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Research Article

A Comparative Analysis of Optimization Techniques for DSTATCOM in a 33 kV Radial Distribution System

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Abstract: Utilization of Distribution Static Compensator (DSTATCOM) has proven to be instrumental in essential strategies aimed at mitigating power losses within electrical network systems. The growing demand for electricity and high maintenance costs have propelled DSTATCOM into a prominent position for discussion and consideration. This paper conducted a comprehensive comparative study employing optimization methods such as Differential Evolution (DE), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). The objectives of this study are to compare the performance in terms of Voltage Profile Improvement (VPI), Power Loss Reduction (PLR), and System Cost (SC) while selecting the best method as a suggestion for future research. The techniques were simulated in a MATLAB environment and a 50-bus system was used for real testing. The DE method emerged as the most effective technique in the analysis of the three objective functions. This outcome suggests that DE holds significant promise as a viable and efficient method for enhancing the performance of DSTATCOM in terms of VPI, PLR, and SC. These findings offer valuable guidance for future research endeavors in the realm of electrical network system optimization.

***Keywords*:** high losses, differential evolution, artificial bee colony, particle swarm optimization, DSTATCOM

1. Introduction

In the realm of electrical distribution networks, ensuring reliable delivery of electricity to consumers is crucial. Maintaining power quality and stability is paramount to meet the increasing demand for electricity [1]. A key element in achieving this is the Distribution Static Synchronous Compensator (DSTATCOM), which plays a critical role in enhancing the performance of electrical distribution systems. DSTATCOMs are implemented to mitigate power quality issues such as harmonics, voltage sag, and voltage swell. By effectively managing these parameters, DSTATCOMs contribute to improved voltage regulation, power factor correction, and overall system stability. Optimizing DSTATCOM is vital for maximizing its effectiveness and efficiency, leading to reduced energy losses and enhanced system performance [2, 3, 4, 5].

However, a crucial question arises regarding the optimal sizing and placement of DSTATCOM to effectively address power quality issues. The severity of problems such as voltage sag, swell, and harmonics in distribution networks can vary significantly based on factors such as network configuration, load characteristics, and external disturbances. Therefore, it is important to demonstrate the severity of these issues and the need to enhance the performance of distribution systems.

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This paper acknowledges potential skepticism regarding the existence and severity of these problems. Nevertheless, extensive research and field studies have shown that in many distribution systems, particularly in complex and heavily loaded networks, these power quality issues are not only present but are significant enough to warrant the deployment of DSTATCOMs [4, 6, 7].

Moreover, the need to optimize DSTATCOM becomes evident when considering the optimal sizing and placement in modern distribution networks. Employing various optimization techniques, such as Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Differential Evolution (DE), to develop effective control strategies for DSTATCOMs is crucial. These techniques have demonstrated promise across different optimization domains, particularly in power systems. PSO's ability to conduct global searches makes it suitable for navigating complex solution spaces. ABC's decentralized approach is well-suited for collaborative optimization scenarios, while DE's proficiency in handling continuous variables is advantageous for refining control strategies in DSTATCOM applications [4, 6, 7, 8].

While each technique offers distinct advantages and methodologies, a research gap exists in evaluating their comparative performance, especially in DSTATCOM applications. This paper aims to address this gap by conducting a comparative analysis within a 33 kV radial distribution system. The study explores potential improvements in Voltage Profile (VPI), Power Loss Reduction (PLR), and System Cost (SC) that these optimization techniques can offer. By doing so, this research seeks to quantify the extent to which DSTATCOM can enhance distribution system performance, thereby addressing concerns about the necessity and magnitude of such improvements.

The study further investigates the specific advantages and methodologies offered by each optimization method. For instance, PSO is known for its simplicity and global search capabilities [4, 6], ABC mimics the foraging behavior of bees [7], and DE excels in handling optimization problems with continuous variables [8]. However, without a comparative analysis, it remains challenging to determine the most effective method for improving Voltage Profile (VPI), reducing Power Loss (PLR), and optimizing System Cost (SC) in DSTATCOM applications.

Through this comparative analysis, the paper aims to provide valuable insights into the performance of PSO, ABC, and DE specifically in DSTATCOM scenarios. These insights will assist researchers and practitioners in selecting the optimal optimization approach tailored to the specific demands of DSTATCOM deployment in distribution systems. Additionally, by demonstrating the measurable improvements that can be achieved, this study addresses concerns about the existence and severity of power quality issues and illustrates the real-world impact of optimizing distribution system performance.

2. Distribution system configuration (33 kV)

The ECG 33 kV distribution network in Ghana's Ashanti Region is designed in a ring configuration in some areas, but it predominantly functions as a radial system. This network supplies electricity to residential, commercial, and industrial customers in the region. To achieve precise representation and analysis, the modeling and simulation were conducted using a combination of ETAP and MATLAB.

ETAP was used to model the Ashanti Region's 33 kV distribution network based on real-world data collected from the field. This software allowed for the extraction of line and bus data, which are crucial for accurately simulating the network's behavior under various conditions. The data includes essential parameters such as resistance, reactance, active and reactive power. These parameters were used to calculate the positive sequence impedance for each branch of the network, considering the physical and electrical characteristics of the distribution system.

The Ashanti region's 33 kV network comprises fifty (50) bus bars, including one main bus bar for the Ghana Grid Company (GridCo), eight bus bars for two base stations, and forty-one bus bars for twenty-one distribution stations. The network spans a total distance of 574.4 km, with forty-nine branches. Figure 1 depicts a single-line diagram of the ECG 33 kV network [9].

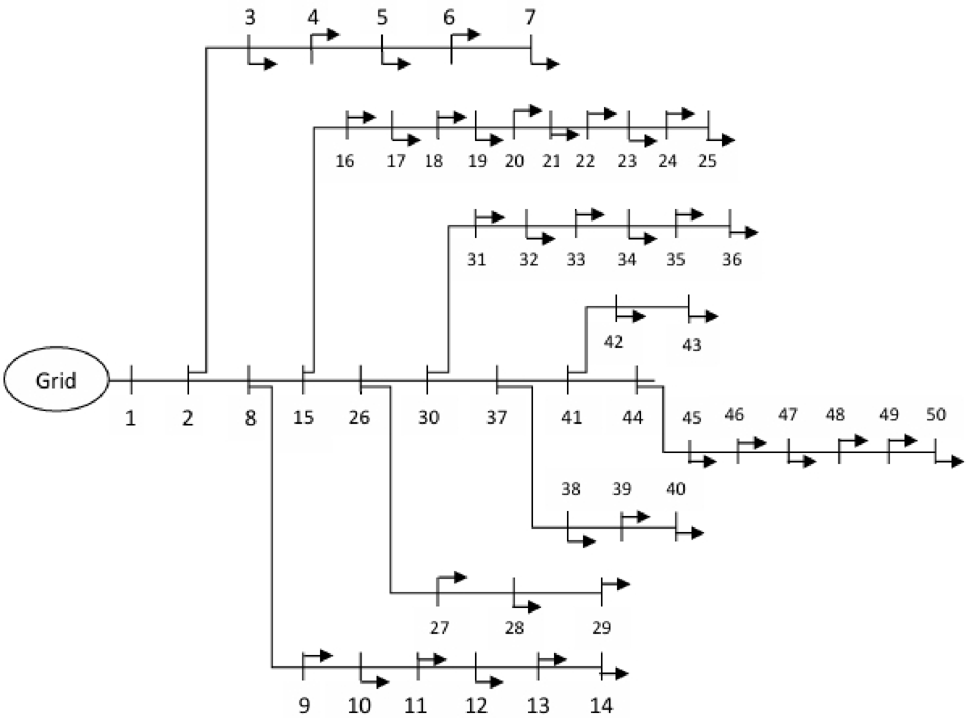

Figure 1. 33 kV distribution network of ashanti region

The MATLAB software was utilized as a platform for implementing optimization techniques such as PSO, ABC, and DE. These techniques were employed to determine the optimal size and location of DSTATCOMs in the 33 kV network. Each optimization technique's performance was evaluated using predefined metrics, including Voltage Profile Improvement (VPI), Power Loss Reduction (PLR), and System Cost (SC).

The effectiveness of these optimization techniques was assessed by simulating the optimized configurations obtained through each method using MATLAB tools. The comparative analysis facilitated the identification of the most effective optimization technique for DSTATCOM deployment within the 33 kV radial distribution system. Table 1 shows the line and bus data of ECG's 33 kV distribution network.

Table 1. Bus and line data of ECG 33 kV distribution network in Ashanti, Ghana

	BUS DATA			LINE DATA			
Bus ID	**P (MW)**	**Q (Mvar)**	**Bus ID**	**From Bus**	**To Bus**	**R**	**X**
1	374.414	137.639	1	1	2	0.04	0.12
2	61.611	23.883	2	2	3	6.21	20.58
3	42.778	13.192	3	3	4	13.03	43.30
4	16.843	4.764	4	3	5	29.12	61.10
5	7.584	2.554	5	5	6	20.60	68.45
6	7.419	2.059	6	2	7	4.97	16.47
7	17.252	5.498	7	1	8	0.04	0.12
8	61.487	24.63	8	8	9	18.62	61.85
9	24.9	4.459	9	9	10	6.21	20.62
10	12.251	2.838	10	8	11	6.21	20.62
11	25.101	11.474	11	11	12	8.69	28.86
12	10.042	4.106	12	11	13	40.98	86.19
13	7.588	2.565	13	13	14	21.10	70.10
14	7.42	2.059	14	1	15	0.04	0.12
15	61.035	23.491	15	15	16	2.91	20.03
16	6.748	1.814	16	16	17	0.01	0.02
17	2.84	0.965	17	15	18	18.62	61.85
18	25.784	5.574	18	18	19	6.21	20.62
19	17.832	4.081	19	19	20	2.00	9.80

Table 1. *Cont.*

	BUS DATA			LINE DATA			
Bus ID	P (MW)	Q (Mvar)	Bus ID	From Bus	To Bus	R	X
20	9.42	1.928	20	20	21	20.60	68.45
21	4.668	0.883	21	15	22	6.21	20.62
22	19.418	8.148	22	22	23	8.69	28.86
23	7.363	2.909	23	22	24	40.98	86.19
24	4.796	1.296	24	24	25	21.10	70.10
25	4.737	1.157	25	1	26	0.04	0.12
26	63.91	25.452	26	26	27	4.01	19.57
27	41.921	14.567	27	27	28	13.03	43.30
28	20.148	6.043	28	26	29	4.97	16.47
29	20.868	5.937	29	1	30	0.04	0.12
30	47.979	15.877	30	30	31	8.01	39.21
31	33.224	6.896	31	31	32	5.60	27.45
32	19.472	2.966	32	32	33	26.69	88.67
33	6.721	1.944	33	33	34	33.51	111.33
34	6.492	1.313	34	34	35	6.70	22.27
35	3.678	0.735	35	30	36	4.32	21.17
36	13.608	3.464	36	1	37	0.04	0.12
37	31.954	10.725	37	37	38	10.49	51.36
38	21.469	6.101	38	38	39	21.60	71.75
39	11.54	2.558	39	39	40	23.59	78.36
40	3.92	1.102	40	1	41	0.04	0.12
41	11.357	3.843	41	41	42	10.49	51.36
42	11.206	3.158	42	42	43	21.60	71.75
43	4.457	1.198	43	1	44	0.04	0.12
44	34.995	9.456	44	44	45	8.01	39.21
45	19.584	4.14	45	45	46	5.60	27.45
46	12.652	2.508	46	46	47	44.07	92.67
47	5.759	0.708	47	47	48	33.51	111.33
48	2.821	0.613	48	48	49	6.70	22.27
49	2.811	0.608	49	44	50	4.32	21.17
50	9.745	2.333					

3. Problem formulation and constraints

When a DSTATCOM is linked to a bus, it has the ability to regulate the reactive power on that particular bus [9]. This, in turn, influences the bus voltage profile, as detailed in [9, 10]. The goal of incorporating DSTATCOM into the distribution system is to reduce overall power losses, enhance system voltage, and optimize system cost. Therefore, the first objective function (Power Loss Reduction) can be formulated as [9],

$$PLR = f_1 = S_{losses} \tag{1}$$

Therefore, $S_{losses} = P_{loss} + Q_{loss}$

$$P_{loss} = \sum_{i=1}^{NBr} R_i I_i^2 \tag{2}$$

$$Q_{loss} = \sum_{i=1}^{NBr} X_i I_i^2 \tag{3}$$

where, f_1 serve as first objective function (which pertains to power losses (S_{losses})), P_{loss} as active power loss, Q_{loss} as reactive power loss, I_i stands as line i current, R_i serve as resistance of i^{th} line, X_i happens as line's reactance of i^{th}, and NBr stands as the number of system branches. The percentage reduction of total power loss can be expressed as [11, 12, 13]:

$$\text{total loss (\%)} = \frac{\text{total loss with DSTATCOM}}{\text{total loss without DSTATCOM}} * 100 \tag{4}$$

where, total loss with DSTATCOM and total loss without DSTATCOM refer to the entire line losses in the system. The system's second objective function, which focuses on improving the voltage profile, can be written as follows,

$$VPI = f_2 = \sum_{i=1}^{NBr} (V_n - V_i)^2 \tag{5}$$

where, VPI represents the improvement in voltage profile, V_n denotes the nominal voltage of the system (set at 1 per unit), V_i signifies the voltage at the i^{th} bus, and NBr serve as the total sum of system buses. One key objective of this study was to evaluate the costs associated with the compensating device, specifically its impact on the distribution system. This includes the expenses related to energy losses, the DSTATCOM, and the total annual savings. The equations representing energy loss and DSTATCOM cost can be found in [9, 14].

The third objective function which serve as total annual saving cost can be formulated as [9],

$$T_{cs} = kq\,(T * P_{Tloss}) - kq\left(T * P_{Tloss}^{with\ DSTATCOM}\right) - \left(kc * DSTATCOM_{\frac{cost}{year}}\right) \tag{6}$$

where, T represents the time period (hour/year), kc signifies the fraction of time when the loss occurs, kq denotes the cost associated with energy losses, P_{Tloss} refers to the total power loss before DSTATCOM integration, and $P_{Tloss}^{with\ DSTATCOM}$ represents the total power loss after DSTATCOM integration. The system constraints and backward/forward sweep load flow formulations can be found in [9, 14, 15, 16, 17, 18].

4. Mathematical formulation of PSO, ABC and DE optimization

4.1 *Particle swarm optimization method*

The potential solutions entail the synchronization of two paths denoting the velocity (V) and position (X) of a particle. After each iteration, the particle that holds the best solution conveys its position coordinates (P_{gbd}) to the entire swarm [19]. The variables within the PSO algorithm are delineated as follows: At a given time (t), the updated position and velocity of the (i^{th}) particle are signified by Equations (7) and (8) respectively.

$$V_{id}^{t+1} = w * V_{id}^{t} + C_1 * r_1 * \left(P^t + X^t\right) + C_2 * r_2 * \left(P_{gbd}^{t} - X_{id}^{t}\right) \tag{7}$$

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} \tag{8}$$

where, C_1 and C_2 represent the acceleration coefficients, $d = 1,\ 2\ldots m$ (members of the particle-searching space). The variables r_1 and r_2 introduce stochasticity (as the model incorporates uniformly distributed random numbers between 0 and 1). The index i signifies the particles in the swarm ($i = 1,\ 2\ldots n$), V_{id}^{t} denotes the current velocity of particle ($'i'$), V_{id}^{t+1} indicates its updated velocity of the particle. P_{id} represents the optimal position of the particle, P_{gbd} represents the best value for the particle group, X_{id}^{t} signifies the current search point of a particle, X_{id}^{t+1} represents the updated search point and w denotes the inertial weight. The function for the inertial weight can be expressed as follows:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} * t \tag{9}$$

The minimum and maximum inertia weights are denoted as $w_{\min}$ and $w_{\max}$, respectively, while $t\ and\ t_{\max}$ refer to the present and maximum iteration.

4.2 *Artificial bee colony method*

A swarm intelligence optimization method called Artificial Bee Colony (ABC) was motivated by honeybees' feeding habits. To identify the best solution to optimization issues, the population-based algorithm, ABC mimics the foraging behavior of bees [7, 20]. The fitness function of ABC quantifies the quality of a candidate solution, which can be expressed as.

$$f_{fit} = \frac{1}{1 + p_{losses}} \tag{10}$$

The onlooker bees improve their solution by examining the information surrounding a food source and updating their memory using Equation (11).

$$f_{ij} = f_{minj} + rand(f_{maxj} - f_{minj}) \tag{11}$$

The solution for the j^{th} variable at its minimum and maximum is denoted by f_{minj} and f_{maxj}, respectively. A random number (rand) is chosen from the range of -2 to 2 [21]. Equation (12) guides the onlooker bee in the random selection of food sources.

$$p_{prob(i)} = \frac{f_{it(i)}}{\sum_k^N f_{it(k)}} \tag{12}$$

where, $f_{it(i)}$ represents the fitness value corresponding to the selected solution (i). The fitness value at every iteration is indicated as $f_{it(k)}$, where the variable length is k. The scout bee utilizes Equation (11) when the newly updated solution is inferior to the previous best solution.

Therefore,

$$f_{it(i)} = \begin{cases} \frac{1}{1+f_i} & if\ f_i \geq 0 \\ 1 + abs(f_i) & if\ f_i < 0 \end{cases} \tag{13}$$

where, f_i denotes the cost value of the objective function.

4.3 *Differential evolution method*

Differential Evolution (DE) is an evolutionary optimization method that relies on populations and stochastic processes to tackle various problems. DE was created in 1997 by Storn and Price and is particularly beneficial for linear and nonlinear optimization applications [22, 23]. The population in successive generations undergoes evolution through the application of evolutionary operators, such as mutation, crossover, and selection, until the specified termination condition is reached. At the start, the population size, and the dimensions of optimization variables within each individual string, known as the target vector (TV), are randomly initialized using Equation (14) [22].

$$TV_{iG}^{j} = round\ [\ TV_{mi}^{j} + rand() * (TV_{mx}^{j} - TV_{mi}^{j})\ ] \tag{14}$$

where $i = 1, 2, ..., Np$, $j = 1, 2, ..., D$, G represents the generation number, and mi and mx denote the minimum and maximum vectors, respectively. Equation (15) generates a mutation vector (MV_i) for each target vector. It can be expressed as:

$$MV_{iG} = TV_{bG} + F * (\ TV_{r1G} - TV_{r2G}) \tag{15}$$

where F represents a constant scaling factor ranging from 0 to 2, and $r1$ and $r2$ are two random selected integers and TV_b denotes the best target vector within the population of that generation (G), determined by the fitness (objective) function values. After the mutation operation, the crossover operation is carried out on each pair consisting of the target vector (TV_{iG}) and its corresponding mutant vector (MV_{iG}) to generate a crossover vector (CV_{jiG}) using the following equation:

$$CV_{jiG} = \begin{cases} MV_{jiG} & if\ rand() \leq CF \\ TV_{jiG} & otherwise \end{cases} \tag{16}$$

where, crossover factor (CF) is a user-defined parameter within the range of $[0,\ 1]$. The selection operation performed after the crossover can be expressed as

$$TV_{iG+1} = \begin{cases} CV_{iG} & if\ f(CF_{iG} \leq f(TV_{iG})) \\ TV_{iG} & otherwise \end{cases} \tag{17}$$

where f denotes the objectives function.

5. Experimental verification of real and simulated data

To ensure long-term reliability and stability in power distribution system analysis, the study focuses on comparing simulated data with real data collected over an extended period, from October 2022 to September 2023 [9]. Figure 2 presents the system verification of the real and the simulated data.

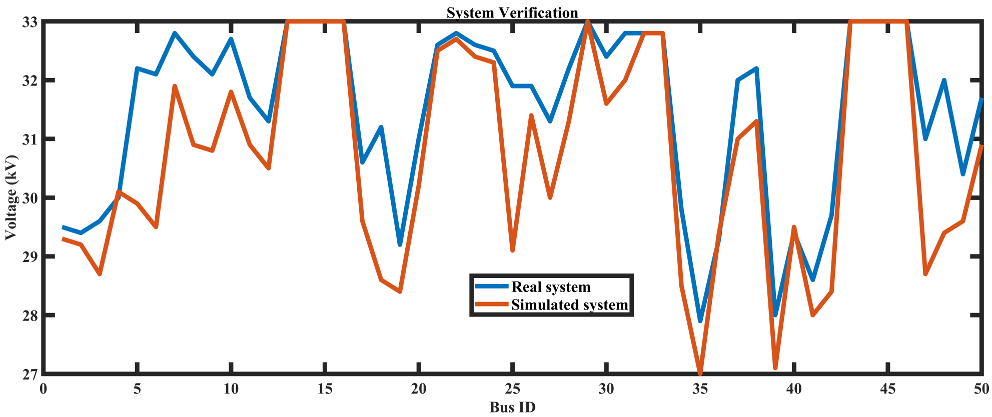

Figure 2. System verification of real and simulated voltages

The error margins of average voltages in the comparison between real and simulated data were found to range between -0.1 kV and 2.8 kV. This falls within the acceptable range according to IEC standards, which allow for a voltage margin of up to 5%. The Pearson correlation coefficient of 0.878 further demonstrates a strong correlation between the real and simulated data, indicating a high level of confidence (95%) in the accuracy of the simulation models.

6. Results and discussion

The assessment of power system is conducted through the utilization of PSO, ABC, and DE methods, with the integration of DSTATCOM as the primary control variable. The optimal system performance relies on the placement and size of the DSTATCOM. To assess the efficacy of the proposed methods, this study investigated four scenarios: the baseline system without DSTATCOM (referred to as Case 1), Case 2 with PSO implementation, Case 3 utilizing ABC, and Case 4 involving DE implementation. The Backward/Forward Sweep power flow analysis technique was utilized to assess the effects of integrating DSTATCOM. This technique allowed for an exploration of different facets of the distribution system, such as active and reactive power losses, voltage profile, and system cost. Through comparison of results obtained with and without DSTATCOM integration, the effectiveness of these techniques was evaluated. The optimization process was conducted using MATLAB software, which offered the essential functionalities for optimizing the integration of DSTATCOM in the 33 kV distribution system.

6.1 *Power losses reduction (active and reactive)*

The results regarding power losses across various cases (Case 1, Case 2, Case 3, and Case 4) were illustrated in Figures 3–6. These figures presented key parameters such as total power losses and the percentage of loss reduction. Specifically, Figures 3 and 4 visually represented the total active loss and its percentage reduction, while Figures 5 and 6 depicted the reactive power loss and its corresponding percentage reduction (PLR).

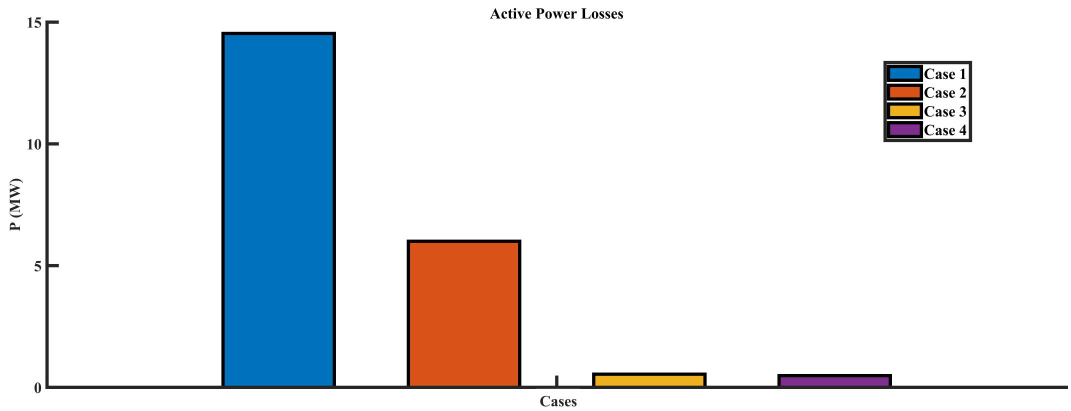

Figure 3. Total active loss of cases 1, 2, 3 & 4

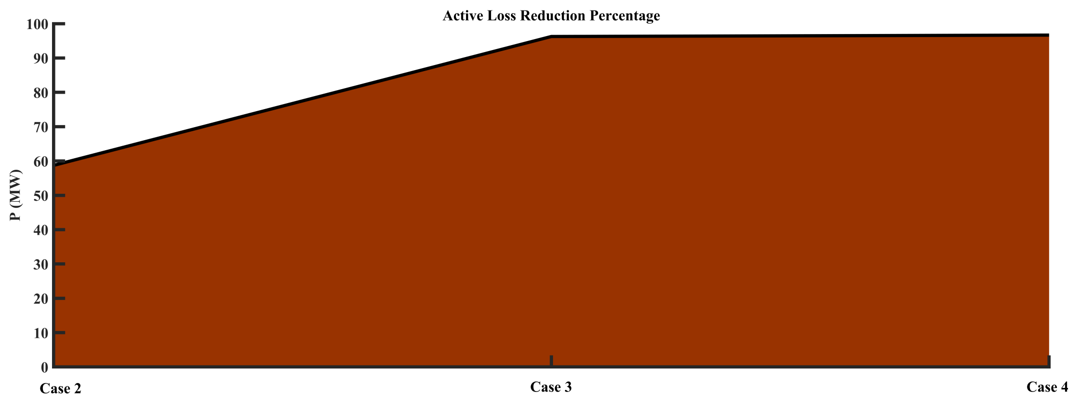

Figure 4. Total active loss reduction percentage

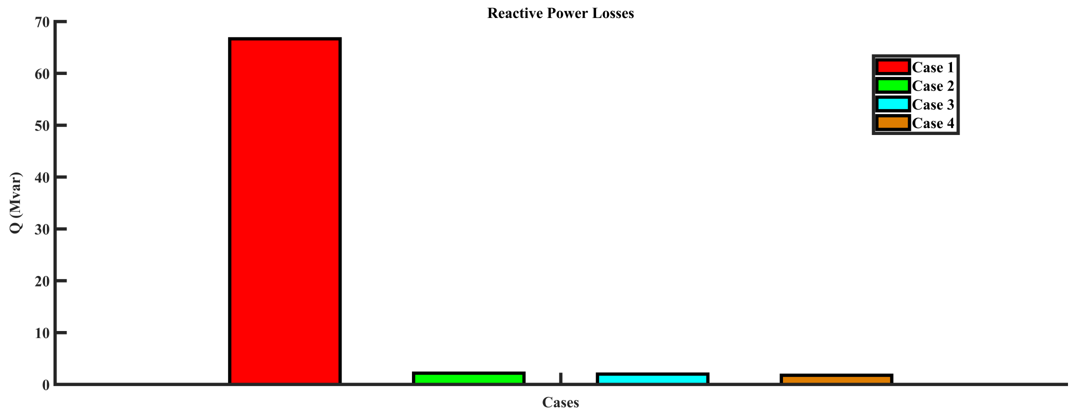

Figure 5. Total reactive loss of cases 1, 2, 3 & 4

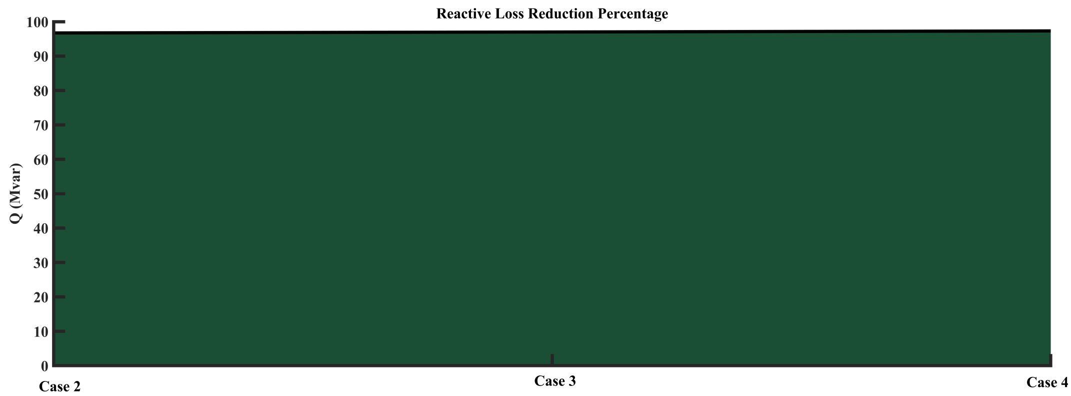

Figure 6. Total reactive loss reduction percentage

A comparison of power loss reductions across these cases with the original system (Case 1) reveals significant differences, as shown in Figures 3–6. In Case 2, total active and reactive power losses were 5.998 MW and 2.181 Mvar, respectively, with reductions of 8.53 MW and 64.469 Mvar, resulting in percentage reductions of 58.72% and 96.73%. Case 3 reported total power losses of 0.543 MW and 1.995 Mvar, with reductions of 13.99 MW and 64.655 Mvar, corresponding to percentage reductions of 96.26% and 97%. In Case 4 (DE), total power losses were 0.484 MW and 1.788 Mvar, achieving reductions of 14.05 MW and 64.862 Mvar, leading to percentage reductions of 99.67% and 97.32%. These results demonstrate that DE outperforms PSO and ABC, showing improvements in active and reactive loss of 37.95% and 0.41%, respectively. The optimal power loss values were achieved through the strategic placement and sizing of DSTATCOM, as detailed in Table 2.

6.2 *Voltage Profile Improvement (VPI)*

Figure 7 depicts the voltage profile improvement (VPI) results for Cases 1, 2, 3, and 4. VPI is evaluated based on the increase in the voltage profile value per unit (p.u).

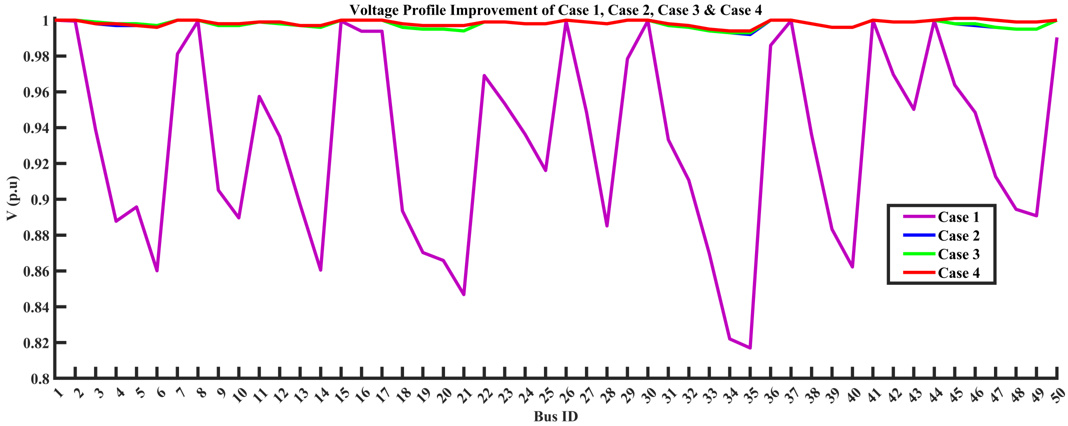

Figure 7. Voltage profile improvement of Cases 1, 2, 3 & 4

The VPI results in Figure 7 show that the DE approach outperforms the PSO and ABC methods, with an improvement from 0.994 p.u. to 1.001 p.u. Furthermore, when comparing PSO and ABC with DE, there are substantial increases at many buses (9, 10, 14, 18, 19, 20, 21, 31, 32, 33, 34, 35, 45, 46, 47, 48, and 49).

6.3 *System Cost (SC)*

The purpose of this study segment was to assess the cost-effectiveness of Cases 1, 2, 3, and 4. This assessment involved analyzing both the overall system cost and the percentage reduction in cost for each case. Figures 8 and 9 illustrate the total system cost and the corresponding percentage reduction.

The data provided in Figures 8 and 9 offers insights into the system cost and the corresponding percentage of cost reduction for various cases within a power system. Case 1, with a system cost of $2,441,040.00, serves as the reference point for evaluating cost reduction across the subsequent cases. Case 2 displays a cost reduction percentage of 58.71%, marking a higher reduction compared to Case 1. Case 3 shows the highest cost reduction percentage, standing at 96.11% relative to Case 1. However, Case 4 surpasses all, with a cost reduction percentage of 96.55% and a notably lower system cost of $84,096.00. This remarkable reduction in system cost in Case 4 indicates the efficacy of the implemented optimizations. Whether in terms of technology, design, or operational strategy, the changes made in Case 4 have successfully contributed to a more efficient and economical power system.

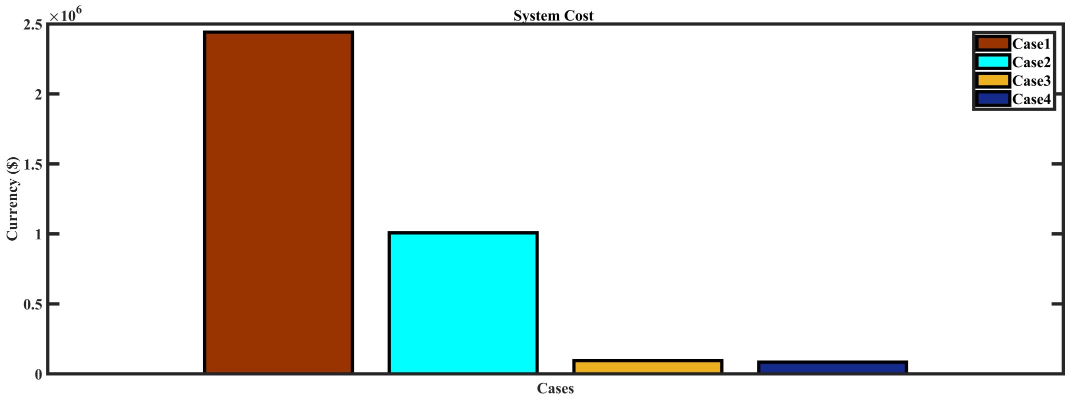

Figure 8. Total system cost of Cases 1, 2, 3 & 4

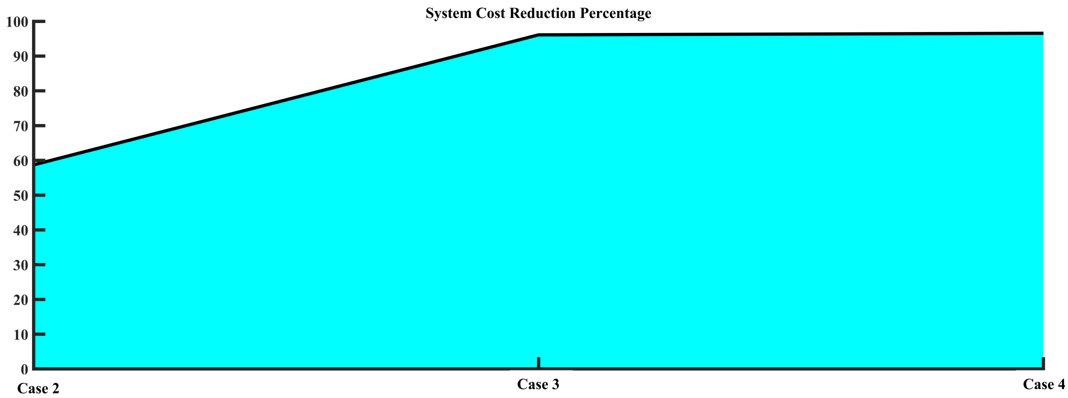

Figure 9. Total system cost reduction percentage of Cases 2, 3 & 4

The high percentage of cost reduction in Case 4 positions it as a favourable option for consideration, especially when balancing the trade-off between system cost and desired performance metrics. The data justifies Case 4 as the most cost-effective option among the analyzed cases, making it a potential preferred solution in the context of the power system analysis. Table 1 contains a full description of the findings from all cases. The data shown in Table 2 can be used to analyze the feasibility and possible benefits of implementing DSTATCOM into similar distribution systems, which could enhance decision-making for future projects.

From Table 2, Case 4 outperforms other cases in the power system evaluation, showcasing superior results in active and reactive power reduction, the lowest energy and system costs, highest net savings, and the shortest payback period. These outcomes affirm Case 4 as the most favourable solution, excelling both in enhancing power system performance and delivering substantial economic benefits.

Table 2. The summary results of all cases

Performance Measurement	Case 1	Case 2	Case 3	Case 4
Minimum Bus Voltage (p.u)	0.817	0.992	0.993	0.994
Maximum Bus Voltage (p.u)	1	1	1	1.001
Total Active Power Loss (MW)	14.53	5.99832	0.543	0.484
Total Reactive Power Loss (MVAR)	67.005	2.2205	1.995	1.788
DSTATCOM Power Injection (kvar) and Location	-	150 at bus 26 150 at bus 30	1200 at bus 26 1200 at bus 8 1200 at bus 15 1200 at bus 30 1200 at bus 3 1200 at bus 44 12,000 at bus 31 1200 at bus 37 1050 at bus 18 1200 at bus 11 750 at bus 9 900 at bus 29 1200 at bus 28 900 at bus 45 1200 at bus 32 450 at bus 19 1200 at bus 4 1200 at bus 36 1200 at bus 46 150 at bus 10	1200 at bus 26 1200 at bus 8 1200 at bus 30 1200 at bus 31 1200 at bus 37 1200 at bus 11 12,000 at bus 9 1200 at bus 29 1200 at bus 45 1200 at bus 19 1200 at bus 4 1200 at bus 36 1200 at bus 46 600 at bus 10
Number of DSTATCOM	-	2	20	14
Active Power Reduction Percentage	-	58.72%	96.26%	96.67%
Reactive Power Reduction Percentage	-	96.73%	97.01%	97.32%
Total Energy Cost ($/kW)	2,441,040.00	1,007,717.76	91,224.00	81,312.00
Total System Cost ($/year)	2,441,040.00	1,007,867.76	95,044.65	84,096.00
Net Saving ($/year)	-	1,433,172.24	2,345,995.35	2,356,944.00
System Cost Reduction Percentage	-	58.71%	96.11%	96.55%
Payback Period	-	7 months	4 weeks	3 weeks and 5 days

7. Conclusions

This study evaluated the impact of deploying Distribution Static Synchronous Compensators (DSTATCOMs) on a 33 kV radial distribution network, focusing on performance improvements and cost efficiency. Various scenarios were analyzed to assess how DSTATCOMs affect power losses, voltage stability, and overall system economics.

Case 1 served as the baseline without DSTATCOMs, with a total system cost of $2,441,040.00. It displayed a minimum bus voltage of 0.817 p.u. and a maximum of 1.0 p.u., highlighting the challenges of voltage maintenance without compensation devices.

Case 2, incorporating 2 DSTATCOMs, reduced active power losses by 58.72% and reactive power losses by 96.73%. This led to a net saving of $1,433,172.24 and a payback period of 7 months. Voltage regulation improved, with the minimum bus voltage rising to 0.992 p.u. and the maximum remaining at 1.0 p.u.

Case 3, with 20 DSTATCOMs, achieved further reductions: 96.26% in active power losses and 97.01% in reactive power losses. The increased number of DSTATCOMs in this case was necessary to provide more granular control and support across the network, thereby achieving superior voltage stability and loss reduction. This configuration led to a net saving of $2,345,995.35, with a reduced payback period of 4 weeks. The minimum bus voltage was 0.993 p.u., and the maximum stayed at 1.0 p.u., indicating improved voltage stability.

Case 4 deployed 14 DSTATCOMs, yielding the highest reductions—96.67% in active power and 97.32% in reactive power. The number of DSTATCOMs in this case was optimized to achieve the best balance between performance and cost. This case had the lowest system cost of $84,096.00 and the fastest payback period of 3 weeks and 5 days. The minimum bus voltage was 0.994 p.u., and the maximum was 1.001 p.u., demonstrating optimal voltage stability and cost efficiency.

Overall, the analysis confirms that DSTATCOM deployment significantly reduces power losses and enhances economic performance. The varying numbers of DSTATCOMs in each case reflect the strategic decisions to balance cost, performance, and voltage stability. Case 4 emerged as the most cost-effective option, offering the greatest reduction in power losses, the lowest system cost, and the quickest payback period, supported by detailed simulations and real data comparisons.

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Conflict of interest

There is no conflict of interest in this study.

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