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A hierarchical approach for balancing service provision by microgrids aggregators

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Abstract: Volatile renewable energy resources are gaining more and more diffusion throughout the power system, and their intermittent production calls for enhanced balancing efforts. With a recent regulation, the European Union endorsed the participation of aggregated microgrids to the balancing of power system. The resulting assets optimization problem, however, features privacy constraints that prevent a full exchange of information, making fully centralized approaches not suitable. To this purpose, this work proposes a hierarchical approach allowing microgrids' aggregators to provide balancing services in an efficient and privacy-friendly fashion. This approach is based on a novel method to describe the power flexibility that each microgrid can provide, allowing to significantly decrease the computational effort.

Keywords: Electric power system, Energy management systems, Hierarchical decision making, Optimization problems, Smart power applications

1. INTRODUCTION

A significant obstacle to the diffusion of Renewable Energy Sources (RESs) is given by their intermittent and unpredictable nature, as they are not able to ensure the continuous balance between generation and absorption in the overall power system. Power balance is of vital importance not only to guarantee a secure supply, but also to avoid serious deviations of network's frequency and voltages, which lead to instability events. The management of the electric power system is therefore required to evolve towards a more flexible paradigm, where generation and demand patterns can be adapted to ensure the overall balance of the grid. In this context, the European Union recently introduced a new player in the power system operation, named *Balance Service Provider* (BSP), that provides balancing services to the Transmission System Operator (TSO), as reported by European Commission (2017). Based on the needs of the power system, the TSO can resort to these balancing services to restore the equilibrium among power production and consumption. To do so, BSPs adjust the power that grid units exchange with the power system. Being the Microgrids (MGs) able to modulate their output power by acting on local micro-Generators (mGENs), Battery Energy Storage Systems (BESSs), and Controllable Loads (CLs), they are ideal providers of balancing services, as reported in Samad et al. (2016). However, single MGs are characterized by rather low power ratings, often insufficient to meet the minimum requirements for the provision of balancing services, as discussed in Yuen et al. (2011). Therefore, a possible solution is to coordinate multiple MGs in an aggregated fashion, coordinating them by means of an Aggregator Supervisor (AGS), see La Bella et al. (2018). The AGS, as shown in Carreiro et al. (2017), can act as a BSP on behalf of the MGs themselves, managing their aggregated power and leading to a simpler power system management.

Each BSP can provide different types of balancing services, in terms of the involved power requirements and activation periods. Considering actual regulations, aggregators are considered more suitable for the provision of manual Frequency Restoration Reserves (mFRR), as discussed in e.g. Poplavskaya and de Vries (2019).This service consists of an initial pre-allocation of power reserve, which are offered in advance (e.g. during the day before the delivery) to the TSO. Then, if the TSO accepts the offered reserves, they are regarded as *pre-contracted* and their availability must be guaranteed during the online system operation, so that the TSO can rely on them to balance the power system. During the intra-day system operation, BSPs can also increase the offered balancing power reserves, considering the current status of their units and the updated - and generally more accurate - power forecasts. Therefore, whenever balancing power is required to restore the power system balance, the TSO can issue balancing power requests to the BSPs, compatibly with the offered reserves.

Centralized optimization frameworks for the provision of balancing services by commercial buildings are addressed in Fabietti et al. (2018) , while in Yuen et al. (2011) the coordination of multiple MGs is discussed. Nonetheless, centralized methods are not advisable for managing ag-

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gregated resources, due to their poor scalability and the necessity to disclose assets' internal and privacy-sensitive information. These issues are usually overcome by distributed optimization schemes. Distributed frameworks for satisfying balancing service requests sent from the TSO are presented in Pei et al. (2016) , but they lack the possibility to adopt mixed-integer variables to model, for example, shiftable and curtailable loads. Indeed, when distributed approaches are applied to non-convex, mixed-integer (MI) optimization problems, feasibility and convergence issues are likely to arise, see Molzahn et al. (2017). Heuristic methods addressing MI problems have been proposed in Mhanna et al. (2016), where however convergence is not guaranteed and units are managed based on energy prices, rather than to fulfill power requests.

The mentioned issues motivated the design of a novel scheduling approach, which allows to efficiently evaluate the overall power availability of the aggregator and to promptly dispatch the power requested by the TSO, also in presence of mixed-integer variables. The approach is designed to be applied during the intra-day operation, assuming that MGs have already scheduled their optimal output power baseline and the pre-contracted power reserves, e.g. through the day-ahead market processes using the method proposed in La Bella et al. (2019b). Moreover, while providing the required balancing services, the so-called *rebound effect* must also be avoided, occurring when MGs are not able to maintain the pre-scheduled power profiles in the time instants following a power request. Same considerations apply to the pre-contracted power reserves, which must be always guaranteed albeit multiple power requests are received. The approach is optimization-based, where MGs initially evaluate their power availability and the associated cost. To do so, we propose the definition of a *flexibility function* for each MG, allowing them to preserve the internal information and to simplify the AGS management from a computational viewpoint. Then, the AGS can exploit this information to both offer additional power reserves and to internally dispatch the TSO power requests. An alternative method to evaluate power flexibility is discussed in Müller et al. (2019), which however deals with day-ahead market operations and it does not allow to consider mixed-integer variables.

The advantages of the approach here proposed are: (i) MGs internal information are not externally disclosed; (ii) the AGS solves a simple and computationally efficient convex optimization problem to satisfy the TSO power request; (iii) MI variables can be safely introduced in MGs' optimization problems. The performances of the proposed method have been compared to a centralized optimization framework, in which the AGS has a complete knowledge of each MG, showing quite satisfactory results in terms of optimality of the solution.

2. MICROGRID MODEL

The aggregator is assumed to be composed by M MGs, collected in the set $\mathcal{N}_M$. The generic i-th MG, denoted by MG_i, is modeled as a discrete-time system with step $\tau = 15\,\mathrm{min}$, therefore the number of steps in the whole day is $N = 24h/\tau = 96$. The proposed approach is supposed to be executed during the online operation at a generic time-step $\tilde{t} \in \{1, ..., N\}$. As a convention, powers are positive is supplied and negative if absorbed. In case a variable p is bounded, $\bar{p}$ and $\underline{p}$ indicate the maximum and minimum values, respectively. The expected power profiles, e.g. loads' and RESs' available forecasts and the pre-scheduled power programs of MG units, are indicated by an hat, i.e. $\hat{p}$. For each MG_i, the available generators, batteries, non-dispatchable elements, and controllable loads are grouped in the sets $\mathcal{N}_i^g = \{1, ..., n_i^g\}$, $\mathcal{N}_i^b = \{1, ..., n_i^b\}$, $\mathcal{N}_i^f = \{1, ..., n_i^f\}$, and $\mathcal{N}_i^{cl} = \{1, ..., n_i^{cl}\}$, respectively. In the following, the model of a generic MG_i is formulated, at any time t in the prediction horizon $\{\tilde{t}, ..., N\}$.

Let us indicate by $p^g_{j_i}$, $p^b_{k_i}$, $p^f_{l_i}$, and $p^{cl}_{m_i}$ the power profiles of MG_i's j-th generator, k-th battery, l-th non-dispatchable element, and m-th controllable load. For each generator $j_i \in \mathcal{N}_i^g$, any power profile can be committed, provided that it lies within generators capability limits, i.e.

$$\underline{p}^g_{j_i} \leq p^g_{j_i}(t) \leq \bar{p}^g_{j_i}\,. \tag{1a}$$

The up/down power reserves of the generators, $r^{g\uparrow}_{j_i}$ and $r^{g\downarrow}_{j_i}$ are defined as the available margin for power increase or decrease, respectively, meaning that

$$r^{g\uparrow}_{j_i}(t) = \bar{p}^g_{j_i} - p^g_{j_i}(t)\,, \quad r^{g\downarrow}_{j_i}(t) = p^g_{j_i}(t) - \underline{p}^g_{j_i}\,. \tag{1b}$$

Concerning the generic battery $k_i \in \mathcal{N}_i^b$, the power capability limits can be accounted by the following constraint:

$$\underline{p}^b_{k_i} \leq p^b_{k_i}(t) \leq \bar{p}^b_{k_i}\,. \tag{2a}$$

For the sake of compactness, batteries are here assumed to be ideal, but the approach can be easily extended to account for the charge and discharge efficiencies. Each battery can thus be modeled as a pure integrator:

$$s^b_{k_i}(t+1) = s^b_{k_i}(t) - \frac{\tau}{C^b_{k_i}} p^b_{k_i}(t)\,, \tag{2b}$$

where $s^b_{k_i}$ is the State of Charge (SOC) of the battery and $C^b_{k_i}$ its capacity. It should be noted that, since batteries are usually operated to avoid full charges and discharges that could harm the battery life itself, energy capability limits are also enforced by prescribing that

$$\underline{s}^b_{k_i} \leq s^b_{k_i}(t) \leq \bar{s}^b_{k_i}\,. \tag{2c}$$

Concerning the power reserves provided by the batteries, denoted by $r^{b\uparrow}_{k_i}$ and $r^{b\downarrow}_{k_i}$, not only the capability limits must be considered, but also the stored energy in future time instants. Indeed, the power reserves granted at each time instant shall not involve a violation of the bound on the minimum and maximum value of the SOC. The satisfaction of this constraint can be enforced as follows. Consider, for example, the up power reserve of the generic battery k_i. The amount of additional energy that can be provided by the battery across the entire horizon is $\min_{k\in[\tilde{t},\,N]} C^b_{k_i}\big(s^b_{k_i}(k+1) - \underline{s}^b_{k_i}\big)$. This energy margin is thus equally divided across the prediction horizon $N - \tilde{t}$. This leads to the following definition:

$$\begin{aligned} r^{b\uparrow}_{k_i}(t) &= \min\left\{\bar{p}^b_{k_i} - p^b_{k_i}(t),\ \min_{k\in[\tilde{t},\,N]}\left(\frac{C^b_{k_i}\big(s^b_{k_i}(k+1) - \underline{s}^b_{k_i}\big)}{\tau\,(N-\tilde{t}\,)}\right)\right\},\\ r^{b\downarrow}_{k_i}(t) &= \min\left\{p^b_{k_i}(t) - \underline{p}^b_{k_i},\ \min_{k\in[\tilde{t},\,N]}\left(\frac{C^b_{k_i}\big(\bar{s}^b_{k_i} - s^b_{k_i}(k+1)\big)}{\tau\,(N-\tilde{t}\,)}\right)\right\}, \end{aligned} \tag{2d}$$

where $\min\{a, b\}$ is the component-wise minimum between vectors a and b. Notice that, despite (2d) is formulated as a set of non-convex constraints, they can be easily recasted as linear inequalities, see La Bella et al. (2019b). In this work, controllable loads are assumed to be discretely-modulable through the use of mixed-integer variables. Let us consider the generic controllable load $m_i \in \mathcal{N}_i^{cl}$, and let $\delta_{m_i}^{cl}(t) \in \{0, ..., \Delta_{m_i}^{cl}-1\}$ be the discrete modulation factor of such load, where $\Delta_{m_i}^{cl}$ denotes the number of modulation levels. Each controllable load is assumed to declare a time interval $\left[\underline{t}_{m_i}^{cl}, \bar{t}_{m_i}^{cl}\right]$ in which modulation is allowed. Outside this interval, the power profile of the load is fixed to the pre-scheduled power profile, denoted by $\hat{p}_{m_i}^{cl}$. Hence, the following constraint can be introduced:

$$\begin{aligned} p_{m_i}^{cl}(t) &= \frac{\delta_{m_i}^{cl}(t)}{\Delta_{m_i}^{cl}-1}\,\bar{p}_{m_i}^{cl} && \text{if } t \in \left[\underline{t}_{m_i}^{cl}, \bar{t}_{m_i}^{cl}\right], \\ p_{m_i}^{cl}(t) &= \hat{p}_{m_i}^{cl}(t) && \text{if } t \notin \left[\underline{t}_{m_i}^{cl}, \bar{t}_{m_i}^{cl}\right], \end{aligned} \tag{3a}$$

where $\bar{p}_{m_i}^{cl}$ is the power corresponding to 100% modulation. Moreover, since the overall energy supplied to the load in the residual time interval must be equal to the pre-scheduled energy, it follows that

$$\tau \sum_{t=\tilde{t}}^{N} p_{m_i}^{cl}(t) = \tau \sum_{t=\tilde{t}}^{N} \hat{p}_{m_i}^{cl}(t). \tag{3b}$$

The power program of MG_i at any time instant t, denoted by $p_i^{mg}(t)$, can be computed as the sum of the power exchanged by each of its elements, i.e.

$$p_i^{mg}(t) = \sum_{j_i \in \mathcal{N}_i^g} p_{j_i}^g(t) + \sum_{k_i \in \mathcal{N}_i^b} p_{k_i}^b(t) + \sum_{l_i \in \mathcal{N}_{l_i}^f} \hat{p}_{l_i}^f(t) + \sum_{m_i \in \mathcal{N}_i^{cl}} p_{m_i}^{cl}(t), \tag{4a}$$

while MG_i's power reserves, $r_i^{mg\uparrow}(t)$ and $r_i^{mg\downarrow}(t)$, are only provided by generators and batteries,

$$\begin{aligned} r_i^{mg\uparrow}(t) &= \sum_{j_i \in \mathcal{N}_i^g} r_{j_i}^{g\uparrow}(t) + \sum_{k_i \in \mathcal{N}_i^b} r_{k_i}^{b\uparrow}(t), \\ r_i^{mg\downarrow}(t) &= \sum_{j_i \in \mathcal{N}_i^g} r_{j_i}^{g\downarrow}(t) + \sum_{k_i \in \mathcal{N}_i^b} r_{k_i}^{b\downarrow}(t). \end{aligned} \tag{4b}$$

The cost function associated with MG management at time $\tilde{t}$ can be stated as follows:

$$\begin{aligned} J_{i,\tilde{t}}^{mg} = \sum_{t=\tilde{t}}^{N} \Bigg\{ & \sum_{j_i=1}^{n_i^g} \underbrace{\left[a_{j_i}^g (p_{j_i}^g(t))^2 + b_{j_i}^g\, p_{j_i}^g(t) + c_{j_i}^g\right]}_{\alpha} \\ & + \sum_{k_i=1}^{n_i^b} \Big[\underbrace{a_{k_i}^b (p_{k_i}^b(t) - p_{k_i}^b(t-1))^2}_{\beta_1} + \underbrace{b_{k_i}^b (s_{k_i}^b(N+1) - \hat{s}_{k_i}^b(N+1))^2}_{\beta_2}\Big] \\ & + \underbrace{c_i^l\, |p_i^{cl}(t) - \hat{p}_i^{cl}(t)|}_{\omega} - \underbrace{\pi^p(t)\,\tau\, p_i^{mg}(t)}_{\eta} \Bigg\}, \end{aligned}$$

where α accounts for generators' costs; β_1 weights batteries' power variations across successive time instants, to avoid frequent and excessive charges and discharges; β_2 incentivizes the restoration of the terminal SOC to the nominal value within the end of the day; ω expresses the discomfort cost for load modulation; η accounts the gain/cost for energy trade, where $\pi^p(t)$ is the energy price.

3. CENTRALIZED BALANCE SERVICE PROVISION

Based on the MGs' model formulated above, a centralized optimization framework for the provision of balancing services is now presented. Consistently with actual regulations, it is supposed that the TSO can require balancing power services to the aggregator with a time resolution of T_R time steps, usually larger than $\tau = 15$ min (e.g. 1 hour). This means that, every T_R steps, the AGS must communicate the power availability of the aggregator to the TSO, which can then issue a balancing power request at the generic time instant $\tilde{t}$, denoted by $\Gamma_{\tilde{t}}^0$. In order to supply the requested balancing power, the AGS must re-schedule the MG units, increasing or decreasing the overall power profile by $\Gamma_{\tilde{t}}^0$ with respect to the pre-scheduled power program for the time period $\{\tilde{t}, \ldots, N\}$. Consider the generic time instant $\tilde{t}$ at which a balancing service can be requested. If $\Gamma_{\tilde{t}}^0 = 0$, it means that no balancing service is requested in the interval $\{\tilde{t}, ..., \tilde{t}+T_R-1\}$. Conversely, if $\Gamma_{\tilde{t}}^0 > 0$ or $\Gamma_{\tilde{t}}^0 < 0$, it means that the AGS is requested to increase or decrease the aggregator output power, respectively. Therefore, in order to actuate such balancing power request, the AGS varies the pre-scheduled power program of each MG. In particular, the balancing power contributed by MG_i, denoted by $\Gamma_{i,\tilde{t}}^{mg}$, is assumed to be constant across the request interval. In light of these considerations, it is prescribed that

$$p_i^{mg}(t) = \hat{p}_i^{mg}(t) + \Gamma_{i,\tilde{t}}^{mg} \quad \forall t \in \{\tilde{t}, ..., \tilde{t} + T_R - 1\}. \tag{5a}$$

After the request period, the pre-scheduled power program must be respected, i.e.

$$p_i^{mg}(t) = \hat{p}_i^{mg}(t) \quad \forall t \in \{\tilde{t} + T_R, ..., N\}. \tag{5b}$$

Furthermore, after the balancing service provision, each MG must guarantee the availability of the pre-contracted power reserves $\hat{r}_i^{mg\uparrow}$ and $\hat{r}_i^{mg\downarrow}$, leading to

$$\begin{aligned} r_i^{mg\uparrow}(t) &\geq \hat{r}_i^{mg\uparrow}(t) \quad \forall t \in \{\tilde{t} + T_R, ..., N\}, \\ r_i^{mg\downarrow}(t) &\geq \hat{r}_i^{mg\downarrow}(t) \quad \forall t \in \{\tilde{t} + T_R, ..., N\}. \end{aligned} \tag{5c}$$

Eventually, the MGs' balancing power contributions shall sum up to the balancing power request by the TSO:

$$\sum_{j \in \mathcal{N}_M} \Gamma_{j,\tilde{t}}^{mg} = \Gamma_{\tilde{t}}^0 + \epsilon, \tag{6}$$

where ϵ is a slack variable introduced to ensure the feasibility of the optimization problem. To summarize, the centralized optimization problem for the provision of balancing services, at time $\tilde{t}$, is stated as follows

$$\begin{aligned} \min_{p_{\forall j_i}^g, p_{\forall k_i}^b, \delta_{\forall m_i}^{cl}, \epsilon} \quad & \left\{ \sum_{i \in \mathcal{N}_M} J_{i,\tilde{t}}^{mg} + \sigma \epsilon^2 \right\} \\ \text{s.t}, \forall i \in \mathcal{N}_M, \quad & (1) \quad \forall j_i \in \mathcal{N}_i^g, \forall t \in \{\tilde{t}, ..., N\}, \\ & (2) \quad \forall k_i \in \mathcal{N}_i^b, \forall t \in \{\tilde{t}, ..., N\}, \\ & (3) \quad \forall m_i \in \mathcal{N}_i^{cl}, \forall t \in \{\tilde{t}, ..., N\}, \\ & (4) \quad \forall t \in \{\tilde{t}, ..., N\}, \\ & (5)\text{-}(6), \end{aligned} \tag{7}$$

where σ is a weight to penalize the use of the slack variable.

4. HIERARCHICAL APPROACH FOR BALANCE SERVICE PROVISION

It is evident that the centralized balance service provision implies that MGs must share all their internal characteristics, profiles and constraints, see (7). This could be an undesired feature of the approach and moreover it leads the AGS to centrally solve a large-scale mixed-integer optimization problem. Therefore, we here propose a novel procedure based on the following operations:

(1) Each MG initially communicate to the AGS both the extent of its power flexibility and the involved operational cost. To do so, we propose the definition of a *flexibility function* for each MG, allowing them to preserve the internal information and to simplify the AGS management from a computational viewpoint;
(2) Using such information, the AGS can offer additional power reserves at a proper price. This operation, based on market mechanisms, is not here described. However, it is assumed that the TSO at a generic time instant issues a power request to the AGS, which must dispatch it minimizing the overall MGs' operational cost. To do this, the AGS employs the flexibility functions previously communicated by the MGs.
(3) Finally, each MG independently re-schedules the operations of its local units to fulfill AGS' power request, maintaining the pre-scheduled power baseline and reserves for the future time instants. These operations are described in details in the following.

4.1 MGs flexibility functions definition

A flexibility function $f^{\Gamma}_{i,\tilde{t}}$ is defined as the following map

$$\check{J}^{mg}_{i,\tilde{t}} = f^{\Gamma}_{i,\tilde{t}}(\check{\Gamma}^{mg}_{i,\tilde{t}}) \,, \tag{8}$$

where $\check{J}^{mg}_{i,\tilde{t}}$ is the minimum operational cost of MG_i for the provision of the power variation $\check{\Gamma}^{mg}_{i,\tilde{t}}$, at time $\tilde{t}$, for the following T_R steps. Precisely, for a given $\check{\Gamma}^{mg}_{i,\tilde{t}}$, the flexibility function can be evaluated solving the following optimization problem

$$J^{mg,*}_{i,\tilde{t}} = \min_{p^g_{\forall j_i}, p^b_{\forall k_i}, \delta^{cl}_{\forall m_i}} \left\{ J^{mg}_{i,\tilde{t}} \right\} \tag{9a}$$

$$\text{s.t.} \quad \left.\begin{array}{l} (1) \quad \forall j_i \in \mathcal{N}^g_i,\, \forall t \in \{\tilde{t}, ..., N\}\,, \\ (2) \quad \forall k_i \in \mathcal{N}^b_i,\, \forall t \in \{\tilde{t}, ..., N\}\,, \\ (3) \quad \forall m_i \in \mathcal{N}^{cl}_i,\, \forall t \in \{\tilde{t}, ..., N\}\,, \\ (4) \quad \forall t \in \{\tilde{t}, ..., N\}\,, \\ (5), \end{array}\right\} \tag{9b}$$

$$\Gamma^{mg}_{i,\tilde{t}} = \check{\Gamma}^{mg}_{i,\tilde{t}} \,. \tag{9c}$$

As evident, (9) is a Mixed-Integer Quadratic Problem (MIQP) and therefore characterizing the shape and the properties of the map $f^{\Gamma}_{i,\tilde{t}}$ is not a trivial task, requiring much information about MG internal optimization objectives, constraints and unit characteristics. Alternatively, an estimation procedure could be carried out, as the one proposed in La Bella et al. (2019a), which however would require a significant amount of data on the solutions of the MGs optimization problems. Therefore, a simple procedure to quickly compute a convex approximation of $f^{\Gamma}_{i,\tilde{t}}$ is here proposed. Initially, each MG must compute the maximum and minimum power variations that can be provided at the time instant $\tilde{t}$ for the following T_R steps. These quantities are denoted by $\bar{\Gamma}^{mg}_{i,\tilde{t}}$ and $\underline{\Gamma}^{mg}_{i,\tilde{t}}$, respectively. To do this, two separate optimization problems are stated. Problem (10) is introduced to spot the maximum power variation that can be provided by MG_i

$$\begin{aligned} \bar{\Gamma}^{mg}_{i,\tilde{t}} \; = & \max_{p^g_{\forall j_i}, p^b_{\forall k_i}, \delta^{cl}_{\forall m_i}} \left\{ \Gamma^{mg}_{i,\tilde{t}} \right\} \\ & \text{s.t.} \quad (9\text{b})\,, \end{aligned} \tag{10}$$

while problem (11) spots the minimum power variation

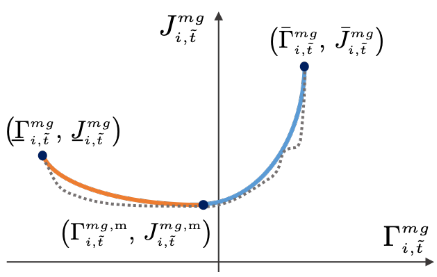


Fig. 1. Sketch of approximated (solid lines) and real (dotted line) flexibility functions.

$$\begin{aligned} \underline{\Gamma}^{mg}_{i,\tilde{t}} \; = & \min_{p^g_{\forall j_i}, p^b_{\forall k_i}, \delta^{cl}_{\forall m_i}} \left\{ \Gamma^{mg}_{i,\tilde{t}} \right\} \\ & \text{s.t.} \quad (9\text{b})\,. \end{aligned} \tag{11}$$

It is reminded that the power variations must be computed such that each MG singularly maintains the pre-scheduled power baseline and pre-contracted reserves in the future time instants, as enforced by constraint (5). The cost associated with the maximum power variation, denoted by $\bar{J}^{mg}_{i,\tilde{t}} = f^{\Gamma}_{i,\tilde{t}}(\bar{\Gamma}^{mg}_{i,\tilde{t}})$, can then be evaluated solving (9), replacing the last constraint with $\Gamma^{mg}_{i,\tilde{t}} = \bar{\Gamma}^{mg}_{i,\tilde{t}}$; the same reasoning is applied to evaluate the cost associated to the minimum power variation, i.e. $\underline{J}^{mg}_{i,\tilde{t}} = f^{\Gamma}_{i,\tilde{t}}(\underline{\Gamma}^{mg}_{i,\tilde{t}})$. A final optimization problem is now performed. This allows to assess which is the optimal power variation for each MG_i, i.e. the one that achieves the minimum value of $J^{mg}_{i,\tilde{t}}$. Indeed, it may happen that, due to forecasts updates or because of previous power variation requests, the pre-scheduled power baseline is no more the optimal operating point. The following optimization problem is thus formulated:

$$\begin{aligned} & \min_{p^g_{\forall j_i}, p^b_{\forall k_i}, \delta^{cl}_{\forall m_i}} \left\{ J^{mg}_{i,\tilde{t}} \right\} \\ & \text{s.t.} \quad (9\text{b})\,. \end{aligned} \tag{12}$$

The optimal values of the cost function and of the power variation computed by (12), are denoted as $J^{mg,\mathrm{m}}_{i,\tilde{t}}$ and $\Gamma^{mg,\mathrm{m}}_{i,\tilde{t}}$, respectively. After solving the sequence of optimization problems (10)-(12), each MG has available three important operating points: the maximum, the minimum and the optimal power variation that can be provided for the next T_R steps, with the associated values of $J^{mg}_{i,\tilde{t}}$. This information is enough to compute a convex approximation of the flexibility function (8), denoted by $\tilde{f}^{\Gamma}_{i,\tilde{t}}(\Gamma^{mg}_{i,\tilde{t}})$. Here, it is proposed to use a piece-wise quadratic approximation defined as follows

$$J^{mg}_{i,\tilde{t}}(\Gamma^{mg}_{i,\tilde{t}}) = f^{\Gamma}_{i,\tilde{t}}(\Gamma^{mg}_{i,\tilde{t}}) \approx \tilde{f}^{\Gamma}_{i,\tilde{t}}(\Gamma^{mg}_{i,\tilde{t}}) =$$
$$\begin{cases} \dfrac{\bar{J}^{mg}_{i,\tilde{t}} - J^{mg,\mathrm{m}}_{i,\tilde{t}}}{(\bar{\Gamma}^{mg}_{i,\tilde{t}} - \Gamma^{mg,\mathrm{m}}_{i,\tilde{t}})^2}(\Gamma^{mg}_{i,\tilde{t}} - \Gamma^{mg,\mathrm{m}}_{i,\tilde{t}})^2 + J^{mg,\mathrm{m}}_{i,\tilde{t}}, & \text{if } \Gamma^{mg}_{i,\tilde{t}} \geq \Gamma^{mg,\mathrm{m}}_{i,\tilde{t}}, \\ \dfrac{\underline{J}^{mg}_{i,\tilde{t}} - J^{mg,\mathrm{m}}_{i,\tilde{t}}}{(\underline{\Gamma}^{mg}_{i,\tilde{t}} - \Gamma^{mg,\mathrm{m}}_{i,\tilde{t}})^2}(\Gamma^{mg}_{i,\tilde{t}} - \Gamma^{mg,\mathrm{m}}_{i,\tilde{t}})^2 + J^{mg,\mathrm{m}}_{i,\tilde{t}}, & \text{if } \Gamma^{mg}_{i,\tilde{t}} < \Gamma^{mg,\mathrm{m}}_{i,\tilde{t}}. \end{cases}$$

The convex quadratic approximation is also motivated by the fact that the optimal cost of parametric quadratic problems (such as the MG one assuming fixed integer variables) is indeed a piece-wise quadratic function with respect to the parameters, as discussed in Bemporad and Filippi (2006). In Figure 1, the piece-wise quadratic approximation is shown. Evaluating the flexibility function at more operating points, the approximation of (8) can be significantly improved. However, as it will be shown in the numerical results section, satisfactory performances are obtained also using the described rough approximation. The AGS is supposed to receive the flexibility functions from all the MGs, together with the maximum and minimum power variations that each MG can provide. By means of this information, the AGS can offer to the TSO the total maximum and minimum power variation of the aggregator during the intra-day operation, associated to the corresponding costs. It is instead assumed that at the generic time instant $\tilde{t}$ the TSO can send to the AGS a balancing power variation request $\Gamma^0_{\tilde{t}}$ with respect to the total pre-scheduled baseline.

4.2 AGS optimal dispatch of TSO power requests

Having knowledge of approximated MGs' flexibility function, the AGs can dispatch the MGs to execute the balancing power requested by the TSO. This is done solving the following optimization problem

$$\min_{\Gamma^{mg}_{\forall i,\tilde{t}}} \Big\{ \sum_{\forall i \in \mathcal{N}_{\mathcal{M}}} \tilde{f}^{\Gamma}_{i,\tilde{t}}\,(\Gamma^{mg}_{i,\tilde{t}}) \Big\} \tag{13a}$$

$$\text{s.t.} \quad \underline{\Gamma}^{mg}_{i,\tilde{t}} \leq \Gamma^{mg}_{i,\tilde{t}} \leq \bar{\Gamma}^{mg}_{i,\tilde{t}}\,, \tag{13b}$$

$$\sum_{\forall i \in \mathcal{N}_{\mathcal{M}}} \Gamma^{mg}_{i,\tilde{t}} = \Gamma^0_{\tilde{t}}\,. \tag{13c}$$

The optimization problem (13) aims to find the optimal power variations for each MG, denoted as $\Gamma^{mg,\star}_{i,\tilde{t}}$, such that the total request from the TSO is satisfied, see (13c), compatibly with the availability that each MG has previously communicated, see (13b). It is evident that, through the approximated MGs information, the AGS is able to efficiently dispatch the balancing power solving (13), which is a static and convex optimization problem with M optimization variables.

4.3 MGs final scheduling

Once the optimal power variations $\Gamma^{mg,\star}_{i,\tilde{t}}$ are computed through (13), each MG_i must reschedule its internal operation to satisfy such request. This is performed by MGs energy management systems, for example solving:

$$\begin{aligned} \min_{p^g_{\forall j_i},\, p^b_{\forall k_i},\, \delta^{cl}_{\forall m_i}} \quad & \big\{ J^{mg}_{i,\tilde{t}} + \sigma_i \epsilon_i^2 \big\} \\ \text{s.t.} \quad & \text{(9b)}\,, \\ & \Gamma^{mg}_{i,\tilde{t}} = \Gamma^{mg,\star}_{i,\tilde{t}} + \epsilon_i\,. \end{aligned} \tag{14}$$

As evident, the last constraint of (14) is defined using a slack variable ϵ_i, which is significantly penalized in the cost function, choosing a high value for σ_i. Indeed, since MGs optimization problems are mixed-integer, it cannot be *a-priori* certified that MG_i is able to provide the exact requested balancing power, $\Gamma^{mg,\star}_{i,\tilde{t}}$, in the range $[\underline{\Gamma}^{mg}_{i,\tilde{t}}, \bar{\Gamma}^{mg}_{i,\tilde{t}}]$.

5. NUMERICAL RESULTS

The algorithm is tested considering an aggregator with $M = 4$ MGs. The controllable loads are assumed to be operated with $\Delta^{cl} = 5$ modulation levels. The pre-scheduled profiles of each unit have been defined using the methods described in La Bella et al. (2019b). It is assumed that the aggregator must always guarantee 1 MW of pre-contracted reserves. For the following numerical results,

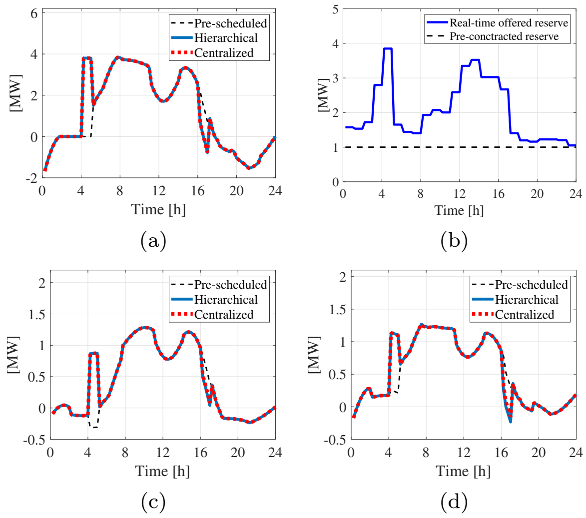
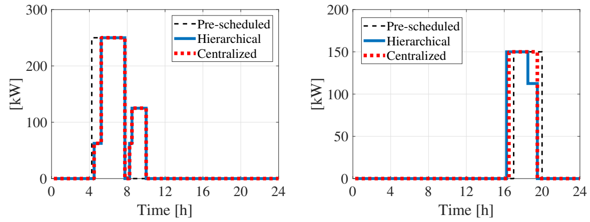


Fig. 2. Aggregator power profile (a) and upward reserve (b); (c) MG_3 and (d) MG_4 output power profile.

it is supposed that the TSO sends two power balancing requests to the aggregator throughout the day. The first is issued at 04:00 and it consists in a power increase of $\Gamma^0_{4h/\tau} = 3.8$ MW with respect to the baseline, that must be maintained for one hour, i.e. $T_R = \frac{1\,h}{\tau} = 4$. The second is sent at 16:00 and it consists in a power decrease of $\Gamma^0_{16h/\tau} = -1.5$MW, always required to be provided for one hour. To assess the performances of the proposed approach, also the centralized optimization problem (7) is solved. As shown in Figure 2(a), the proposed hierarchical approach allow to perfectly track the TSO required power variations with respect to the pre-scheduled baseline, as it is for the centralized case. The contributions of MG_3 and MG_4 are reported in Figures 2(c)-(d), where it can be noted that the optimal power variations computed by the hierarchical and the centralized approach slightly differ. Moreover, it is evident that rebound effects are avoided, as the MG output power is varied with respect to pre-scheduled baseline only during the TSO request periods. In Figure 2(b) the total upward reserve of the aggregator, computed using the hierarchical approach is shown. It is apparent that the pre-contracted quantity of power reserve is always available despite the multiple TSO requests. Figure 3 reports the scheduling of the controllable loads of MG_3 and MG_4. It can be noticed that MG_3 reduces the consumption of its controllable load at 4:00, shifting it ahead in time. Considering the second request, MG_4 anticipates the activation of its controllable load, so as to further decrease its output power profile. As notable, controllable loads are operated at specific consumption levels according to their mixed-integer modeling. The flexibility functions communicated by MG_3 for both requests are shown in Figure 4. The proposed procedure, although simple, satisfactorily describes the real dependence between the MG offered power flexibility and its cost. However, the quality of the approximation significantly depends on which variables MGs manipulate to provide the power variation. For instance, power flexibilities offered by MG_3 for the first power request and by MG_4 for the second rely on the mixed-integer modulation of controllable loads, see Figures 3(e) and (f), implying that real MGs costs



(a) (b)

Fig. 3. CL power modulation: (a) MG_3, (b) MG_4.

vary with a non-smooth behavior, as reported in Figures 4 (a) and (d). Considering the optimality gap between the solution computed by the centralized and the hierarchical approach the following index is introduced

$$\Delta J_{\%} = \frac{\tilde{J}_H - J^*}{J^*} \cdot 100.$$

where $J^* = \sum_{i \in \mathcal{N}_M} J^{mg,*}_{i,\tilde{t}}$, computed using the centralized problem (7), while $\tilde{J}_H = \sum_{i \in \mathcal{N}_M} J^{mg,\star}_{i,\tilde{t}}$, computed using the optimal solution of the proposed hierarchical approach. Concerning the first TSO request, both approaches achieve the same optimal solution, therefore $\Delta J_{\%} = 0\%$. Concerning the second TSO request, the solutions slightly differ, see e.g. Figure 3(f), however the optimality gap is $\Delta J_{\%} = 0.006\%$. The benchmark has been simulated using a laptop equipped with an Intel Core i7-6500U process and 8 GB of RAM. The centralized approach executed the first request in 2.99 sec and the second in 1.13 sec. The hierarchical approach performed the effective dispatch of the first request in 0.5 sec and the second in 0.38 sec. The evaluation of the flexibility functions, performed in advance with respect to the TSO request, has been executed in 1.75 sec for the first request and in 1.3 sec for the second. An advantage of the proposed hierarchical approach is that it performs all the operations in parallel, apart from the AGS dispatch, see (13), which is a simple static and convex problem. Moreover, the centralized approach is not scalable, therefore if the MGs number increases also the computational time will raise, considering also that a mixed-integer optimization problem must be solved.

6. CONCLUSION

This paper presents a hierarchical approach for the provision of balancing power services from aggregators of MGs. The method is based on the definition of the flexibility function, which expresses the power variation that each MG can provide and the corresponding cost. The achievable performances are comparable to the solution computed by a centralized formulation, without requiring MGs to disclose their internal information and units characteristics. Moreover, it allows for a very efficient dispatch of the requested power service, despite the presence of mixed-integer variables for load modulation.

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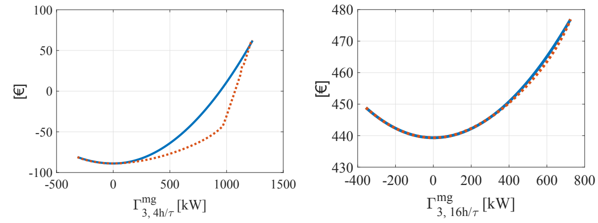

(a) (b)

Fig. 4. Real (dashed line) and approximated (solid line) flexibility functions for MG_3, (a) first power request and (b) second power request.