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Artificial immune algorithm applied to distribution system reconfiguration with variable demand

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ABSTRACT

This paper presents a new methodology to solve the reconfiguration problem of electrical distribution systems (EDSs) with variable demand, using the artificial immune algorithm Copt-aiNet (Artificial Immune Network for Combinatorial Optimization). This algorithm is an optimization technique inspired by immune network theory (aiNet). The reconfiguration problem with variable demand is a complex problem of a combinatorial nature. The goal is to identify the best radial topology for an EDS in order to minimize the cost of energy losses in a given operation period. A specialized sweep load flow for radial systems was used to evaluate the feasibility of the topology with respect to the operational constraints of the EDS and to calculate the active power losses for each demand level. The algorithm was implemented in C++ and was evaluated using test systems with 33, 84, and 136 nodes, as well as a real system with 417 nodes. The obtained results were compared with those in the literature in order to validate and prove the efficiency of the proposed algorithm.

Introduction

In recent years, many investments have been directed toward electrical distribution systems (EDSs) in order to modernize and automate their operations, and increase profitability. These modernization efforts have aimed at meeting several requirements, such as improving the reliability, efficiency, and security of the system, and satisfying strict regulatory rules. In light of these aims, much research is currently being conducted to solve the distribution system reconfiguration (DSR) problem using new approaches and techniques.

The DSR problem consists of identifying the best radial topology for the EDS through the opening and closing of switches in order to optimize an objective function, which is typically the minimization of active power losses. This is subject to the technical operational constraints of the EDS, such as the condition of radiality, nodal voltage limits, branch current capacity limits, and the first and second Kirchhoff's laws (active and reactive power balance). Apart from this typical formulation, the DSR can also be performed primarily to improve the voltage levels, to maintain or enhance the reliability of the network, to help network operators to isolate faults more quickly, and to help prepare plans for preventive maintenance actions [1].

The DSR problem is a complex and combinatorial problem that can be modeled as a mixed-integer nonlinear programming (MINLP) problem [2]. Thus, as the size of the EDS increases, it becomes more difficult to solve this problem using exact methods. As a result, intelligent optimization techniques, such as heuristic and meta-heuristic algorithms, artificial neural networks, and artificial immune systems, among others, are increasingly being applied to solve this problem. These techniques include effective strategies that reduce the search space, enabling the best solution or at least good-quality solutions to be found.

The DSR problem has been widely addressed in the literature, yet most of the approaches have only considered one demand level at each consumption node, corresponding to the peak level. However, since demand varies over time, some authors have addressed the problem considering the variation in demand, for example, separating the demand into the 24 h of the day and following the daily variation of the demand curve. Accordingly, the DSR problem

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with variable demand aims at identifying an unique radial topology that operates at different demand levels, while minimizing the cost of energy losses in a given operation period.

The literature includes references that have used several approaches to address the DSR problem considering fixed demand, such as heuristic algorithms [2,3] and meta-heuristics including genetic algorithms [4], simulated annealing [5], tabu search [6], ant colony [7], artificial neural networks [8], and artificial immunological algorithms [9]. On the other hand, few references have considered the DSR problem with variable demand, as in [10–13].

In this paper, the Copt-aiNet (Artificial Immune Network for Optimization) [14] is proposed to solve the DSR problem with variable demand. This technique is inspired by biological immune systems, providing a computational emulation of the main properties and functionalities of the organism with respect to immune network theory (aiNet). To evaluate the affinity of each antibody, a specialized sweep load flow for radial EDSs is used [15] for each demand level in order to estimate the cost of energy losses in each operation period.

Notably, in this paper, the DSR problem is analyzed with variable demand, representing a natural extension of paper [9] in which the authors analyzed the DSR problem considering only fixed demand.

This paper presents results using test systems with 33, 84, and 136 nodes, and a real system with 417 nodes. These results are compared with the results available in the specialized literature in order to assess the efficiency of the proposed approaches.

Mathematical model for the DSR problem with variable demand

Considering a symmetrical and balanced system with a unique radial topology, the DSR problem with variable demand can be modeled as an MINLP problem, as described in (1)–(9) [16]:

$$Min \quad v = \sum_{d \in \Omega_d} \sum_{ij \in \Omega_l} c_d^l \Delta_d [g_{ij} x_{ij} (V_{i,d}^2 + V_{j,d}^2 - 2V_{i,d} V_{j,d} \cos \theta_{ij,d})] \tag{1}$$

s.a.

$$Ps_{i,d} - Pd_{i,d} - \sum_{j \in \Omega_{bi}} (x_{ij} P_{ij,d}) = 0 \quad \forall i \in \Omega_b, \forall d \in \Omega_d \tag{2}$$

$$Qs_{i,d} - Qd_{i,d} - \sum_{j \in \Omega_{bi}} (x_{ij} Q_{ij,d}) = 0 \quad \forall i \in \Omega_b, \forall d \in \Omega_d \tag{3}$$

$$\underline{V} \leqslant V_{i,d} \leqslant \overline{V} \quad \forall i \in \Omega_b, \forall d \in \Omega_d \tag{4}$$

$$(P_{ij,d}^2 + Q_{ij,d}^2) \leqslant \overline{S_{ij,d}^2} * x_{ij} \quad \forall ij \in \Omega_l, \forall d \in \Omega_d \tag{5}$$

$$x_{ij} \in \{0, 1\} \quad \forall ij \in \Omega_l \tag{6}$$

$$\sum_{(ij) \in \Omega_l} x_{ij} = n_b - 1 \tag{7}$$

In this formulation:

Ω_l is the set of circuits;
Ω_b is the set of nodes;
Ω_{bi} is the set of nodes connected at node i;
Ω_d is the set of demands;
c_d^l is the cost of energy losses at demand level d;
$\Delta_d$is the duration of demand level d;
g_{ij} is the conductance of circuit ij;
$V_{i,d}$ is the voltage magnitude at node i at demand level d;
$\theta_{ij,d}$ is the phase angle difference between nodes i and j at demand level d;
b_{ij} is the susceptance of circuit ij;
$P_{ij,d}$ is the active power flow that goes from node i to node j at demand level d;
$Q_{ij,d}$ is the reactive power flow that goes from node i to node j at demand level d;
$Ps_{i,d}$ is the active power supplied by the substation at node i at demand level d;
$Qs_{i,d}$ is the reactive power supplied by the substation at node i at demand level d;
$Pd_{i,d}$ is the active power demanded at node i at demand level d;
$Qd_{i,d}$ is the reactive power demanded at node i at demand level d;
$\underline{V}$ is the minimum voltage magnitude;
$\overline{V}$ is the maximum voltage magnitude;
$\overline{S_{ij,d}}$ is the maximum apparent power of circuit ij at demand level d;
n_b is the number of nodes in the system;
x_{ij} is the binary decision variable that represents the state (connected or disconnected) of circuit ij.

In this formulation, (1) represents the objective function of the DSR problem with variable demand. It corresponds to the cost of energy losses to be minimized in the EDS. The mathematical model also considers physical constraints, the specifications of system components, and operational conditions.

Constraints (2) and (3) represent the active and reactive nodal balance equations in which the active and reactive power flows $P_{ij,d}$ and $Q_{ij,d}$ are calculated using (8) and (9), respectively.

$$P_{ij,d} = V_{i,d}^2 g_{ij} - V_{i,d} V_{j,d} (g_{ij} \cos \theta_{ij,d} + b_{ij} sen\theta_{ij,d}) \tag{8}$$

$$Q_{ij,d} = -V_{i,d}^2 b_{ij} - V_{i,d} V_{j,d} (g_{ij} sen\theta_{ij,d} - b_{ij} \cos \theta_{ij,d}) \tag{9}$$

Constraint (4) represents the voltage magnitude limits for each node of the EDS, as defined by regulatory standards. The power flow in each circuit is limited by (5). Constraint (6) corresponds to the binary nature of the decision variables, according to which x_{ij} can take two values as follows: when it is 0 (zero), circuit ij is open (or disconnected), and when it is 1 (one), circuit ij is closed (or connected).

Constraint (7) presents one of the necessary conditions to guarantee the radial operation of the EDS, namely, that a solution to the problem must have $(n_b - 1)$ active circuits. The other necessary condition is that the system must be connected (i.e., all nodes connected). This condition is guaranteed by (2) and (3). Thus, satisfying (2), (3), and (7) ensures that any feasible solution, as well as the optimal solution, will be radial [17].

Artificial immune systems

Artificial immune systems (AISs) are compounds of a set of intelligent algorithms inspired by the functioning of biological immune systems. Similar to other bio-inspired methods and meta-heuristics, the main objective of AISs is to solve complex problems that cannot be addressed in a timely manner by classical optimization methods [9,18].

In the literature, AISs have been widely used to solve optimization problems. In this context, the immune algorithms most frequently mentioned in the literature are the CLONALG algorithm (Clonal Selection Algorithm) [19], the aiNet (Artificial Immune Network) [20], the Opt-aiNet algorithm [18], the B-cell (BCA) algorithm [21], and the Copt-aiNet algorithm [14].

In this paper, the Copt-aiNet is used to solve the DSR problem with variable demand.

Copt-aiNet algorithm

The Copt-aiNet was originally proposed in [14]. This technique is an extension of the aiNet to solve combinatorial optimization problems, and can be described in the following steps: