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Electrical Power Distribution System Reconfiguration: Case Study of a Real-life Grid in Croatia ⋆

Branimir Novoselnik * **Martin Bolfek** ** **Marin Bošković** *** **Mato Baotić** *

* *Department of Control and Computer Engineering, Faculty of Electrical Engineering and Computing, University of Zagreb, Unska 3, HR-10000, Zagreb, Croatia, email: branimir.novoselnik@fer.hr, mato.baotic@fer.hr*
** *HEP-ODS d.o.o. Elektra Koprivnica, Služba za tehničke poslove, Ulica Hrvatske državnosti 32, HR-48000 Koprivnica, Croatia, email: martin.bolfek@hep.hr*
*** *HEP-ODS d.o.o., Sektor za tehničke poslove, Služba za mjerenje i obračun, Ulica grada Vukovara 37, HR-10000 Zagreb, Croatia, email: marin.boskovic@hep.hr*

Abstract: This paper describes application of a nonlinear model predictive control algorithm to the problem of dynamic reconfiguration of an electrical power distribution system with distributed generation and storage. Power distribution systems usually operate in a radial topology despite being physically built as interconnected meshed networks. The meshed structure of the network allows one to modify the network topology by changing status of the line switches (open/closed). The goal of the control algorithm is to find the optimal radial network topology and the optimal power references for the controllable generators and energy storage units that will minimize cumulative active power losses while satisfying all system constraints. Validation of the developed algorithm is conducted on a case study of a real-life distribution grid in Croatia. The realistic simulations show that large loss reductions are feasible (more than 13%), i.e. that the developed control algorithm can contribute to significant savings for the grid operator.

Keywords: model predictive control, power distribution system reconfiguration, mixed-integer programming, real-life case study

1. INTRODUCTION

The ever increasing demands for electrical energy, limited conventional fuel reserves, climate change, the desire for energy independence and diversification of energy sources, put in focus the distributed production of electrical energy from renewable sources as a key element in achieving a sustainable development. Since most of the electricity generated in developed countries is consumed in homes, buildings, and industry (see e.g. REN21 (2016)), the idea is to bring the distributed energy production closer to the end-consumers, i.e. to the power distribution level of the overall electrical power system. Hence, the power distribution system ceases to be a passive part of the electrical power system and starts to be actively involved in the production of electrical energy.

Despite all the advantages of distributed production of electrical energy, the rapidly growing penetration of intermittent renewable energy sources and other distributed sources poses vast challenges for electricity distribution systems (Keane et al. (2013)). The challenges mostly relate to the maintenance of grid stability while adhering to the grid codes in order to ensure reliable and efficient power supply to all consumption entities spatially distributed over the distribution grid. Thus, an active grid management strategy is of key importance in achieving the promised benefits of smart grids - reduction of electricity losses, integration of renewable generation and storage units, reduced use of fossil fuels, and improved grid reliability.

Power distribution systems are built as interconnected meshed networks but they, as a rule, operate in a radial topology. The topology of the network can be modified by changing the open/closed status of line switches which gives additional possibilities for the optimal management of the overall system. Merlin and Back (1975) were the first to emphasize the importance of distribution system reconfiguration (DSR) as an active grid management technique. The DSR problem can generally be modeled as a Mixed-

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Integer Nonlinear Program (MINLP). Historically, most of the methods for network reconfiguration relied on heuristics (Merlin and Back (1975)) and artificial intelligence techniques (Khan and Ravichandran (2005); Carreno et al. (2008)). Although these algorithm are generally easy to implement and sometimes very fast on practical networks, global solution optimality is not guaranteed and cannot be formally verified. Furthermore, most of the DSR problem formulations do not take into account the dynamics of the system.

In contrast with existing literature, in Novoselnik and Baotić (2015) the authors proposed a closed-loop nonlinear model predictive control (NMPC) algorithm that can take into account system dynamics and its constraints. The NMPC algorithm builds on ideas from Jabr (2014) and Ben-Tal and Nemirovski (2001). However, in Novoselnik and Baotić (2015) a simplified, small-scale example is used to illustrate the performance of the NMPC algorithm.

In this paper we validate the developed NMPC algorithm for the dynamic reconfiguration of the distribution grid on a realistic case study of a real-life distribution grid from Koprivnica, Croatia. The NMPC algorithm is implemented in Matlab and tested in real-time using data provided by the grid operator HEP-ODS.

The rest of this paper is organized as follows. The control problem considered herein is formulated in Section 2. In Section 3 a case study of a real-life power distribution grid in Koprivnica, Croatia, is described. Simulation results are reported in Section 4. Concluding remarks are given in Section 5.

2. NONLINEAR MPC FORMULATION

Consider a power network represented by the graph $G = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} := \{1, 2, \ldots, n\}$ is the set of nodes, and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of flow lines (i, j), where $i, j \in \mathcal{V}$ and $i \neq j$. Each node, except the substation node, may have photovoltaic (PV) generation, battery storage, and loads connected to them. The network has meshed structure, but it operates radially. It is assumed that all lines are equipped with switches and can participate in the reconfiguration of the network topology.

The control objective is to minimize the total active power losses over a prediction horizon N, i.e. $t \in \{0, 1, \ldots, N\}$. The network losses are equal to the difference between total system active power generation and the total system active power demand. Consequently, the network active power losses at time instant t can be computed as a sum of total active power injections ($P_{i,t}^{\mathrm{I}}$) at all nodes:

$$P_t^{\mathrm{loss}} = \sum_{i \in \mathcal{V}} P_{i,t}^{\mathrm{I}}. \tag{1}$$

The overall nonlinear MPC (NMPC) problem can be formulated as follows:

$$\min_{\mathbf{x}} \sum_{t=0}^{N} P_t^{\mathrm{loss}}(\mathbf{x}) \tag{2a}$$

$$\text{s.t.} \quad g(\mathbf{x}) = 0, \tag{2b}$$

$$f(\mathbf{x}) \leq 0, \tag{2c}$$

where $\mathbf{x}$ is a vector of all decision variables $V_{i,t}$ (voltage magnitude), $\theta_{i,t}$ (voltage angle), $\delta_{ij,t}$ (line switching status), P_t^{S} (active power injection at substation node), Q_t^{S} (reactive power injection at substation node), $Q_{i,t}^{\mathrm{PV}}$ (reactive power injection at PV node), $P_{i,t}^{\mathrm{BAT}}$ (active power injection at battery node), $Q_{i,t}^{\mathrm{BAT}}$ (reactive power of a battery) on a prediction horizon of length N. All operational and physical constraints, i.e. power balance constraints, voltage constraints, battery storage dynamics constraints, constraints that ensure the radiality of grid topology, etc., are included in (2b) and (2c). Since $\delta_{ij,t}$ are binary variables, (2) is a mixed-integer non-linear optimization problem but it can be approximated as a mixed-integer linear program (MILP). More details on the control problem formulation can be found in Novoselnik and Baotić (2015).

In closed-loop, the NMPC problem (2) is solved at every time instant and only the first control action is applied to the system. At the next time instant, (2) is solved again from the new initial state, according to the receding horizon control strategy (see e.g. Rawlings and Mayne (2009)).

Even though the available solvers for mixed-integer linear programs are very mature, mixed-integer problems are still generally NP-hard, meaning that attempting to solve them can very easily lead to demanding (and often intractable) computations. Namely, even the state of the art algorithms implemented in commercial solvers like CPLEX have to check every possible combination of integer variables, which grows exponentially, in the worst case. In order to alleviate this drawback we keep the number of binary variables in our problem formulation as low as possible. To achieve this, the number of topology changes on a prediction horizon was limited to only one, i.e. for steps $k = 0$ to $k = j - 1$ the previous topology is kept and on step $k = j$ a new topology is determined that is to be used until the end of the prediction horizon. Obviously, N such MILP problems can be defined for all $j = 0$ to $j = N - 1$, where N is the length of the prediction horizon. Moreover, these MILP problems can be solved in parallel and then the solution that generates the minimal cumulative cost on a prediction horizon is chosen.

The limitation of only one topology change on a prediction horizon is also motivated by practical reasons. In particular, it is not desirable to use the switching gear too often in order to prolong its life cycle so it makes sense to limit the number of switching actions on a prediction horizon.

3. CASE STUDY

The electrical grid considered in this paper constitutes a part of the electrical power distribution grid in the city of Koprivnica, Croatia. The grid comprises: 28 nodes, 1 transformer station 110/35 kV, 2 transformer stations 35/10 kV, 3984 consumers, which are modelled as 22 aggregated loads, and 28 transmission lines.

The grid data (node data, line data, transformer data; see Appendix A) as well as access to real-time measurements and historical load profiles at different nodes in the network were provided by the grid operator HEP-ODS.

Graph representation of the Koprivnica distribution grid is shown in Fig. 1. Nodes are represented by blue circles