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Preliminary communication

Performance Assessment of Pareto and Non-Pareto Approaches for the Optimal Allocation of DG and DSTATCOM in the Distribution System

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Abstract: This paper proposes a Differential Evolution (DE) optimization algorithm and a Pareto-frontier Multi-Objective Differential Evolution (MODE) optimization algorithm for the optimal allocation of Distributed Generation (DG) and Distribution Static Compensator (DSTATCOM) in a radial distribution system. It considers the minimization of active power dissipation, voltage drop and the annual cost as the objectives of this optimization problem. The proposed techniques are tested on an IEEE 33 bus radial distribution system. To compare the performance of the MODE and DE, the weighted sum approach is carried out. This helps to select one solution from the Pareto front of the MODE. Case studies show that the allocation of both DG and DSTATCOM results in a noticeable reduction of system losses, voltage drop and annual cost. Comparative studies also show that the global convergence characteristics of MODE are better than several other optimization algorithms.

Keywords: differential evolution; distribution static compensator; distribution system distributed generation; multi-objective differential evolution

1 INTRODUCTION

Due to rapid population growth and industrialization, electrical distribution system experiences a huge increment in the load, consequently leading serious problems such as voltage instability, poor power quality and inefficient energy management [1].

Information and communications technology (ICT) solutions have recently been applied for increasing energy efficiency in the modern power grids. For instance, the flow of energy and work such as communication, sensing and computing tasks in computer servers, in a network of intermittent sources of energy, is modelled as Energy Packet Network (EPN) [2]. This model represents the intermittent arrival of energy, its storage and the intermittent use of energy by information and communications technology [3]. Many attempts have been made to optimize EPNs and improve their performance with energy harvesting [2-5].

On the other hand, installing additional active/reactive power compensators in power system is one of the most popular solutions for power quality improvement and voltage stability enhancement. However, with the improvement of technology and the demand for maximum efficiency from an electrical distribution network, the planning of active/reactive devices such as Distribution Generators (DG) and Distributed Static Synchronous Compensators (DSTATCOM) has turned into a true challenge. Although these devices are incorporated into the grid to enhance the quality of the network, the improper capacity and site of these devices may lead to many problems, such as increasing power losses instead of decreasing them [1].

Recently, various types of optimization methods have been projected to determine the optimum site for DGs and DSTATCOMs in distribution grids, which lead to improvements in the networks characteristics. The methods used to solve this optimization problem can be categorized into different groups, such as analytical and heuristic algorithms or single-and multi-objective techniques. Heuristic algorithms are critical-thinking strategies in which the most fitting solution or partial solution is chosen to utilize relative principles. They are regularly utilized in solving the optimization problem including optimum allocation of the DG and DSTATCOM. In light of the working principles of these methods, the solutions acquired frequently have a tendency to be stuck at a good estimate [6].

In 2013, Injeti et al. determined the best site and size for installing several DGs in small, intermediate and outsized radial distribution grids [7]. In 2014, Roy et al. proposed the combination of teaching-learning based optimization technique with quasi-opposition-based learning to investigate the best placement of one DG to decrease the active power dissipation in the standard 33-, 69- and 118-node grids [8]. Furthermore, in 2015 the same authors combined the opposition-based learning algorithm with another heuristic algorithm called krill herd to get the best site for DGs while considering the deduction of the yearly cost as a target [9]. In the same year, Gupta et al. determined the optimal allocation and size of DSTATCOM under a reconfigured network to lessen the power loss [10]. Moreover, Prabha, D. R., & Jayabarathi, T. proposed an invasive weed algorithm for determining the optimum allocation to insert several DGs into the distribution grids and their capacities to achieve several goals such as voltage enhancement, alleviation of energy dissipation and energy retrenchment [11]. In addition, E. S., Ali et al. presented the Ant Lion Optimization Algorithm to determine the optimum sites for adding several renewable DGs to the network and to calculate the most suitable size for them to decrease energy dissipation and to enhance voltage stability [12].

Moreover, in 2017 Partha P. Biswas et al. determined the optimum allocation and capacity of several DGs and capacitors in the distribution grid by applying a multi-objective approach for minimizing power dissipation. Both DGs and capacitors are utilized to lessen both real and reactive power dissipation. The method was evaluated with similar previous studies and notable improvement was observed [13]. Mahesh Kumar, et al. determined the optimal positioning and the capacity of DGs for voltage-dependent load modules in the radial distribution grid. Single and multiple DGs were used (real, reactive and a combination of them). Likewise, five distinct types of load models were utilized. In addition, the load growth for the base and next three years was predicted [14].

In reviewing the literature, it is clear that the heuristic algorithm has attracted more attention in the design and optimization of the distribution system than classical methods; nevertheless, most of the researchers used the aggregation approach instead of the Pareto approach. In addition, the accuracy of the results and the speed of the optimizer have been neglected.

The intention of this study is twofold. First, it is to propose the single and pareto-frontier multi- objective version of differential evolution optimization techniques to investigate the optimum allocation and sizing of the DG and DSTATCOM to reduce power dissipation, voltage drop and annual cost. Furthermore, the second objective is to compare the results of the pareto-frontier Multi-Objective Differential Evolution (MODE) optimizer with the single-objective optimizer Differential Evolution (DE).

The contributions of present research regarding the existing researches can be highlighted as below:

- The application of Differential Evolution optimization algorithm for the optimal allocation of DG and DSTATCOM in the distribution system is presented for the first time.
- A comprehensive performance assessment of pareto and non-pareto approaches for the optimal placement and sizing of both active and reactive power compensators in power system is made. Single and multi-objective approaches are applied and their optimization characteristics are compared in terms of accuracy and speed.
- The costs of DG and DSTATSOM, which were neglected in most of references, are considered and added to the operational cost. For this reason, the obtained results are more realistic and reliable.
- The problem of optimal allocation of multiple DG and DSTATCOM is solved by considering the new cost function. It was previously solved by neglecting DG and DSTATCOM costs.

2 PROBLEM FORMULATION

2.1 Backward/Forward Sweep Load-Flow Algorithm

A load flow is performed to obtain the system condition (voltage, current, power loss...etc.) in the steady state. It is important to check if the system is stable and to determine if there is a need to insert compensation devices to the system. Furthermore, it is necessary to plan in advance. Due to the low X/R ratio in the distribution system, the ordinary techniques such as Newton Raphson and Gauss-Seidel cannot converge to obtain the power flow from the distribution system. So as to get the power flow of such grid, the backward forward sweep strategy can be utilized. The backward forward sweep method is an iterative method in which, at every iteration, two calculation stages are performed, namely the backward sweep and the forward sweep [15].

- **Backward sweep.** In this stage, the load current of every bus of an N bus radial distribution grid is obtained.
- **Forward sweep.** This stage comes after the backward sweep to obtain the voltage at every bus of the distribution grid as follow.

$$\vec{V}(n) = \vec{V}(m) - \vec{I}(m,n) \times \vec{Z}(m,n) \tag{1}$$

where: m and n are the receiving and sending end buses respectively, while $\vec{Z}(m,n)$ represents the impedance of the branch mn; Fig. 1 below presents the flowchart of the backward-forward sweep.

To place the DSTATCOM and DG in the radial distribution grid, both the real and the reactive load power at the bus where DSTATCOM and DG are placed will change. Therefore, it is assumed that the DG is only injecting a real power into the network, and it is placed at i^{th} bus according to the following equation:

$$P_i = P_i - P_{\text{DG},i} \tag{2}$$

In the case of the DSTATCOM, the reactive power is changed by:

$$Q_i = Q_i - Q_{\text{DSTATCOM},i} \tag{3}$$

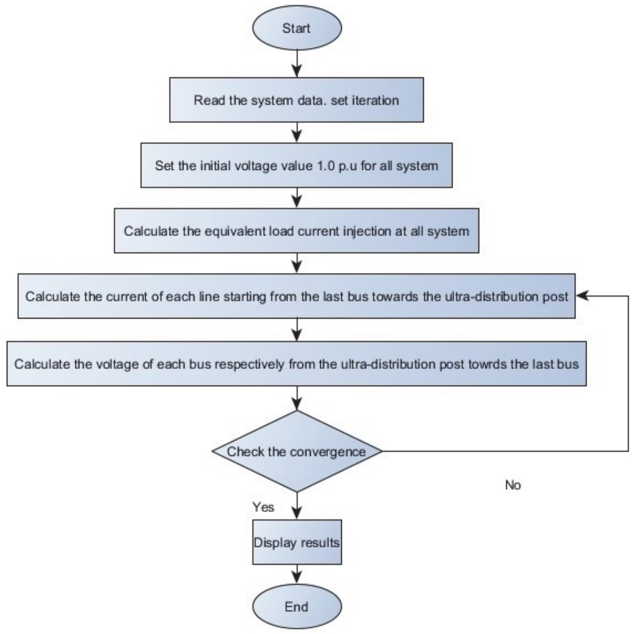

Figure 1 Backward-forward sweep flowchart.

2.2 Optimization Formulation

The problem of the optimum size and place of the DSTATCOM and DG can be expressed as a single objective optimization problem by giving each objective function a weight factor. Therefore, the summation of the weight factors should equal one. This problem aims to minimize the summation of the scaled objective functions. Moreover, it can be expressed as a multi-objective optimization problem. Here, the solution aims to minimize the vector of the objective functions, which consist of the real power dissipation in the grid, the voltage deviation and the annual cost simultaneously. The single objective optimization functions can be expressed as:

$$\text{Minimizing } F = \sum_{i=1}^{m} k_i \times f_i \tag{4}$$

where: k_i is the weight that is given to the i^{th} objective function f_i to decide its corresponding importance. k_i, is decided according to priority of the operation. In this work 0.5 for the power loss, 0.4 for the voltage deviation, and 0.1 for the cost is selected according to reference [16].

On the other hand, multi-objective optimization problem can be stated as:

$$F = \begin{bmatrix} f_1 & f_2 & \cdots & f_n \end{bmatrix} \tag{5}$$

where: n denotes the number of goals to be optimized. In this case, the objective functions will be minimized separately.

2.2.1 Objectives

As mentioned earlier, three objective functions are considered to be optimized. These objectives are the reduction of the total active power dissipation, decrease of the voltage deviation and minimization of the yearly cost. For this minimization problem, first each objective function is normalized by dividing it by its base. These functions are explained below in the following equations. The weighted vector objective function is shown below:

$$F = k_1 \times f_1 + k_2 \times f_2 + k_3 \times f_3 \tag{6}$$

- **Active power losses in the system (f_1)**

In fact, about 13% of total power losses occur in the distribution system [17]. Therefore, the first objective of this study is to minimize the active power losses in the radial distribution grid as described in Eq. (7).

$$f_1 = \frac{\sum_{i=1}^{nb} P_{\text{Loss},i}}{P_{\text{Loss,base}}} \tag{7}$$

where $P_{\text{loss},i}$ is the active power dissipation in branch number i in kW. $P_{\text{loss,base}}$ is the base value for the active power dissipation in kW. nb is the total number of the branches.

- **Voltage deviation (f_2)**

The voltage deviation is an indicator which shows the drop in the voltage at every bus from the nominal one, as shown in Eq. (8).

$$f_2 = \max \left| \frac{V_i - V_{\text{rated}}}{V_{\text{rated}}} \right| \tag{8}$$

where V_{rated} = 1 p.u. and V_i is the voltage at bus number i in p.u.

- **Annual cost (f_3)**

Considering the cost of DG and DSTATCOM , the annual cost function is defined as Eq. (9). This annual cost includes annual energy operation cost, DG cost and DSTATCOM cost. The terms having DG and DSTATCOM costs include annual cost of installed devices considering purchase, installation, operation and maintenance costs. Therefore, the third objective function can be expressed as Eq. (10).

$$C = c_1 T P_{T\text{loss}} + c_2 \sum_{i=1}^{N_{\text{DG}}} P_{\text{DG}_i} + c_3 \sum_{j=1}^{N_{\text{DSTATCOM}}} Q_{\text{DSTATCOM}_j} \tag{9}$$

$$f_3 = \frac{C}{C_{\text{base}}} \tag{10}$$

where $P_{T\text{loss}}$ is the total active power loss in the system in kW, T is number of hours in a year, P_{DG} is installed DG active power in kW, Q_{DSTATCOM} is installed DSTATCOM reactive power in kVar, N_{DG} is number of installed DGs, N_{DSTATCOM} is number of installed DSTATCOMs, c_1 is the energy loss cost ($/kW/year), c_2 is annual cost of DG in ($/kW/year), c_3 is annual cost of DSTATCOM ($/kVar/year) and C_{base} is the cost at the base case.

2.2.2 Constraints

The objective functions in the above equations are subjected to the DG capacity limit and the DSTATCOM capacity, voltage and thermal limits.

- **DG capacity limit**

$$G_{\min} \le G_{\text{capacity}} \le G_{\max} \tag{11}$$

where: $G_{\min}$ and $G_{\max}$ are the minimum and the maximum capacity of the DG respectively, in kW. In this study $G_{\max} \le 2.5$ MW according to reference [7].

- **DSTATCOM capacity limit**

$$D_{\min} \le D_{\text{capacity}} \le D_{\max} \tag{12}$$

where: $D_{\min}$ and $D_{\max}$ are the minimum and the maximum capacity of the DSTATCOM respectively, in kvar.

- **Voltage limit**

$$V_{\min} \le |V_i| \le V_{\max} \tag{13}$$

where: $V_{\min}$ and $V_{\max}$ are the minimum and maximum bus voltages respectively, in p.u.

3 DE IMPLEMENTATION

The key idea of the DE is to use vector differences (addition and subtraction of the agent vectors) for mutating the population vector, unlike the Genetic Algorithm which uses conventional methods for the operations of crossover and mutation of the solutions. The algorithm of the DE for finding the optimum capacity and place of single and multiple DGs and DSTATCOMs in the radial distribution system is shown below.

DE Algorithm:
Step 1: Input the data of the grid.
Step 2: Initialize DE parameters (population size, differential weight, crossover probability, and maximum iteration).
Step 3: Initialize the population.

Step 4: Run the radial load flow and calculate the objective function.
Step 5: Sort the population.
Step 6: Keep the best.
Step 7: While the stopping criterion is not satisfied.
Step 8: For each agent *x*.
Step 9: Find the perturbation vector ***U***.
Step 10: Find the perturbed vector y through the crossover of *x* and ***U***.
Step 11: Run the radial load flow and calculate the objective function.
Step 12: Change *x* to *y* if *y* is better than *x*.
Step 13: End while.

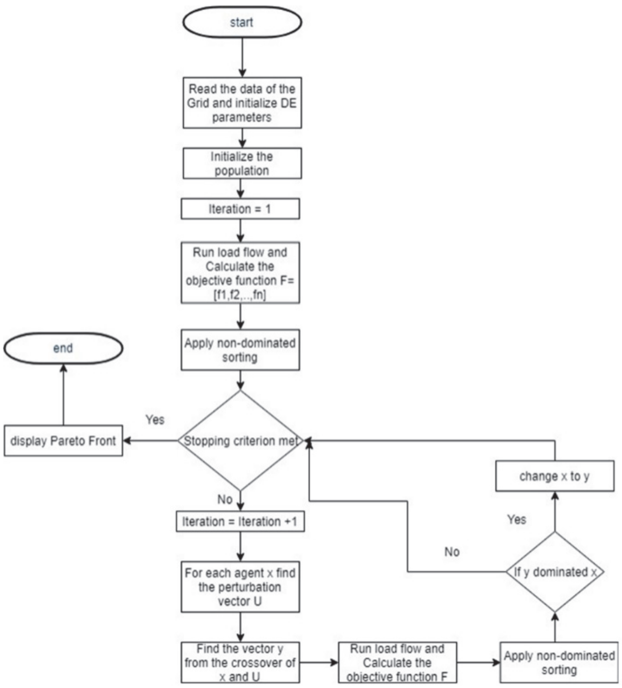

Figure 2 Flowchart of MODE

4 MODE IMPLEMENTATION

In this method, instead of having one optimum solution at the final stage of the optimization procedure, one can obtain the Tradeoff optimal solutions, which is known as Pareto solutions or the non-dominated solution. Here, the non-dominated term refers to the set of solutions which cannot be compared. Fig. 2 shows the flowchart of the MODE for finding the optimum capacity and place for single and multiple DGs and DSTATCOMs in the radial distribution grid.

5 SIMULATION AND RESULTS

In this paper, a constant power load model has been considered for modelling the behaviour of loads of the power system grid. The cost of DG-generated power and DSTATCOM has been neglected for this study. The energy loss cost of \$0.05 per unit has been taken for analysis of the cost-benefit (Shukla, T., et al. [18]). The DG and DSTATCOM annual costs are considered 3.5 (\$/kW) and 5.5 (\$/kVar), repectively.

Three case studies were performed as a single DG allocation, a single DSTATCOM allocation, a combination of a single DG and single DSTATCOM allocation and multiple DG and DSTATCOM allocation for active power loss reduction, voltage profile improvement, and the reduction of the annual cost. The proposed methods are tested on IEEE 33 bus system. This test system consists of 33 buses and 32 branches. The line and bus data are taken from [19]. This system fed on one side, and it has serially connected loads, while the load is assumed to be constant as shown in Fig. 3. The line voltage and real and reactive power loads of the radial distribution grid are 12.66 kV, 2.3219 MW and 1.4375 MVar respectively, while the base MVA is 100 MVA. Tab. 1 below shows the optimal parameters of DE and MODE after applying the trial and error method.

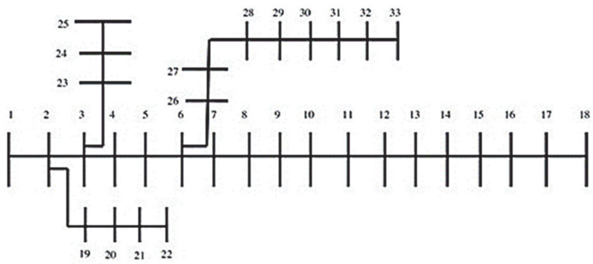

Figure 3 IEEE 33 bus radial distribution system

Table 1 Parameters of DE and MODE

Parameters	DE	MODE
Population Size	30	50
Max. Iteration	30	30
Crossover Probability	0.15	0.2

5.1 Single DG Allocation (Case 1)

In this case, a single DG has been optimally placed into the network to improve its performance by using DE and MODE. To analyse the performance of each one of these algorithms, an IEEE 33 bus system was used. First, a simple load flow was performed. After that, the DG was optimally placed with the help of DE and MODE. Tab. 2 shows the real power losses, voltage deviation, annual energy cost, computation time, locations and size of the DG for DE, while Tab. 3 displays the results of the MODE.

Table 2 Network performance for a single DG allocation

Performances	Base	DE
Power loss / kW	210.9875	113.7027
Voltage deviation / p.u.	0.096222	0.060792
Energy cost / \$	92412.55	59275.1
DG location	-	Bus 5
DG Size / kW	-	2368.33
Comp. Time / sec	-	17.28
Minimum voltage / p.u.	0.90377	0.93921
Weighted vector	1	0.59656

Table 3 Pareto set of MODE (Single DG)

DG		Power loss / kW	Voltage deviation / p.u.	Annual cost / \$	*F*
Bus No.	Size / kW				
8	2408	143.6	0.04877	72528.8	0.6319
7	2176.8	121.9	0.05155	62099.4	0.5798
7	1961.4	118.8	0.05449	59880	0.5813
7	2015.2	119.4	0.05375	60358	0.5804
6	2487.2	112.1	0.05605	59048.6	0.5733
7	2290	124.5	0.05003	63691	0.5818

From the results, it is clear that the minimum power loss, voltage deviation, and energy cost was obtained when MODE was used. The minimum CPU time was 11.47 sec which was achieved when MODE was used. Fig. 4 shows the voltage profile, while Fig. 5 shows the Pareto front when MODE was used. Moreover, Fig. 6 shows the comparison between the results of DE and MODE in terms of the computation time and weighted vector results.

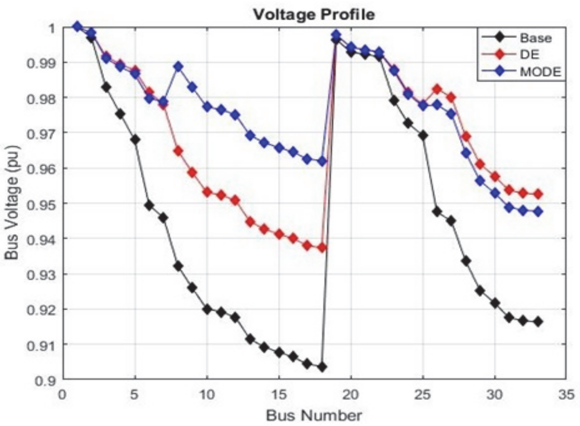

Figure 4 Voltage profiles (Single DG)

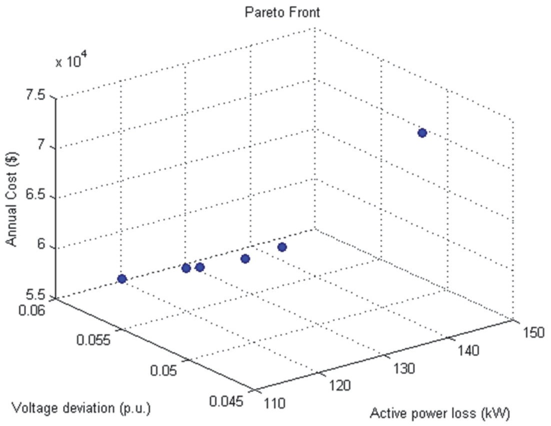

Figure 5 MODE Pareto Front (Single DG)

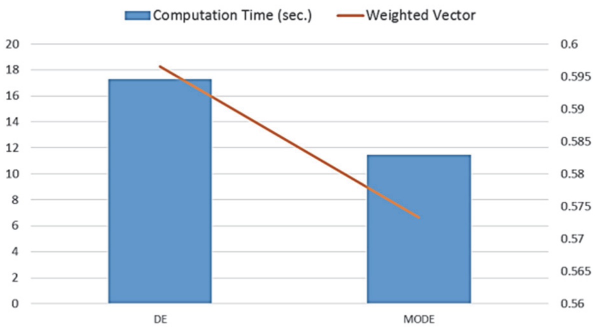

Figure 6 Comparison between DE and MODE for a single DG

5.2 Single DSTATCOM Allocation (Case 2)

In this case, a single DSTATCOM has been optimally placed into the network to improve its performance by using DE and MODE. To analyse the performance of each one of these algorithms, an IEEE 33 bus system is used. First, a simple load flow was performed. After that, the DG was optimally placed with the help of DE and MODE. Tab. 4 shows the real power losses, voltage deviation, annual cost, computation time, locations and size of the DSTATCOM for DE, while Tab. 5 displays the results of the MODE.

Table 4 Network performance for a single DSTATCOM allocation

Performances	Base	DE
Power loss / kW	210.9875	163.6385
Voltage deviation / p.u.	0.096222	0.070222
Annual cost / $	92412.55	79176.86
DSTATCOM location	-	Bus 6
DSTATCOM Size / kVar	-	1875.8019
Comp. Time / sec	-	17.41
Minimum voltage / p.u.	0.90377	0.92977
Weighted vector	1	0.7735

Table 5 Pareto set of MODE (Single DSTATCOM)

DSTATCOM		Power loss / kW	Voltage deviation / p.u.	Annual cost / $	*F*
Bus No.	Size / kVar				
29	1384.1	151.9	0.08234	72068.6	0.7862
28	1500.2	154.1	0.08131	73496.6	0.7892
6	1706.3	163.2	0.07248	78306.8	0.7801
8	1451.1	183.4	0.06997	86133.6	0.8249
29	1715.8	158.6	0.07939	76330	0.7959
7	1278.7	172.6	0.07132	80713.6	0.7983
29	1782.1	160.8	0.07882	77558.8	0.8003
8	1318.2	179.7	0.07111	83981.4	0.818
8	1336.1	180.1	0.07095	84228.2	0.8187

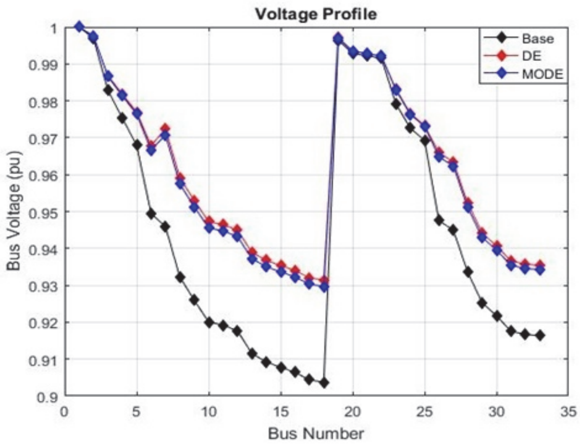

Figure 7 Voltage profiles (Single DSTATCOM)

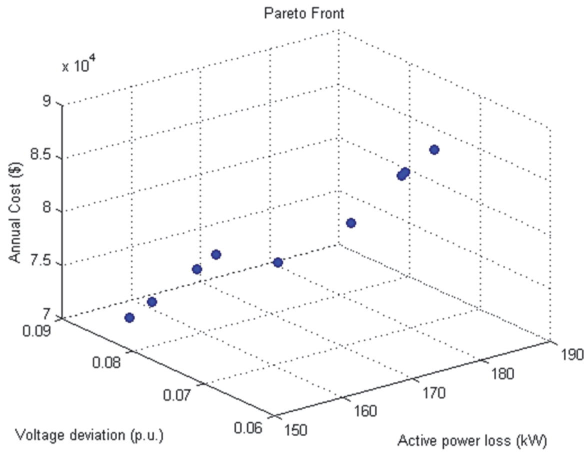

Figure 8 MODE Pareto Front (Single DSTATCOM)

From the results, it is clear that the minimum power loss and cost was obtained when MODE was used. The minimum CPU time was 14.63 sec which was achieved when MODE was used. Fig. 7 shows the voltage profile, while Fig. 8 shows the Pareto front when MODE was used. Moreover, Fig. 9 shows the comparison between the results of DE and MODE in terms of the computation time and weighted vector results.

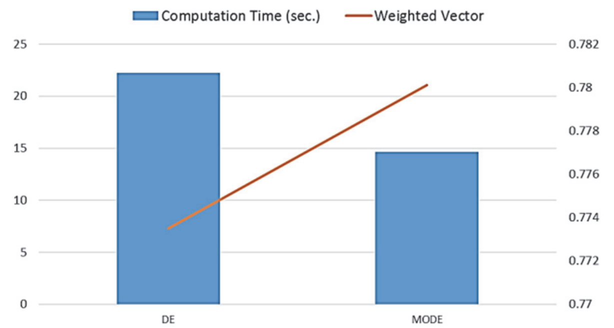

Figure 9 Comparison between DE and MODE for a single DSTATCOM

5.3 Single DG and DSTATCOM Allocation (Case 3)

In this case, a single DG and a DSTATCOM have been optimally placed into the network to improve its performance by using DE and MODE. To analyse the performance of each one of these algorithms, an IEEE 33 bus system was used. First, a simple load flow was performed. After that, the DG was optimally placed with the help of DE and MODE. Tab. 6 shows the real power losses, voltage deviation, annual energy cost, computation time, locations and size of the DG and DSTATCOM for DE, while Tab. 7 displays the results of the MODE.

Table 6 Network performance for a single DG and a DSTATCOM allocation

Performances	Base	DE
Power loss / kW	210.9875	80.4864
Voltage deviation / p.u.	0.096222	0.033689
Annual cost / $	92412.55	503.491.476
DG location	-	Bus 7
DG Size / kW	-	2327.5718
DSTATCOM location	-	Bus 26
DSTATCOM size / kVar	-	1446.4543
Comp. Time / sec	-	18.94
Minimum voltage / p.u.	0.90377	0.96631
Weighted vector	1	0.4016

Table 7 Pareto Set of MODE (Single DG and a DSTATCOM)

DG / kW	DSTATCOM / kVar	Loss / kW	Volt. devia. / p.u.	Ann. cost / $	*F*
1871 (Bus 9)	2060 (Bus 31)	117.9	0.0194	67390	0.4503
2425 (Bus 8)	1426 (Bus 27)	79.16	0.0239	50076	0.3579
2447 (Bus 7)	1877 (Bus 12)	169.4	0.0179	91484	0.5936
2390 (Bus 27)	1791 (Bus 29)	68.03	0.0408	46521	0.3993
1541 (Bus 6)	2000 (Bus 29)	88.89	0.0206	53098	0.3691
1871 (Bus 10)	2060 (31)	115.3	0.0194	66234	0.4429

From the results, it is clear that the minimum power loss and cost was obtained when MODE was used. The minimum CPU time was 12.58 sec which was achieved when MODE has used. Fig. 10 shows the voltage profile, while Fig. 11 shows the Pareto front when MODE was used. Moreover, Fig. 12 shows the comparison between the results of DE and MODE in terms of the computation time and weighted vector results.

To confirm the performance of the suggested algorithms on an IEEE33 bus radial distribution system, the results achieved were compared with previous work results like Genetic Algorithm [18], Immune Algorithm [20], and Loss Sensitivity Method [21] and summarized in Tab. 8.

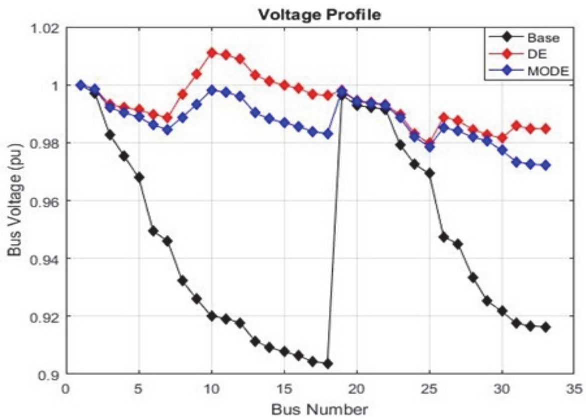

Figure 10 Voltage Profiles (Single DG and a Single DSTATCOM)

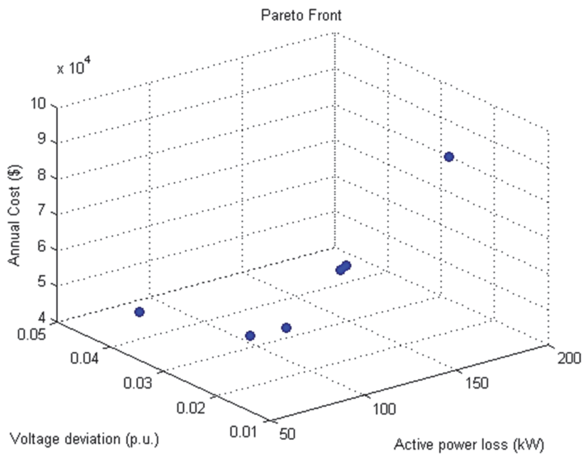

Figure 11 MODE Pareto Front (Single DG and a single DSTATCOM)

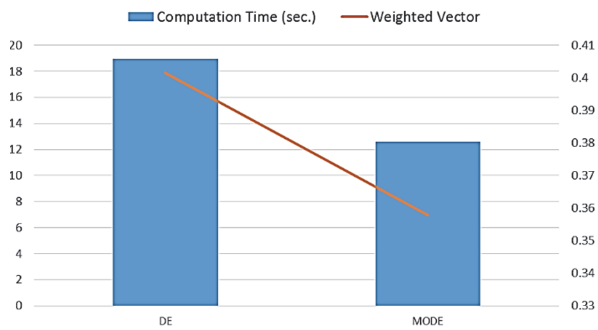

Figure 12 Comparison between DE and MODE (single DG - DSTATCOM)

5.4 Multiple DG and DSTATCOM Allocation (Case 4)

In this case, multiple DGs and DSTATCOMs have been optimally placed into the network to improve its performance by using DE and MODE. Optimal location and size of maximum three DGs and three DSTATCOMS, have been determined to achieve the same objectives. Tab.9 shows the work performance for multiple DG and DSTATCOM allocation. Power loss, voltage deviation, annual cost, weighted vector, minimum voltage and computation time by applying single and multi-objective methods are presented compared with the results of applying bacterial foraging optimization (BFO) algorithm in [16]. The proposed cost function is applied considering DG and DTATCOM costs.

Table 8 Comparative Analysis

Case	Performances	DE	MODE	Genetic Algorithm [18]	Immune Algorithm [20]	Loss Sensitivity Method [21]
Single DG	Base Loss / kW	210.98	210.98	216	202	201
	Location	Bus 5	Bus 6	Bus 6	-	Bus 30
	Size / kW	2368.3	2487.2	2380	-	1000
	Active Loss / kW	113.7	112.1	132	-	113
	Energy Saving / $	42607	43309	36511	-	-
Single DSTATCOM	Location	Bus 6	Bus 6	-	Bus 12	Bus 30
	Size / kW	1875.8	1706.3	-	962.49	3200
	Active Loss / kW	163.64	163.2	-	171	198
	Minimum Voltage / p.u.	0.931	0.93	-	0.925	-
	Time / sec	17.41	11.47	-	-	-
Single DG and DSTATCOM	DG Location	Bus 7	Bus 8	-	-	Bus 30
	DG Size / kW	2327.5718	2425	-	-	1000
	DSTATCOM Location	Bus 26	Bus 27	-	-	Bus 30
	DSTATCOM Size / kVar	1446	1426	-	-	1500
	Active Loss / kW	80.49	79.16	-	-	86
	Minimum Voltage / p.u.	0.98	0.972	-	-	-

Table 9 Network performance for multiple DG and DSTATCOM allocation

Optimization Algorithm	DG / kW	DSTATCOM / kVar	Power loss / kW	Voltage deviation / p.u.	Annual cost / $	Weighted vector	Minimum voltage / p.u.	Comp. Time / sec
DE	823 (Bus 14) 1002 (Bus 25) 1047 (Bus 30)	444 (Bus 12) 516 (Bus 25) 1089 (Bus 30)	13.67	0.0097	20603	0.1108	0.98721	22.63
MODE	1072 (Bus 14) 742 (Bus 25) 947 (Bus 30)	521 (Bus 12) 476 (Bus 25) 1018 (Bus 30)	12.95	0.0089	20488	0.1059	0.99113	11.92
Bacterial Foraging Optimization [16]	850 (Bus 12) 750 (Bus 25) 860 (Bus 30)	400 (Bus 12) 350 (Bus 25) 850 (Bus 30)	15.07	-	22841	-	0.9862	12.96

6 CONCLUSION

In conclusion, this research work demonstrated the formulation and implementation of the single-objective optimizer DE and the Pareto-frontier multi-objective optimizer MODE to help in reducing system real power losses, minimizing voltage deviation and reducing annual costs by allocating DG and DSTATCOM in the radial distribution system. As seen from the results, the best performance for the system was achieved when multiple DGs and DSTATCOMs were used. From the results, MODE proved to be better suited for this optimization as compared to DE and the other optimization algorithms such as Genetic algorithm (GA), Immune Algorithm (IA) and Bacterial Foraging Optimization (BFO). After using the MODE method to study the effects of DG and DSTATCOM allocation on power losses, voltage profile and cost, it was clear that system power losses and voltage deviation were reduced with the optimal allocation of the DG and DSTATCOM in the network, whereas, an unsuitable location or size of DG and DSTATCOM resulted in an increase in system power losses, voltage profile and cost.

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