

META-HEURISTIC APPROACHES TO OPTIMAL PLACEMENT OF ELECTRIC VEHICLE CHARGING STATION

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ARTICLE INFO

Article History

Received: February 9, 2026

Reviewed: June 5, 2026

Accepted: July 5, 2026

Published: July 31, 2026

Keywords:

Distribution System,
Electric Vehicle Charging Station,
Power Flow Analysis,
Ant Colony Optimization,
Particle Swarm Optimization,
Radial Distribution Network
System,
Backward Forward Sweep.

ABSTRACT

Electric vehicles (EVs) have been developed to reduce the emissions of carbon dioxide (CO₂) produced by vehicles with internal combustion engines. As the adoption of EVs increases, the development of a robust and efficient electric vehicle charging station (EVCS) is essential for the widespread adoption of EVs, providing the necessary infrastructure to recharge vehicle batteries. The strategic placement of an EVCS is critical, because it directly affects the efficiency and reliability of the distribution system. Properly located charging stations can enhance grid stability, optimize energy distribution, and reduce peak load pressures. Conversely, a poorly planned EVCS placement can lead to grid congestion, increased operational costs, and potential reliability issues. Strategy for maximizing EV utilization through EVCSs in the Radial Distribution Network System (RDNS) by considering factors such as load voltage deviation and line losses. In this study, the RDNS is segmented into zones, followed by the application of various optimization algorithms, including Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). This approach identifies the optimal locations for the EVCSs in the network for different load growth rates. This was followed by Forward Backward Sweep (FBS) power flow analysis to determine the active and reactive power losses, voltage deviations, and voltage profiles. Extensive simulations using IEEE 33-node test feeders validated the proposed techniques using the MATLAB tool.



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I. INTRODUCTION

Various approaches have been applied to design the optimum placement of EVCS. Charging stations can be optimally designed depending on the EV usage in an enhanced system performance and supply of a peak load. For this reason, reduction in losses, better economics, and minimization of voltage deviation are achieved using EVs [1]. Layout optimization for charging stations is based on maximizing the reliability of a network, and minimizing voltage deviation and power losses is applied using a K-means clustering algorithm [2]. The distribution network voltage deviation, power losses, and charging service were used as multi-objective functions in the optimization placement of charging stations. This problem was tested on a road network of 25 nodes and an IEEE 33 bus network using a cross-entropy method and data envelopment analysis [3]. A hierarchical genetic algorithm was applied to estimate an optimal charging station design based on the cost as an objective function and the constraints of the maximum capacity of a charging station and limits of power loss. The proposed technique was tested using an IEEE 123 bus system [4]. This study applied the ACO and PSO algorithms to solve the EVCS placement problem.

This was followed by load flow analysis using a backward-forward sweep approach to determine the real and reactive power losses and voltage deviation, and to analyze the voltage profile on the IEEE 33 bus system using MATLAB simulations. This paper is organized as follows: i) Section1 provides an introduction; ii) Section 2 details the problem formulation for EV charging stations; iii) Section 3 presents the modeling of the objective with algorithms; iv) further analysis of the simulation results is discussed in Section 4; and v) the conclusion is presented in Section 5.

II. PROBLEM FORMULATION

Deploying an EVCS in an RDNS has several benefits, including reduced line loss, improved voltage stability, enhanced network reliability, and increased security. However, determining the optimal placement of an EVCS involves solving a nonlinear optimization problem with objective functions and constraints related to the power balance, voltage, and current. The proposed solution aims to minimize the peak load power loss and voltage variation, while enhancing the voltage stability in the RDNS. Thus, the multi-objective function can be mathematically expressed as

$$J = \text{Minimum} \{J_1, J_2\} \quad (1)$$

Where J_1 and J_2 correspond to the total power loss and the voltage deviation index respectively. The following is a description of the mathematical equation that represents the multi-objective function.

III. MODELLING OF THE OBJECTIVE FUNCTION

The IEEE 33-bus system was selected as the use case network in this study. The RDNS is broken up into zones such that each zone can have an EVCS with a number of charging spots to serve its own needs. The system consistsof33buses with a total real power load of 3.72 MW and a total reactive power load of 2.30 MVar supplied by source at bus 1. This RDNS was large and balanced at a voltage of 12.66 kV as shown in Fig. 1.

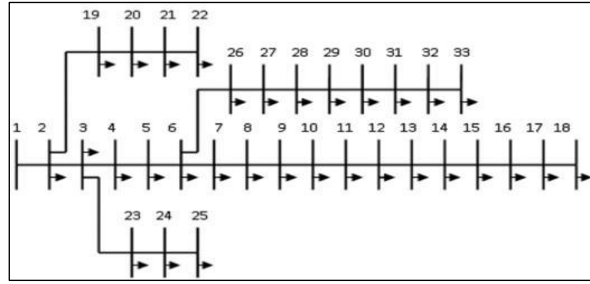


Figure 1: IEEE33 bus system.
Source: Authors, (2026).

III.1 REAL AND REACTIVE POWER LOSSES

By strategically placing EVCSs in the distribution network, the stability caused by the peak loading situations can be mitigated, ensuring that the constraints are not violated. This optimal EVCS placement minimizes power loss while adhering to the limits of the system constraints. The precise branch loss for the distribution system can be obtained using equation (2) and (3) such that the total power loss will be

$$P_{loss}(n, n+1) = \sum_{n=1}^t P_{loss}(n, n+1) \quad (2)$$

$$Q_{loss}(n, n+1) = \sum_{n=1}^t Q_{loss}(n, n+1) \quad (3)$$

Where $P_{loss}(n, n+1)$ and $Q_{loss}(n, n+1)$ are the total real and reactive powers losses from bus i to bus k respectively, V_i and V_k , respectively, represent the voltage of bus i and k , Y_{ik} and $\angle Y_{ik}$ represent, respectively, the admittance and the admittance angle of the line between bus i and bus k . Therefore, the function for the minimum amount of total power loss is given as:

$$J_1 = \text{Min} \sum_{i=0}^n \sum_{k=0}^n (P_{loss}(n, n+1) + Q_{loss}(n, n+1)) \quad i \neq k \quad (4)$$

III.2 VOLTAGE DEVIATION

When the EVCS are incorporated in to the RDNS, the voltage profile changes. The main focus is to minimize thevoltage changes. Each bus in the RNDNS was analyzed individually. To maintain the voltage stability, the difference between the normal bus voltage and the rated bus voltage should be minimal [5]. The equation for voltage deviation from the reference voltage magnitude is given by:

$$\text{Voltage deviation } J_2 = \text{Min} \sum_{j=0}^n \left(1 - \frac{V_j}{V_{ref}}\right)^2 \quad (5)$$

Here

V_j - represents the voltage at bus j

V_{ref} is the slack bus voltage

n - represents the number of buses.

In light of this, transforming Equations (4) and (5) into a minimization function results in the mathematical formulation of the multi-object function represented in Eq. (6)

$$J = \{\beta_1 \times J_1 + \beta_2 \times J_2\} \quad (6)$$

III.3 ANT COLONY OPTIMIZATION (ACO)

The Ant Colony Optimization technique was inspired by the foraging behavior of ant colonies and was first introduced by Marco Dorigo in the 1990s. Ants are eusocial insects that prefer community survival and sustenance to individual species. They communicate using sound, touch and pheromones. Pheromones are organic chemical compounds secreted by ants that trigger social responses in members of the same species. These chemicals are capable of acting like hormones outside the body of the secreting individual, impacting the behavior of the receiving individuals. Because most ants live on the ground, they use the soil surface to leave pheromone trails that may be followed (smelled) by other ants. Ants live in community nests and the underlying principle of ACO is to observe the movement of ants from their nests to search for food in the shortest possible path. Initially, ants began to move randomly in search of food around their nests. This randomized search opens multiple routes from the nest to a food source. Based on the quality and quantity of the food, ants carry a portion of the food back with the necessary pheromone concentration on its return path. Depending on these pheromone trials, the probability of selecting a specific path by the following ants is a guiding factor for the food source. Evidently, this probability is based on the concentration and rate of pheromone evaporation. It can also be observed that the length of each path can be easily accounted for because the evaporation rate of the pheromone is also a deciding factor. The mathematical modelling of the algorithm can be represented as follows: the probability of movement of the ant from node i to node j is given by [6].

$$P_{i,j} = \frac{(\tau_{i,j}^\alpha)(\eta_{i,j}^\beta)}{\sum (\tau_{i,j}^\alpha)(\eta_{i,j}^\beta)} \quad (7a)$$

Where

$\tau_{i,j}$ is the amount of pheromone on edge i, j

α is a parameter to control the influence of $\tau_{i,j}$

$\eta_{i,j}$ is the desirability of edge i, j (typically $1/d_{i,j}$)

β is a parameter to control the influence of $\eta_{i,j}$

Amount of pheromone is updated according to the equation

$$\tau(i,j) = (1 - \rho)\tau_{i,j} + \Delta \tau_{i,j} \quad (8a)$$

Where

$\tau_{i,j}$ is the amount of pheromone on a given edge i, j

ρ is the rate of pheromone evaporation

$\Delta \tau_{i,j}$ is the amount of pheromone deposited typically given by

$$\Delta \tau_{i,j} = \begin{cases} \frac{1}{L_k} & \text{if ant } k \text{ travels on edge } i, j \\ 0 & \end{cases}$$

Where L_k is the cost of the k^{th} ant's tour (typically length), each ant applies it only to the last edge traversed:

$$\tau_{i,j} = (1 - \varphi) \cdot \tau_{i,j} + \varphi \cdot \tau_0 \quad (9a)$$

Where

$\varphi \in (0, 1)$ is the pheromone decay coefficient,

τ_0 is the initial value of the pheromone

Algorithm

Step 1: Start.

Step 2: Read the bus and line data, and initialize the EVCS numbers with the percentage of EV penetration.

Step 3: Initialize parameters of ACO.

Step 4: Apply state transition rule and pheromone update rule.

Step 5: Evaluate fitness function.

Step 6: Apply global pheromone update rule.

Step 7: If the iteration number reaches the maximum limit, proceed to step 8, else, set the iteration index,

$k=k+1$ repeat step 4 to 8 until iteration criteria is met.

Step 8: The optimal location of EVCS is recorded.

Step 9: End.

Parameters of Ant colony optimization:

Table 1a: ACO Parameters.

Parameter	Symbol	Value
Population size	npop	100
Number of iterations	T	25
Pheromone coefficient	α	1
Heuristic coefficient	β	2
Evaporation rate	γ	0.05
Amount of pheromone by best ant	Q	1

Source: Authors, (2026).

III.4 PARTICLE SWARM OPTIMIZATION (PSO)

The PSO working principle is based on the social behaviors of animals, such as fish schooling, 7ato flocking, and bee swarming. They work in a flock and optimize their search to hunt for the best food place. Similarly, the optimal location of the EVCS was determined using this technique. Kennedy and Eberhart presented a work on PSO at a conference on evolutionary computation in 1995. This research is based on solutions to 7ator7f7e optimization problems using PSO. The particles represent the solution to the optimization problems, and the population of solutions is known as the swarm in this algorithm. Velocity and position are the two main properties of particles. The initialization of the particles was performed random positions. The position of the particles changes with the velocity to a new position after each iteration. 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. The equation (7b) is used to determine the velocity of each 7ator7 after each iteration [7].

$$V_i^{k+1} = W^k \times V_i^{k+1} + C_1 \times rand_1 \times (P_{Best,i}^k - X_i^k) + C_2 \times rand_2 \times (G_{Best,i}^k - X_i^k) \quad (7b)$$

Here,

V_i = Velocity of the particle i

C_1 and C_2 = Acceleration coefficients of the particle i

$rand_1$ and $rand_2$ = random variables

P_{best} = Personal 7ator7f particle i

G_{best} = Global 7ator7f particle i

w = Inertia weight 7ator of particle i

k = Current iteration

The location of the particle is obtained as given below:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (8b)$$

Algorithm

Step 1: Start.

Step 2: Read the bus and line data and initialize the EVCS numbers with the percentage of EV penetration.

Step 3: Randomly generate an initial population of particles with random positions and velocities on dimensions with an iteration count set to $k=0$.

Step 4: The fitness value of each particle is evaluated. If the objective value is lower than P_{best} , set this value as the current P_{best} and record the corresponding particle position.

Step 5: Choose the particle associated with the minimum individual best P_{best} of all particles and set the value this value as the current overall G_{best}

Step 6: Update particle velocity and position using steps 4 & 5 respectively.

Step 7: If the iteration number reaches maximum limit proceed to step 8, else set iteration index $k=k+1$ repeat step 4to 7 until iteration criteria is met.

Step 8: The optimal location of EVCS is recorded.

Step 9: End.

The PSO parameters such as population size, acceleration constants, and inertia weight were selected as shown in Table -1b to run the PSO algorithm in MATLAB.

Table 1b: PSO parameter.

Parameter	Symbol	Value
Population size	n_{pop}	100
Number of iterations	T	25
Inertia coefficient	W	1
Cognitive acceleration Coefficient	C_1	1
Social acceleration coefficient	C_2	2

Source: Authors, (2026).

III.5 BACKWARD FORWARD SWEEP APPROACH FOR POWER FLOW ANALYSIS

Power flow analysis was used to determine the performance of the power system operating in a steady state. Two inputs line and load data were required for the analysis. Kirchhoff's current and voltage laws are considered in each iteration of the Backward Forward Sweep (BFS) method to determine the current and voltage [8-10]. The current and load flow solutions in each branch were calculated by maintaining the voltage constant in the backward sweep. The forward sweep calculates the voltage by maintaining the load and current constant. Hence the voltage, real, and reactive power losses are calculated using equations (2), (3), (4) and (5) by the BFS load flow analysis. The assumptions considered are an initial voltage of 1 p.u., initial power losses of both real and reactive are zero and RDNS is balanced in nature [11]. Power flow analysis was used to determine the performance of the power system operating in a steady state. Two inputs line and load data were required for the analysis. Kirchhoff's current and voltage laws are considered in each iteration of the Backward Forward Sweep (BFS) method to determine the current and voltage [8-10]. The current and load flow solutions in each branch were calculated by maintaining the voltage constant in the backward sweep. The forward sweep calculates the voltage by maintaining the load and current constant. Hence the voltage, real, and reactive power losses are calculated using equations (2), (3), (4) and (5) by the BFS load flow analysis. The assumptions considered are an initial voltage of 1 p.u., initial power losses of both real and reactive are zero and RDNS is balanced in nature [11].

Algorithm

Step 1: Start

Step 2: Convert the resistance, reactance, voltage and power per unit form.

Step 3: Calculate matrix [A]: (branch node incidence matrix)

$$A_{i,j} = \begin{cases} -1 & \text{if } j = \text{Sending Node} \\ +1 & \text{if } j = \text{Receiving Node} \end{cases}$$

Step 4: Calculate number of possible paths by computing number of end nodes.

Step 5: The number of nodes on each possible path is determined. Let the lateral have maximum 'm' number of branches, so the bus matrix [B] will be having dimensions ($l * m$).

Step 6: Determine linked branches beyond a branch to form the next-linked node matrix [C]. For load flow

Step 7: Assume flat voltages tart

$$V_i = 1 + 0j \text{ for } i = 1 \text{ to } n$$

$$Pl_j = 0 \text{ and } Ql_j = 0 \text{ for } j = 1 \text{ to } b$$

Step 8: Set iteration count IT= 1 where IT=1 to IT MAX

Step 9: Calculate current from each branch

$$I_j = \left\{ \frac{S_{i+1}}{V_{i+1}} \right\} \text{ for } i = 1 \text{ to } b$$

$$\text{Here, } S_{j+1} = (P_{i+1} + Q_{i+1})$$

Step 10: Backward sweep: The current and load flow solutions were calculated by keeping the voltage constant. It begins at the branch of the end node and moves toward the source node. Each load flow of the branch was updated by considering the voltage of the previous iteration.

$$I_k = \sum_j I_j \text{ for } k = 1 \text{ to } b \text{ where } j \in C_j$$

Here, C_j is the set of next linked node beyond k branch

Step 11: Forward sweep: The voltage was calculated by keeping the load and current constant. It starts from the branch of the source node and continues towards the end node.

$$V_{k+1} = V_k - (I_k * (Z_k))$$

Step 12: Calculate Real and Reactive power losses

Step 13: Check the deviation in the values for the real and reactive power losses from the present and previous iterations.

Step 14: $IT = IT + 1$ until $IT = IT_{MAX}$

Step 15: Return Pl_j , Ql_j , IT , total real and reactive power losses.

IV. RESULTS AND DISCUSSIONS

The optimal location for EVCS placement using the ACO algorithm at penetration levels of 10%, 50% and 100% of the considered load was applied and the results are tabulated in Table 2a.

Table 2a: EVCS placement locations by ACO.

Parameters	10% load	50% load	100% load
Bus number	2, 23, 4, 10, 13	2, 23, 4, 11, 13	2, 23, 4, 10, 13

Source: Authors, (2026).

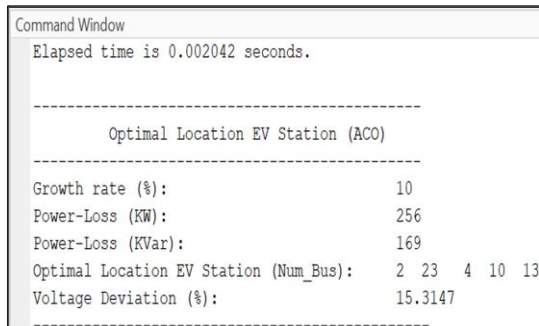


Figure 2a: Results of optimal placement location for 10% load using ACO algorithm.
Source: Authors, (2026).

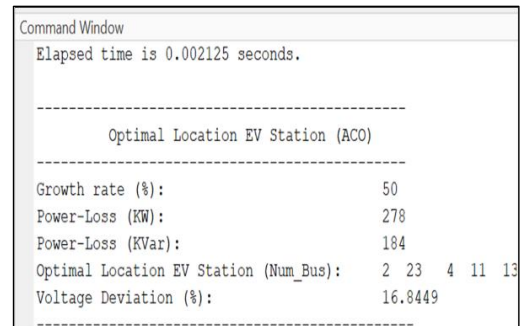


Figure 2b: Results of optimal placement location for 50% load using ACO algorithm.
Source: Authors, (2026).

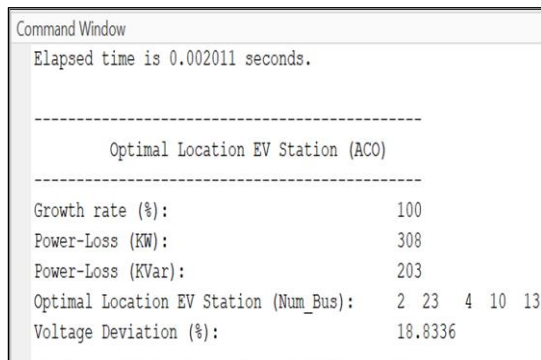


Figure 2c: Results of optimal placement location for 100% load using ACO algorithm.
Source: Authors, (2026).

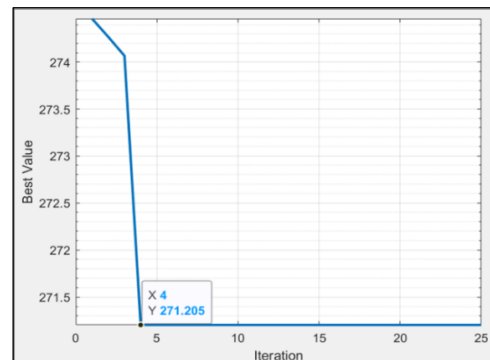


Figure 2d: Convergence graph for 10% load.
Source: Authors, (2026).

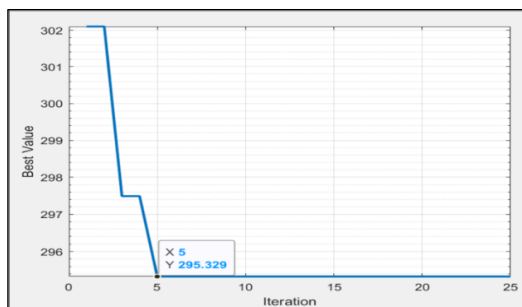


Figure 2e: Convergence graph for 50% load.
Source: Authors, (2026).

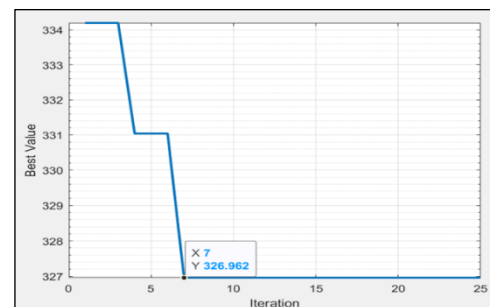


Figure 2f: Convergence graph for 100% load.
Source: Authors, (2026).

The algorithm was executed thrice for each load condition and the most repeated bus numbers were chosen as the final location in the load category. Fig 2a shows the optimal location of EVCS placement for 10% load growth. The final optimal locations obtained for 10% load growth were bus numbers 2, 23, 4, 10, and 13. Fig 2d shows the optimization of the convergence point for a 10% load growth at 4th iterations. Fig 2b shows the optimal location of EVCS placement for 50% load growth. The optimal locations for a 50% load growth are buses 2, 23, 4, 11 and 13. Fig 2e shows the optimization of the convergence point for a 50% load growth at the 5th iterations.

Fig 2c shows the optimal location of EVCS placement for 100% load growth. The optimal location for a 100% growth rate is buses no. 2, 23, 4, 10 and 13. Fig 2f shows the convergence point for 100% growth at 7th iteration. From the results we observe that the number of iterations required for convergence increases as the load increases but converges for a small number of iterations. The computation time is shorter as it converges early.

IV.1 RESULTS AND DISCUSSIONS

The optimal location for EVCS placement using the PSO algorithm at penetration levels of 10%, 50% and 100% of the considered load was applied and the results are tabulated in Table 2b.

Table 2b: EVCS placement locations by PSO.

Parameters	10% load	50% load	100% load
Bus number	2, 3, 4, 9, 13	2, 3, 4, 9, 13	19, 3, 4, 9, 13

Source: Authors, (2026).

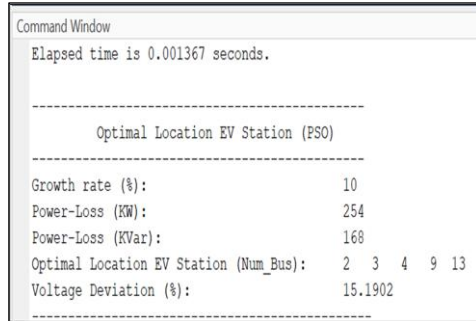


Figure 3a: Results of optimal placement location for 10% load using PSO algorithm.
Source: Authors, (2026).

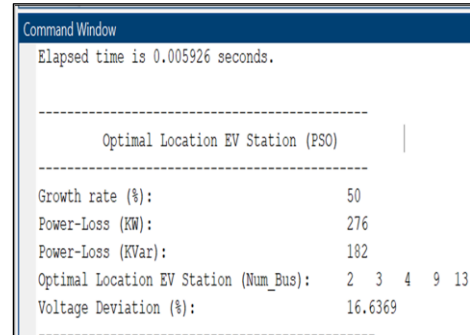


Figure 3b: Results of optimal placement location for 50% load using PSO algorithm.
Source: Authors, (2026).

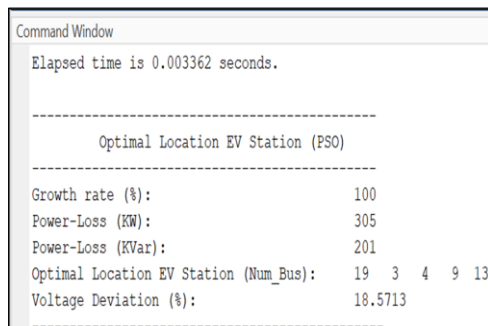


Figure 3c: Results of optimal placement location for 100% load using PSO algorithm.
Source: Authors, (2026).

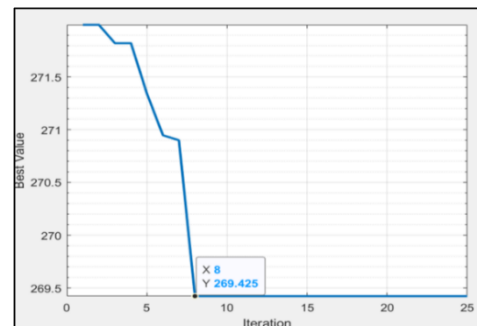


Figure 3d: Convergence graph for 10% load.
Source: Authors, (2026).

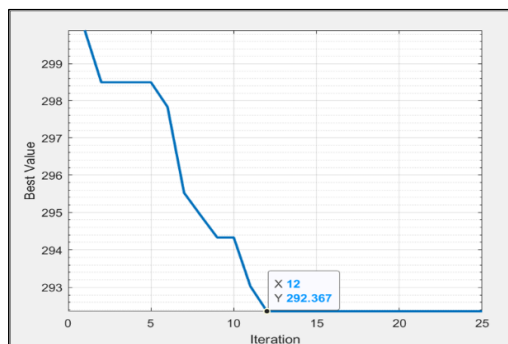


Figure 3e: Convergence graph for 50% load.
Source: Authors, (2026).

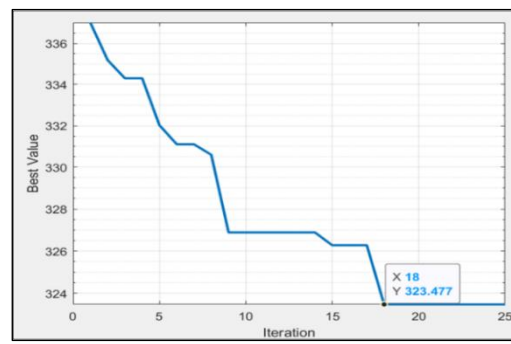


Fig. 3f: Convergence graph for 100% load.
Source: Authors, (2026).

The algorithm was executed thrice for each load condition and the most repeated bus numbers were chosen as the final location in the load category. Fig 3a shows the optimal location of EVCS placement for 10% load growth. The final optimal locations obtained for 10% load growth were bus numbers 2, 3, 4, 9 and 13. Fig 3d shows the optimization of the convergence point for a 10% load growth at 8th iterations. Fig 3b shows the optimal location of EVCS placement for 50% load growth. The optimal locations for a 50% load growth are buses 2, 3, 4, 9, and 13. Fig 3e shows the optimization of the convergence point for a 50% load growth at 12th iterations. Fig 3c shows the optimal location of the EVCS placement for 100% load growth.

The optimal locations for the 100% growth rate are buses 19, 3, 4, 9 and 13. Fig 3f shows the convergence point for 100% growth at the 23rd iteration. The results show that the number of iterations required convergence increases as the load increases. Hence the computation time is greater in this case.

V.1. POWER FLOW ANALYSIS FOR ACO ALGORITHM LOCATIONS

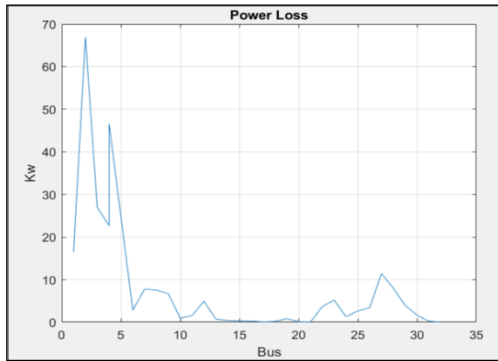


Figure 4a: Power losses at 10% load.
Source: Authors, (2026).

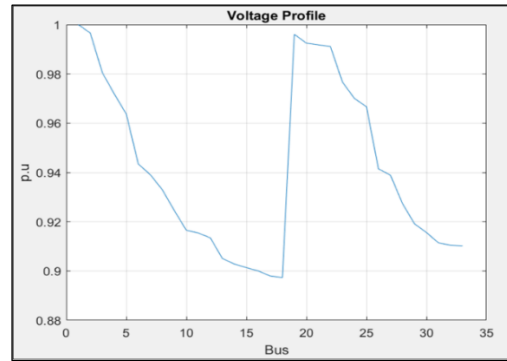


Figure 4b: Voltage profile at 10% load.
Source: Authors, (2026).

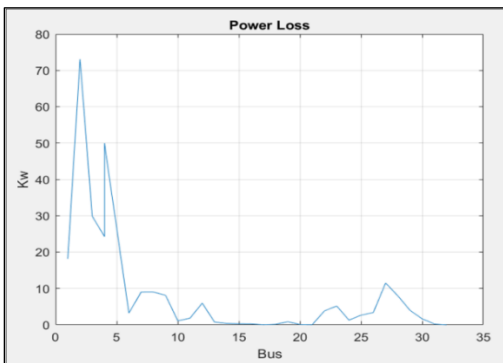


Fig. Figure 4c: Power losses at 50% load.
Source: Authors, (2026).

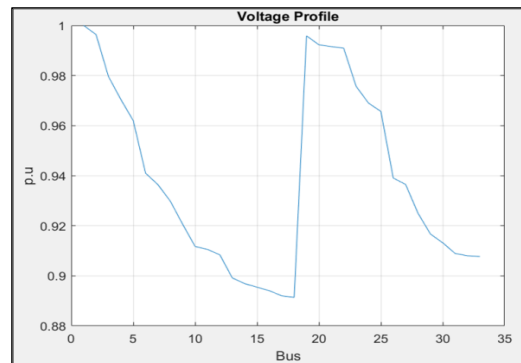


Figure 4d: Voltage profile at 50% load.
Source: Authors, (2026).

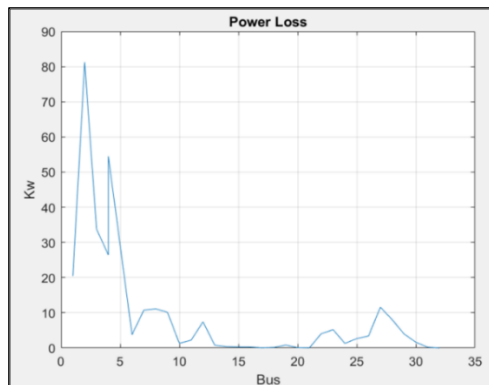


Figure 4e: Power losses at 100% load.
Source: Authors, (2026).

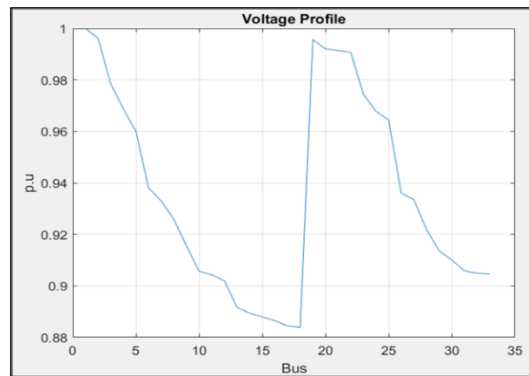


Figure 4f: Voltage profile at 100% load.
Source: Authors, (2026).

For a 10% load the optimal locations identified are bus nos. 2, 23, 4, 10, and 13 with real and reactive power losses of 256 KW and 169 KVAR, respectively. The 50% load optimal locations are 2, 23, 4, 11 and 13 with 278 KW and 184 KVAR real and reactive losses respectively. Finally, 100% load optimal locations are 2, 23, 4, 10 and 13 with 308 KW and 203 KVAR power losses and are tabulated in Table 3a.

Table 3a: Power flow results in ACO.

Parameters	10% of EV	50% of EV	100% of EV
Real power losses in KW	256	278	308
Reactive power losses in KVAR	169	184	203
Voltage deviation	15.314	16.844	18.833
Vmin in p.u	0.8973	0.8914	0.8838
Number of iterations for best value	4	5	7
EVCS placement optimal location	2, 23, 4, 10, 13	2, 23, 4, 11, 13	2, 23, 4, 10, 13

Source: Authors, (2026).

The main objective of load flow analysis is to identify the optimal location with reduced active and reactive power losses, low voltage deviation and an improved voltage profile. Fig. 4a and 4b show the power losses and voltage profiles for the 10% load condition. The optimal locations obtained for the ACO algorithm are bus nos. 2, 23, 4, 10, and 13. The active power loss was 256 kW and the reactive power loss was 169 KVAR in the system. The voltage deviation was 15.314% and the voltage profile minimum value was 0.8973 p.u. The algorithm required four iterations to converge to the best value. Fig. 4c and Fig. 4d show the power losses and voltage profiles for the 50% load condition. The optimal location obtained by the ACO algorithm is bus nos. 2, 23, 4, 11 and 13. The active power loss was 278 kW and the reactive power loss was 184 KVAR in the system. The voltage deviation is 16.844% and the minimum voltage profile value is 0.8914 p.u. The algorithm required five iterations to converge to the best value. Figure 4e and 4f show the power losses and voltage profile for the 100% load condition. The optimal locations obtained by the ACO algorithm are bus nos. 2, 23, 4, 10 and 13. The active power loss is 308 kW and the reactive power loss is 203 KVAR in the system. The voltage deviation was 18.833% and the minimum voltage profile value was 0.8838 p.u. The algorithm requires 18 iterations to converge to the best value. The location with minimum active and reactive losses, low voltage deviation and improved voltage profile is considered to be the best location for placement of the EVCS in each zone in the network. This was tested on a 33bus test system using the MATLAB 2023Ra simulation tool.

V.2 POWER FLOW ANALYSIS FOR PSO ALGORITHM LOCATIONS

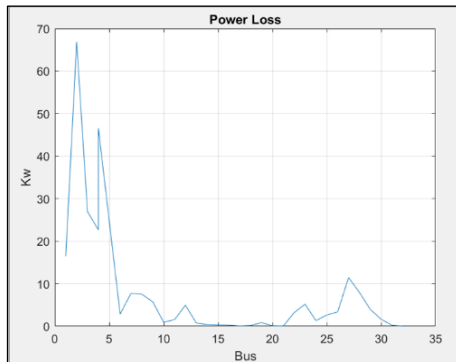


Figure 4g: Power losses for 10% load.
Source: Authors, (2026).

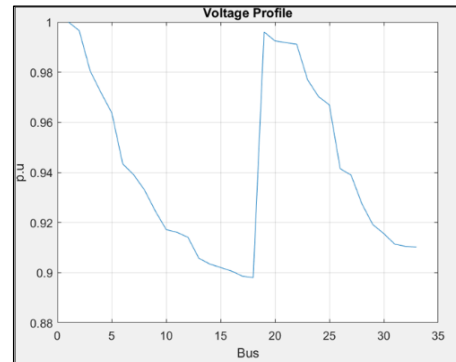


Figure 4h: Voltage profile for 10% load.
Source: Authors, (2026).

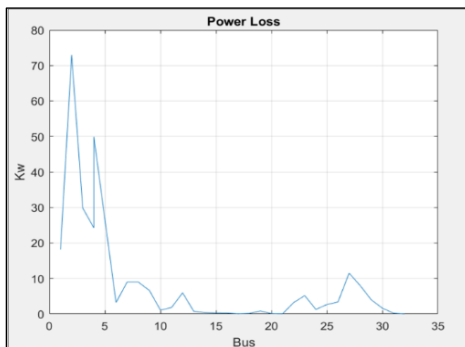


Figure 4i: Power losses for 50% load.
Source: Authors, (2026).

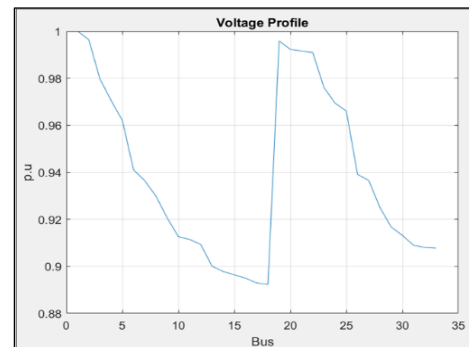


Figure 4j: voltage profile for 50% load.
Source: Authors, (2026).

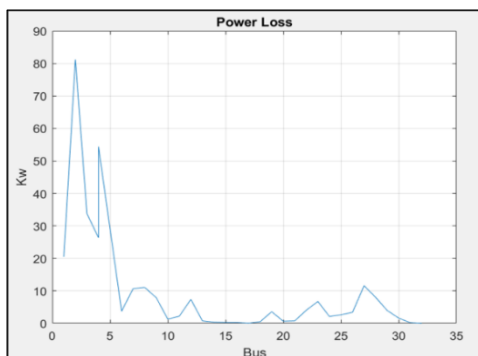


Figure 4k: Power losses for 100% load.
Source: Authors, (2026).

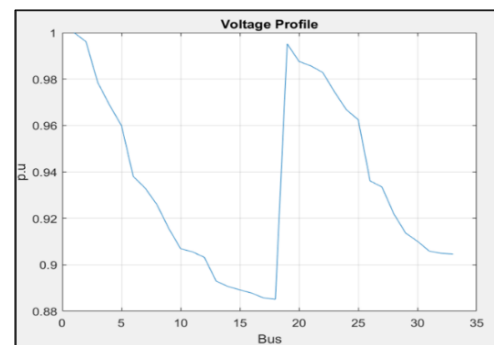


Figure 4l: Voltage profile for 100% load.
Source: Authors, (2026).

For a 10% load the optimal locations identified are bus nos. 2, 3, 4, 9, and 13 with real and reactive power losses of 254 KW and 168 KVAR respectively. The 50% load optimal locations are 2, 3, 4, 9, and 13 with 276 KW and 182 KVAR real and reactive losses respectively. Finally, 100% load optimal locations are 19, 3, 4, 9, and 13 with 308 KW and 203 KVAR power losses and are tabulated in Table 3b.

Table 3b: Power flow results PSO.

Parameters	10% load	50% load	100% load
Real power loss in KW	254	276	308
Reactive power loss in KVAR	168	182	203
Voltage deviation in %	15.190	16.636	18.833
V _{min} in p.u at 18 th bus	0.8980	0.8923	0.8838
Number of iterations for Convergence	8	12	18
EVCS placement optimal Locations	2, 3, 4, 9,13	2, 3, 4, 9,13	19, 3, 4, 9,13

Source: Authors, (2026).

The main objective of power flow analysis is to identify the optimal location with reduced active and reactive power losses, low voltage deviation and an improved voltage profile. Fig. 4g and 4h shows the power losses and voltage profiles for the 10% load condition. The optimal locations obtained by the PSO algorithm are buses no. 2, 3, 4, 9 and 13. The active power loss in the system is 254 kW and the reactive power loss is 168KVAR in the system. The voltage deviation was 15.190% and the voltage profile minimum value was 0.8980 p.u. The algorithm required eight iterations to converge to the best value. Fig. 4i and 4j show the power losses and voltage profiles for the 50% load condition. The optimal locations obtained by the PSO algorithm are buses no. 2, 3, 4, 9 and 13. The active power loss was 276 kW and the reactive power loss was 182 KVAR in the system. The voltage deviation is 16.636% and the minimum voltage profile value is 0.8923 p.u. The algorithm requires 12 iterations to converge to the best value. Fig. 4k and 4l show the power losses and voltage profile for the 100% load condition. The optimal locations obtained by the PSO algorithm are buses no. 2, 25, 4, 9 and 13. The active power loss in the system is 305 kW and the reactive power loss is 201KVAR in the system. The voltage deviation was 18.576% and the minimum voltage profile value was 0.8851 p.u. The algorithm requires 18 iterations to converge to the best value.

VI. COMPARISON BETWEEN PSO AND ACO

The EVCSs were optimally placed in each zone for different load conditions using the PSO and ACO optimization techniques separately. This was done to validate the efficacy of the optimization technique individually for locating the best locations with reduced real and reactive power losses, reduced voltage deviation and improved voltage profile. From Tables 4a and 4b we can observe that the time taken to complete the optimization is greater in the PSO method than in ACO. The number of iterations required to convergence to the best value was comparatively higher in the PSO method than in the ACO method for all load conditions.

Table 4a: Results of EVCS placement location by PSO and ACO optimization.

Parameters	10% load		50% load		100% load	
	PSO	ACO	PSO	ACO	PSO	ACO
Optimal bus no	2,3,4,9,13	2,23,4,10,13	2,3,4,9,13	2,23,4,11,13	19,3,4,9,13	2,23,4,10,13
Time in seconds	0.001367	0.002042	0.005926	0.00215	0.003362	0.002011
Convergence Point	8	4	12	5	18	7

Source: Authors, (2026).

Table 4b: Results of PSO and ACO algorithm with power flow analysis for optimal placement of EVCS.

Parameters	10% load		50% load		100% load	
	PSO	ACO	PSO	ACO	PSO	ACO
Optimal bus no	2,3,4,9,13	2,23,4,10,13	2,3,4,9,13	2,23,4,11,13	19,3,4,9,13	2,23,4,10,13
Real power KW	254	256	276	278	305	308
Reactive power KVAR	168	169	182	184	201	203
V _{min} in p.u	0.8980	0.8973	0.8923	0.8914	0.8851	0.8838
Voltage deviation %	15.190	15.314	16.636	16.844	18.571	18.833
No of iterations	8	4	12	5	18	7

Source: Authors, (2026).

Tables 4a and 4b present the optimal allocation of EVCSs for each zone and the load condition simulation scenario. The PSO and ACO algorithms were employed to test the placement of stochastically sized EVCS. Factors that influence EVCS placement include an improved voltage profile reduced power losses and voltage deviation. Comparing the results obtained by considering all the factors the PSO method is superior to the ACO method.

VII. CONCLUSION

In summary, the rapid adoption of EVs as a means to reduce greenhouse gas emissions in the transportation industry necessitates swift upgrading of distribution networks to support a large number of charging stations. This study employs heuristic techniques, including PSO and ACO to optimize the placement of EV charging stations (EVCSs) in a network. The objective function focused on minimizing the real and reactive power losses voltage deviation and voltage profile. A comparative analysis revealed that the PSO approach outperformed the ACO method, achieving the lowest values of real and reactive power losses and exhibiting robustness in affecting the voltage profile. The study outcomes offer practical implications for policy makers, system planners, and researchers involved in the efficient deployment and management of EV charging infrastructure within community-based distribution networks.

VIII. FUTURE SCOPE

In future research, an important aspect will be the consideration of factors such as battery charge levels and intermittent behaviour of distributed PV systems. By accounting for battery charge levels, this research will be aimed at ensuring the efficient utilization of available energy resources and managing the charging demands of EVs effectively as the current work fails to take this in to account. Additionally, the intermittent nature of distributed PV systems will be considered to leverage renewable energy sources and maximize their integration with the EV charging infrastructure.

IX. AUTHOR CONTRIBUTIONS STATEMENT

Conceptualization: Dr. Satish K R, Mr. Arjun M. S and Dr. Mohan.

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Investigation: Dr. Arunkumar Patil and Dr. Somashekar D. P.

Discussion of results: Dr. Somashekar D. P, Dr. Arunkumar Patil and Mr. Arjun M. S.

Writing – Original Draft: Dr. Somashekar D. P.

Writing – Review and Editing: Dr. Satish K R and Mr. Arjun M. S.

Resources: Dr. Mohan.

Supervision: Dr. Satish K R and Dr. Arunkumar Patil.

Approval of the final text: Dr. Satish K R, Mr. Arjun M. S, Dr. Mohan, Dr. Arunkumar Patil and Dr. Somashekar D. P.

X. ACKNOWLEDGMENTS

I would like to express my sincere gratitude to the Department of Electrical and Electronics Engineering, SJCE, JSS Science and Technology University, for providing us with the necessary resources and environment for conducting this study. Special thanks to our team for their dedicated contributions and collaborative efforts throughout the literature survey.

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