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

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Abstract

This paper describes the 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 the status of the line switches (open/closed). The goal of the control algorithm is to find an optimal radial network topology and optimal power references for controllable generators and energy storage units that will minimize cumulative active power losses while satisfying all system constraints. The validation of the developed algorithm is conducted in a case study of a real-life distribution grid in Croatia. Realistic simulations show that large loss reductions are feasible (more than 13%), i.e., 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 the diversification of energy sources put in focus the distributed production of electrical energy from renewable sources as a key element in achieving sustainable development. Since most of the electricity generated in developed countries is consumed in households, buildings, and industry (see e.g. [9]), 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 ([4]). The challenges mostly relate to the maintenance of grid stability while adhering to the grid codes to ensure reliable and efficient power supply to all consumption entities spatially distributed across 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 offers additional possibilities for the optimal management of the overall system. Merlin et. al in [6] 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-Integer Nonlinear Program (MINLP). Historically, most of the methods for network reconfiguration relied on heuristics ([6]) and artificial intelligence techniques ([2],[5]). Although these algorithms 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 consider the dynamics of the system.

In contrast to the existing literature, the authors in [7] 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 [1] and [3]. However, in [7] 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. A technical description of the algorithm implementation is given in Section 4. The simulation results are reported in Section 5. Concluding remarks are given in Section 6.

2. Nonlinear MPC formulation

Consider a power network represented by the graph $G=(\mathcal{V}, \mathcal{E})$, where $v:=\{1,2,...,n\}$ 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 (i=1), may have loads connected to them. The network has a 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., $t\in\{0,1,...N-1\}$. The network losses are equal to the difference between the total system active power generation and the total system active power demand. Consequently, the active power losses of the network at time instant t can be computed as the sum of the total active power injections ($P^I_{i,t}$) at all nodes:

$$P_t^{loss} = \sum_{i\in\mathcal{V}} P^I_{i,t}. \tag{1}$$

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

$$\begin{aligned} \min_x \sum_{t=0}^{N-1} & P_t^{loss}(x) \\ s.t.\ g(x) &= 0, \\ f(x) &\leq 0, \end{aligned} \tag{2}$$

where x is a vector of all decision variables $V_{i,t}$ (voltage magnitude), $\theta_{i,t}$ (voltage angle), $\delta_{i,t}$ (line switching status), P^s_t (active power injection at substation node), Q^s_t (reactive power injection at substation node), on a prediction horizon of length N. All power injections represent the average power during a discretization interval. Furthermore, all operational and physical constraints, i.e., power balance constraints, voltage constraints, constraints that ensure the radiality of the grid topology, etc., are included in constraints of the optimization problem (2). Since $\delta_{i,t}$ 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 [7].

In closed loop, the NMPC problem (2) is solved at any 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. [8]).

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 exponential complexity since in the worst case every possible combination of integer variables has to be checked. 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. It is not desirable to use the switching gear too often 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 [10] for details) as well as access to real-time

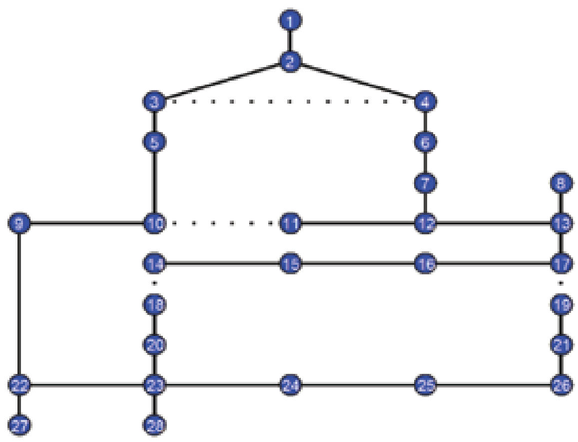

Fig. 1. Graph representation of the distribution grid in Koprivnica.

measurements and historical load profiles at different nodes in the network were provided by the grid operator HEP-ODS.

The graph representation of the Koprivnica distribution grid is shown in Fig. 1. Nodes are represented by blue circles that are numbered from 1 to 28. Lines and transformers that connect nodes are represented as edges of the graph. Full lines represent transmission lines that are switched on, while dotted lines represent transmission lines that are switched off in the current topology. The radial topology depicted in Fig. 1 is the actual topology that was in operation on-site in Koprivnica for four consecutive days. The actual power demand profiles (15-min averages) during those four days in Koprivnica are shown in Fig. 2.

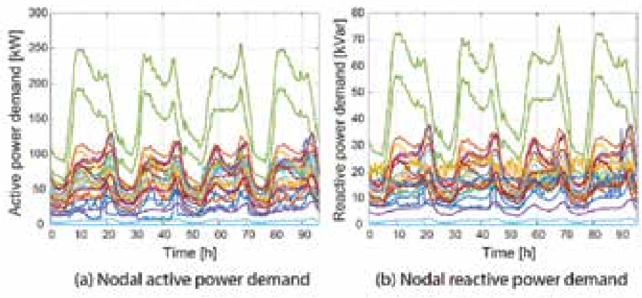

Fig. 2. Nodal power demand profiles in Koprivnica.

4. Simulation results

We ran the following three simulation scenarios:

1.1. In the first simulation run a fixed topology shown in Fig. 1. was kept. This topology was in operation on a real-life power grid in Koprivnica. The results from this simulation are used as a baseline for the following comparisons.

1.2. In the second simulation run the optimal grid topology was computed in each step. Since the grid is in a quasi-static state, there was no need for a prediction horizon. The results of this simulation represent the best that can be achieved by topology reconfiguration in this scenario.

1.3. In the third simulation run, the additional constraint was imposed as follows: only one topology change is allowed on the entire prediction horizon. We used N=6 in our simulation.

All three simulations were run with the entire data set shown in Fig. 2. A time step of 15 minutes was used.

In all three simulations nodal voltage magnitudes were kept safely within the predefined limits of ± 5% around the nominal values (see Fig. 3). For the sake of brevity, we did not include the voltage profiles of other two simulations. The voltages are closer to the upper limit, which makes sense because higher voltages allow for smaller currents in the network and consequently smaller losses.

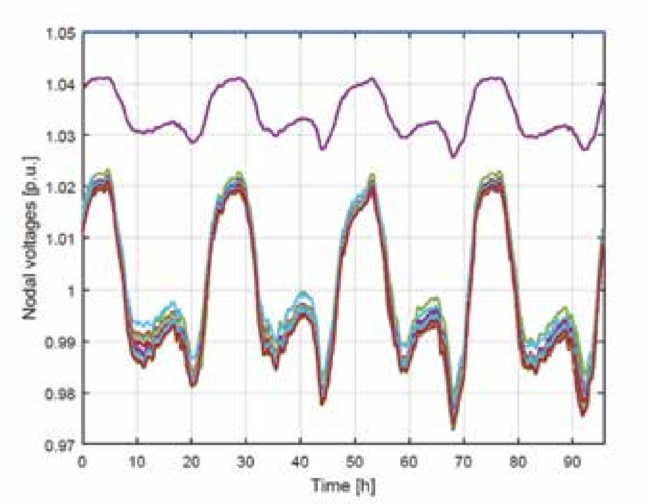

Fig. 3. Nodal voltage magnitudes during simulation 1.3.

The total active power losses during all three simulation runs are shown in Fig. 4. It is evident that in both reconfiguration scenarios a sizable reduction of losses was achieved compared to the baseline scenario where the topology was fixed. Table 1 reports the numeric values of the total active power losses in all three simulations. The losses obtained in simulation runs 1.2 and 1.3 are virtually the same and in both cases the reduction in total losses of around 13.5% compared to the baseline simulation run 1.1 was achieved.

The total number of switching actions per each line in simulations 1.2 and 1.3 are shown in Fig. 5. From this, it is evident that only a handful of lines switched their status on or off over the entire simulation run, while most of the lines never changed their switching status at all. Moreover, some of the lines changed their status rarely, while some of the lines changed their status many times. The total number of switching actions in simulation run 1.2, when the topology was allowed to change in every step, was 158. In simulation 1.3, when the topology could change once in every N steps, this number was 54. Therefore, practically the same performance was achieved with almost three times fewer switching

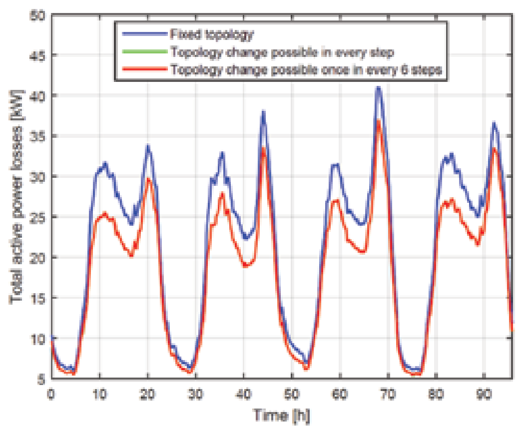

Fig. 4. Total active power losses during all three simulation runs in the scenario 1.

operations, as shown in Table 1. The computation times of the NMPC algorithm in simulations 1.2 and 1.3 are reported in Table 2. Note that the reported computation times for simulation 3 were measured on a single PC solving *N* MILP problems sequentially in every step of the simulation. In practice, these problems could have been solved in parallel and the computation would have been faster.

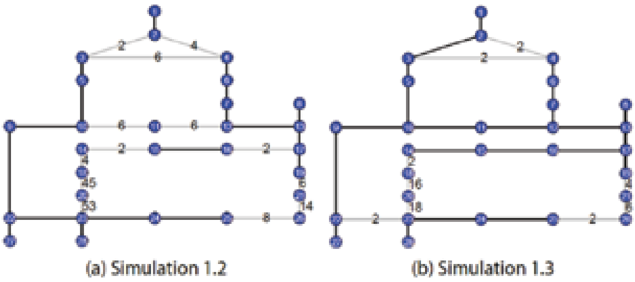

Fig. 5. The total number of switching actions for each line during simulations 1.2 and 1.3.

Table 1. Total active power losses in three simulation runs.

	Total loss [kWh]	Reduction [%]
Simulation 1.1	2068.55	n/a
Simulation 1.2	1788.15	-13.56
Simulation 1.3	1788.48	-13.54

Table 2. Computation times of the NMPC algorithm in simulations 1.2 and 1.3.

	Max [s]	Min [s]	Mean [s]
Simulation 1.2	14.57	2.11	4.81
Simulation 1.3	374.32	100.13	155.02

5. Discussion of results

The presented results of both simulation scenarios 1.2 and 1.3 are very promising and indicate that the applied methods could be implemented in a real-life distribution grid. The most appealing strengths of the method are: (i) process constraints can be systematically taken into account, (ii) certifiably globally optimal solution is obtained in every run of the algorithm, (iii) future power demand and renewable power production profiles can be easily taken into account.

The effectiveness of the reconfiguration depends on the degree of the network automation. In general, the more line switches are available for the dispatcher to change, the higher loss reduction can be achieved, i.e., more different topologies can be considered. In the current grid, the selection of appropriate lines to be updated with the switchgear for remote control of the switch state is based on minimizing a grid fault duration. The results that can be achieved by the reconfiguration algorithm provide an additional benefit to the already existing infrastructure. Consequently, the cost-benefit analysis of the medium voltage level automation system should take this newly added benefit into consideration, which in turn will allow for previously discarded switchgear to be reconsidered for automation. Some of the results presented in this paper provide interesting and valuable information along these lines. In particular, it was assumed in the simulations that all lines are equipped with a switchgear and therefore can change their switch state, although this is not true in the real grid. The results obtained, however, indicate that only some of the lines contributed to the change in the topology during the simulations while other lines never changed their switching state. Obviously, the lines with the highest number of switching actions are natural candidates for possible future upgrades with automatic switchgear in the real-life grid.

A few things should be noted. The algorithm depends on exact knowledge of the future power production and demand profiles. In practice, these profiles can only be predicted, so an accurate predictor is required to enable real-time implementation of the algorithm in a real distribution grid. Furthermore, the algorithm depends on solving a mixed-integer linear program which does not scale well with the size of the problem, i.e., it can easily become very computationally demanding. However, as we have seen in the simulation results, it is not necessary to consider all lines in the grid for topology reconfiguration, because most lines never change their switching status. This means that a smaller number of binary variables is needed to formulate the problem allowing for implementation on even larger power grids.

6. Conclusion

In this paper we have presented the application of an NMPC algorithm for dynamic reconfiguration of power distribution systems in a case study of a real-life power distribution grid in Croatia. The performance of the dynamic reconfiguration algorithm was validated in realistic simulation scenarios using real-life data provided by the grid operator. The results are very promising and show that large loss reductions are feasible (more than 13%). The developed NMPC algorithm has the potential to be applied to a real-life grid and can contribute to significant savings.

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