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Optimal coordination of buildings and microgrids by an aggregator: a bi-level approach

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Abstract: The introduction of renewables, distributed generation, microgrids, electric vehicles, and new market actors, such as aggregators, have led to a remarkable change in the power network. To address the issues that such a profound modification implies on a modern energy system, here a new hierarchical architecture is presented. Specifically, the proposed approach considers the case of an aggregator of consumers in the balancing market, in which incentives for local users (i.e., microgrids, buildings) are considered as well as flexibility assessment for demand response, and CO_2 emissions. The main innovation is related to the overall architecture and to the formalization of the upper level decision problem that aims at coordinating local users in a democratic way, while, at the lower level, consumers want to track the aggregator's reference values performing demand response programs. The approach is applied to a real case study.

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1. INTRODUCTION

The power network has undergone a remarkable change in recent decades, due to the spread of new plants and equipment both at the transmission and distribution level: renewable sources, distributed generation, storage systems, microgrids, and electric vehicles (EVs) are few examples. The distribution grid especially can be negatively affected by renewables due to their unpredictability which can lead to decrease in power quality, in particular voltage variations (both slow and rapid) and undesired power flow reverse at the point of connection between HV networks and MV feeders, resulting in an unacceptable risk of unintentional islanding of a MV feeder. Furthermore, due to the decreasing share of traditional, controllable, bulk generation, the power margins for regulation are less and less available. The characteristics of the new energy system require an increase of the power reserve to face the sudden request of active/reactive injection/absorption from a Distribution System Operator (DSO) in order to compensate for example a sudden drop in the production from a photovoltaic plant. In this framework, demand response (DR), i.e., the possibility for a load to decrease the active power absorption for a given period, or to shift consumption from a period to another, is an effective and reliable strategy for the successful integration of renewable energy sources, handling the demand curve using load flexibility whenever the system requires it (Fontenot and Dong, 2019). A significant share of participants in DR programs can be represented by local users and/or prosumers, which, by themselves, could not participate in the energy market, but are allowed to do if aggregated in cluster managed by a third party, namely an Aggregator (Carreiro et al., 2017). In general, the introduction of new regulation to address new needs and new actors, such as Aggregators, in the smart grid's system opens new challenges for the development of new energy management systems, models and methods. In the recent literature, there are several papers regarding these new operational management strategies for the optimization and control of a distribution network in presence of DR aggregators (Ferro et al., 2020). However, there is not a consolidated framework for optimization problems related to aggregators and flexibility assessment and, specifically, on how to schedule load reduction or production increase among the different customers, in order to achieve an overall load reduction and/or shifting. As an example, in (Saez-Gallego et al., 2018) the authors study the operation of a retailer that aggregates a group of price-responsive loads and submits block-wise demand bids to the day-ahead and real-time markets, in order to consider long term and short-term market dynamics. The work presented in (Soares et al., 2017) proposes a two-stage stochastic model for a large-scale energy resource scheduling problem of aggregators, using Benders' decomposition method. In (Shao et al., 2018) customer aggregators are introduced to supply downstream demand in the most economical way. Generally, in the actual literature, reactive power is not considered, as well as methods to emulate the flexibility of users and their coordination through equity criteria.

In this paper, the problem is addressed by proposing a bilevel hierarchical architecture where an Aggregator (AGG), i.e., the upper level, solves an optimization problem in order to define the optimal values of active and reactive power to be given as reference values to the lower level (represented by

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local users (LUs), i.e., lower level). Specifically, we consider an AGG that has the knowledge of the distribution electrical grid because it is also a DSO or works in strict collaboration with the DSO. The AGG has already bid in the day ahead balancing market (i.e., that session of the market where the Transmission System Operator (TSO) requests for some power flexibility in order to deal with the variation of the demand) the price of energy and the amount of power to be reduced/increased in each time interval during the day. It is now necessary to coordinate the different customers, trying to satisfy power demand reduction and giving incentives to local users for the request. Moreover, in order to define active and reactive power exchanges with the LUs, as well as the incentives (that are expressed as function of active power reduction), it is necessary to guess (and thus to emulate) the demands and the behavior of LUs, knowing a limited set of information. The AGG aims at minimizing different terms of costs: incentives to be paid to LUs, fees (to be paid to the main grid) for not reaching market's request, LUs dissatisfaction through a democratic assignment of power reduction. At the lower level, LUs have the objective to track power reference values, based om the price given by the AGG. Unlike the AGG, LUs have a detailed optimization model for the operational management of production, storage systems and active loads. They also provide parameters in the day ahead as bounds to be included in the higher-level optimization problem. The main contributions of the proposed paper are:

- The development of an optimization-based bi-level architecture for a DSO/AGG for participation in the balancing market;
- The statement of a multi-objective optimization problem for the problem of an AGG/DSO that considers a simplified prosumers' model for flexibility assessment and has to provide set-points for the local users' DR in a democratic way.
- The inclusion of specific dynamical models for the two main classes of local users (polygeneration microgrids and smart buildings).
- The application to a real case study.

The structure of the paper is organized as follows: Section 2 and 3 state the optimization problems related to LUs and the AGG, respectively. Section 3 presents the obtained results on a case study, while Section 4 reports conclusions and future developments.

2. THE LOCAL USERS OPTIMIZATION PROBLEMS

2.1. The microgrids optimization model

Microgrids' objective function aims at following the AGG reference values for active and reactive power while satisfying technical, economic and environmental constraints. The microgrids' system model is similar to the one described in Delfino et al. (2019) except for the objective function, which now defines the tracking of references imposed by the DSO and that a constraint is imposed over a maximum cost to be paid (that generally is an objective function). The overall objective function for each microgrid $j \in M$, with M the set of microgrids, is given by

$$\min = \hat{J}_{M,j} = \sum_{t=0}^{T-1} \beta \left(\mathrm{D}_{j,t} - \tilde{D}_j \right)^2 + (\mathrm{Q}_{M,j,t} - \tilde{Q}_{M,j,t})^2 \quad (1)$$

where $D_{j,t}$ and $Q_{M,j,t}$ are two decision variables representing active and reactive power exchange (respectively) between microgrid j and the main grid in time interval (t, t+1), t=0,…,T-1, $\tilde{D}_{j,t}$ and $\tilde{Q}_{M,j,t}$ are reference values (provided by the AGG, as a result of its optimization problem) for active and reactive power, respectively, exchanged with the main grid, and β is a weighting coefficient.

The objective function is subject to numerous constraints, mainly related to the system model representation. That is:

$$\sum_{h=1}^{H} P_{el,h,j,t} + P_{RES,j,t} - P_{S,j,t} + D_{j,t} = P_{D,j,t} + P_{veh,j,t} - D_{AGG,j,t} \qquad j \in M,\ t = 1,...,T-1 \quad (2)$$

$$Q_{RES,j,t} - Q_{S,j,t} + Q_{M,j,t} = Q_{D,j,t} \qquad j \in M,\ t = 1,...,T-1 \quad (3)$$

$$P_{PE,h,j,t} = \mu_{h,j,t} P_{el,h,j,t} \qquad h \in H_j,\ j \in M,\ t = 1,...,T-1 \quad (4)$$

$$P_{th,h,j,t} = \bar{\mu}_{h,j,t} P_{el,h,j,t} \qquad h \in H_j,\ j \in M,\ t = 1,...,T-1 \quad (5)$$

$$P_{el,h,j,t} \le P_{el,h,j}^{MAX} \qquad h \in H_j,\ j \in M,\ t = 1,...,T-1 \quad (6)$$

$$P_{PE,B,j,t} \eta_{B,j} = P_{th,B,j,t} \qquad j \in M,\ t = 1,...,T-1 \quad (7)$$

$$\sum_{h \in H_j} P_{th,h,j,t} + P_{th,B,j,t} + P_{th,RES,j,t} \ge a_{\min} D_{H,j,t} \qquad h \in H_j,\ j \in M,\ t = 1,...,T-1 \quad (8)$$

$$\sum_{h \in H_j} P_{th,h,j,t} + P_{th,B,j,t} + P_{th,RES,j,t} \le a_{\max} D_{H,j,t} \qquad h \in H_j,\ j \in M,\ t = 1,...,T-1 \quad (9)$$

$$P_{S,j,t} \le -(a_j SOC_{j,t} - b_j) \qquad j \in M,\ t = 1,...,T-1 \quad (10)$$

$$P_{S,j,t} \le -\left(\frac{1}{1 + \left[\dfrac{SOC_{j,t}}{a_{2,j}} \right]^{k_j}} \left(c_{2,j} \cdot SOC_{j,t} - d_{2,j} \right) \cdot \left[\frac{SOC_{j,t}}{a_{2,j}} \right]^{k_j} \right) \qquad j \in M,\ t = 1,...,T-1 \quad (11)$$

$$P_{S,j}^{MIN} \le P_{S,j,t} \le P_{S,j}^{MAX} \qquad j \in M,\ t = 1,...,T-1 \quad (12)$$

$$SOC^{MIN} \le SOC_{j,t} \le SOC^{MAX} \qquad j \in M,\ t = 1,...,T-1 \quad (13)$$

$$C_{TOT,j} \le C_j^{MAX} \qquad t = 1,...,T-1 \quad (14)$$

where: $P_{el,h,j,t}$ is the power produced by microturbine *h*, $h \in H_j$ (where H_j is the set of all the microturbines in microgrid *j)*, in microgrid *j* in time interval (*t*, *t*+1), $P_{RES,j,t}$ is the overall renewable power production*,* $P_{S,j,t}$ is the power exchanged with the storage element, $P_{veh,j,t}$ is the power to the electrical vehicles, $D_{AGG,j,t}$ is the known load reduction requested by the AGG (it corresponds to the optimal value found in the AGG optimization problem), $Q_{RES,j,t}, Q_{S,j,t}$ are the reactive power from renewables and storage respectively while $Q_{D,j,t}$ is the reactive load, $P_{PE,h,j,t}$ is the primary energy consumed by the microturbines, $\mu_{h,j,t}$, $\bar{\mu}_{h,j,t}$ and $\eta_{B,j}$ are efficiency parameters, $P_{th,h,j,t}$ is thermal power production, $P_{th,B,j,t}$ is the thermal power produced by boilers while $P_{PE,B,j,t}$ is the primary energy, $P_{th,RES,j,t}$ is the thermal power produced by renewable energy sources, $D_{H,j,t}$ is the thermal demand, $SOC_{j,t}$ is the state of charge of the storage system, $P_{S,j,t}$ is the power exchanged with the storage, $a_j, b_j, a_{2,j}$ and k_j are parameters, $C_{TOT,j}$ represents the costs of the microgrid, and other symbols $a_{\max}$ and $a_{\min}$, represent bound parameters. Specifically, Equations (2) and (3) represent the active and reactive power balance. Equations (4) and (5) model the electrical and thermal power produced by microturbines as a function of the primary energy, while equation (6) bounds the power production from microturbines with respect to its rated power. The boiler's model is reported in equation (7). The thermal balance of the microgrid is reported in equations (8) and (9). Equations (10)-(13) represent the storage system as presented in (Delfino et al., 2019). Finally, equation (14) states that the costs of the microgrid should not overcome a pre-defined maximum value. Specifically, costs are a function of the decision variables and consider the costs to produce energy and the costs related to CO2 emissions. Costs in (14) are given by:

$$
\begin{aligned}
&C_{TOT,j} = \\
&\sum_{t=0}^{T-1}\left[\left(C_{u,j,t} + f_e C_{CO_2}\right)\max(D_{j,t},0)\Delta + \min(D_{j,t},0)B_{u,t}\Delta - C_{AGG,t}D_{AGG,j,t}\Delta\right] \\
&+\sum_{t=0}^{T-1} P_{PE,B,j,t}\left(f_{j,B}C_{gas,j} + f_{e,B}C_{CO_2}\right)\Delta + \sum_{t=0}^{T-1}\sum_{h\in H_j} P_{PE,h,j,t}\left(f_{j,h}C_{gas,j} + f_{e,h}C_{CO_2}\right)\Delta \\
&\qquad j \in M
\end{aligned}
\tag{15}
$$

where $C_{u,j,t}$ and $B_{u,t}$ are the unit costs for energy bought and sold respectively, Δ is the length of the time interval, $C_{gas,j}$ is the unit cost for one cubic meter of natural gas, $f_{j,h}$ and $f_{j,B}$ are conversion factors from power produced and gas consumed in cogenerative power plants and boilers respectively, f_e is the conversion factor from power purchased from the grid and CO_2 production, C_{CO_2} is the unit cost for kg of CO_2 produced, $f_{e,h}$ and $f_{e,B}$ are conversion factors from the power produced and kg of CO_2 generated in cogenerative power plants and boilers.

2.2 The buildings optimization model

The buildings' optimization problem is similar to the one previously defined, except for the fact that the temperature variation in each room of the building is considered, instead of the thermal balance. The analysis is relevant to buildings equipped with heat pumps. In this case the reactive power is not considered because the building is not able to control it. The overall decision problem is:

$$
\min = \hat{J}_{B,j} = \sum_{t=0}^{T}\left(D_{j,t} - \tilde{D}_{j,t}\right)^2 \qquad j \in B \tag{16}
$$

s.t.

$$
T_{i,j,t+1} = T_{i,j,t} + \frac{\Delta}{C_{i,j}}\left[\begin{array}{l}\eta_s q_{i,j,t} - \dfrac{1}{\tilde{R}_{th,ext,i,j}}\tilde{A}_{i,j,ext}\left(T_{i,j,t} - T_{ext,t}\right) + \\ -\displaystyle\sum_{\substack{r\in R_j \\ r\neq i}}\dfrac{1}{\tilde{R}_{th,i,j,r}}\tilde{A}_{i,j,r}\left(T_{i,j,t} - T_{r,j,t}\right)\end{array}\right] \tag{17}
$$
$$
r, i \in R_j,\ j \in B,\ t = 0,...,T-1
$$

$$
T_{i,j}^{MIN} \le T_{i,j,t} \le T_{i,j}^{MAX} \qquad i \in R_j,\ j \in B,\ t = 0,...,T-1 \tag{18}
$$

$$
P_{RES,j,t} + P_{S,j,t} + D_{j,t} = -D_{AGG,j,t} + \tilde{L}_{j,t} \qquad j \in B,\ t = 0,...,T-1 \tag{19}
$$

$$
\tilde{L}_{j,t} = P_{veh,j,t} + P_{wash,j,t} + q_{HV,j,t} + \tilde{D}_{f,j,t} \qquad j \in B,\ t = 0,...,T-1 \tag{20}
$$

$$
\sum_{t=0}^{T-1} P_{veh,j,t} \ge \tilde{P}_{ev,j} \qquad j \in B \tag{21}
$$

$$
P_{wash,j,t} = P_{wash,j,t}^{fix} + P_{wash,j,t}^{def} \qquad j \in B,\ t = 0,...,T-1 \tag{22}
$$

$$
\sum_{t=0}^{T-1} P_{wash,j,t}^{def} \ge \tilde{P}_{wash,j,t}^{def} \qquad j \in B,\ t = 0,...,T-1 \tag{23}
$$

$$
C_{TOT,j} = \sum_{t=0}^{T-1}\left(\begin{array}{l}\max(D_{j,t},0)\left(C_{u,j,t} + f_e C_{CO_2}\right)\Delta + \\ \min(D_{j,t},0)B_{u,t}\Delta - C_{AGG,j,t}\end{array}\right) \qquad j \in B \tag{24}
$$

$$
C_{TOT,j} \le C_j^{MAX} \qquad j \in B \tag{25}
$$

where R_j is the set of rooms in building *j*, $j \in B$, with *B* the set of buildings.*;* $C_{i,j}$ is thermal capacitance of room *i* in building *j* [B/K]; $T_{ext,t}$ is external temperature [K]; $\tilde{R}_{th,ext,i,j}$ is resistance between room *i* in building *j* and the external environment; $\tilde{R}_{th,i,j,r}$ is resistance between room *i* and room *r* in building j; $\tilde{A}_{i,j,r}$ $\tilde{A}_{i,j,ext}$ are adjacency matrices for rooms and external walls, respectively; $q_{i,j,t}$ is thermal power [kW] (unrestricted in sign) provided by heat pumps in room i in building j (it is important to note that $q_{HV,j,t}=\sum_{i=1}^{I} q_{i,j,t}$); $T_{i,j,t}$ is temperature [K] in room i of building j at time instant t; $\tilde{L}_{j,t}$ and $\tilde{D}_{f,j,t}$ are the load and the fixed consumption; $P_{wash,j,t}$ is the power necessary to feed washing machines; $P^{fix}_{wash,j,t}$ and $P^{def}_{wash,j,t}$ are the fixed and adjustable power of washing machines; $\tilde{P}_{ev,j}$ and $\tilde{P}^{def}_{wash,j}$ are the minimum daily energy consumed by the electrical vehicles and washing machines, respectively.

Constraints (17) show the temperature equation in the rooms of the buildings, (18) are the temperature bounds. The active power balance is reported in (19) and a detailed description of the load is given by (20). Eq. (21) sets a minimum amount of energy given to the EVs. In (22) the power consumed by the washing machines is split into the fixed and the adjustable terms. Equation (23) sets the minimum amount of adjustable power consumed by the washing machines. The overall cost is presented in (24) and its limit in (25). The storage equations presented in (10-13) are used also for the buildings considering $j \in B$.

3. THE AGGREGATOR OPTIMIZATION PROBLEM

The objective function includes the following terms: C_{inc} is the cost providing incentives to the LUs in order to diminish load and/or increase production; B_{DR} is the benefit reducing the load for the external grid; C_{DEA} is a term named "Democratic Energy Assignment" in which the dissatisfaction of each LU is minimized considering the needs of the LUs (i.e. cost minimization) and equalizing the gain/costs that the LUs may have; $C_{emissions}$ is the term which considers the cost of the CO_2 emissions. That is (Ferro et al 2020):

$$\min J = C_{inc} - B_{DR} + C_{DEA} + C_{emissions} \tag{26}$$

$$C_{inc} = \sum_{t=0}^{T-1}\sum_{j\in A} C_{AGG,j,t}\Delta \tag{27}$$

$$C_{AGG,j,t} = a_j (D_{AGG,j,t})^2 + b_j D_{AGG,j,t} + c_j \qquad j \in A,\ t=0,\dots,T-1 \tag{28}$$

$$C_{emissions} = \sum_{t=1}^{T-1}\left(\begin{array}{l} \sum_{j\in A}\max(D_{j,t},0) f_e C_{CO_2}\Delta + \\ \sum_{j\in M} P_{PE,B,j,t} f_{e,B} C_{CO_2}\Delta + \\ \sum_{j\in M}\sum_{h\in H_j} P_{PE,h,j,t} f_{e,h} C_{CO_2}\Delta \end{array}\right) \tag{29}$$

$$DR_t = \max(P_{grid,da,t} - P_{grid,t}, 0) \qquad t=0,\dots,T-1 \tag{30}$$

$$B_{DR} = \sum_{t=0}^{T-1}[C_{Market,t} DR_t - C_{fee,t}\max(MR_t - DR_t, 0)]\Delta \tag{31}$$

$$C_{DEA} = \sum_{t=0}^{T-1}\sum_{j\in A}\sum_{\substack{k\in A\\ k\neq j}} (C_{AGG,j,t} - C_{AGG,k,t})^2 \qquad j \in A,\ t=0,\dots,T-1 \tag{32}$$

where $A = B \cup M$ is the set of the indexes associated to all users, $C_{AGG,j,t}$ is the cost relative to the demand reduction of each user, a_j, b_j and c_j are coefficients, DR_t is the power reduction at the grid node, MR_t is the requested power reduction at the grid node, $P_{grid,t}$ is the new request resulting from the decrease of demand, $P_{grid,da,t}$ is a parameter calculated on the basis of forecasting in the day ahead that cannot be updated, $C_{Market,t}$ is the unit cost of the power bought from the main grid, $C_{fee,t}$ is a unit coefficient which gives a penalty on the dissatisfied demand reduction.

Moreover, the following constraints must be considered, which represent the bounds for DR_t and $C_{AGG,j,t}$:

$$\lambda MR_t \le \mathrm{DR}_t \le MR_t \qquad t=0,\dots,T-1 \tag{33}$$

$$\varphi_{\min} C_{Market,t} D_{AGG,j,t} \le C_{AGG,j,t} \le \varphi_{\max} C_{Market,t} D_{AGG,j,t} \qquad j \in A,\ t=0,\dots,T-1 \tag{34}$$

where $\varphi_{\min}, \varphi_{\max}$ and λ are known coefficients.

The AGG system model for the electrical grid is represented by the power flow equations:

$$p_{n,p,t} = G_{n,p}\left(v_{n,t} - v_{p,t}\right) - B_{n,p}(\delta_{n,t} - \delta_{p,t}) \tag{35}$$

$$q_{n,p,t} = -B_{n,p}\left(v_{n,t} - v_{p,t}\right) - G_{n,p}(\delta_{n,t} - \delta_{p,t}) \tag{36}$$

with $n, p \in N, n \neq p$ (with N set of indexes associated to the distribution grid nodes) where $G_{n,p}$ and $B_{n,p}$ are conductance and susceptance parameters for the line (n,p), $v_{n,t}$ and $\delta_{n,t}$ are the voltage magnitude and phase at node n, respectively, $p_{n,p,t}$ and $q_{n,p,t}$ active and reactive power flows, respectively. Then, there are equations related to the power balance for active and reactive power as well as bounds for control variables. That is

$$\sum_{j\in A} A_{n,j} D_{j,t} + \sum_{\substack{p\in N\\ p\neq n}} P_{n,p,t} = 0 \ \ \forall (s,d) \in O/D \qquad j \in A,\ t=0,\dots,T-1 \tag{37}$$

$$\sum_{j\in A} Q_{M,j,t} + \sum_{\substack{n\in N\\ n\neq p}} Q_{n,p,t} = 0 \qquad j \in A,\ t=0,\dots,T-1 \tag{38}$$

$$P_{grid}^{MIN} \le P_{grid,t} \le P_{grid}^{MAX} \qquad t=0,\dots,T-1 \tag{39}$$

$$D_j^{MIN} \le D_{j,t} \le D_j^{MAX} \qquad t=0,\dots,T-1 \tag{40}$$

$$Q_{M,j}^{MIN} \le Q_{M,j,t} \le Q_{M,j}^{MAX} \qquad t=0,...,T-1 \tag{41}$$

where: $A_{n,j}$ is equal to 1 if the element j is connected to n and 0 otherwise. $P_{n,p,t}$ is the power, unrestricted in sign, from node n to node p in kW, i.e. the p.u. value ($p_{n,p,t}$) multiplied by the base S_b. $Q_{M,j,t}$ is reactive power exchange with the main grid and $Q_{n,p,t}$ represents reactive power flows in kVAR. Other parameters represent bounds for decision variables.

3.1 Emulation of the LUs system model

The AGG emulates the behaviour of the LUs based on limited information, thus using a simplified version of the system model adopted in 3.1 and 3.2. Specifically, the constraints related to the emulation of microgrids are (Ferro et al 2018) :

$$P_{el,j,t} + P_{RES,j,t} + P_{S,j,t} + D_{j,t} = -D_{AGG,j,t} + D_{f,j,t} \quad j \in M,\ t=0,...,T-1 \tag{42}$$

$$Q_{RES,j,t} + Q_{S,j,t} + Q_{M,j,t} = Q_{f,j,t} \quad j \in M,\ t=0,...,T-1 \tag{43}$$

$$P_{th,j,t} + P_{th,B,j,t} + P_{th,RES,j,t} \ge D_{H,j,t} \quad j \in M,\ t=0,...,T-1 \tag{44}$$

$$SOC_{j,t+1} = a_{j,t} SOC_{j,t} - \frac{\eta_{j,t} P_{S,j,t} \Delta}{CAP_j} \quad j \in M,\ t=0,...,T-1 \tag{45}$$

$$\eta_{j,t} = \begin{cases} \eta_{c,j} & if \quad P_{S,j,t} > 0 \\ 1/\eta_{d,j} & otherwise \end{cases} \quad j \in M,\ t=0,...,T-1 \tag{46}$$

$$Q_{S,j,t}^{MIN} \le Q_{S,j,t} \le Q_{S,j,t}^{MAX} \qquad j \in M,\ t=0,...,T-1 \tag{47}$$

$$D_{\mathrm{AGG},j,t} \le D_{AGG,j,t}^{MAX} \qquad j \in M,\ t=0,...,T-1 \tag{48}$$

$$\sum_{t=0}^{T-1} D_{\mathrm{AGG},j,t} \le D_{AGG,TOT,j} \qquad j \in M \tag{49}$$

where $P_{el,j,t}$ is the power from the traditional sources, $D_{f,j,t}$ is the forecasted electrical load of each microgrid, $Q_{f,j,t}$ is the forecasted reactive load, $P_{th,j,t}$ is the thermal power from traditional sources, CAP_j is the capacity of the storage in microgrid j, $\eta_{c,j}, \eta_{d,j}$ are efficiency parameters in charging and discharging modes, $a_{t,j}$ is a loss coefficient due to the internal losses, $D_{AGG,TOT,j}$ is the daily maximum total amount of demand reduction.

In the case of buildings, the considered constraints are:

$$P_{RES,j,t} + P_{S,j,t} + D_{j,t} = -D_{AGG,j,t} + L_{j,t} \quad j \in B,\ t=0,...,T-1 \tag{50}$$

$$L_{j,t} = q_{HV,j,t} + D_{f,j,t} \qquad j \in B,\ t=0,...,T-1 \tag{51}$$

$$Q_{RES,j,t} + Q_{S,j,t} + Q_{M,j,t} = Q_{f,j,t} \quad j \in B,\ t=0,...,T-1 \tag{52}$$

$$T_{j,t+1} = T_{j,t} + \frac{\Delta}{C_j}[\eta_s q_{j,t} - \frac{1}{\tilde{R}_{th,ext,j}} (T_{j,t} - T_{ext,t})] \quad j \in B,\ t=0,...,T-1 \tag{53}$$

$$T_j^{MIN} \le T_{j,t} \le T_j^{MAX} \qquad j \in B,\ t=0,...,T-1 \tag{54}$$

where $L_{j,t}$ is the load given by the electrical power consumed by heat pumps $q_{HV,j,t}$ plus the forecasted electrical demand $D_{f,j,t}$, $T_{j,t}$ is the temperature of the overall building j, C_j is the thermal capacitance in building j [J/K], $T_{ext,t}$ is the external temperature [K], $q_{j,t}$ is the thermal power provided by heat pumps, $\tilde{R}_{th,ext,j}$ is the resistance between building j and the external environment, and η_s is a known conversion parameter.

4. CASE STUDY APPLICATION

The developed bi-level architecture has been applied to a case study with four different LUs. Half of them are buildings and the remaining part are microgrids (Delfino et al., 2019). For the sake of brevity, only the results of one building and one microgrid (whose indexes are 1 and 3 respectively) will be reported. Moreover, the thermal part will not be presented.

The results of the upper level are the reference values for the LUs. The optimal solutions in Fig. 1 and Fig. 2 show the additional power reduction and the power exchange with the main grid, respectively. The load reduction is lower in buildings and higher in the microgrids: this can be explained by considering that, in the present example, the microgrids are characterized by a larger overall electricity consumption than single buildings, resulting in higher flexibility.

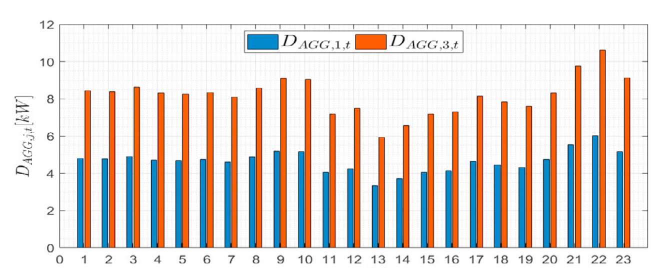

Fig. 1. Reference values for power reduction in each LU.

The local users track the optimal reference values coming from the upper level. Fig. 3 shows the resulting optimal power exchange $D_{j,t}$ with the grid compared with its reference value $\tilde{D}_{j,t}$.

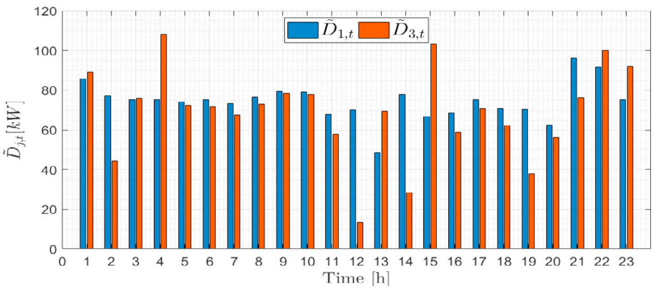

Fig. 2. Reference values of power exchanged between the grid and the LUs.

Instead, Fig. 4 shows the resulting electrical balance of the microgrids. In the case of buildings, Fig. 5 represents the power exchange between the considered building and the grid compared with the reference value provided by the AGG. Both in the case of the building and in the one of the microgrid, the LU optimization makes it possible for the users to follow the reference values specified by the AGG.

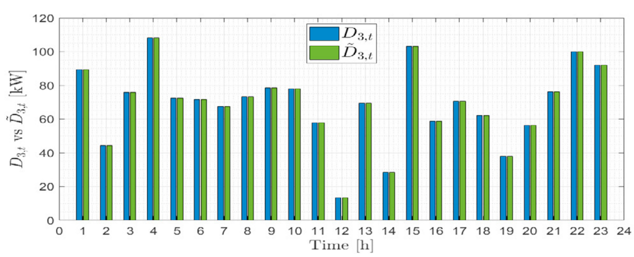

Fig. 3. The power exchange between the microgrids and the grid, compared to the reference value.

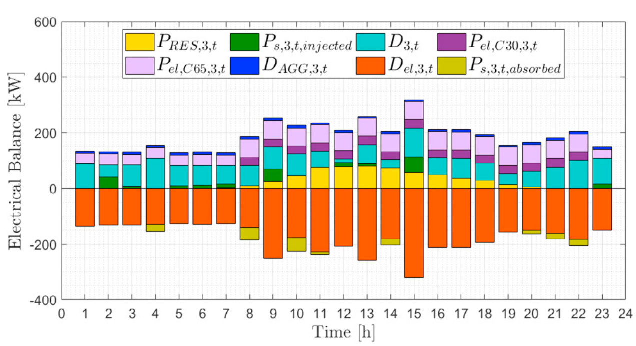

Fig. 4. Electrical balance for microgrid 3.

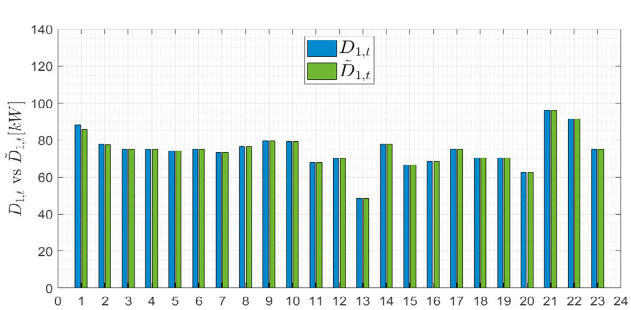

Fig. 5. The power exchange between building 1 and the grid, compared to the reference value.

5. CONCLUSIONS AND FUTURE DEVELOPMENTS

In this paper, a new two-stage hierarchical architecture for an aggregator of consumers in the balancing market is proposed. The lower level makes the users follow the reference values given by the upper level as close as possible; the upper level minimizes the costs, assigning load reduction set-point to the user in a democratic way. The application of the presented decision scheme could be exploited within a receding-horizon framework, in which at each time step, only the solution referring to the next time discretization interval is applied. Future developments will concern a solution based on distributed optimization and/or the analytical solution of some of the decision models. Then, a stochastic optimization problem can be formalized.

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