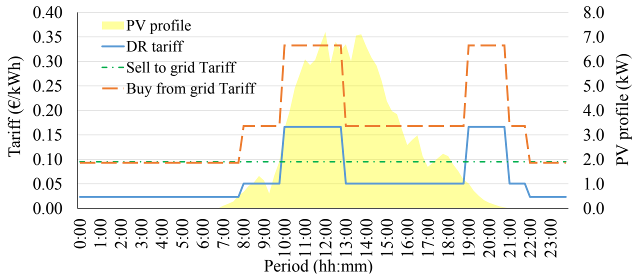

Fig. 2. Considered tariffs and PV generation base profile.

be equivalent to 10% of the total load in peak hours (i.e., hours 10-13 and 19-21). We also assume that each user allows the reduction of their net load for DR purposes up to 15% in peak hours and 5% in intermediate hours.

5. RESULTS AND DISCUSSION

In this section, we present the results of our methodology applied to the case study of Sect. 4. The experiments were implemented using a CPLEX solver in MATLAB2014b/TOMSYM^{TM}, in a computer with Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16GB of RAM running Windows 10.

We perform different experiments based on the available equipment that households possess. Table 1 shows four cases, identified by the letter C1-C4, related to the available equipment in houses. Therefore, households are able to perform DR only if part of their total load can be interrupted using the inverter.

Table 1. Available equipment in houses for analysing the impact of storage and DR.

Case	Battery	Inverter (DR)	PV
C1			✓
C2	✓		✓
C3		✓	✓
C4	✓	✓	✓

5.1 Baseline: No DR capabilities (cases C1 and C2)

Table 2 shows the results of the baseline cases C1 and C2, i.e., households with no DR capabilities. It can be seen that C1 case represents the higher costs that households can pay since neither the option of storage energy nor performing a reduction of their load for compensation is available. Yet, households can obtain some revenue by selling their excess of PV generation to the grid. The optimization procedure considering 1000 households takes around 20 seconds. On the other hand, when households are equipped with batteries (i.e., C2 case), the total cost slightly decreases from 3111.5 EUR (C1) to 3020.8 EUR (C2) considering 1000 households. While this quantity seems to be low (around 3% of improvements daily), it can represent consistent profits when considering broader horizons of time (for instance, a daily reduction of 1 cent per household correspond to around 3 EUR a month, and 36 EUR a year). Regarding the time of optimization, when the batteries are considered, it takes three times more time to find the optimal solution. This can be explained since adding one battery per household into the model increases

Table 2. Baseline results considering 1000 households with no DR capability.

No. Houses	Total Cost	Mean Cost	Mean Revenue	Mean Profit	Time
C1	3111.5	4.72	1.61	-3.11	19.97
C2	3020.8	4.58	1.56	-3.02	62.99

*Negative value in profits represents costs. Costs, Revenues and Profits in EUR. Time in seconds.

the number of variables to $96 * 5 * N_A$ (96 corresponding to the period T, and five corresponding to the battery: P^{ch}, P^{dch}, E^{bat}, Bin^{Pch}, and Bin^{Pdch}), which results in a large-scale search space when a large number of households is considered.

5.2 Households with DR capability and aggregator influence

Table 3 presents the results considering DR capabilities. To this end, we assume that an aggregator requires flexibility (i.e., load reduction) in peak hours from households. We considered a maximum of 10% reduction capacity from households and an equivalent request of flexibility from the DSO to avoid unbalance. Results show that the total cost can be reduced using DR. Despite low 10% reduction capacity, the reduction seems to be logical, since households are consuming less energy in peak hours, reducing the cost they are paying to the grid and at the same time getting incentives for such reduction. Compared to baseline C1, the mean revenues have increased around 20 cents for each household, highlighting the benefits that DR can bring to end-users. Moreover, compared to the baseline C1, the total costs decreased around 27% for C3 and 30% for C4 (e.g., from 3111.5 EUR to 2280 EUR and 2205 EUR respectively), resulting in significant savings if longer periods of time are considered.

The flexibility requested by the DSO has an impact on the quality of solutions and is also critical in the aggregator planning phase. This can be appreciated in Eq. 3, since a strong penalty (5 times the DR remuneration in this paper) is assumed by the aggregator if a deviation of the agreed flexibility occurs. To analyse the impact of such parameter $Flex^{DSO}_{(t)}$, we have varied the flexibility requested from 10% to 90% of the total load, in increments of 10%. Table 4 shows the cost of the aggregator (equivalent to the revenues of the households), the revenues of the aggregator for the flexibility provision, the penalties imposed by the

Table 3. Results considering 1000 households with DR capabilities.

Houses					
	Total Cost	**Mean Cost**	**Mean Revenue**	**Mean DR**	**Mean Profit**
C3	2280.5	4.62	1.87	0.48	-2.28
C4	2205.2	4.49	1.81	0.48	-2.21
Aggregator*					
	Cost DR	**Revenue**	**Penalty**	**Profit**	**Time**
C3	479.82	503.81	0	24.99	26.52
C4	479.82	503.81	0	23.99	102.07

*Negative value in profits represents costs. Costs, Revenues and Profits in EUR. Time in seconds.

Table 4. Varying the total among of Flexibility procured by the DSO.

DSO Request	Aggregator Cost	Revenue	Penalty	Profit
10%	479.82	503.81	0.00	23.99
20%	960.61	1008.64	0.03	48.00
30%	1440.92	1512.96	0.00	72.05
40%	1921.22	2017.28	0.00	96.06
50%	2401.53	2521.61	0.00	120.08
60%	2833.57	2975.25	241.34	-99.66
70%	3181.78	3340.87	901.82	-742.73
80%	3472.89	3646.53	1847.80	-1674.16
90%	3715.76	3901.55	3034.94	-2849.16

*Negative value in profits represents costs. Costs, Revenues and Profits in EUR. Time in seconds.

DSO for the deviation of the flexibility requested, and the total profit achieved. It can be seen that when the request is below 50% of the total load, the aggregator is able to achieve almost zero deviation, increasing its profits gradually. However, when the request is 60% or higher, the aggregator is not able to provide the flexibility (either by non-existing capacity or because households have no interests in selling their available flexibility). This is an extreme case, and in principle, the aggregator should have state countermeasures for these situations in their established contracts with households. However, this experiment highlights some situations that might arise when a modification of the load profile (i.e., flexibility) is sold to an upper-level party.

5.3 Scalability analysis: Varying number of households

To test the scalability of our approach, we generate 10, 100, 1000, and 10000 households with similar characteristics using the same randomized function, as explained in Section 4.

Table 5 shows the execution time for the different cases. It can be seen that the optimization time remains similar for C1 and C3, showing that the consideration of DR does not impact the execution time severely (even though, an increase in time started to be noticed when 10000 households were considered). However, the addition of batteries makes the execution times to increase more drastically. For instance, C1 considering 100 households takes around 20 seconds, while taking up to 60 seconds (three times more) with the addition of batteries (case C2). Considering batteries (C2 and C3), When the number is scaled to 10000, e.g. one order of magnitude, the optimization times grow exponentially, which might undermine the applicability of the approach when a massive number of resources is considered.

Table 5. Execution time (in seconds) varying the number of households.

Households	C1	C2	C3	C4
10	3.25	3.14	3.01	3.07
100	4.74	7.44	4.77	7.82
1000	19.97	62.99	26.53	102.07
10000	205.27	1435.24	582.75	7624.27

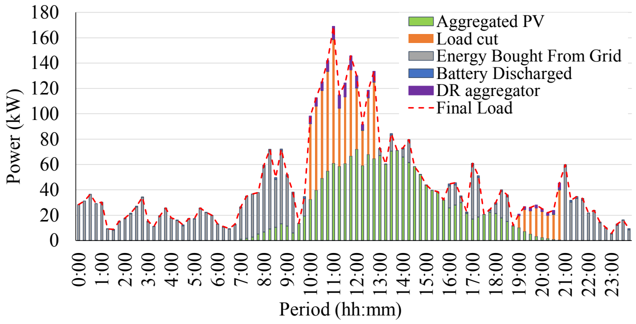

Fig. 3. Generation scheduling and total consumption

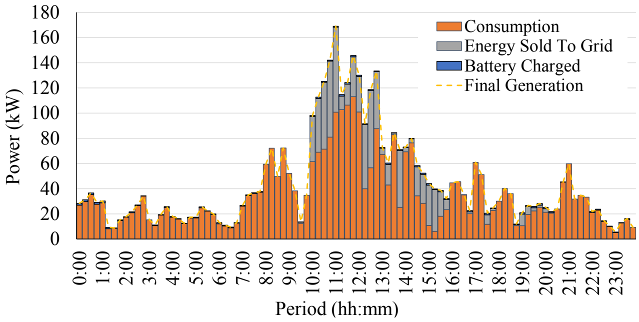

Fig. 4. Consumption scheduling and total generation

5.4 Aggregated scheduling, Balance and DR use

To analyze in more detail the resulting scheduling, Figs. 3 and 4 present the aggregated energy scheduling of the case C4 considering 10 households. C4 is interesting to analyze since more resources are available. Notice that increasing the number of households only results in a proportional increase in energy due to the optimization design. It can be seen that a balance between generation and consumption is achieved (following Eq. 4). Also, notice that the cut of controllable loads of households, and the DR reduction offered to the aggregator (orange and purple colors in Fig. 3) is only used in peak hours, being a support to the existing PV generation in those periods. This is because the DR request input was limited to 10% of the total consumption (in line with the DR capabilities of households of the case study), and has been designed to simulate situations related with congestion management which are expected to occur in peak load hours.

6. CONCLUSIONS

In this paper, a MILP model was tested considering up to 10000 households, demonstrating capabilities to solve large-scale instances of the problem, even when the optimization time increases with the number of houses. Also, it was shown that profits for households and the aggregator can be obtained as long as enough flexibility is available. When the request for flexibility surpasses the available resources, severe penalties might affect aggregator incomes. Despite validating the approach through a realistic case study, several assumptions were made, which open different lines for future research. For instance, a small battery size (1.2 kWh) was used in this study, so the impact of DR capability might be strongly affected by considering batteries with a large capacity. Also, battery degradation was not considered, yet its impact due to many cycles of charge and discharge may affect the profits of households in the long-term. Another line is related to the available flexible assets like electric vehicles, A/C units or dryers, that usually make up for more than 10% of the total load if they run. Hence it would be interesting to see results based on this model with values significantly higher than 10 % (up to 80 %). Besides, considering network constraints can be interesting to validate the operation of resources at the local level. Finally, the intermittent and unpredictable nature of PV generation and consumption suggest the application of stochastic programming or robust optimization to incorporate uncertainty in the formulation.

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