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Optimal Reconfiguration of Radial Distribution Networks Using a Multi-Objective Differential Evolution Algorithm

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***Abstract*— The power grid is hierarchical, consisting of three main parts with distinct functions. The transmission system's primary role is to transport high-voltage energy from production centers to consumption areas. The distribution network, on the other hand, directly supplies large industrial consumers and also delivers electricity to medium- and low-voltage consumers. With the latest advancements in industry and technology, the demand for electricity is continually increasing. These developments necessitate the optimization of the distribution network to balance supply and demand effectively.A significant portion of power losses and voltage deviation problems in power systems occurs in the distribution network, where power losses are estimated to account for approximately 14%. This paper explores the application of a multi-objective Differential Evolution (DE) algorithm, developed in MATLAB, to optimize the distribution network reconfiguration with the goals of minimizing power losses and improving voltage deviation.To evaluate the effectiveness of the proposed algorithm, IEEE 33 bus distribution systems is used. The results from two objective functions are compared to demonstrate the algorithm's performance.**

Keywords— Radial distribution network, multi objective optimization, differential evolution, evolutionary algorithms, Optimal Radial Distribution Network Reconfiguration.

I. Introduction

As electricity demand continues to rise, the distribution network must now be capable of analyzing and adapting to new uses. Specifically, it needs to accommodate the growing integration of renewable energy sources (such as wind and photovoltaics), the rise of electric vehicles, and the overall increase in electricity consumption. These changes require the development of new tools to continuously optimize the network and maintain a balance between electricity supply, demand, and system constraints.

Power flow calculations are among the most commonly performed analyses in electrical power systems. The goal is to determine the complete electrical state of the network, including voltages at all buses, power flows along all lines (branches), and power losses, based on specified consumption and production at each bus. A significant portion of power losses in power systems occurs in the radial distribution network (RDN). Approximately 14% of all the power conveyed by distribution networks is lost due to these losses. This high level of loss has led distribution companies to focus on mitigating losses and addressing voltage deviation issues in the RDN.

Given initial configuration data and the fact that active power demand is fixed, reducing voltage deviation and power losses can be achieved through optimal RDN reconfiguration, a concept introduced by Merlin and Back in 1975 [1][2].

Solving the optimal RDN reconfiguration problem involves determining the optimal states of switches while ensuring that system constraints are satisfied. The objective function focuses on reducing power losses and minimizing voltage deviation, thereby improving operational reliability and enhancing the security of various network configurations. Several techniques have been proposed in the literature to address the optimal distribution network reconfiguration problem, aiming to minimize power losses and/or improve the voltage profile in the network.

In [3], a multi-agent system (MAS) based on game theory is applied, where each agent evaluates the impact of its decisions based on available information. M. Farrokhifar et al. [4] developed a genetic algorithm focused on reducing power losses, incorporating the varying nature of load and energy costs in the loss calculation. Additionally, L. Zamboni and L. H. A. Monteiro [5] applied an algorithm inspired by ant behavior to the distribution system in São Paulo (Brazil), demonstrating that the solution found outperformed the results provided by the concessionary company.

In [6], the authors propose a multi-objective reconfiguration approach using a discrete particle swarm algorithm to find non-dominated solutions along the Pareto front. The results are compared with other approaches available in the literature. A. R. Jordehi [7] summarizes various optimization algorithms applied to distribution system optimization problems, noting that meta-heuristics have proven to be effective. A. Asrari [8] emphasizes the importance of artificial intelligence algorithms for optimizing distribution topology and proposes a new adaptive fuzzy-based parallel genetic algorithm (GA) that leverages parallel computing to identify the optimal network configuration.

According to the literature review by the author in [9], evolutionary algorithms, particularly differential evolution, are the most commonly used methods for solving network reconfiguration optimization problems. These algorithms are favored due to their lower complexity, ease of implementation, and higher robustness compared to other evolutionary algorithms. In this paper, a multi-objective differential evolution (DE) algorithm is used to address the distribution system reconfiguration problem, aiming to minimize power loss and improve voltage deviation.

II. Problem Formulation

The function of distribution networks is to deliver electricity from high-voltage substations to consumers, adjusting the voltage levels as necessary. There are two main operating modes: normal and disturbed. In normal mode, the system operates with a radial topology, and all electrical constraints are satisfied. This includes maintaining the voltage at each bus within a specified range and ensuring that the currents in the lines do not exceed their maximum permissible values. However, even when all constraints are met, there may be a need to change the network topology to better align with customer needs and the goals of network operators. These operators aim to reduce costs by minimizing power losses, reducing voltage drops, and balancing currents—this is the essence of optimal radial distribution network (RDN) reconfiguration.

A. Objective Function

In this work, graph theory is employed to identify the optimal topology of the distribution network. A multi-objective differential evolution (DE) algorithm is used to automatically generate a network configuration that minimizes two key objectives: power losses and voltage drops. These objectives are represented by the following non-linear functions:

$$f_{obj} = \alpha f_{obj1} + \beta f_{obj2} \tag{1}$$

With

$$\begin{aligned} f_{obj1} &= \min \sum_{i=1}^{N_{br}} P_{loss}(i) \\ f_{obj2} &= \min \sum_{i=1}^{N_{br}} dV(i) \end{aligned} \tag{2}$$

Where

Nbr is the number of branches in the distribution network.
Ploss is the power loss in one branch.
dV is the voltage drop.

α and β are the weighting factors for power loss and voltage deviation, respectively, used to prioritize the relative objective functions.
The first objective function is formulated as follows:

$$f_{obj1}(X) = \min \sum_{i=1}^{N_{br}} K_i * R_i * I_i^2 \tag{3}$$

Ki =1, if branch i is closed, and Ki=0, if branch i is open. X is the vector of decision variables that represents the state of the switches in the distribution system. Each switch is encoded in integer format, corresponding to the candidate for radial configuration [10]–[12].

The second objective function is formulated as follows:

$$f_{obj2}(X) = \min \sum_{i=1}^{N_{br}} \left(\frac{V_i - V_{ref}}{V_{ref}}\right)^2 \tag{4}$$

B. Problem Constraints

The equality constraints of the problem are represented by the power flow equations, which are defined as follows:

$$\begin{aligned} P_i - V_i \sum_{j=1}^{N_{bus}} V_j Y_{ij} \cos(\sigma_i - \sigma_j - \theta_{ij}) = 0 \\ Q_i - V_i \sum_{j=1}^{N_{bus}} V_j Y_{ij} \sin(\sigma_i - \sigma_j - \theta_{ij}) = 0 \end{aligned} \tag{5}$$

The inequality constraints are given by:

$$\begin{aligned} V_{imin} \le |V_i| \le V_{imax} \\ |I_i| \le I_{imax} \end{aligned} \tag{6}$$

Topology constraints: The distribution network must maintain a radial structure. This is expressed as:

$$N_{br} = N_{bus} - 1 \tag{7}$$

Where:

N_{br}: Number of branches in the distribution network, including normally open switches that maintain the radial structure.

N_{bus}: Number of connected buses.

The number of branches, N_{br}, ensures that the network remains a connected tree structure, with all buses connected to the source node [13].

III. Proposed Method

The optimal RDN reconfiguration problem is typically defined as finding the switching configuration of network branches that minimizes power losses while maintaining an appropriate voltage profile, ensuring the power system operates at full efficiency. As such, the reconfiguration problem is formulated as an optimization challenge requiring a robust and effective solution method.

Solving this optimization problem is complex due to the numerous interacting factors involved. Meta-heuristic algorithms are among the most widely used methods for addressing this challenge. These algorithms are often inspired by natural processes, such as evolution, and can be described as stochastic, iterative techniques. They operate by manipulating one or more populations of solutions to search for the global optimum. Through successive iterations, these algorithms aim to improve solutions progressively, avoiding stagnation at local optima and converging toward the optimal configuration.

The Differential Evolution (DE) Algorithm is a simple yet effective Evolutionary Algorithm (EA) initially proposed by R. Storn and K. Price [14] as a global optimization technique for continuous spaces. Like other evolutionary algorithms, DE is based on three key operators: mutation, crossover, and selection. The core idea of DE is to use the difference between two randomly selected vectors to create a new vector solution. For each candidate solution in the current population, a new solution is generated through these evolutionary operators. The old solution (parent) and the new one are then compared, with the better solution selected for the next generation.

An initial population of N_p individuals (potential solutions), each of dimensionality D, is uniformly generated within the search space. Each individual X_G in generation G undergoes mutation and crossover operations.

The mutation operator is defined as:

$$X_i'^{G} = X_{r3}^{G} + F(X_{r1}^{G} - X_{r2}^{G}) \qquad (8)$$

In the mutation operator,

r_1, r_2, and $r_3 \in \{1,...,N_p\}$ are randomly selected indices such that $r_1 \neq r_2 \neq r_3$. $F$is a scaling factor that controls the speed and robustness of the search, with its value typically ranging between [0.4,1] [15]–[19]. A higher value of F leads to faster convergence but increases the likelihood of converging to a local optimum.

The crossover operator is applied to each pair of the individual X_i^G and its mutated vector $X_i^{G'}$ to generate a trial vector $X_i^{G''}$ [14]. The standard version of the crossover can be expressed as:

$$X_{i,j}''^{G} = \{X_{i,j}'^{G} if(rand_j[0,1] \leq C_R) or (j = j_{rand}) \\ X_i^G otherwise \qquad (9)$$

Where j rand is an integer randomly selected within the range $[1,N_p]$, and the crossover probability C_R is a user-specified parameter in the range [0,1]. The indices i=1,…,N_p and j=1,…,D represent the individuals and the imensionality of the solution, respectively.

Finally, the selection operator is used to choose the better individuals for the next generation. In DE, local selection is performed, where each parent is compared to its offspring, and the better of the two is selected to be part of the next generation.

$$X_i^{G+1} = \{X_{i,j}'^{G} if(f(X_i'^{G}) \leq f(X_i^G) \\ X_i^G otherwise \qquad (10)$$

It is evident that proper tuning of key algorithm parameters such as population size (Np), mutation factor (F), and crossover factor (CR) plays a critical role in enhancing the effectiveness of the method.

The flowchart of the proposed algorithm is shown in Fig. 1, illustrating the step-by-step process of the Differential Evolution (DE) algorithm for solving the optimization problem.

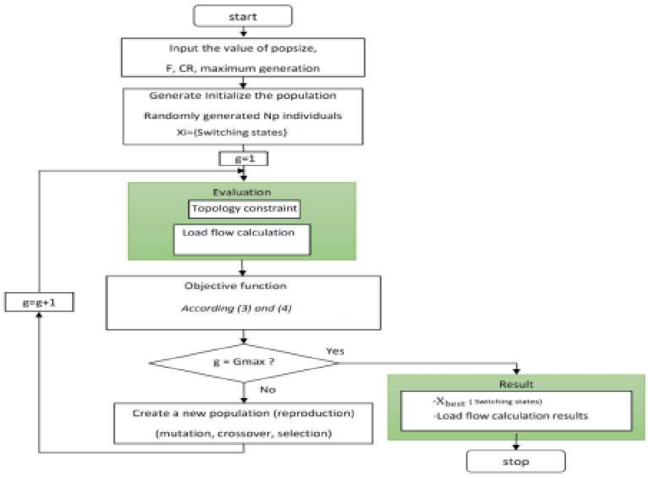

Fig. 1. Flow chart of proposed methodology

IV. Results and Discussions

An application of the Differential Evolution (DE) algorithm has been presented to determine the optimal configuration for radial distribution networks. The proposed method was tested on IEEE 33 bus distribution system, with the results discussed in this section.

The application parameters for the DE algorithm, used to solve the distribution network reconfiguration problem and achieve an optimal configuration, are as follows:

Problem dimension (D) = 5

Population size (Np) = 5×D=25

Mutation factor (F) = 0.5

Crossover factor (CR) = 0.75

Maximum generations (GENmax) = 100

Fig. 2 presents the single-line diagram of the IEEE 33-bus radial distribution system.

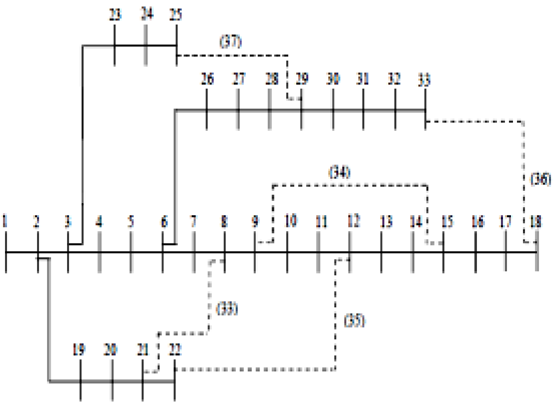

Fig. 2. Single line diagram of the IEEE 33 bus

The system initially includes five open switches (33, 34, 35, 36, and 37), represented by dotted lines in Fig. 2, while the normally closed switches (132) are shown as solid lines. The initial power losses of this system are 0.1940 MW and 0.1039 MVAR, with the minimum node voltage observed at node 18, recorded at 0.9539 pu.

After reconfiguration using the DE algorithm, the power losses are reduced to 0.1374 MW and 0.0787 MVAR. The minimum node voltage remains at node 18 but improves to 0.9829 pu. The results of the reconfiguration process are summarized in Table 1.

TABLE I. RSULTS BEFORE AND AFTER RECONFIGURATION FOR IEEE 33 BUS SYSTEM

State	Base case	Optimal case (DE)
Switches(from-to)	8-21;9-15;12-22 ;18-33;25-29	6-7;11-12;14-15 ;20-21;25-29
Active loss(MW)	0.1940	0.1374
Reactive loss(MVAR)	0.1039	0.0787
Voltage (pu)	0.9539	0.9829
Voltage node	18	18

The system voltage profiles, comparing the voltage profile obtained after reconfiguration using DE with the initial voltage profile before reconfiguration, are depicted in Fig. 3.

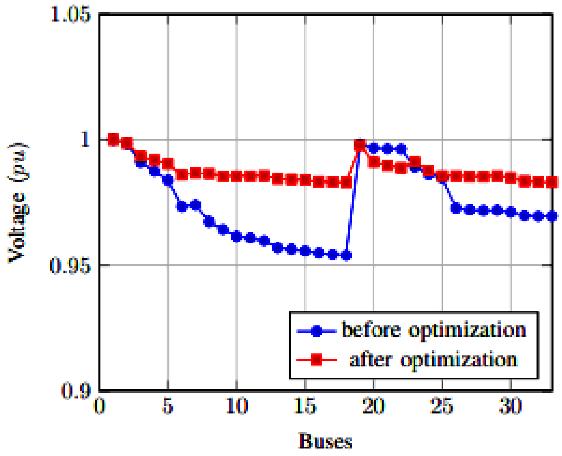

Fig. 3. System voltage profiles for IEEE 33 Bus System

V. CONCLUSION

This paper presented a Multi-Objective Differential Evolution (DE) algorithm successfully applied to the distribution network reconfiguration problem. The algorithm aimed to minimize total power losses and improve voltage deviation. The results demonstrated an approximately 11% reduction in active power losses, with all voltages remaining within their acceptable limits. Future work should explore the impact of large-scale integration of distributed generation (DG) and renewable energy sources on the distribution system. Additionally, investigating the optimal placement of these sources could further enhance the performance and efficiency of radial distribution networks (RDNs).

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