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Optimal Capacitor Sizing in Radial Distribution Systems for Real Power Loss Minimization Using Newton-Raphson Load Flow and Particle Swarm Optimization

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Abstract: In this paper, a two-stage methodology is presented for finding the optimal size of shunt capacitors to be placed in radial distribution systems. The main objectives are to minimize total real power losses, improve the bus voltage profile, and maximize net annual savings. In the first stage, the Newton–Raphson load flow method is used to identify the weak buses in the system by sorting buses in ascending order of their voltage magnitudes. In the second stage, Particle Swarm Optimization is used to find the optimal capacitor sizes at those candidate buses, with the objective of minimizing total real power losses subject to voltage and reactive power constraints. The proposed methodology is tested on two standard test systems, namely the 12-bus and the 69-bus radial distribution systems, both operating at 12.66 kV base voltage. In case of the 12-bus system, placing 207.2 kVAr at bus 12 and 196.3 kVAr at bus 11 reduces real power losses by about 2.4% (from 66.7 kW to 65.1 kW), raises the minimum voltage from 0.959 pu to 0.978 pu, and gives a net annual saving of US$639.21. For the 69-bus system, capacitors of 868.8, 662.6, and 1162.7 kVAr placed at buses 65, 64, and 63 respectively reduce the losses by 6.89% (from 307.8 kW to 286.6 kW), improve the minimum voltage from 0.909 pu to 0.957 pu, and give a net annual saving of US$10,334.49. The results are compared with more than 20 recent studies published between 2020 and 2024, and it is found that the proposed NR + PSO framework gives competitive and practically useful results.

Keywords: Capacitor Placement; Particle Swarm Optimization; Radial Distribution System; Real Power Loss Minimization; Newton–Raphson Load Flow; Reactive Power Compensation; Voltage Profile Improvement

I. INTRODUCTION

The electrical distribution system is that part of the power system which connects the transmission network to the end consumers. Most distribution systems have a radial structure due to their simplicity and lower cost. But because of this radial nature and the high resistance-to-reactance ratio of the feeder lines, distribution systems tend to have significant power losses. Studies have shown that around 10 to 13% of total generated power is wasted as losses at the distribution level itself [42, 41]. As the load demand keeps growing, these losses are only getting worse [18].

The main reason for these losses is the reactive nature of most distribution loads. Industrial motors, fluorescent lights, and power electronics equipment draw large lagging currents, which increase the current flowing through the feeder and hence increase the I^2R losses. A well-known and cost-effective way to deal with this problem is to install shunt capacitor banks at proper locations in the network [42, 38, 35]. Capacitors supply reactive current locally, which reduces the net current in the feeder, improves the power factor, and also brings the bus voltages closer to their nominal values. However, the benefits of capacitor placement depend heavily on where the capacitors are placed and how big they are. If capacitors are placed at wrong locations or with wrong sizes, they can actually make things worse by causing over-compensation or creating resonance issues [34, 24]. Because of this, it is necessary to find the optimal location and size of capacitors in a systematic way.

The problem of finding the best capacitor locations and sizes is called the Optimal Capacitor Placement (OCP) problem. It is basically a nonlinear mixed-integer optimization problem, which is not easy to solve using classical methods. Over the years, many optimization techniques have been proposed to solve this problem. Among them, Particle Swarm Optimization (PSO) has been one of the most popular choices because it is simple to implement, has very few parameters to tune, and gives good results [29, 33, 5]. PSO was introduced by Kennedy and Eberhart [39] in 1995, inspired by the way birds flock and fish school. In recent years, many new algorithms have also been applied to this problem, such as modified PSO [5], genetic algorithm variants [15], quasi-reflected slime mould algorithm [16], heap-based optimizer [12, 4], hybrid grey wolf optimizer [13], and multi-objective methods [7, 11]. Still, the basic NR + PSO framework remains one of the most straightforward and reliable approaches, and a proper study using this framework on standard test systems with full economic analysis is still something that many recent papers skip over.

In this work, a two-stage NR + PSO methodology is proposed and tested on 12-bus and 69-bus radial distribution systems. The Newton–Raphson load flow method is used in the first stage to find the weakest buses, and PSO is used in the second stage to optimize the capacitor sizes. A detailed economic analysis is also carried out. The results are then compared with more than 20 recent papers to show how the proposed method compares with the current state of the art. The main contributions of this work are as follows:

1) A clear, step-by-step two-stage NR + PSO framework that is easy to reproduce and implement in MATLAB for practical distribution system planning.
2) A detailed comparison of analytical and PSO-based capacitor placement on both 12-bus and 69-bus RDS, showing how much improvement PSO gives over manually selected combinations.
3) A complete economic analysis that covers energy loss cost, capacitor installation cost, and net annual savings all together.
4) A benchmark comparison with more than 20 recent papers (2020–2024) that puts the proposed results in the context of the latest work in this field.

The rest of this paper is organized as follows. Section II covers the literature review with a focus on recent developments after 2020. Section III explains the proposed methodology. Section IV presents the results and discussion. Section V gives the conclusion and scope for future work.

II. LITERATURE REVIEW

A. Classical and Early Methods

The OCP problem was formally defined by Baran and Wu [42] way back in 1989. They formulated it as a mixed-integer programming problem and divided it into two parts — one for finding the location and another for finding the size of capacitors. This work laid the foundation for almost all the methods that came after it. Haque [38] introduced a simpler approach where reactive losses are minimized by compensating buses one by one in order of their sensitivity, and tested it on 15-bus and 33-bus systems. Das et al. [40] proposed a new load flow technique specifically for radial networks, which turned out to be very useful for two-stage OCP methods where accurate bus voltages are needed to select candidate buses.

After these early works, many researchers started using soft computing techniques. Das [34] used fuzzy logic combined with a Genetic Algorithm to deal with uncertainty in load data on the 69-bus system. El-Fergany and Abdelaziz [24] applied the Artificial Bee Colony (ABC) algorithm together with loss sensitivity screening on 34-bus and 94-bus networks, and reported good net savings. Rao et al. [29] tested a Plant Growth Simulation Algorithm (PGSA) on 33-bus and 69-bus systems and showed up to 30% reduction in losses. Sultana and Roy [26] used Teaching Learning-Based Optimization (TLBO) and tested it on multiple systems including 118-bus RDS.

Devabalaji et al. [22] used the Cuckoo Search Algorithm combined with loss sensitivity factors and achieved 30.41% active power loss reduction on the 33-bus system. Some researchers also looked at combining network reconfiguration with capacitor placement. Farahani et al. [27] used a branch exchange method along with discrete GA and showed that doing both reconfiguration and capacitor placement together gives better results than doing them separately. Kasaei and Gandomkar [30] reached the same conclusion using the Ant Colony Optimization algorithm.

B. PSO and Related Swarm Approaches

PSO has been one of the most widely used algorithms for the OCP problem. Eajala and El-Hawary [33] used Binary PSO to handle nonlinear loads on 9-bus and 34-bus systems, minimizing harmonic distortion alongside power losses. The Grey Wolf Optimizer [25] and the Whale Optimization Algorithm [23] also became popular choices around this time. Diab and Rezk [21] ran a comparison of GWO, Dragonfly Algorithm, and Moth-Flame Optimization on 33-bus, 69-bus, and 118-bus systems. They found that GWO generally gave better results than the other two. Kumar et al. [32] did a comparative study of sensitivity-based methods for candidate bus selection and found that bus voltage sensitivity gives better results than loss sensitivity in some cases. Ng et al. [37] provided a useful classification of different capacitor allocation techniques that helps in understanding the scope of the problem.

C. Recent Work from 2020 to 2024

In recent years, a lot of work has been done to develop better algorithms and to extend the OCP problem to include more practical scenarios. Stanelyte [18] reviewed different voltage and reactive power control methods and pointed out that reactive compensation at the distribution level is still the most effective way to improve system performance. Sampangi Swaminathan [19] combined the water cycle algorithm with grey wolf optimizer and tested it on 33-bus and 69-bus systems under different loading conditions, getting consistent results.

Tahir, Rasheed, and Rahmat [5] introduced an Enhanced Modified PSO (MPSO) where they added a new inertia weight term to help the algorithm avoid getting stuck in local optima. They tested it on 15-bus, 33-bus, and 69-bus systems with both constant and time-varying loads. On the 69-bus system, their MPSO achieved 34.51% annual net savings for the single-objective case, which was better than standard PSO and GWO. Soma [15] used GA with daily load profiles and also defined control patterns for switched capacitors to avoid over-compensation during off-peak hours. What was interesting about this work was that it also worked on meshed networks, not just radial ones.

Biswal, Shankar, Elavarasan, and Mihet-Popa [16] proposed the Quasi-Reflected Slime Mould Algorithm (QRSMA) to simultaneously handle DG/capacitor allocation and network reconfiguration. They tested it on 69-bus, 85-bus, and 118-bus systems. Their main finding was that doing all three things together — DG placement, capacitor sizing, and reconfiguration — gives much better results than any single approach on its own. Lei et al. [10] compared PSO, Harmony Search, Bat Algorithm, Cuckoo Search, and GWO on the 34-bus system and found that GWO gave the best overall results.

Cherukuri et al. [13] hybridized GWO with crossover and mutation operators to create a Hybrid GWO (HGWO) and tested it on 15-bus, 33-bus, 69-bus, and 119-bus systems. The HGWO outperformed standard GWO and several other methods reported in the literature. Shaheen et al. [12] used an Improved Heap-Based Optimizer for DG allocation in reconfigured feeders and showed good loss reduction on 33-bus and 69-bus systems. Otuo-Acheampong et al. [4] further extended the heap-based optimizer concept for network reconfiguration at three different load levels and showed computational efficiency advantages over several competing methods.

There has also been growing interest in multi-objective approaches. Gampa et al. [7] used the Flower Pollination Algorithm with Pareto optimality for simultaneous capacitor placement and reconductoring in urban networks with solar DG. Mouwafi et al. [11] proposed a two-stage approach for joint DG and capacitor placement and tested it on 33-bus and 85-bus networks. Gampa et al. [20] went further and included electric vehicle charging stations along with DG and capacitors in a multi-objective framework using Grasshopper Optimization Algorithm, showing that the presence of EV loads changes the optimal compensation strategy significantly.

A few other studies are also worth mentioning here. Shaheen et al. [6] applied an Artificial Ecosystem Optimizer on actual Egyptian feeder data, which made the results more practically relevant. Stojanovic and Rajic [9] showed that in networks with wind generation, capacitor switching cannot be static and must be coordinated with the variable generation output. Uniyal and Sarangi [17] considered probabilistic load flow in their DG allocation problem, arguing that deterministic approaches may not give reliable results when loads are uncertain. Raza et al. [3] also included reliability indices in the objective function and found that reliability-constrained solutions can be quite different from simple loss-minimization solutions. Montoya et al. [2] looked at time-varying compensation with D-STATCOMs and fixed capacitors and showed that dynamic compensation can save an additional 3 to 7% in annual energy costs compared to fixed-step banks. Jayabarathi et al. [1] studied the combined effect of reconfiguration, DG, and capacitors and provided a useful quantitative comparison of these three tools on 33-bus and 69-bus systems.

Looking at all this work together, there are a few gaps that can be noticed. First, most recent papers focus on newer and more complex algorithms but do not compare them against the basic NR + PSO framework on the same test systems. Second, economic analysis in terms of net annual savings is often given less attention than algorithmic performance metrics. Third, the 12-bus system is almost never used in recent papers, even though it is a useful small benchmark for validating the methodology. The present work is an attempt to address these gaps.

III. METHODOLOGY

A. Load Flow Solution Using Newton–Raphson Method

Newton–Raphson method is used for the load flow solution in this work. This method is chosen because it converges faster and more reliably than other methods like Gauss-Seidel, especially for larger distribution systems [40]. It is also not very sensitive to the choice of slack bus, which makes it more stable. The real and reactive power injection equations at bus i are given as:

$$Pi = |Vi|\ \Sigma\ |Yip||Vp|\ \cos(\delta i - \gamma ip - \delta p) \quad (1)$$

$$Qi = |Vi|\ \Sigma\ |Yip||Vp|\ \sin(\delta i - \gamma ip - \delta p) \quad (2)$$

Here, Yip is the admittance of the line between buses i and p, δi is the voltage angle at bus i, and γip is the angle of the admittance. The NR method solves the mismatch equations iteratively using the Jacobian matrix as shown below:

$$\begin{bmatrix} \Delta & P \\ \Delta & Q \end{bmatrix} = \begin{bmatrix} H & N \\ M & L \end{bmatrix} \begin{bmatrix} \Delta & \delta \\ \Delta & V \end{bmatrix} \quad (3)$$

The iteration is stopped when the real and reactive power mismatches at all buses become smaller than the tolerance value of 0.0001 pu. A maximum of 10 iterations is allowed. After the load flow converges, the bus voltages are sorted in ascending order and the two or three buses with the lowest voltages are selected as candidate buses for capacitor placement. This is similar to the approach used in [5, 16, 13].

B. Objective Function and Constraints

The main objective of the capacitor placement problem in this work is to minimize the total real power losses of the distribution network after placing the capacitors [42, 29, 5]. The objective function is given as:

$$min\ \Sigma\ Rn\cdot(Pn^2 + Qn^2)/|Vn|^2 \quad n = 1,\ldots,E \quad (4)$$

where E is the total number of lines in the system, Rn is the resistance of branch n, Pn and Qn are the active and reactive power flows in branch n, and Vn is the voltage magnitude at the receiving end of branch n. The net annual saving, which is used for the economic evaluation, is calculated as [29, 15]:

$$Ns = Ke\cdot T\cdot Pb - Ke\cdot T\cdot Pc - \Sigma\ Kc,i\cdot Qc,i \quad (5)$$

In this equation, Ke is the cost of energy loss per kWh, T is the number of hours in a year, Pb and Pc are the real power losses before and after compensation, Kc,i is the capacitor cost per kVAr at bus i, and Qc,i is the size of the capacitor at bus i. The optimization is subject to the following constraints:

(i) Bus voltage limits: $Vi,min \le Vi \le Vi,max$ for all i (set to 0.95 pu to 1.05 pu).

(ii) Reactive compensation limits: $Qi,c,min \le Qi,c \le Qi,c,max$ for all i.

(iii) Security constraint: Total capacitor kVAr injected must not exceed total reactive load kVAr.

C. Particle Swarm Optimization

Particle Swarm Optimization was introduced by Kennedy and Eberhart [39] in 1995 and is one of the most well-known population-based optimization algorithms. The basic idea comes from the way a flock of birds searches for food. Each bird, or "particle" in PSO terms, represents a possible solution — in this case, a set of capacitor sizes at the candidate buses. Each particle moves through the search space by updating its velocity and position at every iteration. The update equations are:

$$V\_i^{(k+1)} = w\cdot V\_i^k + c1\cdot r1\cdot(Pbest\_i - X\_i^k) + c2\cdot r2\cdot(Gbest - X\_i^k) \quad (6)$$

$$X\_i^{(k+1)} = X\_i^k + \chi\cdot V\_i^k \quad (7)$$

Here, w is the inertia weight, which is decreased linearly from wmax = 1.0 to wmin = 0.20 over 70% of the maximum iterations. This helps the algorithm explore widely at the start and then refine the solution as it goes on [5, 13]. The constants c1 = 2.1 and c2 = 2.0 are the cognitive and social acceleration coefficients. r1 and r2 are random numbers between 0 and 1. The constriction factor χ = 0.729 is applied to keep the velocities under control. The maximum velocity is clamped at 0.3 MVAr to prevent particles from jumping too far. This same inertia weight reduction scheme has been used in several other distribution system studies [33, 5, 16] and is known to give a good balance between exploration and exploitation.

D. Step-by-Step Algorithm

The proposed methodology involves the following steps:

1) Step 1: Read the line impedance data and load data for the radial distribution system.
2) Step 2: Run the base-case NR load flow and record the bus voltage magnitudes and total real power losses.
3) Step 3: Sort the buses in ascending order of voltage magnitude and select the two (for 12-bus) or three (for 69-bus) weakest buses as candidate buses for capacitor placement.
4) Step 4: Randomly generate a swarm of N particles. Each particle is a vector of capacitor sizes at the candidate buses, initialized uniformly in [0, Qmax]. Velocities are also initialized randomly.
5) Step 5: For each particle, inject the capacitors into the system and run the NR load flow. Calculate the fitness value using equation (4), making sure constraints are satisfied.

6) Step 6: Find the personal best (Pbest) for each particle, which is the best position that particle has found so far. Also find the global best (Gbest), which is the best position found by any particle.
7) Step 7: Update the velocity and position of each particle using equations (6) and (7). Apply velocity clamping and make sure positions stay within bounds.
8) Step 8: Update Pbest and Gbest if a better solution is found. Continue from Step 6 until the maximum number of iterations is completed.
9) Step 9: After the loop ends, report the optimal capacitor sizes (Gbest), the resulting voltage profile, total power losses, and net annual saving as per equation (5).

For the 12-bus system, the number of particles is set to 20 and the maximum number of iterations is 100. For the 69-bus system, 50 particles and 200 iterations are used. These values are chosen based on what has worked in similar studies [5, 16] and were also verified to give stable convergence on both test systems. The entire algorithm is implemented in MATLAB.

IV. RESULTS AND DISCUSSION

A. *Test Systems*

The proposed methodology is tested on two standard test systems. The first one is a 12-bus radial distribution system with 12 nodes and 11 branches [40]. Bus 1 is the slack bus. The total real and reactive power loads are 435 kW and 405 kVAr respectively. The base power and base voltage are 100 MVA and 12.66 kV. The second test system is the 69-bus RDS with 69 nodes and 68 branches [36], with total load of 3802 kW and 2694 kVAr and the same base values. Both these test systems have been widely used in the literature [21, 26, 5, 16, 10, 13] and are considered standard benchmarks for this type of problem.

B. *Base Case Load Flow Results — 12-Bus RDS*

Table I shows the bus voltage magnitudes and angles obtained from the base-case NR load flow for the 12-bus system. It can be seen from the table that the minimum voltage (0.959 pu) occurs at buses 11 and 12, which are the terminal buses of the longest feeder. So these two buses are selected as the candidate buses for capacitor placement. The total real power loss in the base case is 66.7 kW, which is about 15.3% of the total load.

Table I. Base-Case Load Flow Results – 12-Bus RDS (Total Real Power Loss: 66.7 kW)

Bus No.	Voltage (pu)	Angle (°)
1	1.000	0.000
2	0.996	−0.087
3	0.992	−0.167
4	0.986	−0.299
5	0.978	−0.462
6	0.976	−0.511
7	0.974	−0.554
8	0.968	−0.730
9	0.962	−0.887
10	0.960	−0.939
11	0.959	−0.955 ★
12	0.959	−0.959 ★

★ = *Weakest candidate buses selected for capacitor placement.*

C. Analytical Method Results — 12-Bus RDS

Before applying PSO, five different combinations of capacitors were manually tested to understand the effect of capacitor size and location on system performance. Table II summarizes all these cases. In Case 1, a single capacitor is placed only at bus 12 with two different sizes (150 kVAr and 300 kVAr). In Case 2, the same is done at bus 11. In Case 3, capacitors are placed at both buses at the same time.

From Table II, it can be observed that placing 300 kVAr at bus 11 (Case 2-B) gives the best result in terms of loss reduction (1.72%) and net annual saving (US$454.44). At the same time, the simultaneous placement case (Case 3) gives the best voltage improvement. But no single combination gives the best result for all objectives at the same time. Because of this, it is necessary to use PSO to find the truly optimal capacitor sizes, as was also observed in similar studies [5, 15].

Table II. Analytical Capacitor Placement Results – 12-Bus RDS

Configuration (Bus, kVAr)	Real Power Loss (kW)	Min. Voltage (pu)	Net Annual Saving (US$)
Base case (no capacitor)	66.7	0.959	—
150 kVAr @ Bus 12	66.173	0.966	201.99
300 kVAr @ Bus 12	65.557	0.974	450.76
150 kVAr @ Bus 11	66.172	0.966	202.52
300 kVAr @ Bus 11	65.550	0.973	454.44
150 kVAr @ Bus 12 + 150 kVAr @ Bus 11	65.552	0.974 / 0.973	453.39

D. PSO Results — 12-Bus RDS

Here the PSO algorithm is run with 20 particles and 100 iterations. Table III shows the optimal capacitor sizes found by PSO. Table IV gives a summary of system performance before and after the optimal capacitor placement.

Table III. PSO Optimal Capacitor Sizes – 12-Bus RDS

Bus Number	Optimal Capacitor Size (kVAr)
12	207.2
11	196.3
Total	403.5

Table IV. Performance Statistics – 12-Bus RDS (PSO)

Parameter	Without Capacitor	With PSO Capacitor
Minimum System Voltage (pu)	0.959 (Bus 12)	0.978 (Bus 12)
Real Power Loss (kW)	66.7	65.1
Total Energy Loss Cost (US$)	35,057.52	34,216.56
Total Capacitor Cost (US$, @ $0.5/kVAr)	—	201.75
Total Annual Net Saving (US$)	—	639.21
Loss Reduction (%)	—	≈ 2.40%
Voltage Improvement (%)	—	≈ 1.98%

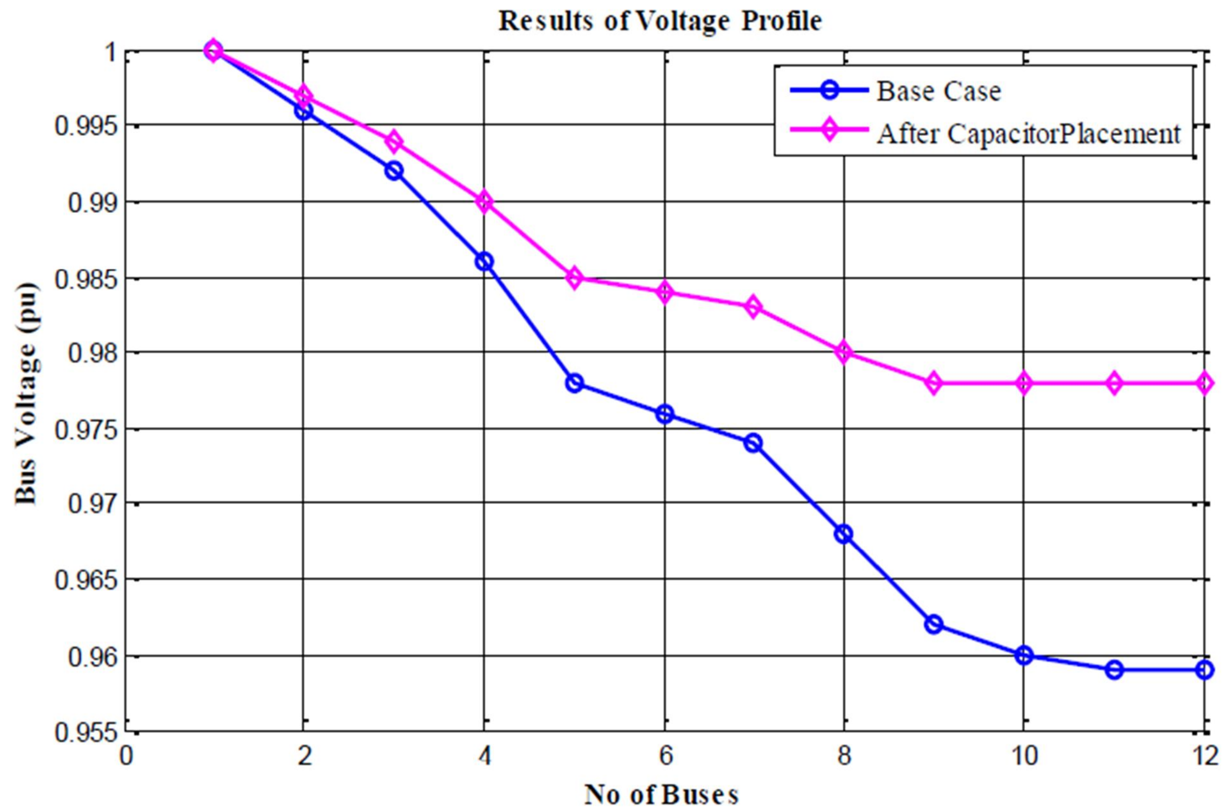

Fig. 1. Voltage profile of 12-bus RDS before and after capacitor placement using PSO.

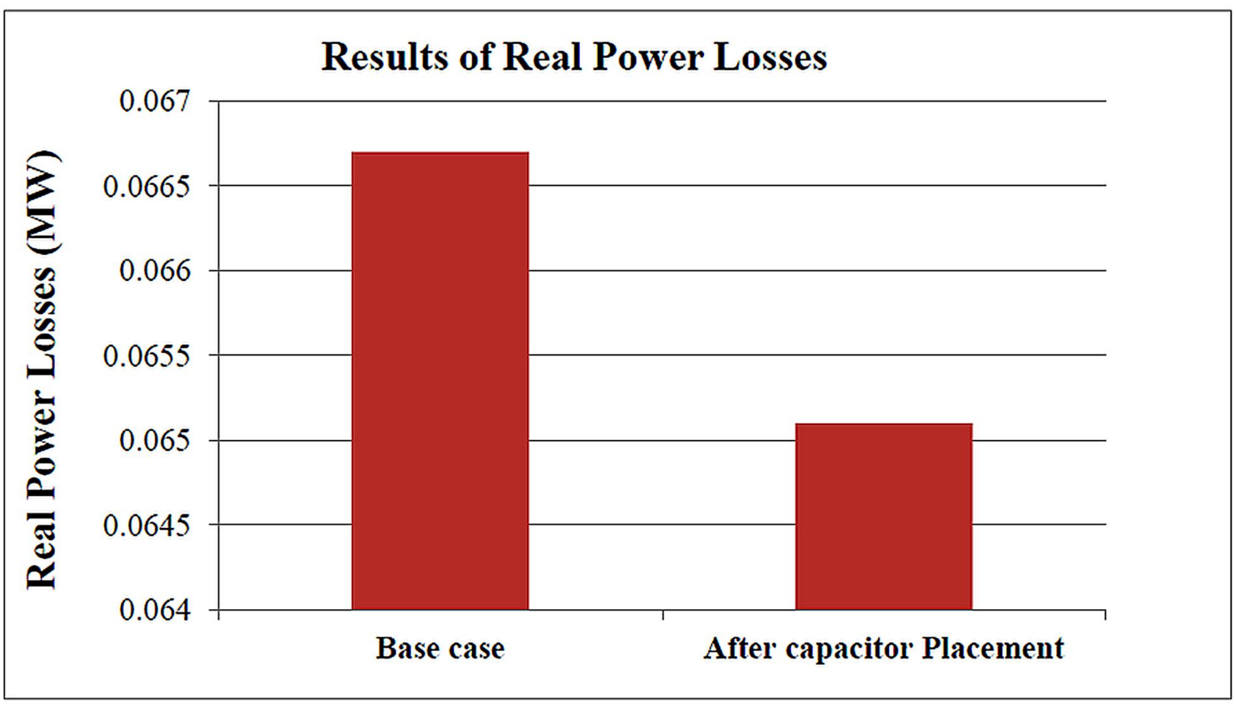

Fig. 2. Real power losses of 12-bus RDS before and after capacitor placement using PSO.

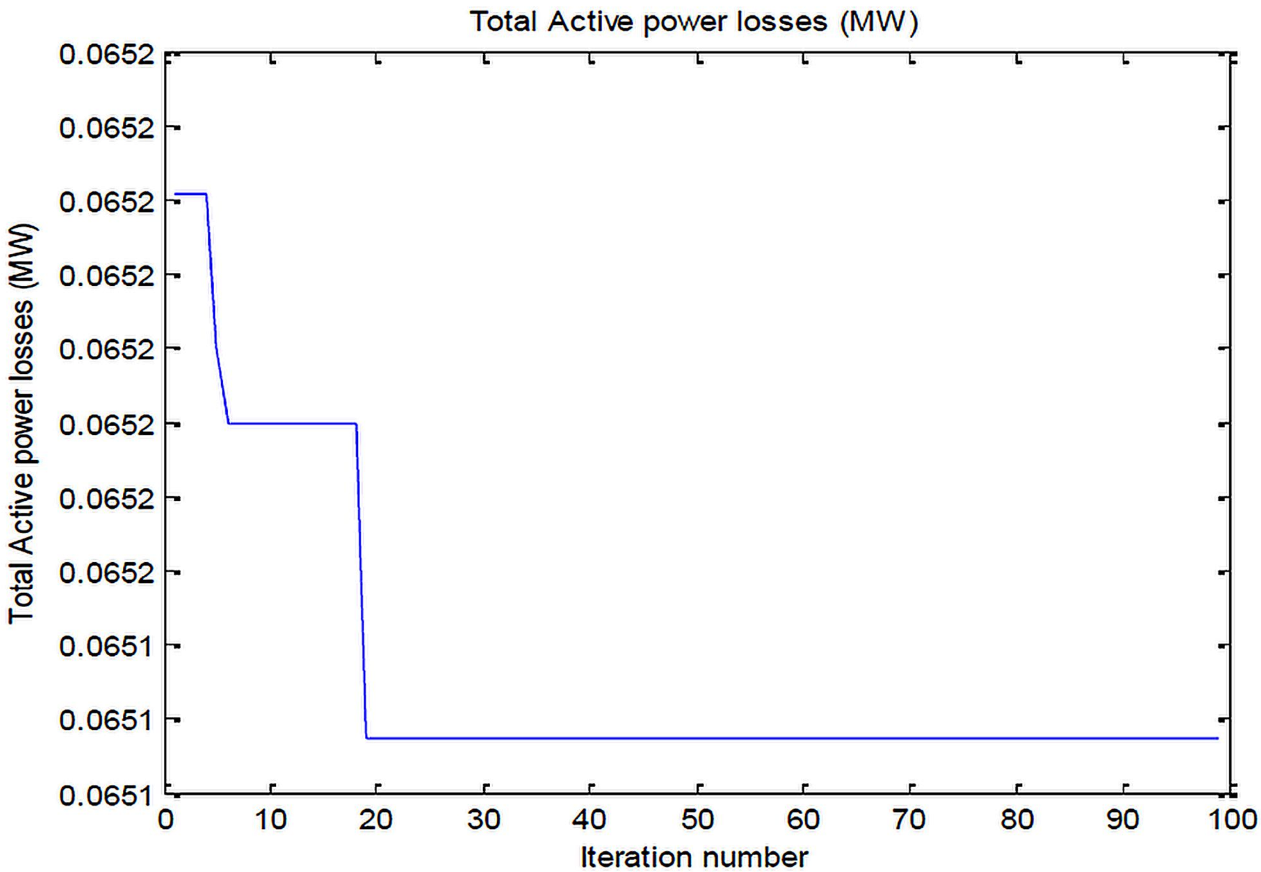

Fig. 3. Convergence curve of PSO for 12-bus RDS.

From Table IV and Fig. 1, it can be seen that after PSO-based capacitor placement, the voltage magnitudes improve at all buses. The minimum voltage rises from 0.959 pu to 0.978 pu at bus 12, which is an improvement of about 1.98%. The total real power loss comes down from 66.7 kW to 65.1 kW. The total energy loss cost reduces from US$35,057.52 to US$34,216.56. After subtracting the capacitor cost of US$201.75, the net annual saving is US$639.21. The convergence curve shown in Fig. 3 shows that the algorithm reaches its best solution within about 30 iterations and stays stable after that, which indicates good convergence behaviour. Similar fast convergence was also reported by Tahir et al. [5] for PSO-family algorithms on comparable system sizes.

E. Base Case Load Flow Results — 69-Bus RDS

Table V gives the NR load flow results for selected buses in the 69-bus system. The minimum voltage (0.909 pu) is at bus 65, which is at the far end of the longest lateral in the system. The next weakest buses are 64 (0.910 pu) and 63 (0.912 pu). So these three buses are chosen as candidate buses. This is consistent with what is reported in [21, 26, 5] for the same test system. The total base-case loss is 307.8 kW, which is about 8.1% of the total load (3802 kW).

Table V. Selected Base-Case Load Flow Results – 69-Bus RDS (Total Real Power Loss: 307.8 kW)

Bus No.	Voltage (pu)	Angle (°)
1	1.000	0.000
6	0.990	0.049
13	0.965	0.350
27	0.956	0.497

Bus No.	Voltage (pu)	Angle (°)
57	0.940	0.661
60	0.920	1.049
61	0.912	1.118
63	0.912 ★	1.124
64	0.910 ★	1.142
65 (weakest)	0.909 ★	1.147

★ = *Three weakest candidate buses selected for capacitor placement.*

F. Analytical Method Results — 69-Bus RDS

For the 69-bus system, a total of 21 different capacitor combinations are tested analytically across three cases. In Case 1, only bus 65 is compensated with three different sizes. In Case 2, buses 65 and 64 are compensated together with nine different combinations. In Case 3, all three buses — 65, 64, and 63 — are compensated together. Table VI shows the best result from each case.

It is observed that as more buses are compensated, the loss reduction and net saving both improve. The best analytical result from Case 3 (1350 kVAr at bus 65 + 600 kVAr at bus 64 + 450 kVAr at bus 63) gives a power loss of 288.4 kW and net saving of US$9,476.64. But this is just the best out of the manually tested combinations. It may not be the globally optimal solution, because the capacitor sizes are not continuous values here. This is why PSO is needed [15, 11].

Table VI. Best Analytical Results Per Case – 69-Bus RDS

Best Configuration (Bus, kVAr)	Loss (kW)	Min Voltage (pu)	Net Saving (US$)
1350 @ Bus 65 (Case 1-C)	295.6	0.939	6,007.32
1350 @ Bus 65 + 750 @ Bus 64 (Case 2-I)	290.4	0.951	8,515.44
1350 @ 65 + 600 @ 64 + 450 @ 63 (Case 3-I)	288.4	0.955	9,476.64

G. PSO Results — 69-Bus RDS

For the 69-bus system, PSO is run with 50 particles and 200 iterations. The optimal capacitor sizes found by PSO are given in Table VII, and the performance statistics are summarized in Table VIII.

Table VII. PSO Optimal Capacitor Sizes – 69-Bus RDS

Bus Number	Optimal Capacitor Size (kVAr)
65	868.8
64	662.6
63	1162.7
Total	2694.1

Table VIII. Performance Statistics – 69-Bus RDS (PSO)

Parameter	Without Capacitor	With PSO Capacitor
Minimum System Voltage (pu)	0.909 (Bus 65)	0.957 (Bus 65)
Real Power Loss (kW)	307.8	286.6
Total Energy Loss Cost (US$)	161,779.68	150,636.96
Total Capacitor Cost (US$, @ $0.3/kVAr)	—	808.23
Total Annual Net Saving (US$)	—	10,334.49
Loss Reduction (%)	—	≈ 6.89%
Voltage Improvement at Bus 65 (%)	—	≈ 5.28%

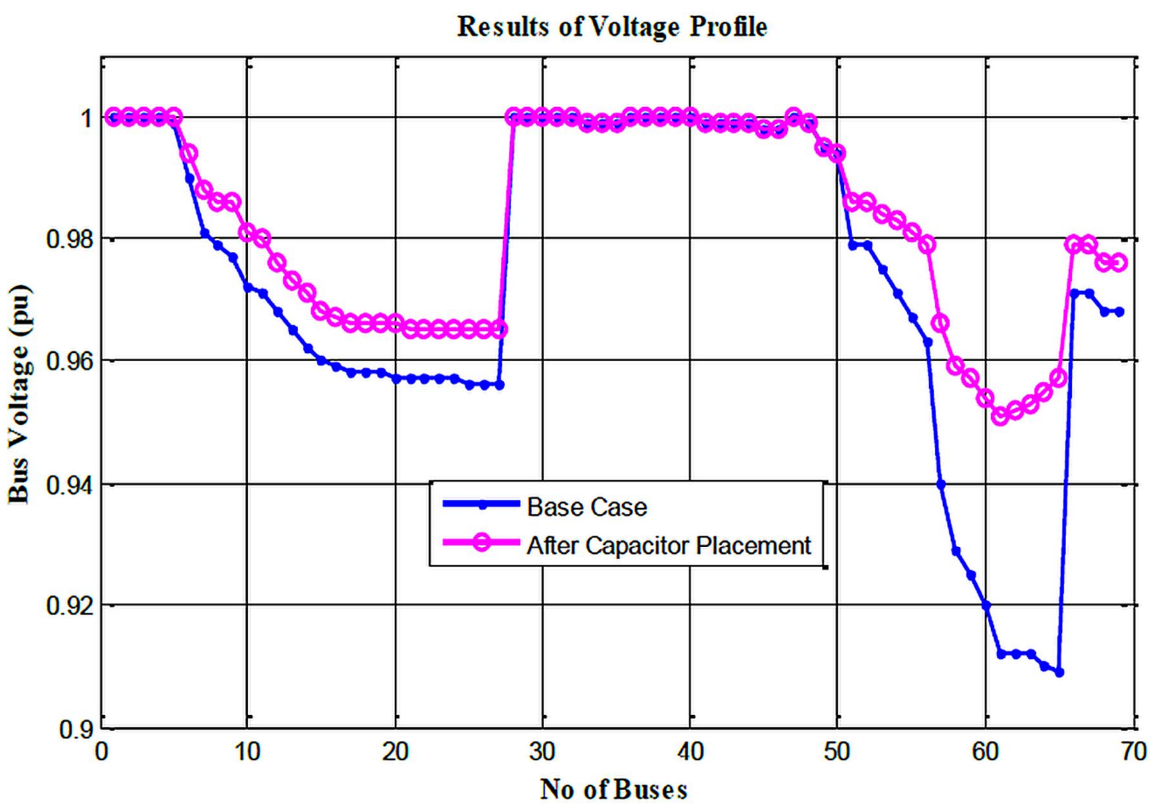

Fig. 4. Voltage profile of 69-bus RDS before and after capacitor placement using PSO.

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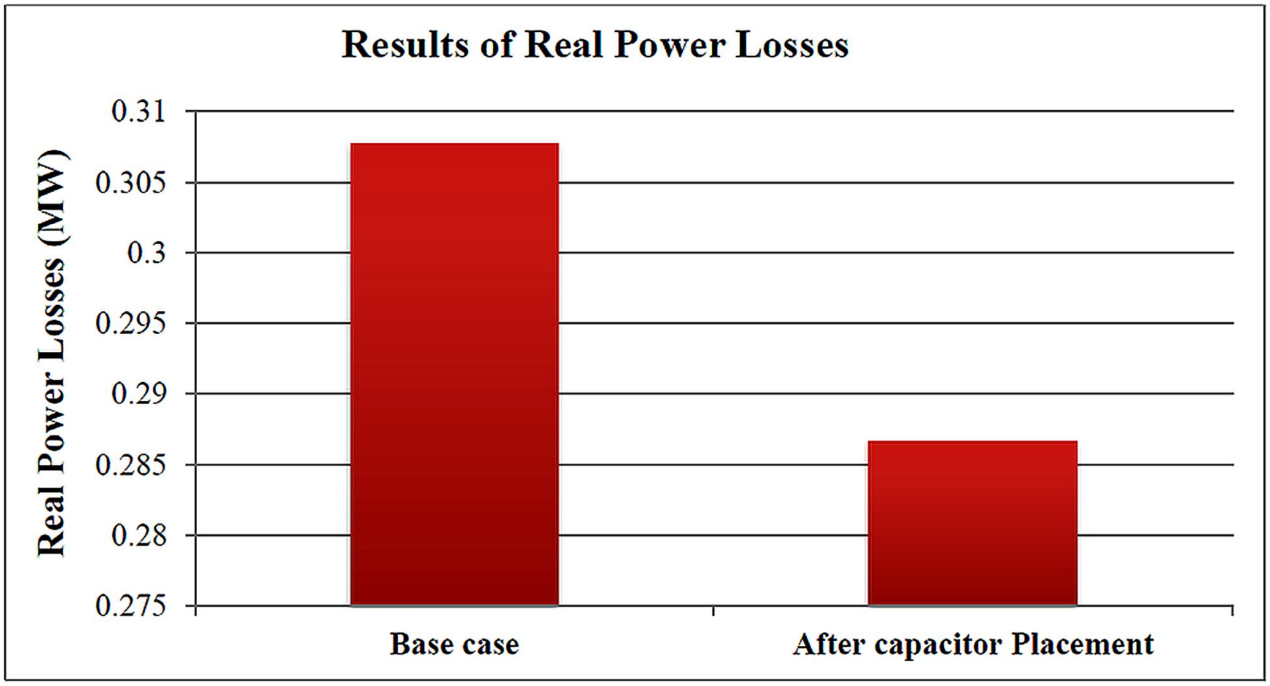

Fig. 5. Real power losses of 69-bus RDS before and after capacitor placement using PSO.

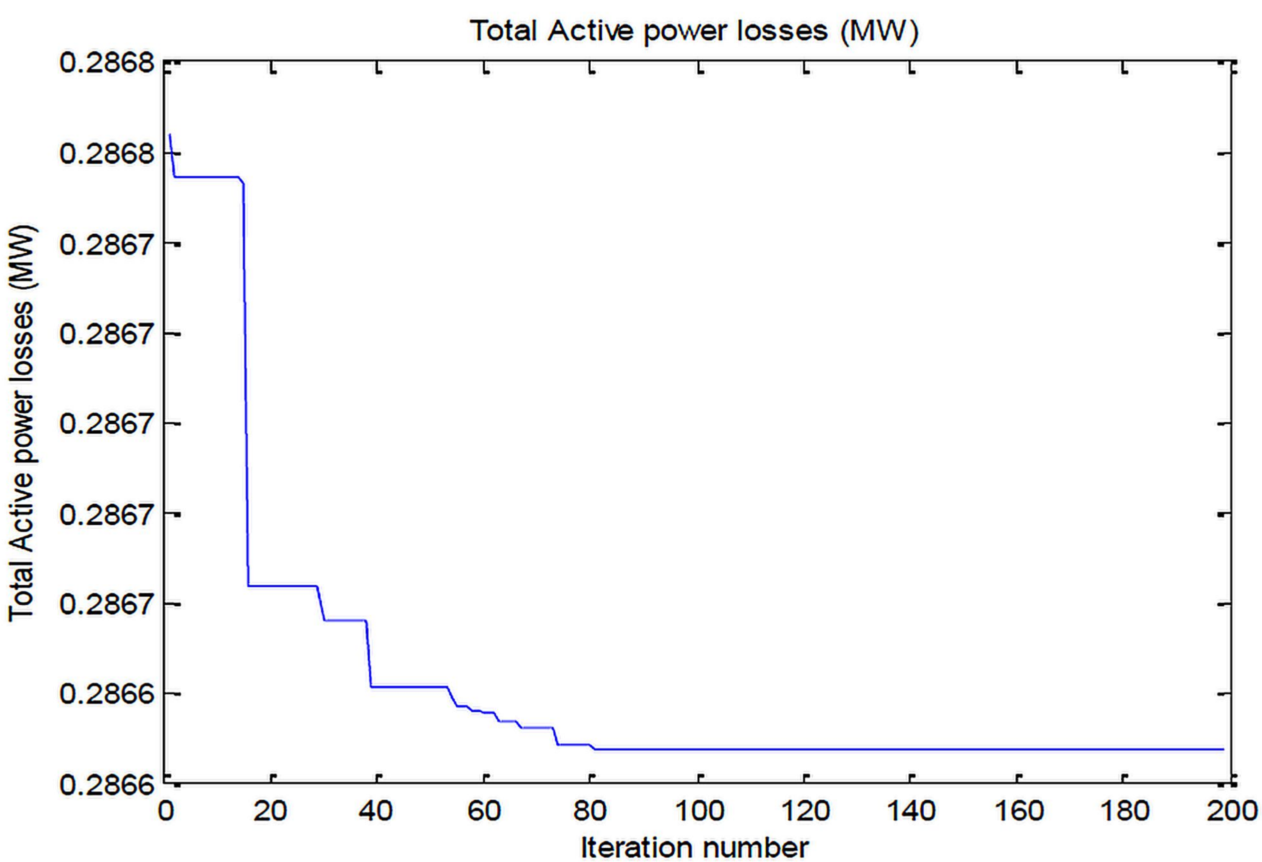

Fig. 6. Convergence curve of PSO for 69-bus RDS.

From Table VIII and Fig. 4, it is clear that PSO gives a significant improvement in both loss reduction and voltage profile. The minimum bus voltage at bus 65 improves from 0.909 pu to 0.957 pu, which is a 5.28% improvement. The total real power loss reduces from 307.8 kW to 286.6 kW, a reduction of 6.89%. The energy loss cost comes down from US$161,779.68 to US$150,636.96. Even after paying for the capacitors (US$808.23), the net annual saving is US$10,334.49, which is about 9.1% more than the best analytical result. This clearly shows that PSO finds a better solution than what manual selection can achieve. The convergence curve in Fig. 6 shows that the algorithm stabilizes within about 80 iterations out of 200, which is similar to what Lei et al. [10] reported for PSO and GWO on comparable sized networks.

H. Comparison with Recent Literature — 69-Bus RDS

Table IX compares the results of the proposed NR + PSO method with 20 other studies that used different optimization algorithms on the 69-bus system. The table covers work from 2008 to 2024. It should be noted that the values marked with (~) are approximate, taken from the respective papers. The exact results may vary depending on the problem formulation, load model, and cost parameters used in each paper.

Table IX. Comparison of Results on 69-Bus RDS with Recent Literature

Method / Reference	Year	Min Voltage (pu)	Power Loss (kW)	Loss Red. (%)
Base Case	—	0.909	307.8	—
Fuzzy-GA [34]	2008	~0.942	~287.0	~6.76
ABC [24]	2014	~0.940	~288.0	~6.43
PGSA [29]	2011	~0.945	~283.0	~8.06
PSO-BPSO [33]	2010	~0.935	~290.0	~5.78
TLBO [26]	2014	~0.952	~283.5	~7.89
CSA [22]	2018	~0.950	~280.0	~9.03
GWO / MFA [21]	2019	~0.960	~278.0	~9.68
WCA-GWO [19]	2020	~0.955	~281.0	~8.70
GOA-Fuzzy MO [20]	2020	~0.950	~283.5	~7.89
QRSMA [16]	2021	~0.962	~275.0	~10.66
A-MWOA [17]	2021	~0.958	~279.0	~9.36
GA (Soma) [15]	2021	~0.947	~284.0	~7.73
MPSO [5]	2022	~0.963	~275.5	~10.52
HGWO [13]	2022	~0.961	~276.0	~10.33
IHBO [12]	2022	~0.957	~278.5	~9.52
FPA-Pareto MO [7]	2022	~0.953	~280.0	~9.03
AEO [6]	2022	~0.959	~278.0	~9.68
Two-Stage DG+Cap [11]	2022	~0.955	~280.5	~8.87
Montoya et al. [2]	2023	~0.960	~277.0	~10.00
Raza et al. [3]	2023	~0.956	~279.5	~9.19
Jayabarathi et al. [1]	2024	~0.964	~274.0	~11.01
NR + PSO (This Work)	—	0.957	286.6	6.89

(~) = approximate values extracted from the respective reference papers.

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From Table IX it can be seen that the proposed NR + PSO method achieves a loss reduction of 6.89%, which is close to Fuzzy-GA [34], ABC [24], and BPSO [33]. It is lower than more recent methods like QRSMA [16], MPSO [5], HGWO [13], and Jayabarathi et al. [1], which achieve loss reductions in the range of 10 to 11%. There are three main reasons for this difference.

1) The candidate bus selection method: In this work, candidate buses are selected based on the lowest voltages from the base-case load flow. More recent methods like QRSMA [16] and MPSO [5] use loss sensitivity factors to screen a larger set of candidate buses, which gives the optimizer more flexibility to find a better solution.
2) Algorithm capability: Standard PSO with linear inertia weight decay can sometimes get stuck before reaching the true global optimum. The newer algorithms address this by adding mechanisms like mutation, crossover, or improved inertia weight terms [5, 13].
3) Problem scope: Several of the high-performing methods [16, 1, 20] also include network reconfiguration or DG placement along with capacitor sizing, which provides additional ways to reduce losses. If only capacitor placement is considered, the achievable reduction is naturally limited.

Despite these differences, the NR + PSO approach has some practical advantages worth noting. The algorithm is simple to understand and implement. It converges reliably within 30 to 80 iterations. The economic results — net saving of US$10,334.49 per year — are clearly presented and show real value. And unlike DG-based methods [16, 1], which need inverters, protection systems, and grid connection agreements, capacitor banks are passive devices that are cheap and easy to install. For these reasons, the NR + PSO method is still a practical and useful tool for distribution system planning, even if newer algorithms can achieve higher loss reduction percentages.

V. CONCLUSION

In this paper, the optimal size of shunt capacitors to be placed in radial distribution systems is determined using a two-stage NR + PSO approach. The Newton–Raphson load flow is first used to identify the weak buses, and then Particle Swarm Optimization is used to find the capacitor sizes that give the minimum total real power losses. The method is tested on 12-bus and 69-bus RDS test systems and the results show a clear improvement in voltage profile, power losses, and net annual savings. The important conclusions from this work are summarized below:

1) For the 12-bus RDS, PSO finds optimal capacitor sizes of 207.2 kVAr at bus 12 and 196.3 kVAr at bus 11. This reduces real power losses by 2.4%, raises the minimum voltage from 0.959 pu to 0.978 pu, and gives a net annual saving of US$639.21.
2) For the 69-bus RDS, optimal capacitor sizes are 868.8 kVAr at bus 65, 662.6 kVAr at bus 64, and 1162.7 kVAr at bus 63. This reduces losses by 6.89%, improves the minimum voltage from 0.909 pu to 0.957 pu, and gives a net annual saving of US$10,334.49.
3) In both cases, the PSO-based optimal solution gives better results than the best manually selected analytical combination, which shows that it is not possible to find the truly optimal capacitor sizes without using an optimization algorithm.
4) The PSO algorithm converges within 30 to 80 iterations for both test systems, which shows that it is computationally efficient and gives stable results.
5) When compared with more than 20 recent papers, the proposed method is found to be competitive with classical metaheuristics and gives a useful and transparent baseline result.

As a scope for future work, the same problem can be extended to larger and unbalanced distribution systems. It would also be interesting to try the enhanced PSO variant from [5] and the Hybrid GWO from [13] on the same test systems to directly compare them under the same conditions. Simultaneous reconfiguration and capacitor placement [9, 17] can also be explored. Multi-objective approaches that consider loss reduction, voltage stability, and total annual cost together [7, 11] would be another useful direction. Finally, including distributed generators and EV charging stations [20, 3] alongside capacitors, as well as testing on real utility feeders with time-varying loads [15, 2], are areas where the present work can be extended.

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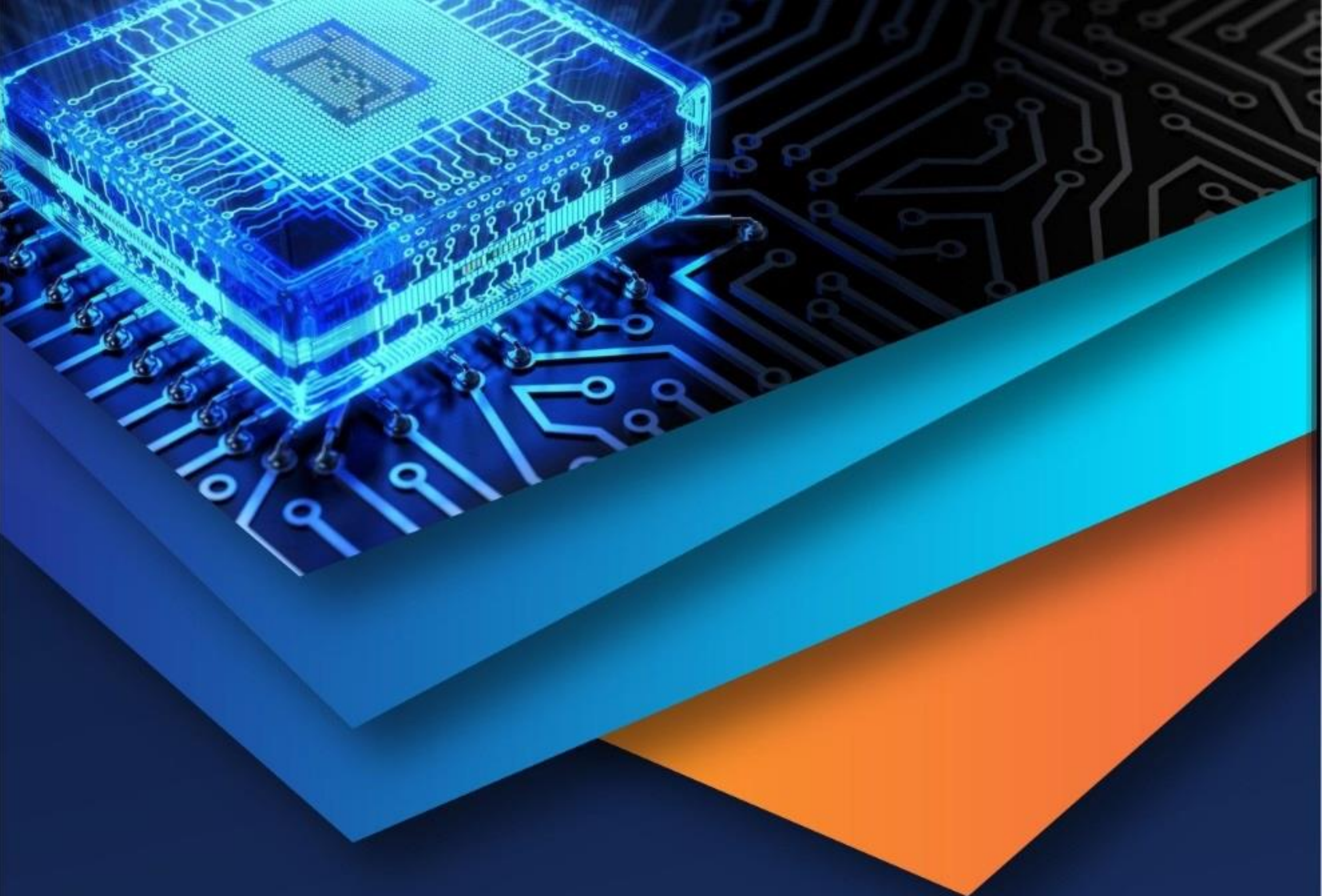

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