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Integration of Distributed Generators and Shunt Capacitor Banks to Minimize Power Loss and Enhance Voltage Stability Index

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Abstract

A substantial quantity of real power loss is accounted for the distribution system due to its radial nature. Efficient and secure operation of a distribution system, it is necessary to minimize the active power loss and the system's voltage stability index (VSI). Power loss and VSI in the distribution system can be minimized with the optimal integration of distributed generation (DG), shunt capacitor banks (SCB), and optimal feeder reconfiguration. In this regard, this paper presents a constraint composite differential evolution (C^2oDE) algorithm for the optimal siting and sizing of DG and SCB along with network reconfiguration. Moreover, the proposed algorithm is combined with the two representative constraint handling techniques (feasibility rule and epsilon constraint method) to find a feasible solution. The proposed approach aims to achieve technical benefits such as minimization of active power loss, voltage deviation (VD), and voltage stability index (VSI). During the optimization process, these technical benefits are considered objective functions. Various six study cases are formulated to measure the performance of a proposed method. Simulation is carried out on IEEE standard 33 and 69-bus radial networks. The simulation results show that the proposed method and the feasibility rule constraint technique is effective and superior compared to the other recent applied optimization methods. Also, simulation results of case 6 (b), where the power factor of DG is controlled, give the best performance and minimum values of all the objective functions compared to all the other cases.

Keywords: ***Distributed generation, Shunt capacitor bank, Distribution system, Composite differential evolution, constraint handling techniques***

1. Introduction

The power system is comprised of generation, transmission, distribution, and utilization. The distribution system is the portion between the power transmission network and utilization. The distribution system is designed as the weakly meshed scheme (comprised of tie and sectionalizing switches), but its operation is radial. Due to the radial nature of the distribution system, a large portion of active power loss appears (Akbar et al., 2022). In the literature, one of the techniques is network reconfiguration has been used to minimize power loss (Ali et al., 2023). Interchanging of tie and sectionalizing switches is called network reconfiguration. Tie switches are generally opened, and sectional switches are closed. Recently, some metaheuristic techniques are used for optimal network reconfiguration. These includes runner-root algorithm (RRA) (T. T. Nguyen, Nguyen, Truong, Nguyen, & Phung, 2017), modified bacterial foraging optimization (MBFO)

(Naveen, Sathish Kumar, & Rajalakshmi, 2015), parallel genetic membrane computing (PGMC) (Lei, Wu, Shi, & Shi, 2015), modified particle swarm optimization (MPSO) (Flaih, Xiangning, Dawoud, & Mohammed, 2016) and cuckoo search algorithm (CSA) (T. Nguyen & Truong, 2015).

Moreover, integrating appropriate distributed generation position and capacity can give several technical, environmental, and economic benefits. Recently numerous techniques have been studied to find the proper location and degree of various DGs categories (like a solar photovoltaic, wind turbine, diesel generator etc.). In (Meena, Swarnkar, Gupta, & Niazi, 2015), Taguchi method (TM) was used for the optimal site and size of DG allocation to show its effectiveness considering the 33-bus test system. In (Injeti & Kumar, 2011) genetic algorithm (GA) was proposed for the optimal capacity and allocation of DG in distribution system considering real power loss minimization. Hybrid GA-PSO was presented in the reference (Moradi & Abedini, 2012) considering the objective function of power loss, VD, and VSI. Authors in (Saravanamutthukumaran & Kumarappan, 2012) considered the various voltage-dependent load model for the optimal DG and capacity using the multiobjective optimization technique. Ant lion optimizer (ALO) (Palanisamy & Muthusamy, 2021) and hybrid ALO and fuzzy logic controller in (Samala & Mercy Rosalina, 2021) are applied to find the optimal site and size of DG. Non-dominated based multiobjective modified krill herd (MKH) algorithm (Davodi, Esapour, Zare, & Rostami, 2015) was considered for optimal DG allocation.

Like DGs, shunt capacitor banks (SCBs) are also used to minimize power loss and improve voltage profile. SCBs should also be effectively and efficiently allocated in the distribution system. Integration of SCBs added locally reactive power in the system to improve load-bus voltage and reduce power losses. It also reduces the costs of reactive power from the substations. In the literature, numerous optimization techniques have been presented for the optimal allocation of SCBs. That are PSO (Prakash & Sydulu, 2007), hybrid PSO and crow search algorithm (CSA) (Askarzadeh, 2016), differential evolution (DE) (Neelima & Subramanyam, 2011), hybrid DE and pattern search (PS) called DE-PS (El-fergany, 2013), teaching learning-based optimization (TLBO) (Sultana & Roy, 2014) and direct search algorithm (DSA) (Raju, Murthy, & Ravindra, 2012),. Moreover, the distribution system's operation and the loss minimization can be effectively achieved by considering simultaneous DGs and SCBs allocation. Therefore, hybrid integrations of DGs and SCBs can significantly minimize the distribution network losses and enhance system performance. In the literature, various number of optimization techniques has been used for the optimal allocation of simultaneous DGs and SCBs. Recently, some metaheuristic algorithms that includes harmony search algorithm (HSA) (Rao, Ravindra, Satish, & Narasimham, 2013), bacterial foraging optimization (BFO) (Mohamed Imran & Kowsalya, 2014), water cycle algorithm (WCA) (El-Ela, El-Sehiemy, & Abbas, 2018), a multi objective evolutionary algorithm based on decomposition (MOEA/D) (Partha P Biswas, Mallipeddi, Suganthan, & Amaratunga, 2017), enhanced sine cosine algorithm (ESCA) (Saeidi, Niknam, Aghaei, & Zare, 2019), intersect mutation differential evolution (IMDE) (Khodabakhshian, Andishgar, & Systems, 2016) and backtracking search algorithm (BSA) (Fadel, Kilic, & Taskin, 2017) have been used for finding the DG and SCBs allocation. Fireworks algorithm (FWA) (Mohamed Imran, Kowsalya, & Kothari, 2014), adaptive cuckoo search algorithm (ACSA) (T. T. Nguyen, Truong, & Phung, 2016) and uniform voltage distribution based constructive reconfiguration (UVDA) in (Bayat, Bagheri, & Noroozian, 2016) have been used to find the simultaneous optimal reconfiguration and DG allocation. However, to our understanding, few researchers conduct ideal network reconfiguration in conjunction with optimal sizing and positioning of DGs and SCs that includes GA (Saonerkar & Bagde, 2014), linear population size reduction success history-based parameter adaption technique of DE (L-SHADE) LSHADE (P. P. Biswas, Suganthan, & Amaratunga, 2018) minimization of power loss as the objective function.

This paper proposes the constraint composite differential evolution (C2oDE) (Wang, Li, Li, & Wang, 2018) algorithm integrated with the most widely used constraint handling techniques in the optimization era for optimal reconfiguration and DGs SCBs allocation. The proposed integrated optimization technique is intended to achieve the following advantages.

1. Maximum penetration of DGs and SCBs improves the distribution system's technical problems such as minimization of power loss and VD and improving VSI.
2. Integration of uncontrollable power factor (PF) of DG (unity PF) and controllable PF of DG (operating between 0.8 and 1 lagging) considered for the flexible distribution system operation.
3. Six study cases of single and weighted sum multi-objective functions are formulated to find the optimal reconfiguration, DGs, and SCBs allocations considering IEEE 33 and 69-bus systems.

The remaining portion of the paper is prepared as; load flow, objective functions and constraints are discussed in section 2, whereas section 3 provides the structure of the proposed optimization method. Test systems, case studies, and parameters of C^2oDE are discussed in section 4, while sections 5 and 6 present the simulation results and conclusion.

2. Problem Formulation

Simultaneous DG and SCB allocation, along with reconfiguration, are constrained optimization problems (COPs). Generally, the objective function (OF) of COP subject to inequality $g_j(\vec{x}_i)$ and equality $h_j(\vec{x}_i)$ constraints can be described as:

$$\begin{aligned} &\min_{\vec{x}_i} f(\vec{x}_i),\ \vec{x}_i \in S,\ L_i \le x_i \le U_i\ \ \forall\, i = 1,2,\dots,D \\ &\text{Subject to}\ \ g_j(\vec{x}_i) \le 0,\ j = 1,\dots,l \qquad (1) \\ &h_j(\vec{x}_i) = 0,\ j = l+1,\dots,m \end{aligned}$$

Whereas, $\vec{x}_i$ is the decision vector, D is the number of dimensions in decision vector, S is the entire search space where L and U are the bounds, l and m are the number inequality and equality constraints. For the computation of objective function, equality and inequality constraints consider the typical configuration of a radial distribution network and the injection of DG and SCB is given in Fig. 1.

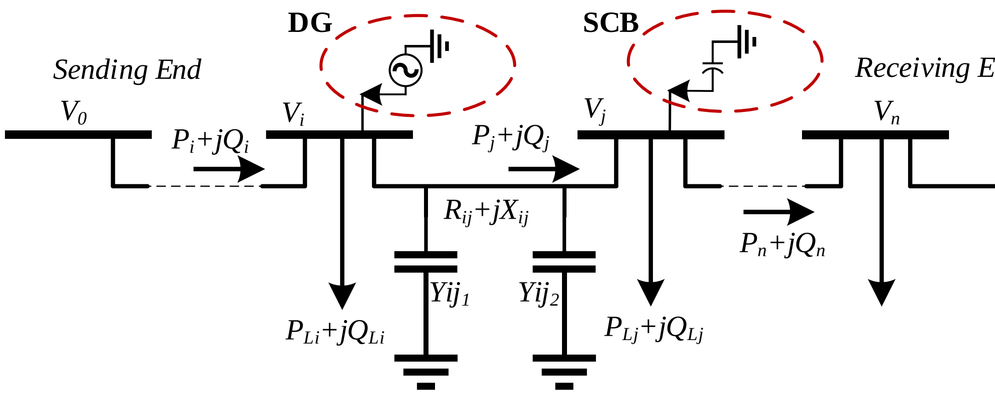

Fig. 1. One line of typical radial feeder

This study aims to determine the best capacity and position of both DGs and SCBs to minimize power loss and voltage deviation with maximization of VSI. For the computation of objective functions, it is first to calculate the magnitude of voltage and its angle at each bus using direct search based forward-backward sweep load flow technique; for detail, see reference (Jen-Hao, 2003). In this paper, DG and SCB are considered negative PQ loads at power factor between 0.8 and 1 and the bus at which DG unit is connected that bus is categorized as PQ bus. If the DG is added to the bus i and having output power P_{DG} then the load at that bus changes from P_{di} to $(P_{di}-P_{DG})$. Likewise, if SCB of reactive power Q_C is added to j^{th} bus in the distribution system, it alters the reactive load Q_{dj} to $(Q_{dj}-Q_C)$. During the optimization process, the proposed algorithm checks all possible places with all feasible sizes of both DGs and SCBs to find the appropriate grouping that reduces active power loss and VD while maximum VSI. Three objective functions (OF), such as power loss, VD, and VSI are considered in this work. In the first OF, real power loss (f_1) is minimized that can be expressed as (P. P. Biswas et al., 2018):

$$f_1(x) = min\left(\sum R_{ij}.\frac{P_i^2+Q_i^2}{|V_i|^2}\right) \qquad (2)$$

Whereas, P_i and Q_i show the active and reactive power injection at bus i as shown in “Fig.1”. In the second technical objective function (f_2) voltage deviation index is considered in which a better voltage profile is preserved and given as (Mohamed Imran et al., 2014)

$$f_2(x) = \min \sum_{i=1}^{N} \left(\frac{vi - v_i^{spcc}}{v_i^{max} - v_i^{min}} \right)^2 \qquad (3)$$

Whereas VSI is the third objective function (f_3), which is one of the most significant indicators for secure operation. VSI between bus i and j can be expressed as (Mohamed Imran et al., 2014):

$$VSI_j = V_i^4 - 4 \times \left(P_{Lj,eff} R_{ij} + Q_{Lj,eff} X_{ij}\right) \times V_i^2 - 4 \times (P_{Lj,eff} X_{ij} - Q_{Lj,eff} R_{ij})^2 \quad (4)$$

Where, $P_{Lj,eff}$ and $Q_{Lj,eff}$ are the effective real and reactive load demand fed through bus j, R_{ij} and X_{ij} are the line resistance and inductive reactance, respectively linking between bus i and j. During operation, a bus with the lowest value of VSI, among all others, needs to be maximized to enhance the entire network's voltage level. Therefore, for the maximization of VSI, a third objective function is given as:

$$f_3(x) = max\left(1/min\left(VSI_{ij}\right)\right) \ \forall \ i, j \qquad (5)$$

Equality constraints: Power balance constraints are satisfied during the load flow and is described as:

$$\sum_{i=1}^{NG} P\, G_i = P_L + P_{Loss} \qquad (6)$$

$$\sum_{i=1}^{NG} Q\, G_i = Q_L + Q_{Loss} \qquad (7)$$

Inequality constraints: The bus voltage, branch flow during reconfiguration, and active/reactive power generated from the DGs along with DG power factor (PF) and installed capacitor limit should not increase beyond the permissible limit of the distribution network and given as:

$$V_i^{min} \le |V_i| \le V_i^{max} \qquad (8)$$

$$I_{ij} \le I_{ij(\max)} \qquad (9)$$

$$\sum_{i=1}^{N_{DG}} P_{DG,i} \le P_{DG}^{max} \qquad (10)$$

$$\sum_{i=1}^{N_{DG}} Q_{DG,i} \le Q_{DG}^{max} \qquad (11)$$

$$\sum_{i=1}^{N_C} Q_{C,i} \le Q_C^{max} \qquad (12)$$

$$PF_i^{min} \le PF_i \le PF_i^{max} \qquad (13)$$

Where, V_i^{min} and V_i^{max} are the minimum and maximum allowable voltage limits for any bus i, I_{ij} is the branch current. P_{DG}^{max} and Q_C^{max} are the maximum ratings of DG and SCB respectively, N_{DG} and N_c are the number of DGs and SCBs.

3. Proposed optimization algorithm

Optimal reconfiguration combined with optimum capacity and position of both DGs and SCBs allocation problem is constrained optimization problem (COP). Since in the past two decades, evolutionary algorithms (EAs) have involved noticeable attention in resolving practical constrained optimization problems efficiently. Differential evolution (DE) is a popular EA. It has numerous attractive advantages for finding the feasible solution to COP because of simple implementation, includes few control parameters and achieves top rank in many computations. In the literature, numerous DE variants have been applied to find constrained type engineering problems. In this work, constrained composite DE (C^2oDE) global optimizer (Wang et al., 2018) is proposed and added with two different representative constraint techniques to find the balance between constraints and objective functions. In the next sub-sections, the proposed constraint handling techniques (CHTs) and the C^2oDE optimization framework are introduced.

4.1 C^2oDE algorithm

In the C^2oDE algorithm, differential vectors are used for the generation of offspring. Fundamentally, there are four stages in the proposed algorithm. In the first stage, randomly generation of an initial population $\vec{x}_i^t(i \in \{1 \dots NP\})$ in the range of lower and upper bound of search space. After that, in the second stage, mutation operators are used for the generation of mutant vector $\vec{v}_i^t(i \in \{1 \dots NP\})$, in this stage, three types of mutation operators were used:

1) current-to-rand/l

$$\vec{v}_i^t = \vec{x}_i^t + F \cdot (\vec{x}_{r1}^t - \vec{x}_i^t) + F \cdot (\vec{x}_{r2}^t - \vec{x}_{r3}^t) \qquad (14)$$

2) Modified rand-to-best/l

$$\vec{v}_i^t = \vec{x}_{r1}^t + F \cdot (\vec{x}_b^t - \vec{x}_{r2}^t) + F \cdot (\vec{x}_{r3}^t - \vec{x}_{r4}^t) \qquad (15)$$

3) current-to-best/l

$$\vec{v}_i^t = \vec{x}_i^t + F \cdot (\vec{x}_b^t - \vec{x}_i^t) + F \cdot (\vec{x}_{r1}^t - \vec{x}_{r2}^t) \qquad (16)$$

Where, $\vec{x}_{r1}^t$ to $\vec{x}_{r4}^t$ are the mutually different decision vectors randomly selected from 1 to *NP* individuals, $\vec{x}_b^t$ shows the best solution of current generation *t*. Each mutation vector has distinct features for example mutation vector given in Eq. (14) can explore the entire search space and hence increase the diversity however, in Eq. (15) and (16) are accelerating the convergence to get information from the best individual. In the third step trial vector $\vec{u}_i^t$ is generated using a binomial crossover operator between each pair of $\vec{v}_i^t$ and $\vec{x}_i^t$, It can be noticed from Fig. 2 that, for each target vector, three offsprings are generated with distinct advantages of exploration and exploitation using trail vector generation strategy and pool of parameters.

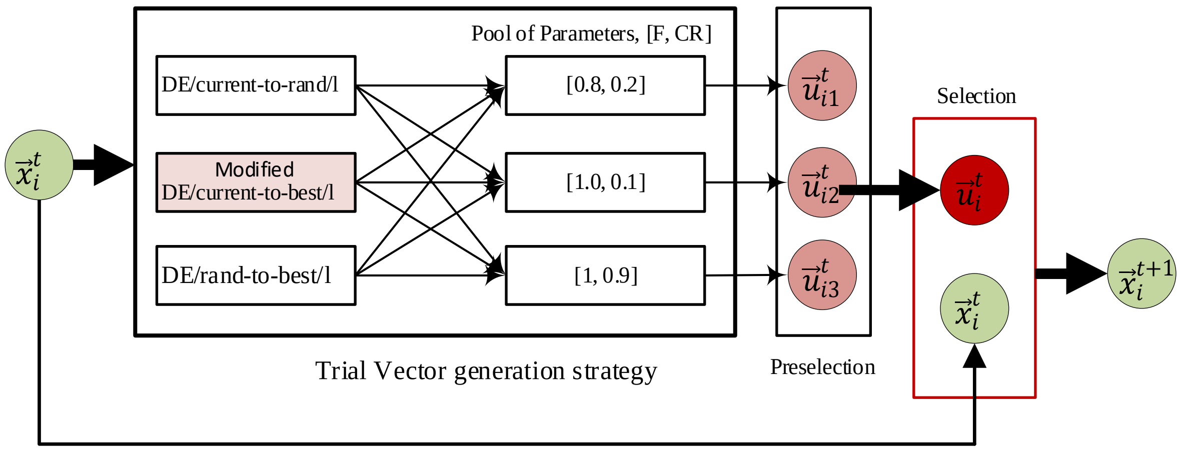

Fig. 2. Framework of proposed C²oDE algorithm (Wang et al., 2018)

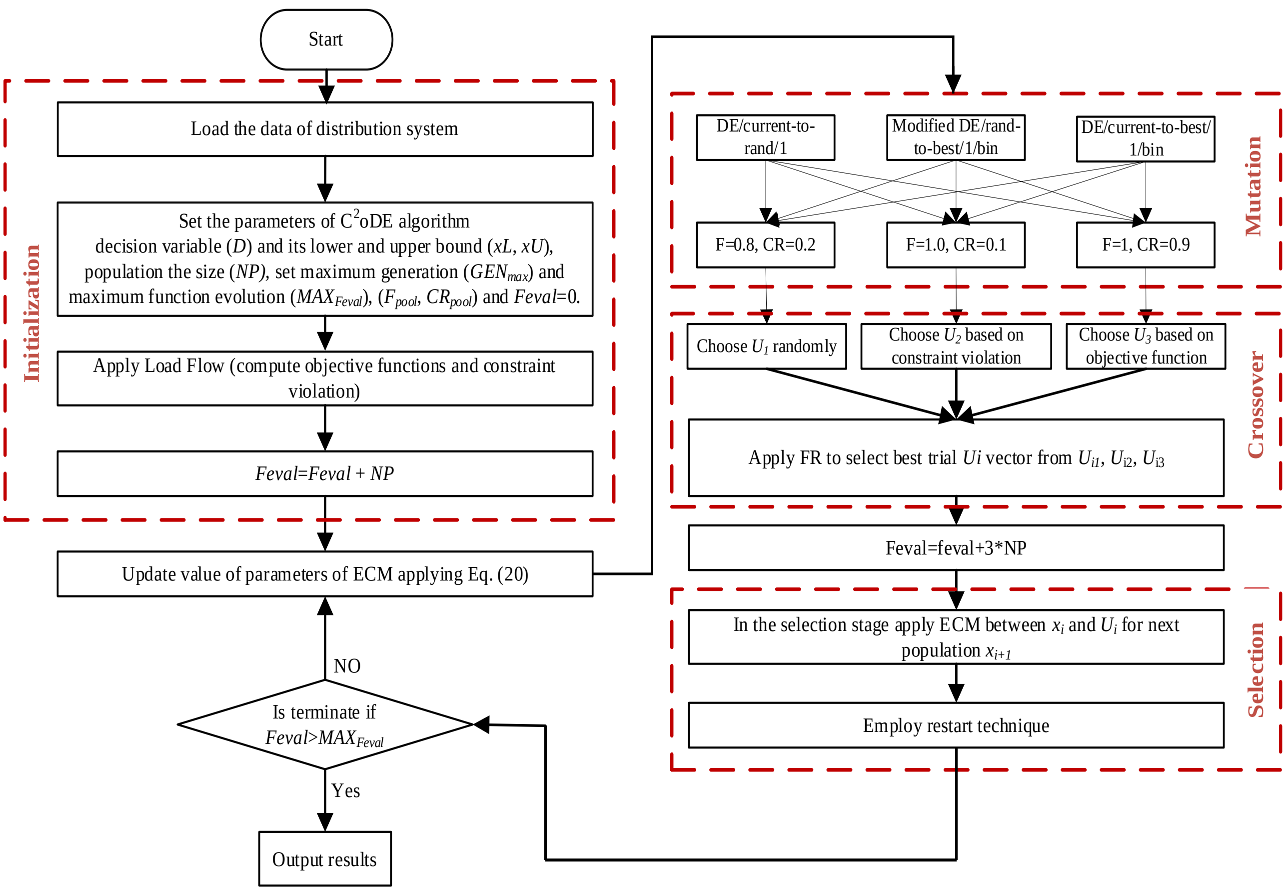

Fig. 3. Flow chart for the implementation of C²oDE

Furthermore, the feasibility rule (FR) and ε constrained method (ECM) are implemented with the proposed algorithm at phase of preselection and selection to select feasible solutions for the next generation. Both the constraint techniques can be defined by considering the equality and inequality constraints as shown in Eq. (1), and then to compute the overall constraint violation as:

$$G_j(\vec{x}) = \begin{cases} max\left(0, g_j(\vec{x})\right) & 1 \leq j \leq l \\ max\left(0, \left|h_j(\vec{x})\right|\right) & l+1 \leq j \leq m \end{cases} \quad (18)$$

$$G(\vec{x}) = \sum_{j=1}^{m} G_j(\vec{x}) \quad (19)$$

In FR two members of trail vector are randomly selected (say $\vec{u}_i$ and $\vec{u}_j$) and compare them as follows:

i. If both $\vec{u}_i$ and $\vec{u}_j$ are feasible, select the one which has a minimum objective function value.
ii. If both $\vec{u}_i$ and $\vec{u}_j$ are infeasible, select the one which has minimum constraint violation.
iii. If $\vec{u}_i$ is feasible and $\vec{u}_j$ is an infeasible, always select feasible one

In ECM, let it be assumed that $\vec{u}_i$ is superior to $\vec{x}_i$ at the selection stage if and only if the following conditions are satisfied:

$$\begin{cases} f(\vec{u}_i) < f(\vec{x}_i), if\ G(\vec{u}_i) < \mathcal{E}\ and\ G(\vec{x}_i) < \mathcal{E} \\ f(\vec{u}_i) < f(\vec{x}_i), if\ G(\vec{u}_i) = G(\vec{x}_i) \\ G(\vec{u}_i) < G(\vec{x}_i) \end{cases} \quad (20)$$

Whereas, parameter $\mathcal{E} = \mathcal{E}_o(1 - \mathrm{t/T})^{cp}$, if the ratio between current and maximum generation (t/T) is less than 50%, otherwise 0. However, $\mathcal{E}_o$ is the initial threshold, and in the starting it is equal to the maximum constraint violation. The parameter cp can be calculated as:

$$cp = -\frac{log\ \varepsilon_0 + \lambda}{log\ (1-p)} \quad (21)$$

Where λ is set to 6, and p controls the exploitation of objective function. The flow diagram of C^2oDE is given in Fig. 3.

4. Test Systems, Case studies, and Parameters of Algorithm

In this paper, IEEE standard 33 and 69-bus test systems are used for finding the appropriate allocation of DG and SCB along with reconfiguration. The total complex power demand of the proposed methods is 3715+j2300 kVA and 3802+j2694 kVA, respectively. The proposed distribution network's line and load data are given in (Biswas et al., 2018), and the base configuration is as shown in Fig. 4 and 5. Before and after network reconfiguration, sectionalizing and tie switches must be the same in number. Both the networks have five loops shown in Fig. 4 and 5. There must be an open switch in the entire loop, and all the buses are connected with the root bus (sub-station/slack bus) to ensure radial constraint. Optimal combination of tie and sectionalizing switches, the proposed algorithm conducts inspections of all such possible combinations. The developed basic loops of both the study systems are shown in Table 1.

In case 1 to 4 maximum rating of DG injection is 2 MW in 33-bus test network and 2.25 MW in 69-bus system, whereas; SCB rating is limited to less than the demand MVAr rating (Biswas et al., 2017). Moreover, to increase DGs' penetration (only in cases 5 and 6), the maximum rating of DGs and SCBs is less than active and reactive power demand. The parameters of C^2oDE algorithm are shown in Table 2.

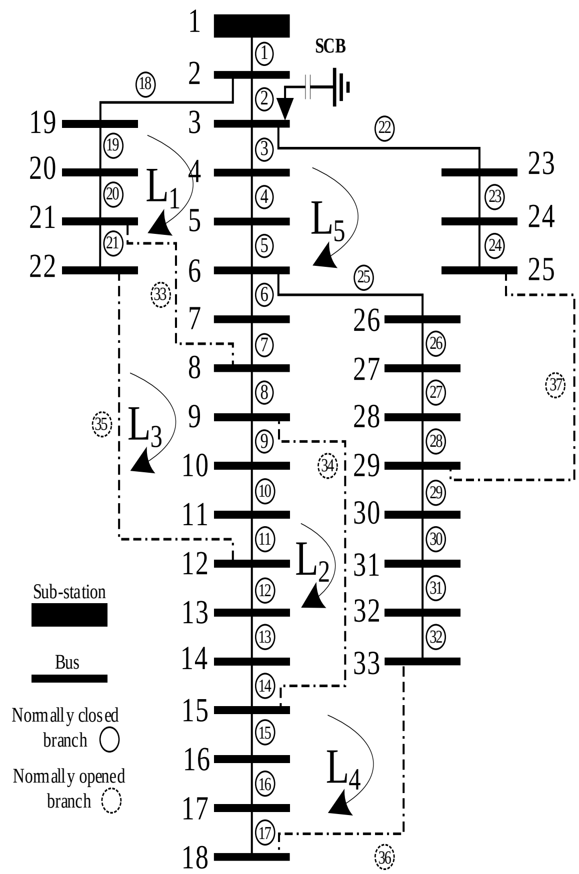

Fig. 4. Base configuration of 33-bus

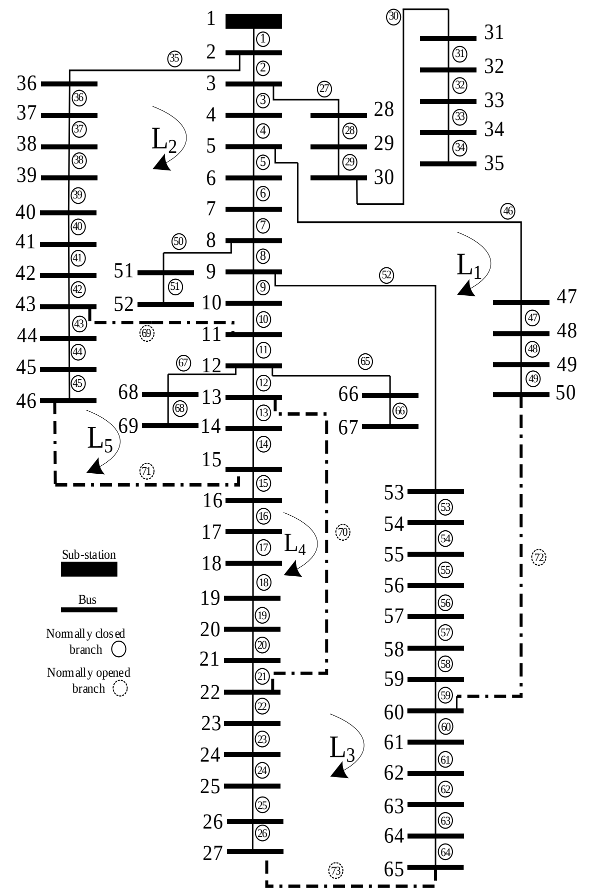

Fig. 5. Base configuration of 69-bus

TABLE I. Fundamental loops of 33 and 69-bus networks

Network	Switches (sectionalizing and Ties) in Fundamental Loops	# Switches
33-bus	2, 3, 4, 5, 6, 7, 18, 19, 20, **33**	10
	12, 13, 14, **34**	4
	8, 9, 10, 11, 21, 33, **35**	7
	15, 16, 17, 29, 30, 31, 32, **36**	8
	22, 23, 24, 25, 26, 27, 28, **37**	8
69-bus	3, 4, 5, 6, 7, 8, 9, 10, 35, 36, 37, 38, 39, 40, 41, 42, **69**	17
	15, 16, 17, 18, 19, 20, **70**	7
	11, 12, 13, 14, 43, 44, 45, **71**	8
	46, 47, 48, 49, 52, 53, 54, 55, 56, 57, 58, **72**	12
	21, 22, 23, 24, 25, 26, 59, 60, 61, 62, 63, 64, **73**	13

TABLE II. Parameters of Co^2DE for case 1 to case 6

Study Cases	Pop size	Power Factor (PF)	Decision variable	Max Gen
Case 1 to 4	100	1	5, 6, 6, 12	100
Case 5	150	1	17	150
Case 6	150	[0.8, 1]	20	150

Furthermore, six study cases of single and weighted sum multi objective are considered.

Case	Description
1	Power loss minimization considering the only reconfiguration
2	Power loss minimization considering only DG
3	Power loss minimization considering only SCB
4	Power loss minimization considering simultaneous DG and SCB
5	(a) Power loss minimization considering simultaneous DG (without controllable power factor) and SCB allocation along with optimal reconfiguration. (b) Weighted sum multiobjective optimization (power loss, VD, and VSI) considering simultaneous DG (without controllable power factor) and SCB allocation along with optimal reconfiguration.
6	(a) Single objective (minimization of power loss) considering simultaneous DG (with controllable power factor) and SCB allocation along with optimal reconfiguration. (b) Weighted sum multiobjective optimization (power loss, VD, and VSI considering simultaneous DG (with controllable power factor) and SCB allocation along with optimal reconfiguration.

5. Simulation Results, Discussion and Comparison

The simulation results are illustrated, evaluated, and contrasted in this section with similar previous research. Each case is run ten times, and in each run, output results are compatible with insignificant differences between separate runs.

5.1 33-bus Distribution Network

The simulation results and comparison of the proposed algorithm with the most recent algorithms for case 1 (only reconfiguration) are shown in Table 3.

C^2oDE accomplishes the minimum kW loss in case 1 along with some other algorithms as mentioned in Table 3. Results and comparison of case 2 to case 4 given in table 4 and it is clearly shown that the solution of C^2oDE algorithm is good compared to most of the algorithms in terms of small cumulative rating of DGs, SCBs, and objective functions. Simulation results of case 2 compared with that of HSA (Rao et al., 2013), PSO (Moradi & Abedini, 2012), FWA (Mohamed Imran et al., 2014), TM (Meena et al., 2015), BFOA (Mohamed Imran & Kowsalya, 2014), GA and hybrid GA/PSO (Moradi & Abedini, 2012). C^2oDE algorithm gives 79.02 kW losses with 61.0% compared to the base case. DGs are allocated at buses 25, 30 and 14 with the injection of 0.4266, 0.9055 and 0.6678 MW, respectively. The minimum voltage level (0.9595 p.u) appeared on bus 33. Simulation results of case 3 (only SCBs allocation) are compared with the other methods BFOA (Mohamed Imran & Kowsalya, 2014), and PSO (Moradi & Abedini, 2012). In this case, SCBs are optimally allocated at bus numbers 30, 24 and 13 with the injection of 1.143, 0.566, and 0.423, respectively.

TABLE III**.** Simulation results and comparison of Case1

Algorithm	**Tie Switches**	**Ploss (kW)**	**Vmin (bus)**
Base	33, 34, 35, 36, 37	202.6	0.9131 (18)
C^2oDE	**7, 9, 14, 32, 37**	**139.55**	**0.9378 (32)**
RRA (T. T. Nguyen et al., 2017)	7, 9, 14, 32, 37	**139.55**	0.9378 (32)
CSA (T. Nguyen & Truong, 2015)	7, 9, 14, 32, 37	**139.55**	0.9378 (32)
FWA (Mohamed Imran et al., 2014)	7, 9, 14, 28, 32	139.98	0.9413 (32)
ACSA (T. T. Nguyen et al., 2016)	7, 9, 14, 28, 32	139.98	0.9413 (32)
UVDA (Bayat et al., 2016)	7, 9, 14, 32, 37	**139.55**	0.9378 (32)

In addition, Table 4 shows that the C2oDE effectively finds the optimal capacity and site of SCB with the lowest operational losses of 132.16 kW and connected SCBs capacity is 2.132 MVAr with the minimum voltage 0.938 p.u appeared on bus number 18. Case 4 suggests the injection of three DGs at three different buses 14, 25 and 30 with the injection of 0.605, 0.507 and 0.873 MW respectively and three SCBs at buses 11, 30 and 24 of the rating 0.447, 1.017 and 0.414 respectively. Power loss18.878 kW is reached in comparison to GA [31], BFOA [20], LSHADE [32] and WCA [21]

TABLE IV. IEEE 33-Bus Simulation Results and Assessment of Case 2 to Case 4

Case #	Method	DG size (bus #)	SCB size (bus #)	Ploss (kW)	Vmin (bus #)
Case 2	**C^2oDE**	**0.4266 (25), 0.9055 (30) 0.6678 (14)**	--	**79.02**	**0.9595 (33)**
	HSA (Rao et al., 2013)	0.5724 (17), 0.107 (18), 1.0462 (33)	--	96.76	0.967 (29)
	FWA (Mohamed Imran et al., 2014)	0.5897 (14), 0.189 (18), 1.0146 (32)	--	88.68	0.968
	TM (Meena et al., 2015)	0.5876 (15), 0.1959 (25), 0.783 (33)	--	91.305	0.958 (30)
	BFOA (Mohamed Imran & Kowsalya, 2014)	0.633 (17), 0.09 (18), 0.9470 (33)	--	98.3	0.964
	GA (Moradi & Abedini, 2012)	1.50 (11), 0.4228 (29), 1.0714 (30)	--	106.3	0.981 (25)
	PSO (Moradi & Abedini, 2012)	1.1768 (8), 0.9816 (13), 0.8297 (32)	--	105.35	0.980 (30)
	GA/PSO (Moradi & Abedini, 2012)	0.9250 (11), 0.8630 (16), 1.2 (32)	--	103.4	0.980 (25)
Case 3	**C^2oDE**	**--**	**1.143 (30), 0.566 (24), 0.423 (13)**	**132.16**	**0.938 (18)**
	BFOA (Mohamed Imran & Kowsalya, 2014)	--	0.349 (18), 0.821 (30), 0.277 (33)	144.04	0.936

	PSO (Askarzadeh, 2016)	--	0.9 (2), 0.45 (7), 0.45 (31), 0.3 (15), 0.45 (29)	132.48	0.945
Case 4	**C²oDE**	**0.605 (14), 0.507 (25), 0.873 (30)**	**0.447 (11), 1.017 (30), 0.414 (24)**	**18.87**	**0.981 (18)**
	WCA (El-Ela et al., 2018)	0.973 (25), 1.04 (29), 0.563 (11)	0.465 (23), 0.565 (30), 0.535 (14)	24.688	0.980 (33)
	GA (Saonerkar & Bagde, 2014)	0.25 (16), 0.25(22), 0.50 (30)	0.30 (15), 0.30 (18), 0.30 (29), 0.60 (30)	71.25	0.971
	LSHADE (P. P. Biswas et al., 2018)	0.665 (14), 0.446 (25), 0.889 (30)	0.950 (3), 0.341 (14),1.009 (30)	19.37	0.9863 (8)
	BFOA (Mohamed Imran & Kowsalya, 2014)	0.542 (17), 0.160 (18), 0.895 (33)	0.163 (18), 0.338 (33), 0.541 (30)	41.41	0.978

TABLE V. IEEE 33-Bus Results of C²oDE for Case 5 and 6

Case No.	**DGs (MW)**		**SCB (MVAr)**	**Open Switches**	**Objective function**	**Ploss (kW)**	**VD (p.u)**	**VSI (p.u)**	**min Voltage (bus)**
	Power Factor	Size (location)	Size (Location)						
Case 5 (a)	1	0.696 (33), 1.221 (25), 1.226 (8)	0.242 (33), 0.991 (30), 0.606 (08)	11, 4, 13, 15, 23	8.839	**8.839**	**0.000404**	0.9919 (14)	**1.0336 p.u**
Case 5 (b)	1	0.796 (31), 1.035 (25), 1.057 (9)	0.651 (25), 0.796 (30), 0.514 (9)	33, 6, 13, 17, 25	**4.9062**	**9.286**	**0.028101**	0.9940 (17)	**1.02397**
Case 6 (a)	0.9745, 0.9401, 0.9016	0.8038 (33), 1.002 (8), 1.2661 (25)	0.145 (15), 0.469 (30), 0.157 (17)	35, 20, 12, 30, 27	**7.6859**	**7.686**	**0.000302**	**0.9946 (22)**	**1.0247**
Case 6 (b)	0.9022, 0.9396, 0.9273	0.902 (8), 0.939 (25) 0.927 (32)	0.001 (10), 0.652 (30) 0.1477 (23)	35, 5, 12, 15, 25	**4.1969**	**7.827**	**0.07678**	0.9876 (13)	**1.0558**

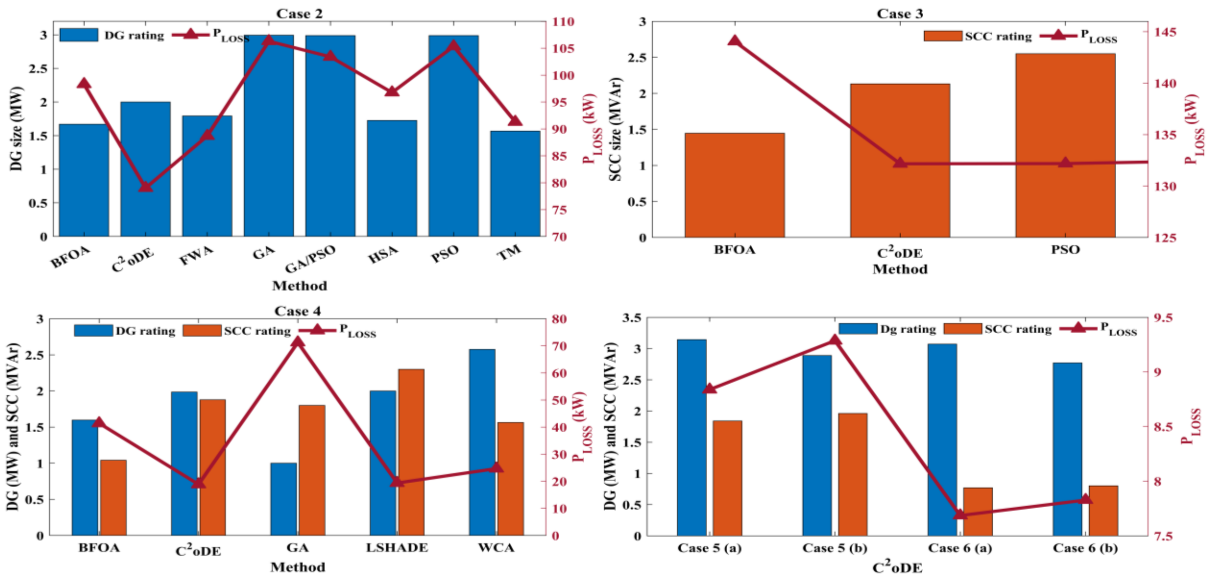

Fig. 6. DG and SCB rating of all the cases of 33-bus

Minimum p.u voltage 0.9813 is found at bus 18. The last column of Table 3 and Table 4 indicates minimum voltage experiences the bus in the system. Suggested capacity and allocation of DG and SCB, C2oDE gives better voltage deviation from the 1 p.u. As shown in Fig. 6, C2oDE gives the smallest active power loss as compared to other methods along with optimal DG and SCB injection. Further, Table 5 shows the simulation results of cases 5 and 6 in which controlled and uncontrolled PF of DG is considered. In Case 5 (a) (single objective) objective function 8.839 kW loss whereas 0.000404 p.u VD and 1.0336 p.u VSI appear by reconfiguration and cumulative 3.1439 MW DGs and 1.8397 MVAR of SCBs injection. In Case 5 (b) (multi-objective) power loss, VD and VSI incurs 9.2864 kW, 0.028101p.u and 1.02397p.u respectively, whereas weighted sum multi objective function is approach is 4.9062 with 50, 25 and 25 priorities. Cumulative DG and SCB injection are 2.25 MW and 2.69 MVAR.

However, in case 6, each DG's PF is controlled and considered the decision vector in the optimization process. In Case 6 (a) (single objective), objective function power loss is reduced up to 7.6859 kW, approximately 95% reduction with the integration of a total of 3.0722 MW and 0.7705 MVAr. However, in case 6 (b) (weighted sum multi objective), minimize the active power loss up to 7.82755 kW, slightly less than case 6 (a) with the injection of 2.7691 MW and 0.802 MVAr.

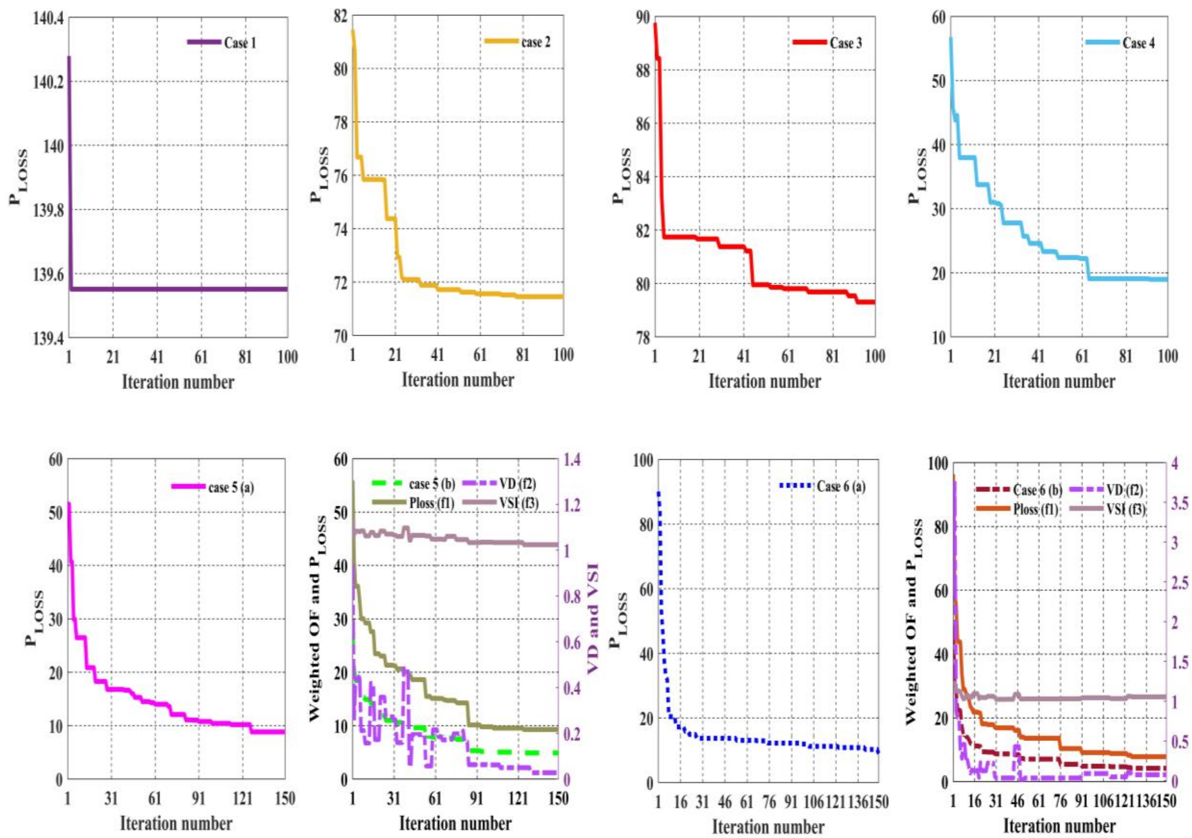

Fig. 7. Convergence curve of case 1 to case 6 of 33-bus test system

However, in case 6, each DG's PF is controlled and considered the decision vector in the optimization process. In Case 6 (a) (single objective), objective function power loss is reduced up to 7.6859 kW, approximately 95% reduction with the integration of a total of 3.0722 MW and 0.7705 MVAr. However, in case 6 (b) (weighted sum multi objective), minimize the active power loss up to 7.82755 kW, slightly less than case 6 (a) with the injection of 2.7691 MW and 0.802 MVAr. It is concluded from the simulation results of cases 5 and 6, as shown in "Table 5", that the optimal network reconfiguration with optimum DG allocation considering controllable PF and SCBs such as case 6 (a and b) is effective. Fig. 7 shows the convergence of the objective function for Case 1 to Case 6. Fig. 8 shows a comparison between the voltage level of all the study cases of 33-bus network. The voltage profile of case 6 (a) (PF of DG is controlled) close to 1 p.u compared to other cases.

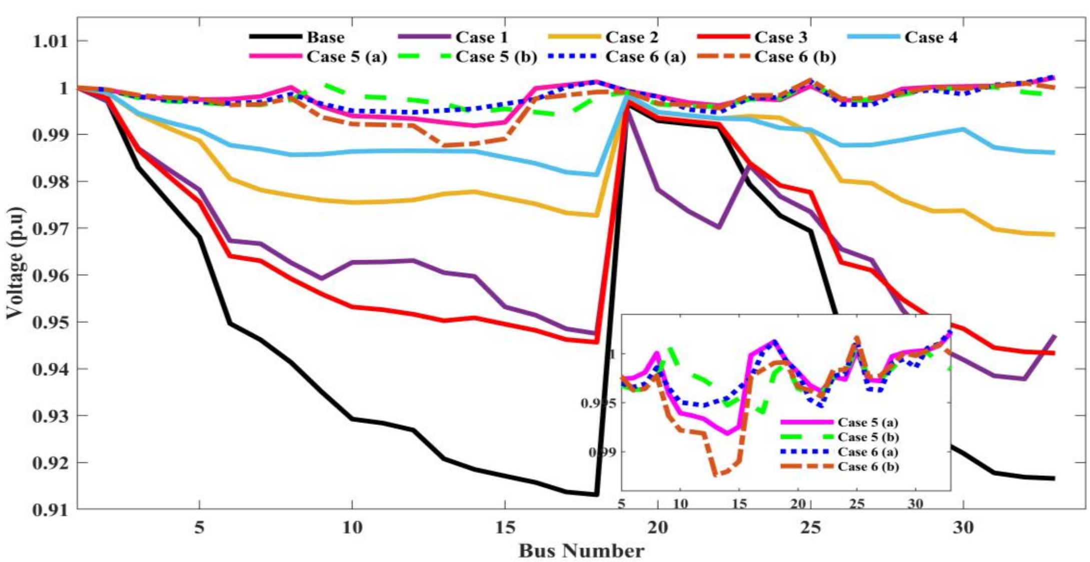

Fig. 8. 33-bus voltage curve of all the case studies

5.2 69-bus Radial Distribution System

Tables 6 and 7 presents the simulation results of case 1 to case 4. In case 1 (only reconfiguration) , the proposed algorithm achieves the lowest active power loss and the UVDA algorithm. Howev er, a small variation in the performance of different algorithms is due to network data approximat ion. In Case 1, switches between 55 to 58 can be on/off in the subsequent loops with no significa nt changes.

TABLE VI. Simulation Results of 69-Bus System For Case 1

Algorithm	Tie Switches	Ploss (kW)	Vmin (bus)
Base	69, 70, 71, 72, 73	225	
C^2oDE	14, 58, 61, 69, 70	**98.58**	0.9495 (61)
CSA (T. Nguyen & Truong, 2015)	14, 57, 61, 69, 70	98.59	0.9495 (61)
FWA (Mohamed Imran et al., 2014)	14, 56, 61, 69, 70	98.59	0.9495 (61)
ACSA (T. T. Nguyen et al., 2016)	14, 57, 61, 69, 70	98.59	0.9495 (61)
UVDA (Bayat et al., 2016)	14, 58, 61, 69, 70	**98.58**	0.9495 (61)

In Table 7, in comparison to other algorithms, C2oDE attains minimum power loss. In cases 2 and 3, losses are 70.77 and 145.11 kW, respectively. Further, in both cases, a minimum voltage appears on 65th bus equal to 0.9749 and 0.9314 p.u.

In both the cases (case 2 and case 3), obtained results are assessed and compared with that of HSA [19], GA [35], WCA [21], FWA [28], RGA [36], CVSI [37], PSO [13], DE [15] , DE-PS [16], TLBO [17], and DSA [18]. Simulation results are shown in Table 7, which clearly shows that C2oDE is efficient for finding the optimal capacity and site of SCB and DG allocation with the smallest losses. Moreover, case 4 suggests that the injection of three DGs and SCBs at three different buses significantly reduces more power loss than a single DG and SCB of the same rating. In Case 4, three DGs injection at three different buses 61, 22, and 69 with the injection of 1.6422, 0.3582, and 0.2493 respectively and three SCBs at buses 61, 22, and 11 of the rating 1.1987, 0.2321 and 0.3663 respectively. Smallest power loss 5.2669 kW is reached in comparison to LSHADE [32], WCA [21], MOEA/D [22] and IMDE [24]. Furthermore, Fig. 9 shows the comparison between the DG and SCB injection of various algorithms with respect to active power loss minimization and C2oDE gives the smallest active power loss as compared to other methods along with optimal DG and SCB injection.

Fig. 9 shows that, compared to cases 2 and 3, simulation results of case 4 is more useful to reduce power loss and inject minimum cumulative rating of DG and SCB. Table 8 shows the simulation results of cases 5 and 6, in which the optimal integration of DG and SCB are computed. In Case 5 (a) (single-objective), C2oDE attains 4.3364 kW power loss, about 98% reduction with 0.0382 VD and 1.0262 VSI, cumulative 2.9876 MW of DGs, and 1.7409 MVAR of SCBs injection. Case 5 (b) weighted sum objective function is 2.4794 with priority factor of 50, 25, and 25 percent.

TABLE VII. Simulation Results of Case 2 To Case 4

Case	Algorithm	DG size (bus)	SCB size (bus #)	Ploss (kW)	Vmin (bus)
Case 2	**C^2oDE**	**0.2811 (12), 0.3128 (21), 1.6560 (61)**		**70.77**	**0.9749 (65)**
	HSA (Rao et al., 2013)	0.1018 (65), 0.3690 (64), 1.3024 (63)		86.77	0.967
	GA (Nara, Shiose, Kitagawa, & Ishihara, 1992)	1.9471		88.5	0.969
	RGA (Zhu, 2002)	1.7868		87.65	0.968

	CVSI (Gantayet & Mohanty, 2015)	1.895 (61)		83.18	0.968 (27)
	WCA (El-Ela et al., 2018)	0.775 (61), 1.105 (62), 0.4380 (23)		71.5	0.987 (65)
	FWA (Mohamed Imran et al., 2014)	0.2258 (27), 1.1986 (61), 0.4085 (65)		77.85	0.974 (62)
Case 3	**C^{2}oDE**		**1.4112 (61), 0.4310 (11), 0.2464 (21)**	**145.11**	**0.9314 (65)**
	PSO (Prakash & Sydulu, 2007)		1.015 (59), 0.241 (61), 0.365 (65)	156.14	0.934
	DE (Neelima & Subramanyam, 2011)		0.2 (16), 0.7 (60), 0.5 (61)	149.55	0.928
	DE-PS (El-fergany, 2013)		0.95 (61), 0.2 (64), 0.05 (65), 0.15 (95), 0.3 (21)	146.13	0.931
	TLBO (Sultana & Roy, 2014)		0.6 (12), 1.050 (61), 0.150 (64)	146.35	
	DSA (Raju et al., 2012)		0.9 (61), 0.45 (15), 0.45 (60)	147	
Case 4	**C^{2}oDE**	**1.6422 (61), 0.3582 (22), 0.2493 (69)**	**1.1987 (61), 0.2321 (22), 0.3663 (11)**	**5.2669**	**0.9942 (50)**
	LSHADE (P. P. Biswas et al., 2018)	0.310 (12), 0.313 (21), 1.627 (61)	0.582 (12), 0.881 (49), 1.227 (61)	**5.81**	0.9943 (65)
	WCA (El-Ela et al., 2018)	0.5408 (17), 2 (61), 1.1592 (69)	1.1879 (2), 1.2373 (62), 0.2697 (69)	33.339	0.994 (50)
	MOEA/D (Partha P Biswas et al., 2017)	0.520 (17), 1.731 (61)	0.353 (17), 1.239 (61)	7.20	0.9943 (69)
	IMDE (Khodabakhshian et al., 2016)	479 (24), 1738 (62)	1.192 (61), 0.109 (63)	13.83	0.9951

TABLE VIII. Simulation Results of Case 5 and Case 6

Case No.	**DGs (MW)**		**SCB (MVAr)**	**Open Switches**	**Objective function**	**Ploss (kW)**	**VD (p.u)**	**VSI (p.u)**	**min Voltage (bus)**
	Power factor	Size (location)	Size (location)						
Case 5 (a)	1	0.7143 (12), 0.6323 (49), 1.6410 (61)	1.2173 (61), 0.2881 (13), 0.2355 (69)	10, 56, 13, 17, 73	**4.3365**	**4.3365**	**0.0382**	**1.0262**	0.9935 (65)
Case 5 (b)	1	0.3611 (66), 1.7956 (61), 0.3982 (19)	0.4642 (50), 1.2369 (61), 0.3902 (22)	9, 57, 13, 16, 73	**2.4794**	**4.6091**	**0.0256**	**1.0183**	0.9962 (69)
Case 6 (a)	0.8706, 0.8597, 0.8844	1.6821 (61), 0.6949 (12), 0.6582 (50)	0.2162 (64), 0.0765 (22), 0.0901 (41)	69, 54, 14, 17, 73	**2.9203**	**2.9203**	**0.0239**	**1.0149**	0.9962 (17)
Case 6 (b)	0.8739, 0.8207 0.9204	0.6139 (61), 1.7331 (61), 0.8644 (50)	0.0678 (68), 0.0918 (29), 0.1947 (67)	8, 72, 71, 16, 64	**1.9362**	**3.3636**	**0.0057**	**1.0119**	0.9968 (69)

With these priorities, active power loss, VD and VSI are 4.6091 kW, 0.0256 p.u, and 1.0183 p.u, respectively. Optimal total DGs injection of 2.5549 MW and SCBs 2.0913 MVAR injection. However, in case 6, each DG's PF is controlled and considered the decision vector in the optimization process. In Case 6 (a) (single-objective), power loss minimized up to 2.9203 kW approximately 98.5% reduction with 3.0352 MW of DGs and 0.3828 MVAr of SCBs injection. However, in case 6 (b) (weighted sum multi-objective) minimize the objective function up to 1.9362 with priority factors of 50, 25 and 25 that gives 3.3636 kW, 0.0057p.u and 1.0119 p.u of power loss, VD and VSI respectively, with the injection of 3.2114 MW and 0.3543 MVAr. It is concluded from the simulation results of case 5 and 6, that the optimal network reconfiguration with DG allocation considering controllable PF and SCBs is useful to reduce power loss and VD with maximization of VSI.

Furthermore, the convergence curve of all the study cases is shown in Fig. 10. From the convergence curve viewpoint, C2oDE converges in 100 iterations for cases 1 to case 4, while up to 150 iterations, it gives a global or near-global solution for case 5 and case 6. However, Fig. 11 shows a comparison between the voltage level of all the study cases of a 69-bus network. In all the cases voltage levels are within desirable limit, and case 6 (b) is more effective than other cases

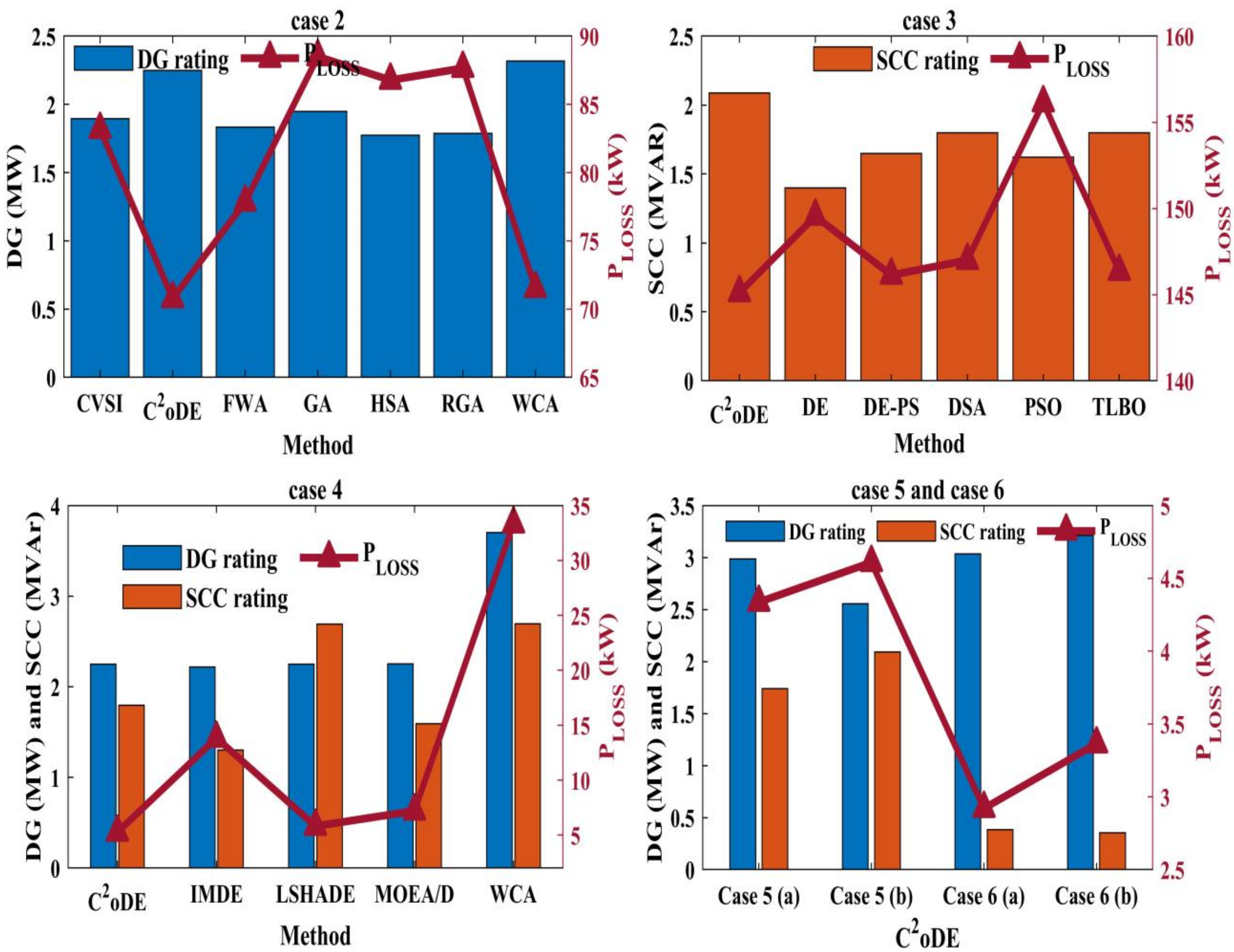

Fig. 9. DG and SCB rating of all cases vs. past methods

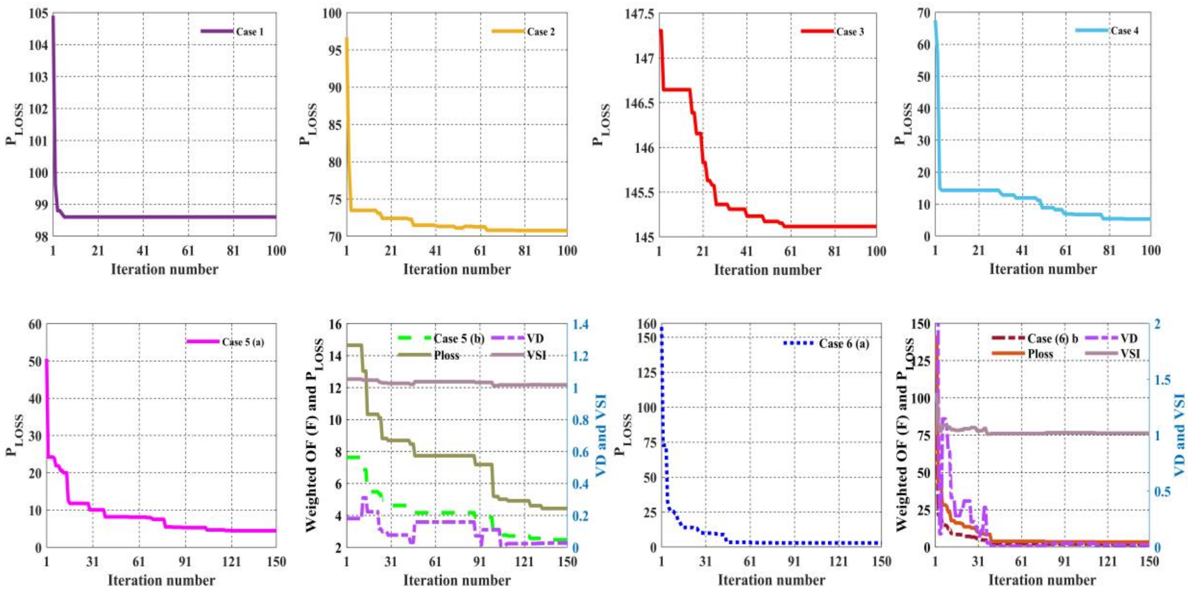

Fig. 10. Convergence curve of case 1 to case 6 of 69-bus test system

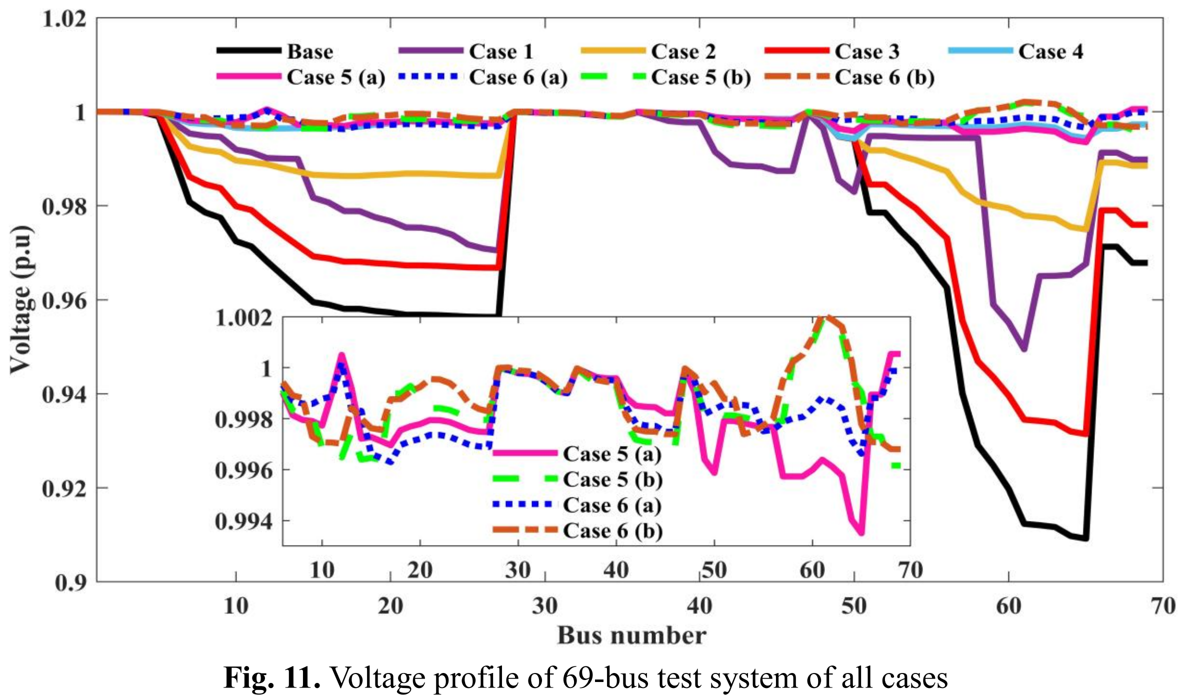

Fig. 11. Voltage profile of 69-bus test system of all cases

6. Conclusion

In this paper, a constrained composite differential evolution algorithm is used to optimize network reconfiguration along with site and size of DG and SCB allocation. Six cases of single and weighted sum multi objective functions are formulated to optimized power loss, VD, and VSI. IEEE 33-bus and 69-bus test systems have been considered to show the proposed algorithm's superiority and performance. Simulation results and comparison with the most recent methods show that the proposed method can find the optimal global solution to non-linear and mixed-integer problems. It is clear from the simulation results that optimal reconfiguration and optimum site and capacity of DG and SCB are most efficient. The proposed algorithm has fully and efficiently utilized the installed capacity of DGs and SCBs.

In comparison to all the cases, case 6 (b) effectively integrate the active and reactive power of DG and find the best compromise values of objective functions. Furthermore, the integration of controlled PF DG enables to increase the overall security of the system. Overall voltage profile and minimum voltage at the bus enhanced with the integration of reactive power of DG. In the future, the cost of DG and SCB and emission factors shall be considered for finding the effectiveness of the proposed algorithm.

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