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MINIMIZATION OF POWER LOSS IN RADIAL DISTRIBUTION NETWORK USING OPTIMAL FEEDER RECONFIGURATION AND DISTRIBUTED GENERATION ALLOCATION.

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ABSTRACT: Due to the radial nature of the distribution system (DS), real power losses are unpreventable due to a variable and unbalanced nature of load and high value of R/X ratio. For the efficient and inexpensive process of the distribution network, real power losses shall be minimized as much as possible. In this paper, the advanced technology is presented for the selection of optimum capacity and position of distributed generation (DG) accompanied by the optimal reconfiguration as an objective to minimize line losses. The meta-heuristic composite differential evolution (CoDE) algorithm is put forward for consideration of appropriate capacity and allocation of DGs in the presence of feeder reconfiguration of IEEE standard 33 and 69-bus DS. Furthermore, voltage at each bus and current carrying capacity in each branch are considered as the constraints at the time of evolution of objective function. In the correct conditions to find the best feeder reconfiguration and DG allocation, several case studies are well-thought-out to examine the superiority of the suggested technique. Furthermore, simulation results ensure the best accomplishment as regards to the quality of outcome and computational efficiency using the proposed algorithm.

Keywords: Distribution system; Distributed generation; Differential evolution; Reconfiguration; Power Loss

INTRODUCTION

Planning and Control of distribution system (DS) are more complex because the load is increased day by day and highly intermittent in nature. Generally, the notable quantity of real power loss (I^2R), more than 13% of the total generated power has appeared across the distribution network. Line losses in the distribution are varied for a fixed network configuration in case of an increase in load. Therefore, reconfiguration is accomplished to decrease I^2R losses of a distribution area. In the DS, feeder reconfiguration is explained as the altering of topological assembly of feeders by moving the position of the tie and sectionalizing switches where the load is uncertain. At the period when generation capacity is less than system demand, that makes the releasing of additional demand on the feeders and practically it is not possible. Therefore, actual value of voltage in distribution system is decreased beyond a certain limit and produces high I^2R losses and may cause interruption. So as to meet the required level of voltage, distributed generation (DG) is added into the distribution system (Rao *et al.*, 2013). As yet, optimal site and size of DG units and optimum feeder reconfiguration are considered individually by many authors in the literature.

Minimization of real power loss and enhancement in voltage level through the use of the feeder reconfiguration is done by many researchers using different optimization methods. Rearrangement of sectionalizing and tie switches in DS was first suggested to utilize a branch-and-bound technique. A major limitation of such optimization technique is that it is time-consuming because the technique searches the order of 2^n feeder reconfiguration, where n shows number of sectionalizing and tie switches. Furthermore, heuristic algorithm based on branch and bound technique proposed, which has the disadvantage that during feeder configuration simultaneous switching is not considered. A very simple formula for the calculation of loss reduction using feeder reconfiguration based on heuristic set of rules to reduce line losses was recommended. However, this method has the drawback that feeder reconfiguration depends on the initial status of switch and at a time only single couple of normally open (NO) and normally closed (NC) switching process is considered. Genetic algorithm (GA) based methodology is given by Nara *et al.* (Nara *et al.*, 1992) for optimum feeder reconfiguration considering the reduction of real power loss. Other methods for optimal reconfiguration using meta-heuristic techniques include harmony search algorithm (HAS) (Rao *et al.*, 2013), fireworks algorithm (FWA) proposed (Mohamed and Kowsalya, 2014), particle swarm optimization (PSO) (Yaprakdal *et al.*, 2019) Cuckoo search algorithm (CSA) and modified PSO (MPSO) (Flaih *et al.*, 2016).

Capacities of DG units inject near the load center typically between 200 kW to 10 MW. In the literature number of researchers proposed the various methods to allocate the best size and position of DG in order to minimize I^2R losses in recent years. Celli *et al.* (Celli *et al.*, 2005) were suggested a genetic algorithm (GA) based method to optimize multi-objective functions to compute the appropriate site and capacity of DG units. Furthermore, a large amount of research on the optimization of DGs site and size to achieve minimum line losses is available in the literature. These include the analytical approach (Ayodele 2015), hybrid artificial bee colony (ABC) and artificial immune system (AIS), combination of ant colony optimization (ACO) and ABC (hybrid ACO-ABC) in (Kefayat *et al.*, 2015). Moreover, few studies have been achieved for DG allocation along with optimal reconfiguration that includes fireworks algorithms (FWA) (Mohamed and Kowsalya, 2014), harmony search algorithm (HAS) (Rao *et al.*, 2013), metaheuristic cuckoo search algorithm (CSA). This work presents the novel technique based on composite differential evolution (CoDE) (Wang *et al.*, 2011) for finding the best capacity and position of DG along with optimum feeder reconfiguration subjected to minimize active power loss and enhancement of voltage profile. Moreover, standard 33 and 69-bus DS are considered to examine the superiority of the suggested method, also the output results are compared with the latest available research work.

The CoDE algorithm for determining the feasible decision vector is combined with the feasibility rule (Deb 2000) in this paper. Small to large distribution networks 33 and 69-bus distribution test systems are regarded to incorporate CoDE in conjunction with the technique of constraint. Almost in all the literature of optimal DG allocation and network reconfiguration problems, the penalty function method is suggested to test the violation of the constraint and the drawback of this approach is the choice of the penalty coefficient. A small penalty coefficient is over-exploring the infallible area, which can slow the process of seeking feasible solutions and converge unnecessarily into an infeasible solution. Despite the large penalty coefficient, the infeasible area may not be investigated, leading to ultimate convergence. In this paper, feasibility rule constraint handling technique is combined with the CoDE search algorithm for finding the global optimal solution of DG and Network reconfiguration allocation problem. The results show that the CoDE, along with optimal reconfiguration compared to the methods in the literature, could find the global optimal solution of the DG allocation problem.

MATERIALS AND METHODS

Load flow equations: The feeder of typically distribution system (DS) is fed at one end only, consequently, *X/R* ratio of DS is very low and connected load is always unbalanced. Therefore, variables of distribution systems are different during load flow analysis as compared to the transmission line and don't converge efficiently using conventional power flow algorithms. In this work, power flow of the DS is calculated by using forward and backward sweep (FBS) technique (Ghosh and Sonam, 2008). In FBS technique, actual value of voltage and its angle at each bus are intended by means of simplified set of equations and derived from the one-line schematic representation as shown in Figure 1.

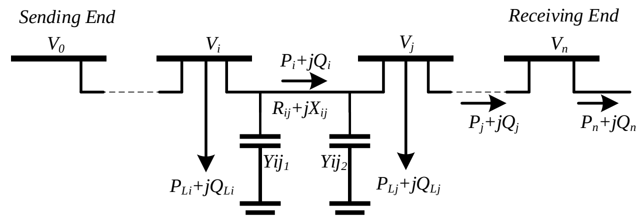

Figure 1. Typical single-line diagram of radial DS

$$P_j = P_i - P_{Loss,ij} - P_{Lj} \tag{1}$$

$$Q_j = Q_i - Q_{Loss,ij} - Q_{Lj} \tag{2}$$

$$|V_j|^2 = -2\left(R_{ij}P_i + X_{ij}\left(Q_i + Y_{ij}|V_i|^2\right)\right) + |V_i|^2 + \frac{R_{ij}^2 + X_{ij}^2}{|V_i|^2}\left(P_i^2 + \left(Q_i + Y_{ij}|V_i|^2\right)^2\right) \tag{3}$$

In Eq. (1) to (3) P_i and Q_i show active and reactive power flows out from bus *i*; P_{Lj} and Q_{Lj} are real and reactive power demand connected to bus *j*. R_{ij} and X_{ij} are the branch resistance and reactance. $P_{Loss,ij}$ and $Q_{Loss,ij}$ are the active and reactive power losses and given as

$$P_{Loss,ij} = R_{ij}.\frac{(P_i^2 + Q_i^2)}{|V_i|^2} \tag{4}$$

$$Q_{Loss,ij} = X_{ij}.\frac{(P_i^2 + Q_i^2)}{|V_i|^2} \tag{5}$$

The total amount of active losses ($P_{T,Loss}$) in the feeder is calculated by accumulation the power loss of each of the lines, say *n* (total number of branches), and is given by:

$$P_{T,Loss} = \sum_{ij=1}^{n} P_{Loss,ij} \tag{6}$$

Reduction of real power loss using feeder reconfiguration: Optimum feeder reconfiguration means interchanging the position of sectionalizing and tie switches that gives the minimum I^2R losses subject to fulfill the operating constraints, which include the current carrying capacity of feeder and voltage level of network. After optimal reconfiguration of distribution network, power losses$P_{Loss,ij}^R$ among the nodes, *i* and *j* can be calculated by using equation (7) and the total power loss, $P_{T,Loss}^R$ in the network can be calculated using equation (8)

$$P^{R}_{Loss,ij} = R_{ij}.\frac{(P_i'^{2} + Q_j'^{2})}{|V_i'|^2} \quad (7)$$

$$P^{R}_{T,Loss} = \sum_{ij=1}^{n} P'_{Loss,ij} \quad (8)$$

Amount of power losses minimization after optimal feeder reconfiguration is denoted by $\triangle P^{R}_{Loss}$, it is calculated simply by subtracting Eq. (8) from Eq. (6) as

$$\Delta P^{R}_{Loss} = \sum_{ij=1}^{n} P_{Loss,ij} - \sum_{ij=1}^{n} P'_{Loss,ij} \quad (9)$$

Reduction of real power loss using dg allocation: Optimum size and position of DG allocation give various positive impacts these include minimization of losses, improvement of voltage profile, releasing overloading of line, peak demand shaving, differed investment to upgrade transmission line and distribution networks. In this paper, DGs are able to supply only active power at unity power factor and are considered as negative *P* (active power) load. Let P_{DG} is active power generated by DG associated with bus *i*, then load of bus deviate from P_{Li} to (P_{Li}–P_{DG}). Figure 2 shows typical radial distribution system when DG is allocated at i^{th} bus and add P_{DG} active power locally in the network, mathematically real power loss with DG allocation in-branch *ij* is $P^{DG}_{Loss,ij}$ given by

$$P^{DG}_{Loss,ij} = \frac{R_{ij}}{V_i^2}[(P_i - P_{DG})^2 + Q_i^2] \quad (10)$$

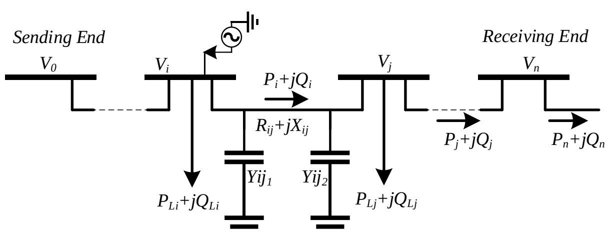

Figure 2. Typical radial DS with DG integration at bus *i*

Total power loss reduction $\triangle P^{DG}_{Loss}$ with the addition of DG in the system can be calculated by subtracting the (4) from (10) and is given by

$$\triangle P^{DG}_{Loss} = \frac{R_{ij}}{V_i^2}(P^2_{DG} - 2P_iP_{DG}) \quad (11)$$

If $\triangle P^{DG}_{Loss}$ is positive, which indicates the power loss is reduced by DG allocation. On the other hand, if $\triangle P^{DG}_{Loss}$ is negative which means DG allocation causes a higher power loss. In this paper, the reduction of active power loss is the objective function, which is specified by

$$Manimize\ f = min(P^{R}_{T,Loss} + P^{DG}_{T,Loss}) \quad (12)$$

Subjected to $V_{\min} \leq |V_i| \leq V_{\max}$
and $|I_{i,j}| \leq |I_{ij,\max}|$

$$\sum_{i=1}^{n} P_{DG,i} \leq \sum_{i=1}^{n} (P_i + P_{Loss,ij})\} \quad (13)$$

Composite differential evolution (CODE): The Differential Evolution (DE) was first developed by Rainer Storn and Kenneth Price in 1997 (Storn and Price, 1997). Similar to other metaheuristic algorithms DE starts with initial population, which utilizes three operators at each generation. These operators are mutation, crossover, and selection. Suppose $f(\vec{x})$ is objective function whose value is to be minimized, where $\vec{x} = (x_1, \cdots, x_D) \in \Re^D$ is the decision vector and feasible solution space is $\Omega = \prod_{i=1}^{D}[L_i, U_i]$. *L* and *U* are the user defined lower and upper bound of decision vector $\vec{x}$. So as to minimize the objective function, steps of differential evolution are as follows:

Initialization: DE starts with uniformly distributed initial population N_P over the range of *L* and *U*. The D-dimensional randomly sampled decision parameters at generation, *G*=0 defined by

$$\vec{x}_{i,0} = (x_{i,1,0}, x_{i,2,0}, \dots, x_{i,D,0}), \quad i = 1,2, \dots, N_P \quad (14)$$

The initial population is selected randomly in such a way to uniformly distribute in the entire space.

Mutation: DE creates mutant vector $v_{i,G}$ from target vector $\vec{x}$ (also called individual) at each generation. The most extensively used five mutation operators of DE are given as follows

I. Classic DE "rand/1" is added to the base vector

$$\vec{v}_{i,G} = \vec{x}_{r1,G} + F \cdot (\vec{x}_{r2,G} - \vec{x}_{r3,G}) \quad (15)$$

II. "best/1" best vector in the current population is chosen as a base vector at which objective function is minimum and one vector difference is added to the selected base vector

$$\vec{v}_{i,G} = \vec{x}_{best,G} + F \cdot (\vec{x}_{r1,G} - \vec{x}_{r2,G}) \quad (16)$$

III. "Current-to-best/1" current vector is selected base vector; it adds to the difference of best to current and one random difference

$$\vec{v}_{i,G} = \vec{x}_{i,G} + F \cdot (\vec{x}_{best,G} - \vec{x}_{i,G}) + F \cdot (\vec{x}_{r1,G} - \vec{x}_{r2,G}) \quad (17)$$

IV. "Best/2" base vector is selected as best and two random vector differences are added to selected base

$$\vec{v}_{i,G} = \vec{x}_{best,G} + F \cdot (\vec{x}_{r1,G} - \vec{x}_{r2,G}) + F \cdot (\vec{x}_{r3,G} - \vec{x}_{r4,G}) \quad (18)$$

V. "Rand/2" base vector is randomly chosen and adds with two randomly difference vectors

$$\vec{v}_{i,G} = \vec{x}_{r1,G} + F \cdot (\vec{x}_{r2,G} - \vec{x}_{r3,G}) F \cdot (\vec{x}_{r4,G} - \vec{x}_{r5,G}) \tag{19}$$

From equations (15)−(19), F is scaling factor, $\vec{x}_{best}$ is the best individual in [1, N_P] current population and $r1-r5$ are dissimilar randomly chosen numbers from current population, also differ from i.

Crossover: After the mutation operator, DE starts to perform binomial crossover, that is the selection between target vector $\vec{x}_{i,G}$ and mutation vector $\vec{v}_{i,G}$ to create trial vector $u_{i,G}$, as

$$u_{i,j,G} = \begin{cases} v_{i,j,G}, & if\ rand_j(0,1) \le C_r\ or\quad j = j_{rand} \\ x_{i,jG}, & otherwise \end{cases} \tag{20}$$

Where, j_{rand} is randomly selected integer nominated from [1, D], C_r is constant called crossover parameter selected between [0, 1] and $rand_j(0,1)$ is the generation of uniform distributed random number for each decision vector j. If any decision variables $u_{i,j,G}$ for the generation of trial vector $u_{i,G}$ is out of range then it is rearranging as follows

$$u_{i,j,G} = \begin{cases} min\,\{U_j, 2L_j - u_{i,j,G}\}, & if\ u_{i,j,G} < L_j \\ max\,\{L_j, 2U_j - u_{i,j,G}\}, & if\ u_{i_j,G} > U_j. \end{cases} \tag{21}$$

In Eq. (21) U and L are the upper and lower bound of decision space at i^{th} population, j^{th} dimension, and G current generation.

Selection: It is the process of selection among the parent solution $x_{i,G}$ and trial vector $u_{i,G}$ using binary crossover for the population of next generation

$$\vec{x}_{i,G+1} = \begin{cases} \vec{u}_{i,G}, & if\ f(\vec{u}_{i,G}) \le f(\vec{x}_{i,G}) \\ \vec{x}_{i,G}, & otherwise. \end{cases} \tag{22}$$

Generation of trial vector and control parameter of code: The performance of differential evolution mainly depends upon two components, first generation of trial vector ($U_{i,G}$) and second its control parameters (initial population size N_P, scaling parameter F, crossover parameter C_r). In the proposed composite DE (CoDE) (Wang *et al.*, 2011) algorithm randomly combine appropriate three different values of control parameters associated with three trial vector generation strategy as shown in Figure 3.

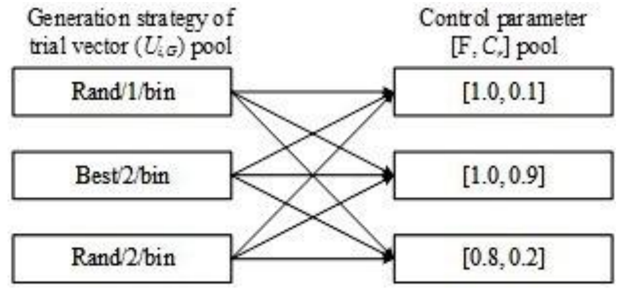

Figure 3. Random association of trial vector strategy pool and control parameters pool

Three strategies for the generation of a trial vector are

"rand/1/bin"

$$u_{i,j,G} = \begin{cases} x_{r1,j,G} + F \cdot (x_{r2,jG} - x_{r3,jG}), if\ rand < C_r\ or\ j = j_{rand} \\ x_{i_j,G}, \quad otherwise \end{cases} \tag{23}$$

"rand/2/bin"

$$u_{i,j,G} = \begin{cases} x_{r1,j,G} + F \cdot (x_{r2,j,G} - x_{r3,j,G}) + F \cdot (x_{r4,j,G} - x_{r5,j,G}), \\ \quad if\ rand < C_r\ or\ j = j_{rand} \\ x_{i_j,G}, \quad otherwise \end{cases} \tag{24}$$

"best/2/1"

$$\vec{u}_{i,G} = \vec{x}_{best,G} + rand \cdot (\vec{x}_{r1,G} - \vec{x}_{2,G}) + F \cdot (\vec{x}_{r3,G} - \vec{x}_{r4,G}) \tag{25}$$

In the proposed algorithm, these three trial vector strategies are generated and randomly associated with three appropriate values of control parameters at each generation. The final $\vec{u}_{i,G}$ is selected by using feasibility rule (Deb, 2000)

Application of code for optimum reconfiguration and DG allocation: This segment defines the applications of CoDE in optimal reconfiguration and DG injection problem for the reduction of I^2R losses. Both DG allocation and reconfiguration of distribution systems are complex combinatorial optimization problems. So as to understand the implementation of DG allocation and feeder reconfiguration simultaneous, 33-bus distribution network is considered for simplicity. Initially, all possible radial structures of the system are produced randomly using (14) without violating the constraints. In the 33-bus network five normally open (NO) tie switches having line numbers from 33 to 37, which forms five fundamental loops L_1 *to* L_5 respectively, fundamental loops are given in equation (26) and 32 normally closed (NC) sectionalizing switches shown in Figure 4. Furthermore, at the time of initial population, assume that the buses at which optimal allocations of DG injection are 8, 22 and 24 as shown in Figure 4.

L_1 = [22 23 24 25 26 27 28 37];
L_2 = [2 3 4 5 6 7 18 19 20]; (26)

L_3 = [15 16 17 29 30 31 32 36];
L_4 = [8 9 10 11 21 33 35];
L_5 = [12 13 14 34];

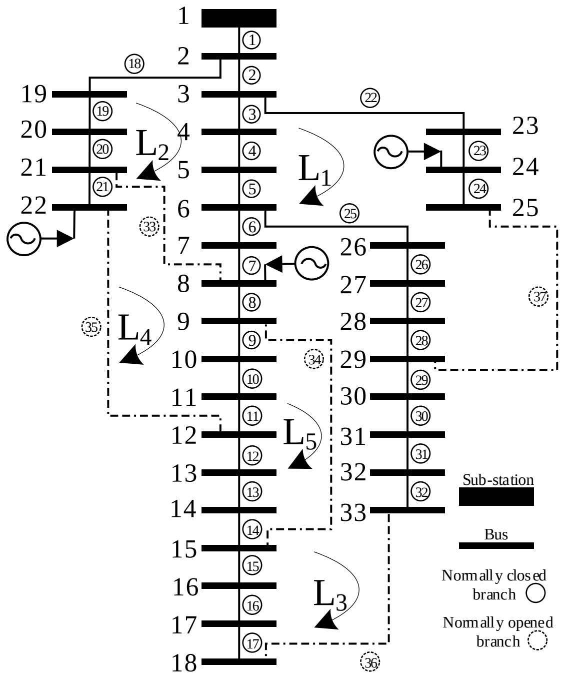

Figure 4. IEEE Standard 33-bus DS reconfiguration and DG integration

In order to show the best reconfiguration, only positions of NO switches need to be known. In the 33-bus system quantity of NO switches are five and hence the length of decision parameters in the first part of the solution is five. Whereas the second part is the optimal rating of DG injection at the optimal number of buses. Therefore, eleven decision variables for the simultaneous DG allocation and feeder reconfiguration, are formed as;

$$\vec{x} = (\underbrace{NO_1, NO_2, NO_3, NO_4, NO_5,}_{\substack{Best\ normally\ open\ (NO)\\ switches}} \underbrace{B_6, B_7, B_8,}_{\substack{Site\ of\ buses\\ at\ DGs\ allot}} \underbrace{R_9, R_{10}, R_{11}}_{\substack{Rating\ of\\ DGs\ (kW)}}) \quad (27)$$

Likewise, all the probable solution vectors are created and updated by using (14)−(22) without violating any constraints. Using the trial vector strategy pool and their corresponding randomly selected control parameter, the initial generated population is replaced by the new population at which power loss is minimum. The process is repetitive until the termination conditions are met. Flowchart of the suggested CoDE algorithm is shown in Figure 5 and pseudocode is given in Table 1.

RESULTS AND DISCUSSION

So as to validate the successfulness of the CoDE algorithm, it is applied to various different study cases. It can be noticed from the literature review that, minimization of active power loss mainly based on optimum capacity and position of DG allocation. If large number of DGs are added into the system, it may not be feasible beyond the certain limit technically as well as commercially. Furthermore, cumulatively too large injection of DG power might increase the short circuit level of distribution components. It is therefore required to limit the number of DGs and their rating with past literature for the valid comparison. IEEE 33-bus and 69-bus standard DS are adopted for the simulation of three different study cases to validate the dominance of the suggested algorithm that includes

Case I: Only reconfiguration
Case II: Only with DG allocation
Case III: Simultaneous DG and feeder reconfiguration

In the subsequent sub-sections, simulation results of 33-bus and 69-bus test system are presented.

33-bus distribution system: Detailed data for a 33-bus DS is considered from (Baran and Wu, 1989), structurally this network comprised of 32 NC switches and 5 NO switches. The cumulative rating of active and reactive load demand on different nodes are 3.7 MW and 2.3 MVAr correspondingly. Output results and comparison with the past studies of 33-bus test system by means of CoDE method are summarized in Table 2.

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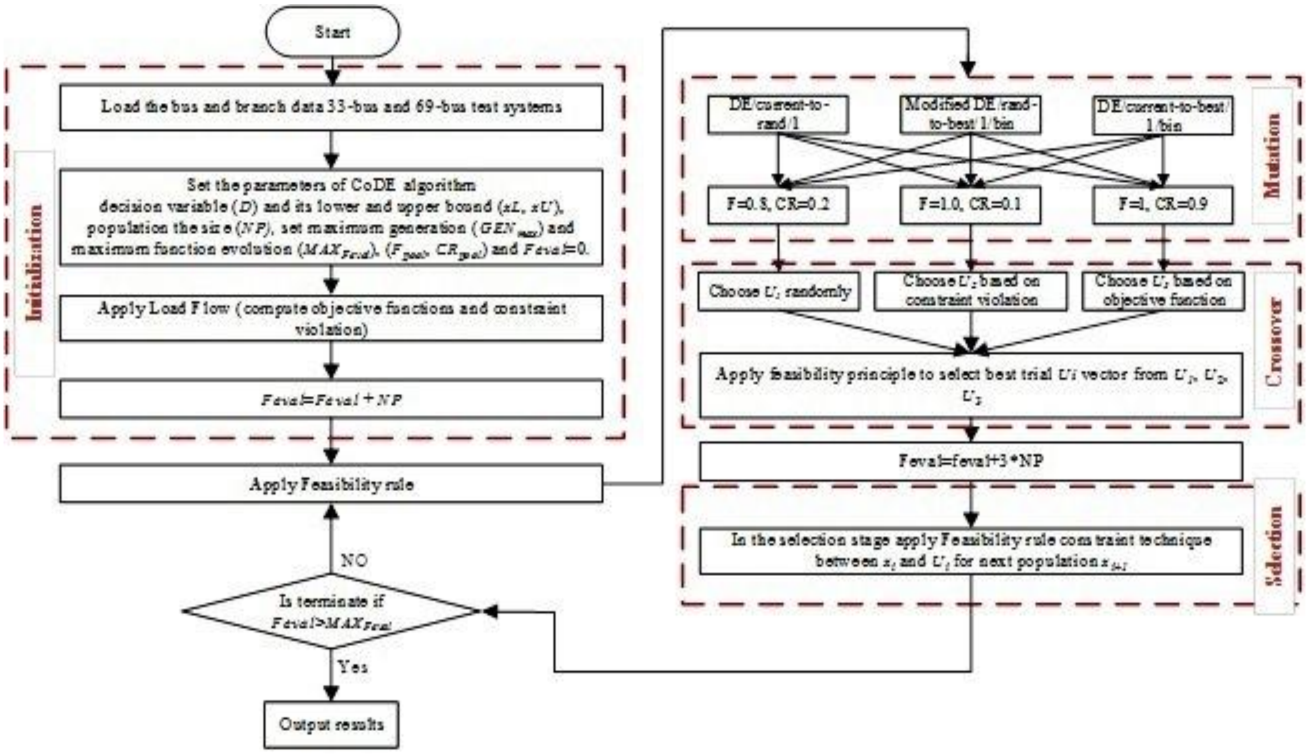

Figure 5. Flowchart of CoDE algorithm

Table 1. Pseudocode of proposed CoDE algorithm.

Proposed CoDE Algorithm:

1. Input

D; /*set the number of decision variable*/
x_i^L and x_i^U; /*set the lower and upper bound of decision variables*/
N_P; /*Set population size*/
MAX_{Feval}; /*set the maximum function evolution (stopping criteria) */

2. Initialization

t=1; /*Set the generation number*/
$\vec{x}_i^t (i \in \{1 \dots NP\})$; /*Randomly generate initial population between lower (L) and upper (U) bounds*/
F_{pool}; CR_{pool}; /*Set CoDE parameters, pool of mutation factor (F) and cross over rate (CR)*/

3. Evaluation

i. Evaluate objective function and overall constraint violation using eq. (13) of $\vec{x}_i^t$;
ii. $FEs=N_p$; /* FEs shows the number function evaluation*/
iii. $\vec{x}_i^{t+1} = \emptyset$; /* pre-allocate the population for the next generation*/

4. Main Loop

iv. for i=1: Np do
v. Generate three mutation vectors $\vec{v}_{i1}^t$, v_{i2}^t and $\vec{v}_{i3}^t$ using Eqs. (15), (18) and (19);
vi. Generate three offspring $\vec{u}_{i1}^t$, $\vec{u}_{i2}^t$ and $\vec{u}_{i3}^t$ are generated by using Eqs. (23), (24) and (25);
vii. Evaluate the objective function and constraint violation using $\vec{u}_{i1}^t$, $\vec{u}_{i2}^t$ and $\vec{u}_{i3}^t$;
viii. Select trial vector $\vec{u}_i^t$ for $\vec{x}_i^t$ from $\vec{u}_{i1}^t$, $\vec{u}_{i2}^t$ and $\vec{u}_{i3}^t$ by applying feasibility rule (Deb 2000);
ix. Compare $\vec{u}_i^t$ and $\vec{x}_i^t$ by using Eq. (22), and put better one for the next population $\vec{x}_i^{t+1}$;
x. $FEs=FEs+3$;
xi. end /*for loop end*/;
xii. $t=t$+1;
xiii. if $FEs \geq MAX_{Feval}$, then save the results
xiv. Otherwise go to iii.

Study Cases	Items	Optimization algorithms				
		CoDE	**HSA (Rao *et al.* 2013)**	**FWA (Mohamed and Kowsalya, 2014)**	**ACSA (Nara *et al.*, 1992)**	**UVDA (Bayat *et al.*, 2016)**
Case I (Reconfiguration only)	Switches opened	9, 7, 14, 32, 37	7, 9, 14, 32, 37	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 32, 37
	Real power loss	139.55	**138.06**	139.98	139.98	139.55
	Bus voltage min (bus)	0.9378 (32)	0.9342 (32)	0.9413 (32)	0.9413 (32)	0.9378 (32)
Case II (DG only)	Open switches	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37
	Real power loss	**72.63**	96.76	88.68	74.26	74.21
	DG size kW (bus no.)	1.045 (30), 740.28 (14), 764.14 (25)	107.0 (18), 572.4 (17), 1046.2 (33)	589.7 (14), 189.5 (18), 1014.6 (32)	779.8 (14), 1125.1 (24), 1349.6 (30)	875 (11), 931 (24), 925 (29)
	Bus voltage min (bus)	0.9664 (33)	0.9670 (33)	0.9680 (30)	**0.9778** (33)	0.962 (33)
Case 3 (simultaneous reconfiguration and DG)	Open switches	9, 7, 14, 30, 27	7, 14, 10, 32, 28	7, 11, 14, 28, 32	11, 28, 31, 33, 34	7, 10, 13, 27, 32
	Real power loss	**52.89**	73.05	67.11	53.21	57.29
	DG size MW (bus no.)	1237.0 (25), 567.5 (12), 745.4 (32)	525.8 (32), 558.6 (31), 584.0 (33)	531.5 (18), 615.8 (29), 536.7 (32)	964.6 (7), 896.8 (18), 1438.1 (25)	649 (15), 486 (21), 1554 (29)
	Bus voltage min (bus)	0.9710 (17)	0.9700 (--)	0.9713 (14)	**0.9806** (31)	0.976 (32)

Table 2 shows that, in case 1 of IEEE 33-bus test scheme, the proposed technique achieves minimum power loss along with UVDA (Bayat *et al.*, 2016). The proposed algorithm CoDE in the study case 2 achieves the value of real power loss 72.63 kW, least among all. Furthermore, in case 2 cumulative rating of DG injection is 2.55 MW in the proposed algorithm whereas ACSA (Nara *et al.*, 1992) algorithm selects more than 3.2 MW. Furthermore, due to an increase in DG size, overall efficiency of distribution system is increased. Though, there are few real-world limitations upon which large DG power injection such as increase in real power loss and higher installation cost. It is also clear from Table 2 that higher DG injection results in greater improvement in voltage profile. ACSA injects more DG output power than UVDA. However, it is easy to understand from Table 2 that the output results produced by UVDA (Bayat *et al.*, 2016) are better than ACSA (Nara *et al.*, 2016).

Moreover, in the simulation results of case 3 value of the objective function is 52.89 kW lowest among all other algorithms. ACSA injects more than 3 MW cumulative power of DGs which is about 90 percent loading of network. On the other hand, the proposed CoDE algorithm optimally injects only 2.55 MW of DGs cumulative power and optimally opened the sectionalizing switches in order to get the lowest power loss. In FWA (Mohamed and Kowsalya, 2014), sequential approach is selected for DG site and capacity, as said by that optimal network reconfiguration is implemented first and then optimal DG site and size is selected. It is also clear from the comparison shown in TABLE 2 that in case 3, at the same time optimum DG integration and feeder reconfiguration is more successful to reduce line losses compared to case 1 and 2.

The final network of DS after simultaneous DG integration and network reconfiguration of case 3 is shown in Figure 6 and Figure 7 Shows the voltage level of all study cases of IEEE 33-bus standard DS. It is easy to comprehend from Figure 7 that voltage waveform is best in case 3 compared to case 1 and 2. The convergence curve of proposed CoDE algorithm for the 33-bus test systems considering all the study cases is as shown in Figure 8, and it is clear from Figure 8, in which lowest value of objective function is achieved in case 3.

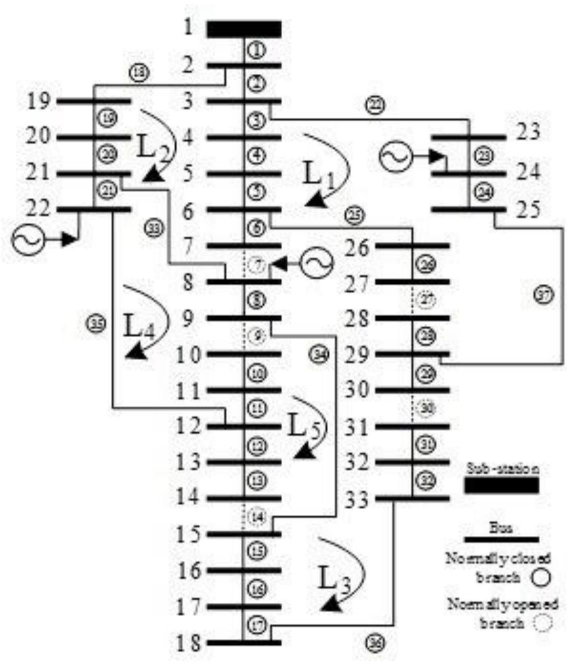

Figure 6. Final network after the DG integration and reconfiguration

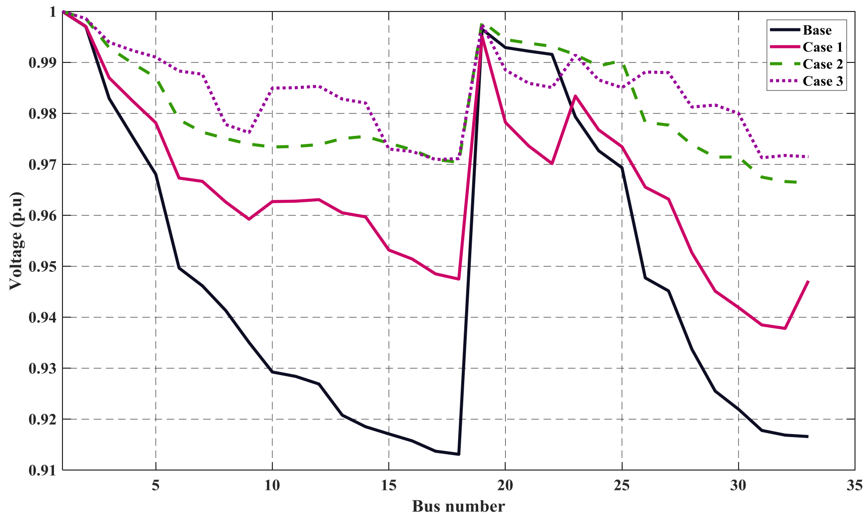

Figure 7. Comparison of voltage level of all cases

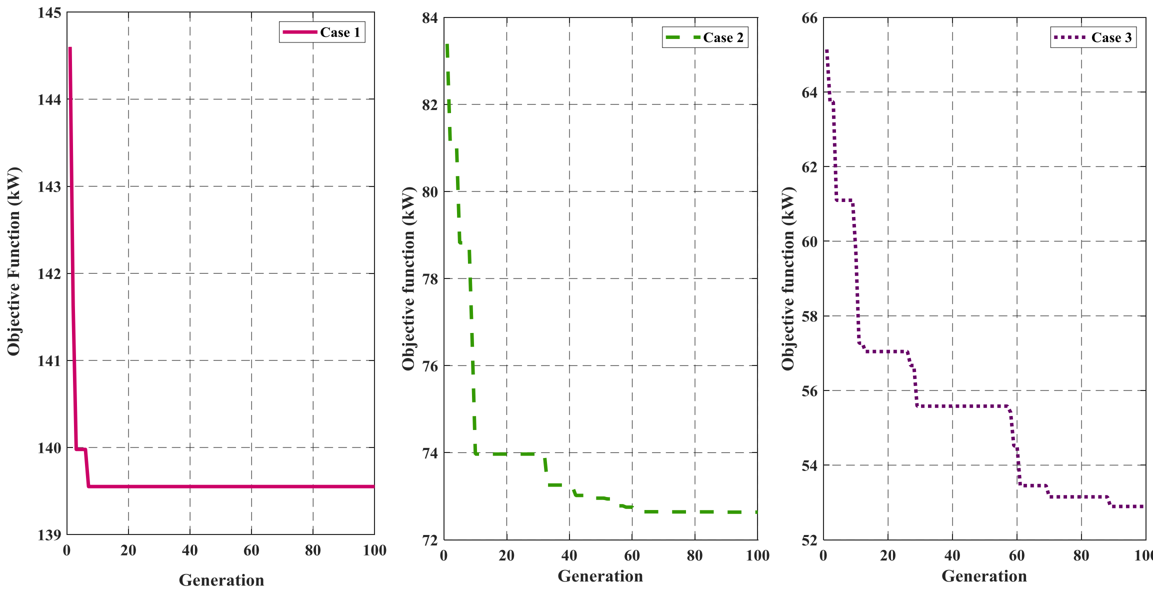

Figure 8. Convergence curve for the minimization of real power loss.

69-bus distribution system: Detailed data of 69-bus test DS is marked from (Savier and Das, 2007). This network comprised of 68 NC switches and 5 NO switches. Overall active and reactive power load demand on different nodes is 3.8 MW and 2.6 MVAr correspondingly. The comparison of output results with the past studies of 69-bus standard test system using proposed CoDE algorithm summarizes in Table 3.

In case 1, the CoDE method reduces real power loss compared to HSA, FWA, and ACSA from 225 kW to 98.59 kW. In case 2, the lowest total line losses of 62.43 kW are attained by the proposed CoDE method, whereas ACSA (Nguyen and Truong 2016) injects the largest value of DG. For the study case 3, the proposed algorithm minimizes real power loss up to 35.2 kW smallest among all algorithms along with the smaller value of DG injection compared to ACSA and UVDA algorithms. It is clear from TABLE 3 that case 3 is more effective as compared to case 2 and 3 for the enhancement of voltage level and minimization of active line losses. For case 3, the candidate buses at which optimal size of DG injections are 11, 64, 61 and best position of normally open switches are 70, 56, 69, 14, 61. Figure 9 displays the voltage level of all cases of 69-bus standard DS under study, it is also observed from Figure 9 that case 3 offers the best voltage level compared to all other cases. The sample of convergence curves of 69-bus test systems considering case 1, 2 and 3 are given in Figure 10. Figure 10 clearly shows that the minimum value of objective function appears in case 3 in comparison to other cases.

Table 3. Simulation Results and Comparison of IEEE 69-bus test system with Past Studies.

Study Cases	Items	Optimization algorithms				
		Proposed CoDE	**HSA (Rao *et al.*, 2013)**	**FWA (Mohamed and Kowsalya, 2014)**	**ACSA**	**UVDA (Bayat *et al.*, 2016)**
Case 1 (Reconfiguration only)	Open switches	70, 56, 69, 14, 61	69, 18, 13, 56, 61	14, 56, 61, 69, 70	14, 57, 61, 69, 70	14, 58, 61, 69, 70
	Real power loss	**98.59**	99.35	98.59	98.59	98.58
	Bus voltage min (bus)	0.9495 (61)	0.9428	0.9495 (61)	0.9495 (61)	0.9495 (61)
Case 2 (DG only)	Open switches	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73	69, 70, 71, 72, 73
	Real power loss	**62.43**	86.77	77.85	72.44	72.63
	DG size kW (bus no.)	1705.9 (61), 380.8 (18), 463.2 (11)	101.8 (65), 369.0 (64), 1302.4 (63)	225.8 (27), 1198.6 (61), 408.5 (65)	602.2 (11), 380.4 (18), 2000 (61)	604 (11), 417 (17), 1410 (61)
	Bus voltage min (bus)	**0.9831** (64)	0.9677 (--)	0.9740 (62)	0.9890 (65)	0.9688 (65)
Case 3 (simultaneous reconfiguration and DG)	Open switches	70, 56, 69, 14, 61	69, 17, 13, 58, 61	13, 55, 63, 69, 70	14, 58, 61, 69, 70	14, 58, 63, 69, 70
	Real power loss	**35.2**	40.3	39.25	37.02	37.11
	DG size MW (bus no.)	593.6 (11), 495.5 (64), 1460.8 (61)	1066.6 (61), 352.5 (60), 425.7 (62)	1127.2 (61), 275.0 (62), 415.9 (65)	541.3 (11), 1724.0 61), 553.6 (65)	538 (11), 673 (17), 1472 (61)
	Bus voltage min (bus)	**0.9819** (61)	0.9736	0.9796 (61)	0.9869 (50)	0.9816 (63)

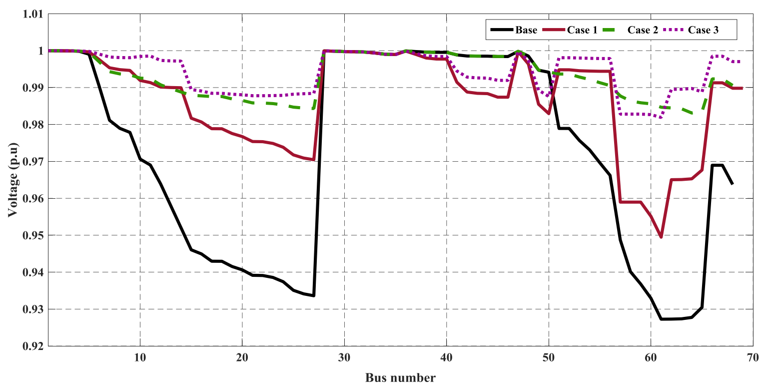

Figure 9. Comparison of voltage profile between cases 1, 2 and 3 of IEEE 69-bus test system

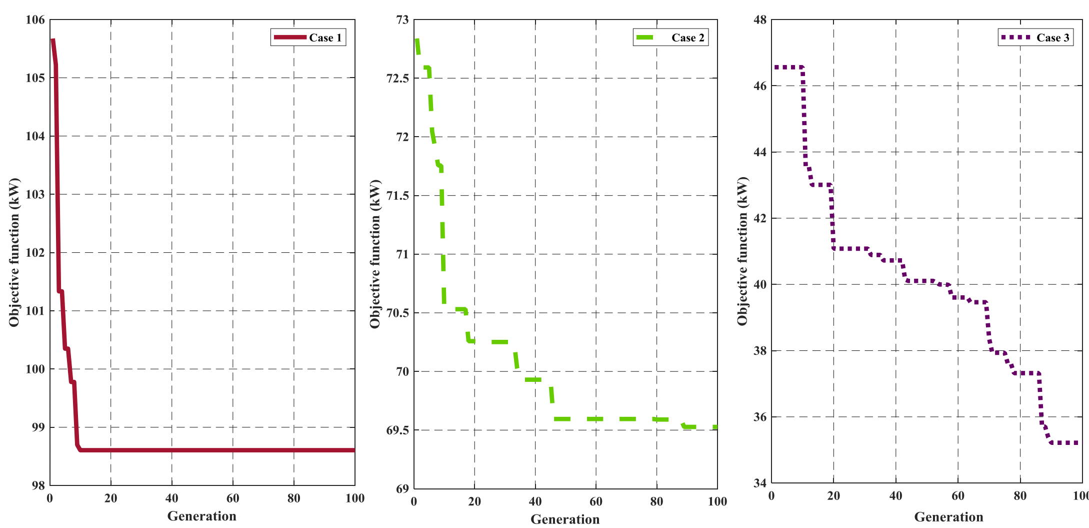

Figure 10. Convergence curves of all the cases of IEEE 69-bus DS

Conclusion: In this article, a new optimization method (CoDE) has been recommended for the optimum site and capacity of DG injection along with the best selection of switches for feeder reconfiguration. In order to show the superiority and effectiveness of the proposed method, it is applied to standard 33 and 69-bus IEEE distribution systems, considering the reduction of active line losses as the objective function. Furthermore, three different study cases for the reduction of objective function are simulated. The obtained results clearly show that the proposed technique has the ability to find global optimization value in all the study cases. It is also observed from the simulation results that, case 3 is more effective to decrease line losses and improve voltage associated with all other cases. The effectiveness of CoDE algorithm is validated by comparing it with the methods available in the recent literature. The simulation results have shown that using CoDE algorithm, best results are achieved compared with the results of ACSA, FWA, HSA, and UVDA in most of the cases.

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REFERENCES

Ayodele, T.R., A.S.O. Ogunjuyigbe, and O.O. Akinola. (2015). Optimal Location, Sizing, and Appropriate Technology Selection of Distributed Generators for Minimizing Power Loss Using Genetic Algorithm. Journal of Renewable Energy 2015.

Baran, M.E. and F.F. Wu (1989). Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Transactions on Power Delivery, 4(2), 1401-1407.

Bayat, A., A. Bagheri and R. Noroozian (2016). Optimal siting and sizing of distributed generation accompanied by reconfiguration of distribution networks for maximum loss reduction by using a new UVDA-based heuristic method. International Journal of Electrical Power & Energy Systems, 77, 360-371.

Celli, G., E. Ghiani, S. Mocci and F. Pilo (2005). A multiobjective evolutionary algorithm for the sizing and siting of distributed generation. Ieee Transactions on Power Systems, 20(2), 750-757.

Deb, K. (2000). An efficient constraint handling method for genetic algorithms. Computer Methods in Applied Mechanics and Engineering, 186(2), 311-338,

Flaih, F.M. F., X. Lin, S.M. Dawoud and M.A. Mohammed (2016). Distribution system reconfiguration for power loss minimization and voltage profile improvement using Modified particle swarm optimization. In 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), 25-28 Oct. 2016 2016 (pp. 120-124).

Ghosh, S. and S.K. Sonam (2008). An Efficient Method for Load−Flow Solution of Radial Distribution Networks (Vol. 1).

Kefayat, M., A.A. Lashkar and S.A. Nabavi Niaki (2015). A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources. Energy Conversion and Management, 92, 149-161.

Mohamed I.A. and M. Kowsalya (2014). A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using Fireworks Algorithm. International Journal of Electrical Power & Energy Systems, 62, 312-322.

Nara, K., A. Shiose, M. Kitagawa and T. Ishihara (1992). Implementation of genetic algorithm for distribution systems loss minimum re-configuration. IEEE Transactions on Power Systems, 7(3), 1044-1051, doi:10.1109/59.207317.

Rao, R., K. Ravindra, K. Satish and S. Narasimham (2013). Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. IEEE Transactions on Power Systems, 28(1), 317-325.

Savier, J. S. and D. Das (2007). Impact of Network Reconfiguration on Loss Allocation of Radial Distribution Systems. IEEE Transactions on Power Delivery, 22(4), 2473-2480, doi:10.1109/TPWRD.2007.905370.

Storn, R. and K. Price (1997). Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. Journal of Global Optimization, 11(4), 341-359, doi:10.1023/A:1008202821328.

Wang, Y., Z. Cai and Q. Zhang (2011). Differential Evolution With Composite Trial Vector Generation Strategies and Control Parameters. IEEE Transactions on Evolutionary Computation, 15(1), 55-66, doi:10.1109/TEVC.2010.2087271.

Yaprakdal, F., M. Baysal and A. Anvari-Moghaddam (2019). Optimal Operational Scheduling of Reconfigurable Microgrids in Presence of Renewable Energy Sources. Energies, 12(10), doi:10.3390/en12101858.