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ORIGINAL RESEARCH

PSO-based optimal placement of electric vehicle charging stations in a distribution network in smart grid environment incorporating backward forward sweep method

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Abstract

The transition from conventional fossil-fuel vehicles to electric vehicles (EVs) is critical for mitigating environmental pollution. The placement of electric vehicle charging stations (EVCS) significantly impacts the utility operator and electrical network. Inappropriately placed EVCS lead to challenges such as increased load, unbalanced generation, power losses, and reduced voltage stability. Incorporating distributed generation (DG) helps mitigate these issues by maximizing EV usage. This study focuses on optimizing EVCS and DG placement in radial distribution networks. The methodology employs a backward and forward sweep method for load flow analysis and utilizes the particle swarm optimization (PSO) algorithm to determine optimal EVCS and DG locations and sizes. This approach, validated on the IEEE-33 bus system, outperforms existing methods. Results indicate a 2.5 times greater power loss reduction compared to simulated annealing (SA), 1.6 times better than artificial bee colony, and parity with genetic algorithm (GA). Overall, the PSO algorithm demonstrates superior optimization effectiveness and computational efficiency, showcasing 1–2.5 times better performance than other methodologies. Employing this approach yields significantly improved results, making it a promising technique for optimizing EVCS and DG placement in distribution networks.

1 | INTRODUCTION

The continual progress in transportation has increased in the last decades, boosting the development of the automobile sector. Increasing oil prices, global pollution, sustainable qualities, carbon dioxide (CO_2) emissions, and commercial potential have made electric vehicles (EVs) attractive in the transportation industry. Electric vehicle charging stations (EVCSs) can lower CO_2 emissions. Numerous advantages are offered by the invention of EVs, such as improvement in air quality and the capability to save fossil fuels. Many nations implement battery-powered ways of travel throughout the world to reduce pollution [1]. As a result of this reason, EVs deployed by different countries reached so high, for example, 1.5% in China, 28.8% in Norway, and 6.5% in the Netherlands. Furthermore, soon 100% use of EVs will be proposed by some countries as the permanent mode of transportation. By the end of the year 2022, it is estimated that 35 million EVs will be on the road throughout the world [2].

In the power system, the controller of the power distribution system faces new obstacles in facilitating long-term charging services for the EV users due to the increasing proliferation of EVs. A huge number of charging infrastructure is required due to the increased prevalence of EVs in the urban sector to charge EVs. The automobile industry is based on the framework provided by EVCSs and the power supplied to EVs. Despite the reality that transportation using EVs is eco-friendly, the electrical power supply is significantly affected by the charging of the EVs [3].

The capacity of the feeder to transfer load and reserve capacity of the substation is lowered by the increasing system demand due to the charging of EVs. When refurbishing the system using the alternative feeder, it is important to continuously transfer load. Consequently, the power system is affected directly. Along with this, the purpose of EVs has not been fulfilled if the traditional sources of power charge EVs. On the contrary, the benefits of EVs are increased if the EV load is charged using wind or solar energy. The batteries of EVs are charged by the grid. The changes in the network that is delivered to the charging station of EVs, facilities of affiliated consumers, and distributed generators (DGs) are provided by the distributed system operators following European Union electricity power rules [4].

Mostly, the production of electricity is provided by gas or thermal-based power generation. The power demand increases when the EVs are charging, which unbalances the power system. The distributed generators are placed in the distribution network (DN) to compensate for the unbalance issues. Due to the increase in high power consumption, it is very difficult for the planning engineer to incorporate many EVs into the power distribution network. In the total life cycle, the location of the EVCS is incredibly important because of which, the operational effectiveness and level of service of EVCS are strongly affected by the early efforts in the development of the EVCS. Nominal voltage variations and proper placement of EVs help to minimize energy loss to a minimum. The location of EVs determines the cost of installing a charging station.

The batteries of the EVs are charged when riding on the road, and adopting suitable techniques is greatly affected by the selection of the optimal location of the EVCS. The functioning of the power system is significantly affected by the capability and position of the EVCS. Because of the current and voltage limit violation, the distribution network is weak, and planning is made impossible by the unplanned deployment of EVs. Simultaneously the optimal location of EVCS is significantly affected by the road networks. Because of this, the optimal allocation of EVCS road and distribution networks should be considered [5]. When the EVs charge their batteries at the charging station, power loss, and bus voltage are important factors that must be considered.

The proposed work is summarized as follows:

- The objective functions, that is, voltage and power loss, are calculated using a computationally efficient load flow method, that is, backward and forward sweep (BFS).
- The impact of EVCS on the distribution network is investigated, and distributed generators are incorporated to mitigate these impacts.
- The Particle Swarm Optimization (PSO) technique demonstrates the performance of the distribution network, that is, the IEEE-33 bus system, and compares the outcomes of PSO with the other existing approaches.

The rest of the paper is organized as follows: Section 2 presents a background study on the optimal placement of the electric vehicle charging station and distributed generators. Section 3 presents the proposed optimization and load flow analysis. In Section 4, outcomes are presented and discussed, and Section 5 presents the conclusion of the proposed work.

2 | RELATED WORK

The management of charging and discharging of EVs by using optimization and control methodologies is discussed in the study [6] to examine the effect of EVs on the distribution network. However, it is lacking in real-world case studies. The optimal location of EVCS is determined, and by using different solution techniques, the best solution is obtained by reviewing the problem formulation offered by different researchers in [7]. However, it lacks specific insights into results, obvious advantages and drawbacks of various tactics, and applicable instances. The impact of electric drive vehicles (EDVs) on the reliability of the power system is examined by using different optimization models in batteries of EDVs, such as expected energy not served (EENS) and loss of load expectation (LOLE) in [8]. However, the absence of precise quantitative data and thorough real-world case studies slightly weakens the study's merits.

The authors in [9] aimed to minimize peak loads caused by multiple EVs charging at electric vehicle supply equipment (EVSEs) by using an EVSE selection scheme in conjunction with a peak load management model. This is done by making a profit from the unused stored energy in EV batteries within the framework of time-of-use pricing (TOUP). Moreover, grid stability and optimization cost are achieved. As demand-side management (DSM) is a critical coordinator of the energy transaction in addition to the shift from fossil fuel to renewable power sources. In [10], the implementation of several DSM approaches in the context of modern power grids is reviewed. Moreover, to facilitate reasoning through all research that is taken into consideration, existing DSM techniques are outlined and classified along with informative suggestions.

The analysis investigates the influence of EVCS load on IEEE-33 bus test systems, such as power loss, voltage stability, and reliability indices in the study [11]. The study has drawbacks, such as omitting factors like system dependability, network expansion needs, and traffic congestion, which should be investigated in further study. Whale optimization algorithm (WOA) and grey wolf optimization (GWO) optimization strategies are used for the allocation of EVs in the radial distribution network by the division of EVCS services into three different areas in [12]. There are several noticeable restrictions to take into consideration though. Although the study acknowledges the trade-off between client convenience and network performance, it does not provide a definitive answer. Additionally, the research lacks thorough validation, such as simulations or real-world case studies, which might enhance the practical applicability of the suggested technique.

The impact of plug-in hybrid electric vehicles on the power system is demonstrated to investigate the reliability characteristics of the distribution network using the Monte Carlo simulation technique [13]. The impact of optimal placement of EVCS on the distribution system network is examined with overlapping residential areas, road networks, and supermarkets. The high load is obtained on the distribution network because of high demand, so different charging scenarios are considered for the placement of EVCS. The 2 m point estimation is used to deal with EV uncertainties. The objectives are optimized using the Harris Hawks optimization (HHO) and other differential evolution (DE) techniques [14].

The problem in the EVCS's optimal location in the district of Beijing is considered a dual objective optimization model because of the increased and decreased cost. When the load on the charging station increases, geographic information system (GIS) is used to provide the extension as alternative placement sites to reduce the power losses and cost of the power system [15]. The impact of the allocation of charging stations for electric vehicles on the power system in Guwahati, India, is demonstrated in [16], such as power loss, voltage stability, reliability, and accessibility of EV users. These are taken as a multi-objective framework. These optimal placement problems are solved using different optimization techniques, including teaching learning-based optimization (TLBO), Pareto dominance-based hybrid algorithm, and chicken swarm optimization (CSO). The analysis is done on a 25-node road network superimposed with an IEEE 33-bus system.

The interaction between distribution network (DN) and electric vehicles demonstrates the bi-level of EVCS and DG allocation. The k++ clustering algorithm develops the daily scenario of photovoltaic wind load. A more advanced harmony PSO method is utilized to resolve the bi-level programming problems [17]. Some research work reduces the severity of EVs. The improvement in voltage is done, and power loss of the radial distribution network is reduced by incorporating the DGs in a distribution network. This work uses a mixed-integer non-linear programming technique [18].

Under the different load conditions, power loss reduction in a distribution network is done by the optimal placement and sizing of DGs using the genetic algorithm (GA) technique [19]. The distributed generator's location and optimal sizing in the distribution network are done utilizing the one-rank cuckoo search algorithm (ORCSA) and fuzzy approach to lessen the system's power losses. The analysis is done on the 15, 33, and 69 bus systems [20]. In the study [21], power losses are minimized by incorporating the shunt capacitors and DGs in the system in the distribution network. As the suitable position of capacitors and DGs in the system is a major concern, the power loss index (PLI) approach is used for finding the location of the shunt capacitor, and the index vector method (IVM) approach is used for finding the DG location in the system. The size of DGs and capacitors are determined by the optimization techniques, that is, G_{best} guided artificial bee colony (GABC), based on the population and a meta-heuristic approach. When many plug-in electric vehicles charge at the charging station, the load on the grid increases, which results in power loss, voltage instability, and overloading, so the RT-SLM (real-time smart load management) control technique is used to reduce energy losses and generation costs [22].

During the peak load, EVS's impact on the voltage of the distribution network is examined. The power factor correction and voltage regulation problem of EVCS is solved by providing the reactive power compensator [23]. The impact of plug-in electric vehicles (PEVs) on the distribution network is examined. So, the optimal placement of distributed generators is performed in the distribution network using a GA to mitigate the impact of PEVs [24]. The impact of sizing and optimal instalment of the plug-in electric vehicle on an unbalanced radial distribution network is examined. The impact on voltage stability and power loss is found, and for mitigation, distributed generators are located at different locations in the system using PSO. This analysis is done on the 19 and 25 bus test systems [25].

In IEEE 33-bus, IEEE 69-bus, and Indian 85-bus systems, the power losses are minimized, and voltage profiles are improved by the optimal allocation of distributed generators by using the meta-heuristic algorithm hybrid grey wolf optimizer [26]. The placement of EVs in the distribution network is illustrated using the modified primal-dual interior-point algorithm in the IEEE 123-node test system [27]. The PSO and bacterial foraging optimization algorithm (BFOA) techniques are used to place the EVs optimally in the distribution network. The power losses are reduced, and voltage stability is maximized by installing a photovoltaic (PV) system in the distribution network [28]. The voltage stability is improved, and power losses are decreased by the optimal placement of the distributed generator and network reconfiguration of the distributed network using adaptive shuffled frogs leaping algorithms [29].

Overall, the studies under consideration provide important contributions to the crucial areas of placing distributed generators in power distribution networks and improving electric car charging infrastructure. Their ability to handle immediate problems regarding energy efficiency, power loss reduction, and voltage profile enhancement is only one of their many capabilities. Many publications use tried-and-true optimization techniques and evaluate their approaches using IEEE test systems, which lends some usefulness to their study. Some studies also take into consideration cutting-edge elements like vehicle-to-grid (V2G) technology, which makes their contributions applicable to current grid concerns. There are, however, flaws that these studies all share. Many lack rigorous comparisons with alternative optimization techniques, which makes it difficult to evaluate their effectiveness fully. Sometimes there are little details regarding the optimization parameters, or algorithms used, which makes replication and implementation difficult. Additionally, most articles only sometimes validate their findings using actual case studies or data, which limits their usefulness. Future research in this field should aim for more thorough validation, thorough methodology explanations, and robust comparisons with existing optimization techniques to improve their contributions.

The proposed work is motivated by the existing research on the optimal placement of EVCS. This work investigates the impact of the optimal placement of the EVCS and DGS. The

PSO technique is suggested for the placement of EVCS. To compensate for the impact of the optimal allocation of EVCS, that is, reduction in voltage profile and enhancement in the power losses, distributed generators are utilized. This work is investigated on the IEEE 33 distribution network.

3 | METHODOLOGY

Throughout the world, the electrification of the transport sector is normalized, which has increased anxiety because of the serious concern about environmental pollution and the reduction in natural resources like fossil fuels. The most effective way to reduce transportation pollution is to electrify the transportation sector. As a result, it is estimated that the number of plug-in electric vehicles in the next generation will increase significantly. The number of charging stations increased due to the use of EVs. So, the power grid is severely affected by EVCS. Particularly, the functioning of the power grid is greatly affected by the location of the EVCS. That is why the optimal location of EVCS in the distribution network is very important. Here, by considering the optimal loads of the buses, EVCSs are installed in a distribution network. The voltages and power losses are obtained by the load flow analysis.

3.1 | Problem formulation

3.1.1 | Objective function

Power loss minimization is the objective function and is represented by:

$$F = \min\left(P_{loss}\right) = \sum_{j=1}^{nb} I_j^2 \, R_j \tag{1}$$

where F is the overall power loss of the system, nb is the number of branches, I_j and R_j are the current and resistance of the jth branch.

3.1.2 | Operational constraints

The following constraints apply to the objective function given in Equation (1).

Equality constraint
Equality constraint is given as follows:

a. Active and reactive power balance

The active and reactive power generation and consumption are balanced in each bus in the distribution network.

$$\sum Power\ In - \sum Power\ In = 0 \tag{2}$$

$$P^{substation} + \sum_{k=1}^{Nbus} P^{DG}(k) - \sum_{j=1}^{Nbranch} P_{loss}^{j}(k, k+1) - \sum_{k=1}^{Nbus} P_{D,k} - P_{EVCS}^{k} = 0 \tag{3}$$

$$Q^{substation} + \sum_{k=1}^{Nbus} Q^{DG}(k) - \sum_{j=1}^{Nbranch} Q_{loss}^{j}(k, k+1) - \sum_{k=1}^{Nbus} Q_{D,k} = 0 \tag{4}$$

where

$P^{substation}$ and $Q^{substation}$ = Real and reactive power supply from the substation.
$P^{DG}(k)$ = Real and reactive power injection at kth by DG.
P_{loss}^{j} = jth branch Real and reactive power loss.
$P_{D,k}$ = kth bus real and reactive demand.
P_{EVCS}^{k} = Electric vehicle charging station load at kth bus.
$Nbus$ = Number of buses in the distribution network.
$Nbranch$ = Number of branches in the distribution network.

Inequality constraints
The inequality constraints are given as follows:

a. Voltage limit: Limit the lowest and maximum permissible voltage levels (0.95–1.05 p.u.) at each bus in the network to maintain voltage stability.

$$V_{min,k} \le V_k \le V_{mix,k} \quad k = 1,\ 2,\ 3, \ldots\ldots\ldots, \text{Nbus} \tag{5}$$

b. Limit of DG injection: The amount of active and reactive power that DGs inject must stay within certain limits.

$$P_{DG,k}^{min} \le P_{DG,k} \le P_{DG,k}^{max} \tag{6}$$

$$Q_{DG,k}^{min} \le Q_{DG,k} \le Q_{DG,k}^{max} \tag{7}$$

where

$P_{DG,k}^{min}$ = Minimum active power limit of kth DG
$P_{DG,k}^{max}$ = Maximum active power limit of kth DG
$Q_{DG,k}^{min}$ = Minimum reactive power limit of kth DG
$Q_{DG,k}^{max}$ = Maximum reactive power limit of kth DG

c. Line current: The maximum allowable line current shall not be exceeded by the actual current flows in any given line.

$$I_j \le I_j^{max} \quad j = 1,\ 2,\ 3 \ldots\ldots\ldots, \text{Nbranch} \tag{8}$$

where

I_j = Actual current in jth branch
I_j^{max} = Maximum limit of current in jth branch

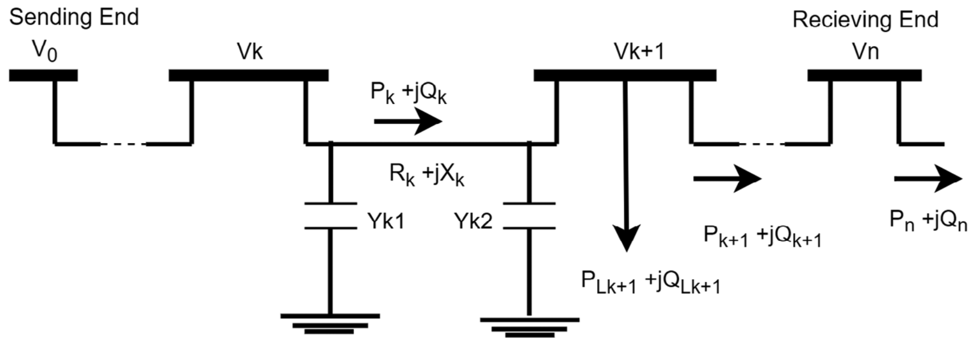

FIGURE 1 Single-line diagram of the distribution network.

The objective function is calculated by the load flow analysis.

3.2 | Load flow analysis

The load flow analysis determines static performance in any distribution network. Two inputs, that is, line data and load data, are required for load flow analysis to find the characteristics of an electrical network. Once the voltage profile of any generator, load, or network is determined, it is easy to find the real power losses, reactive power losses, and branch current flowing from each branch.

The single-line diagram of the distribution system is shown in the Figure 1 and the power flows are determined by the two recursive Equations (9) and (10) in load flow analysis. The load flow analysis is utilized to determine the power losses and voltage profile of the IEEE 33-bus system. To find the load flow is the objective function.

$$P_{k+1} = P_k - P_{Loss,k} - P_{Lk+1} \tag{9}$$

$$Q_{k+1} = Q_k - Q_{Loss,k} - Q_{Lk+1} \tag{10}$$

where P_k and Q_k are the real and reactive power flowing out of the bus and P_{k+1} and Q_{k+1} are the real and reactive loads at bus $k + 1$.

$$P_{loss}(k, k+1) = R_k \frac{P_k^2 + Q_k^2}{V_k^2} \tag{11}$$

$$Q_{loss}(k, k+1) = X_k \frac{P_k^2 + Q_k^2}{V_k^2} \tag{12}$$

The buses k and $k + 1$ is connected by the line section and the power loss in it is calculated by the Equations (3) and (4). Where P_{loss} $(k, k + 1)$ and Q_{loss} $(k, k + 1)$ are real and reactive power losses.

$$P_{T,loss}(k, k+1) = \sum\nolimits_{k=1}^{n} P_{loss}(k, k+1) \tag{13}$$

$$Q_{T,loss}(k, k+1) = \sum\nolimits_{k=1}^{n} Q_{loss}(k, k+1) \tag{14}$$

Similarly, total power losses are determined by adding power losses in all line sections as given in Equations (6) and (7), where $P_{T,\ loss}$ $(k, k + 1)$ and $Q_{T,\ loss}$ $(k, k + 1)$ are the total real and reactive power losses in the line section.

The proposed work performs a load flow analysis on the IEEE 33 bus system by the BFS method. Figure 2 shows the flow chart of load flow analysis by the BFS method. It is popular among network operators and engineers due to its rapid convergence, precision, ease of implementation, and adaptability. The BFS method's complexity is based on the distribution network's topology and size. The complexity of this approach is linear with respect to the number of branches and buses. This method is reliable and computationally effective for small and medium-sized distribution networks like the IEEE-33 bus system as discussed in this work.

Some factors make the BFS method more effective than the Newton-Raphson method or any other method because of some factors. These factors involve a constant change in the connected load, imperfection and uncertainty of network parameters, a greater number of branches and nodes, and a high R/X ratio. So, it is encouraged to use the BFS method for load flow analysis because of the high convergence [30] and low computational load. In this method, load flow analysis is performed in iteration using recursive equations. Kirchhoff's current and voltage laws are considered in each iteration of the BFS method to determine the current and voltage [31]. One recursive equation is a backward sweep, and the other is a forward sweep, as shown in Figure 3.

Backward sweep: The current and load flow solutions in each branch are calculated by keeping the voltage constant in the backward sweep. It begins from the end node's branch and moves toward the source node. Each load flow of the branch is updated by considering the previous iteration's voltage.

Forward sweep: The forward sweep calculates the voltage by keeping the load and current values constant. It starts from the branch of the source node towards the end node. Mainly the forward sweep is used to find the voltage at the branch of the reference node of the feeder. In this method, the voltage of the network is set to 0.99 p.u. value at the start. The voltage, real, and reactive power losses are calculated using the BFS load flow analysis. The optimal placement of EVCS and DGs is determined by the PSO algorithm.

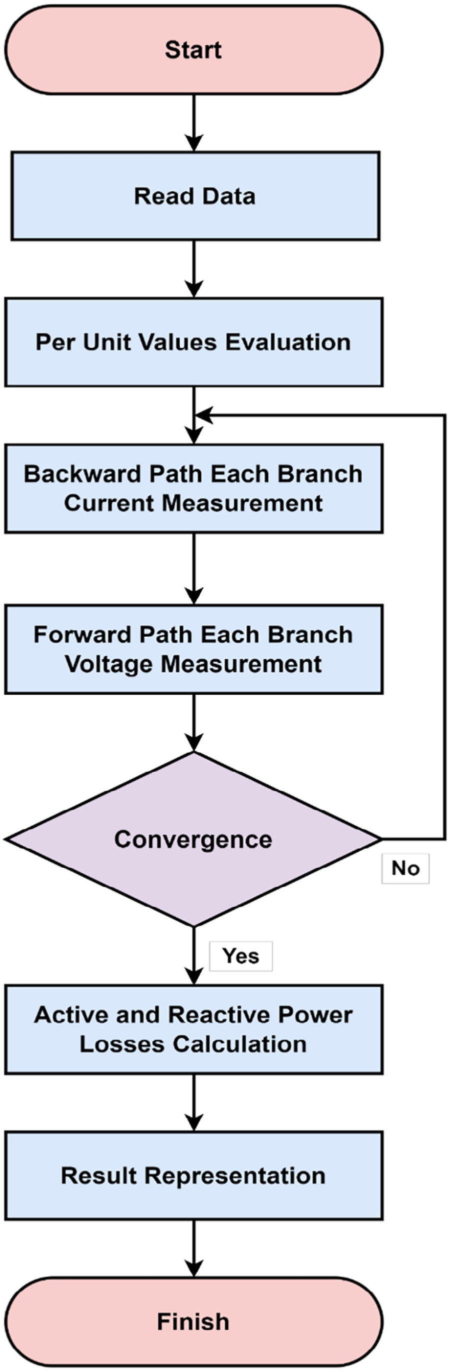

FIGURE 2 Flow chart of load flow analysis by backward and forward sweep method.

3.3 | Particle swarm optimization

The PSO working principle is based on the animal's social behaviour, like fish schooling, birds flocking, and bee swarming. They work in the flock and optimize their search to hunt for the best food place. Similarly, the search for the optimal location of the EVCS is determined by this technique. Kennedy and Eberhart presented work on PSO at the conference on evolutionary computation in 1995 [32]. The research is based on the solutions to different optimization problems by PSO. The particles represent the solution to the optimization problems, and the population of solutions is known as the swarms in this algorithm. Velocity and position are the two main properties of the particles. Figure 4 shows the start of the search process; the initialization of particles is done by random positions. The particles' position changes with velocity to the new position after each iteration [33]. They reach the new global best G_{best} and personal best P_{best} position. The P_{best} is the best position of the particle achieved till now, and G_{best} is the overall best position of the particle.

Based on personal and global best, V_{pbest} and V_{gbest} are the velocities of the particles. The idea of velocity is used to express the personal best and global best positions. The acceleration coefficient is weighted by the random terms so that the efficiency of convergence and local search to the optimum global position is determined. By considering the different numbers of acceleration, different G_{best} and P_{best} positions are obtained. The equation below is used to determine the velocity of each agent after each iteration.

$$V_i^{k+1} = w^k \times V_i^{k+1} + C_1 \times rand_1 \times (P^k_{Best,i} - X_i^k + C_2 \times rand_2 \times \left(G^k_{Best,i} - X_i^k\right) \quad (15)$$

where

V_i = velocity of the particle i
C_1nd C_2 = acceleration coefficients of the particle i
$rand_1$ and $rand_2$ = random variables
P_{Best} = personal best of the particle i
G_{Best} = global best of the particle i
w = inertia weight factor of the particle i

The weight function is given by:

$$w^k = w_{max} - \left(\frac{w_{max} - w_{min}}{k_{max}}\right) \times k \quad (16)$$

where

w_{max} = maximum weight
w_{min} = minimum weight
k = current iteration
k_{max} = maximum iteration

The above equation calculates the velocity at personal best and global best. In the searching space, the current location of the particle is obtained by the equation given below:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (17)$$

$$i = 1, 2 \ldots .., n,$$

where

X_k = current position of the particle i
X_{k+1} = New position of the particle i

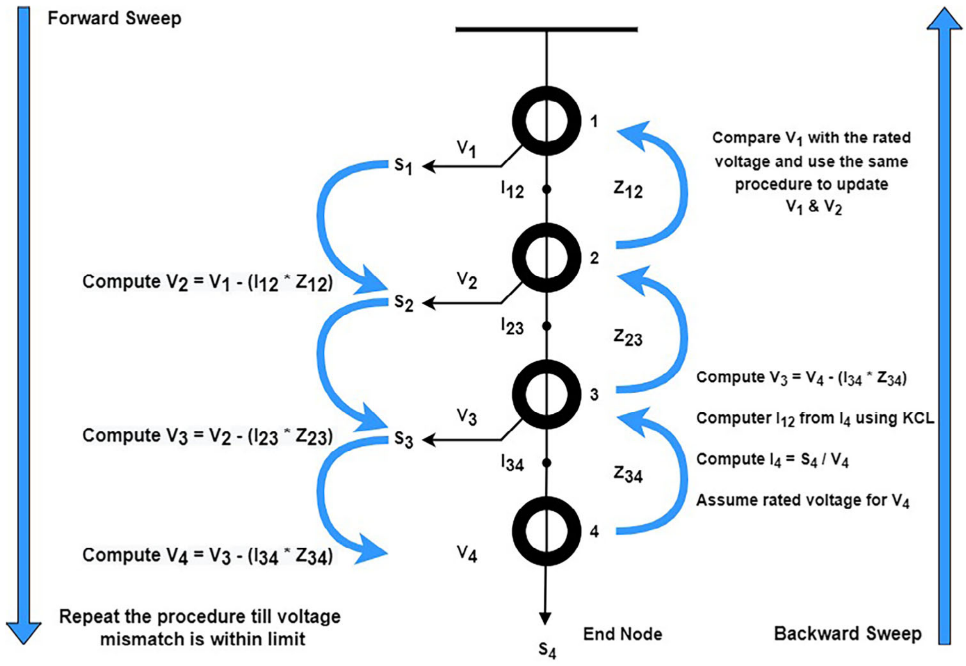

FIGURE 3 Backward and forward sweep method.

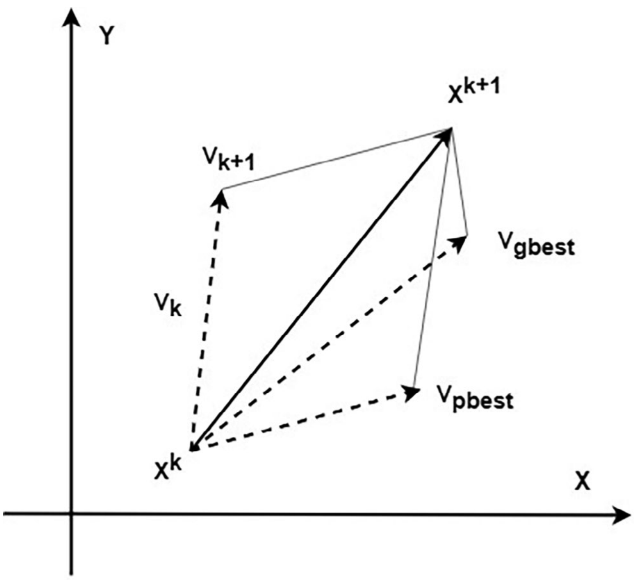

FIGURE 4 Concept of searching points by particle swarm optimization.

V_{k+1} = New velocity of the particle i
n is the number of particles in the search space.

PSO is a metaheuristic optimization approach that may be used for distribution network problems, including optimum power flow and voltage management. Due to its capacity to solve complex, complicated optimization problems with various objectives and constraints, PSO is well-suited for these situations. Moreover, it is computationally efficient, making it applicable to real-world applications. Furthermore, PSO can locate global optimum solutions, which is essential in distribution network optimization because poor solutions can result in major operational and financial effects [17]. The PSO's complexity depends on different factors like convergence behaviour, the dimensionality of problems, implementation, and population size. The PSO is the most efficient algorithm computationally for small to moderate dimensions problems and populations. Its effectiveness is greater than the computational cost of finding the optimal location of electric vehicles.

PSO has many advantages over the GA, simulated annealing (SA), ABC, and other optimization techniques. The requirement for memory storage is less. By using this algorithm, a better solution is obtained, programming is easy, and convergence is faster than GA.

3.3.1 | Fitness Function

The fitness function, which guides the search for optimal solutions, is an essential part of the PSO method. In our research, the fitness function was created to assess how well potential solutions performed in terms of reducing power losses and enhancing voltage profiles within the distribution network. We have described the formulation and integration of this fitness function into our PSO implementation to direct the algorithm towards identifying the best placement of DGs and EVCSs in the IEEE 33-bus distribution network. In our work, the fitness function is calculated by:

$$Fit = PL + VD$$

The above equation shows that the fitness function (Fit) is calculated by the sum of the voltage variation (VD) and power loss (PL). The PSO method aims to find the optimal

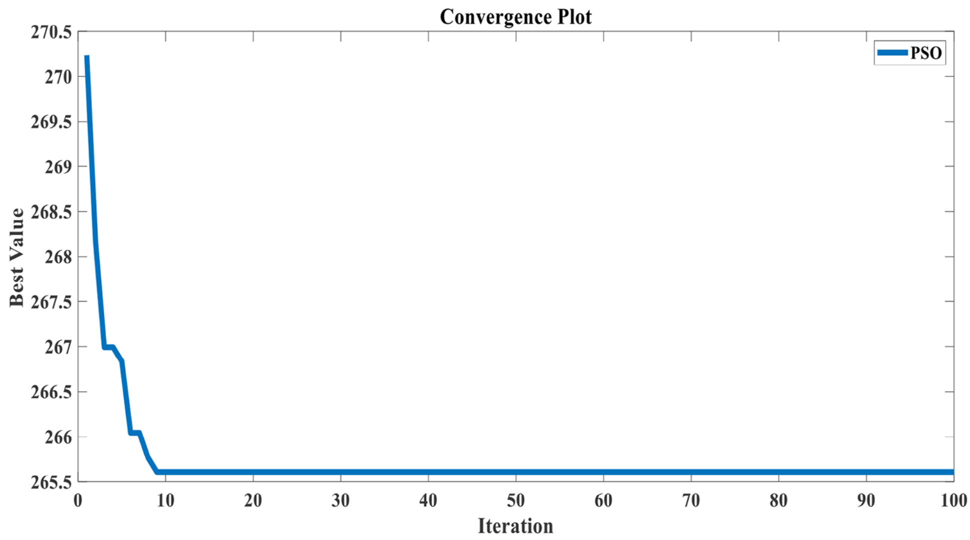

FIGURE 5 Convergence plot of particle swarm optimization.

TABLE 1 Parameters of particle swarm optimization.

Parameter	Description	Value
Matrix	Maximum number of iterations	50
n-pop	Size of swarm	150
w	Inertia weight	0.7298
c1	Cognitive acceleration coefficients	1.4962
c2	Social acceleration coefficients	1.4962

configuration of EV stations that results in the smallest power loss and voltage variation by minimizing this fitness function over several iterations.

The change in the fitness value over the number of iterations is determined by the convergence graph as shown in Figure 5. the x axis of the figure shows the number of iterations while y axis shows the Best Value that is the fitness value. The plotted line in the graph shows how the PSO algorithm converges towards an optimal solution over time.

3.3.2 | Parameters of particle swarm optimization

In the proposed work, the EVCS and DGs are placed optimally in the IEEE 33-bus distribution network using PSO. The parameters used in the proposed techniques are mentioned in Table 1.

3.3.3 | Procedure of particle swarm optimization

As shown in Figure 6, following steps are involved in the placement of EVCS and DGs by using the PSO technique in the IEEE 33-bus distribution network.

1. Read the bus and line data and initialize EVCS and DG numbers.
2. Initialize the number of iterations and other parameters of PSO along with EVCSs and DG lower and upper bound limits.
3. Initialize the velocities and positions of the particle's population in the swarms.
4. Set the iteration to one.
5. The load flow analysis evaluates the best particle's index, velocities, position, and power losses.
6. Global best and Local best are selected.
7. By Equations (1) and (3), velocities and positions are updated.
8. The best particle index for EVCS and DG is determined, and the best value is evaluated.
9. Global best and local best of swarms are updated.
10. Repeat steps 6–12 with incremental iteration by 1 if iterations reach the maximum iteration.
11. The optimal location of EVCS and distributed generators (DG), along with capacities, voltages, and power losses, are printed.
12. End.

4 | RESULTS AND DISCUSSION

The proposed work is tested on the IEEE 33 bus radial distribution system (RDS), as shown in Figure 7. The IEEE 33-bus system has 32 branches and 33 nodes. The RDS's operating voltage and base values are 12.66 KV and 100 MVA. The total real power demand of the system is 3715 kW, and the total reactive power demand of the system is 2300 kVar. The number of EVs at charging stations in each region in IEEE-33 bus system has been considered. when determining the charge criteria for that region. A combination of DC and AC chargers has been used to fulfil the various demands of these areas. In this case, in region 1, nine vehicles may be charged effectively without going over the load capacity due to a combination of rapid DC charging

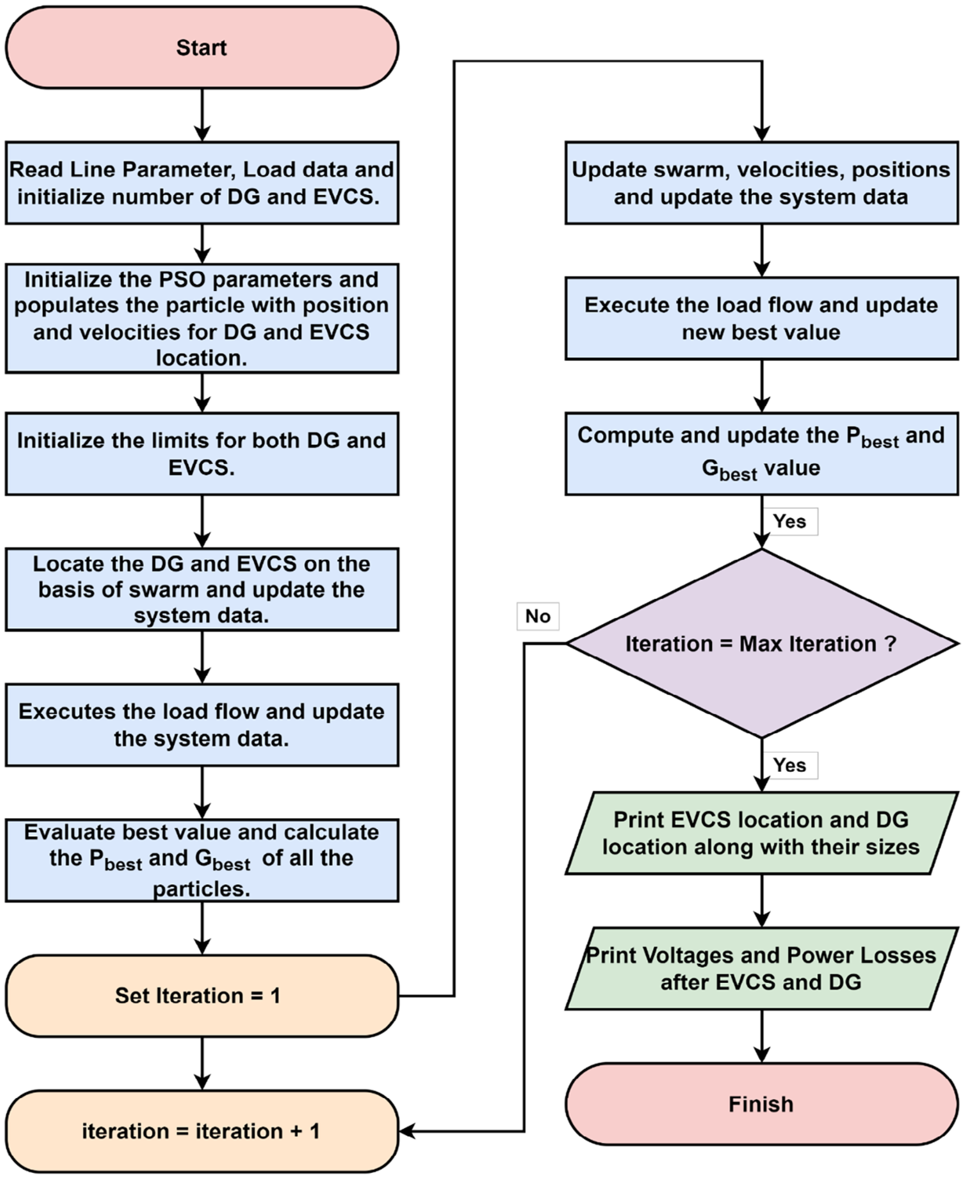

FIGURE 6 Flow chart of particle swarm optimization with the optimal position of electric vehicle charging station (EVCS) and distributed generation sources (DGs).

(one DC charger at 120 kW) and various AC chargers (four AC chargers at 3.3 kW each). The charge profiles for regions 2, 3, 4, and 5 are also customized according to the regions' particular infrastructure requirements and EV numbers. A direct approach-based load flow analysis determines the distribution network's voltage and power losses. The real power loss of the system is recorded as 206.6303 kW, and the reactive power loss is 137.8083kVar. The minimum value of the voltage is 0.9023 p.u. at bus 18, and the maximum value of the voltage is 0.9900 p.u. at bus 1. The EVCS are optimally installed in the IEEE 33-bus radial distribution network. The installation of EVCSs increases the power losses of the system. DGs are installed in the system to compensate for these power losses. The optimal placement of EVCSs and DGs is done using the PSO algorithm.

The proposed approach to the impact of EVCS and DGs on the voltage profile and power losses of the radial distribution network is investigated in five different cases, which are given below:

- Case 1: Load flow analysis of radial distribution network such as IEEE 33-bus system with existing load
- Case 2: Optimal placement of three EVCSs in IEEE 33 bus radial distribution network.
- Case 3: Optimal placement of five EVCSs in IEEE 33 bus radial distribution network.
- Case 4: Optimal placement of one DG id IEEE 33 bus radial distribution network.
- Case 5: Optimal placement of two DGs in IEEE 33 bus radial distribution network

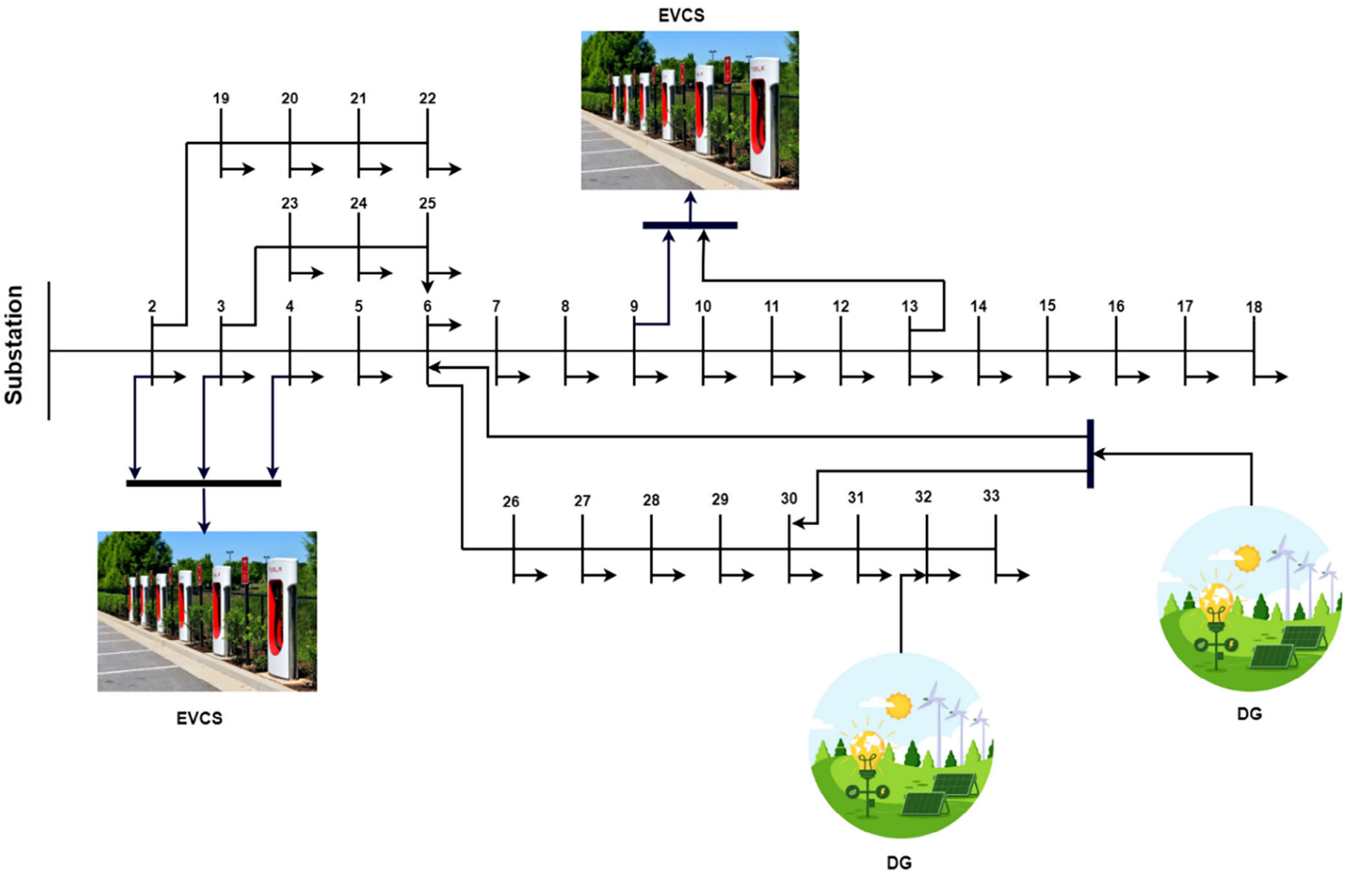

FIGURE 7 Single-line diagram of IEEE-33 bus distribution networks with electric vehicle charging station (EVCS) and distributed generation sources (DGs).

4.1 | Effect of EVCSs and DGs on the IEEE 33 Bus distribution network's voltage profile

The voltage profile of the IEEE 33 bus system is highly affected when EVCSs are installed. When EVCSs are installed at different nodes in the system, the demand for EVs increases. The voltage of the system decreases to a specific limit due to the increasing demand for EVs. The placement of DGs compensates for the voltage in the IEEE-33 bus system. Figure 8 shows the voltage profile of the IEEE 33 bus distribution network when different numbers of EVCS and DGs are placed in the network. The impact of the optimal placement of EVCS and distributed generators is demonstrated in the graph. The graph shows that when the demand for EVs increases at the charging station, the bus system's voltage profile decreases. It reduces voltage when three EVCSs are placed at buses 2, 3, and 4. The number of EVCS in the system increases to five, and placed at the location of 2, 3, 4, 9, and 13 results in a further decrease in the voltage. DGs are located along with EVCSs in the system to deal with such disturbances. The RDS is positively affected by the DG placement and maximizes the system's voltage. The voltage of the system rises when one DG is installed in the system. As the number of DGs installed in the system increases, the system's voltage also increases. In any bus system, voltage always depends on the apparent power losses, so the voltage increment is done by reducing the power losses in the system. The allocation of 1 DG results in the improved voltage of 0.9247 p.u. in the bus system at bus number 18. Locating two DGs in the distribution system leads to a further increase in the voltage to 0.9378 p.u. The findings make it clear that improved voltage profiles are achieved by increasing the appropriate location of DGs in the system.

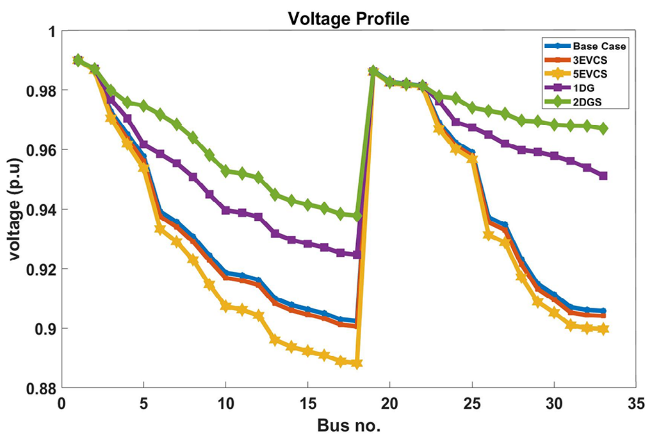

FIGURE 8 33-bus distribution network's voltage profile after electric vehicle charging station (EVCS) and distributed generation sources (DGs) instalment.

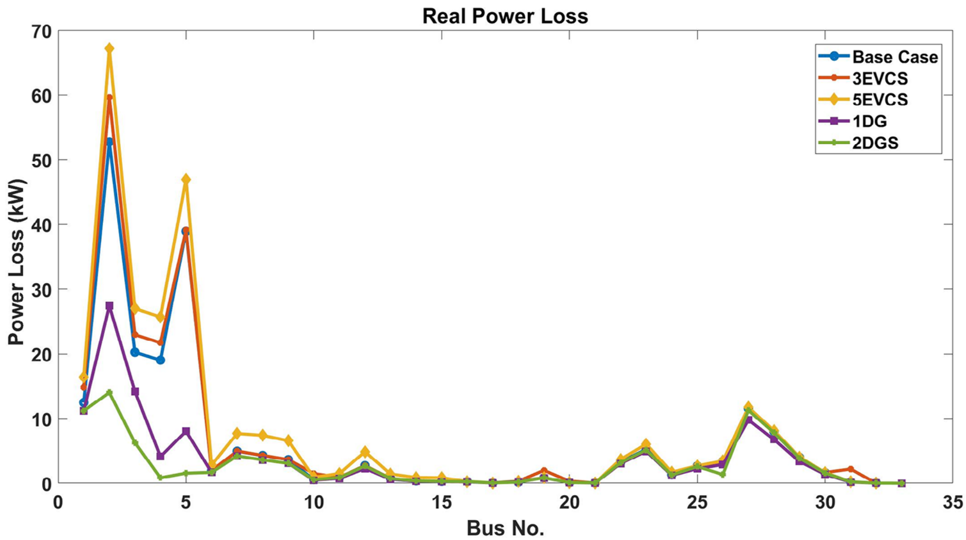

FIGURE 9 Real power loss of IEEE 33 bus system after optimal installation of electric vehicle charging station (EVCS) and distributed generation sources (DGs).

4.2 | Impact EVCSs and DGs on the power losses of IEEE-33 bus system

When large numbers of EVs are charged at the charging station, the load at the charging station (CS) increases, resulting in a disturbance in the distribution network. Due to this, the system's voltage decreases, and the power losses of the system increase. At the time of installation of EVCS, some points should be kept in mind. Try to locate a charging station where EV users will easily charge their vehicles and have the least power losses. It is clear from the proposed work that when the number of EVCSs increases the distribution network's power losses also increase. In many research papers, power losses of the distribution network are lowered by the mitigation of I^2R losses. But in the proposed work, the power losses are reduced by the optimal placement of distributed generators at different locations in the system so that the voltage of the distribution network rises with the reduction of power losses in the distribution system.

4.2.1 | Real power losses

When the fixed size of the three EVCSs is placed optimally at 2, 3, and 4 in the IEEE 33 bus distribution network, the real power losses increase to 219 kW, as presented in Figure 9. Then five EVCSs are installed at 2, 3, 4, 9 and 13. The real power losses rise to 255 KW. The losses increase when the load on the charging station increases. To reduce the losses, a single DG of size 1310.805 kW is optimally placed at bus 30 in the distribution network, which lowers the losses to 111. 5737 KW. When two DGs are installed, one at bus 6 with size 1310.805 kW and the second at bus 32 with size 873.8701 kW in the distribution system, lower the real power losses to 71.85 kW.

TABLE 2 Real and reactive power loss with location after installing EVCS and DGS on IEEE 33 bus system using PSO.

Cases	Bus number	Real power loss (kW)	Reactive power loss (kVar)
Base	–	206.6303	137.3083
3 EVCS	2,3,4	219	169
5 EVCS	2,3,4,9,13	255	144
1 DG	30	111.5737	72.9387
2 DGS	6,32	71.85	49.6781

4.2.2 | Reactive power loss

Reactive power losses in the IEEE 33 bus distribution network grow to 144 kVar when EVCS are optimally allocated at buses 2, 3, and 4 of the bus the system depicted in Figure 10. When the number of EVCS optimally placed in the distribution network grows to five at locations 2, 3, 4, 9, and 13, reactive losses also rise and become 165 kVar. Distributed generators are installed in the distribution network to lower power losses so that EVs consumers can easily charge their vehicles without any disturbance in the distribution system. One DG is installed in the bus system at bus 30 with a capacity of 1310.805 kW. The reactive power loss decreases to 72.9387 kVar. Two DGs with the capacity of 1310.805 and 873.8701 kW are optimally located at buses 6 and 32 in IEEE 33 bus systems. The installation of two DGs lowers the reactive power loss to 49.6781 kVar.

The real and reactive power losses after the optimal placement of EVCS and DGs in the 33-bus distribution network, along with their location, are demonstrated in Table 2. It is clear from the table that the active power losses increase to 255 kW and reactive losses to 144 kVar after the optimal allocation of

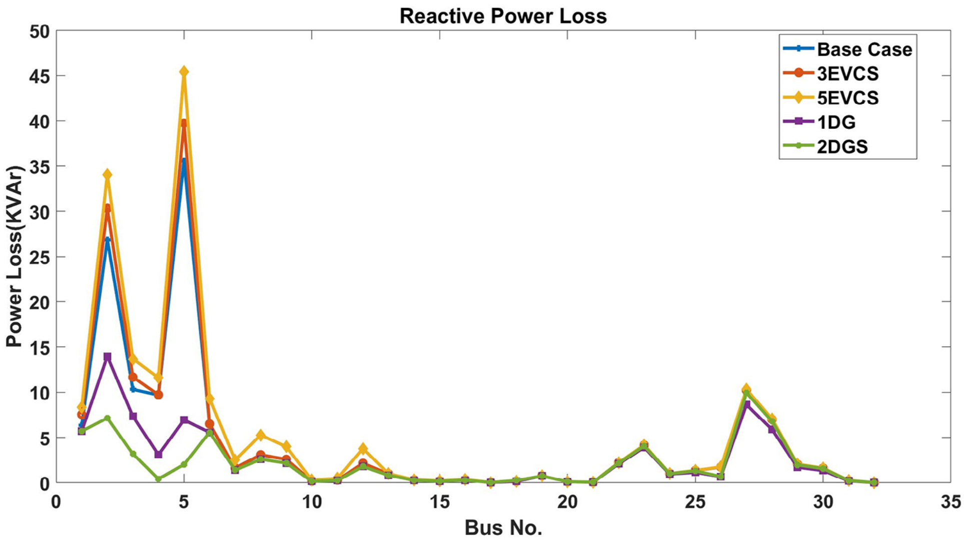

FIGURE 10 Reactive power loss following the installation of electric vehicle charging station (EVCS) and distributed generation sources (DGs).

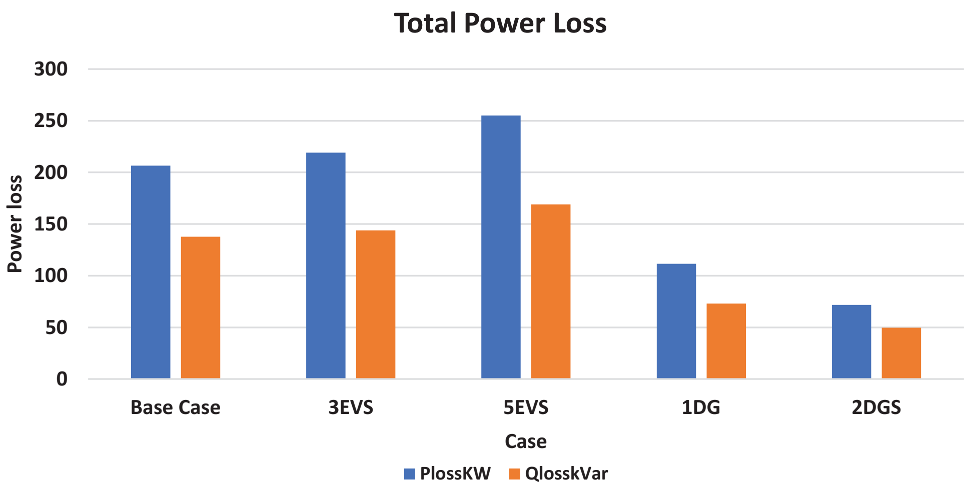

FIGURE 11 Total power loss on IEEE- 33 bus distribution network after the integration of electric vehicle charging station (EVCS) and distributed generation sources (DGs).

EVCS and decrease to 71.85 kW and 49.6781 kVar after placing the distributed generator. Figure 11 shows the variation in power losses, and Figure 12 shows the voltage improvement following the best arrangement of EVCS and DGs.

From the proposed methodology by the optimal placement of one DG, power losses, including real and reactive, are lessened to 46.003% and 47.0253%, respectively. The reduction in power losses due to the deployment of two DGs is 65.2278% and 63.8201%, respectively.

Table 3 shows the comparison of the reduction in the power losses and improvement in voltage profile using PSO with other optimization techniques such as SA, ABC, and GA. It is clear from the table that power loss reduction by PSO is 2.5 times better than SA, 1.6 times better than ABC, and 1 times better than GA. This also shows that PSO takes less computational time and is more efficient and flexible than other optimization techniques.

5 | CONCLUSION AND FUTURE RECOMMENDATIONS

The incorporation of electric vehicles reduces the pollution resulting from fossil fuel transportation. The increased use of electric vehicles led to the installation of EVCS. So, the EVCS placement affects the power system negatively. Here, the impact of EVCS on the power system is presented using the BFS load flow analysis. The power losses of the system increase, and voltage decreases when many electric vehicles charge. Distributed generators are placed optimally for compensation for such losses and improvements in the voltage. Optimal placement is demonstrated using PSO. The proposed work is validated on the IEEE-33 bus system. Moreover, the results obtained from this work ensure the reduction in power losses and enhancement in the voltage profile. The PSO results are compared with the other existing optimization techniques and show improved

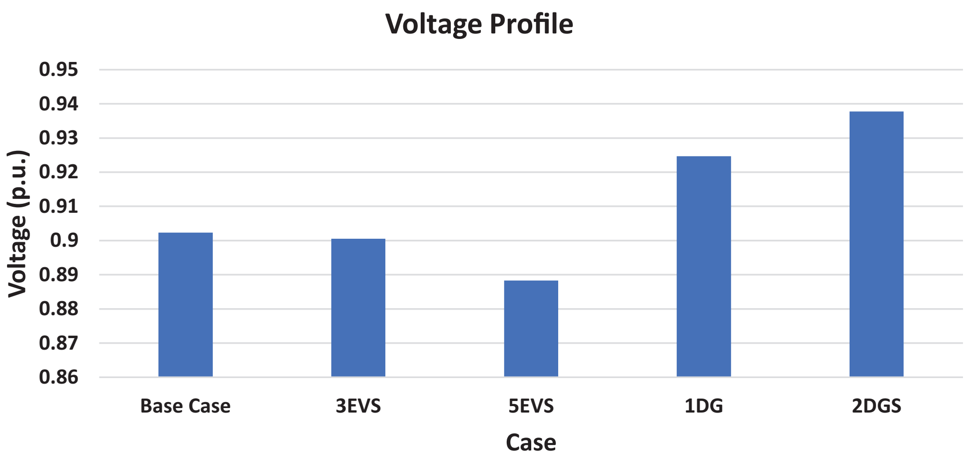

FIGURE 12 Voltage after the placement of electric vehicle charging station (EVCS) and distributed generation sources (DGs) in IEEE 33 bus system.

TABLE 3 Comparison of power loss reduction in IEEE 33 bus systems using particle swarm optimization (PSO) and other optimization techniques.

Techniques	DG location	DG size (KW)	Min. voltage (p.u)	Active power loss in kW (Without DG)	Active power loss in kW (With DG)	Power loss reduction (%)
Simulated annealing [34]	30,13	79.45,96	0.918	199.102	178.28	10.458
Artificial bee colony [35]	29,30	1017,628	0.928	210.97	121.89	42.22
Genetic algorithm [36]	29,8,32,16	500,500,500,500	0.932	210.61	78.920	62.52
Particle swarm optimization [Proposed]	6,32	873.8,1310.8	0.9378	206.63	71.850	65.27

results. The reduction in power loss by the suggested algorithm is 1–2.5 times better than existing techniques. Compared to the existing techniques, better performance with less computational time is obtained using PSO.

In the proposed work, the consideration of a medium-sized network, that is, an IEEE 33-bus system is the limitation. Moreover, dynamic factors like fluctuating load and output of the variable renewable energy are not considered. This research has multiple applications in addition to optimizing the locations of DG and EVCS. It may be enhanced to better manage electric car fleets across a variety of industries, connect energy storage devices to distribution networks, and assist grid modernization programs. Its usefulness also includes resolving cybersecurity issues in the context of integrating EVCS and DG, demand response programs, residential microgrid setups, and smart city planning.

Some of the future recommendations regarding this study are given below.

1. In this research, we focused on the optimal placement of EVCSs and distributed generators (DGs) in distribution networks to reduce power losses and voltage concerns. While our study did not get into the scheduling process of EV charging and discharging. This dynamic scheduling difficulty might be addressed in the future by applying advanced algorithms to balance grid limits, customer preferences, and operational efficiency. Integrating placement and scheduling considerations can result in a more holistic approach to managing distribution network operations in the face of increasing demand for electric vehicles.
2. In our research, PSO is used for the optimal placement of EVCS and DGs in IEEE-33 bus systems while its incorporation in DSM leads to critical challenges like power system protection, fraud detection, and fault management. So, in the future, we will work on the integration of cybersecurity security measures, anomaly detection methods, and fault detection algorithms into the PSO–DSM framework to improve the framework's resilience and flexibility in the face of problems with power system protection, faults, and fraud.
3. When it comes to DSM strategies, especially those that employ the PSO algorithm, it is critical to take the size of the problem's instance and the nature of the optimization problem into account. PSO can be computationally efficient if the DSM problem has reasonable dimensions, but this efficiency is dependent on other different variables like the problem's complexity and participant distribution. To decide if PSO or other optimization approaches are best, it is important to analyze the characteristics of the DSM scenario, including the number of devices, customers, and the nature of constraints involved. The requirements and limitations of the situation ultimately determine which algorithm is best.

4. Investigate more test cases on the IEEE-33 bus system and other larger distribution networks in the future.
5. The evaluation of the adaptability and robustness of the proposed methodology is done on larger and more complex distribution networks like the IEEE-69 bus system, Indian 85-bus test systems, and IEEE-118 system in the future.
6. Variations in daylight load, as well as changes in environmental factors such as irradiance, temperature, and wind speed which may impact DGs like wind turbines and solar PV should be considered in the future. Moreover, for more precise predictions and optimization in complex and large distribution network settings, combine PSO with machine learning approaches in the future.

NOMENCLATURE

ABC	Ant bee colony
ASFLA	Adaptive shuffled frog leaping algorithm
BFOA	Bacterial foraging optimization algorithms
CO_2	Carbon dioxide
CSO	Chicken swarm optimization
DE	Differential evolution
DG	Distributed generation
DN	Distributed network
DSM	Demand-side management
DSO	Distributed system operators
EDV	Electric drive vehicles
EENS	Expected energy not served
EV	Electric vehicle
EVCS	Electric vehicle charging stations
EVSE	Electric vehicle supply equipment
GA	Genetic algorithm
GIS	Geographic information system
GWO	Grey wolf optimization
HGWO	Hybrid grey wolf optimizer
HHO	Harris Hawks optimization
IVM	Index vector method
LOLE	Loss of load expectation
MPDIPA	Modified primal-dual interior point algorithm
ORCSA	One-rank cuckoo search algorithms
PEV	Plugin electric vehicles
PLI	Power loss index
PSO	Particle swarm optimization
RT-SLM	Real-time smart load management
SA	Simulated annealing
TLBO	Teaching learning-based optimization
TOUP	Time of use pricing
WOA	Whale optimization algorithm

AUTHOR CONTRIBUTIONS

Mishal Altaf: Conceptualization; formal analysis; writing—original draft. **Muhammad Yousif**: Conceptualization; formal analysis; resources; software; writing—original draft. **Haris Ijaz**: Conceptualization; formal analysis; software; validation; visualization. **Mahnoor Rashid**: Formal analysis; investigation; methodology; writing—review and editing. **Nasir Abbas**: Conceptualization; investigation; methodology; resources; visualization; writing—review and editing. **Muhammad Adnan Khan**: Conceptualization; formal analysis; methodology; software; visualization; writing–review and editing. **Muhammad Waseem**: Conceptualization; formal analysis; funding acquisition; project administration; supervision; writing–original draft; writing–review and editing. **Ahmed Saleh**: Conceptualization; funding acquisition; project administration; visualization; writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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