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Scalable algorithm for the dynamic reconfiguration of the distribution network using the Lagrange relaxation approach

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ABSTRACT

This paper proposes a new methodology for the dynamic reconfiguration of the distribution network (DRDN) which is based on the Lagrange relaxation approach. The aim of DRDN is to determine the optimal topologies (configurations) of the distribution network over the specified time interval. The objective is to minimize the active power losses, subject to the following constraints: branch power flow capacities, allowed ranges of bus voltages, radial network configuration, and limited number of switching (open/-close) operations for all switching devices. The paper first introduces the "path-switch-to-switch" approach for the modelling of distribution networks, which is used to formulate DRDN as the mixed integer linear programming (MILP) problem. Then, the specified MILP problem is solved using the Lagrange relaxation approach in two-step procedure. In the first step, the associated Lagrange dual problem is solved, which is created by relaxing the switching operation constraints. The Lagrange dual problem is decoupled and much easier to solve than the original problem. In the second step, the solution of the Lagrange dual problem is used to perform the heuristic search, providing the suboptimal, though feasible solution of the original problem. Finally, the presented DRDN model is extended to multi-objective formulation, which also includes the impact of the network reliability and the switching costs to the DRDN process. The robustness and scalability of the developed algorithm (for application in large-scale distribution networks) are demonstrated with two test examples: 15-bus test benchmark and 1021-bus real-world test system.

Note that vectors and matrices are denoted in bold.

1. Introduction

1.1. Motivation and aim

The reconfiguration of distribution networks is an optimization procedure which determines the optimal network configuration by changing the status (open/close) of switching devices. It is widely used in distribution networks for active power losses reduction, relief of overloads (load balancing), Volt/Var support (maximizing the loadability), supply restoration, and others [1].

In many studies, the network reconfiguration is treated as the *static* problem, where the optimal network configuration is determined for a fixed operation point (load/generation condition). However, this approach is not suitable for real-time applications, due to the time-varying nature of distribution networks: variable loads, increased penetration of renewable resources, storage systems, plug-in vehicles, and other stochastic elements. To enable efficient and secure distribution network operations in such environment, many researches define the network reconfiguration as a *dynamic* problem, where a set of network configurations is determined to optimize the network operations over the specified time period.

The DRDN is applicable to fully automated distribution networks only. In cases where the level of automation is limited to normal open- and mid-points, optimal reconfiguration is typically performed once a year. The recent trend towards the fully automated distribution networks creates opportunities for the application of intra-day reconfigurations in distribution networks to optimize daily network operation. However, the dynamic reconfiguration is quite limited with the number of switching operations, namely too frequent switching operations may have a negative impact on the distribution network, such as: reducing the expected life span of switching devices, increased risk of outages, stability problems during switching procedures and others. Therefore, the limits on the number of switching operations need to be considered in the dynamic reconfiguration problem.

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Nomenclature

Variables
- $CLOSS$ total cost of energy losses
- CCI total cost of customer interruption
- CSW total cost of switching operations
- g subgradient of the Lagrange dual function
- P, Q active and reactive powers, respectively
- P_{Loss} active power losses
- U, θ bus voltage magnitude and phase angle, respectively
- x switch status (1 – closed switch, 0 – open switch)
- y change of the switch status (1 – status change, 0 – no status change)
- z auxiliary variable
- w indicator for active path (1 – active, 0 – not active)
- λ Lagrange multiplier
- $\mathcal{J}$, $\mathcal{D}$ Lagrange function and Lagrange dual function, respectively

Indices
- b entry in the bundle $\mathcal{B}$ ($b = 1, 2, \cdots, N_B$, where N_B is the total number of entries) (lower index)
- c switch-to-switch segment ($c = 1, 2, \cdots, N_C$, where N_C is the total number of switch-to-switch segments) (lower index)
- h discrete time interval ($h = 1, 2, \cdots, N_H$, where N_H is the total number of time intervals) (upper index)
- i,j buses ($i,j = 1, 2, \cdots, N_N$, where N_N is the total number of buses) (lower index)
- $k = 1, 2, 3, 4$ inequality index used for modelling the switching operation constraints (lower index)
- l branch ($l = 1, 2, \cdots, N_L$, where N_L is the total number of branches) (lower index)
- (n) iteration of the bundle algorithm (upper index)
- m path of the switch-to-switch segment (lower index)
- s switch ($s = 1, 2, \cdots, N_{SW}$, where N_{SW} is the number of switches) (lower index)
- t interval of the power flow linearization ($t = 1, 2, \cdots, N_{TP}$ (N_{TQ}), where N_{TP} (N_{TQ}) is the number of intervals chosen to linearize the active (reactive) power flows, respectively) (lower index)

Vectors and sets
- Π_l set of paths which contain the lth branch
- Π_c set of paths associated to the cth switch-to-switch segment
- $\mathbf{\Omega}_{SW}$ N_{SW}-dimensional vector of branches equipped with switches, corresponding to switch numbers $s = 1, 2, \ldots, N_{SW}$
- $\Omega(\pi_{cm})$ set of switches on the switch-to-switch segment π_{cm}
- $\Pi(i, \pi_{cm})$ set of branches which connects the ith bus with the source bus along the path π_{cm}

Parameters
- N_{SP} number of supply points
- A coefficients in inequalities used for modelling the switching operation constraints
- cp,cq active and reactive power slopes of the piecewise linear function, respectively
- C_{Loss} cost of energy losses, in $ per kWh
- C_{Ij} cost of customer interruption for the load at the jth bus, in $ per kWh
- C_{SWs} cost of switching action for the sth switch, in $
- g, b element of bus conductance and susceptance matrices, respectively
- L section length
- M parameter in the bundle algorithm
- N_{SW}^{MAX} maximum number of allowed switch operations per switch during an optimization time interval
- $\bar{P}$, $\bar{Q}$ upper bound of the branch active and reactive powers, respectively
- P_{Lj}^h customer load at the jth bus in the hth time interval
- R,X branch resistance and reactance, respectively
- $S_l^{\max}$ maximum allowed VA power flow in the lth branch
- T^h duration of the hth time interval
- TI_{lj}^h duration of service interruption of the jth bus for the lth outaged branch in the hth time interval
- T^{REP}, T^{RES} reparation and restoration time, respectively
- $U_i^{\min}$, $U_i^{\max}$ minimum and maximum allowed voltage for the ith bus, respectively
- λ outage rate

Symbols
- $\|\cdot\|$ Euclidean norm
- $\boldsymbol{\lambda}^*$ optimal solution of the Lagrange dual problem
- $\bar{\boldsymbol{\lambda}}$ current solution in the bundle algorithm
- ($\tilde{\mathbf{x}}$,$\tilde{\mathbf{y}}$,$\tilde{\mathbf{w}}$) solution of the relaxed convex version of the DRDN problem
- ($\hat{\mathbf{x}}$,$\hat{\mathbf{y}}$,$\hat{\mathbf{w}}$,$\hat{\mathbf{P}}$,$\hat{\mathbf{Q}}$) feasible solution of the DRDN problem

Abbreviations
- DRDN dynamic reconfiguration of the distribution network
- MILP mixed integer linear programming
- MINLP mixed integer nonlinear programming

In general, the static distribution network reconfiguration is a non-linear combinatorial optimization problem, where for N_{SW} open-close (0-1) switching devices, the number of possible network configurations is $2^{N_{SW}}$. The specified problem becomes much more complex and time consuming if the time dimension is considered. For example, if the DRDN considers N_H time intervals, the number of possible solutions is $2^{N_{SW}N_H}$. Therefore, this is an $\mathcal{NP}$-hard problem and cannot be solved in polynomial time. Our aim is to develop the DRDN algorithm which is sufficiently fast to be usable in the real-world distribution network practice.

1.2. Literature review

A great deal of research in the area of network reconfiguration has been done regarding the reconfiguration as a static problem. The early studies in this area were focused on minimizing the active power losses and load balancing among the distribution feeders [2–4]. To overcome the shortcoming of a fixed operation point, specialized methods have been developed, determining the optimal network configuration that minimizes the energy losses [5] and operation costs [6] over a specified time period. Optimization methods used for the static reconfiguration problem can be divided into deterministic optimization methods and heuristic methods. The first set of optimization methods includes mixed-integer programming [7–12] and Benders decomposition based algorithms [13]. The advantage of these methods is in their potential to solve the network reconfiguration problem with global optimality using standard solvers. There are also several heuristic methods, such as genetic algorithm [12,14], artificial neural networks [15], particle swarm optimization [16], simulated annealing