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Blackbox optimization for loss minimization in power distribution networks using feeder reconfiguration

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Abstract : Modern power distribution networks (DNs) increasingly incorporate active distribution network technologies, such as distributed energy resources (DERs) and remotely activated switches. As DNs are naturally unbalanced due to a multi-phase, fluctuating demand, DERs which can lead to bidirectional power flows amplify the phase imbalances, reducing the system reliability and efficiency. The proposed network topology reconfiguration method uses tie and sectionalizing switches to minimizes power losses in a three-phase, unbalanced DN equipped with DERs. Strict feasibility of the solution is ensured through a high-accuracy load-flow simulator and a blackbox optimization (BBO) formulation. To circumvent the computational burden of BBO, combinatorial optimization-inspired algorithms are adapted to the DN context, namely the variable neighbourhood search metaheuristic and the branch-and-bound framework. The methods are tested on the IEEE 34-bus, 136-bus, and IEEE 8500-bus systems, all integrating DERs. Results demonstrate the direct impact of combining local generation with network reconfiguration to improve DN efficiency. Notably, the solution typically results in a topology different from the original one. Moreover, power losses are considerably reduced across all test cases, with decrease of at least 36.94 % for the largest test system and 9.82 % for the practical IEEE 8500-bus case. The results also permit to identify the most suitable methods for practical deployments based on prioritized requirements.

Keywords: Blackbox Optimization, branch-and-bound, distributed energy resources, power distribution network, power losses, reconfiguration, unbalanced phases, variable neighbourhood search

Résumé : Les réseaux de distribution électrique modernes (RDE) intègrent un nombre croissant de technologies associées aux réseaux de distribution actifs, telles que les ressources énergétiques distribuées (REDs) et les interrupteurs contrôlables à distance. Naturellement débalancés en raison des fluctuations et de la nature multi-phasée de la demande, ces réseaux voient leur débalancement de phases amplifié par les REDs. Notamment, ceux-ci peuvent induire un écoulement de puissance bidirectionnel qui tend à réduire la fiabilité et l'efficacité du système. La méthode de reconfiguration de la topologie du réseau qui est proposée introduit des commutateurs bidirectionnels et des sectionneurs afin de minimiser les pertes en puissance dans un RDE triphasé, débalancé, et équipé de REDs. La réalisabilité de la solution est garantie grâce à l'utilisation d'un simulateur d'écoulement de puissance à haute précision et de la formulation du problème sous forme d'optimisation de boîtes noires (BBO). Afin de réduire la charge computationnelle de la BBO, des algorithmes inspirés de l'optimisation combinatoire sont adaptés au contexte de RDE, notamment la méthode méta-heuristique de recherche par voisinages variables (*Variable Neighbourhood Search*) et la méthode de séparation et évaluation (*Branch-and-Bound*). Ces approches sont testées sur les réseaux IEEE 34-bus, 136-bus, et IEEE 8500-bus, tous intégrant des REDs. Les résultats mettent en évidence les impacts issus de la combinaison entre la production de puissance locale et la reconfiguration de réseau pour améliorer l'efficacité du RDE. Notamment, la solution résulte généralement en une topologie différente de celle du cas original. De plus, la réduction des pertes est considérable pour tous les réseaux testés, avec une réduction minimale de 36.94 % pour le plus grand problème, le 136-bus, et de 9.82 % pour le cas plus réaliste du IEEE 8500-bus. Les résultats permettent également d'identifier les méthodes les plus adaptées à une mise en oeuvre pratique, en fonction des priorités visées.

Mots clés : Branch-and-bound, optimisation de boîtes noires, phases débalancées, pertes en puissance, recherche en voisinages variables, reconfiguration, réseau de distribution électrique, ressources énergétiques distribués

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1 Introduction

The power distribution network (DN) is a three-phase system, usually operated in a radial topology. The phases are typically unbalanced because of the multi-phase loads and the demand uncertainty. Unbalanced phases impact power losses, network safety, and voltage levels, and impose additional stress on the network infrastructure [16]. Modern DNs are becoming more than just a passive load connected to the transmission network, for example, with the development of active distribution networks (ADNs). ADNs are defined by a high integration of distributed energy resources (DERs) to diversify and decentralize power production, combined with a flexible network topology using remotely controlled switching components, such as tie and sectionalizing switches [15]. This infrastructure enables a dynamic response of the network to demand and renewable generation fluctuations during nominal operations, enhancing energy efficiency and mitigating constraints violations such as abnormal voltage profiles and equipment overloading [3]. However, this also results in bidirectional power flows that tend to increase phase imbalances and power losses. Such impacts are critical for network operators, as they influence efficiency, service quality and network safety, and operational costs [13].

The main approaches to minimize power losses in DNs are phase or load balancing [16] and topology reconfiguration [11, 14]. Distribution network reconfiguration (DNR) aims to find the radial topology that minimizes power losses by opening and closing tie and sectionalizing switches. The resulting problem combines the non-linearity of the alternating current optimal power flow problem (AC-OPF) to the combinatorial nature of switch statuses, yielding a mixed-integer non-linear program (MINLP). Due to the problem complexity, most methodologies simplify the problem or solve it using heuristics. The preferred methods are heuristics, convex relaxations, linear approximations, and machine learning methods [12, 24].

Heuristics are used for DNR as they can provide fast solutions, are fairly simple to implement, and can be applied directly to MINLPs [12,23]. However, they lack convergence properties and are generally suboptimal. Prior work on DNR include approaches based on the minimum spanning tree [1], branch exchange method [11, 14], tabu search, simulated annealing, and population-based optimization such as genetic algorithms and particle swarm optimization. Mathematical optimization for DNR [12,24] is slower and more complex but provides a deterministic solution. These methods, commonly based on approximations and/or convex relaxations of the MINLP, provide globally optimal solutions with respect to the approximated or relaxed problem but may lead to infeasibility when applied to the original problem. Mixed-integer linear programming uses linear approximations of the power flow like LinDistFlow [15], or other formulations like linearized trigonometric terms and disjunctive constraints in [30]. Convex relaxations, including mixed-integer convex quadratic programming [19] and mixed-integer second-order cone programming [33] are also common. Machine learning techniques like reinforcement learning [10] and artificial neural network have also been applied to DNR as surveyed in [12]. In particular, physics-informed graph neural network can deal with reconfiguration problems while considering physical constraints, such as load-flow constraints [9, 29]. While machine learning-based DNR can provide fast solutions, especially for online applications, it lacks the feasibility guarantee for practical deployments.

Alternatively, state-of-the-art load-flow solvers and blackbox optimization (BBO) can be combined for DNR. This process has scarcely been used in the context of electrical power systems optimization in general, with only a few applications in reconfiguration problems. An optimization algorithm based on a blackbox is most reliable in terms of feasibility because it models the desired system with a high level of details, leading to a very accurate representation of the DN constraints. However, BBO may require a large number of evaluations in order to converge, therefore leading to long computation times to achieve a "good" solution. This limitation is exacerbated when the problem dimension grows. BBO algorithms like the mesh adaptive direct search (`MADS`) [6] yields provable local convergence properties, under mild assumptions, while guaranteeing the feasibility of the solution with respect to a detailed load-flow solution, which is crucial for network operators. In [32], a reconfiguration method based on `MADS` and the `NOMAD` software [8] is proposed. The approach integrates DERs and tests both integer and binary decision variables. It also consider, without any simplifications, a highly detailed three-phase, unbalanced DN modelled with an open-source simulator. The implementation is tested on a single medium test feeder (IEEE 123-bus) with a limited number of switches and the DERs are treated as constant components. Reference [17] proposes a multi-objective reconfiguration problem for DNR with constant DERs that uses `MADS`. The AC-OPF is modelled using polar coordinates and the DN is approximated as an equivalent topology using graph theory mapping rules to reduce the problem dimensions. Performance evaluation is done on the balanced IEEE 33-bus test feeder. By proposing a BBO-based method, we leverage a highly accurate load-flow model for decision-making that prioritize feasibility over optimality. This contrasts with traditional approach pursuing optimality over feasibility as in mathematical optimization, heuristics, and machine learning, which can limit their practical deployments. For improved performance, our approach is focused on both the combinatorial aspect of DNR and the integration of DERs, examining the interactions and impacts they may have on one another as well on the overall DN operation. As opposed to [17, 32], we do not treat the DERs as constant components, but rather as integral parts of the optimization process. Moreover, this work focuses on the decision-making process and therefore, assumes a fully automated DN, while aspects related to communication and infrastructure management are left for future work.

2 Distribution network reconfiguration model and blackbox optimization

This section presents the motivations and model of DNR, and the integration of BBO within this problem.

2.1 Distribution network reconfiguration

DNs are highly dependant on consumer behaviour, as loads can vary much during the day. DN hosts three main types of loads: residential and commercial loads that are mostly single-phased, and three-phased industrial loads. Load variations, combined with their multi-phase nature, result in a highly unbalanced network. Moreover, integrating DERs such as solar photovoltaics and storage systems can, on the one hand, mitigate the network's equipment overloading, and abnormal voltage profiles. On the other hand, DERs can induce bidirectional power flows, which may exacerbates phase imbalances. Integrated DNR and DERs optimization can thus play a crucial role in ensuring efficient and safe DN operations.

We represent a three-phase power distribution network as the graph $(\mathcal{N}, \mathcal{L})$ consisting of a set of vertices, i.e., buses, $i \in \mathcal{N} \subset \mathbb{N}$ and a set of edges, i.e., lines, $(i, j) \in \mathcal{L}$. Let the superscript $\phi \in \{a, b, c\}$ denote the phase. Let $\mathcal{G} \subset \mathcal{N}$ be the set of generation buses where $\mathcal{N}^{\mathrm{r}} \subseteq \mathcal{G}$ is the set of substations, $\mathcal{N}^{\mathrm{DER}} \subseteq \mathcal{G}$ is the set of buses equipped with DERs, and $\mathcal{L}^{\mathrm{s}} \subset \mathcal{L}$ be the set of lines equipped with switches. Let $Y_{ij} \in \mathbb{C}^{3\times 3}$ be the three-phase admittance of a line $(i, j) \in \mathcal{L}$. Let $P_{ij} \in \mathbb{R}^3$ and $Q_{ij} \in \mathbb{R}^3$ be the active and reactive three-phase power flowing through a line $(i, j) \in \mathcal{L}$. We define $\overline{S}_{ij} \in \mathbb{R}^3$ as the maximum apparent power (thermal limit) that can flow through line $(i, j) \in \mathcal{L}$ for each phase. Let $\tau_{ij} \in \mathbb{R}^3$ and $\rho_{ij} \in \mathbb{R}^3$ be auxiliary variables representing the active and reactive three-phase power for lines equipped with switches $(i, j) \in \mathcal{L}^{\mathrm{s}}$. Let $p_i \in \mathbb{R}^3$, $q_i \in \mathbb{R}^3$, $p_{d,i} \in \mathbb{R}^3$, $q_{d,i} \in \mathbb{R}^3$, $p_{g,i} \in \mathbb{R}^3$, $q_{g,i} \in \mathbb{R}^3$, and $v_i \in \mathbb{C}^3$ denote the active and reactive power, the active and reactive demand, the active and reactive generation and voltage at bus $i \in \mathcal{N}$ on all phases, respectively. Let $p_{\mathrm{DER},i} \in \mathbb{R}^3$, $q_{\mathrm{DER},i} \in \mathbb{R}^3$ be the generated or consumed active and reactive power for the DERs on all phases, and $\overline{s}_{\mathrm{DER},i} \in \mathbb{R}$ denote the cumulative maximum apparent power over all phases at bus $i \in \mathcal{N}^{\mathrm{DER}}$. We define $Z_{ij} \in \{0, 1\}$ to indicate the power flow direction between buses i and j on line $(i, j) \in \mathcal{L}$, and $X_{ij} \in \{0, 1\}$ to represent the state of the switch on line $(i, j) \in \mathcal{L}^{\mathrm{s}}$. Finally, let $\mathcal{M} \gg 0$ be a large constant. DNR can be effectively visualized using the AC-OPF three-phased equations and disjunctive constraints, leading to the AC-OPF-DNR model expressed as follows:

$$\min_{P,Q,p,q,\tau,\rho,p_{\mathrm{DER}},q_{\mathrm{DER}},v,Z,X} \sum_{(i,j)\in\mathcal{L}} \sum_{\phi\in\{a,b,c\}} P_{ij}^{\phi} + P_{ji}^{\phi} \tag{1a}$$

s.t.

$$P_{ij} + \jmath Q_{ij} = v_i(v_i^* - v_j^*)Y_{ij}^* \qquad (i,j)\in\mathcal{L}\backslash\mathcal{L}^{\mathrm{s}}, \tag{1b}$$

$$\tau_{ij} + \jmath \rho_{ij} = v_i(v_i^* - v_j^*)Y_{ij}^* \qquad (i,j)\in\mathcal{L}^{\mathrm{s}}, \tag{1c}$$

$$p_i^{\phi} = \sum_{(i,j)\in\mathcal{L}} P_{ij}^{\phi},\ \ q_i^{\phi} = \sum_{(i,j)\in\mathcal{L}} Q_{ij}^{\phi} \qquad i\in\mathcal{N},\ \phi\in\{a,b,c\}, \tag{1d}$$

$$(P_{ij}^{\phi})^2 + (Q_{ij}^{\phi})^2 \le (\overline{S}_{ij}^{\phi})^2 \qquad (i,j)\in\mathcal{L},\ \phi\in\{a,b,c\}, \tag{1e}$$

$$\underline{v} \le |v_i^{\phi}| \le \overline{v} \qquad i\in\mathcal{N},\ \phi\in\{a,b,c\}, \tag{1f}$$

$$\underline{p}_i \le p_i^{\phi} \le \overline{p}_i,\ \ \underline{q}_i \le q_i^{\phi} \le \overline{q}_i \qquad i\in\mathcal{N},\ \phi\in\{a,b,c\}, \tag{1g}$$

$$\underline{p}_{\mathrm{g},i} \le \sum_{\phi\in\{a,b,c\}} p_{\mathrm{g},i}^{\phi} \le \overline{p}_{\mathrm{g},i},\ \ \underline{q}_{\mathrm{g},i} \le \sum_{\phi\in\{a,b,c\}} q_{\mathrm{g},i}^{\phi} \le \overline{q}_{\mathrm{g},i} \qquad i\in\mathcal{N}^{\mathrm{r}}, \tag{1h}$$

$$p_i^{\phi} = p_{\mathrm{g},i}^{\phi} - p_{\mathrm{d},i}^{\phi},\ q_i^{\phi} = q_{\mathrm{g},i}^{\phi} - q_{\mathrm{d},i}^{\phi} \qquad i\in\mathcal{G},\ \phi\in\{a,b,c\}, \tag{1i}$$

$$p_i^{\phi} = -p_{d,i}^{\phi},\ q_i^{\phi} = -q_{d,i}^{\phi} \qquad i\in\mathcal{N}\backslash\mathcal{G},\ \phi\in\{a,b,c\}, \tag{1j}$$

$$\left(\sum_{\phi\in\{a,b,c\}} p_{\mathrm{DER},i}^{\phi}\right)^2 + \left(\sum_{\phi\in\{a,b,c\}} q_{\mathrm{DER},i}^{\phi}\right)^2 \le (\overline{s}_{\mathrm{DER},i})^2 \quad i\in\mathcal{N}^{\mathrm{DER}}, \tag{1k}$$

$$|P_{ij}^{\phi}| \le \mathcal{M}X_{ij},\ \ |Q_{ij}^{\phi}| \le \mathcal{M}X_{ij} \qquad (i,j)\in\mathcal{L}^{\mathrm{s}},\ \phi\in\{a,b,c\}, \tag{1l}$$

$$|P_{ij}^{\phi} - \tau_{ij}^{\phi}| \le \mathcal{M}(1-X_{ij}),\ \ |Q_{ij}^{\phi} - \rho_{ij}^{\phi}| \le \mathcal{M}(1-X_{ij}) \quad (i,j)\in\mathcal{L}^{\mathrm{s}},\ \phi\in\{a,b,c\}, \tag{1m}$$

$$Z_{ij} \ge 0 \qquad (i,j)\in\mathcal{L}, \tag{1n}$$

$$\sum_{j\in\mathcal{N}^{\mathrm{r}}} Z_{ij} = 0 \qquad i\in\mathcal{N}, \tag{1o}$$

$$Z_{ij} + Z_{ji} = X_{ij} \qquad (i,j)\in\mathcal{L}^{\mathrm{s}}, \tag{1p}$$

$$Z_{ij} + Z_{ji} = 1 \qquad (i,j)\in\mathcal{L}, \tag{1q}$$

$$\sum_{i\in\mathcal{N}} Z_{ij} = 1 \qquad j\in\mathcal{N}\backslash\mathcal{N}^{\mathrm{r}}, \tag{1r}$$

$$X_{ij} \in \{0,1\} \qquad (i,j)\in\mathcal{L}^{\mathrm{s}}, \tag{1s}$$

where (1a) represents active power losses, (1b) and (1c) are the power flow constraints for the lines with and without switches, respectively, (1d) are the nodal power balances, (1e) is the thermal line limits, (1f) is the voltage magnitude limits, (1g)–(1j) are the power limits at each bus, (1h) and (1j) being the case specifically for buses with generation, and (1i) being the case specifically for buses without generation, (1k) is the power limit of the DERs, (1l) and (1m) are disjunctive constraints indicating if power flows or not in the lines with switches, and (1n)–(1r) are the radiality constraints. Constraints (1b), (1c), and (1f) are non-convex, while constraints (1l), (1m), (1p), and (1s) are mixed-integer. The MINLP (1) is $\mathcal{NP}$-hard and is impractical to solve, especially at the scale of a full DN. Moreover, such mathematical model lacks details of practical implementations, such as precise network components and their behaviour, which load-flow simulators can provide.

In this work, we propose a reconfiguration method that prioritize feasibility and practicality of the solution, over optimality or speed. For this purpose, we consider DN with all its specificity, without any relaxation or approximation of the power flow and the network components, and use BBO, which is introduced next.

2.2 Blackbox optimization

BBO [7] considers problem of the form

$$\min_{\mathbf{x}\in\mathcal{X}\subseteq\mathbb{R}^n} \quad f(\mathbf{x}) \tag{2a}$$

$$\text{s.t.} \quad g_i(\mathbf{x})\le 0 \qquad i=1,2,\ldots,m, \tag{2b}$$

where $f:\mathcal{X}\subseteq\mathbb{R}^n\to\mathbb{R}\cup\{\infty\}$ is the objective function and $g_i:\mathcal{X}\subseteq\mathbb{R}^n\to\mathbb{R}\cup\{\infty\}$, for $i=1,2,\ldots,m$, are constraint functions. The f and g_i functions are the outputs of a *blackbox*, most commonly a computer simulation, viz., a load-flow simulation in our case. The set $\mathcal{X}$ is the domain of these functions and may include bound constraints. These functions are set to ∞ in cases where the blackbox fails to provide an output. Contrarily to classical mathematical optimization, where the gradients of f and g_i can be exploited, in BBO, no derivative information is available, and so-called *derivative-free methods* must be considered. In addition, querying the functions relying on the blackbox can be resource and time intensive. In our context, BBO allows to accurately model DNs with all the complexities using a dedicated load-flow simulator, instead of variations of the AC-OPF. In the engineering community, these problems are often solved with heuristics due to their relative simplicity of implementation. However, they do not have convergence properties, unlike derivative-free algorithms, such as `MADS`. For a comprehensive overview of BBO applications, see [2]. In the sequel, we employ `MADS` because it can handle multiple types of variables, including continuous and integers, and is publicly available with the `NOMAD` software package [8]. Sustained research and development in electrical power network analysis led to several highly accurate simulators capable of modelling and testing multiples settings and components. Our methods allow to leverage highly accurate load-flow solvers, ensuring feasibility in the decision-making process.

3 Blackbox optimization for distribution network reconfiguration

This section introduces the dedicated BBO model and the proposed resolution methods.

3.1 Optimization model

We reformulate (1) as a BBO problem. We consider the DN as a three-phase unbalanced system that is radially operated and equipped with DERs. In order to fully consider the impact of the ADN technologies, the decision variables are both the switches states and the power injections and absorptions (active power p, reactive power q) of DERs. As described in [13, 17], DERs are typically modelled either with a deterministic formulation, i.e., constant, viewed as a “negative load”, or with a probabilistic formulation, i.e., viewed as a probability density function. For both, the power factor is usually considered constant, thus overlooking the impact of the DN structure (topology, loads, capacitors, etc.). In our model, we consider the DERs as deterministic PQ-controlled components, thus with constant power factor. Because these are decision variables, we study how their output adapts based on the network’s topology and equipments, thus assessing the impacts on the DN itself. This differs from [17, 32] that considers constant DERs, optimizing only on the switches state.

The optimization workflow is detailed below in Figure 1. An evaluation of `NOMAD` represent one cycle of this workflow. Let the input of decision vector $\mathbf{x}$ be

$$\mathbf{x}=\left(\left[\sum_{\phi\in\{a,b,c\}} p^{\phi}_{\mathrm{DER},i}\right]_{i\in\mathcal{N}^{\mathrm{DER}}},\left[\sum_{\phi\in\{a,b,c\}} q^{\phi}_{\mathrm{DER},i}\right]_{i\in\mathcal{N}^{\mathrm{DER}}},[X_{ij}]_{(i,j)\in\mathcal{L}^s}\right).$$

Our goal is to minimize the DN power losses. Let $I_{ij}\in\mathbb{C}^3$ and $r_{ij}\in\mathbb{R}^3$ be the three-phase current phasor and resistance of line $(i,j)\in\mathcal{L}$, respectively. In a radial system, minimizing generation is equivalent to minimizing power losses:

$$\arg\min \sum_{(i,j)\in\mathcal{L}} \sum_{\phi\in\{a,b,c\}} r_{ij}^{\phi}|I_{ij}^{\phi}|^2 = \arg\min \sum_{(i,j)\in\mathcal{L}} \sum_{\phi\in\{a,b,c\}} P_{ij}^{\phi} + P_{ji}^{\phi}$$
$$= \arg\min \sum_{i\in\mathcal{N}} \sum_{\phi\in\{a,b,c\}} p_{g,i}^{\phi} - p_{d,i}^{\phi}$$
$$= \arg\min \sum_{i\in\mathcal{G}} \sum_{\phi\in\{a,b,c\}} p_{g,i}^{\phi} \ .$$

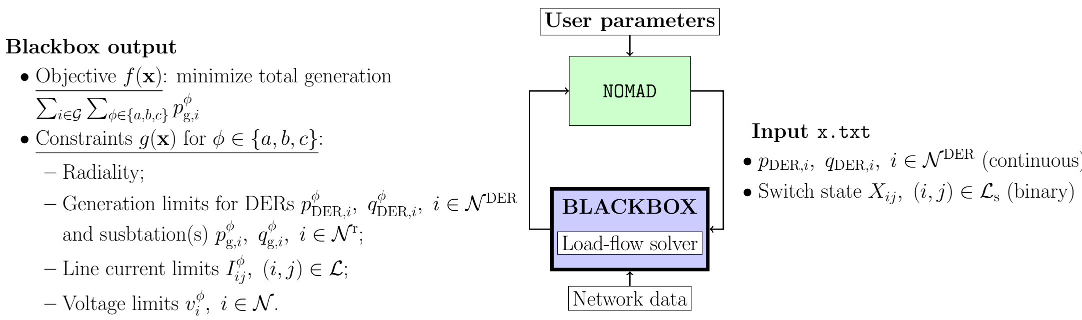


Figure 1: DNR blackbox optimization workflow.

Next, we adapt the DNR constraints to the BBO settings, incorporating typical power system requirements: voltage magnitude at each bus, generated power, including DERs, and line current flows, as defined by

$$|v_i^{\phi}| - \overline{v} \le 0,\ \ \underline{v} - |v_i^{\phi}| \le 0 \qquad i \in \mathcal{N},\ \ \phi \in \{a,b,c\} \tag{3a}$$
$$\left(\sum_{\phi\in\{a,b,c\}} p_{\mathrm{DER},i}^{\phi}\right)^2 + \left(\sum_{\phi\in\{a,b,c\}} q_{\mathrm{DER},i}^{\phi}\right)^2 - (\overline{s}_{\mathrm{DER},i})^2 \le 0 \qquad i \in \mathcal{N}^{\mathrm{DER}} \tag{3b}$$
$$|I_{ij}^{\phi}| - \overline{I}_{ij}^{\phi} \le 0 \qquad (i,j) \in \mathcal{L},\ \ \phi \in \{a,b,c\} \tag{3c}$$
$$\underline{p}_{\mathrm{g},i} - \left(\sum_{\phi\in\{a,b,c\}} p_{\mathrm{g},i}^{\phi}\right) \le 0,\ \ \left(\sum_{\phi\in\{a,b,c\}} p_{\mathrm{g},i}^{\phi}\right) - \overline{p}_{\mathrm{g},i} \le 0 \qquad i \in \mathcal{N}^{\mathrm{r}} \tag{3d}$$
$$\underline{q}_{\mathrm{g},i} - \left(\sum_{\phi\in\{a,b,c\}} q_{\mathrm{g},i}^{\phi}\right) \le 0,\ \ \left(\sum_{\phi\in\{a,b,c\}} q_{\mathrm{g},i}^{\phi}\right) - \overline{q}_{\mathrm{g},i} \le 0 \qquad i \in \mathcal{N}^{\mathrm{r}}, \tag{3e}$$

where (3a) represent the voltage limits in p.u., (3c) enforces the line ampacity limit $\overline{I}_{ij}$, and (3d)–(3e) are the active and reactive power limits of the substation(s). Finally, (3b) represents the apparent power limit of the DERs. The voltage magnitude limit, upper and lower bounds are, respectively, set to $\overline{v} = 1.05$ p.u and $\underline{v} = 0.95$ p.u. The set (3) is enforced continuously throughout the optimization process, ensuring that the resulting solution is feasible. The number of constraints composing (3) is linked to the network size, which can lead to dimensionality issues. To simplify the constraint set in the BBO solver, (3) is aggregated using a formulation inspired by the constraints violation function [7]:

$$g_i(\mathbf{x}) = \sum_{j\in\mathcal{J}} \max\{c_j(\mathbf{x}), 0\}^2 \le 0 \qquad \mathcal{J} = \{1,2,\ldots,m\},\ i = 1,2,\ldots,8, \tag{4}$$

where $g_i(\mathbf{x})$ represents constraints (3a)–(3e), and $c_j(\mathbf{x})$ represents a single instance of the constraint for a given bus, line and phase, e.g., $i = 1$ for (3a), $j = 3$ for bus 3, phase a, yields $c_3(\mathbf{x}) = v_3^a - \overline{v} \le 0$.

At each iteration of the BBO workflow in Figure 1, the load-flow solver is used to evaluate the network's electrical values given $\mathbf{x}$, i.e., a topology and DERs settings. Preceding the load-flow, the radiality and connectivity of $\mathbf{x}$ are verified through graph-theoretic functions. Because micro-grids are not considered, each bus of the network must be connected to the substation. Thus, a feasible topology is a radial and fully connected DN. Islanding is left for future work. The BBO-DNR reconfiguration problem is

$$\min_{\mathbf{x}} \quad \sum_{i\in\mathcal{G}} \sum_{\phi\in\{a,b,c\}} p^{\phi}_{\mathrm{g},i} \tag{5a}$$

$$\text{s.t.} \quad g_i(\mathbf{x}) \leq 0 \qquad i = 1, 2, \ldots, 8, \tag{5b}$$

$$\mathbf{x} \text{ represents a fully radial and connected network,} \tag{5c}$$

where $g_i(\mathbf{x})$, $i = 1, 2, \ldots, 8$ are calculated based on the load-flow results and the input vector $\mathbf{x}$.

3.2 Resolution methods

We propose methods to reduce the resolution time of the BBO-DNR problem (5). Because the BBO solver usually performs better given a limited budget with only continuous variables, we split the mixed-integer problem into a continuous formulation solved by BBO (DERs optimization, fixed topology) and a binary formulation (topology optimization, fixed DER injections) solved using combinatorial optimization-inspired algorithms. This results in an iterative process, with combinatorial optimization seeking a good binary topology, followed by continuous optimization on the DER variables.

3.2.1 Branch-and-bound

The branch-and-bound algorithm [26] (B&B) is a combinatorial optimization method consisting in the exploration of a branching tree until convergence to a local optimal solution. The B&B algorithm partitions the mixed-integer problem in sub-problems, each of them being a different node of the tree. At each level of the tree, a new binary variable of the topology is fixed until we obtain a complete binary solution. Convergence occurs when no more nodes are left to evaluate. In our case, each node of the tree is evaluated with the BBO solver given a limited evaluation budget. The binary variables that are not already fixed are relaxed to continuous variables, meaning that BBO only considers continuous variables, i.e., DERs injections and relaxed switches. Relaxing the switch states is done in the simulator by making the line impedance a continuous variable between 0 and its nominal value, thus affecting the power that can flow through this line. While having no physical meaning, this temporary relaxation allows for a more efficient use of the BBO solver. In typical B&B algorithms, exact upper and lower bounds are used to guarantee convergence to a local optimum solution. However, we can only guarantee that an approximation of these bounds is available given that the problem is not solved to optimality when provided with a limited evaluation budget. In theory, an asymptotic result guaranteeing a local optimum solution could be reached if an infinite evaluation budget was permitted at each step.

3.2.2 Variable neighbourhood search

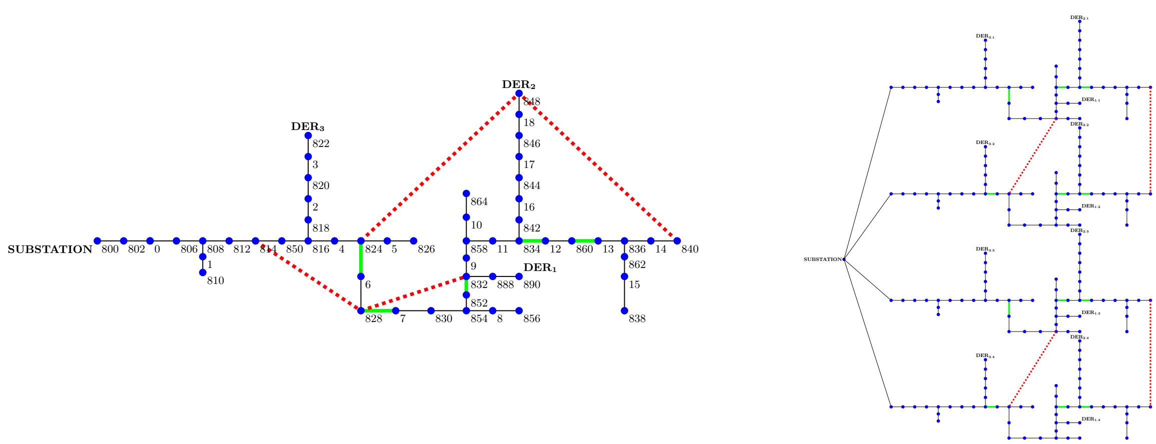
Variable neighbourhood search [25] (VNS) is a meta-heuristic for combinatorial optimization. It performs a local search in the neighbourhood of an initial solution. The procedure selects a new random feasible topology from the neighbourhood of the initial solution. BBO is then carried out for this fixed topology given a limited evaluation budget, and solely focused on continuous variables, i.e., DERs injections. The neighbourhood is incremented, e.g., from two to three switch changes, if there is no improvement compared to the incumbent solution. The stopping criteria is based on a global evaluation budget. As with most meta-heuristic methods, VNS does not have convergence properties.

3.2.3 Combined methods

Finally, we develop methods that combine the speed-up of combinatorial-inspired optimization methods and the feasibility guarantee of BBO to obtain "good" topologies result in a reasonable time and a limited budget. As both algorithms performance are sensitive to the initial conditions, BBO is used both as part of these algorithms and as a warm start. The resolution methods tested are sequences of BBO, VNS, and B&B. First, we implement BBO-VNS and BBO-B&B alone. Second, two longer sequences, BBO-VNS-B&B and BBO-B&B-VNS, are tested to investigate if there is an advantage to combine both combinatorial-inspired algorithms, i.e., if the second can improve the first solution when used as a warm start. The BBO evaluation budget in all these methods is limited and determined in a tuning phase, which is specific to the considered DN. These four resolutions methods are compared to a base case in which BBO is utilized alone with a sufficiently large evaluation budget. The B&B adapted to our problem is an approximation of the exact B&B algorithm while the VNS is a meta-heuristic. Hence, both do not have any convergence guarantee, but the methods used in this work can lead to a "good" solution, likely local optimum. The solution will, however, always be feasible with respect to the network constraints due to the embedded BBO steps, thus ensuring the practicality of our approach.

4 Case studies

We evaluate the performance of our methods on three different DN benchmarks: the IEEE 34-bus test system, a 136-bus, made of four 34-bus test systems, and the IEEE 8500-bus system. All networks are modified to integrate a number of DERs, and tie and sectionalizing switches. The test cases are modelled and simulated using a state-of-the-art commercial load-flow solver and connected to the numerical implementation of our methods via a dedicated API. The DERs are modelled as PQ-controlled load-flow components and the substation as a slack source. All switches are modelled as ideal switching components. We remark that our methods are independent of the load-flow simulator and any other software could be used, as long as the output/input formatting is the same as described in Figure 1.



(a) IEEE 34-bus network

(b) 136-bus network

Figure 2: Test systems models (green line: sectionalizing switch; red dashed line: tie switch).

4.1 IEEE 34-bus test feeder

The IEEE 34-bus test feeder [20] is a 24.9 kV multi-phase network with unbalanced loads, consisting of primary three-phase buses and secondary single-phase buses on the laterals. The DERs are positioned in critical undervoltage regions, as seen on the base case, which is coherent with [18]. As for the switches, they are placed to facilitate network reconfiguration while ensuring radiality and connectivity, based on [18, 21]. The modified network is illustrated in Figure 2a, where green and red dashed lines are sectionalizing and tie switches, respectively. The DERs are located at buses 890, 848, and 822. There are a total of three DERs, five sectionalizing switches, and four tie switches, resulting in a 15 decision variables in the optimization problem, where six are continuous, i.e., two variables per DER, and nine are binary.

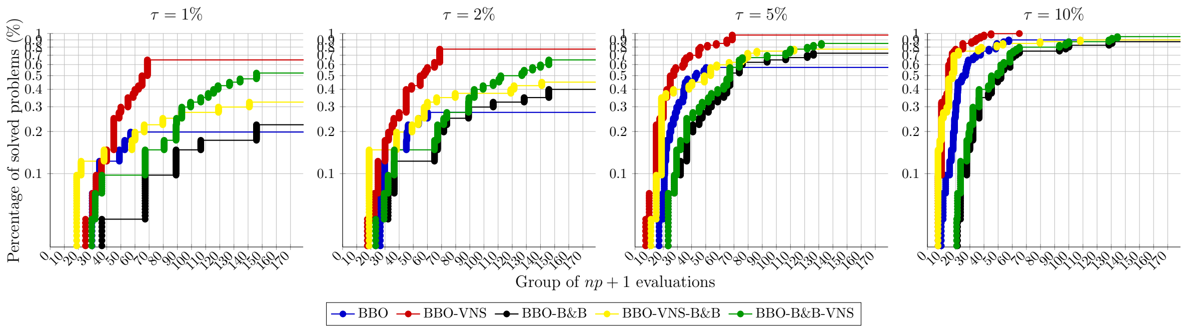


Figure 3: Results for the 34-bus network for tolerances τ of 1, 2, 5, and 10 %.

Figure 3 presents data profiles for the 34-bus system. Data profiles compare the efficiency and the robustness of optimization algorithms. To obtain the profiles, each algorithm is run on the same set of 40 problems, with random variations in load profiles and initial points to test robustness. Data profiles present the proportion of problems solved within a certain tolerance $\tau > 0$ compared to others, given a certain number of evaluations. The tolerance indicates how close the solution is to the best result obtained among all algorithms for the same problem. A small tolerance means a high level of precision, while a larger one indicates a less strict level of precision [7].

As shown in Figure 3, the best-performing method is BBO-VNS, followed by BBO-B&B-VNS, where adding a VNS step after B&B significantly improves performance. As seen with BBO-B&B-VNS, B&B is more computationally demanding but competes with VNS and BBO after enough evaluations. VNS, as anticipated for a meta-heuristic, is the fastest and appears to be the most consistent in reducing losses. All methods are generally more consistent in minimizing the power losses than the base case BBO. Table 1 shows the mean power loss reduction and the corresponding standard deviation achieved by each method, compared to the base case. The base case consists of the original topology (opened tie switches and closed sectionalizing switches) with DERs injections ensuring network constraint are satisfied, as without DERs the base case is unfeasible. We see that loss reduction is important and ranges from 78.06% for BBO-B&B to 80.14% for BBO-VNS. Moreover, solutions across all algorithms typically differs from the original topology. When deployed, the choice of resolution methods depends mostly on the practical requirements. If computation time and feasibility are the main drivers, BBO-VNS is the best option. However, BBO-B&B-VNS may be preferred when higher confidence on the solution quality is desired, and a larger budget is allowed.

4.2 136-bus system

The 136-bus is a setup of four instances of the IEEE 34-bus, resulting in a four feeder configuration. The base case for this network also considers DERs injections, otherwise the network constraint are not satisfied. As described previously, three DERs are added at buses 890, 848, and 822 for each feeder. Four tie switches, as seen in Figure 2b as dashed red lines, enables connection between pairs of feeders. To ensure radiality and connectivity, three sectionalizing switches are placed on each feeder and are illustrated by green lines in Figure 2b. There are a total of 12 DERs, 12 sectionalizing switches, and four tie switches, which results in 40 decisions variables, where 24 are continuous and 16 are binary.

This is a much larger problem instance when compared to the IEEE 34-bus and, therefore, is more challenging to solve.

Figure 4 provides the data profiles for the 136-bus system. Both BBO-B&B-VNS and BBO-VNS-B&B are more consistent than BBO-VNS, achieving overall lower losses with a sufficient evaluation budget. In particular, the VNS step in BBO-VNS-B&B provides an efficient warm start, allowing it to outperform quickly the other methods. We notice that fewer problems are solved by our methods, suggesting that the higher dimension poses significant challenges. Specifically, for BBO-VNS, we had to double the evaluation budget to avoid under-performance compared to the other methods. This suggests that the reconfiguration problem is challenging and prone to dimensionality issues. Moreover, the more guided process of B&B appears to have an advantage over the random VNS process due to these difficulties. From Table 1, we see that the loss reduction compared to the base case is slightly less than for the 34-bus but still significant, ranging from 36.94% for BBO-B&B to 60.90% for BBO-VNS. Again, the solution for all problems across all algorithms typically differs from the original topology. Similar to the 34-bus example, the choice of resolution method for this benchmark depends on how the system operator prioritizes the balance between computational time and the desire to minimize power loss consistently, where the former would correspond to BBO-VNS, whereas the latter to BBO-VNS-B&B.

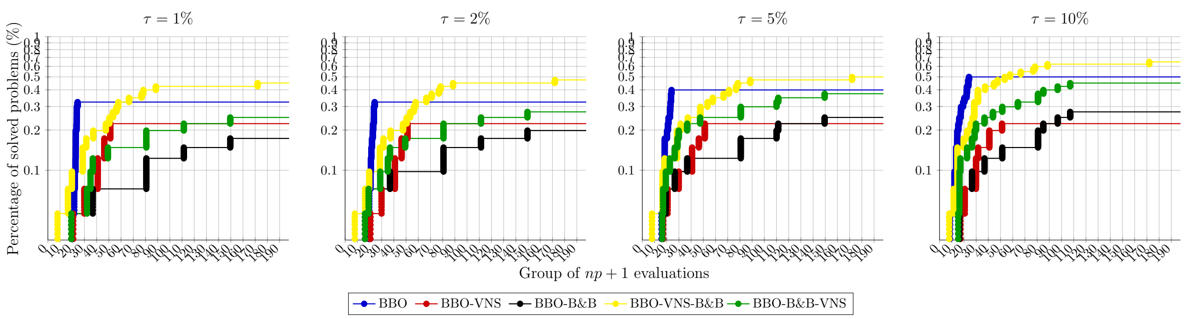


Figure 4: Results for the 136-bus network for tolerances τ of 1, 2, 5, and 10 %.

4.3 IEEE 8500-bus

The IEEE 8500-bus [5] power network is a complex, unbalanced distribution network with one feeder powered by a 115 kV HV substation. It includes a primary 12.47 kV MV three-phase network and one- or two-phase laterals, which are connected to secondary 208 V LV loads through distribution transformers. Five DERs are added the network, with their positions partially inspired by [4, 28]. These are either regions at risk of undervoltage, as seen in [22], regions far from the substation or at strategic line splits. For network reconfiguration, the three tie switches are based on [27], the DER positions, and the network structure, and the five sectionalizing are placed to ensure radiality and connectivity. There are a total of five DERs, five sectionalizing switches, and three tie switches. This adds up to 18 decisions variables for the mixed-integer optimization problem, where 10 are continuous, and 8 are binary. This problem is larger than the IEEE 34-bus test feeder but smaller than the 136-bus in terms of optimization variables. However, the 8500-bus system effectively captures key aspects of a DN, i.e., realistic size, varying voltage levels, unbalanced loads, and different types of phase connections. For this reason, it is crucial to assess the practical performance of our methods.

Table 1 shows results using the same parameters as the 136-bus examples, applying the methods once. The base case without DERs and reconfiguration is unfeasible due to undervoltages at buses and line current limit violations. Given the network's complexity, finding arbitrary DER injections that render the network feasible is difficult. Therefore, the DER injections are the first ones obtained with BBO, for the fixed original topology, that satisfy the network constraints. Additionally, voltage limits are relaxed to $\overline{v} = 1.1$ p.u and $\underline{v} = 0.9$ p.u. Table 1 shows that BBO-VNS achieves the largest power loss reduction, followed by BBO-B&B-VNS, both being the only methods that produced a different topology from the initial one. We note that the VNS process may return different outcomes, as observed, for example, when comparing the BBO-VNS-B&B to the BBO-VNS, where the former significantly underperformed the latter despite using a VNS process at the same stage. This highlights the stochastic nature of the VNS step and its potential variability in results.

System	Base case (MW)	Mean power loss reduction (standard deviation) [%]				
		BBO	BBO-VNS	BBO-B&B	BBO-VNS-B&B	BBO-B&B-VNS
34-bus	0.0714	78.74 (2.290)	80.14 (0.969)	78.06 (5.148)	78.83 (2.204)	79.96 (2.016)
136-bus	0.1459	43.99 (15.005)	60.90 (13.918)	36.94 (23.841)	48.08 (15.376)	47.86 (18.200)
8500-bus	0.6249	10.78	32.24	9.82	9.82	11.34

Table 1: Summary of the results observed for the base load profile, along with results for the 8500-bus.

5 Conclusion

To efficiently integrate DERs in DNs, a reconfiguration method is essential to mitigate potential impacts, such as bidirectional power flows, increased phase imbalances, abnormal voltages, and power losses. The proposed methods are dedicated to DNR and DER integration in DNs. They combine BBO, that leverage a high-accuracy load-flow solver to ensure feasibility, with combinatorial optimization-inspired techniques to improve efficiency. They rely either on heuristics or approximations. While they do not guarantee a global optimum, they instead always provide feasible solutions likely close to local optima. The results highlight how DERs influence the network structure and illustrate the benefits of combining them with DNR to reduce power losses and ensure constraints feasibility, namely, a voltage magnitude profile satisfying both upper and lower operational limits, which is challenging with conventional optimization techniques based on approximations and relaxations. In all test cases, the average power loss reduction compared to the base case is more than 36.94% for the 136-bus system, 78.06% for the 34-bus system, and 9.82% for the IEEE 8500-bus practical case. The highest loss reductions for the IEEE 8500-bus are achieved when the methods generate a topology different from the initial one, further demonstrating the efficiency of the proposed methods for DNR with DERs integration. The results highlight two choice of methods for deployments. If computational time is the main concern, BBO-VNS is the best option. However, if higher confidence in the solution and greater power loss reduction are desired, BBO-B&B-VNS or BBO-VNS-B&B are preferred, with BBO-VNS-B&B proving more efficient for higher-dimensional problems, as demonstrated in the 136-bus system case. Presently, DNR is typically applied in response to network perturbations, such as a line faults, or based on pre-programmed scenarios. In the context of DER integration in ADN, we view it as an active strategy to mitigate and improve network constraints during nominal operation. We plan to conduct a more extensive case study on the IEEE 8500-bus to better assess the methods' performance on such a complex network. Additionally, we aim to explore techniques for scaling the algorithms to larger problems, i.e., large-scale DN with many switches and DERs, and investigate means to integrate load and DER uncertainty within the BBO formulation.

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