Optimal Integration of EV Charging Stations and Capacitors for Net Present Value Maximization in Distribution Network

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***Abstract*—The widespread adoption of electric vehicles (EVs) is crucial for reducing greenhouse gas emissions from traditional vehicles. Central to this adoption is the strategic deployment of electric vehicle charging stations (EVCS), whose improper positioning can pose challenges to electrical networks and utility operators. This paper introduces a novel hybrid approach for optimizing the placement of EVCS and capacitors (CAP) in the distribution network (DN) to mitigate active power loss (APL) and enhance operational efficiency. The methodology includes the optimal placement of CAP banks and EVCS across the network, which is evaluated using the Net Present Value (NPV) criterion. Additionally, the study comprehensively considers the integration of vehicle-to-grid (V2G) capabilities, enhancing network reliability. The proposed hybrid algorithm combines the genetic algorithm (GA) and particle swarm optimization (PSO), i.e., HGAPSO, which leverages their respective strengths in exploration and exploitation. A comprehensive sensitivity analysis is conducted for the IEEE 33, 69, 85, 118, and Brazil 136-bus systems, focusing on cost variables such as energy prices, maintenance costs, and system parameters. This analysis further validates the robustness of the proposed approach, demonstrating significant reductions in APL and maximization of net profit. Comparative results verify the superiority of the hybrid approach over conventional GA and PSO in optimizing the locations of charging stations and reactive power sources within networks.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9278

***Index Terms*—Capacitors, Distribution Network, Electric Vehicle Charging Stations, Net Present Value, Sensitivity Analysis, Vehicle-to-Grid.**

I. Introduction

ELECTRIC vehicles (EVs) represent a transformative shift in the automotive industry, offering significant advantages such as lower emissions, higher energy efficiency, and reduced reliance on fossil fuels compared to traditional internal combustion engine vehicles [1]. The global market for EVs is experiencing robust growth, with projections indicating sales could reach approximately 17 million units in 2024, representing more than one-fifth of total vehicle sales worldwide [2]. This surge underscores the pressing need for expanded charging infrastructure to support the increasing number of EVs on the roads. However, scaling up charging stations poses challenges, including impacts on the electrical grid's capacity and stability. Addressing these challenges requires strategic improvements in grid infrastructure and the deployment of technologies like smart grids and CAP at charging stations to optimize efficiency and maintain grid stability [3]-[5]. As the EV market continues to evolve, navigating these issues will be crucial to facilitating a smooth and sustainable transition towards widespread EV adoption globally.

The optimal placement of CAP in DN is crucial for enhancing network efficiency and reliability. This process addresses challenges such as voltage fluctuations, power losses, and compliance with power quality standards like IEEE-519. Strategic determination of the locations, types, sizes, and control strategies of CAPs is necessary to minimize losses, improve voltage profiles, and manage reactive power. Recent research has utilized various advanced computational methods to achieve these goals.

Several studies have addressed the CAP placement problem using sophisticated algorithms such as GA, ant colony optimization, simulated annealing, fuzzy logic, and hybrid approaches combining these techniques. These methods aim not only to optimize placement but also to consider multiple objectives, including economic costs, power quality improvements, and compliance with voltage and current harmonic standards.

For instance, the hybridization of Tabu Search with GA and simulated annealing has shown promising results in optimizing both the quality and cost of solutions [6]. Additionally, ACO has been effective in determining optimal CAP locations for reactive power compensation in DN [7]. Microgenetic algorithms combined with FL have addressed the economic savings from reducing energy losses while considering voltage constraints [8]. These methodologies underscore the significance of integrating computational intelligence with engineering principles to tackle the complexity of DN optimization. The [9], [10] introduces and tests a scenario-based stochastic model designed for multistage joint expansion planning of distribution systems and EV charging stations.

Furthermore, recent advancements include GA-based approaches that simultaneously improve power quality and optimize CAP placement under IEEE standards [11], [12]. Such algorithms incorporate fuzzy approximate reasoning to enhance decision-making under uncertainty, aiming for global solutions with reduced dependency on initial conditions.

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Moreover, the deployment of optimization algorithms like PSO, teaching-learning-based optimization, and their hybrids have demonstrated effectiveness in determining capacitor sizes and locations across various DS configurations [13], [14]. These methods not only minimize losses but also enhance system reliability by considering load variations and operational constraints.

In the realm of electric vehicle integration, strategic placement of EVCS within DN is essential to mitigate challenges such as voltage stability and power loss [15]. Research has shown that combining EVCS with CAP can significantly improve system reliability and efficiency. For instance, GA has optimized the placement of EVCS and CAP in a 34-bus network, resulting in substantial reductions in APL and enhanced voltage stability [16]. Efforts to optimize fast charging station networks have integrated energy storage devices and optimized power allocation, enhancing service quality while reducing grid strain during peak demand [17]. Other studies have utilized biogeography-based optimization to allocate EVCS and CAP, improving network performance through congestion management and reactive power compensation [18].

Hybrid optimization techniques, such as GWO combined with PSO, have effectively minimized APL and enhanced network reliability by optimizing EVCS and CAP locations [19], [20], [21]. Additionally, integrating battery energy storage systems with CAP has been proposed to stabilize voltage and improve efficiency in DN [22]. Further enhancements have been achieved through hybrid PSO and direct search methods, which optimize EVCS and CAP placement by maximizing coverage, minimizing losses, and reducing voltage deviations in DN [23].

The integration of EVs into DN necessitates a comprehensive examination of various charging strategies [24]. Additionally, optimizing charging schedules is crucial for reducing operational costs and preventing transformer overload, particularly within the Brazilian context [25]. The determination of optimal locations for EVCS and CAP plays a pivotal role in enhancing overall system performance [26]. Furthermore, evaluating the feasibility of renewable energy sources, such as wind-powered EVCS paired with battery storage, contributes to sustainable energy solutions [27]. Employing hybrid algorithms is vital for minimizing power losses and improving voltage regulation across DN [28], [29, [30]. In light of these considerations, [31] proposes a three-step method for optimal CAP placement in unbalanced DN by combining power flow optimization, GA, and binary optimization to minimize energy losses. The [32] investigates model-based estimation for a wind-powered EVCS with a vanadium redox flow battery. In [33] evaluates strategies for improving hosting capacity and reducing power losses using a multi-objective GA in a Python-based simulation environment.

In this paper, the primary contribution is the optimal placement of EVCS and CAP banks in order to enhance the efficiency and sustainability of radial DN. Accordingly, at first, a cost-benefit analysis is employed using the NPV criterion that integrates the energy-saving benefits and cost factors to optimize the net profit. This includes a comprehensive analysis of the cost factors, including the operating and installation costs of EVCS and CAP. Then a novel method is proposed to strategically locate CAP banks and EVCS to minimize the power loss. A novel optimization approach utilizing GA and PSO, namely HGAPSO, is used to validate the proposed approach across various standard and practical DN. Finally, the study demonstrates that integrating EVCS in radial networks with the participation of EVCS in a V2G mode reduces APL and increases the NPV.

The remainder of this paper is structured as follows: In Section 2, we delve into the problem formulation by introducing a formula to calculate power loss in radial DN and discuss the NPV criterion used for project evaluation. Section 3 presents the methodology employed to optimize the placement of EVCS and CAP. Following this, Section 4 offers a detailed presentation of our simulation results. Lastly, Section 5 concludes the paper by summarizing key findings and outlining potential avenues for future research.

II. Problem Formulation

A. Power Loss in a Radial Distribution Network

Feeders in radial DN have more resistance than transmission systems, which means their feeders are primarily resistive rather than reactive, or in other words, these feeders have a higher R/X ratio. The traditional methods for analyzing power flow, like Gauss-Seidel and Newton-Raphson, are better suited for transmission systems, where the reactive component is more significant [16]. The main aim of placing EVCS and CAP within networks is to reduce APL. This power loss significantly affects yearly sales. We use a method called backward-forward sweep (BFS) analysis to figure out this loss [34]- [35]. Indeed, in a DN, the total power loss is calculated by summing the power loss across all system branches. For feeders, the power loss can be assessed using the simple formula:

$$P_{loss} = I_i^2 \cdot R_i \tag{1}$$

Where P_{loss} represents the power loss, I_i is the current flowing through the ith branch, and R_i is the resistance of the ith branch of the system.

B. EVCS Model

This study delves into the impact of EVCS on the distribution network. These stations offer dual functionality: They can act as Load Consumers (G2V mode) or Grid Supporters (V2G mode). During charging, EVCSs draw power from the grid, adding to the overall load. During Grid Supporters (V2G mode), when not in use, EVs plugged into EVCSs can actually return power to the grid. This helps reduce stress on the grid during peak demand periods. The load model can be expressed as [19]:

$$P_{\text{load}}^{\text{new}} = \sum_{i=1}^{nb} P_{\text{load}}^{\text{base}} + \gamma \sum_{i=1}^{nb} P_{\text{load}}^{\text{evcs}} \tag{2}$$

where γ represents the factor that could vary based on whether it's in G2V or V2G mode.

$$\gamma = \begin{cases} + & \text{G2V mode} \\ - & \text{V2G mode} \end{cases} \tag{3}$$

C. Capacitor Model

In this study, CAP are employed to compensate for reactive power. This compensation reduces the reactive power requirement at bus n, which is achieved by utilizing the reactive power output of the CAP. Equation (4) provides the mathematical representation of this relationship [20].

$$Q_{load}^{new} = Q_{load}^{base} - Q_{load}^{cap} \tag{4}$$

D. Objective Function and Constraints

1) Evaluation of Net Present Value: A commonly adopted method to assess a project's economic feasibility is by comparing the investment cost and expected revenue over the project's lifetime. The NPV presents the user with the net value of the project by subtracting the initial investment from the present value of the net annual cash flow. In this paper, NPV is enlisted to ascertain if a project is economical. The project can be implemented if the NPV is positive, i.e., it adds value to the utility. On the other hand, if the NPV is negative, the project cannot be implemented.

An investment's NPV is determined by summing up the present values of annual profits over the investment period and then subtracting the initial investment cost. The objective is to maximize NPV, assuming fixed values of parameters, including the discount rate, initial costs, and annual savings derived from reduced energy losses. This method, however, does not account for factors such as inflation or dynamic changes in costs over time. The NPV is calculated by the following formula [5]:

$$NPV = \sum_{t=1}^{T} \frac{P_{ann}}{(1+D)^t} - C_{inv} \tag{5}$$

where D denotes the discount rate and T is the expected lifetime of the project.

The net annual profit P_{ann} is calculated by:

$$P_{ann} = S_{ann} - OM_{evc} \tag{6}$$

where S_{ann} represents the annual savings due to the reduction in the cost of energy loss after placing EVCS and CAP, and OM_{evc} is the total operation and maintenance cost for both CAP banks and EVCS.

2) Cost of Energy Loss: The annual savings in the system due to EVCS and CAP banks are given in the equation below.:

$$S_{ann} = C_{ann}^{base} - C_{ann}^{evc} \tag{7}$$

where C_{ann}^{base} represents the base cost of the system without EVCS or CAP, and C_{ann}^{evc} represents the cost after adding EVCS and CAP. The annual cost due to power loss is given by:

$$C_{ann} = P_{loss} \cdot CE \cdot 8760 \tag{8}$$

$$where \quad P_{loss} = \begin{cases} P_{Loss}^{base} & \text{Base case } P_{loss} \\ P_{Loss}^{evc} & P_{loss} \text{ with EVCS and CAP} \end{cases} \tag{9}$$

While calculating the base cost, C_{ann}^{base} is used. When considering the cost after the installation of EVCS or CAP, C_{ann}^{evc} is applied in the above calculation, and CE represents the cost of energy.

The financial aspects related to both the ongoing maintenance and the initial costs associated with CAP banks and EVCS are given below the equation

Total Operation and Maintenance Cost (OM^{evc}) [20], [21]:

$$OM^{evc} = N^c \cdot C_{OM}^c + N^{ev} \cdot C_{OM}^{ev} \tag{10}$$

where:

- N^c and N^{ev} represent the standard number of units for CAP banks and EVCS,
- C_{OM}^c and C_{OM}^{ev} represent the maintenance costs for each CAP bank and each EVCS, respectively.

Initial Investment Cost (C_{inv}) [16]:

$$C_{inv} = C_{inst}^{evc} + C_{pur}^{evc} \tag{11}$$

$$\begin{aligned} C_{inv} = {} & [N^c \cdot C_{inst}^c + N^{ev} \cdot C_{inst}^{ev}] + \\ & [N^c \cdot C_{pur}^c + N^{ev} \cdot C_{pur}^{ev}] \end{aligned} \tag{12}$$

where:

- C_{inst}^{evc} is the installation cost of CAP and EVCS.
- C_{pur}^{evc} is the purchase cost of CAP and EVCS.
- C_{inst}^{c} is the installation costs for CAP banks.
- C_{inst}^{ev} is the installation costs for EVCS.
- C_{pur}^{c}, is the purchase costs for CAP banks.
- C_{pur}^{ev} is the purchase costs for EVCS.

3) Percentage Saving in Cost of Energy Loss: The percentage saving in cost of energy loss (S_{cost}) after installing EVCS and CAP is calculated from the difference of the costs of energy loss for the base case and after EVCS/CAP allocations, as follows:

$$S_{\text{cost}} = \left(\frac{C_{ann}^{\text{evc}} - C_{ann}^{\text{base}}}{C_{ann}^{\text{base}}} \right) \times 100 \tag{13}$$

where C_{ann}^{base} represents the cost of energy loss before EVCS/CAP installation, and C_{ann}^{evc} represents the cost of energy loss after EVCS/CAP installation.

4) Constraints: The objective function is formulated considering equality and inequality constraints that must be satisfied during CAP planning to mitigate the charging impact of EVCS.

a) Equality Constraints: The overall electricity generated must balance with the total losses and the demand for load. The cumulative active and reactive power supplied by the substation must correspond with the total demand for active and reactive power, inclusive of the load requirements for charging stations and the total losses in the system [21].

$$P_{ss} = \sum_{i=1}^{Nb} P_{D_i} + \sum_{i=1}^{Nb} P_{ev_i} + \sum_{r=1}^{Nr} P_{L_r} \tag{14}$$

$$Q_{ss} + \sum_{i=1}^{Nb} Q_{C_i} = \sum_{i=1}^{Nb} Q_{D_i} + \sum_{r=1}^{Nr} Q_{L_r} \tag{15}$$

- P_{ss}, Q_{ss} : Active and Reactive power supplied by the substation,
- Nb: Total number of buses,
- Nr: Total number of branches,
- Q_{C_i}: Reactive power provided by CAP at bus i,
- P_{D_i}, Q_{D_i}: Active and reactive power demand at bus i,
- P_{ev_i}: Active power from EVCS at bus i,
- P_{L_r}, Q_{L_r}: Active and reactive power loss in branch r.

b) Inequality Constraints:

- The voltage at each bus must stay within the range of 0.95 to 1.05 p.u.:

$$V_{min} \leq V_i \leq V_{max}, \quad i = 1, 2, \ldots, Nb \tag{16}$$

- The current in any line should not surpass its maximum limit:

$$I_i \leq I_{max}, \quad i = 1, 2, \ldots, Nr \tag{17}$$

- The reactive power injected at each bus must be within specified bounds:

$$Q_{C_{min}} \leq Q_{C_i} \leq Q_{C_{max}}, \quad i = 1, 2, \ldots, Nb \tag{18}$$

III. Methodology

The paper proposes a method for the optimal placement of EVCS and CAP in DN to reduce power loss. The objective function focuses on three main aspects: Reducing the cost of energy loss, Evaluating investment costs (IC), and determining the NPV. APL, calculated using Equation (1), is crucial for estimating annual savings. The function also considers operational and installation costs to assess IC. The decision variables involve determining the optimal locations and sizes for EVCS and CAP, posing a complex nonlinear problem. Traditional methods for solving such problems are computationally demanding, leading researchers to adopt metaheuristic algorithms (MAs).

MAs, such as GA [36] and PSO [37], are widely used for optimization tasks, including the placement of components in DN. In this study, the Hybrid GA-PSO (HGAPSO) method [21] & [38] is applied to optimize the placement and sizing of CAP and EVCS in DN. By combining the global search strength of GA with the local search capabilities of PSO, HGAPSO effectively finds near-optimal solutions to complex problems with multiple constraints and objectives. The performance of the HGAPSO method heavily depends on parameter tuning, which is detailed in Table 1. The key parameters include the crossover rate, mutation rate, and inertia weight. The crossover and mutation rates in GA help maintain diversity during the exploration phase of the algorithm, while the inertia weight in PSO ensures efficient exploitation of the solution space in the later stages. Initially, the algorithm uses GA operators to explore the solution space broadly and then shifts towards exploitation, refining the solutions using PSO's local search capabilities. This balance between exploration and exploitation enables HGAPSO to converge effectively to a near-optimal solution. The detailed implementation of the HGAPSO algorithm, including its basic structure and pseudocode, is illustrated in Figure 1, highlighting how the hybridization of GA and PSO improves performance over using either method alone.

Here are the steps involved in implementing the proposed objective function using the analytical approach:

1) Load the line and bus data of the IEEE 33, 69, 85, 118, and the practical Brazil 136-bus system.
2) Use BFS load flow analysis to find out the voltage levels at each bus and the currents flowing through each branch.

TABLE I
PARAMETERS USED IN THE HGAPSO ALGORITHM [21], [38]

Name of Parameter	Symbol	Value	Algorithm
Population Size	n	50	GA, PSO
Crossover Probability	cp	0.8	GA
Mutation Probability	mp	0.2	GA
Distribution Index for Crossover	cd	20	GA
Distribution Index for Mutation	md	20	GA
Inertia Weight	w	0.4-0.9	PSO
Cognitive Component	c1	2.01	PSO
Social Component	c2	2.02	PSO

ALGORITHM: Pseudocode for HGAPSO

1 **Input**: Search agent, parameters of GA & PSO
2 **Output:** best fitness function
3 **Input Parameters:** Population Size (n), Number of Iterations (T), Bounds (lb, ub), Crossover Probability (cp), Mutation Probability (mp), Distribution Index (cd, md), Inertia Weight (w), Acceleration Factors (c1, c2)
4 **Initialization:**
P_{GA} = Initialize Population (n, lb, ub) // GA Population Evaluate Fitness (P_{GA}) // Calculate f(X) for each individual
G_{best} = Get Global Best (P_{GA}) // Best individual in GA population
fG_{best}= Fitness (G_{best})
5 t = 1
while t <= T **do**
6 **GA Operations**
7 for i = 1 to n/2 do // Tournament Selection
8 P_a, P_b = Tournament Selection (P_{GA}, k) // Select parents
9 **SBX crossover**:
$O_a - O_b = \beta(P'_a - P'_b)$ // Generate offspring using the SBX Crossover
$$\beta = \begin{cases} (2\mu)^{\frac{1}{(\eta_c - 1)}} & if\ \mu \leq 0.5 \\ \left(\frac{1}{2(1-\mu)}\right)^{\frac{1}{(\eta_c-1)}} & otherwise \end{cases}$$
$O_a = 0.5\,[(1+\beta)P'_a + (1-\beta)P'_b]$ \\The offspring are then computed
$O_b = 0.5\,[(1-\beta)P'_a + (1+\beta)P'_b]$
10 **polynomial mutation**
$$\delta = \begin{cases} (2r)^{\frac{1}{(\eta_m+1)}-1} & if\ r \leq 0.5 \\ 1 - [2(1-r)]^{\frac{1}{(\eta_m+1)}} & if\ \geq 0.5 \end{cases}$$ \\The offspring are then computed
$O = O + (X" - X') \times \delta$ \\Update the offspring position
11 Ensure offspring values are within bounds and evaluate their fitness
12 P_{GA} = Update Population (P_{GA}, O_a, O_b) // with Offspring
G_{best} = Get Global Best (P_{GA}) // Update global best
t = t + 1
13 end for GA loop
14 **PSO Operations**
15 P_{PSO} = Initialize PSO Population (P_{GA}) // Use best individuals from GA
Evaluate Fitness (P_{PSO}) // Calculate fitness for PSO population
P_{best} = P_{PSO} // Initialize personal bests
G_{best} = Get Global Best (P_{PSO}) // Get global best from PSO
16 for i = 1 to n do
17 Generate two random numbers 'r1' and 'r2' between 0 and 1
18 // Update Velocity
$V_i(t+1) = WV_i(t) + c_1r_1[P_{best}(t) - X_i(t)] + c_2r_2[G_{best}(t) - X_i(t)]$
19 $X_i(t+1) = X_i(t) + V_i(t+1)$ // Update Position
20 $X_i(t+1)$ = Bound ($X_i(t+1)$,lb, ub) // Bound Position
21 // Evaluate Fitness
$fitness_{new}$ = Evaluate Fitness ($X_i(t+1)$)
if $fitness_{new}$ < Fitness (P_{best}[i]) then
P_{best}[i] = $X_i(t+1)$ // Update personal best
22 G_{best} = Get Global Best (P_{PSO}) // Update Global Best
t = t + 1
23 **end** of loop
24 $P_{combined}$ = Combine (P_{GA}, P_{PSO}) // Combine both populations
Evaluate Fitness ($P_{combined}$) // Evaluate fitness of combined population
25 return G_{best} // Return the best solution found
26 **end of** the loop

Fig. 1. Pseudo-code for the HGAPSO hybrid approach.

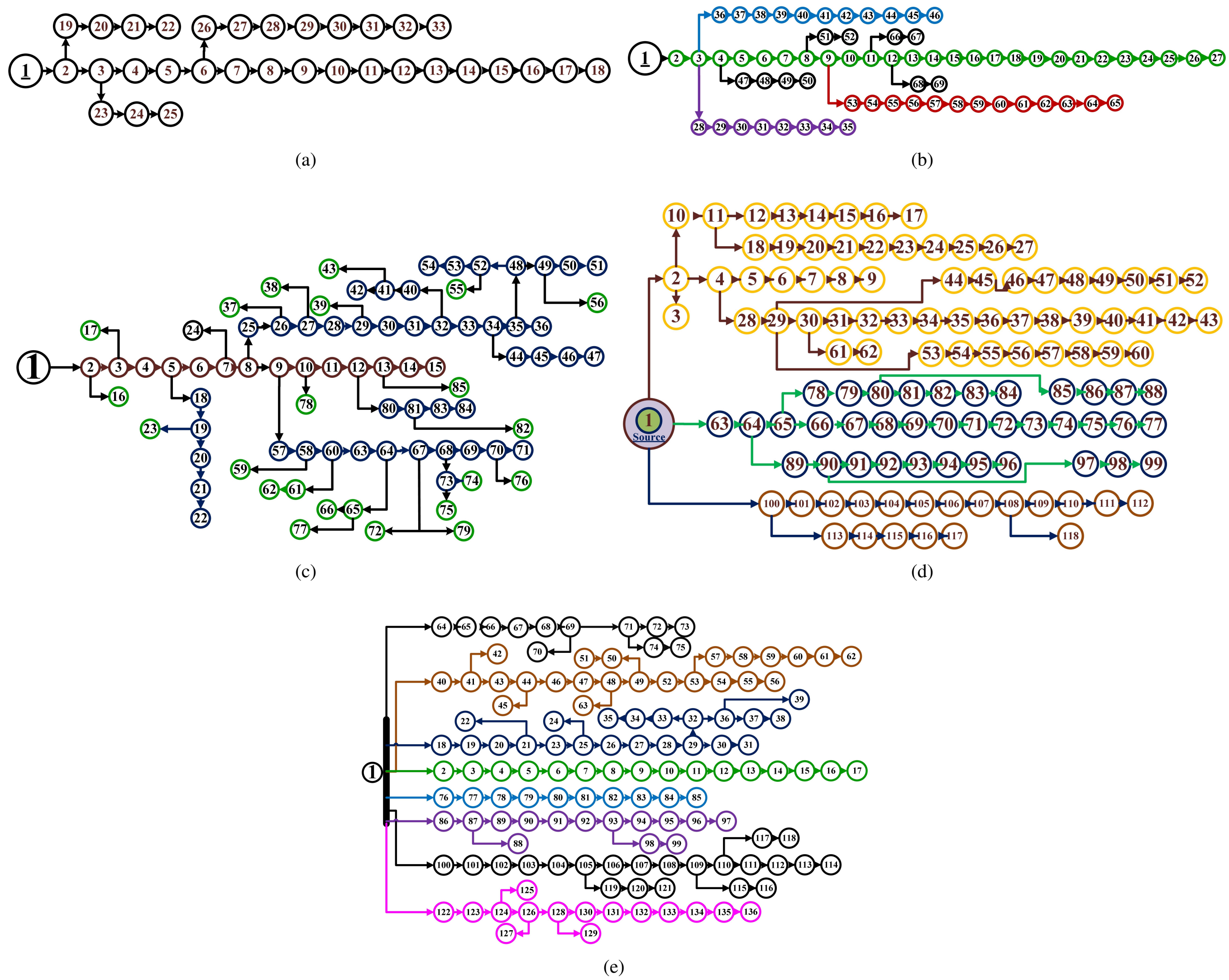


Fig. 2. Single line diagram of various radial distribution systems considered for the study: (a) IEEE-33 Bus system, (b) IEEE-69 Bus system, (c) IEEE-85 Bus system, (d) IEEE-118 Bus system, and (e) Practical Brazil-136 Bus system.

3) Compute the cost of energy loss for the base case.
4) Consider the integration of multiple CAP in the presence of EVCS for optimal performance.
5) Set up the initial parameters for optimization algorithms.
6) Compute the cost of energy loss with CAP and EVCS.
7) Evaluate the objective function as per equation no 5, with the equality and inequality constraints.
8) Stop the process when the maximum number of iterations is reached.

IV. Results and Discussion

The proposed methodology and algorithm are validated by testing in including IEEE 33, 69, 85, 118, and the practical Brazil 136-bus system. The optimization model was implemented and simulated on a robust Intel i9 64-bit PC with a 3.20 GHz CPU and 32 GB RAM (12th Gen) using MATLAB-R2024a. The performance was evaluated based on power loss, voltage profile improvement, and economic feasibility using NPV. The objective function evaluation uses several parameters, as shown in Table I, that are computed for each test system.

The paper investigates four cases to validate the methodology:

- **Case 1:** Base Case (without EVCS or CAP): Establishes a baseline for comparison with subsequent scenarios that introduce EVCS and CAP.
- **Case 2:** Integrated with Charging Station (EVCS integration without CAP): Evaluates the impact of EV charging on system performance.
- **Case 3:** Charging Station with CAP: Studies the combined effect of EVCS and CAP placement on the DN.
- **Case 4:** Integrated with Charging Station in V2G Mode: Analyzes the scenario where EVs can provide power back to the grid (Vehicle-to-Grid, V2G).

TABLE II
CONSTANT PARAMETERS IN CALCULATION [5], [20], [21]

Parameter	Symbol	Value
Cost of Energy ($/kWh)	CE	1.136
Discount Rate (%)	D	7
Installation Cost of CAP ($/loc)	C^{c}_{inst}	1500
Installation Cost of EVCS ($/loc)	C^{ev}_{inst}	3000
O & M Cost of CAP ($/yr/loc)	C^{c}_{OM}	800
O & M Cost of EVCS ($/yr/loc)	C^{ev}_{OM}	1200
Purchase Cost of CAP ($/kVAR)	C^{c}_{pur}	25
Purchase Cost of EVCS ($/kW)	C^{ev}_{pur}	10
Time (hours)	T	8760

A. Case 1: Base Case without EVCS and Capacitor

The proposed method was tested and validated on various distribution system: standard systems (IEEE 33, 69, 85, and 118-bus) and a practical system (Brazil 136-bus). The distribution system are represented as radial networks, where Node 1 is the designated source node. Fig 2 illustrates the network configurations of the study systems considered for this work, including the standard systems and practical systems. It's crucial to note that this study focused on the base case or initial system configuration. This analysis did not consider the installation of EVCS and CAP, which can enhance the system.

Table II provides essential information on these systems, including initial values of the operating voltage and base MVA and the system's total active and reactive power load. After conducting the BFS load flow for these systems, the results obtained are also tabulated in Table II. These computed parameters for the base case include power loss (both active and reactive power loss) and a minimum voltage obtained with their bus numbers for different systems. Thus, the results and findings presented in Table II pertain specifically to the base case scenario without EVCS and CAP.

TABLE III
SYSTEM PARAMETERS AND INITIAL PERFORMANCE (AFTER LOAD FLOW ANALYSIS)

Parameters	Initial Values		Power Load		Power Loss		Min Voltage
Test case	Operating Voltage	Base MVA	Active (kW)	Reactive (kVAr)	Active (kW)	Reactive (kVAr)	Value (p.u.) at
33-bus [39]	12.66	100	3715	2300	202.7012	135.5124	0.9131 (18)
69-bus [40]	12.66	100	3802.2	2694.6	221.8368	100.8158	0.9099 (54)
85-bus [41]	11	100	2570.3	2622.2	308.0921	193.6096	0.8731 (54)
118-bus [42]	11	100	22710	17041	1260.6	947.1182	0.8706 (77)
136-bus [43]	13.8	100	18314	7934	318.3315	698.423	0.9312 (118)

B. Case 2: Integrated with Charging Station

By considering EVs as loads and modeling EVCS as constant power loads, the study assumes that EVs primarily function as electrical power consumers rather than potential energy sources through V2G operations. The EV charging station considered has 30 serving points with a fixed capacity of 1500 kW. This configuration can accommodate 30 EVs simultaneously, with each charger consuming 50 kW. In this study, two charging stations, each rated at 1500 kW, are installed and connected to separate buses to accommodate more EV users.

The results obtained by the evaluation of the objective functions and after the conduction of BFS load flow using the proposed method indicate that there is a potential increase in APL and a negative impact on the voltage profile compared to the base case. Table III indicates the effect of EVCS load on the performance of various test systems.

The table highlights the power losses (APL & RPL) and the minimum voltage of the system for the optimal bus locations of the installed EVCS. For the IEEE 33-bus system, the optimal buses are No. 2 and 19; for the IEEE 69-bus system, they are No. 2 and 28; for the IEEE 85-bus system, No. 2 and 16; and for the IEEE 118-bus system, No. 2 and 63. Additionally, in the practical Brazil 136-bus system, the optimal bus locations are No. 2 and 100.

TABLE IV
EFFECT OF THE EVCS LOAD ON THE PERFORMANCE OF VARIOUS TEST SYSTEMS

Parameters		Load of the System			Power Loss		Voltage
Bus System	Bus No	Base	EVCS	Total	Active (kW)	Reactive (kVAr)	Vmin
33	2	3715	1500	5215	211.1464	139.8771	0.9121
	2&19		3000	6715	225.7292	148.9082	0.9112
69	2	3802.2	1500	5302.2	221.8837	100.9238	0.9099
	2&28		3000	6802.2	222.0608	101.3436	0.9099
85	2	2570.3	1500	4070.3	318.7367	200.9399	0.8715
	2&16		3000	5570.3	348.3275	217.3346	0.8700
118	2	22710	1500	24210	1271.1	951.1308	0.8706
	2&63		3000	25710	1277.5	960.3918	0.8072
136	2	18314	1500	19814	336.4834	740.2959	0.9312
	2&100		3000	21314	337.0616	741.6296	0.9311

C. Case 3: Charging Station with Capacitors

To enhance the voltage profile and reduce power loss, CAP are strategically placed near EVCS and at the ends of feeders to provide reactive power. The optimal locations and capacities of the CAP in the presence of EVCS using the proposed hybrid method, GA and PSO are articulated in Table IV. Table IV also depicts the performance of optimal location and size of the capacitance for the IEEE 33, 69, 85, 118, and Brazil 136 bus systems, comparing the performance of the proposed hybrid HGAPSO approach with individual GA and PSO.

The application of the HGAPSO technique for optimal CAP placement and rating in power DN has yielded significant improvements in reducing APL, as evident from the results in Table IV.

Fig. 3 illustrates the voltage profiles of the various IEEE standard and practical systems under three different scenarios. From Figures 3a, 3b, 3c, 3d, and 3e, it is evident that the introduction of EVCS reduced the voltage profile across all the buses in the network compared to the base case. However, the strategic introduction of CAP with optimal size and location, along with EVCS, improved the voltage profile across all the buses in the considered DN. From the said figures, it is evident the suggested HGAPSO approach effectively maintains a healthy voltage profile for the entire DN.

Table V presents the system parameters that include APL, min voltage V_min (p.u), S_cost, NPV, and Convergence time (CT) in sec for the optimized location and size of the CAP and

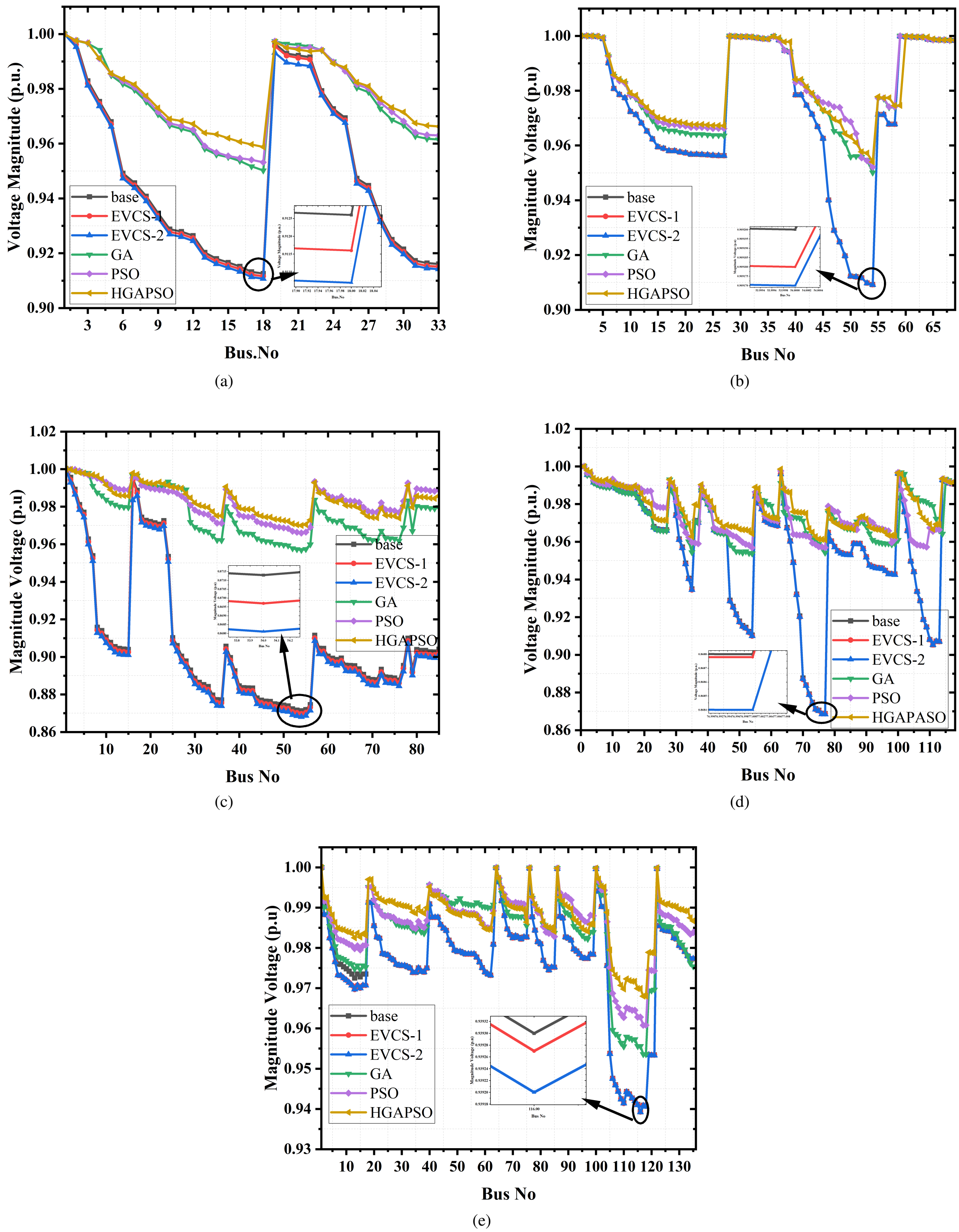


Fig. 3. Voltage profile comparison of various bus systems under different scenarios: (a) IEEE-33 Bus system, (b) IEEE-69 Bus system, (c) IEEE-85 Bus system, (d) IEEE-118 Bus system, and (e) Practical Brazil-136 Bus system.

EVCS. Table V has articulated these parameters for different system configurations that include the IEEE standard system and practical system for base case, and with optimization algorithms including GA, PSO, and HGAPSO.

Comparing the APL from Table V for the 33-bus system: The optimal CAP installation in the presence of EVCS results in a substantial decrease in APL from the base case of 202.7012 kW to 138.9197 kW, yielding a 31.46 % reduction

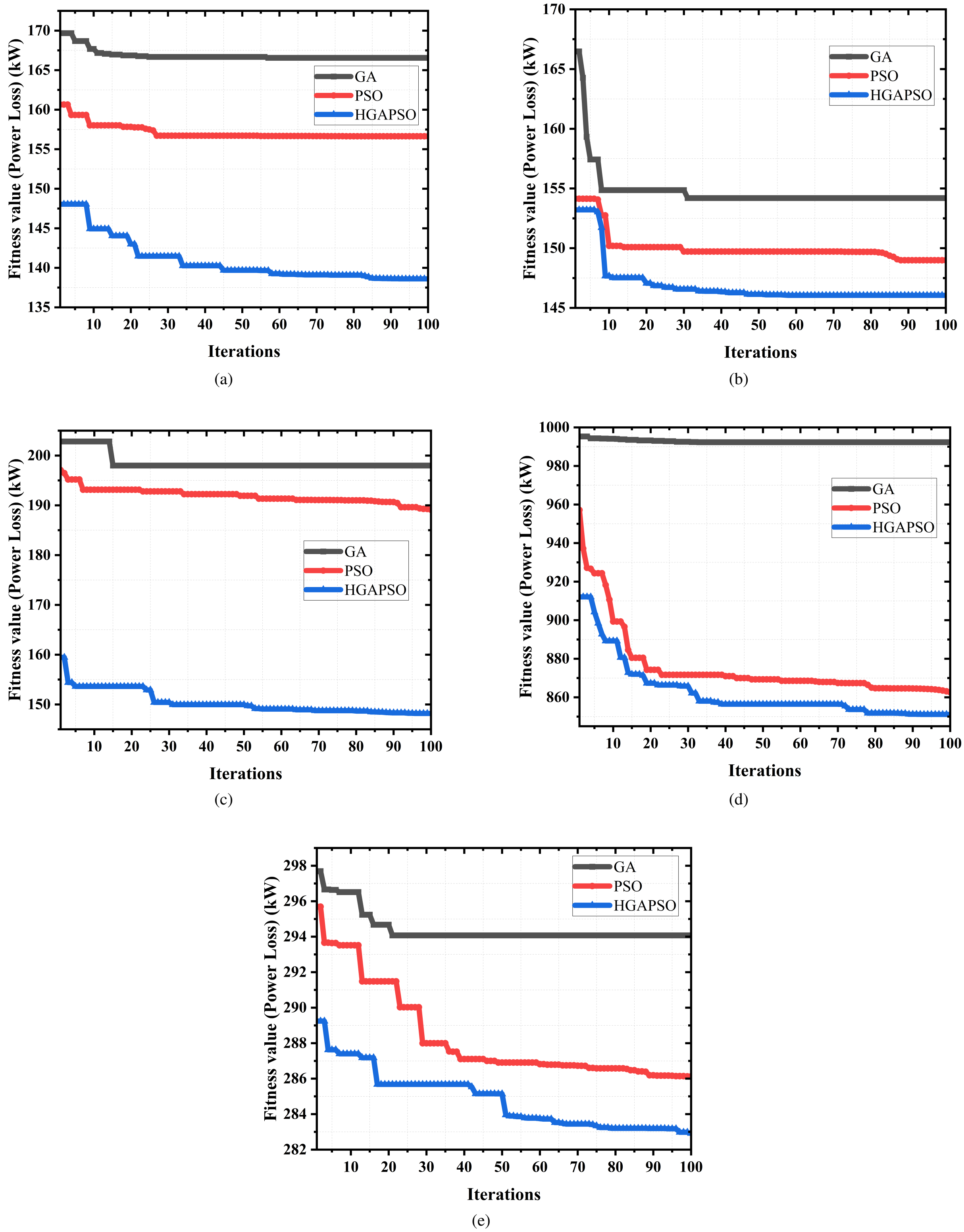


Fig. 4. Convergence curve of various bus systems under different scenarios: (a) IEEE-33 Bus system, (b) IEEE-69 Bus system, (c) IEEE-85 Bus system, (d) IEEE-118 Bus system, and (e) Practical Brazil 136-Bus system.

in the annual cost of energy loss using the proposed hybrid approach. This improvement in energy savings percentage highlights the effectiveness of the HGAPSO algorithm applicability in an IEEE standard DN.

In the 69-bus system, the optimal CAP placement leads to even more significant savings. The APL reduces from 221.8368 kW to 144.7690 kW, translating to a 34.74 % improvement in annual energy saving using the hybrid ap-

TABLE V
OPTIMAL CAP VALUES AND LOCATIONS ACROSS VARIOUS OPTIMIZATION ALGORITHMS AND TEST

Test Case	Algorithm	OPTIMAL VALUES Optimal location and rating of the CAP	Total Kvar
33	GA	10/386, 24/150, 5/426, 30/1049	2011
	PSO	30 / 650, 5/750, 33/188, 14/265	1853
	HGAPSO	13/549, 22/150, 25/382, 30/696	1777
69	GA	16/150, 29/1150, 43/150, 50/891	2341
	PSO	59/1200, 38/650, 40/920, 50/1200	3970
	HGAPSO	16/450, 50/1127, 39/518, 49/150	2245
85	GA	14/528, 9/289, 42/658, 48/831	2306
	PSO	68/450, 34/777, 85/304, 57/685	2216
	HGAPSO	67/150, 80/1155, 34/150, 8/574	2029
118	GA	10/1200, 21/1200, 41/1200, 47/1200, 61/1200, 72/1200, 81/1200, 90/1200, 112/1200	10800
	PSO	50/1200, 27/581, 43/667, 48/1200, 74/1200, 80/1200, 91/1200, 112/1200, 113/1047	9495
	HGAPSO	20/183, 8/1130, 35/530, 50/791, 74/1004, 80/780, 91/771, 108/607, 113/965	6761
136	GA	108/1004, 16/192, 25/162, 34/870, 51/501, 60/637, 75/989, 84/986, 89/851, 121/458, 127/1200	7850
	PSO	17/666, 39/929, 41/407, 52/769, 71/552, 80/150, 89/1200, 106/1200, 136/522, 13/150, 84/449	6994
	HGAPSO	14/674, 18/454, 40/619, 52/311, 69/556, 82/609, 89/373, 106/601, 133/812, 108/192, 29/220	5009

TABLE VI
COMPARATIVE ANALYSIS OF APL REDUCTION, VOLTAGE PROFILE IMPROVEMENT, AND NPV USING GA, PSO, AND HYBRID ALGORITHMS ON VARIOUS BUS SYSTEMS

Parameters		**33 BUS**		
Algorithm	Base	GA	PSO	HYBRID
APL (kW)	202.7012	157.3869	155.7872	138.9197
Vmin (p.u)	0.9131	0.9502	0.9532	0.9588
S_{cost} (%)	-	22.35	23.15	31.46
NPV ($/yr)	-	1,39,960	1,46,160	2,24,780
CT (sec)	-	18.4160	22.1880	20.9450
		69 BUS		
APL (kW)	221.8368	152.8025	147.7029	144.7690
Vmin (p.u)	0.9099	0.9501	0.9521	0.9540
S_{cost} (%)	-	31.11	33.41	34.74
NPV ($/yr)	-	2,45,860	2,30,930	2,88,900
CT (sec)	-	27.8700	22.3960	21.7910
		85 BUS		
APL (kW)	308.0921	195.7415	187.1116	148.77837
Vmin (p.u)	0.8731	0.9569	0.9660	0.9700
S_{cost} (%)	-	36.46	39.26	51.7
NPV ($/yr)	-	4,72,780	5,61,070	7,56,360
CT (sec)	-	28.8460	29.4500	25.4600
		118 BUS		
APL (kW)	1260.6	981.0726	854.2416	842.9498
Vmin (p.u)	0.8706	0.9542	0.9569	0.9610
S_{cost} (%)	-	22.17	32.23	33.13
NPV ($/yr)	-	11,90,700	17,62,000	17,86,500
CT (sec)	-	90.5680	97.9620	39.4350
		136 BUS		
APL (kW)	318.332	292.6024	284.7569	281.6196
Vmin (p.u)	0.9312	0.9536	0.9608	0.9680
S_{cost} (%)	-	8.08	10.54	11.53
NPV ($/yr)	-	53,261	65,104	71,633
CT (sec)	-	94.4420	99.1230	64.7280

proach. On the other hand, the other algorithms, including GA and PSO, obtained a 31.11% and 33.41% increase in annual savings. This shows the algorithm's ability to identify optimal CAP configurations in the presence of EVCS for medium-sized DN.

For the 85-bus system, the HGAPSO algorithm demonstrates its effectiveness. The optimal CAP configuration yields a substantial reduction in APL from 308.0921 kW to 842.9498 kW, achieving a notable 39.87 % improvement in benefit. This improvement underscores the algorithm's capability to optimize CAP placement in the presence of EVCS in larger and more complex DN.

In the case of the 118-bus system, the optimal CAP placement results in a reduction of APL from 1260.6 kW to 186.94 kW, representing a 33.13% improvement in annual energy savings. This highlights the algorithm's effectiveness in optimal CAP placement and rating in larger DN to achieve significant savings in the presence of EVCS.

Lastly, for a practical system, i.e., the 136-bus system, the optimal CAP placement in the presence of EVCS using a GA and PSO. Provided an APL reduction of 292.6024 kW and 284.7569 kW, respectively. This Translating to 8.08% and 10.51% improvement in annual savings. On the other hand, the proposed hybrid algorithm achieved a remarkable 11.53% improvement in annual savings, corresponding to a reduction in APL from 318.332 kW to 281.6196 kW. While the percentage reduction is smaller compared to the other systems, the absolute savings are still substantial due to the larger scale of the network. Thus, the HGAPSO algorithm provided a better APL improvement in savings compared to the individual optimization algorithms.

In addition, Table V presents a comprehensive analysis of the NPV achieved after integrating EVCS and CAP into various bus systems using three optimization algorithms: GA, PSO, and the proposed HGAPSO. For each bus system analyzed (33-bus, 69-bus, 85-bus, 118-bus, and 136-bus systems), the HGAPSO algorithm yielded a higher NPV, indicating superior performance in optimizing the placement and operation of EVCS and CAP. The improved NPV values for the different bus systems are as follows: 154,797.5780 $/yr for the 33-bus system, 298,325.0103 $/yr for the 69-bus system, 549,562.3642 $/yr for the 85-bus system, 1,846,426.1127 $/yr for the 118-bus system, and 65,056.6595 $/yr for the 136-bus system, respectively.

The convergence time (CT) and curves of optimization algorithms are indeed essential metrics for evaluating their efficiency and performance. The CT represents the duration taken by each algorithm to reach the termination criterion, indicating its speed and effectiveness in finding optimal solutions. Table V presents the CT for the HGAPSO, GA, and PSO algorithms mentioned for the case of EVCS and CAP installation.

Additionally, Fig 4 provides a graphical representation of the convergence curves for the various bus systems for visual assessment of the convergence behavior of these algorithms. This figure allows for a comparative analysis of how the HGAPSO, GA, and PSO algorithms converge over time, offering insights into their relative performance for different systems like IEEE 33, 69, 85, and 118 bus systems and the practical Brazil 136-bus system.

D. Case 4: Integrated with Charging Station in V2G MODE

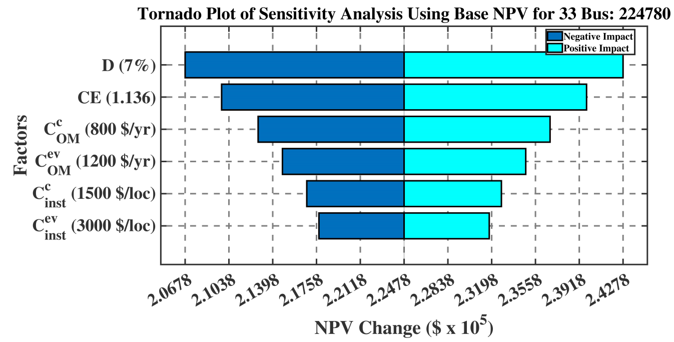
In the study of integrating EVCS with CAP in DN, the V2G mode plays a crucial role in maintaining system reliability. When EVs have surplus energy, they can feed this extra energy back into the grid, helping the grid operator maintain an acceptable voltage profile and reduce power loss. The study investigates the impact of V2G mode on the IEEE 33, 69, 85, and 118 bus systems and the practical Brazil 136-bus system for the optimal size and location of CAP. Employing the HGAPSO techies, four scenarios with varying EV penetration in V2G mode were analyzed: 5%, 10%, 15%, and 20% of total EVs, as shown in Table VI.

TABLE VII
COMPARATIVE ANALYSIS OF APL REDUCTION AND NPV USING HGAPSO ON VARIOUS BUS SYSTEMS IN V2G MODE AT DIFFERENT PENETRATION LEVELS

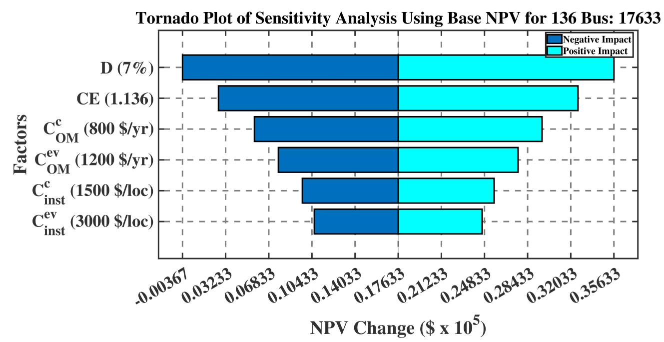
Penetration	**5%**	**10%**	**15%**	**20%**
Parameters		**33 BUS**		
APL (kW)	130.5684	129.8836	129.2366	128.6274
S_{cost} (%)	35.58	35.92	36.24	36.54
NPV ($/yr)	2,65,780	2,69,250	2,72,520	2,75,600
		69 BUS		
APL (kW)	144.5441	144.5387	144.5338	144.5294
S_{cost} (%)	34.84	34.84	34.84	34.84
NPV ($/yr)	2,90,030	2,90,060	2,90,090	2,90,110
		85 BUS		
APL (kW)	146.2165	145.5809	145.0539	144.6353
S_{cost} (%)	52.54	52.74	52.91	53.05
NPV ($/yr)	7,69,320	7,72,530	7,75,200	7,77,320
		118 BUS		
APL (kW)	825.7168	824.9627	824.2147	823.4727
S_{cost} (%)	34.49	34.55	34.16	34.67
NPV ($/yr)	18,73,700	18,77,500	18,81,300	18,85,000
		136 BUS		
APL (kW)	262.3947	261.7077	261.0413	260.3956
S_{cost} (%)	17.57	17.78	17.99	18.19
NPV ($/yr)	97,254	1,00,729	1,04,100	1,07,367

Table VI demonstrates that increasing Vehicle-to-Grid (V2G) participation leads to a decrease in APL, a reduction in the percentage of energy loss costs, and an increase in NPV for the proposed approach. Specifically, as the penetration of EVs in V2G mode rises from 5% to 20%, there is a noticeable decrease in APL across the grid. This reduction in power loss results in significant cost savings for grid operators. Additionally, for all bus systems analyzed, an increase in EV penetration percentage correlates with higher savings in cost (s_{cost}) and an increased NPV. For instance:

- In the 33 bus system, as the V2G penetration is increased from 5% to 20%, the APL decreased from 130.5684 kW to 128.6274 kW, resulting in a cost savings of 36.54%. Also, for this increment in penetration, the NPV increased from 2,65,780 $/yr to 2,75,600 $/yr.
- In the 69-bus system, as the V2G penetration is increased from 5% to 20%, the APL decreased from 144.5441 kW to 144.5294 kW, resulting in a cost savings of 34.84%. Also, for this increment in penetration, the NPV increased from 2,90,030 $/yr to 2,90,110 $/yr.
- In the 85-bus system, as the V2G penetration is increased from 5% to 20%, the APL decreased from 146.2165 kW to 144.6353 kW, resulting in a cost savings of 53.05%. Also, for this increment in penetration, the NPV increased from 7,69,320 $/yr to 7,77,320 $/yr.
- In the 118-bus system, as the V2G penetration is increased from 5% to 20%, the APL decreased from 825.7168 kW to 823.4727 kW, resulting in a cost savings of 34.67%. Also, for this increment in penetration, the NPV increased from 18,73,700 $/yr to 18,85,000 $/yr.
- In the 136-bus system, as the V2G penetration is increased from 5% to 20%, the APL decreased from 262.3947 kW to 260.3956 kW, resulting in a cost savings of 18.19%. Also, for this increment in penetration, the NPV increased from 97,254 $/yr to 1,07,367 $/yr.



(a)



(b)

Fig. 5. Tornado plot of sensitivity analysis for NPV: (a) IEEE-33 Bus system and (b) Practical Brazil 136-Bus system.

These results affirm the technical and economic benefits of integrating EVs in V2G mode using the HGAPSO optimization technique.

E. Sensitivity Analysis

A sensitivity analysis of the NPV was conducted to evaluate the economic viability of integrating EVCS and CAP in the IEEE 33, 69, 85, 118, and Brazil 136-bus systems, focusing on parameters like the discount rate, energy cost, and installation costs for CAP and EVCS, as well as operating and maintenance costs.

Figure 5 presents a tornado plot of the sensitivity analysis results with a ±10% variation for each parameter. Although the analysis was conducted across all systems, the figure specifically illustrates results for the 33 and 136-bus systems, representing the smallest and largest cases. The results were consistent across all cases. The analysis shows that the discount rate has the most significant impact on NPV, indicated by the longest bar in the plot. Energy cost and EVCS installation costs also considerably influence NPV, highlighting their importance for the project's financial sustainability. Conversely, the installation cost of CAP and operating and maintenance expenses have a lower impact on NPV, as shown by the shorter bars.

These insights guide decision-makers in prioritizing strategies to secure the project's financial health. By focusing on managing the discount rate and energy costs, risks to economic performance can be mitigated. Optimizing CAP installation and maintenance, although less influential, can still contribute to stronger financial results.

V. Conclusion

In this study, we focused on optimizing the deployment of EVCS and CAP in DN to maximize NPV while considering the benefits of energy loss reduction and investment costs. Using the HGAPSO algorithm, the research demonstrated effective planning across the IEEE 33, 69, 85, 118, and Brazil 136-bus systems. Initially, integrating EVCS into Radial RDN can lead to increased APL and reduced voltage profiles. However, through the strategic placement of CAP alongside EVCS, significant reductions in APL and improvements in voltage profiles have been achieved. The proposed algorithm achieved notable reductions in active power losses of 31.46%, 34.74%, 51.7%, 33.13%, and 11.53% for the IEEE 33-bus, 69-bus, 85-bus, 118-bus, and 136-bus systems, respectively, when compared to the base case. Additionally, the corresponding annual maximum NPVs were 224,780 $/year, 288,900 $/year, 756,360 $/year, 1,786,500 $/year, and 71,633 $/year for these systems. The HGAPSO algorithm has proven instrumental in swiftly identifying optimal locations and sizes for CAP, surpassing the effectiveness of standalone optimization approaches. Our findings highlight the superior performance of the proposed algorithms in facilitating precise cost-benefit analyses, particularly in the context of V2G operations. Implementing CAP banks alongside EVCS at optimized sites not only enhances network efficiency but also yields substantial positive NPV, providing tangible benefits to utility providers. The analysis across varying penetration levels (5% to 20%) shows a consistent reduction in APL for all bus systems. For the IEEE 33-bus system, APL decreased from 130.5684 kW to 128.6274 kW. For the 69-bus system, APL was reduced from 144.5441 kW to 144.5294 kW. In the 85-bus system, APL dropped from 146.2165 kW to 144.6353 kW. For the 118-bus system, APL decreased from 825.7168 kW to 823.4727 kW. Finally, for the 136-bus system, APL reduced from 262.3947 kW to 260.3956 kW. These results emphasize the effectiveness of the proposed approach in optimizing operational performance in distribution networks.

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