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On a fault tolerant strategy for efficient energy management in microgrid systems

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Abstract: This paper addresses the microgrid energy management problem within a coherent framework of control tools based on Mixed-Integer Linear Programming (MILP) and constrained Model Predictive Control (MPC). These help characterize the microgrid components' dynamics and the overall system control architecture. A fault tolerant strategy is considered in order to ensure the proper amount of energy in the storage devices such that (together with the utility grid) the essential consumer demand is reliably covered. Simulation results on a particular microgrid architecture validate the proposed approach.

Keywords: Microgrid energy management, Model Predictive Control (MPC), Mixed-Integer Linear Programming (MILP), Fault Tolerant Control (FTC).

1. INTRODUCTION

Microgrids have captured both the research and industrial communities as an umbrella label for a diverse set of activities increasingly available to the grid's distributed energy resources Johansson [2013]. The flexible configuration and operation of microgrids helps avoid cascading failures and, thus, blackouts and losses of stability.

Proposed techniques for the minimization of microgrid operating costs include heuristics Sanseverino et al. [2011], robust optimization Rahimiyan et al. [2014] and priority rules Tsikalakis and Hatziargyriou [2011]. There are only few recent examples of Model Predictive Control (MPC) use in microgrids applications (see, for instance Rawlings and Mayne [2009] for details on MPC usage). A method based on the combination of empirical mean, dynamic programming and MPC has been used in Hooshmand et al. [2012] for solving a power management problem within a microgrid in islanded mode operation. In Parisio and Glielmo [2011], a preliminary study has addressed the application of a receding horizon approach for optimizing microgrid operations while satisfying time-varying demands and operational constraints. In Pérez et al. [2013], an approach based on MPC has been designed to manage in real-time the power production of a grid-tied photovoltaic plus energy storage power plant with a reduced energy storage system capacity. Next, Negenborn et al. [2009] applied a model predictive controller for controlling the energy flows inside a household system equipped with a "micro" combined heat and power unit. In addition, the household was deemed capable to buy and sell electricity from/to the energy supplier; heat and electricity was stored in specific storage devices.

In our opinion the current state of the work still leaves room to explore additional avenues in control theory. More precisely, our goal is to provide a general management/scheduling of the microgrid system which efficiently:

- minimizes energy costs (minimizes buying, maximizes selling);
- minimizes wear and tear (especially for the storage components);
- maintains a reliable functioning of the microgrid under fault events (e.g., generator output outages), i.e., we provide an adaptive control which can handle fault events via subsequent control reconfiguration.

The present work extends the optimization-based control approach developed in Prodan and Zio [2014] in several important directions. Foremost is the fault tolerant implementation but we may also mention the formalized characterization of the microgrid system. The microgrid energy control in this paper is done via a centralized scheme which assumes global state, inputs and outputs which appear in the description of the dynamics, constraints and costs. We proceed by defining and illustrating in the rest of the paper these signals and associated matrices, as needed.

2. MICROGRID SYSTEM DESCRIPTION

Any microgrid system is topologically characterized by a directed graph with generator, storage and consumer nodes and edges which assure the node interconnection. For further use we denote the power generators as G_i, storage elements as S_j, consumers as D_k and (if not in

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islanded mode) the external power grid as E. Scalars N_g, N_s and N_d denote the number of generators, storage units and consumers, respectively.

The generic interconnection signals which appear in a typical microgrid system are denoted by $u_{ab}^{ij}(t)$, which is to be read as "*link from the i-th element of type 'a' to the j-th element of type 'b' at time 't'* ". For example, $u_{sd}^{jk}(t)$ denotes the electrical power transmitted by the electrical storage S_j to the consumer D_k at time step t. Let us introduce the adjacency matrices characterizing the links between components: adjacency matrix 'M_{ab}' is a matrix of size $N_a \times N_b$ where the cell of coordinates (i,j) is '1' if there exists link u_{ab}^{ij} and '0' otherwise. The number of non-zero entries in an adjacency matrix M_{ab} is $N_{ab} = \sum\limits_{M_{ab}(i,j)\neq 0} M_{ab}(i,j)$. For illustration, consider $M_{sd} \in \{0,1\}^{N_s \times N_d}$ which characterizes the existence of links from storage units towards consumers and N_{sd} denotes the number of these links (non-zero entries in M_{sd}). The previous notation and microgrid structure is depicted in Figure 1.

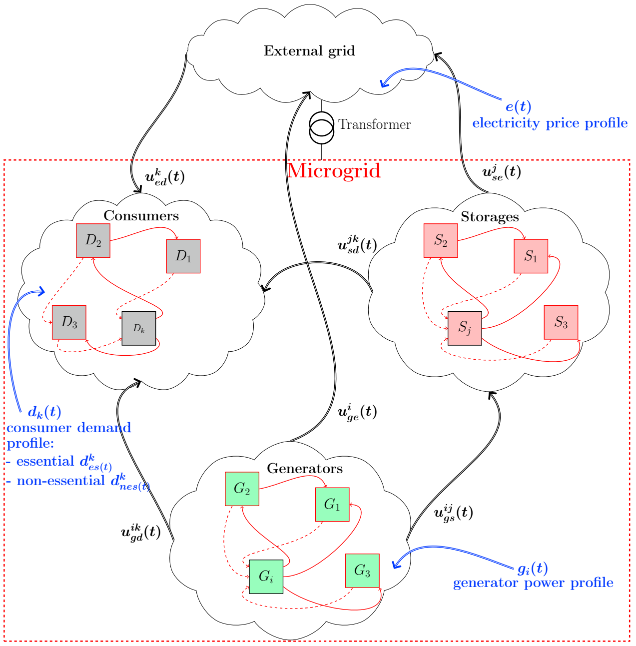

Fig. 1. Interconnections in a typical microgrid system.

2.1 Microgrid constraints

In what follows we characterize the constraints which appear in a typical microgrid. We start with the storage units dynamics[1] :

$$x_j(t+1) = (1-\sigma_j)x_j(t) + \sum_{M_{gs}(i,j)\neq 0} u_{gs}^{ij}(t) - \qquad (1)$$

$$- \sum_{M_{sd}(i,j)\neq 0} u_{sd}^{jk}(t) - \sum_{M_{se}(j,k)\neq 0} u_{se}^{j}(t) + w_j(t),$$

with the *mixed-integer* conditions:

$$\begin{cases} 0 \leq u_{gs}^{ij}(t) \leq M\alpha_j(t), & \forall i \text{ with } M_{gs}(i,j) \neq 0, \\ 0 \leq u_{sd}^{jk}(t) \leq M(1-\alpha_j(t)), & \forall k \text{ with } M_{sd}(j,k) \neq 0, \\ 0 \leq u_{se}^{j}(t) \leq M(1-\alpha_j(t)), & \text{if } \exists j \text{ with } M_{se}(j) \neq 0, \end{cases} \qquad (2)$$

where $x_j(t) \in \mathbb{R}$ represents the amount of energy stored in S_j at time step t, $u_{gs}^{ij}(t) \in \mathbb{R}$, $u_{sd}^{jk}(t) \in \mathbb{R}$ and $u_{se}^{j}(t) \in \mathbb{R}$ denote the charging and respectively the discharging inputs (charge from generators and discharge towards users and external grid), σ_j denotes the hourly self-discharge decay and the additive noise $w_j(t)$ accounts for the various sources of variation appearing in the storage dynamics. The switched behavior of the storage units (the charge or discharge mode is kept constant along a sampling interval) is modeled via mixed-integer constraints (2) where $\alpha_j(t) \in \{0,1\}$ are auxiliary binary variables which govern the mode switching and M is an appropriately chosen constant (i.e., significantly larger than the rest of the variables and playing the role of a relaxation constant).

In addition we consider magnitude and variation bounds on the quantity of stored energy:

$$B_{min}^{j} \leq x_j(t) \leq B_{max}^{j}, \quad V_{min}^{j} \leq \Delta x_j(t) \leq V_{max}^{j}, \qquad (3)$$

with $B_{min}^{j}, B_{max}^{j}, V_{min}^{j}, V_{max}^{j} \in \mathbb{R}$ chosen appropriately.

The generator outputs $g_i(t)$ can be sent to other various microgrid nodes: to the storage unit for further use, directly to the users or even to the external grid for selling:

$$0 \leq \sum_{M_{gs}(i,j)\neq 0} u_{gs}^{ij}(t) + \sum_{M_{gd}(i,k)\neq 0} u_{gd}^{ik}(t) + \sum_{M_{ge}(i)\neq 0} u_{ge}^{i}(t) \leq g_i(t). \qquad (4)$$

Furthermore, the consumer demand $d_k(t)$ is partitioned into essential, $d_{es}^{k}(t) \in \mathbb{R}$ and non-essential demand, $d_{nes}^{k}(t) \in \mathbb{R}$, respectively (i.e., $d_k(t) = d_{es}^{k} + d_{nes}^{k}(t)$). For a reliable management of the energy system it is necessary to ensure that at time t the electricity purchased by the consumers from the three types of sources will satisfy at least the essential demands:

$$d_{es}^{k}(t) < \sum_{M_{gd}(i,k)\neq 0} u_{gd}^{ik}(t) + \sum_{M_{sd}(j,k)\neq 0} u_{sd}^{jk}(t) + \sum_{M_{ed}(k)\neq 0} u_{ed}^{k}(t) \leq d_k(t). \qquad (5)$$

2.2 Microgrid costs

Depending on the type of storage unit, we may need to take into account wear and tear issues. While in the short/medium term it makes sense to exploit aggressively the storage unit (i.e., the energy should flow to and from the storage unit at all times, to ensure that energy costs are minimized) in the longer term it is counter-productive to over-use a component if the price of replacing it is larger than the actual gains from its use. To account for this, we choose to penalize the switch between charge/discharge modes (as this particularly affects the chemical batteries):

$$C_s(t) = \sum_{j=1}^{N_s} (\alpha_j(t) - \alpha_j(t-1)), \qquad (6)$$

with $\alpha_j(t) \in \{0,1\}$ as in (2).

Another cost is the difference between provided load and required demand:

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[1] Note that while $x_j(t)$ denotes the energy stored at time step t the variables $u_{gs}^{ij}(t)$, $u_{sd}^{jk}(t)$, $u_{se}^{j}(t)$ and $w(t)$ are electrical powers which are multiplied by the sampling time $\Delta t = 1$ hour. For a streamlined presentation, Δt is hidden in (1) and in the following equations.