ON THE DESIGN OF A MICROGRIDS AGGREGATION MANAGEMENT FRAMEWORK TO PROVIDE ANCILLARY SERVICES

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ABSTRACT

The number of grid-connected microgrids is expected to significantly increase in the next years as they proved to be a key solution for locally managing distributed generation. However, these are commonly designed to pursue the self-profit, based on the internal production costs and on the grid energy prices, without considering the overall system needs. A distributed optimization algorithm is proposed such that the single microgrids cooperate as part of a unique aggregation in order to provide ancillary services to the external grid.

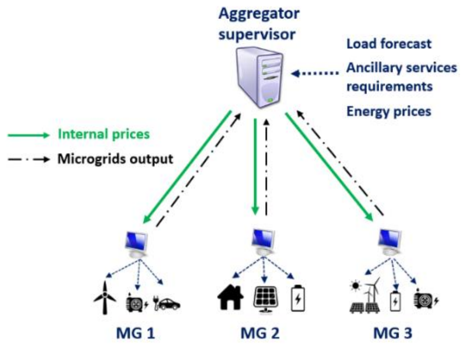

Figure 1 – Negotiation framework for aggregation of microgrids

INTRODUCTION

Microgrids (MGs) can be defined as controlled clusters of micro-generators, renewable sources, loads and storage units which can be operated either in connected or in isolated operating mode. These are usually managed by hierarchical control structures which aim to the best resources management considering both forecasts and the external grid prices [1]-[2]. Nevertheless, the spread of connected MGs may affect the main grid system since the system operators (e.g. DNO or TSO) would remain the only in charge of ensuring the proper network conditions in a framework constituted by increasing amounts of non-deterministic and bidirectional power flows, and where these independent agents just care about their internal profit. A possible solution is to manage the MGs internal resources not only to satisfy the internal load demand but also to provide ancillary services to the external grid. MGs are clusters of distributed generators and therefore they could modulate their active power production based also on the overall system requirements other than just economic objectives. A single MG may have a very small impact on the grid system since it is usually characterized by limited generation capability, having also to satisfy its internal loads. To exploit the potential of MGs to help the overall grid system, 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 unique system for the system operator, reaching also the right size to provide external ancillary services to the grid [3]. According to the authors, a centralized management of the MGs aggregation would not be feasible due to communication and computational issues, as well as to the fact that MGs unrealistically would allow to have their devices externally controlled. A more efficient solution is the one where each MG autonomously optimizes its resources, while an aggregator supervisor, without requiring sensitive internal information about the single MGs (e.g. loads consumption and generators characteristics), ensures that the community is globally providing the requested services.

For the design of this management system, distributed optimization algorithms based on the *dual decomposition theory* have been exploited which have shown to be particularly promising for this application. These algorithms involve a sort of internal negotiation, through the definition of internal prices, between the supervisor and the single microgrids such that the overall requirements are satisfied and the best management is achieved; in a schematic of the interactions between the agents is showed according to the proposed algorithm. The optimization problem here presented can be collocated as part of the day-ahead market operation, where the aggregator supervisor agrees with the MGs the overall power profile based on the grid prices and system forecasts, and then it communicates its overall power profile to the system operator for the following day.

In this work, two main ancillary services are considered: the *primary frequency reserve*, commonly called also *frequency containment reserve*, and the *line 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. 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 microgrids, as well explained in [3]. 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 to compensate external unbalances. Regarding the congestion management service, the aggregator supervisor 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. 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, the amount of provided reserve is a paid service and it will be a gain for the microgrids during their scheduling processes. The paper is structured as follows. Firstly, the whole optimization problem formulation is presented, both at the MG and at the eAG level, and the distributed optimization algorithm is described. Then, the numerical results of the implemented scheduling process will be presented considering a standard test benchmark. Moreover, a comparison with the pure decentralized case is given in order to assess the advantages of the MGs cooperation. Finally, some conclusions are drawn.

MICROGRID PROBLEM FORMULATION

The overall microgrid aggregation can be modelled as a discrete time system with sampling period of 15 minutes, i.e $\tau = 0.25\,h$. This choice is since this is the conventional time-rate 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 $N = \frac{24h}{\tau} = 96$ steps. For the sake of compactness, here the active power microgrid model and local optimization problem is not explicitly described but a compact form is provided (for a more detailed microgrid modelling please refers to [1], [4]).

$$\min_{\boldsymbol{u}_i\,(\forall t)} \sum_{t=1}^{N} f_i(\boldsymbol{x}_i(t)) + g_i(\boldsymbol{y}_i(t)) \tag{1}$$

subject to

$$\boldsymbol{x}_i(t) \in X_i \qquad \forall t = 1,..,N \tag{2}$$

$$\boldsymbol{y}_i(t) = C_i\,\boldsymbol{x}_i(t) + M_i\,\boldsymbol{d}_i(t) \tag{3}$$

The vector variable $\boldsymbol{x}_i$ includes the internal microgrids variables, e.g. generators power set-points, batteries state of charges, while the variables $\boldsymbol{d}_i$ include all the internal microgrids disturbances such as load demand and renewable sources power production. The vector variable $\boldsymbol{y}_i = [\boldsymbol{y}_i^{\boldsymbol{p}}, \boldsymbol{y}_i^{r\uparrow}, \boldsymbol{y}_i^{r\downarrow}]$, includes the MGs output variables: the output active power, $\boldsymbol{y}_i^{\boldsymbol{p}}$, the provided up active power reserve, $\boldsymbol{y}_i^{r\uparrow}$, and the provided down active power reserve, $\boldsymbol{y}_i^{r\downarrow}$. The constraint (2) comprehends the MG internal modelling and generators capabilities, while the constraint (4) expresses the output variables as a function of the internal variables and disturbances. Concerning the cost function, it possible to see that two different functions are introduced which depend on the MG internal and output variables, respectively. The former, $f_i(\boldsymbol{x}_i)$, includes the MG internal production costs and resource management strategies, the latter, $g_i(\boldsymbol{y}_i)$, comprehends the gain/cost because of the external energy trading and of the provided reserves. While the internal production costs and management strategies can be arbitrarily defined, and they can be different for each microgrid, the $g_i(y_i(t))$ function will be defined in the next Section since it depends on the distributed management of the eAG. Having defined the local microgrid optimization problem and model, now the overall centralized problem can be formulated. Please notice that the requirements for the ancillary service provision has not been mentioned so far; in fact, this duty will regard the aggregator supervisor system.

CENTRALIZED PROBLEM FORMULATION

Initially, it is assumed that the aggregator supervisor can centrally control all the MGs units, implying that it has a complete knowledge of all the generator characteristics and of all the load demands of the aggregate. An eAG network can be modelled as a radial bi-directional graph with nodes $V = \{1, \dots, n\}$ and edges $E = V \times V$. An eAG generally may include several grid elements such as n_M microgrids, n_L non-controllable loads and n_R individual renewable source plants indicated as $MG_1, \dots, MG_{n_M}$, $L_1, \dots, L_{n_L}$ and $R_1, \dots, R_{n_R}$ respectively. In Table 1 the parameters concerning the overall eAG optimization problem are described.

Table 1 – eAG parameters

Symbol	Description
p^e	Energy price [€/kWh]
$p^{r\uparrow}, p^{r\downarrow}$	Up/down power reserve price [€/kWh]
$\underline{r}_{AG}^{\uparrow}, \underline{r}_{AG}^{\downarrow}$	Up/down minimum eAG active power reserve [kW]
d^L	Output active power of an eAG non-controllable load node [kW]
d^R	Output active power of an eAG individual renewable source plant [kW]
$\overline{P}_{(l,m)}$	Maximum active power flow for line *(l,m)* ∈ *E* [kW]

Therefore, the aggregator supervisor should solve the following centralized optimization problem

$$\min_{\boldsymbol{u}_{\forall i}\,(\forall t)} (J_{AG}) = \sum_{t=1}^{N} \left\{ \sum_{i=1}^{n_M} \left(f_i(\boldsymbol{x}_i(t)) - p^{r\uparrow}(t)\ \boldsymbol{y}_i^{r\uparrow}(t) + \right. \right.$$
$$\left. \left. - p^{r\downarrow}(t)\,\boldsymbol{y}_i^{r\downarrow}(t) \right) - p^e(t)\,\tau \left(\sum_{i=1}^{n_M} \boldsymbol{y}_i^{\boldsymbol{p}}(t) - \sum_{j=1}^{n_L} \boldsymbol{d}_j^{\boldsymbol{L}}(t) + \sum_{h=1}^{n_R} \boldsymbol{d}_h^{\boldsymbol{R}}(t) \right) \right\}$$

subject to

$$\boldsymbol{x}_i(t) \in X_i$$

$$\boldsymbol{y}_i(t) = C_i\,\boldsymbol{x}_i(t) + M_i\,\boldsymbol{d}_i(t) \qquad \forall\, i = \{1, \dots, n_M\}$$

$$\sum_{i=1}^{n_M} \boldsymbol{y}_i^{r\uparrow}(t) \geq \underline{r}_{AG}^{\uparrow}(t) \tag{4}$$

$$\sum_{i=1}^{n_M} \boldsymbol{y}_i^{r\downarrow}(t) \geq \underline{r}_{AG}^{\downarrow}(t) \tag{5}$$

$$\left| \sum_{i=1}^{n_M} B_i^{(l,m)}\,\boldsymbol{y}_i^{\boldsymbol{p}}(t) - \sum_{j=1}^{n_L} C_j^{(l,m)} \boldsymbol{d}_j^{\boldsymbol{L}}(t) + \sum_{h=1}^{n_R} D_h^{(l,m)} \boldsymbol{d}_h^{\boldsymbol{R}}(t) \right| \leq \overline{P}_{(l,m)} \tag{6}$$

The cost function of the centralized problem considers the microgrid internal production 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. Then, additional global constraints are included consider the ancillary services requirements. The total up and down reserve power are imposed to respect the predefined minimum amounts for the whole eAG. Regarding the congestions management, the active power flow for each line $(l,m) \in E$ must be lower the predefined maximum limit (the absolute value of the power flow is constrained since bidirectional power flows are allowed). 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 clarity, from now on the following variable is introduced to define the active power flow in the $(l,m) \in E$ line:

$$P_{(l,m)} = \sum_{i=1}^{n_M} B_i^{(l,m)} \boldsymbol{y}_i^{\boldsymbol{p}}(t) - \sum_{j=1}^{n_L} C_j^{(l,m)} \boldsymbol{d}_j^{\boldsymbol{L}}(t) + \sum_{h=1}^{n_R} D_h^{(l,m)} \boldsymbol{d}_h^{\boldsymbol{R}}(t)$$

As it is possible to notice, to solve the centralized problem the aggregator supervisor should know all the internal information about the MGs modelling, units' constraints, and production costs. This is a great drawback considering privacy and computational issues; however, it can be solved through the proposed distributed optimization algorithm.

DISTRIBUTED OPTIMIZATION

The distributed optimization framework relies on the fact that microgrids are usually equipped with the so-called Microgrid Central Controllers (MGCC). Therefore, the optimization problem previously presented can be split among this control units instead of being centrally solved by the aggregator supervisor. Since there are some global constraints to respect, e.g. the total up/down reserve and the maximum active power flows, a negotiation procedure is needed until the convergence is reached. The proposed algorithm is based on the *dual decomposition* approach [5]. The *Lagrangian* function must be defined adding to the previously defined cost function the global problem constraints (4)-(6), properly weighted through the variables $\mu = [\mu^{\uparrow}, \mu^{\downarrow}, \mu^{P1}_{\forall(l,m)\in E}, \mu^{P2}_{\forall(l,m)\in E}]$.

$$\boldsymbol{L} = J_{AG} + \sum_{t=1}^{N} \left\{ \mu^{\uparrow}(t) \left(\underline{r}_{AG}^{\uparrow}(t) - \sum_{i=1}^{n_M} \boldsymbol{y}_i^{r\uparrow}(t) \right) + \mu^{\downarrow}(t) \left(\underline{r}_{AG}^{\downarrow}(t) + - \sum_{i=1}^{n_M} \boldsymbol{y}_i^{r\downarrow}(t) \right) + \sum_{\forall (l,m)\in E} \mu^{P1}_{(l,m)}(t) (P_{(l,m)}(t) - \overline{P}_{(l,m)}) + + \sum_{\forall (l,m)\in E} \mu^{P2}_{(l,m)}(t) (-P_{(l,m)}(t) - \overline{P}_{(l,m)}) \right\}$$

The variables $\mu = [\mu^{\uparrow}, \mu^{\downarrow}, \mu^{P1}_{\forall(l,m)\in E}, \mu^{P2}_{\forall(l,m)\in E}]$ work as internal prices and they will be iteratively updated during the distributed optimization algorithm until the global constrains are respected. The advantage of defining the *Lagrangian* function is that it can be separately minimized by the MGCCs since the global constraints are now terms to minimize. Therefore, the following algorithm can be now applied.

Distributed optimization algorithm

Define as $\boldsymbol{k}$ *the iteration index and define a tuning parameter* $\boldsymbol{\alpha > 0}$

while convergence is not met

1) *MGCCs solve in parallel their local optimization subproblems based on the actual internal prices*

$$(\boldsymbol{x}_i^k, \boldsymbol{y}_i^k) = \underset{s.t.(2)-(3)}{\operatorname{argmin}} \{L(\boldsymbol{x}_i, \boldsymbol{y}_i, \mu^{\uparrow,k}, \mu^{\downarrow,k}, \mu^{P1,k}_{\forall(l,m)}, \mu^{P2,k}_{\forall(l,m)})\}$$

2) *The aggregator supervisor gathers the microgrids outputs and it updates the internal prices based on the global constraints residuals*

$$\mu^{\uparrow,k+1} = \max\left(\mu^{\uparrow,k} + \frac{\alpha}{\sqrt{k}} \left(\underline{r}_{AG}^{\uparrow} - \textstyle\sum_{i=1}^{n_M} \boldsymbol{y}_i^{r\uparrow,k} \right), 0\right)$$
$$\mu^{\downarrow,k+1} = \max\left(\mu^{\downarrow,k} + \frac{\alpha}{\sqrt{k}} \left(\underline{r}_{AG}^{\downarrow} - \textstyle\sum_{i=1}^{n_M} \boldsymbol{y}_i^{r\downarrow,k} \right), 0\right)$$
$$\mu^{P1,k+1}_{(l,m)} = \max\left(\mu^{P1,k}_{(l,m)} + \frac{\alpha}{\sqrt{k}} \left(P^k_{(l,m)} - \overline{P}_{(l,m)} \right), 0\right)$$
$$\mu^{P1,k+2}_{(l,m)} = \max\left(\mu^{P2,k}_{(l,m)} + \frac{\alpha}{\sqrt{k}} \left(-P^k_{(l,m)} - \overline{P}_{(l,m)} \right), 0\right)$$

$k = k + 1$

end while

It can be proved that, if the MGs cost functions and constraints respect some mild assumptions (e.g. convexity), the proposed distributed algorithm achieves the same optimal solution of the centralized case at convergence. Therefore, through this distributed optimization framework, the aggregator supervisor would be able to coordinate its eAG providing the required active power reserve and respecting all the line power limits without knowing or directly controlling the MG units.

NUMERICAL RESULTS

The proposed algorithm has been tested considering the IEEE 13-bus system network, a low-voltage radial distribution network. As showed in Figure 2, it has been supposed that three MGs, three loads and a non-controllable generation source are present. In Figure 3(a)-(c)-(d), the load and renewable production forecasts are presented, while in Table 2 the characteristics of the MGs dispatchable generation units are described. In Figure 3(b), the day-ahead energy prices are presented while the reserve prices have been supposed to be constant as: $p^{r\uparrow} = 4e^{-3}$€$/kWh$ and $p^{r\downarrow} = 2e^{-3}$€$/kWh$. Concerning the ancillary services provision, it is requested a minimum up and down reserve equal to 100 kW for the whole aggregation, while the maximum active power flow for each line is constrained to 500 kW. The proposed distributed algorithm is compared with a decentralized management, where the ancillary services requests are split among the MGs. As it can be noted in Figure 4, the 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 aggregator supervisor can 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 this framework 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 Figure 5(c)-(d). Indeed, 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 can be not achievable if each MG agent just cares about its internal profit without involving any cooperation mechanism with the neighboring units.

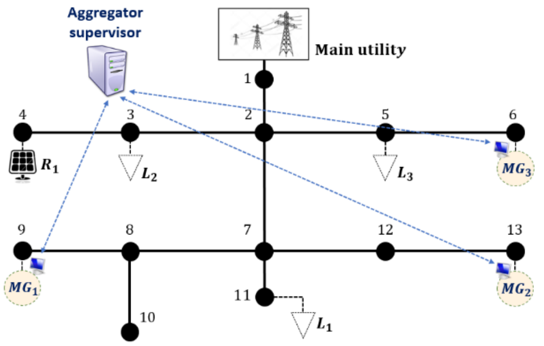

Figure 2 – eAG network (IEEE 13 bus system)

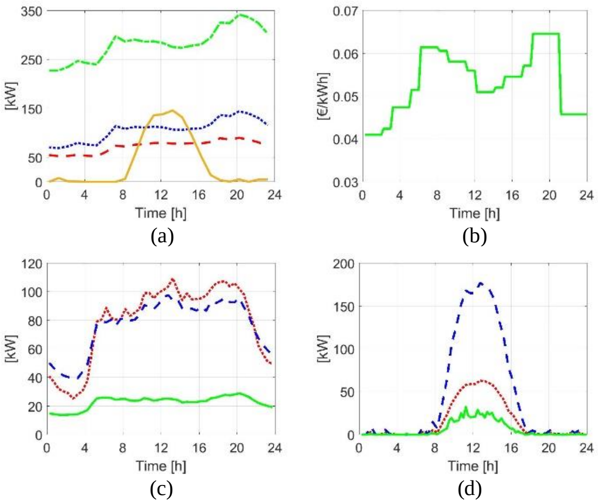

Figure 3– (a) L_1 (dashed), L_2 (dotted), L_3 (dash-dotted) power absorption and R_1 (solid) power production; (b) Day-ahead energy price; (c)&(d) Loads absorption and renewable power production in MG1 (dotted), MG2(dashed) and MG3 (solid).

Table 2 – Microgrids generation units

	Owner	Capability	Capacity
Micro-generator	MG1	(20, 250) kW	-
Micro-generator	MG1	(20, 250) kW	-
Battery	MG1	±40 kW	50 kWh
Micro-generator	MG2	(10, 150) kW	
Battery	MG2	±30 kW	40 kWh
Battery	MG2	±40 kW	50 kWh
Micro-generator	MG3	(10, 80) kW	
Battery	MG3	±30 kW	50 kWh

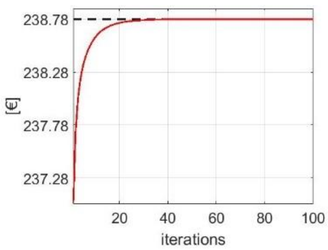

Figure 4 – Total cost function over the iterations of the distributed algorithm: centralized (dashed) and distributed case (solid).

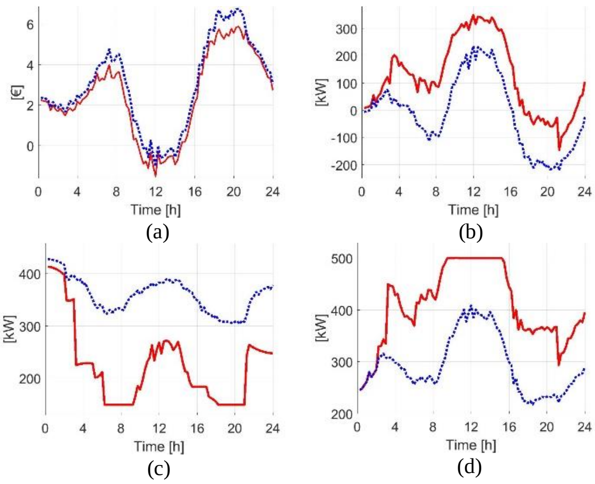

Figure 5– (a) Cost function over the time horizon, (b) eAG power output, (c) eAG up power reserve, (d) line 2-7 power flow: decentralized (dotted) and distributed case (solid).

CONCLUSIONS

It has been shown a framework to manage 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. The proposed distributed optimization algorithm, based on the *duality theory*, guarantees internal information privacy and computational scalability, involving a proper negotiation mechanism between the agents. The numerical results showed the effectiveness of the proposed approach.

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