Resilient Distributed MPC Algorithm for Microgrid Energy Management under Uncertainties

Vittorio Casagrande[1], Ionela Prodan[2], Sarah K. Spurgeon[1] and Francesca Boem[1]

Abstract— **This paper proposes a resilient distributed energy management algorithm able to cope with different types of faults in a DC microgrid system. A distributed optimization method allows to solve the energy management problem without sharing any private data with the network and reducing the computational cost for each agent, with respect to the centralised case. A distributed MPC scheme based on distributed optimization is used to cope with uncertainty that characterizes the microgrid operation. In order to be resilient to faults that limit the amount of power available to consumers, we propose to adaptively store an amount of power in the storage systems to support the loads. A soft constraint on the minimum energy stored in each battery is introduced for feasibility and to cope with persistent faults. The effectiveness of the method is proved by extensive simulation results considering faults on three types of components: renewable generator, distribution grid and communication network.**

I. INTRODUCTION

The microgrid control is typically deployed in three layers [24]. In particular, the design of the higher layer (or tertiary level) is made difficult by uncertainties in power generation and demand. Moreover, in order to manage the energy optimally, the future power trajectories of loads and generators have often to be shared with a central unit or the other grid players and this can cause privacy issues. Finally, if the number of agents of the network is high, a large computational power may be required. In this paper, we consider these challenges by proposing a distributed method for Energy Management System (EMS) that is privacy-preserving, reduces the computational cost with respect to the centralised case and allows to deal with uncertainties.

Moreover, the possible occurrence of faults can pose an additional challenge to the controller design. Indeed, microgrids offer advantages in terms of system reliability [19]: for example, since they are designed to operate both in grid connected mode or in island mode, in case of fault of the distribution grid, the microgrid can be disconnected and it is possible to deliver to the loads the power that is produced by renewable generators or stored in the batteries. As soon as the fault is recovered, the microgrid can be reconnected to the electricity grid. Hence, it is clear that a microgrid EMS has to be reconfigured in case of fault occurrence to take into account and mitigate the effects of a fault.

Multiple variants of optimization-based algorithms for energy management have been proposed in the literature. In particular, MPC-based methods are very successful thanks to their ability to efficiently compensate uncertainty and handle constraints. Centralised MPC algorithms have been used in [20], [17] and [9] to schedule the operation of loads, generators and electric vehicles charging. To improve performances under uncertainty in power production and consumption, stochastic MPC algorithms have been proposed in [3] and [11]. Centralised MPC may not be suitable for LSSs because of the computational power required and in the case that private data cannot be shared with a central unit or other microgrid players. Distributed MPC algorithms have been proposed to overcome these limitations. In [16] and [4], methods to coordinate microgrid players and multiple microgrids are presented; in [1] a large scale problem is solved at each time step using Alternating Direction Method of Multipliers algorithm. The main drawback of these methods is that they require a central unit for coordination, hence they are not fully distributed. Alternative methods are presented in [18] and [26], however the coordination is achieved sharing the future trajectories with the other microgrid agents. In [14] a fully distributed algorithm based on distributed optimization is proposed however faults and uncertainty that characterizes the microgrid operation is not considered as well as the specific microgrid topology.

Although many papers propose algorithms for energy management, a few consider the possible occurrence of faults and propose centralised methods to handle them. In [12] and [7] a certain amount of backup power is preserved in the storage systems to ensure power delivery to the loads during power outages. However, being a fixed amount (20-30% of the capacity), the future power requirement of the loads is not taken into account. In [21] a centralised architecture able to cope with generator faults is presented but requiring the loads to share their future power demand with a central unit at each time step. A different approach is proposed in [10] where resilience against planned power outages is considered, updating objectives and constraints as soon as a fault occurs. Finally, authors of [22] propose to use the power stored in the battery of electric vehicles to sustain loads during power outages (vehicle-to-home technology) and, at the same time, controlling the operation of loads' appliances.

The goal of this paper is to present a distributed fault-tolerant and resilient architecture for the tertiary level control

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[1] Dept. of Electronic and Electrical Engineering, University College London, UK. Email: {vittorio.casagrande.19, s.spurgeon, f.boem} @ucl.ac.uk).

[2]Univ. Grenoble Alpes, Grenoble INP, LCIS, F-26000 Valence ionela.prodan@lcis.grenoble-inp.fr

of microgrids. Specifically, we propose a controller reconfiguration algorithm that allows to guarantee that the critical amount of power is provided to loads during different types of faults. The paper builds on preliminary work, recently presented in [2], where a distributed optimisation-based MPC for energy management is proposed. In this paper we address the problem of possible faults occurring in the microgrid system. Moreover, further novel contributions of the paper are:

- the constraint on the backup energy is enforced without sharing the future power demand of loads, thus preserving privacy among different local controllers;
- the constraint on minimum battery charge is relaxed to cope with persistent faults of unknown duration;
- the method is resilient to faults in the communication network used to share the variables among local controllers.

The remainder of the paper is organized as follows. In Section II the model of the microgrid and the possible faults are described. In Section III the proposed energy management algorithm is presented. Finally, Sections IV and V report simulation results and conclusions.

II. MICROGRID MODEL

In this section the model of each microgrid component as well as the communication network and the types of faults are presented. The microgrid includes four types of components (loads, renewable generators, storage systems and connections to the utility grid) assumed to be provided with computation and communication capabilities.

A. Microgrid agents

Loads connected to a microgrid are characterized by a power demand which is composed of a critical $P_{l,i}^{m}(t)$ and a non-critical part. In particular, we assume that for each power demand profile it holds:

$$P_{l,i}^{m}(t) \leq P_{l,i}(t) \leq P_{l,i}^{M}(t), \tag{1}$$

where $P_{l,i}(t)$ is the power demand of load i and $P_{l,i}^{M}(t)$ is the target power demand. Each load will try to draw the target power demand at each time step, hence the finite horizon cost of each load is:

$$J_{l,i} = \sum_{t=0}^{T-1} w_l \left[P_{l,i}^{M}(t) - P_{l,i}(t)\right]^2 \tag{2}$$

where T is the horizon length and w_l is a weight term used to balance the objectives functions.

Renewable generators produce the power that is sold to the other microgrid agents. The amount of power that they can inject in the microgrid is limited by the power that they produce:

$$0 \leq P_{r,i}(t) \leq P_{r,i}^{M}(t) \tag{3}$$

where $P_{r,i}(t)$ is the power demand of renewable generator agent i at time t and $P_{r,i}^{M}(t)$ is the maximum power that can be injected. Since we cannot predict exactly how much power they will produce, we rely on predictions on the maximum power production. Each generator agent will try to maximise the amount of power that it sells to the hence, the objective function is set as:

$$J_{r,i} = w_{r,i} \sum_{t=0}^{T-1} \gamma^t \left[P_{r,i}^{M}(t) - P_{r,i}(t)\right]^2, \tag{4}$$

where $w_{r,i}$ is a weight parameter used to balance the objectives functions and $\gamma \in [0;1]$ is used to reduce progressively the importance of time steps further away in the future.

A storage system is modelled as a first-order linear system:

$$s_i(t+1) = s_i(t) + \mu_{i,c/d} T_s P_{s,i}(t) \tag{5}$$

where $s_i(t)$ is the state of charge of storage i, $\mu_{i,c/d}$ is the energy conversion efficiency for charging and discharging ($\mu_{i,c} < 0$ and $\mu_{i,d} > 0$), T_s is the sample time of the controller and $P_{s_i}(t)$ is the power flow. The amount of energy which can be stored in a storage is limited by a maximum and a minimum value:

$$s_i^m \leq s_i(t) \leq s_i^M \tag{6}$$

In order to increase the battery lifetime and avoid a quick degradation of its performance the lower limit of charge is higher than zero. The power that can be drawn from (or injected in) the grid is limited by a maximum value:

$$-P_{s,i}^{M} \leq P_{s,i}(t) \leq P_{s,i}^{M} \tag{7}$$

The objectives of each storage system can be written in terms of power and state of charge:

$$J_{s,i} = \sum_{t=0}^{T-1} w_{P_{s,i}} \left[P_{s,i}(t) - \bar{P}_{s,i}(t)\right]^2 + w_{s,i}\left[s_i(t) - \bar{s}_i(t)\right]^2 \tag{8}$$

where w_{P_s} and w_s are weights used to balance the objectives functions and $\bar{P}_{s,i}(t)$ and $\bar{s}_i(t)$ are the target values.

A microgrid may be connected to the utility grid in one or more points and power can flow in both directions, from the microgrid to the distribution grid and vice versa. The power sign is assumed positive when energy is sold to the utility grid. The limit on the maximum power that can flow is:

$$P_{g,i}^{m} \leq P_{g,i}(t) \leq P_{g,i}^{M} \tag{9}$$

where $P_{g,i}(t)$ is the power drawn from the distribution grid, $P_{g,i}^{m}$ and $P_{g,i}^{M}$ are the minimum and maximum power flows respectively. The goal of this agent is to minimize the energy that is bought, hence its objective function is:

$$J_{g,i} = -\sum_{t=0}^{T-1} \lambda_g(t) P_{g,i}(t) \tag{10}$$

where λ_g is the electricity price and T is an horizon length.

B. Buses and lines

Each agent of the microgrid is connected to a bus and buses are connected through lines, hence these interconnections represent additional constraints [13][11]. The first constraint is the power balance, that is, the sum of the powers exchanged with each bus has to be equal to zero:

$$\sum_{i=1}^{N_B} P_{B_i} = 0. \tag{11}$$

The second constraint limits the maximum power flow for each line:

$$|P_{L,i}(t)| \leq P_{L,i}^{M} \tag{12}$$

The line power flow can be calculated using the DC power flow equation [23]:

$$\mathbf{P}_L(t) = \mathbf{b}\mathbf{A}_B^L \mathbf{B}^{-1}\mathbf{P}_B(t) \tag{13}$$

where $\mathbf{P}_L(t) \in \mathbb{R}^{N_L}$ is the vector obtained stacking the power flowing in each line $P_{L,i}$, $i \in \{1, \dots N_L\}$, at time t, $\mathbf{b} \in \mathbb{R}^{N_L \times N_L}$ is a diagonal matrix in which each element $b(i,i)$ is the susceptance of line i, $\mathbf{B} \in \mathbb{R}^{N_B \times N_B}$ is the admittance matrix and $\mathbf{P}_B \in \mathbb{R}^{N_B}$ is the vector obtained by stacking all the bus power injections P_{B_i}. The entries of the adjacency matrix $\mathbf{A}_B^L \in \mathbb{R}^{N_L \times N_B}$ are $A_B^L(i,j) \in \{0, 1, -1\}$ respectively if the line i and the bus j are not connected, line i starts at bus j or line i ends at bus j.

C. Communication network

The communication network is used by the agents to exchange data to run the distributed optimization algorithm. It is modelled as an undirected graph $G(\mathcal{V}, \mathcal{E})$ in which $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges. Since each microgrid agent is provided with a local controller, the cardinality of the set of nodes is the total number of agents:

$$|\mathcal{V}| = N_l + N_s + N_r + N_g \tag{14}$$

where N_* is the number of renewable generators, loads, storage systems and connections to the utility grid. The adjacency matrix of the graph at time t is denoted by $A(t) \in \mathbb{R}^{|\mathcal{V}| \times |\mathcal{V}|}$ ($a_{i,j}(t) = 1$ if component i can communicate with component j, $a_{i,j}(t) = 0$ otherwise). The adjacency matrix depends on time since communication network can change over time due to faults in the communication network.

D. Fault models

In this paper we consider three types of faults which may affect a microgrid system: a distribution grid fault (e.g. a power outage), a renewable generator fault and a communication network fault. In the first case, the power cannot be drawn from the distribution grid anymore, which is equivalent to set the lower and upper limit of equation (9) to zero:

$$P_g(t) = 0 \quad \forall \; t \in \left[T_{GF}^i, T_{GF}^f\right], \tag{15}$$

where T_{GF}^i and T_{GF}^f are the initial and the final fault time. In the second case, a renewable generator cannot provide power to the loads anymore, hence the maximum available power in (3) is set to zero:

$$P_{r,i}(t) = 0 \quad \forall \; t \in \left[T_{RF_i}^i, T_{RF_i}^f\right], \tag{16}$$

where $T_{RF_i}^i$ and $T_{RF_i}^f$ are the initial and the final renewable generator fault time. Finally, a fault in one link of the communication network prevents two agents from exchanging data. A faulty link is modelled through the adjacency matrix of the communication graph; specifically, if the communication link among agent i and j is broken, the corresponding entries of the matrix A are set to zero $a_{i,j}(t) = a_{j,i}(t) = 0$. Differently from the previous faults, a communication network fault does not affect the power flows, however it degrades the algorithm performances.

III. Energy Management System

The EMS is formulated as an MPC whose optimization problem is solved by a distributed algorithm to obtain a fully distributed controller. In this framework, at each time step, each agent of the network formulates a local small-scale optimization problem which is interconnected to the others through a number of so-called coupling constraints [15].

A. Distributed optimization-based MPC

Similarly to [14] the energy management problem for a network of N agents is formulated as an MPC problem to be solved using a distributed optimization algorithm. At each step the following constrained-coupled problem is solved:

$$\min_{\{\mathbf{x}_1, \dots \mathbf{x}_N\}} \quad \sum_{i=1}^{N} f_i(\mathbf{x}_i) \tag{17a}$$

$$\textit{s.t.} \quad \mathbf{x}_i \in X_i, \tag{17b}$$

$$\sum_{i=1}^{N} \mathbf{g}_i(\mathbf{x}_i) \leq 0. \tag{17c}$$

The local decision variable is the power profile of agent i over the prediction horizon $\mathbf{x}_i = \{P_i(t), \dots P_i(t+T-1)\}$.

The local objective functions f_i have been introduced in Section II. The global objective function to be minimized can be expressed as the sum of the local objectives:

$$\sum_{i=1}^{N} f_i(\mathbf{x}_i) = \sum_{i=1}^{N_l} J_{l,i} + \sum_{i=1}^{N_r} J_{r,i} + \sum_{i=1}^{N_g} J_{g,i} + \sum_{i=1}^{N_s} J_{s,i}, \tag{18}$$

The local constraint set of each agent is composed of the bounds on power (1), (3), (7) and (9), states (6) and system dynamics (5). As for the storage agent, there is an additional constraint on the current state value.

The coupling constraint (17c) is used to model the interconnections of the microgrid agents and it is represented by equations (11) and (12).

In this paper we make use of the distributed dual subgradient method presented in [5]. This algorithm allows to converge to the optimal solution sharing only dual variables with the other agents of the network hence keeping private any sensitive information. Due to length constraints, the details of the adopted distributed optimization algorithm [5] are omitted; however such algorithm can be employed in the described scenario since objectives and constraints of the agents are separable, objective functions f_i are convex and the sets X_i are compact.

B. Resilient energy management system

In this subsection, the method used to make the distributed energy management algorithm resilient to faults is outlined. We propose to store the energy to sustain the loads during faults in storage systems. Thanks to distributed optimization algorithms this can be done through the coupling constraints, thus without sharing the future energy requirement of the loads with other agents. The minimum energy requirement of the microgrid for the next δ time steps is:

$$\tilde{s}_\delta(t) = \sum_{i=1}^{N_l} \sum_{\tau=t}^{t+\delta} T_s P_{l,i}^m(\tau) \tag{19}$$

Hence, in order to store enough energy stored for the next δ steps it is sufficient to set:

$$\sum_{i=1}^{N_s} s_i(t) \geq \tilde{s}_\delta(t) \tag{20}$$

In some cases it is tolerable to drain a battery below the lower limit (for example refer to [8] for the case of electric vehicles). Since the duration of a fault is not known in advance, this additional amount of energy can be used to cope with persistent faults. The lower bound is set as a soft constraint to avoid frequent discharges of the battery in the following way. A new optimization variable $\varepsilon \in \mathbb{R}$ is introduced for storage agents together with the replacement of constraint (6) when a fault is detected:

$$s_i^m - \varepsilon_i \leq s_i(t) \leq s_i^M, \tag{21}$$

$$0 \leq \varepsilon_i \leq s_i^m. \tag{22}$$

This optimization variable is accounted in the objective function (18) by considering the term:

$$J_{\varepsilon,i} = \rho\, \varepsilon_i^2. \tag{23}$$

The weight $\rho \in \mathbb{R}$ needs to be tuned and depending on its value, it is more or less likely to drain the energy of the battery below its minimum value.

The MPC algorithm reformulates the optimization problem (17a)-(17c) at each time step, hence it allows to modify the cost functions and the constraints depending on the current situation. When a faulty component is detected, its power is set to zero and the controller switches to safe mode enabling (21), (22) and its corresponding cost term (23) while disabling (20) in order to allow full discharge of the batteries.

The algorithm steps can be computed independently by each agent, then the optimization problem is solved via the distributed dual subgradient exchanging only the dual variables of the optimization problem. Hence, since each agent has a partial knowledge of the problem, it is not possible to reconstruct the power profile of each agent.

IV. SIMULATION RESULTS

In this Section results obtained applying the algorithm to the 4-bus system microgrid [25] in Figure 1 are presented. The microgrid is composed of 1 load L_1, 1 renewable generator R_1, 1 battery S_1 and one connection to the distribution grid G_1. The main simulation parameter values are given in Table I and Figure 2 shows the electricity price profile.

The distributed optimization problem is solved at each simulation step using the distributed dual subgradient algorithm presented in [5] with the number of iterations set to 1000 and a decreasing step-size defined as $\frac{1}{(k+1)^{0.1}}$ where k is the algorithm iteration. Simulations have been implemented using the DISROPT Python package [6]. Given the

Variable	Value	Variable	Value	Variable	Value
T	20	δ	2 h	w_s	0
T_s	1 h	N_g	1	ρ	10
s_1^M	2184 Wh	N_l	1	w_r	10
s_1^m	500 Wh	N_r	1	w_l	10
$P_{g,1}^M$	2100 W	N_s	1	w_{P_s}	0
$P_{g,1}^m$	-4200 W	$\mu_{1,c}$	0.95	$\mu_{1,d}$	1.05

TABLE I

MAIN SIMULATION DATA

MPC prediction horizon of 20 steps, the resulting optimization problem for this case study has 80 decision variables, 223 local constraints and 220 coupling constraints. Power and SoC profiles obtained running three different simulations are shown in Figures 3, Table II instead gives some numerical results. In particular, the three scenarios are compared based on the following performance indices:

- total energy cost $\mathrm{C} = \sum_{k=0}^{23} \lambda_g(k) P_{g,i}(k)$
- energy delivered to load with respect to the maximum load energy demand $E_l^{\%} = \frac{E_l}{E_l^M} \times 100$
- energy injected in the grid by the generator with respect to the total produced energy $E_r^{\%} = \frac{E_r}{E_r^M} \times 100$

Variables E_l and E_r are computed as $E_* = \sum_{k=0}^{23} P_*(k) T_s$, in which $*$ denotes either l or r. The maximum energy E_*^M is computed accordingly by using P_l^M and P_r^M.

A. Simulation scenarios

In the first simulation scenario no faults are simulated over the 24 hours simulation, while in the second scenario a renewable generator fault occurs between $t = 10$ and $t = 22$. Finally, in the last simulation scenario a utility grid fault is simulated in the same time span. The time period in which there is a faulty component is highlighted in grey in the figures.

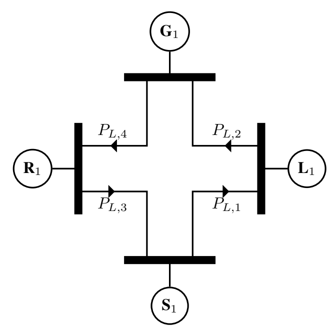

Fig. 1. Microgrid system.

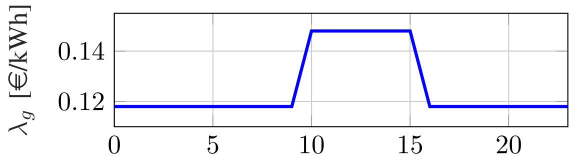

Fig. 2. Electricity price profile.

In simulation scenario 1 all the critical and non-critical power demand is delivered to the load. At time $t = 8$, at the peak of renewable power production the PV panels are sustaining the load, charging the battery at maximum rate and selling power to the utility grid. Since at this time step all power flows are at their maximum a little amount of renewable power cannot be injected in the grid. The storage SoC is kept always above its minimum value $\tilde{s}_\delta$, hence in case of fault of the utility grid and the renewable generator, the battery would be able to sustain the load critical demand for 2 hours. The auxiliary variable ε_1 is always equal to 0, meaning that the controller predicts that it will not be necessary to discharge the battery below its lower value s_1^m.

In the second simulation scenario a renewable generator fault is simulated, hence during this time period the power injected in the microgrid by the renewable generator is zero (top right plot of Figure 3). The load draws fully its critical and non-critical power demand, however this comes at the cost of an higher energy price. Indeed, during the fault occurrence power has to be provided mostly by the electricity grid. Since during faults constraint (20) is disabled, the battery charge drops below $\tilde{s}_\delta$.

In the last simulation scenario a power outage is simulated, hence power cannot be exchanged with the distribution grid during fault. At $t = 10$, when the fault starts, the renewable power production is still high enough to sustain the load. At the following time steps, since the renewable power production decreases, the load can draw power only from the storage, hence the load power has to be curtailed. Indeed, during the whole fault duration the load absorbs only the critical power demand, making the storage SoC drop below its lower limit s_1^m. This is allowed since during faults the lower SoC constraint is softened (see equations (21)-(23)) and the auxiliary variable ε_1 is at its maximum value. The auxiliary variable is at its maximum value before the battery is discharged below its lower limit since ε_1 is a scalar value used for the whole prediction horizon. It is clear from Table II that the main effect of this fault is a curtailment of the load energy demand, however the safety constraints described in paragraph III-B allows to provide the critical energy demand to the load.

B. Communication network fault

In case of faults or attacks on the communication network, some communication links are disabled. Though convergence is guaranteed as long as the communication graph remains connected [5], the number of active communication links affects the convergence time of the optimisation algorithm.

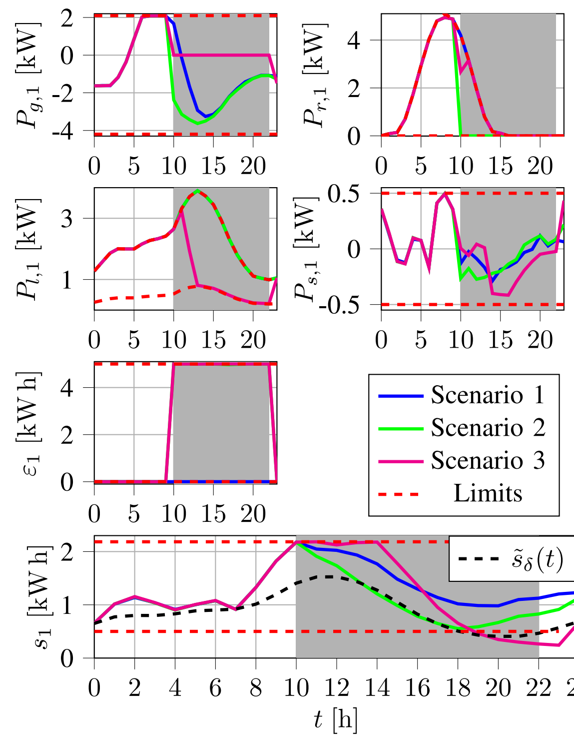

Fig. 3. Power and state of charge profiles.

Scenario	$E_l^{\%}$ [%]	$E_r^{\%}$ [%]	C [€]
1	100	99.6	2.6
2	100	69.7	4.1
3	62.8	95.2	-0.1

TABLE II
NUMERICAL RESULTS CORRESPONDING TO SCENARIO 1

Figure 4 shows the convergence of the cost in Eq. (18) to the cost obtained using a centralised optimisation algorithm, over the first 500 algorithm iterations in two different cases:

- case 1: 100% comm. links are active (6 out of 6 links);
- case 2: 50% comm. links are active (3 out of 6 links).

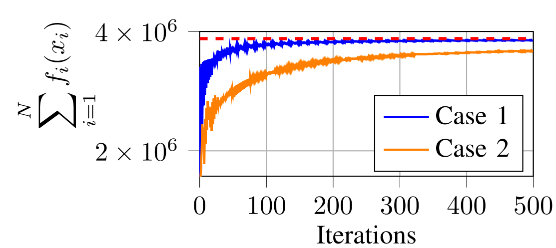

Fig. 4. Convergence of the distributed costs to the centralised cost.

V. CONCLUSIONS

In this paper a novel resilient and privacy-aware distributed method for energy management in microgrids is presented. Resilience is achieved by storing energy in the storage systems to supply to the loads when it is not available from other sources. This can be done without sharing with the network the future power profiles of loads, thanks to the employed distributed optimization algorithm. Since the duration of faults is typically not known, we introduced a soft constraint on the minimum energy stored in the batteries in order to use this backup energy only when it is necessary. Future work will take into account the estimated duration of a fault in the optimization problem. Moreover we will investigate the fault detection problem.

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