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A Hybrid Pso–Emsocp Approach for Optimal Ev Charging Station Placement and Distributed Generation Planning in Radial Distribution Networks

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ABSTRACT

The growing adoption of electric vehicles (EVs) has led to a significant rise in electricity demand, creating challenges for the reliability of distribution networks. Strategic placement of EV charging stations (EVCSs) is crucial for ensuring grid stability and minimizing disruptions. To mitigate the impact of EVCSs on radial distribution networks (RDNs), this study explores the integration of distributed generators (DGs) within a reconfigured network, where optimal switch positions and power flow adjustments enhance overall system efficiency. However, poor placement and sizing of DGs and EVCSs can significantly affect system performance. This study analyses the impact of EVCSs on RDNs using Particle Swarm Optimization (PSO). The planning process consists of two stages: first, using PSO to determine the best location for EVCSs, and second, reconfiguring the network while simultaneously determining the optimal locations and sizes of DGs using Second-Order Cone Programming (SOCP) to ensure greater system stability. The methodology, validated on the IEEE 33-bus network, aims to reduce power losses and enhance voltage stability. The outcomes demonstrate how well the suggested strategy works to maximize DG and EVCS installation without sacrificing grid stability. This planning strategy not only optimizes network configuration by reducing power losses and voltage deviations but also contributes to a more resilient and efficient power distribution system in the era of widespread EV adoption.

1. INTRODUCTION

Since they have an impact on the system's overall performance, voltage stability, and power consumption, adding electric vehicle charging stations (EVCSs) to radial distribution systems (RDSs) has become a significant problem. Feeder congestion, voltage reductions, and additional losses are caused by increased demand from EVCSs. To address these problems, network reconfiguration (NR) and distributed generation (DG) are required. The significance of EVCS deployment, DG integration, and NR in preserving the stability and effectiveness of distribution networks has been more and more supported by recent assessments. The addition of EVCSs to radial distribution systems (RDSs) is a major issue since they affect the system's operation, voltage management, and power consumption. Additional demand from EVCSs frequently causes feeder congestion, voltage drops, and additional losses. Planners must use two sorts of solutions to address this problem: network reconfiguration (NR) and distributed generation (DG). Recent studies have gradually shown how crucial NR, DG integration, and EVCS installation are to preserving the stability and effectiveness of distribution networks. networks for rapid dissemination. The network would experience significant load if EVCSs were deployed in unanticipated ways without NR. However, combining them can boost power flow, save costs, and improve system dependability [1].

Numerous studies have used various optimisation strategies to determine the ideal locations for EVCSs and DGs. The selection of weighting factors in [2] implies subjectivity and limits universal applicability, despite the fact that EVCS allocation is a weighted multi-objective optimisation problem. Second-order cone programming is used in Reference [3] to capture time-varying distributed generation and load demand,

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simplifying modelling. However, the strategy mostly relies on static network settings and disregards the need for flexible reconfiguration.

Also, there has been a lot of research on metaheuristic-based approaches. The African Vultures Optimisation Algorithm (AVOA) in [4] and the Grasshopper Optimisation Algorithm (GOA) in [5] show how to combine EVCSs, DGs, and compensating devices to allocate EVCSs, DGs, and compensating devices in a way that reduces losses and increases voltage. But these analyses often rely on complex fuzzy or multi-stage frameworks, which require more computer resources and may be more difficult to scale. En outre, when forecasting EV charging, people tend to rely on static or simple assumptions that do not take into account the network's potential to change during reconfiguration.

To deal with unpredictability and the necessity to achieve various goals, more intricate planning frameworks have been proposed. For instance, in the context of uncertainty, [6] uses a mixed-integer linear programming model that incorporates both private EVCS investments and NR. However, the nonlinear flow of power cannot be explained by the linear approximation. In [7] and [8], several important pieces of information on adaptive planning and demand response integration are revealed. They could, however, render the application unfeasible due to their high data requirements and computational complexity. Recent hybrid and advanced optimization techniques (SMA [9], HAVOPS [10], BSSA [11], and QGDA [12]) enhance voltage stability and reduce losses by combining Electric Vehicle Charging Stations (EVCSs) with Distributed Generators (DGs), energy storage systems, and reactive power devices. These approches fonctionnent bien, bien qu'ils parlent souvent d'amélioration de la performance et non de changement de la structure du réseau. They tend to regard EVCS deployment as part of DG allocation rather than a separate planning issue.

Current research has exhaustively examined EVCS placement, DG allocation, and NR; however, most studies examine these modules either sequentially or within complex multi-objective structures. Particularly, (i) the synergy of NR with EVCS planning is not fully explored, (ii) EVCSs are often conceptualized alongside DGs, despite their distinct operational characteristics, and (iii) insufficient attention is given to the combination of metaheuristic search with convex optimization techniques to enhance solution quality and computational efficiency.

Coordination planning paradigm for EVCS placement, DG scale and allocation, and network reconfiguration. A particle swarm optimisation (PSO) is employed to locate the best EVCSs, and second-order cone programming (SOCP) is employed to locate the best sizes and positions for DGs in a reconfigured network. The proposed solution distinguishes EVCSs from DGs and uses NR to enable flexibility. This reduces power loss and improves voltage profiles while making the calculations easier.

2. METHODOLOGY

2.1 Power flow equations

B.P. Swaminathan [14] first introduced the Branch Flow Model (BFM), also known as the DistFlow model, as a precise reformulation of the Optimal Power Flow (OPF) problem. This model shows radial distribution networks by focusing on how power flows through the lines. This sets it apart from other models, like the Bus Injection Model (BIM), which shows how power flows through the network based on injection equations at different buses. A set of recursive equations known as distribution flow branch equations can be used to describe the power flow in a radial distribution network (Figure1).

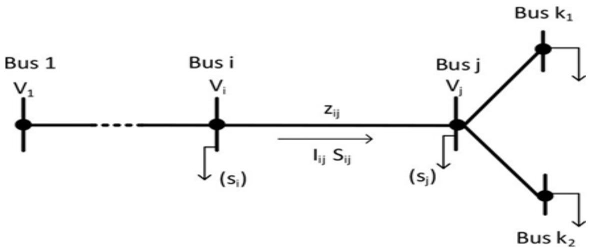

Figure 1. Branch Flow Model.

For this network, the BFM model can be described by the following complex equations [13]:

$$\sum_{k:(i,k)\in E} p_{ik} = p_{ji} - r_{ij} I_{ij}^2 - p_i^L \quad (1)$$

$$\sum_{k:(i,k)\in E} q_{ik} = q_{ji} - x_{ij} I_{ij}^2 - q_i^L \quad (2)$$

$$v_i^2 = v_j^2 - 2\left(r_{ij} p_{ji} + x_{ij} q_{ji}\right) + I_{ij}^2 \left(r_{ij}^2 + x_{ij}^2\right) \quad (3)$$

$$I_{ij}^2 = \frac{p_{ji}^2 + q_{ji}^2}{v_j^2} \quad (4)$$

With p_{ij} and q_{ij} express the active and reactive powers of bus i to bus j, v_i voltage magnitude, and p_i^L, q_i^L real and reactive loads at bus *i*. Note that p_{ij} and q_{ij} do not equal p_{ji} and q_{ji}. Since v_i does not appear in our formulation, we consider v_i^2 is considered as a variable itself. Let V represent all the buses and E the set of lines, and r_{ij}, x_{ij}, represent the resistance and the reactance of the line, respectively. Single-index constraints represent all (i) in V, and double-index constraints represent all (i, j) in E. The advantage of the branch flow model is that the power flow equations take a neat recursive structure, simplifying computation.

2.2 Mixed-Integer Second-Order Cone Programming (MISOCP)

By leaving out only the final term in equation (3), we create a Mixed Integer Second-Order Cone Programming (MISOCP) approximation of the DistFlow equations that permits voltage to vary from one per unit (p.u.). The fact that this term is much less than the others due to the squared p.u. resistance and reactance justify this change.

An MISOCP is obtained for loss minimization by coupling the quadratic objective:

$$\min_{p,q,y,z} \sum_{(i,j)} r_{ij}\left(p_{ij}^2 + q_{ij}^2\right) \tag{5}$$

$$\sum_{j:(i,j)\in E} p_{ij} = p_i^F \qquad i \in V^F \tag{6}$$

$$\sum_{j:(i,j)\in E} q_{ij} = q_i^F \qquad i \in V^F \tag{7}$$

with the linear set of constraints.

$$0 \le p_{ij} \le M z_{ij} \tag{8}$$

$$0 \le q_{ij} \le M z_{ij} \tag{9}$$

$$z_{ij} \ge 0 \tag{10}$$

$$z_{if} = 0 \qquad f \in V^F \tag{11}$$

$$z_{ij} + z_{ji} = 1, \qquad (i,j) \in E \setminus E^S \tag{12}$$

$$z_{ij} + z_{ji} = y_{ij}, \qquad (i,j) \in E^S \tag{13}$$

$$\sum_{j:(i,j)\in E} z_{ji} = 1 \qquad i \in V / V^F \tag{14}$$

$$y_{ij} \in \{0,1\}, \qquad (i,j) \in E^S \tag{15}$$

The radiality constraint has represented by two variables z_{ij} and z_{ji} which are assigned to each line indicating which direction, if any, the flow can travel. Each switched line is associated with a single binary variable y_{ij}, which will be equal to zero if the switch is open and equal to one if closed.

The constraints related to the SOCP approximation are [14]:

$$\tilde{p}_i = -p_i^L + \sum_{j:(i,j)\in W} p_{ji} - p_{ij} \tag{16}$$

$$\tilde{q}_i = -q_i^L + \sum_{j:(i,j)\in W} q_{ji} - q_{ij} \tag{17}$$

$$\tilde{v}_i^2 \le v_j^2 + M(1 - z_{ji}) \tag{18}$$

$$\tilde{v}_i^2 \ge v_j^2 - M(1 - z_{ji}) \tag{19}$$

$$r_{ij}(p_{ji}^2 + q_{ji}^2) \le \tilde{v}_i^2 \tilde{p}_i \tag{20}$$

$$x_{ij}(p_{ji}^2 + q_{ji}^2) \le \tilde{v}_i^2 \tilde{q}_i \tag{21}$$

$$v_i^2 \le v_j^2 - 2\left(r_{ij} p_{ji} + x_{ij} q_{ji}\right) + M\left(1 - z_{ji}\right) \tag{22}$$

$$v_i^2 \ge v_j^2 - 2\left(r_{ij} p_{ji} + x_{ij} q_{ji}\right) - M\left(1 - z_{ji}\right) \tag{23}$$

$$v_i^2 = 1\ pu \quad i \in B^F \tag{24}$$

We utilize disjunctive constraints in (18), (19), (22), and (23), which are only activated when $z_{ji} = 1$. Specifically, when $z_{ij} = 1$, these constraints align with (3) but exclude the final term. Conversely, for $z_{ij} = 0$, they impose no restrictions, assuming M is sufficiently large. Additionally, the combination of (18), (19), (20), and (25) ensures that (1) and (2) hold when $z_{ij} = 1$, while remaining inactive when $z_{ji} = 0$. The additional variables and are introduced to reformulate the constraints into a Mixed Integer Second-Order Cone Programming (MISOCP) structure that can be efficiently processed by commercial solvers.

2.2.1 Extended Mixed-Integer Second-Order Cone Programming (EMSOCP)

Three decision variables are introduced: and, which are continuous variables representing the size of the distributed generators (DGs), and hi, a binary variable indicating whether the ith DG is installed. The bus where a DG is placed is treated as a feeder. Consequently, two additional constraints, (26) and (27), are incorporated to simultaneously optimize network reconfiguration alongside the placement and sizing of DGs.

The new objective function power loss minimization is represented by:

$$\min_{p,q,p^{dg},q^{dg},y,z,h} \sum_{(i,j)} r_{ij}\left(p_{ij}^2 + q_{ij}^2\right) + \alpha \sum_{k=1}^{N_{bus}} \left(p_k^{dg} + q_k^{dg}\right)\ldots + \lambda \sum_{k=1}^{N_{bus}} h_k \tag{25}$$

$$\sum_{j:(i,j)\in V^{DG}} p_{ij} - p_{ji} = h_i \cdot p_i^{dg} \quad i \in V^{DG} \tag{26}$$

$$\sum_{j:(i,j)\in V^{DG}} q_{ij} - q_{ji} = h_i \cdot q_i^{dg} \quad i \in V^{DG} \tag{27}$$

$$\sum_{i=1}^{Ndg} h_i = N_{DG} \qquad i \in V^{DG} \tag{28}$$

Size of DG units should be within specific limits:

$$\begin{cases} p_{i,\min}^{dg} \le p_i^{dg} \le p_{i,\max}^{dg} \\ q_{i,\min}^{dg} \le q_i^{dg} \le q_{i,\max}^{dg} \end{cases} \quad i \in V^{DG} \tag{29}$$

Where $p_{i,\max}^{dg}$, $q_{i,\max}^{dg}$ and $p_{i,\min}^{dg}$, $q_{i,\min}^{dg}$ are maximum and minimum power supplied by DG, respectively. The optimization problem formulated in equations (5–29) is classified as an Extended Mixed-Integer Second-Order Cone Programming (*EMSOCP*) model. The objective function (26) is a convex quadratic function, while most constraints are affine. However, constraints (26) and (27) introduce nonlinearity. To address this, they can be substituted with alternative linear constraints (30) and (31) using the Big-M method.

$$\begin{cases} \sum_{j:(i,j)\in E} p_{\text{ij}} - p_{\text{ji}} \le p_i^{dg} & i \in V^{DG} \\ p_i^{dg} \le M \cdot h_i \end{cases} \tag{30}$$

$$\begin{cases} \sum_{j:(i,j)\in E} q_{\text{ij}} - q_{\text{ji}} \le q_i^{dg} & i \in V^{DG} \\ q_i^{dg} \le M \cdot h_i \end{cases} \tag{31}$$

When h_i is equal to one, (30) and (31) are disabled, otherwise p_i^{dg} and q_i^{dg} are set to zero.

$$nDG^{\min} \le \sum_{k=1}^{nBus} h_k \le nDG^{\max} \tag{32}$$

Since non-RES distributed generators (PQ+-type) can inject both active and reactive power, this study places restrictions on both. To guarantee that all loads are supplied, the distribution network's radial topology must also be maintained. If a solution doesn't satisfy these requirements, it will be considered invalid.

2.3 Optimal EVCS Placement in RDN Using PSO

The PSO algorithm mimics natural collective behavior, such as fish schools and bird flocks, to increase searches. Here, it is used to determine the appropriate location for EVCS. A swarm is a group of particles, each of which represents a possible solution. The particles' position and velocity are iteratively modified and initialized at random to improve the solution. The method tracks the global best (Gbest) and personal best (Pbest) locations, which indicate the best solutions at the individual and swarm levels. Velocity updates rely on random variables and acceleration coefficients and influence convergence and search efficiency. By altering these factors, the swarm can be guided toward the optimal solution. PSO aims to identify the ideal placement for EV charging stations by repeatedly optimizing the fitness function to minimize power losses. [15]

$$V_i^{k+1} = \gamma \times \left[V_i^{k+1} + c_1 r_1 \times \left(P_{Best,i}^k - X_i^k \right) + c_2 r_2 \times \left(G_{Best,i}^k - X_i^k \right) \right] \tag{33}$$

Compute Constriction Factor [12]:

$$\gamma = \frac{2}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}} \tag{34}$$

Where:
V_i = velocity of the particle i;
φ_1= Cognitive coefficient;
φ_2= Social coefficient;
$c_1 = \gamma \cdot \varphi_1$: Personal Learning Coefficient;
$c_2 = \gamma \cdot \varphi_2$: Global Learning Coefficient;
$\varphi = \varphi_1 + \varphi_2$: Total acceleration coefficient;
r_1, r_2 = random numbers in [0,1]
P_{Best} = personal best of the particle i;
G_{Best} = global best of the particle i;
The equation above determines the velocity at both the personal best and global best positions. Within the search space, the particle's current position is updated using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \qquad i = 1, 2 \cdots, n \tag{35}$$

Where:
X_k = current position of the particle i;
X_{k+1} = New position of the particle i;
V_{k+1} = New velocity of the particle *i*
n is the number of particles in the search space.
One effective metaheuristic method for electrical distribution network optimization is particle swarm optimization, or PSO. It uses an iterative search directed by particle collaboration to arrive at the best answer, drawing inspiration from the collective behavior of natural swarms. PSO is used in distribution networks to address issues like improving the voltage profile, minimizing active losses, and achieving optimal power flow. Its capacity to effectively manage multi-objective problems while adhering to a complicated set of operational and technical restrictions sets it apart. PSO is a powerful instrument for enhancing the functionality, dependability, and financial effectiveness of contemporary electrical networks because of its quick convergence, simplicity in deployment, and resilience.

2.3.1 Particle Swarm Optimization Process:

The procedures shown in Figure 2 are followed by the PSO-based method for positioning EVCS in the IEEE 33-bus distribution network as efficiently as possible:

1. Load bus and line data, then initialize EVCS.
2. Define the number of iterations and set PSO parameters, including the upper and lower limits for EVCS placement.
3. Initialize the velocities and positions of particles within the swarm.

4. Set the iteration counter to one.
5. Perform load flow analysis to evaluate the best particle's index, velocities, positions, and power losses.
6. Identify the global best and local best solutions.
7. Update velocities and positions using Equations (33) and (35).
8. Determine the best particle index for EVCS and evaluate the optimal value.
9. Update the global and local best solutions for the swarm.
10. If the maximum number of iterations is reached, proceed to the next step; otherwise, increment the iteration counter and repeat steps 6–9.
11. Display the optimal EVCS locations along with their capacities, voltage levels, and power losses.
12. Terminate the process.

Figure 3 presents the convergence graph, which illustrates how the fitness value evolves throughout the iterations. The horizontal axis represents the iteration count, while the vertical axis displays the Best Value, corresponding to the fitness score. The curve in the graph depicts the progression of the PSO algorithm as it gradually approaches an optimal solution.

This study employs the Backward and Forward Sweep (BFS) method to examine the load flow of the IEEE 33-bus system. This technique's method is shown in Figure 4. Because it is very accurate, flexible, easy to use, and converges quickly, distribution network engineers often use the BFS method. The size and structure of a network determine how hard it is to compute, which goes up linearly with the number of buses and branches. For small to medium-sized distribution networks, like the IEEE 33-bus system that this study looks at, BFS is a reliable and effective solution. This study evaluates the impact of EV charging station placement by incorporating the BFS methodology into the PSO algorithm.

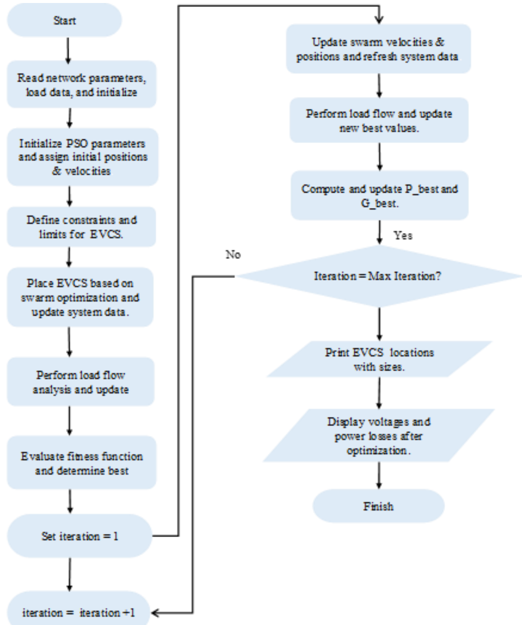

Figure 2. Flow chart of PSO with the optimal position of electric vehicle charging station (EVCS).

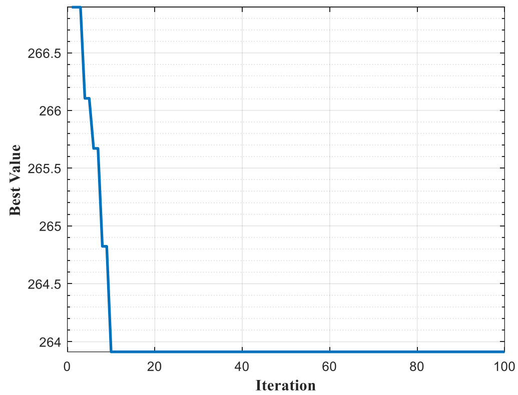

Figure 3. PSO algorithm convergence curve.

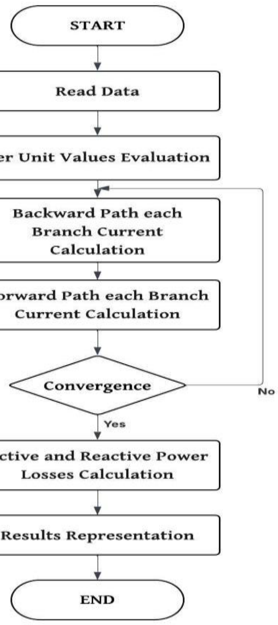

Figure 4. Flow chart of load flow analysis by backward and forward sweep method.

3. RESULTS AND DISCUSSION

We tested the efficacy of the suggested approach using the IEEE 33-node radial distribution network (RDS). There are 37 switches, 32 disconnectors, and 5 interconnectors in this network. Normally, switches 33, 34, 35, 36, and 37 are open, and the rest are closed. The system requires 3,715 kW of total active power, 2,300 kVAr of reactive power, and 12.66 kV of network voltage. The graphic illustrates how this distribution network is separated into five different zones. To accommodate the various charging requirements of these zones, direct current (DC) and alternating current (AC) charging stations were set up. For instance, a charging station in Zone 1 that has one high-capacity 120 kW DC fast charger and four 3.3 kW AC chargers may charge up to nine electric vehicles at once without going over the grid's capacity. The charging mechanisms in regions 2 through 5 (see Figure 5) are comparable. These systems are made to adjust to each zone's unique infrastructure and pace of electric car adoption.

The IEEE 33-bus network strategically places electric vehicle charging stations (EVCSs) to enhance overall system performance. First, Particle Swarm Optimization (PSO) is used to determine the optimal locations for EVCSs. However, EVCS integration increases total power losses and modifies the voltage profile. To solve these issues, the network is first reconfigured to improve power flow distribution and reduce losses. Distributed generators (DGs) are then added to provide enhanced system stability and further loss reduction, and their optimal locations and sizes are determined using Second-Order Cone Programming (SOCP).

This study investigates the combined impacts of DG allocation, network reconfiguration, and EVCS integration on power losses and voltage profile in a radial distribution network under both the original and modified operating conditions. Three distinct case studies serve as the foundation for the research and are described as follows:

- **Case 1**: Placement of electric vehicle charging stations (EVCS) without network reconfiguration and DG placement.
- **Case 2:** Reconfiguration of the distribution network after optimal placement of five EVCS;
- **Case 3**: Simultaneous placement of five EVCS and optimal integration of one distributed generator (DG) and network reconfiguration.
- **Case 4**: Simultaneous placement of five EVCS and optimal integration of three distributed generators (DGs) and network reconfiguration.

Literature findings indicate that the inclusion of more Distributed Generator (DG) units beyond a certain point yields minimal impact on reducing power losses in radial distribution networks (RDNs). As a result, this study limits the number of DG units to three for the test case. Nevertheless, the model remains flexible, allowing for adjustments in the number of units if necessary. It is also assumed that each bus can accommodate only a single DG unit and EVCS.

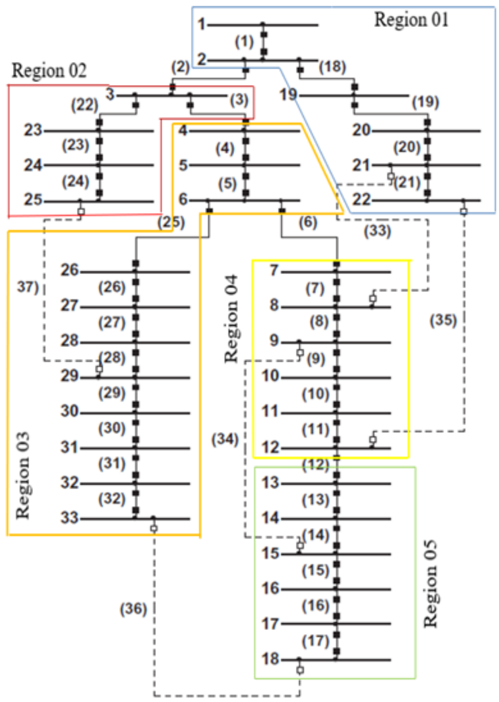

Figure 5. IEEE 33 bus split into five regions.

Base Case Analysis: The base case reflects the typical operating conditions of the IEEE 33-bus distribution network, without the integration of Distributed Generators (DGs), Electric Vehicle Charging Stations (EVCSs), or any network reconfiguration strategies. This configuration serves as a benchmark for evaluating the performance improvements achieved through subsequent modifications. In the base case, the system supports total active, reactive, and apparent power loads of 3715 kW, 2300 kVAr, and 4369,4 kVA, respectively. The corresponding power losses are calculated as 202,66 kW for active power and 135.14 kVAr for reactive power. As a result, the total active power drawn from the main grid or substation amounts to 3917,66 kW. These values establish a baseline against which the effects of DG and EVCS integration, as well as network reconfiguration strategies, are assessed in later sections.

Case-1: EVCS Integration without network reconfiguration and DG placement: In this scenario, five electric vehicle charging stations (EVCSs) are deployed, each with the capacity to support up to 50 electric vehicles (EVs), as outlined earlier in the study. The primary goal is to minimize power losses by determining the most effective locations for these EVCSs within the distribution network (RDN). The outcomes, detailed in Table 1, are obtained following optimization via the Particle Swarm Optimization (PSO) technique. The results show that 120 EVs are successfully charged at buses 2, 3, 4, 9 and 13. The lowest power loss achieved is 250,03 kW, marking a 23,37% increase compared to the base case scenario. Additionally, the minimum voltage level observed is 0,8991 p.u. at bus 18 (see Figure 6). These results indicate that the integration of EVCSs, in the absence of reconfiguration or DG support, leads to increased power losses and voltage deviations, such adverse effects may be alleviated through network reconfiguration and judicious siting and sizing of DG units.

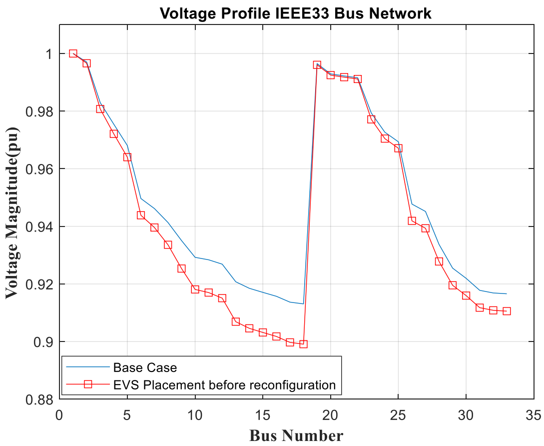

Figure 6. Pre-reconfiguration voltage profile during EVCS deployment.

Case-2: the Reconfiguration of the Radial Distribution Network (RDN) after EVCS Integration:

To mitigate these effects, the first step is to reconfigure the network, combined with optimal positioning of the EVCS. The planning strategy used in this study uses the PSO algorithm for the best location of EVCSs and the EMSOCP algorithm for network reconfiguration in order to minimize overall power losses. Table 1 provides information on the quantity of electric cars allotted and the bus locations of the charging stations that correspond to those vehicles. The system achieves a minimal power loss of 163,97 kW in this configuration, which is 19,09% less than in the basic case. Furthermore, the voltage profile exhibits a notable improvement over instance 1, with bus 32 recording the lowest voltage at 0,9399 p.u. (see Figure 7).

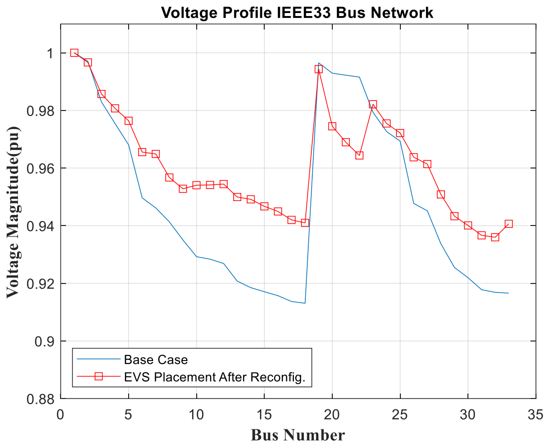

Figure 7. Post-reconfiguration voltage distribution during EVCS integration.

Table 1. Results of different cases for 33 bus RDN considering total power loss minimization objective.

	Base Case	**Case 1**	**Case 2**	**Case 3**	**Case 4**
Open tie switches	33; 34; 35; 36; 37	33; 34; 35; 36 ;37	5; 10; 13; 23; 33	5 ;10 ;13 ; 23 ;33	3; 9; 17; 21; 24
DG size in MW (Bus number).	--------	--------	--------	0,278+ j0,181 (29)	0,108+ j0,055 (07) 0.074+ j0.037 (13) 0.125+ j0.112 (30)
EVCS bus number.	--------	2 ;3 ;4 ;9; 13	2; 3; 4; 9; 13	2; 3; 4; 9; 13	2; 3; 4; 9; 13
Active power loss (in kW).	202,66	250,03	163,97	42,81	13,29
Active power loss reduction (in %).	--------	- 23,37	19,09	78,88	93,44
Reactive power loss (in kVar).	135,14	165,45	121,92	36,70	11,26
Reactive power loss reduction (in %).	--------	- 22,43	9,78	72,85	91,67
Minimum voltage in p.u. (bus number)	--------	0,8991 (18)	0,9399 (32)	0,9753 (14)	0,9914 (24)

Table 2. Comparison of power loss reduction in the IEEE 33-bus distribution system using the proposed hybrid PSO–EMSOCP approach and other optimization techniques.

Techniques	DG Location	DG size (kW)	Min. Voltage (pu)	Active Power loss in kW (Without DG)	Active Power loss in kW (With DG)	Power loss reduction (%)
Simulated annealing [16]	30,13	79.45,96	0.918	199.102	178.28	10.458
Artificial bee colony [17]	29,30	1017,628	0.928	210.97	121.89	42.22
Genetic algorithm [18]	29,8,32,16	500,500,500,500	0.932	210.61	78.920	62.52
Particle swarm optimization [19]	6,32	873.8,1310.8	0.9378	206.63	71.850	65.27
Hybrid PSO–SOCP [Proposed]	7,13,30	108,74,125	0,9914	164.53	13,29	91,92

Cases 3 and 4: Co-optimized Placement of EV Charging Stations and Distributed Generation with Network Reconfiguration: In these scenarios, electric vehicle charging stations (EVCS) and distributed generators (DGs) are strategically deployed together within the IEEE 33-bus distribution network, with dynamic grid reconfiguration. The optimization process, executed using the EMSOCP algorithm, focuses on minimizing total active power losses. Table 1 outlines the optimal bus locations for both DGs and EVCS. For Scenario 3, involving a single DG, the system achieves a reduced power loss of 42,81 kW (an 78,88% reduction from the base case). In Scenario 4, with three DGs integrated, losses drop further to 13,29 kW (93,44% lower than the initial scenario). Additionally, voltage stability improves markedly over earlier cases (Scenarios 1 and 2), with the minimum voltage recorded at 0,9753 p.u. (Bus 14) and 0,9914 p.u. (Bus 24), respectively (see Figure 8).

The analysis of reactive power losses in the IEEE 33-bus distribution network reveals notable variations across different configurations. Initially, when EVCSs are optimally allocated at buses 2, 3, 4, 9, and 13 without applying network reconfiguration, the reactive losses reach 165.45 kVAr—an increase from the baseline value of 135,14 kVAr. However, when EVCS placement is combined with optimal network reconfiguration, reactive power losses significantly drop to 121,92 kVAr (see Figure 9). Additional improvements are achieved through the integration of distributed generation (DG). The installation of a single DG rated at 0,278+ j0,181 MVA on bus 29 further reduces reactive losses to 36,70 kVAr, while the deployment of three DG units—rated at 0,108+ j0,055 MVA, 0.074+ j0.037 MVA, and 0.125+ j0.112 MVA at buses 7, 13, and 30 respectively—results in a final reduction to 49.68 kVAr.

These results, summarized in Table 1, highlight the effectiveness of combining EVCS allocation, network reconfiguration, and strategic DG placement in enhancing the reactive power performance of the system.

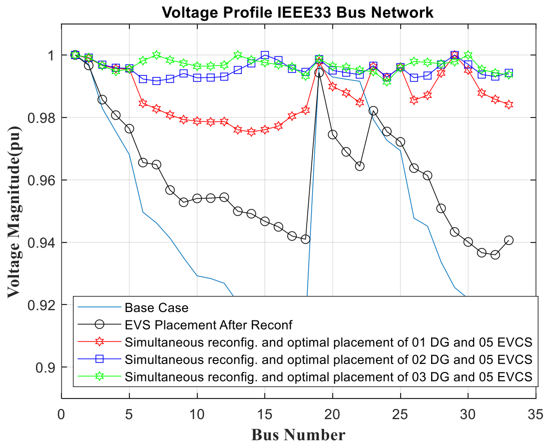

Figure 8. Voltage profile after reconfiguration under simultaneous EVCS–DG integration.

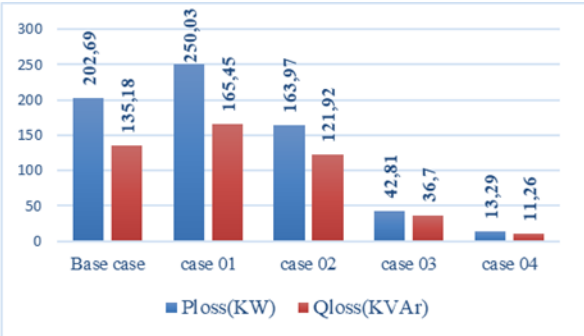

Figure 9. Overall power losses in the IEEE-33 bus distribution system following reconfiguration and the integration of EVCS and DG units.

Table 2 details a comparative assessment of the hybrid PSO-EMSOCP algorithm against established methods, including, SA, ABC, GA, and PSO, focusing on minimizing active power losses and improving the voltage profile. The results reveal that the PSO-EMSOCP method achieves a power loss reduction approximately ninefold greater than SA, twofold greater than ABC, 1.5-fold greater than GA, and 1.4-fold greater than standard PSO. Additionally, the proposed algorithm offers marked advantages in processing time, overall efficiency, and

implementation flexibility over the benchmarked techniques.
Beyond the technical analysis, it is important to consider the practical implications of integrating electric vehicle charging stations (EVCS) and distributed generators (DGs). Adding DG units involves economic trade-offs, as each unit incurs investment and maintenance costs that need to be balanced against the savings from reduced energy losses and improved voltage quality. For utility operators, the co-integration of EVCS and DGs not only reduces active and reactive losses but also enhances operational flexibility and network resilience under varying load profiles, particularly those associated with electric vehicles. Finally, the system's sensitivity to parameters such as DG ratings, EVCS capacities, and network topology indicates that small variations can significantly affect losses and voltage levels, emphasizing the need for careful planning and robust optimization tools.

4. CONCLUSION

The deployment of electric vehicles (EVs) constitutes an effective strategy for reducing greenhouse gas emissions from traditional fossil-fuel-based transportation. However, the extensive integration of electric vehicle charging Stations (EVCSs) introduces significant operational complexities within electrical networks distribution, primarily through elevated power losses and deterioration in voltage regulation. This study assesses the impact of EVCS implementation on the IEEE 33-bus distribution network, demonstrating increased active power losses and voltage profile degradation when mitigation strategies are not employed. To counter these effects, a comprehensive methodology combining network reconfiguration and the optimal allocation of distributed generators (DGs) is proposed. EVCS placement was optimized using the Particle Swarm Optimization (PSO) algorithm, whereas grid reconfiguration and the optimal sizing and siting of DG units were carried out via the Enhanced Mixed Second-Order Cone Programming (EMSOCP) technique. Simulation outcomes reveal notable enhancements in network performance, including a substantial reduction in total power losses and significant improvement in voltage stability. Despite the positive results, the scope of this work is limited to a medium-sized distribution network and does not incorporate dynamic variables such as temporal load variations or the intermittency of renewable energy sources. Future investigations should aim to adapt and scale this framework for larger, more diverse distribution systems, integrating time-dependent behaviors and energy storage technologies. This study could also be extended in several promising directions.

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