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DISTRIBUTION NETWORK RECONFIGURATION FOR LOSS MINIMISATION USING DIFFERENTIAL EVOLUTION ALGORITHM

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ABSTRACT

This paper presents a method of reducing the losses and balancing the loads in the radial distribution network. Differential evolution strategy is used for reconfiguration of the radial distribution network. Multiple objectives such as loss reduction, voltage deviation and maximum branch current are considered. These objectives are integrated into the objective function through weighting factors and the configuration with minimum objective function is selected for each tie-switch operation. The proposed methodology is tested and validated on 33 radial bus distribution networks. Performance is assessed by using the results of the implemented algorithm with various other algorithms.

Keywords: radial distribution network, differential evolution, tie-switch, Multiobjectives.

1. INTRODUCTION

Distribution network acts as an interface between the transmission network and consumers. Because of low short circuit current and easier protection co-ordination radial configuration is preferred. On the same note, radial structure has a check on the reliability of the consumers, increase in the real power losses, voltage deviations, and increase in the branch currents etc.

Out of totally generated electrical power, 13% of power is accounted for distribution losses. These losses must be reduced so that power system costs due to increase in losses can be improved. Feeder reconfiguration is an important strategy in order to keep check on the problems arising due to the radial structure of the distribution system.

Serious researches have been carried out in the reconfiguration strategies and many new methods have been formulated. Merlin *et al*. [1] were the first to report a method for distribution system reconfiguration to minimize line losses. They formulated the problem as integer mixed non-linear optimization problem and solved it by a discrete branch-and-bound technique. Baran *et al*. [3] developed a heuristic algorithm based on the idea of branch exchange for loss minimization and load balancing. To assist in the search, two approximated load flows for radial networks with different degrees of accuracy were used. They are simple Distribution flow method and back and forward update of distribution flow method. The method is very time consuming due to the complicated combinations in large-scale system and converges to a local optimum solution, that is, convergence to the global optimum is not guaranteed. Martín *et al*. [5] presented a new heuristic approach of branch exchange to reduce the power losses of distribution systems based upon the direction of the branch power flows. Mendoza *et al*. [6] proposed a new methodology for minimal loss reconfiguration using GA by the help of fundamental loops. Yu and Wu [7] reported an efficient global optimization algorithm named core schema genetic shortest algorithm (CSGSA) for problems of large-scale distribution network reconfiguration. CSGSA changes from branches combination to loads combination. CSGSA has a powerful global optimum using core schema algorithm. Huang [9] proposed an enhanced GA based on fuzzy multi-objectives approach maximizing the fuzzy satisfaction allows the operator to simultaneously consider the multiple objectives of the network reconfiguration to minimize the power loss, deviation of voltage and current constraints as well as switching number, which subject to a radial network structure in which all loads must be energized. In [9], Swarnkar introduced an efficient method for the multi-objective reconfiguration of radial distribution networks in fuzzy framework using adaptive particle swarm optimization. The initial population of particle swarm optimization is created using a heuristic approach and the particles are adapted with the help of graph theory to make feasible solutions. Mori and Shimomugi [10] proposed a new method using multi-objective meta-heuristics (MOMH) in order to power losses and voltage deviation minimization in distribution networks. A differential evolution algorithm (DEA) is an evolutionary computation method that was originally introduced by Storn and Price in 1995 [11]. Furthermore, they developed DEA to be a reliable and versatile function optimizer that is also readily applicable to a wide range of optimization problems [13]. DEA uses rather greedy selection and less stochastic approach to solve optimization problems than other classical EAs. There are also a number of significant advantages when using DEA, which were summarized by Price in [14]. Most of the initial researches were conducted by the differential evolution algorithm inventors (Storn and Price) with several papers [11, 13, 14, 15] which explained the basis of differential evolution algorithm and how the optimization process is carried out.

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2. PROBLEM FORMULATION

A. Constraints and objectives

The objective functions and the constraints of the reconfiguration problem are described below:
Minimization of power losses

$$Min\ f(x) = \sum_{i=1}^{N_i} r_i \frac{P_i^2+Q_i^2}{V_i^2} \tag{1}$$

Considering safety operation, the voltage magnitude at each bus must be maintained within its limits. The current in each branch must satisfy the branch's capacity. These two constraints are expressed below:

$$\mathrm{I_i} \le \mathrm{I_i^{max}}; \mathrm{j} \in \mathrm{N_i} \tag{2}$$

$$\mathrm{V_{min}} \le \mathrm{V_j} \le \mathrm{V_{max}}; \mathrm{j} \in \mathrm{N_i} \tag{3}$$

Equation (1) presents the power losses through the branches of the network, respectively, that should be minimized. Equation (2) corresponds to limit branch current and substation current capacities within permissible limits. Equation (3) considers voltage constraints for each node of the system. The i corresponds to the number of busses in the network.

B. Distribution load flow

The distribution power flow is different from the transmission power flow due to the radial structures and high R/X ratio of transmission line. Because of this conventional transmission power flow algorithms does not converge for distribution systems. In this work the forward and backward algorithm is implemented to determine the transmission losses and the voltage profile.

A) Backward propagation

The updated effective power flows in each branch are obtained in the backward propagation computation by considering the node voltages of previous iteration. It means the voltage values obtained in the forward path are held constant during the backward propagation and updated power flows in each branch are transmitted backward along the feeder using backward path. This indicates that the backward propagation starts at the extreme end node and proceeds towards source node. The Figure-1 shows the representation of 2 nodes in a distribution line. Consider a branch 'j' is connected between the nodes 'i' and 'i+1'. The active power (P_i) and reactive power (Q_i) flows are calculated using equations (4) and (5).

$$\mathrm{P_i} = \mathrm{P'_{i+1}} + \mathrm{r_j}\frac{\mathrm{P'^2_{i+1}+Q'^2_{i+1}}}{\mathrm{V^2_{i+1}}} \tag{4}$$

$$\mathrm{Q_i} = \mathrm{Q'_{i+1}} + \mathrm{x_j}\frac{\mathrm{P'^2_{i+1}+Q'^2_{i+1}}}{\mathrm{V^2_{i+1}}} \tag{5}$$

Where

P_{Li+1} and Q_{Li+1} are loads that are connected at node 'i+1'.

P_{i+1} and Q_{i+1} are the effective real and reactive power flows from node 'i+1'.

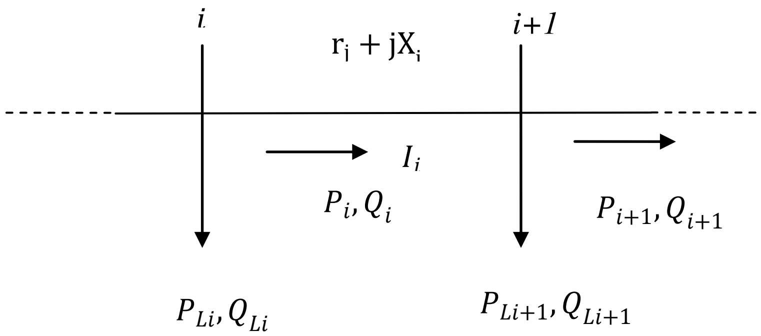

Figure-1. Representation of 2 nodes in a distribution line.

B) Forward propagation

The purpose of the forward propagation is to calculate the voltages at each node starting from the feeder source node. The feeder substation voltage is set at its actual value. During the forward propagation the effective power in each branch is held constant to the value obtained in backward walk. The node voltage magnitudes are calculated using equation (7). The voltage angle is calculated using equation (6).

$$\mathrm{V_{i+1}} = \left[\mathrm{V_i}^2 - 2(P_i r_j + Q_i x_j) + (r^2{}_j x^2{}_j)\frac{P^2{}_i+Q^2{}_i}{V^2{}_i}\right] \tag{6}$$

$$\tan(\delta_{i+1} - \delta_i) = \frac{Q_i r_j + P_i x_j}{V^2{}_i - P_i r_j + Q_i x_j} \tag{7}$$

The real and reactive power losses of branch 'j' can be calculated as in equation (8) and (9),

$$P_{loss(j)} = r_j \frac{P_i^2+Q_i^2}{V_i^2} \tag{8}$$

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$$Q_{loss(j)} = x_j \frac{P_i^2+Q_i^2}{V_i^2} \tag{9}$$

C) Convergence criterion

The voltages calculated in the previous and present iterations are compared. In the successive iterations if the maximum mismatch between the voltages is less than the specified tolerance i.e., 0.0001, the solution is said to be converged. Otherwise new effective power flows in each branch are calculated through backward walk with the present computed voltages and then the procedure is repeated until the solution is converged.

3. DIFFERENTIAL EVOLUTION

Differential evolution (DE) is a population-based stochastic optimization algorithm for real-valued optimization problems. In DE each design variable is represented in the chromosome by a real number. The DE algorithm is simple and requires only three control parameters: weight factor (F), crossover rates (CR), and population size (NP). The initial population is randomly generated by uniformly distributed random numbers using the upper and lower limitation of each design variable. Then the objective function values of all the individuals of population are calculated to find out the best individual $x_{best,G}$ of current generation, where G is the index of generation. Three main steps of DE, mutation, crossover, and selection were performed sequentially and were repeated during the optimization cycle.

A. Mutation

For each individual vector xi, G in the population, mutation operation was used to generate mutated vectors in DE according to the following scheme equation (10):

$$V_{i,G+1} = X_{best,G} + F(X_{r2,G} - X_{r2,G}),$$
$$i = 1,2,3,\ldots,NP \tag{10}$$

The selected two vectors, $x_{r1,G}$ and $x_{r2,G}$ are used as differential variation for mutation. The vector $x_{best,G}$ is the best solution of current generation. And $V_{i,G+1}$ are the best target vector and mutation vector of current generation. Weight factor F is the real value between 0 to 1 and it controls the amplification of the differential variation between the two random vectors. There are different mutation mechanisms available for DE, as shown Table-1, which may be applied in optimization search process. The individual vectors $x_{r1,G}$, $x_{r2,G}$, $x_{r3,G}$, $x_{r4,G}$, $x_{r5,G}$, are randomly selected from current generation and these random number are different from each other. So the population size must be greater than the number of randomly selected ion if choosing Rand/2/exp mechanism of DE mutation, the NP should be bigger than 5 to allow mutation.

Table-1. The mutation mechanism of DE.

Mechanism	Mathematical equation
Best /1/ exp	$V_{i,G+1} = X_{best,G} + F(X_{r1,G} - X_{r2,G})$
Rand /1/ exp	$V_{i,G+1} = X_{r3,G} + F(X_{r1,G} - X_{r2,G})$
Rand-to-Best	$V_{i,G+1} = X_{i,G} + F(X_{r1,G} - X_{r2,G}$
Best/2/exp	$V_{i,G+1} = X_{best,G} + F(X_{r1,G} + X_{r2,G} - X_{r1,G} + X_{r2,G})$
Rand/2/exp	$V_{i,G+1} = X_{r5,G} + F(X_{r1,G} + X_{r2,G} - X_{r3,G} + X_{r4,G})$

B. Crossover

In the crossover operator, the trial vector $u_{i,G+1}$ is generated by choosing some arts of mutation vector, $v_{i,G+1}$ and other parts come from the target vector $x_{i,G}$. The crossover operator of DE is shown in Figure-2.

Where Cr represents the crossover probability and j is the design variable component number. If random number R is larger than Cr value, the component of mutation vector, $v_{i,G+1}$ will be chose to the trial vector. Otherwise, the component of target vector is selected to the trial vectors. The mutation and crossover operators are used to diversify the search area of optimization problems.

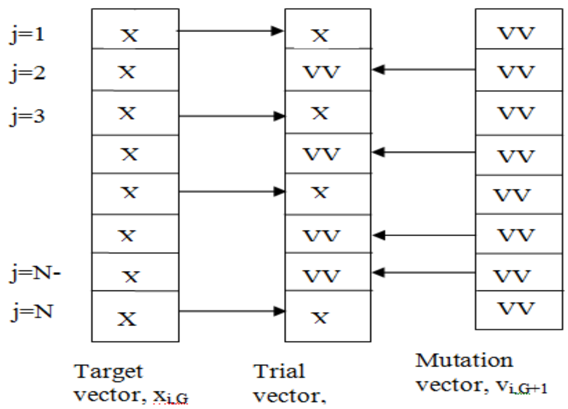

Figure-2. Schematic diagram of crossover operation.

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C. Selection operator

After the mutation and crossover operator, all trial vectors *u*i, G+1 have found. The trial vector *u*i, G+1 are compared with the individual vector *x*i, G for selection into the next generation. The selection operator is listed in the following description (11) and (12):

$$X_{j,G+1} = U_{i,G+1,} \text{if } f(u_{i,G+1}) > f(X_{j,G}) \tag{11}$$

$$X_{j,G+1} = U_{i,G+1,} \text{if } f(u_{i,G+1}) > f(X_{j,G}),$$

$$i = 1,2,\ldots,NP \tag{12}$$

If the objective function value of trial vector is better than the value of individual vector, the trial vector will be chosen as the new individual vector $x_{i,G+1}$ of next generation. On the contrary, the original individual vector $x_{i,G}$ will be kept as the individual vector $x_{i,G+1}$ in next generation. The optimization loop of DE runs iteratively until the stop criteria are met. There are three stop criteria used in the program. The first criterion is maximum number of optimization generation. The second criterion is maximum number of consecutive generations that no better global optimum is founded in the whole process. If the improvement of objective functions between two consecutive generations is less than the threshold set by program, it will be considered as fitting convergence requirement. The last stop criterion is conformed if the accumulated number of generations fitted convergence requirement is greater than maximum counter set by the program. The flowchart of DE is shown in Figure-3. The flowchart of differential evolution:

The basic procedure of DE is summarized as follows.

Step-1: Randomly initialize the population of individual for DE.

Step-2: Evaluate the objective values of all individuals, and determine the best individual.

Step-3: Perform mutation operation for each individual in order to obtain each individual's corresponding mutant vector.

Step-4: Perform crossover operation between each individual and its corresponding mutant vector in order to obtain each individual's trial vector.

Step-5: Evaluate the objective values of the trial vectors.

Step-6: Perform selection operation between each individual and its corresponding trial vector so as to generate the new individual for the next generation.

Step-7: Determine the best individual of the current new population with the best Objective value then updates best individual and its objective value.

Step-8: If a stopping criterion is met, then output gives its bests and its objective value

Otherwise go back to step 3.

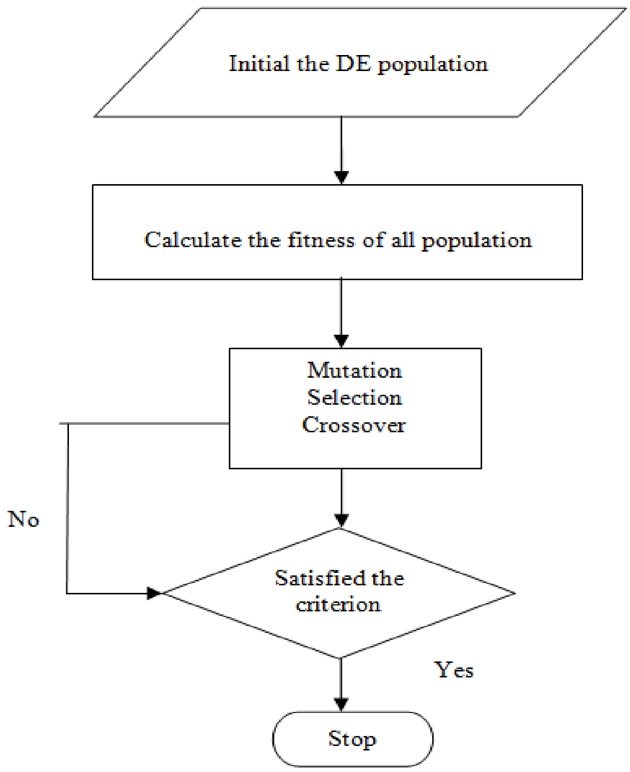

Figure-3. Flowchart of differential evolution process.

4. EXPERIMENT AND RESULTS

The proposed Differential evolution algorithm for loss reduction and load balancing is evaluated by implementing it on the IEEE 33 bus systems. The result obtained is encouraging and satisfactory when it is compared to various other algorithms. The original configuration is shown in Figure-4.

A. Test case

The IEEE 33 bus system has 12.66Kv and 100MW as base values with 5 tie-line switches. The total loads for this test system are 3, 801.89 kW and 2, 694.10 kVAr. The minimum and maximum voltages are set at 0.95 and 1.05 p.u. Figure-4 shows the diagrammatic representation of the IEEE 33 radial distribution system.

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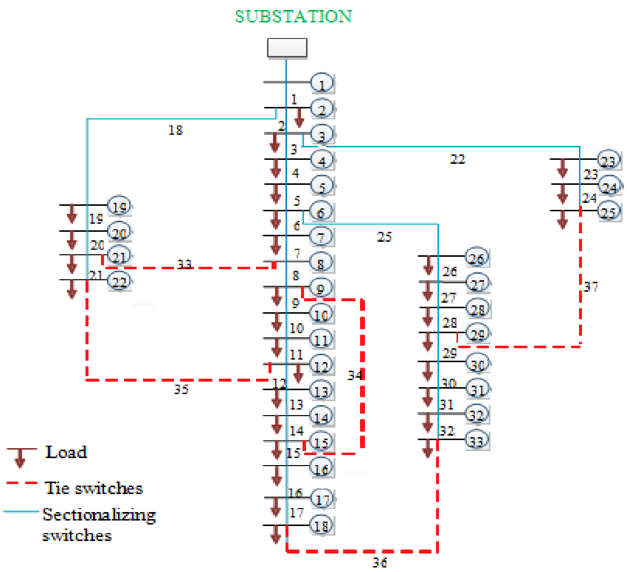

Figure-4. Line Diagram of IEEE 33 radial distribution system.

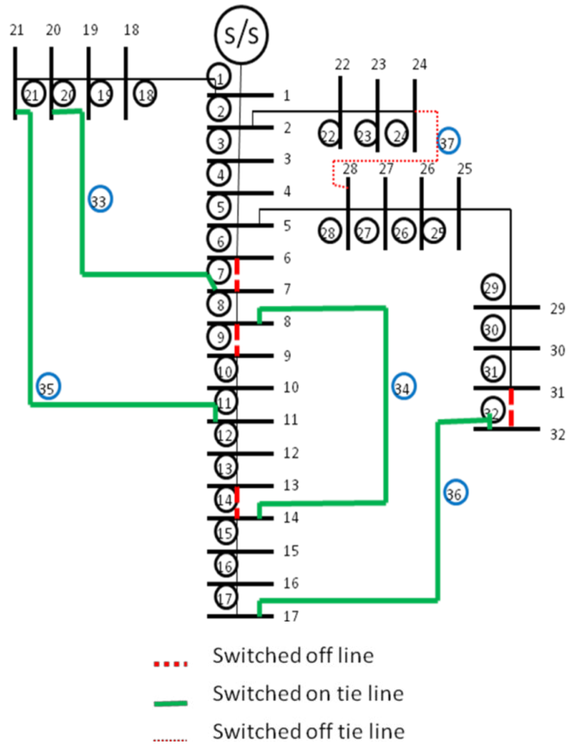

Figure-5. Reconfigured switching plan of IEEE 33 bus radial distribution system.

The reconfigured switching plan for the IEEE 33 bus system is shown in the Figure-5 where switches 7, 9, 14, 32 are being opened so that the total losses in the system is reduced from 202.7 MW to 139.54 MW. Table-2 shows the comparison of the proposed algorithms in terms of program execution time.

In order to compare the proposed algorithm in terms of program execution time Artificial Bee Colony (ABC), Genetic Algorithm, Refined Genetic algorithm (RGA), Branch and Bound algorithms were considered.

Table-2. Comparison of DE with other algorithms.

	ABC [16]	GA [17]	RGA [18]	DE	B and B
Tie line switches Off	33,14,8, 32,28	33,9,34, 28, 36	7,9,14, 32, 37	7,9,14, 32,37	7,9,14, 32,37
Power loss (kW)	139.5	140.6	139.5	139.5	139.5
Min. Node Voltage (pu)	0.9437 (Node 33)	0.9371 (Node 33)	0.9371 (Node 33)	0.9378 (Node32)	0.9371 (Node 33)
Power loss Reduction (%)	31.2	30.6	31.2	31.2	31.2
CPU Time (s)	5.3	15.2	13.8	23	17

From the Table-2 it can be inferred that using differential evolution algorithm the initial loss 202.71 kW loss has been reduced to 139.54 kW which is approximately 31.2% reduction and also the program execution time of the reconfiguration process using Differential Evolution (DE) is 2.3 seconds which is less when compared to other algorithms.

5. CONCLUSIONS

In this paper, minimum power loss is achieved by optimal reconfiguration in the network using Differential

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Evolution algorithm. In the optimization process, the applied constraints are voltages of nodes, currents branches, and radial condition of the network. The minimum power losses with improved voltage profile have been achieved. The proposed Differential Evolution algorithm has been tested on 33-bus, network. It is concluded that after comparing with various algorithms, differential evolution process execution time is very less and also DE has upper hand over other algorithms in terms of less complexity in program coding. The power distribution utilities can prioritize their network improvements optimally using the above results.

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