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Microgrids aggregation management providing ancillary services

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Abstract— **The electrical grid is facing a significant shift from a centralized generation system to a more distributed setting where each portion of the grid is managed by a local control system and it can work both as a producer and as a consumer. This brings many advantages, but a cooperation mechanism between the different players needs to be established in order to ensure the overall network proper working conditions. This paper presents an optimization framework for the management of an aggregation of microgrids. The main objective is to show that, if properly coordinated, microgrids can give a significant support in terms of ancillary services provision. Finally, a distributed algorithm is described, designed in such a way each microgrid preserves its internal information and the control of its resources.**

I. INTRODUCTION

The future electricity network is expected to be characterized by the growing presence of microgrids (MGs). MGs are defined as self-controlled clusters of dispatchable micro-generators, renewable sources, loads and storage units which can be operated either in connected or in isolated mode with respect to the utility grid. MG operation is characterized by novel technical issues and consequently many research works have focused on the design of proper microgrid central controllers (MGCC) taking into account resources constraints and costs, as well as the available load or weather forecasts, to ensure the system proper and safe management [1]–[3]. However, the spread of connected microgrids may affect the system operator activity since these independent grids agents are commonly designed to pursue self profit. In view of this, the system operator would remain the only in charge of ensuring the proper network conditions in a framework constituted by an increasing amount of nondeterministic and bidirectional power flows.

To solve this issue, distributed generators must be properly managed not only to satisfy the load demand at the microgrid level, but also to provide ancillary services to the external grid [4]. MGs are controlled clusters of dispersed generators and therefore they can be regarded as a great opportunity for the system operator to modulate their power production based also on the overall system requirements other than just economical objectives. Nevertheless, a single MG has a negligible impact on the grid system since it is usually chacterized by limited production capability, having also to satisfy its iternal loads. Therefore, to exploit the potential of MGs, a possible solution could be to coordinate groups of interconnected MGs as parts of a unique electrical aggregator (eAG) such that they act as a whole entity for the system operator, reaching also the proper size to provide some ancillary services to the grid [5].

A number of research works have been proposed aiming to establish management strategies for MG communities but most of them are focused on the definition of an economic framework instead of considering the ancillary services provision, e.g. [6], [7]. It is worth noticing that a centralized control of the MG community by an eAG supervisor (AGS) brings about a number of critical issues, i.e. privacy problems and the increase of the size of the control problem to be solved at the eAG level. These critical issues can be efficiently solved by devising suitable optimization sub-problems to be tackled at the MG levels, while the AGS takes the role of a coordinator to globally provide ancillary services without requiring sensitive information about the single MGs, e.g. internal loads consumption and generators characteristics. Distributed optimization algorithms based on the *dual decomposition* approach show to be particularly promising. This work can be considered as a first step towards the complete solution of the eAG problem. The optimization problem here presented can be collocated as part of the day-ahead market operation, where the AGS schedules its units production based on the grid prices and system forecasts, and then it communicates its overall power profile to the system operator for the following day.

The paper is structured as follows. In Section II, the whole optimization problem formulation is presented, both at the MG and and at the eAG level, and the distributed algorithm is described. Section III shows the numerical results of the implemented scheduling process and a comparison with the pure decentralized case is given in order to asses the advantages of the MGs cooperation. Finally, some conclusions are drawn in Section IV.

II. PROBLEM STATEMENT AND FORMULATION

As depicted in Figure 1, an eAG generally includes several grid elements and it can be constituted by n_{M} MGs, n_{L} non-controllable loads and n_{R} individual renewable source plants indicated as $MG_1, \ldots, MG_{n_M}$, $L_1, \ldots, L_{n_L}$ and $R_1, \ldots, R_{n_R}$, respectively. The main goal of the AGS is to schedule the dispatchable resources production such that the global optimum is achieved while satisfying the ancillary service requirements. Before going into the detail of the problem formulation, the main assumptions are initially given.

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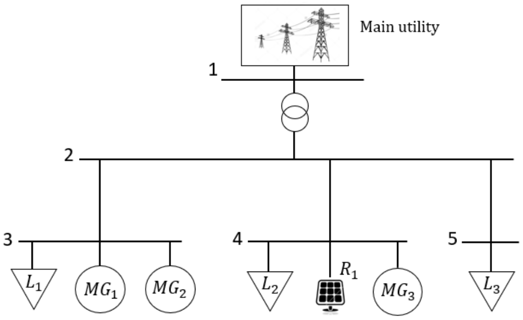

Fig. 1: Electrical aggregator

A. Main assumptions

In this work, two main ancillary services are considered: *primary frequency reserve*, commonly called also *frequency containment reserve*, and *congestion management*. The former refers to the allocation of a minimum amount of power reserve by the whole eAG that will be autonomously used by the frequency primary controllers, implemented at each generation unit, in case of severe frequency deviations. This service, generally requested to traditional generation plants, could be provided also by interconnected MGs aggregating the power reserves of their resources. Although other types of power reserves could be provided, e.g. secondary and tertiary, here just primary reserve is considered due the limited capability production of MGs, even if aggregated [5]. Specifically, two kinds of power reserve will be considered: up reserve capacity and down reserve capacity. They correspond to the power margins for increasing and decreasing the output power with respect to its setpoint in order to compensate external unbalances. Regarding the congestion management service, the AGS will be in charge of coordinating the MGs power outputs not to exceed the maximum line power flows in order to avoid over-current and over-voltage issues. Here, just active powers are considered while the reactive power/voltage regulation is assumed to be carried out by other control layers [8], [9]. It is supposed that daily forecasts of the energy price are available either from historical data or from the day-ahead market negotiations; moreover as for existing ancillary services market, e.g. the German one [10], the amount of provided reserve is a paid service and it will be a gain for the MGs during their scheduling processes.

B. MG modelling and problem formulation

The MG system is described by a discrete time model with sampling period of 15 minutes, i.e $\tau = 0.25$ h. This choice is based on the conventional time frame used for energy prices and weather forecasts. The scheduling process will be carried out considering the whole day, i.e., with a time horizon of $N = 24h/\tau = 96$ steps. The variables and parameters related to each MG, indicated as MG$_i$ with $i \in \{1, \dots, n_M\}$, are presented in Table I. Given the large sampling time, the dispatchable power sources are assumed to instantaneously follow the set-points, which are positive if the power is generated and negative if the power is absorbed.

TABLE I: MG variables and parameters

Symbol	Description
u^g	Micro-generator active power set-point [kW]
u^b	Battery active power set-point [kW]
s^b	State of charge (SOC) [%]
$r^{g\uparrow}, r^{g\downarrow}$	Micro-generator up/down power reserves [kW]
$r^{b\uparrow}, r^{b\downarrow}$	Battery up/down power reserves [kW]
y_i^P	MG$_i$ output active power [kW]
$y_i^{r\uparrow}$	MG$_i$ total up power reserve [kW]
$y_i^{r\downarrow}$	MG$_i$ total down power reserve [kW]
d_i^l	Load absorption in MG$_i$ [kW]
d_i^r	Renewable sources production in MG$_i$ [kW]
$\bar{u}^g, \underline{u}^g$	Micro-generator power limits [kW]
$\bar{u}^b, \underline{u}^b$	Battery power limits of battery [kW]
$\bar{s}^b, \underline{s}^b$	SOC limits [%]
C^b	Battery capacity [kWh]
c^b	Battery usage cost [€/kWh^2]
a^g, b^g, c^g	Micro-generator cost coefficients [€/kWh^2, €/kWh, €]
p^e	Energy price [€/kWh]
$p^{r\uparrow}$	Up reserve capacity price [€/kWh]
$p^{r\downarrow}$	Down reserve capacity price [€/kWh]

The generation units at time step t must be constrained by the capability limits:

$$\underline{u}^g_{j_i} \le u^g_{j_i}(t) \le \bar{u}^g_{j_i} \tag{1}$$

$$\underline{u}^b_{p_i} \le u^b_{p_i}(t) \le \bar{u}^b_{p_i} \tag{2}$$

where the indices $j_i \in \{1, \dots, n_i^g\}$ and $p_i \in \{1, \dots, n_i^b\}$ represent the j^{th} micro-generator and the p^{th} battery installed in MG$_i$, respectively. The SOC dynamics is modelled as an integrator and it is bounded by predefined limits; it is also assumed that the SOC at the end of the day must be equal to the one at the beginning in order to start the next day with the same initial conditions.

$$\begin{aligned} s^b_{p_i}(t+1) &= s^b_{p_i}(t) - 100\,\frac{\tau}{C^b_{p_i}}\,u^b_{p_i}(t) \\ \underline{s}^b_{p_i} &\le s^b_{p_i}(t) \le \bar{s}^b_{p_i} \\ s^b_{p_i}(N) &= s^b_{p_i}(0) \end{aligned} \tag{3}$$

The power reserve provided by fuel-based micro-generators corresponds to the difference between the power limits and the actual production.

$$r^{g\uparrow}_{j_i}(t) = \bar{u}^g_{j_i} - u^g_{j_i}(t) \tag{4}$$

$$r^{g\downarrow}_{j_i}(t) = u^g_{j_i}(t) - \underline{u}^g_{j_i} \tag{5}$$

The same reasoning can not be applied to batteries since the delivering/absorbing power is also limited by the amount of stored energy. Therefore, the power reserves of batteries are defined as the minimum between the power margin with respect to the physical limits and the maximum delivering/absorbing power depending on the actual SOC.

$$r^{b\uparrow}_{p_i}(t) = \min\left\{ \bar{u}^b_{p_i},\ \left(s^b_{p_i}(t) - \underline{s}^b_{p_i}\right)\frac{C^b_{p_i}}{\tau} \right\} - u^b_{p_i}(t)$$

$$r^{b\downarrow}_{p_i}(t) = \min\left\{ -\underline{u}^b_{p_i},\ -\left(s^b_{p_i}(t) - \bar{s}^b_{p_i}\right)\frac{C^b_{p_i}}{\tau} \right\} + u^b_{p_i}(t)$$

Since the above expressions are nonlinear, the batteries up and down reserve capacities are then reformulated through the following constraints.

$$r^{b\uparrow}_{p_i}(t) + u^b_{p_i}(t) \leq \bar{u}^b_{p_i} \tag{6}$$

$$r^{b\uparrow}_{p_i}(t) + u^b_{p_i}(t) \leq \left(s^b_{p_i}(t) - \underline{s}^b_{p_i} \right) \frac{C^b_{p_i}}{\tau} \tag{7}$$

$$r^{b\downarrow}_{p_i}(t) - u^b_{p_i}(t) \leq - \underline{u}^b_{p_i} \tag{8}$$

$$r^{b\downarrow}_{p_i}(t) - u^b_{p_i}(t) \leq - \left(s^b_{p_i}(t) - \bar{s}^b_{p_i} \right) \frac{C^b_{p_i}}{\tau} \tag{9}$$

Being the provided reserve a benefit for the MG, the optimizer reasonably makes the battery reserves take values on the constraints so achieving the minimum between the two expressions both for the up and the down reserve.

The total MG power output is given by the internal power balance and it is defined to be positive if injected in the external grid and negative if assorbed, see (10). The total provided power reserves correspond to the sum of the reserves provided by each generation unit as reported in (11) and (12). Since renewable sources can not raise their produced power, they can only provide down reserve capacity by decreasing their output power.

$$y^P_i(t) = \sum_{p_i=1}^{n^b_i} u^b_{p_i}(t) + \sum_{j_i=1}^{n^g_i} u^g_{j_i}(t) - d^l_i(t) + d^r_i(t) \tag{10}$$

$$y^{r\uparrow}_i(t) = \sum_{p_i=1}^{n^b_i} r^{b\uparrow}_{p_i}(t) + \sum_{j_i=1}^{n^g_i} r^{g\uparrow}_{j_i}(t) \tag{11}$$

$$y^{r\downarrow}_i(t) = \sum_{p_i=1}^{n^b_i} r^{b\downarrow}_{p_i}(t) + \sum_{j_i=1}^{n^g_i} r^{g\downarrow}_{j_i}(t) + d^r_i(t) \tag{12}$$

Having formulated all the system model and constraints, the MG_i economic cost function to be minimized is defined

$$\begin{aligned} J_i = & \sum_{t=1}^{N} \underbrace{\sum_{j_i=1}^{n^g_i} (a^g_{j_i} \tau^2 (u^g_{j_i}(t))^2 + b^g_{j_i}\, \tau\, u^g_{j_i}(t) + c^g_{j_i})}_{\alpha} + \\ & + \sum_{t=2}^{N} \underbrace{\sum_{p_i=1}^{n^b_i} c^b_{p_i} \tau^2 \left(u^b_{p_i}(t) - u^b_{p_i}(t-1) \right)^2}_{\beta} + \\ & - \sum_{t=1}^{N} \tau (\underbrace{p^e(t) y^P_i(t)}_{\gamma} + \underbrace{p^{r\uparrow}(t) y^{r\uparrow}_i(t) + p^{r\downarrow}(t) y^{r\downarrow}_i(t)}_{\delta}) \end{aligned} \tag{13}$$

where all the costs/prices are multiplied by the sampling time τ since they are commonly referred to the energy cost/gain. In (15), the fuel-generator cost α is assumed to depend on the produced power through a quadratic polynomial function [11]. The cost of batteries usage β is assumed to be proportional to the square of the power variation in order to limit excessive charges and discharges. The traded energy γ is expressed through a linear relationship which becomes either a cost or a gain depending on the sign of eAG output power, i.e. $y^P_i(t)$. Finally, the last term δ defines the benefits related to the provided reserves.

Before describing the optimization problem for the whole eAG, for the sake of clarity the MG optimization problem is reformulated in a more compact form. Therefore, x_i is defined as the vector of MG_i internal variables, d_i is the vector of disturbances and y_i are the outputs, i.e.

$$x_i = [(u^g_{j_i}, r^{g\uparrow}_{j_i}, r^{g\downarrow}_{j_i})_{\forall j_i \in (1, n^g_i)}, (u^b_{p_i}, r^{b\uparrow}_{p_i}, r^{b\downarrow}_{p_i}, s^b_{p_i})_{\forall p_i \in (1, n^b_i)}]$$
$$d_i = [d^l_i,\, d^r_i]$$
$$y_i = [y^P_i,\, y^{r\uparrow}_i,\, y^{r\downarrow}_i]$$

where the time indices have been discarded for notational compactness. Moreover, from now on the bold symbols are referred to the vector of optimization variables for the whole prediction horizon, e.g. $\mathbf{x}_i = [\, x_i(1), ..., x_i(N)\,]$ and $\mathbf{y}_i = [\, y_i(1), ..., y_i(N)\,]$. In this way, the MG cost function (13) can be rewritten as $J_i(\mathbf{x}_i, \mathbf{y}_i) = f_i(\mathbf{x}_i) - g_i(\mathbf{y}_i)$, where $f_i(\mathbf{x}_i)$ includes the internal costs α and β, while $g_i(\mathbf{y}_i)$ includes the external trading terms γ and δ. The internal constraints and relationships (1)-(12) can be expressed in compact form through the following set of inequalities (recall that an equality can be expressed by two inequalities).

$$A_i \begin{bmatrix} \mathbf{x}_i \\ \mathbf{y}_i \end{bmatrix} \leq b_i \tag{14}$$

For the sake of generality, this compact version will be considered while formulating the eAG optimization problem. Actually, the MG variables relationships, constraints and cost function here defined can be differently formulated since the AGS could actually deal with MGs having diverse resource management strategies, as well as different units composition. Furthermore, please note that so far just the internal economical resource management has been tackled without considering the minimum requirements for the mentioned ancillary services provision; this duty will concern the AGS system.

TABLE II: eAG variables and parameters

Symbol	Description
$\underline{r}^{\uparrow}_{\text{AG}}, \underline{r}^{\downarrow}_{\text{AG}}$	Minimum up and down eAG power reserve [kW]
d^{L}	Absorption by an eAG load node [kW]
d^{R}	Production by an eAG renewable source node [kW]
$\bar{P}_{(l,m)}$	Maximum active power flow for line $(l,m) \in \mathcal{E}$ [kW]

C. AGS centralized optimization formulation

In this section it is assumed that the AGS can centrally control the MGs generation units for managing its eAG. The eAG network can be modelled as a bi-directional radial graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ with nodes $\mathcal{V} = \{1, ..., n\}$ and edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. As mentioned before, this network is generally composed by n_M active nodes, i.e. the MGs, n_L load nodes and n_R non-dispatchable generation nodes (e.g. individual renewable power fields). The eAG parameters and variables are described in Table II, while the overall centralized problem is defined in (15)-(20).

$$\min_{(\mathbf{x_i},\mathbf{y_i})\,\forall i}\{\sum_{i=1}^{n_M} f_i(\mathbf{x}_i) - \mathbf{p}_r^{\downarrow\prime}\tau(\sum_{i=1}^{n_M}\mathbf{y}_i^{r\downarrow} + \sum_{j=1}^{n_R}\mathbf{d}_j^R) +$$
$$-\mathbf{p}_r^{\uparrow\prime}\tau\sum_{i=1}^{n_M}\mathbf{y}_i^{r\uparrow} - \mathbf{p}_e{}'\tau(\sum_{i=1}^{n_M}\mathbf{y}_i^P - \sum_{j=1}^{n_L}\mathbf{d}_j^L + \sum_{j=1}^{n_R}\mathbf{d}_j^R)\} \tag{15}$$

$s.t.$

$$A_i\begin{bmatrix}\mathbf{x_i}\\ \mathbf{y_i}\end{bmatrix} \le b_i \qquad \forall i \in \{1,\ldots,n_M\} \tag{16}$$

$$\sum_{i=1}^{n_M}\mathbf{y}_i^{r\uparrow} \ge \underline{\mathbf{r}}_{AG}^{\uparrow} \tag{17}$$

$$\sum_{i=1}^{n_M}\mathbf{y}_i^{r\downarrow} + \sum_{j=1}^{n_R}\mathbf{d}_j^R \ge \underline{\mathbf{r}}_{AG}^{\downarrow} \tag{18}$$

$$\sum_{i=1}^{n_M} B_i^{(l,m)}\mathbf{y}_i^P + \sum_{j=1}^{n_L} C_j^{(l,m)}\mathbf{d}_j^L + \sum_{h=1}^{n_R} D_h^{(l,m)}\mathbf{d}_h^R \le \bar{\mathbf{P}}_{(l,m)} \tag{19}$$

$$\sum_{i=1}^{n_M} B_i^{(l,m)}\mathbf{y}_i^P + \sum_{j=1}^{n_L} C_j^{(l,m)}\mathbf{d}_j^L + \sum_{h=1}^{n_R} D_h^{(l,m)}\mathbf{d}_h^R \ge -\bar{\mathbf{P}}_{(l,m)} \tag{20}$$

$$\forall (l,m) \in \mathcal{E}$$

The AGS cost function (15) considers for all MGs, the internal costs, the energy trading with the main grid, which depends on the eAG power balance, and the gain for the overall up and down reserve capacity. The MGs internal constraints, relationships and forecasts are defined in (16), meaning that the AGS is assumed to know all the required information about the MGs resources and management strategies if the problem is solved centrally. Then, additional global constraints are included to take into account the ancillary services requirements. The total up and down reserve power are imposed to respect the predefined minimum amount through (17)-(18). Regarding the congestions management, two sets of global constraints are imposed in order to consider for the same line $(l,m) \in \mathcal{E}$ both direction of power flows (19), (20). The matrices $B_i^{(l,m)}$, $C_j^{(l,m)}$ and $D_h^{(l,m)}$ are properly defined such that they select the power outputs of the aggregate elements composing the line (l,m) active power flow.

For the sake of notational compactness, also in this case a concise problem formulation is reported to facilitate the description of the eAG optimization algorithm.

$$\min_{(\mathbf{x_i},\mathbf{y_i})\,\forall i}\{\sum_{i=1}^{n_M}(f_i(\mathbf{x_i}) - g_i(\mathbf{y_i})) + h(\mathbf{w})\} \tag{21}$$

$s.t.$

$$A_i\begin{bmatrix}\mathbf{x_i}\\ \mathbf{y_i}\end{bmatrix} \le b_i \qquad \forall i \in \{1,\ldots,n_M\} \tag{22}$$

$$\sum_{i=1}^{n_M} G_i\mathbf{y_i} \le R(\mathbf{w}) \tag{23}$$

Precisely, the non-decisional terms in the eAG cost function (15) are expressed by the function $h(\mathbf{w})$ in (21) where the vector $\mathbf{w} = [\mathbf{d}_{1,\ldots,n_L}^L, \mathbf{d}_{1,\ldots,n_R}^R]'$ represents the systems disturbances, i.e. eAG individual loads and renewable sources. The global constraints (17)-(20) are condensed in a set of inequalities, see (23), through the proper definition of the matrices G_i and the vector $R(\mathbf{w})$, which actually depends on the system disturbances.

As it will be shown in Section III, the global coordination of interconnected MGs as part of an eAG brings many advantages achieving a better resource management and providing also additional services to the main utility. However, the whole AGS centralized management problem may be prone to computational and communication scalability problems, as well as to privacy issues. Being each MG equipped with a local MGCC which can autonomously manage the internal resources, it would be more efficient to distribute the optimization burden among the MGs agents. Therefore, in section II-D it will be shown how it is possible to distributively optimize the eAG problem such that the internal information is preserved and autonomously managed by the local MGCCs.

D. AGS distributed optimization algorithm

The eAG scheduling problem is particularly suited for distributed algorithms based on the *dual decomposition* approach. There are in fact different independent agents, i.e MGs, wanting to optimize their resources without sharing the internal information, and they must be coordinated by an external entity, the AGS, in order to respect some global, also called complicating, constraints. This approach, based on the Lagrange relaxation of the global constraints, allows to decompose the overall centralized problem among the MGs agents. This means that the global constraints are transferred to a new objective function, called *Lagrangian*, as a proper weighted sum through the introduction of the *Lagrange multipliers*, usually called *dual variables* or *shadow prices*. Therefore, the dual vector μ is introduced to relax the inequality constraint (23) and the overall Lagrangian expression is defined.

$$\boldsymbol{L}(\mathbf{x}_{\forall i}, \mathbf{y}_{\forall i}, \mu) = \sum_{i=1}^{n_M}(J_i(\mathbf{x}_i, \mathbf{y}_i)) + h(\mathbf{w}) + \mu'(\sum_{i=1}^{n_M} G_i\mathbf{y}_i +$$
$$-R(\mathbf{w})) = \sum_{i=1}^{n_M}(J_i(\mathbf{x}_i, \mathbf{y}_i) + \mu' G_i\mathbf{y}_i) + h(\mathbf{w}) - \mu' R(\mathbf{w})$$

Then, according to the dual decomposition procedure [12], the *dual problem* is formulated

$$\boldsymbol{g}^* = \max_{\mu\ge 0} g(\mu) = \max_{\mu\ge 0}(\inf_{A_i\begin{bmatrix}\mathbf{x}_i\\ \mathbf{y}_i\end{bmatrix}\le b_i,\forall i}\{\boldsymbol{L}(\mathbf{x}_{\forall i}, \mathbf{y}_{\forall i}, \mu)\})$$

where $\boldsymbol{g}^*$ coincides with the dual optimal solution and the dual variable μ must be constrained to be positive being the global constraint an inequality [12]. This procedure allows to solve separately the MGs optimization sub-problems with respect to the internal variables given a fixed value of the dual variable. To maximize the dual function $g(\mu)$ it has been chosen to use the *sub-gradient method* where the Langrange multiplier μ is iteratively updated based on the global constraints violation, as described in **Algorithm 1**.

Algorithm 1 Dual decomposition optimization of an eAG

Initialization : $k = 0$ and $\mu^k = \mu_0$
while convergence is not met **do**
  Each MGCC solves locally its sub-problem given μ^k:
  for all $i \in i \in \{1, \ldots, n_M\}$ **do**
    $$(\mathbf{x}_i^k, \mathbf{y}_i^k) = \underset{A_i \left[\begin{smallmatrix}\mathbf{x}_i \\ \mathbf{y}_i\end{smallmatrix}\right] \le b_i}{\text{argmin}} \{f_i(\mathbf{x}_i) - g_i(\mathbf{y}_i) + \mu^{k\prime} G_i \mathbf{y}_i\}$$
  end for
  The AGS gathers all the $\mathbf{y_i}^k$ to update μ^k
  $\mu^{k+1} = \max(\, \mu^k + \alpha^k(\, \sum_{i=1}^{n_M} G_i \mathbf{y}_i^k - R(\mathbf{w})\,)\,, \mathbf{0})$
  $k = k + 1$
end while

The *sub-gradient method* converges if the step-size α^k is chosen to be decreasing with the number of iterations [13]. Indicating the centralized problem (21)-(23) as *primal problem* and its optimal solution as $\boldsymbol{p}^*$, it should be underlined that the dual optimal solution is generally a lower bound with respect to the primal one, meaning that $\boldsymbol{g}^* \le \boldsymbol{p}^*$. However, if the overall problem is convex and under some other mild assumptions, called *constraint qualifications* (e.g. *Slater's condition*), the duality gap reduces to zero, i.e. $\boldsymbol{g}^* = \boldsymbol{p}^*$ [12]. It could be easily shown that the optimization problems defined in sections II-B and II-C satisfy the required properties and therefore the primal problem can be equivalently solved by the dual one.
Considering the practical interpretation and implementation of this algorithm, the eAG problem eventually consists of the following iterative procedure: 1) the MGCCs initially perform in parallel their local optimizations based on the actual *shadow prices*; 2) the AGS updates the prices based on the global constraints violation which are actually referred to the ancillary services it has to provide. This means that the distributed optimization algorithm involves a sort of internal negotiation between the AGS and the MGCCs such that the optimal amount of reserve is allocated and the internal congestions avoided.

III. Numerical results

The simulation results have been carried out considering the eAG network shown in Figure 1. The dispatchable units characteristics and costs are described in Table III and Table IV, while the non-dispatchable power forecasts are depicted in Figure 2. The batteries' SOC are supposed to be at 50% at the beginning of the day. Regarding the external trading with the main grid, the daily energy prices have been extrapolated from the Italian electricity day-ahead market and they are shown in Figure 3, while the reserve prices, supposed to be constant for the whole day, are $p^{r\uparrow} = 4e^{-3}$ €/kWh and $p^{r\downarrow} = 2e^{-3}$ €/kWh.
The distributed algorithm has been implemented as described in section II-D, with a stepsize $\alpha^k = \beta/\sqrt{k}$ and $\beta = 1e^{-5}$ [13]. Also a decentralized scheduling process has been tested for comparison in order to evaluate the benefits of the MGs cooperation. In this case the AGS unit is not present and the ancillary services requirements have been equally split among the three MGs such that they are however globally satisfied.

TABLE III: Micro-generators

Owner	$(\underline{u}^g, \bar{u}^g)$	a^g	b^g	c^g
MG1	$(20, 250)$	$3.2e^{-4}$	$2e^{-2}$	$3e^{-2}$
MG1	$(20, 250)$	$8e^{-5}$	$3.6e^{-2}$	$3e^{-2}$
MG2	$(10, 150)$	$1.2e^{-4}$	$2e^{-2}$	$3e^{-2}$
MG3	$(10, 80)$	$1.6e^{-5}$	$4e^{-3}$	$1e^{-2}$

TABLE IV: Batteries

Owner	$(\underline{u}^b, \bar{u}^b)$	$(\underline{s}^b, \bar{s}^b)$	C^b	c^b
MG1	$(-40, 40)$	$(0.2, 0.8)$	50	$1.6e^{-3}$
MG2	$(-30, 30)$	$(0.2, 0.8)$	40	$1.6e^{-3}$
MG2	$(-40, 40)$	$(0.2, 0.8)$	50	$1.6e^{-3}$
MG3	$(-30, 30)$	$(0.2, 0.8)$	50	$1.6e^{-4}$

As it is possible to notice from Figure 4, the implemented distributed algorithm converges to the same level of optimality of the centralized case in around 40 iterations. Therefore, without the necessity of knowing all the internal MGs information, the AGS through is able to manage its eAG both economically and for the ancillary services provision achieving the same performances of the centralized case.
Another important aspect concerns the fact that the AGS-MGs interaction is also beneficial from an economic perspective: Figure 5(a) shows that the decentralized cost function value is always greater with respect to the distributed case at each time step. This is related to the fact that the cooperation leads also to a more efficient management of the system global constraints, as shown in Figures 5(c) and 5(d). Indeed, thanks to the AGS-MGs interaction, it is possible, in certain periods, to push the ancillary services provision to the constraints limits, eventually resulting in a higher amount of output power exported by the eAG to the main grid as reported in Figure 5(b). This outcomes can be not achievable if each MG agent just cares about its internal management without involving any cooperation mechanism with the neighbouring units.

IV. Conclusions

In this paper it has been shown how to design an aggregation of MGs leading to several benefits both for the external provision of ancillary services and for a better resources management from the economic perspective. A distributed optimization framework based on the *duality theory* has been defined, guaranteeing internal information privacy and computational scalability while managing the whole eAG. The considered algorithm involves a proper negotiation mechanism between the AGS and the MGCCs.
Future lines of research will include the distributed management of the eAG reactive power flows and voltages, as well as the development of a more structured distributed algorithm dealing with a more general problem formulation with guaranteed performances, e.g. possibly considering MGs *non-convex* optimization problems.

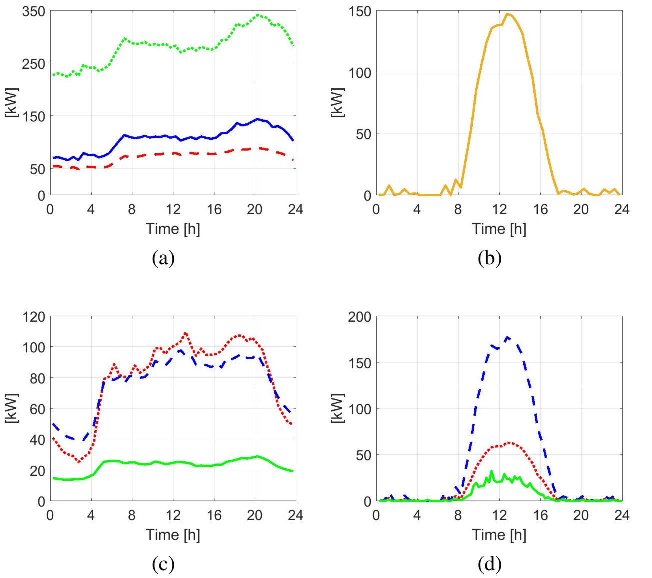

Fig. 2: (a) L_1 (dashed), L_2 (continuous) and L_3 (dotted) power absorption, (b) R_1 power production, (c)&(d) load power absorption & non-dispatchable power generation in MG_1(dotted), MG_2 (dashed) and MG_3 (continuous)

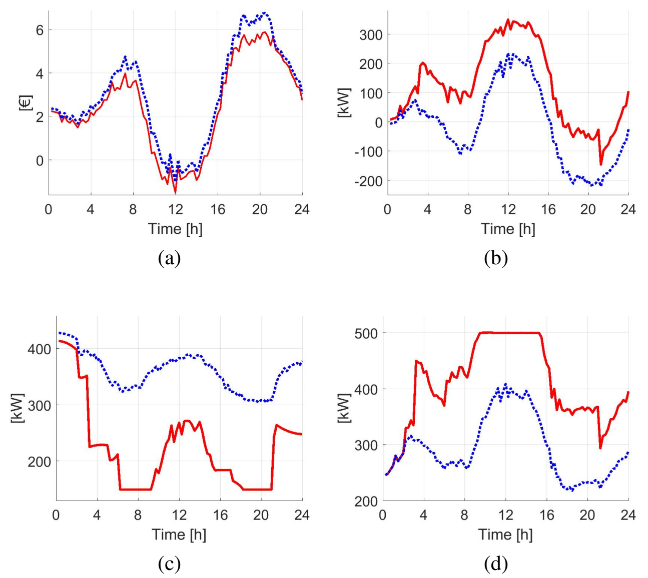

Fig. 5: (a) Cost function over the time horizon, (b) eAG power profile, (c) eAG up power reserve, (d) line 3-2 power flow: decentralized (dotted) and distributed case (dashed)

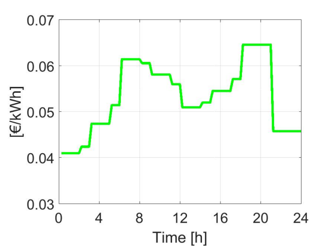

Fig. 3: Main utility energy price profile

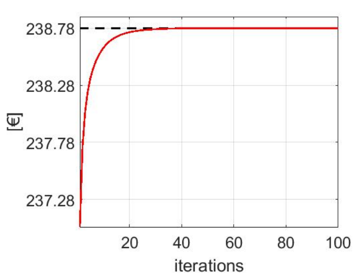

Fig. 4: Total cost function over distributed algorithm iterations: centralized (dashed) and distributed case (continuous)

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