Article

Annual Cost and Loss Minimization in a Radial Distribution Network by Capacitor Allocation Using PSO

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Abstract: Increasing power demand from passive distribution networks has led to deteriorated voltage profiles and increased line flows. This has increased the annual operations and installation costs due to unavoidable reinforcement equipment. This work proposes the reduction in annual costs by optimal placement of capacitors used to alleviate power loss in radial distribution networks (RDNs). The optimization objective function is formulated for the reduction in operation costs by (i) reducing the active and reactive power losses, and (ii) the cost and installation of capacitors, necessary to provide the reactive power support and maintain the voltage profile. Initially, the network buses are ranked according to two loss sensitivity indices (LSI_1), i.e., active loss sensitivity with respect to node voltage (LSI_1) and reactive power injection (LSI_2). The sorted bus list is then fed to the particle swarm optimization (PSO) for solving the objective function. The efficacy of the proposed work is tested on different IEEE standard networks (34 and 85 nodes) for different use cases and load conditions. In use case 1, the values finalized by the algorithm are selected without considering their market availability, whereas in use case 2, market-available capacitor sizes close to the optimal solution are selected. Furthermore, the static and seasonal load profiles are considered. The results are compared with recent methods and have shown significant improvement in terms of annual cost, losses and line flows reduction, and voltage profile.

Keywords: costs; load flow control; optimization methods; particle swarm optimization; power distribution; power system management; size control

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1. Introduction

Increases in power losses at the consumer's end necessitates an increase in the generation of energy, and its effects on the power system are manifold. While it increases the operation and maintenance costs, it also increases the stress on the power system, leading to the voltage profile deterioration and several other challenges [1]. Increasing the generation may also require additional time to respond to the problem and incur additional costs for installation of newer generation plants/facilities. It is noteworthy that the losses and voltage profile significantly depend upon the reactive power injection. Therefore, reactive power injection, if done optimally, can be more time- and cost-efficient [2].

Various methods are used for injecting reactive power in distribution system for reducing power losses, including the method of capacitor placement [3], distribution generator (DG) [4], FACT devices [5], and synchronous condenser (SC) [6]. The SC is a conventional and well-established method for power loss compensation. However,

nowadays, SCs are rarely used because they require special arrangements to start. They also cannot be adjusted rapidly with changes in load [7]. In recent years, (DGs) have been widely preferred, as they could (i) minimize power losses; (ii) improve the voltage profile; and (iii) due to the green onsite generation. Due to the fact that the conventional power system is designed for unidirectional power flow, additional care must be taken in order to avoid reverse power flow [5]. Using (FACTS) devices, power flow and oscillation damping can be controlled. However, initial and maintenance costs of these devices are very high. They may also not achieve sufficient damping over oscillation [8].

Capacitor placement in the distribution system for minimization of power losses is widely used because they are more economical and reliable than the methods discussed above [9]. Other advantages of capacitor placement are power loss minimization, improvement in voltage profile, power factor improvement and control, and minimization of total system cost. However, improper installation of the capacitor in a distribution system can increase power loss and worsen the voltage profile [10]. In order to achieve optimum benefits, the optimally sized capacitors should be installed at proper locations [3], which is a challenging task [11]. This optimization problem includes finding the total number, location, and optimal size for the capacitors, so that maximum benefits can be achieved while satisfying system constraints.

To tackle this complex optimization problem, an effective optimization tool is required because the nature of these problems is non-linear and complex. The available algorithms in the literature for solving optimization problems are classified as analytical, artificial intelligence, numerical programming, and heuristic algorithm [12]. For optimization of the power system, classical methods have been proposed by researchers in [13]. Solving optimization problems with classical approaches has limitations, such as the difficulty to escape local minima and being unable to handle discrete control variables properly [14].

Recently, researchers have paid more attention to the optimal capacitor allocation problem—a combinatorial problem used to determine heuristic approaches [15]. An optimization technique called grasshopper optimization algorithm (GHOA) is used to allocate a capacitor bank in a distribution system optimally [16]. However, the installation and maintenance cost was not considered in this study. A two-loop hybrid method is utilized for placing capacitors optimally with the objective of maximizing the annual profit of the distribution system [17]. Tamilselvan et al. used the flower pollination algorithm (FPA) to determine the optimal size and location for the capacitors with the objective of minimizing losses and costs of the capacitors [18]. However this algorithm sometimes converge prematurely, which increases the possibility of inaccurate results. The water cycle algorithm (WCA) was implemented in [3] for placement of the capacitor and DGs in the distribution system, to minimize power losses and voltage deviation in the network. Although the results are efficient and acceptable, this approach is prone to very slow convergence to the global optima and needs more computational time. A hybrid search-GA is utilized for placing optimally sized capacitors at ideal locations, aiming to minimize both active and reactive power losses [19]. However, increasing the size of the network required a longer computational time and slow convergence. Hussain et al. reported distribution system reconfiguration and an optimal capacitor placement based hybrid approach to enhance the voltage profile and minimize the losses [20]. Despite producing good results, this method yields continuous capacitor values instead of discrete values, which may not be available in the market. A new approach, called Ant Lion Algorithm (ALO), was introduced to place the capacitor optimally in the distribution system to increase the net annual saving [21]. However, consideration is also only given to fixed capacitors (continuous value), which may not be available in the market. Voltage, loss, and cost are formulated as multi-objective functions in [22], solved by (PSO) and the gravitational search algorithm (GSA)-based hybrid PSOGSA algorithm. The hybrid algorithm has produced significantly convincing results; however, the purchasing and installation costs are missing in the problem formulation. Annual capacitor cost and cost of power losses are minimized in [23] using PSOGSA, however, the voltage stability is ignored in this work.

Particle swarm optimization (PSO) is a powerful technique with an additional benefit of easy implementation. Kennedy et al. proposed the PSO algorithm to solve the optimization problem [24]. This method has gained popularity for addressing complex optimization problems and is widely utilized in power system optimization. For example, PSO is utilized for optimal sizing and allocation of DGs in the radial distribution network (RDN) [25], while PSO is utilized for stability analysis of the power system by Kennedy and Eberhar [26]. The optimal dispatch problem, i.e., optimal power generation sizing, is done by PSO [27]. Meanwhile, PSO is used for optimal control of the smart nano grid [28]. Researchers have also utilized PSO for the optimal design of the grid-connected solar system in [29]. The authors in Reference [30] presented a brief survey of the methods used for loss reduction in low voltage networks.

The optimal capacitor placement for reducing the active power losses and system annual costs is done using PSO [31], ant colony optimization (ACO) [32], plant growth simulation algorithm (PGSA) [33], direct search algorithm (DSA) [34], genetic algorithm (GA) [35], and bacteria foraging algorithm (BFA) [36]. IEEE 33 and 48 node RDNs are also considered for implementation and validation [31]. It is worth noting that even though a reactive power injection impacts the reactive power flow and losses directly, it is not considered in these works. Moreover, contrary to practical scenarios, these methods considered static load only. Additionally, the methods need to be tested for larger networks.

The prime contribution of this paper are: (i) the reduction of active and reactive power losses; (ii) minimization of total annual cost; and (iii) voltage profile improvement in RDNs. To assess the efficacy and usefulness to the fullest, the proposed method is tested for both static and seasonal load profiles. Moreover, two use cases of capacitor sizes, i.e., the discrete capacitor sizes, according to their market availability and continuous sizes as calculated by the algorithm, are considered. Loss sensitivity indices (LSIs) are used to rank the buses according to their sensitivity for capacitor placement [37]. The sizes of the capacitors are found using PSO. To make the proposed system more suitable for larger networks, the simulation is performed for IEEE 34 and 85 node RDNs. The results are validated by comparing them with those from recent approaches, such as ACO [32], PGSA [33], DSA [34], GA [35], and BFA [36].

This article is organized as follows: the motivation, literature review, and the contributions of the work are detailed in Section 1, followed by the optimization problem formulation in Section 2. The implementation strategy of the proposed method is explained in Section 3. This section also elaborates on the losses in RDNs, the LSIs, the PSO algorithm, and the steps involved for implementation of the proposed method. The results are summarized in Section 4. Finally, the conclusion is presented in Section 5.

2. Problem Formulation

Line losses contribute significantly to increasing the operation costs of the power system. Hence, costs are reduced by reducing the losses. Moreover, for systems with extensive reactive power demand, the reactive power compensation is performed by installing capacitors, which contribute to the installation, operation, and maintenance costs. The objectives considered in this work contain all of the above costs and is given as (1):

$$F_{\text{Minimize}} = C_P P_{\text{loss}}^{\text{Tot}} + C_Q Q_{\text{loss}}^{\text{Tot}} + C_C Q_C^{\text{Tot}}. \quad (1)$$

where,

$$P_{\text{loss}}^{\text{Tot}} = \sum_{k=1}^{N_b-1} P_{\text{loss}k},$$

$$Q_{\text{loss}}^{\text{Tot}} = \sum_{k=1}^{N_b-1} Q_{\text{loss}k},$$

and

$$Q_C^{\text{Tot}} = \sum_{q=1}^{NC} Q_{Cq}$$

So,

$$F_{\text{Minimize}} = C_p \sum_{k=1}^{N_{b-1}} P_{\text{loss}k} + C_q \sum_{k=1}^{N_{b-1}} Q_{\text{loss}k} + C_c \sum_{q=1}^{NC} Q_{Cq} \quad (2)$$

If n is the life expectancy of the capacitors, the annual cost of the capacitor is given by (3):

$$\text{Total cost of capacitors} = \frac{C_c Q_C^{\text{Tot}}}{n} \frac{z}{\text{Year}} \quad (3)$$

where z is the cost of single capacitor. The operation and maintenance costs are neglected [32]. The objective function shown in (2) is subjected to the following constraints;

Node voltage: each node voltage should be in its minimum and maximum limits:

$$V_q^{\min} \leq V_q \leq V_q^{\max} \quad (4)$$

Size of capacitor: injected reactive power for compensation through capacitors must be in their defined limits.

$$Q_{Cq}^{\min} \leq Q_{Cq} \leq Q_{Cq}^{\max} \quad (5)$$

Number of total capacitor: the number of capacitors to be placed must be equal or less than the possible maximum locations.

$$N_C \leq N_C^{\max} \quad (6)$$

Total reactive power injection: injection of total reactive power must be less than or equal to the total reactive power load.

$$Q_C^{\text{Tot}} \leq Q_L^{\text{Tot}} \quad (7)$$

3. Implemented Strategy

The aim of this paper is to find the best location(s) and size(s) of capacitor(s) in order to inject the reactive power in the system, thereby ensuring the minimum loss operation. This ultimately reduces the total cost of the system, while keeping the system within suitable operating limits. The problem is divided into two parts: optimal location selection and the size of the capacitor(s) for RDN. In the first stage, two *LSIs* are used to rank the candidate buses on the basis of their reactive power requirement. This reduces the search space for the optimization process. Both *LSIs* select 50% of total buses of the system for the capacitor placement [31]. In the second stage, optimal size(s) of capacitor(s) at optimal location(s) from the *LSIs*-based shortlisted nodes is selected using PSO.

3.1. Loss Sensitivity Indices (LSI)

Two *LSIs* are used to efficiently shortlist the candidate load buses for capacitor installation. *LSIs* rank the load buses according to active power loss sensitivity for voltage and the reactive power demand at the receiving end. In Figure 1, two buses are shown, which are linked by line k , taken from a distribution system. The sending bus is p with voltage of V_p at the voltage angle of δ_p . The receiving end bus is q with voltage of V_q at the voltage angle of δ_q . P_p and Q_p are active and reactive power, respectively, flowing from bus p to bus q through the k^{th} line with line impedance $R_k + jX_k$. P_p and Q_p are provided by (8) and (9), respectively. The current through the line k is i_k .

Figure 1. Two nodes representation of distribution system.

$$P_p = P_{Lq} + P_{lossk} \quad (8)$$

$$Q_p = Q_{Lq} + Q_{lossk} \quad (9)$$

$$P_{lossk} = i_k^2 R_k = \left[\frac{(P_{Lq}^2 + Q_{Lq}^2)}{|V_q|^2} \right] R_k \quad (10)$$

$$Q_{lossk} = i_k^2 X_k = \left[\frac{(P_{Lq}^2 + Q_{Lq}^2)}{|V_q|^2} \right] X_k \quad (11)$$

The loss sensitivity is calculated with respect to the bus voltage and the reactive power load, both at the receiving end bus. Therefore, LSI_1 and LSI_2 are defined as the partial derivative of P_{lossk} with respect to V_q and Q_{Lq} , respectively, as given by (12) and (13).

$$LSI_1 = \frac{\delta P_{lossk}}{\delta V_q} = -2R_k \frac{P_{Lq}^2 + Q_{Lq}^2}{V_q^3} \quad (12)$$

$$LSI_2 = \frac{\delta P_{lossk}}{\delta Q_{Lq}} = 2R_k \frac{Q_{Lq}}{V_q^2} \quad (13)$$

It is trivial to deduce that LSI_1 are negative values whereas LSI_2 are positive values. The more negative the value of LSI_1 for a bus, the higher the impact of voltage variation of the bus on power loss. Such a bus will have a higher chance of selection as an optimal location because minor variations in bus voltage can have high impacts on loss reduction. Contrary to LSI_1 , for LSI_2 the higher positive values translate to higher chances of selection as a candidate bus due to the fact that power loss has positive sensitivity, with respect to reactive power demand at receiving end bus. The buses are ranked in ascending order according to their LSI_1 , and in descending order according to their LSI_2 . The top 50% of buses are shortlisted for the input to the PSO algorithm in order to logically reduce the search space; hence, reducing the simulation burden and time. A detailed calculation of $LSIs$ is given in [32].

3.2. Proposed Algorithm

Particle swarm optimization (PSO) is a powerful algorithm that has proved its exceptional performance in solving complex optimization problems, including power system optimization problems, as detailed in [38]. This algorithm is a swarm-based meta-heuristic optimization tool, invented by Kennedy and Eberhart in 1995 [24].

The basic idea behind PSO is that, initially, population (swarm) of individuals (particles) is generated. Initially every particle has its own position X_i^k and moves in a D-dimensional search space with random velocity Vel_i^k and searches for optima. Each particle modifies its velocity Vel_i^{k+1} and position X_i^{k+1} , according to (14) and (15), respectively. All particles update their personal best position P_{best}^P in every iteration. Among all P_{best}^P , global best position G_{best}^P is determined and is considered as a global optimum solution until the current iteration. In this way, after several iterations, all particles will reach toward global optima. The movement of single particle is shown in Figure 2.

$$Vel_i^{k+1} = wVel_i^k + c_1r_1(P_{best}^p - X_i^k) + c_2r_2(G_{best}^p - X_i^k) \quad (14)$$

$$X_i^{k+1} = X_i^k + Vel_i^{k+1} \quad (15)$$

Figure 2. Movement of a single particle in swarm.

3.3. Steps for Implemented Methodology

The following are the steps involved in getting the optimal location and sizes of the capacitors in order to minimize the cost.

1. Read system data, specify base values for S, V, I, and Z.
2. Run load flow to find P_{loss}^{Tot} and Q_{loss}^{Tot} , V_{min} and V_{max} at each node, i.e., uncompensated values.
3. Calculate *LSIs* for each bus using (12) and (13) and arrange in respective order. Top 50% of buses from *LSI* list will be stored in 'a' (reduced search space) and considered for capacitor placement.
4. Set 'nvar', i.e., total number of capacitors to be placed. In this work, it is 10–15% of total buses.
5. Initialize PSO parameters, i.e., set number of particles (N_p), w , c_1 , c_2 , r_1 , and r_2 .
6. Generate random particles (candidate solutions) with position and velocity.
7. Set the iteration count i to zero.
8. Using (14) and (15), the velocity and the position of the particle are updated, respectively.
9. The local best, i.e., $bparticle(i)$ and global best, i.e., $gparticle(i)$ solutions are found as:
 if $particle(i).cost < bparticle(i).cost$ than
 $bparticle(i) = particle(i)$;
 else $bparticle(i).cost < gparticle.cost$ than
 $gparticle(i) = bparticle(i)$;
 end
10. Among total N_p , $gparticle.pos[i] = (Q_{C1}, ..., a)$ correspond to the number of candidate buses and $gparticle.pos[i + a]$ correspond to each capacitor size to be placed.
11. Place the capacitors at the respective buses and calculate P_{loss}^{Tot} , Q_{loss}^{Tot} and Q_C^{Tot} .
12. Evaluate fitness function given by (1).
13. If $i \geq N_p$, display results and end, else go to step 7.

These steps are briefed in the flowchart given in Figure 3.

Figure 3. Flow chart for the proposed method.

4. Results and Discussion

The efficiency of the proposed method is assessed by simulation in MATLAB ®version R2015 on the networks of variable sizes and complexities, i.e., IEEE 34 (N_1) and 85 (N_2) nodes RDNs. The computer system used for simulation of the proposed method has Intel®Core™ i3-2350M CPU with frequency of 2.30GHz and the RAM of 4 GB. System

data are taken from [32]. The minimization problem given in (1) is solved through the step given in Section 3.3.

To test the accuracy and efficiency of the proposed method, static and seasonal load profiles (where load varies in different seasons) are considered, termed as case study 1 (CS₁) and case study 2 (CS₂), respectively. In CS₁, total active and reactive loads for N_1 is 4636 kW and 2873 kvar, while for N_2 , 2514.3 kW and 2564.6 kvar, respectively throughout the year. The load data for both RDNs, according to CS₂, is given in Table 1. Other parameters used are: $C_p = 168\$/\text{kWyear}$, $C_q = 25\$/\text{kvaryear}$, $C_c = 5\$/\text{kvar}$, and capacitor life expectancy = 10 years. Figures 4 and 5 explain the load demand for N_1 and N_2 for CS₂, respectively.

Table 1. Seasonal load profile for both networks.

Months	Active Load (kW)		Reactive Load (kvar)	
Network	N_1	N_2	N_1	N_2
January–March	4636	2514	2873	2564
April–June	8345	4525	5172	4616
July–September	6491	3520	4022	3590
October–December	6027	3268	2061	3333

Figure 4. Seasonal load profile for N_1 .

Figure 5. Seasonal load profile for N_2 .

Furthermore, two use cases are considered according to the selection of capacitor values. In use case 1, the capacitor sizes are taken as continuous variables, as calculated by the algorithm, irrespective of the market availability. In use case 2, the capacitor sizes are taken as discrete values in near proximity of the calculated values by the algorithm. This is done in order to select the capacitors available in the market. For both use cases, the capacitor values correspond to the reactive power supply range from 150 kvar to 1200 kvar. However, in use case 2, the capacitor values are incremented in steps of 150 kvar in order to get market available sizes.

Maximum and minimum voltage limits are taken to be 0.9–1.1 pu for both networks. Furthermore, the results are compared with other approaches, as mentioned earlier.

4.1. 34 and 85 Node RDNs – CS₁

For N_1 , the voltage profile has improved significantly after using the proposed capacitor placement, as shown in Table 2. Prior to compensation, minimum and maximum voltage in the network was 0.9411 pu at node 27 and 0.9941 pu at node 2, respectively. For use case 1, these values are improved to 0.9504 pu and 0.9954 pu, respectively. For use case 2, minimum voltage is improved to 0.9503 pu and maximum voltage is improved to 0.9949 pu. Voltage profile and line flow for N_1 are shown in Figures 6 and 7, respectively. In these figure results of the uncompensated case, use case 1 and use case 2 are shown.

Figure 6. Voltage profile for N_1 in CS₁.

Figure 7. Line flow for N_1 in CS₁.

Initially the total annual cost of N_1 is USD 37,241/year (uncompensated) that is reduced to USD 26,655/year in use case 1 with USD 10,586.03/year of net saving, while for use case 2, it is reduced to USD 26,894/year with USD 10,347/year of net saving. From Table 2, Figures 6 and 7, it is obvious that the results of use case 1 is better than use case 2. One reason for this can be the limitation on capacitor values in use case 2, i.e., the

Table 3. Results comparison of N_2 for CS_1 .

Items	Uncom- pensated	Compensated						
		PGSA	DSA	GA	ACO Algorithm		Proposed Algorithm	
					Use Case1	Use Case2	Use Case1	Use Case2
kvar injected at node	-			48.4 (26)				
				214 (28)				
				103.1 (37)				
			150 (6)	120.3 (38)	186 (4)			
			150 (8)	178 (39)	150 (7)		150(27)	
			150 (14)	100 (51)	210 (9)	150 (7)	150 (29)	300(25)
			150 (17)	212.5 (54)	10 (13)	300 (8)	203.5 (30)	150 (48)
			150 (18)	101.5 (55)	280 (18)	300 (19)	439.4 (64)	600 (51)
		200 (7)	150 (20)	4.6 (59)	320 (26)	300 (27)	295 (51)	150 (64)
		1200 (8)	150 (26)	157 (60)	250 (31)	300 (32)	150 (50)	300 (18)
		908 (58)	150 (30)	112.5 (61)	205 (35)	300 (48)	150 (67)	150 (68)
			450 (37)	104 (62)	200 (53)	300 (61)	150 (19)	300 (12)
			150 (57)	9.3 (66)	220 (61)	300 (68)	161 (46)	150 (61)
			150 (61)	100 (69)	330 (68)	300 (80)	286 (80)	150 (44)
			150 (66)	67 (72)	196 (80)			
			300 (69)	112.5 (74)				
			150 (80)	71.9 (76)				
				356.2 (80)				
				31.2 (82)				
Total kvar injected	-	2308	2550	2207	2726	2550	2134.9	2250
Active loss (kW)	319	174.9	144.0	146	143.3	143.9	140.9	145.2
Reactive loss (kvar)	182	-	-	-	-	-	80.7	82.6
Active loss reduction (%)	-	44	54.4	53.7	54.6	54.4	55.8	54.5
Reactive loss reduction (%)	-	-	-	-	-	-	55.7	54.6
V_{min} at node	0.85 (76)	0.90 (54)	0.92 (54)	0.92 (55)	0.92 (54)	0.92 (27)	0.91 (76)	0.91 (76)
V_{max} at node	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)
Annual cost USD (\$)/year	53,619	29,385	24,194	24,538	24,082	24,171	23,670	24,394
Capacitor cost USD (\$)/year	-	1154	1275	1103	1363	1275	1067.4	1125
Net saving USD (\$)/year	-	24,234	29,425	29,081	29,537	29,448	29,949	29,225

Figure 8. Voltage profile for N_2 in CS_1 .

Figure 9. Line flow for N_2 in CS_1 .

4.2. 34 and 85 Node RDNs – CS_2

For this case study, two scenarios are considered.

Scenario 1 (S_1): optimization is conducted for the period of January to March. Capacitor locations and sizes are determined. After an increase in load, no variations in capacitor size and location are made. Based on these sizes and locations, the results are analyzed for coming seasons.

Scenario 2 (S_2): optimization is conducted for the same duration of January to March. Capacitor locations and sizes are determined. After variations in loads in coming seasons, optimal sizes of capacitors are determined, and results are compared with those of S_1 .

Tables 4 and 5 contain the data for uncompensated N_1 and N_2 for CS_2 , respectively. For N_1 , results of seasonal load are displayed in Table 6 according to S_1 . For the January to March season, optimal capacitor placement is performed and kept for other forthcoming seasons. For use case 1, capacitors of sizes 150, 481, 836, and 539 are placed at locations 19, 21, 24, and 8. The active power loss is reduced to 158 from 221 kW—a 28.52% reduction. Similarly, reactive power loss has been reduced to 43 from 65.1007 kvar, i.e., a 33% reduction. Capacitor sizes for use case 2 are 300, 300, 600, and 600, placed at locations 17, 20, 23, and 8. The active power losses are reduced to 160 from 221 kW, i.e., a 27.88% reduction. Similarly, reactive power loss was reduced to 43 from 65.23 kvar, i.e., 30.52% reduction.

For April–June, the load is increased to 1.8 times of the January–March load. With an increase in load, the losses also increased as shown in Table 4. Keeping sizes and locations of capacitors fixed at the January–March season results, it is observed that the active power loss reduction is 8% for use case 1 and 7.7% for use case 2. Similarly, reactive power loss reduction is 9.7% for use case 1 and 8.7% for use case 2. Consequently, the annual cost reduction is USD 120,883/year in use case 1. These results highlight the need for optimal capacitor placement in each season according to the respective load. Based on this observation, the results are improved in S_2 .

The outcomes of the seasonal load profile for N_1 are detailed in the Table 7 for S_2 . The increasing load alternatively increased system power losses, requiring optimization at each season. After the load change, according to the season, the results improved significantly if the capacitor placement was re-analyzed for updated network conditions. For example, when the load increased to 1.8 times of January–March in the second quarter, the losses increased to 782.1081 from 221.67 kW and to 229.309 kvar from 65.1007 kvar. To achieve better loss reduction and, hence, better annual savings, the sizes of the capacitors need to be updated only while installing them at similar locations, as in S_1 . The updated sizes are now 160, 1134, 1200, and 853, injecting the total of 3347 kvar. It can be seen in Table 7 that the active power loss is reduced to 28.99%, which is only 8% in S_1 . Similarly, a reduction in

reactive power loss is 28.75%, which is 7.7% in S_1 for use case 1. Likewise, results of use case 2 for S_2 are better than that of S_1 , as shown in Table 7. Net savings for use case 1 is USD 10,511 and USD 38,101/year for S_1 and S_2 , respectively.

The same procedure is done for N_2 . The CS_2 results of N_2 for each scenario are shown in Tables 8 and 9, respectively. In S_1 , the annual cost is significantly reduced by placing optimal capacitors of sizes 150, 150, 203, 439, 295, 150, 150, 161, and 286 at optimal locations (27, 29, 30, 64, 51, 50, 67, 19, 46, and 80). The active and reactive power losses are reduced to 55.85% and 55.68% for use case 1, respectively. This loss reduction only corresponds to 12% and 12.5% for active and reactive losses, respectively, for the April–June season, as shown in Table 8. Consequently, the annual cost reduction is USD 70,058/year for use case 1. Due to reasons discussed earlier, the S_2 produced improved results and are discussed in Table 9.

Results of N_2 for S_2 are shown in Table 9. For April–June season, sizes of optimal capacitors are updated at the same location. Moreover, for N_2 , some new capacitors are needed to be installed at new locations for this specific season to ensure better annual cost savings in both use cases. Unlike S_1 , after optimization, the reduction in active power loss is 30.8%, which is 12% in case of S_1 (use case 1). Moreover, for (April–June) reactive power loss is reduced to 27.9%, which is 12.5% in case of S_1 . Comparing both scenarios, results of S_2 are better than S_1 in all aspects shown in Table 9. Unlike N_1 , installation of capacitors at new location in N_2 may need better optimization. However, as per common practice, the capacitors are installed at various locations and brought into the operation as and when needed.

Table 4. Base data (uncompensated) of N_1 for CS_2 .

Months	Uncompensated			
	January–March	April–June	July–September	October–December
Active loss (kW)	221.7	782.1	674	523.5
Reactive loss (kvar)	65.1	229.3	198	153
Total cost (USD (\$)/year)	37,241	131,394	113,372	87,991
V_{min} at node	0.94 (27)	0.89 (27)	0.88 (27)	0.90 (27)
V_{max} at node	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)

Table 5. Base data (uncompensated) of N_2 for CS_2 .

Months	Uncompensated			
	January–March	April–June	July–September	October–December
Total active loss (kW)	319.2	1436.9	717.6	595.7
Reactive loss (kvar)	182.1	810.9	407.7	338.9
Total cost (USD (\$)/year)	53,619.6	241,406.4	120,556.7	100,082.8
V_{min} at node	0.85 (76)	0.67 (76)	0.77 (76)	0.79 (76)
V_{max} at node	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)

Table 6. Results comparison of N_1 for CS_2 (Scenario 1).

Months	Compensated							
	January–March		April–June (1.8)		July–September (1.4)		October–December (1.3)	
Use Cases	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2
kvar injected at node	150 (19)	300 (17)	150 (19)	300 (17)	150 (19)	300 (17)	150 (19)	300 (17)
	481 (21)	300 (20)	481 (21)	300 (20)	481 (21)	300 (20)	481 (21)	300 (20)
	836 (24)	600 (23)	836 (24)	600 (23)	836 (24)	600 (23)	836 (24)	600 (23)
	539 (8)	600 (8)	539 (8)	600 (8)	539 (8)	600 (8)	539 (8)	600 (8)
Total kvar injected	2007	1800	2007	1800	2007	1800	2007	1800
Active loss (kW)	158	160	719	722	611	613	460	462
Reactive loss (kvar)	43.3	45.2	207	209	176	78	131	133
Active loss reduction (%)	28.5	27.9	8	7.7	9.5	9	13	11.7
Reactive loss reduction (%)	33.4	30.5	9.7	8.7	11	10	14	13
V_{min} at node	0.95 (27)	0.95 (27)	0.79 (27)	0.77 (27)	0.80 (27)	0.80 (27)	0.86 (27)	0.82 (27)
V_{max} at node	0.99 (2)	0.99 (2)	0.90 (2)	0.90 (2)	0.93 (2)	0.92 (2)	0.94 (2)	0.94 (2)
Annual cost (USD (\$)/year)	26,655	26,894	120,883	121,277	102,602	103,169	76,553	77,697
Capacitor cost (USD (\$)/year)	1003	900	1003	900	1003	900	1003	900
Net saving (USD (\$)/year)	10,586	10,347	10,511	10,117	10,777	10,203	11,438	10,294

Table 7. Results comparison of N_1 for CS_2 (Scenario 2).

Months	Compensated							
	January–March		April–June (1.8)		July–September (1.4)		October–December (1.3)	
Use Cases	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2
kvar injected at node	150 (19)	300 (17)	160 (19)	600 (17)	426 (19)	450 (17)	445 (19)	450 (17)
	481 (21)	300 (20)	1134 (21)	600 (20)	475 (21)	450 (20)	353 (21)	600 (20)
	836 (24)	600 (23)	1200 (24)	600 (23)	722 (24)	600 (23)	602 (24)	300 (23)
	539 (8)	600 (8)	853 (8)	600 (8)	723 (8)	600 (8)	589 (8)	450 (8)
Total kvar injected	2007	1800	3347	2400	2350.9	2100	1990	1800
Active loss (kW)	158	160	555	557	479	497	370	375
Reactive loss (kvar)	43.3	45.2	156.5	162.8	140.3	143	105	109
Active loss reduction (%)	28.5	27.9	28.9	28.7	28.9	26.2	29.2	28.2
Reactive loss reduction (%)	33.4	30.5	31.7	28.9	29.1	27.4	31.6	28.7
V_{min} at node	0.95 (27)	0.95 (27)	0.91 (27)	0.90 (27)	0.90 (27)	0.89 (27)	0.91 (27)	0.90 (27)
V_{max} at node	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)
Annual cost (USD (\$)/year)	26,655	26,894	93,292	93,613	80,505	83,624	62,252	63,111
Capacitor cost (USD (\$)/year)	1003	900	1673	1200	1175	1050	995	900
Net saving (USD (\$)/year)	10,586	10,347	38,101	37,781	32,866	29,748	25,740	24,880

Table 8. Results comparison of N_2 for CS_2 (Scenario 1).

Months	Compensated							
	Jan–March		April–June (1.8)		July–September (1.4)		October–December (1.3)	
Use Cases	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2
kvar injected at node	150 (27)		150 (27)		150 (27)		150 (27)	
	150 (29)	300 (25)	150 (29)	300 (25)	150 (29)	300 (25)	150 (29)	300 (25)
	203 (30)	150 (48)	203 (30)	150 (48)	203 (30)	150 (48)	203 (30)	150 (48)
	439 (64)	600 (51)	439 (64)	600 (51)	439 (64)	600 (51)	439 (64)	600 (51)
	295 (51)	150 (64)	295 (51)	150 (64)	295 (51)	150 (64)	295 (51)	150 (64)
	150 (50)	300 (18)	150 (50)	300 (18)	150 (50)	300 (18)	150 (50)	300 (18)
	150 (67)	150 (68)	150 (67)	150 (68)	150 (67)	150 (68)	150 (67)	150 (68)
	150 (19)	300 (12)	150 (19)	300 (12)	150 (19)	300 (12)	150 (19)	300 (12)
	161 (46)	150 (61)	161 (46)	150 (61)	161 (46)	150 (61)	161 (46)	150 (61)
	286 (80)	150 (44)	286 (80)	150 (44)	286 (80)	150 (44)	286 (80)	150 (44)
Total kvar injected	2134	2250	2134	2250	2134	2250	2134	2250
Active loss (kW)	140.9	145.2	1257	1262	3341	3346	3089	3094
Reactive loss (kvar)	80.7	82.6	708	710	3488	3490	3231	3233
Active loss reduction (%)	55.8	54.5	12	12	24.9	24.5	30	29
Reactive loss reduction (%)	55.7	54.6	12.5	12.3	25	24.7	30	29
V_{min} at node	0.91 (76)	0.90 (76)	0.79 (76)	0.68 (76)	0.70 (76)	0.70 (76)	0.70 (76)	0.73 (76)
V_{max} at node	0.99 (2)	0.99 (2)	0.89 (2)	0.89 (2)	0.87 (2)	0.83 (2)	0.88 (2)	0.87 (2)
Annual cost (USD (\$)/year)	23,670	24,394	212,438	212,438	90,538	91,120	70,058	71,059
Capacitor cost (USD (\$)/year)	1067	1125	1067	1125	1067	1125	1067	1125
Net saving (USD (\$)/year)	29,950	29,225	28,968	28,968	30,018	29,436	30,024	29,023

Table 9. Results comparison of N_2 for CS_2 (Scenario 2).

Months	Compensated							
	Jan–March		April–June (1.8)		July–September (1.4)		October–December (1.3)	
Use Cases	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2	Use Case 1	Use Case 2
kvar injected at node			300 (27)		150 (27)			
			150 (29)	600 (25)	205 (29)			
			1200 (30)	300 (48)	212 (30)	600 (25)		150 (25)
	150 (27)	300(25)	446 (64)	600 (51)	511 (64)	150 (48)	150 (27)	300 (48)
	150 (29)	150 (48)	330 (51)	300 (64)	299 (51)	600 (51)	556 (29)	600 (51)
	203 (30)		179 (50)	600 (18)	150 (50)	600 (64)	366 (30)	150 (64)
	439 (64)	600 (51)	465 (67)	600 (68)	150 (67)	450 (18)	632 (64)	150 (18)
	295 (51)	150 (64)	150 (19)	600 (12)	150 (19)	150 (68)	401 (51)	150 (68)
	150 (50)	300 (18)	287 (46)	600 (61)	372 (46)	600 (12)	210 (50)	300 (12)
	150 (67)	150 (68)	270 (80)	600 (44)	363 (80)	600 (61)	150 (19)	600 (61)
	150 (19)	300 (12)	1046 (35)	150 (50)	875 (35)	150 (44)	906 (80)	150 (44)
	161 (46)	150 (61)	150 (45)	150 (67)	150 (45)	150 (50)	297 (57)	150 (50)
	286 (80)	150 (44)	1200 (68)	150 (19)	1168 (68)	600 (80)		150 (61)
			482 (10)	600 (80)	190 (60)			
			150 (17)	150 (2)	150 (17)			
			740 (9)					
Total kvar injected	2134	2250	7545	6000	5096	4650	3668	2850
Active loss (kW)	140	145	993	1119	387	410	273	289
Reactive loss (kvar)	80	82	584	679	223	237	159	164
Active loss reduction (%)	55.8	55.5	30.8	22.1	46	42	54	51
Reactive loss reduction (%)	55.7	54.6	28.0	22.1	45	41	52	51
V_{min} at node	0.91 (76)	0.90 (76)	0.91 (76)	0.90 (76)	0.90 (76)	0.90 (76)	0.90 (76)	0.90 (76)
V_{max} at node	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)	0.99 (2)
Annual cost (USD (\$)/year)	23,670	24,394	166,960	188,020	65,037	69,015	45,862	48,627
Capacitor cost (USD (\$)/year)	1067	1125	3772.5	3000	2548	2325	1834	1425
Net saving (USD (\$)/year)	29,950	29,225	74,446	53,383	55,519	51,541	54,220	51,455

5. Conclusions

In this work, we presented the annual costs of operations and reinforcement with capacitors, to reduce losses and improve the voltage profile, while keeping the network constraints. It is observed that the annual savings are significant if the proposed method is utilized for installation of the capacitors in RDNs. Moreover, system performance in terms of voltage profile, line flows, and losses improved significantly compared to recent methods presented in the literature. The ranking of buses, based on loss sensitivity, with respect to the voltage and reactive power injection at the neighboring buses, has reduced the search space for PSO without compromising the quality of results. Net annual saving for 34- and 85-node RDNs with static loads can be as high as USD 10,586 and USD 29,950/year, respectively. For seasonal load profiles, net annual savings are recorded to be USD 10511 and USD 38,101/year for the 34-node RDNs in scenarios 1 and 2, respectively. Similarly, for the 85-node RDN, USD 30,024 and USD 74,446/year is the net annual saving in scenarios 1 and 2, respectively. we conclude that better net annual cost savings is expected if the capacitor sizes and locations are updated according to seasonal load variations. Moreover, the method proposed in this work produced better results in comparison to recent novel methods. The work can be extended by considering other variables, such as the operation and maintenance costs.

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Abbreviations

The following abbreviations are used in this manuscript:

F	Total cost per year (\$/Year)
C_p	Cost of per unit active power loss per year (\$/kW-Year)
C_q	Cost of per unit reactive power loss per year (\$/kvar-Year)
C_C	Purchasing and installation cost of capacitor installed (\$/kvar)
P_{loss}^{Tot}	Total active power loss kW
Q_{loss}^{Tot}	Total reactive power loss kvar
Q_C^{Tot}	Total injected reactive power (kvar)
Q_{cq}	Reactive power injection at location q
N_b	Number of nodes in the system
N_c	Number of capacitors to be placed in system
N_C^{max}	Maximum permissible number of capacitors to be placed in the system
n	Life expectancy of the capacitors
Q_L^{Tot}	Total required reactive power by load
V_q	Bus voltage at node q
V_q^{min}	Minimum voltage at node q
V_q^{max}	Maximum voltage at node q
Q_{Cq}	Reactive power injection at node q
Q_{Cq}^{min}	Minimum reactive power injection at node q
Q_{Cq}^{max}	Maximum reactive power injection at node q
P_{Lq}	Total active power loads beyond the bus q
Q_{Lq}	Total reactive power loads beyond bus q
P_{lossk}	Total active power loss in line k
Q_{lossk}	Total reactive power loss in line k
i_k	Total current flowing over the line k
R_k	Total resistance of the line k
X_k	Total reactance of the line k
X_i^k	Initial position of i^{th} particle in k^{th} iteration
Vel_i^k	Initial velocity of i^{th} particle in k^{th} iteration
Vel_i^{k+1}	Modified velocity of i^{th} particle in $k + 1^{th}$ iteration
X_i^{k+1}	Modified position of i^{th} particle in $k + 1^{th}$ iteration
P_{best}^p	Personal best position of the particle
G_{best}^p	Global best position of the particle
w	The inertia weight
c_1	Constant for acceleration
c_2	Constant for acceleration
r_1	Random numbers between 0 and 1
r_2	Random numbers between 0 and 1

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