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Optimizing electric vehicle charging station placement integrates distributed generations and network reconfiguration

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ABSTRACT

The surge in adoption of electric vehicles (EVs) within the transportation sector can be attributed to the growing interest in sustainable transportation initiatives. It is imperative to position electric vehicle charging stations (EVCS) strategically and distribute generations (DGs) to mitigate the effects of electric vehicle loads. This research employs the whale optimization algorithm (WOA) to optimize the placement of EVCS and DGs alongside network reconfiguration. The backward-forward sweep (BFS) power flow technique is utilized to compute load flow under varying load conditions. The primary objective of this investigation is to minimize power losses and enhance the voltage profile within the system. The proposed approach was tested on IEEE-33 and 69 bus systems and compared with particle swarm optimization (PSO) and genetic algorithm (GA) techniques. The simulation outcomes affirm the effectiveness of whale optimization algorithm in determining that integrating 3 EVCS with 3 DGs yields optimal outcomes following network reconfiguration, resulting in a 56.22% decrease in power losses for the IEEE-33 bus system and a 76.13% reduction for the IEEE-69 bus system. The simulation results indicate that the proposed approach enhances system performance across all metrics, showcasing the superior performance of WOA compared to PSO and GA in accomplishing set objectives.

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1. INTRODUCTION

The increasing demand for electric vehicle charging stations (EVCS) has emerged as a primary concern in supporting the sustainable growth of electric vehicles. Despite the rapid advancements in electric vehicles (EVs) technology, the need for charging infrastructure remains vital due to the limited range of electric vehicles compared to their fossil fuel counterparts. Many countries worldwide are adopting battery-based transportation modes to reduce pollution [1]. Notably, Norway has achieved a 74.8% EVs adoption rate, followed by 45% in Iceland and 32.2% in Sweden [2]. Furthermore, several nations are planning to fully embrace EVs as the future mode of transportation, with projections estimating around 14 million EVs sales by the end of 2023, marking a 35% year-on-year increase [3].

Apart from environmental benefits, EVs charging has the potential to significantly impact the reliability of the power grid [4]. The augmented demand stemming from electric vehicle charging stations (EVCS) diminishes the reserve capacity of substations and the capabilities for transferring loads through feeders [5]. Most distribution grids are characterized by a radial configuration featuring low ratios of reactance to resistance. The energy landscape has experienced notable transformations in recent years, primarily instigated by the integration of electric vehicles (EVs) and renewable energy sources such as distributed generations (DGs) [6], [7].

The whale optimization algorithm (WOA) is a newly developed optimization algorithm that draws inspiration from the collective behavior exhibited by whales [8]. Though it boasts simplicity and low computational cost, it may not utilize data from inapplicable solutions, which could be beneficial for addressing problems with dominant non-compatible regions. When compared with the WOA method, several other optimization methods have their own advantages and challenges. Genetic methods (GA) are easy to implement and computationally efficient, but can be expensive for complex assignment problems [9]. Particle swarm optimization (PSO) methods can be parallelized easily and do not require information gradients, but may be prone to getting stuck in local optima and require higher computation [10].

Based on the above background, it is evident that the need for EVCS to support the growth of sustainable EVs is becoming increasingly urgent. The proposed research can contribute to determining the optimal position and Tie Switch number for EVCS and DGs, combined with network reconfiguration using WOA. This study aims to predict the power losses using the backward-forward sweep (BFS) load flow approach. Therefore, this research is proposed with the objective of finding the best solution to integrate EVCS and DGs with network reconfiguration using WOA.

2. METHOD

2.1. Constraints

The integration of EVCS and DGs coordination problem formulation can be divided into objective functions and constrained functions [11]. The objective function in this simulation is to reduce power losses, which can be seen in (1). Where $Nbranch$ denotes the total number of branches or channels present within the system. R_k stands for the resistance on branch k, while I_k represents the current flowing through branch k [12].

$$\min F_{obj}(x) = \sum_{i=1}^{Nbranch} R_k * |I_k|^2 \tag{1}$$

Active and reactive power generation and consumption are balanced on each bus in the distribution network [7]. Active power balance is achieved when the active power generated at each bus equals the active power consume [13]. This principle ensures efficient and stable operation of the network, as outlined (2), (3).

$$P_{substation} + \sum_{k=1}^{Nbus} P^{DG}(k) - \sum_{j=1}^{Nbranch} P_{loss}^{j}(k, k+1) - \sum_{k=1}^{Nbus} P_{D,k}(k) - P_{EVCS}^{k} = 0 \tag{2}$$

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

In this context, $P_{substation}$ and $Q_{substation}$ denote the power originating from the substation, respectively. $Nbus$ signifies the total count of buses [14]. The power produced by generators at bus k are represented by $P_{DG}\ (k)$ and $Q^{DG}\ (k)$ respectively. $Nbranch$ stands for the total of branches. The power loss between buses k and $k+1$ is symbolized by $P_{loss}^{j}\ and\ Q_{loss}^{j}$, respectively. The power demand at bus k is indicated by $P_{D,k}\ (k)$ and $Q_{D,k}\ (k)$. P_{EVCS}^{k} and Q_{EVCS}^{k} is the power demand of EVCS load at bus k. Inequality constraints are a mathematical expression that describes a relationship between variables in which one side of the equation is greater or less than the other side [15]. The limits of the lowest and maximum permissible voltage levels (0.90-1.06 p.u.) (4).

$$V_{min,k} \le V_k \le V_{max,k}, k = 1, 2, 3, \dots, Nbus \tag{4}$$

The amount of active and reactive power injected by DGs must remain within specific limit [16]. $P_{DG,k}^{\min}$ is the minimum active power limit for DG at bus k, $P_{DG,k}$ is the current active power at bus k, and $P_{DG,k}^{\max}$ is the maximum active power limit for DG at bus k. Similarly, $Q_{DG,k}^{\min}$ represents the minimum reactive power limit for DG at bus k, $Q_{DG,k}$ is the current reactive power at bus k, and $Q_{DG,k}^{\max}$ is the maximum reactive power limit for DG at bus k. The formula is given by (5), (6).

$$P_{DG,k}^{\min} \le P_{DG,k} \le P_{DG,k}^{\max} \tag{5}$$

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

The active and reactive power injected by EVCS must also remain within certain limits [17]. $P_{EVCS,k}^{\min}$ is the minimum active power limit for EVCS at bus k, $P_{EVCS,k}$ is the current active power at bus k, and $P_{EVCS,k}^{\max}$ is the maximum active power limit for EVCS at bus k. For reactive power, $Q_{EVCS,k}^{\min}$ represents the minimum reactive power limit for EVCS at bus k, $Q_{EVCS,k}$ is the current reactive power at bus k, and $Q_{EVCS,k}^{\max}$ is the maximum reactive power limit for EVCS at bus k. The formula is given by (7), (8).

$$P_{EVCS,k}^{\min} \leq P_{EVCS,k} \leq P_{EVCS,k}^{\max} \tag{7}$$

$$Q_{EVCS,k}^{\min} \leq Q_{EVCS,k} \leq Q_{EVCS,k}^{\max} \tag{8}$$

2.2. Whale optimization algorithm

WOA has been theoretically considered a global optimization algorithm due to its exploration/ exploitation capabilities, utilizing a hypercube mechanism to define the search space around the best solution [8]. The WOA algorithm assumes whales that are looking for prey are considered the best solution candidates at this time [18]. Key parameters in WOA include $\vec{a}$ is a convergence factor with random values between 2 to 0, $\vec{r}$ is a random value between 0 to 1 and $\vec{A}$ with $\vec{C}$ which are variation coefficients represented in (9), (10).

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{9}$$

$$\vec{C} = 2\vec{r} \tag{10}$$

These whales move in different directions in the search for prey, and each whale's move is considered a step in the search for the best solution [19]. Parameters probability p for position updates with random values between 0 and 1, and a constant b for the spiral shape, which is set to 1. Additionally, the random value l ranges between -1 to 1, and the spiral equation $\vec{D'}$ is used to update positions, transitioning whales from their current position $\vec{X}(t)$ to the next position $\vec{X}(t+1)$, with $\vec{X}_{best}(t)$ representing the global best position. If coefficients $\vec{A}$ is < 1, the formula (11) to (14) is used to update the new position.

$$\vec{D'} = \vec{C} \mid \vec{X}_{best}(t) - \vec{X}(t) \mid, \text{if p} \leq 0.5 \tag{11}$$

$$\vec{X}\ (t + 1) = \vec{X}_{best} - \vec{A} \cdot \vec{D}, \text{ if p} \leq 0.5 \tag{12}$$

$$\vec{D'} = \mid \vec{X}_{best}(t) - \vec{X}(t) \mid, \text{if p} \geq 0.5 \tag{13}$$

$$\vec{X}(t + 1) = \vec{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}(t), \text{if p} \geq 0.5 \tag{14}$$

Humpback whales move randomly based on each other's positions. Random values above or below 1 are used to keep search agents away from reference whales. During exploration phase, agent positions are based on randomly chosen agents rather than the best one found. Emphasize exploration if $\vec{A}$ is ≥ 1 for global search in WOA algorithm [8].

$$\vec{D} = |\vec{C} \cdot \vec{X}\ rand - \vec{X}(t)\ | \tag{15}$$

$$\vec{X}\ (t + 1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{16}$$

The WOA algorithm commences with a collection of randomized solutions. During each iteration, the search agents enhance their positions by considering the chosen random search agents and the most optimal solution identified thus far. The adaptive modification of the search vector A enables the WOA algorithm to shift smoothly between exploration and exploitation. This is achieved by diminishing A, with specific iterations dedicated to exploration (|A| ≥ 1) and others dedicated to exploitation (|A| < 1) [8], [20].

2.3. Test system

The data for the study consists of the IEEE-33 bus and 69 bus distribution systems. The test systems for distribution in 33 and 69 bus, have experienced a surge in popularity among researchers and practitioners, emerging as a widely adopted tool to investigate various problems encountered in conventional distribution systems [21]. A diagram in Figure 1 shows the IEEE-33 Bus system with 33 buses, 32 closed branches, and 5 open branches [22].

The IEEE 69 bus distribution system while enhancing the test benchmark to closely reflect real operational limitations [20]. Figure 2 shows the IEEE-69 Bus systems single line diagram, a radial distribution system with 69 buses, 68 closed branches, and five open branches. This diagram provides overview of the network's topology [23].

The data variables observed in the study were the influence due to network reconfiguration [24]. The addition of EVCS and DGs which varied with the simulated load increase in MATLAB software [25]. The variables observed in this study are:

a. Power loss (KW)
b. Voltage profile (p.u)
c. EVCS, DGs and Network Reconfiguration allocation, including:
   Case 1: Base case/Existing
   Case 2: EVCS allocation without DGs
   Case 3: DGs allocation without EVCS
   Case 4: Integration of EVCS and DGs allocations
   Case 5: Network reconfiguration
   Case 6: EVCS allocation without DGs after network reconfiguration
   Case 7: DGs allocation without EVCS after network reconfiguration
   Case 8: Integration of EVCS and DGs allocations after network reconfiguration

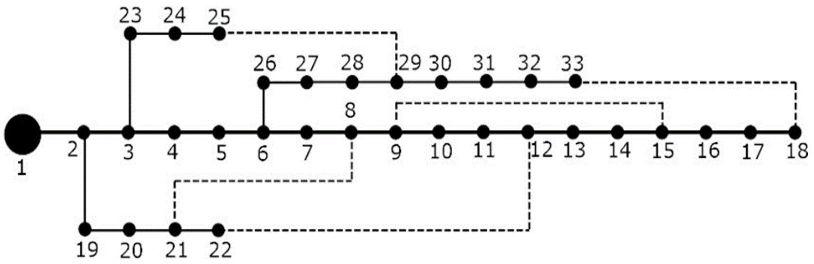

Figure 1. Single line diagram of IEEE-33 bus system

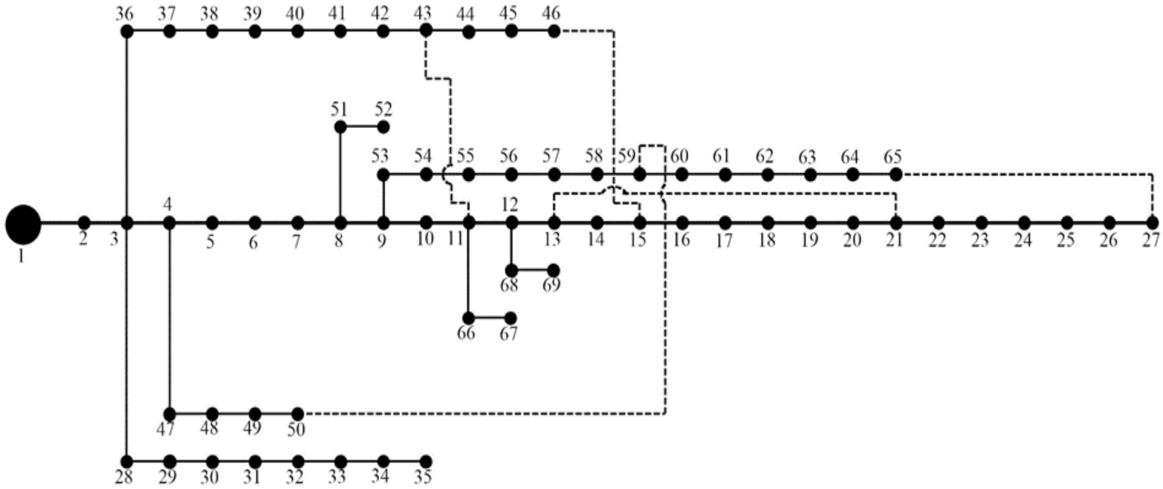

Figure 2. Single line diagram of IEEE-69 bus system

3. RESULTS AND DISCUSSION

3.1. IEEE-33 Bus system simulation

In the voltage profile of the IEEE-33 Bus simulation, as the follow parameters in Table 1 there is a significant voltage variation between different buses for fixed conditions. Whenever an EVCS is co-located with a DG, the system voltage profile will improve. The graphical form of the simulated voltage profile of all scenarios of IEEE-33 bus base load fixed conditions can be seen in Figure 3.

Table 1. Simulation parameters

Parameter	Fixed		Non-fixed	
	Value	Unit	Value	Unit
Bus type	33 and 69	bus	33 and 69	bus
Voltage level	12, 66	kV	12, 66	kV
Power rating	100	MVA	100	MVA
No. EVCS	3	-	3	-
No. DGs	3	-	3	-
Power factor (pf)	0,90	-	0,90	-
Population	100	-	100	-
Iteration	100	-	100	-
No. max switch open	5	-	5	-
Initial switch open	33, 34, 35, 36, 37 and 69, 70, 71, 72, 73	-	33, 34, 35, 36, 37 and 69, 70, 71, 72, 73	-
Capacity DGs min	350	kW	100	kW
Capacity DGs max	350	kW	550	kW
No. EV min	30	-	30	-
No. EV max	30	-	50	-
Base load percentage	100	-	100	-
EVCS rating	50	kW	50	kW

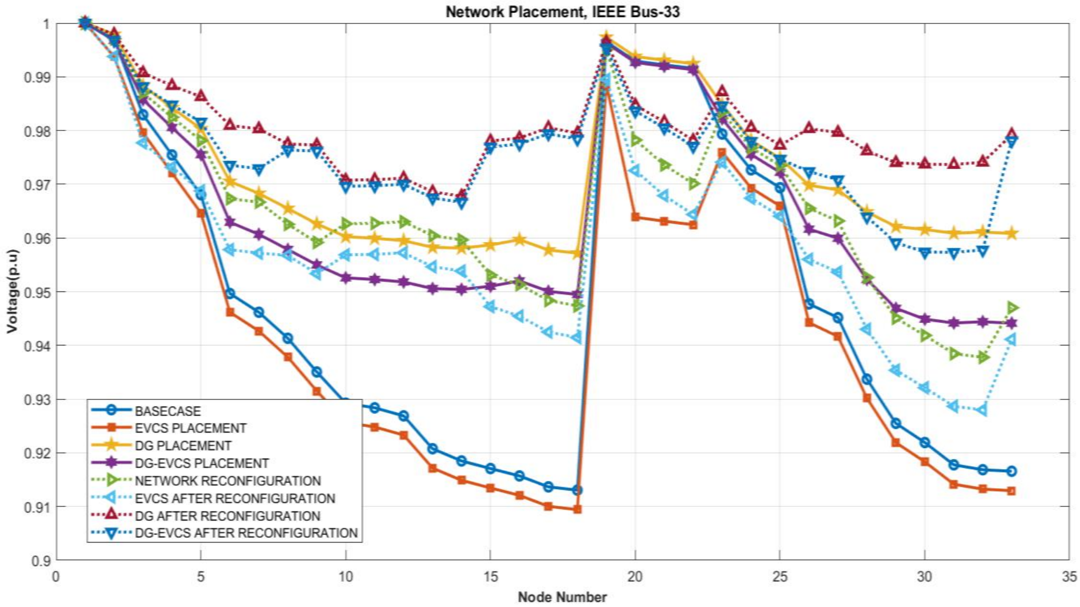

Figure 3. Voltage profile of all IEEE-33 bus scenarios with WOA

In Figure 3, the value of the voltage profile decreases as the additional load from the EVCS. However, the minimum voltage value still meets the constraints with a value of 0.90943 p.u at bus 18. The reduction in value can be overcome by the addition of DGs with a minimum state of 0.95717 p.u and will decrease slightly in the integration of EVCS with DGs to 0.94413 p.u at bus 33. where the best state occurs when the integration of EVCS with DGs is carried out after network reconfiguration with a value of 0.95732 p.u at bus 31.

The WOA demonstrates the fastest convergence compared to PSO and GA as shown in Figure 4. Under fixed conditions, WOA achieves the lowest loss value within 20 iterations, indicating its high efficiency in finding optimal solutions in fewer iterations. PSO achieves the lowest loss value within 65 iterations. Although slower than WOA, PSO still shows good convergence and can reach optimal solutions relatively quickly. GA achieves the lowest loss value within 75 iterations, which is the slowest compared to WOA and PSO. However, GA still demonstrates the ability to converge to optimal solutions, albeit requiring more iterations.

Figure 5 shows that from all cases, it is confirmed that case-8 is the condition with the smallest power loss, so it is confirmed that the integration of EVCS and DGs with network reconfiguration is the optimal solution. In the base case, WOA yields the lowest active and reactive power losses of 202.68 kW and 135.14 kVar, respectively. However, when EVCS are introduced, WOA's performance deteriorates, with active and reactive power losses rising to 299.07 kW and 205.99 kVar. Conversely, PSO and GA exhibit higher losses in with EVCS integration, achieving 354.82 kW and 234.83 kVar for PSO and 354.82 kW and 234.83 kVar for GA, respectively. The addition of DG further reduces losses across algorithms, with WOA recording 74.24 kW and 48.49 kVar, PSO with 85.37 kW and 54.52 kVar, and GA with 78.37 kW and 50.52 kVar. However, when DG and EVCS are combined, WOA outperforms the other algorithms, showing active and reactive power losses of 112.01 kW and 72.16 kVar, respectively. Network reconfiguration enhances performance, with reductions in losses observed across all scenarios and algorithms. The combination of DG and EVCS with reconfiguration yields the lowest losses across all algorithms, with WOA achieving 87.72 kW in active power loss and 60.67 kVar in reactive power loss.

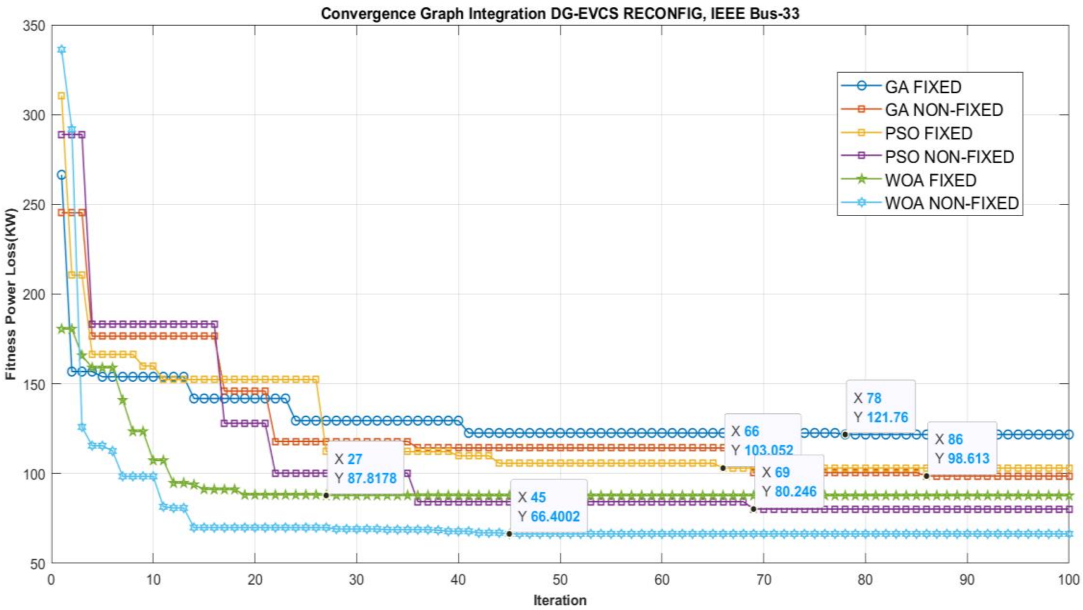

Figure 4. Convergence characteristics simulation IEEE-33 bus

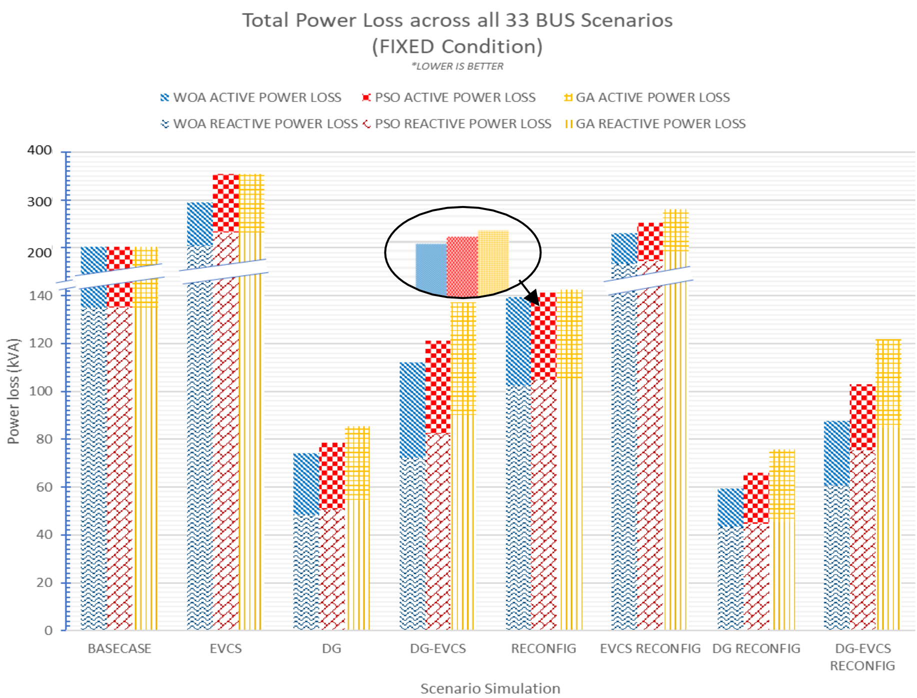

Figure 5. Comparison of performance of optimization methods across IEEE-33 bus scenarios

Table 2 presents a comparison of the results obtained using different techniques, namely PSO fixed, GA fixed, and WOA fixed, in addition to the proposed WOA non-fixed technique. For the "Best solution" for each technique, Case-8 is reported, which indicates that the best solution has been achieved for this case. This statement is in line with the goals that the integration of EVCS and DGs with network reconfiguration can produce the smallest power loss value. Regarding the number of tie switches, each technique shows different choices, with the proposed WOA achieving the highest reduction of 56.22% has better than PSO and GA to minimize power losses. The proposed non-fixed WOA only as a proof of whether the algorithm can find the minimum capacity to produce the optimal power loss value.

Similarly, in the condition of providing load variation to test whether the voltage profile condition can be improved in the case of integration of EVCS and DGs with network reconfiguration, Table 3 presents a comparison of the results obtained using the WOA technique with different load variations (100%, 125%, 150%, and 200% load) for the IEEE-33 bus system. In terms of the location of EVCS and DG, as the load increases, the location shifts, which indicates adaptability to changing load conditions.

Table 2. Comparisons results with other techniques IEEE-33 bus

IEEE-33 BUS	PSO fixed	GA fixed	WOA fixed (Proposed)	WOA non-fixed (Proposed)
Best solution	Case-8	Case-8	Case-8	Case-8
EV and DGs location	19, 2, 4 and 33, 7, 31	2, 3, 19 and 25, 16, 11	2, 2, 2 and 17, 32, 2	2, 2, 2 and 15, 2, 31
Tie switch number	37, 11, 14, 7, 32	28, 9, 32, 7, 14	7, 9, 14, 37, 32	14, 32, 37, 10, 7
Existing Ploss (KW)	202.677+ j135.141			
Ploss (KW)	153.052+ j95.496	151.759+ j94.777	87.724+ j60.677	66.400+ j45.645
% Reduction in Ploss	26.07%	26.67%	56.22%	66.93%
Total DGs Size (KW)	1050+j508.54			1650+j799.131
Total number EV (unit) and EVCS size (KW)	90 and 4500+j2179.5			110 and 5500+j2663.77
Execution time (s)	512.7346	612.7745	463.6473	436.3494

Table 3. Comparisons WOA under load variations IEEE-33 bus

WOA IEEE-33 BUS	100% load	125% load	150% load	200% load
EVCS and DGs location	2, 2, 2 and 17, 32, 2	2, 2, 2 and 31, 2, 18	2, 2, 2 and 32, 33, 31	2, 2, 2 and 31, 2, 32
Tie switch number	7, 9, 14, 37, 32	32, 7, 10, 28 14	14, 7, 9, 28, 32	9, 14, 32, 37, 7
Existing Ploss (KW)	202.677+ j135.141	329.855+ j220.0803	496.3505+ j331.3961	975.7124+ j652.4997
Ploss (KW)	87.724+ j60.677	144.142+ j109.7742	197.9762+ j143.1467	467.1251+ j349.2957
% Reduction in Ploss	56.22%	54.47%	59.09%	50.44%
Existing minimum voltage (p.u)	0.91306	0.88885	0.86335	0.80742
Minimum voltage (p.u)	0.95732	0.94117	0.92073	0.88753

3.2. IEEE-69 Bus system simulation

In the voltage profile of the IEEE 69 Bus simulation, as the follow parameters in Table 1 there is a significant voltage variation between different buses for fixed conditions. The graphical form of the simulated voltage profile of all scenarios of IEEE-69 bus base load fixed conditions can be seen in Figure 6. Its figure the value of the voltage profile decreases as the additional load from the EVCS. However, the minimum voltage value still meets the constraints with a value of 0.90895 p.u at bus 65. The reduction in value can be overcome by the addition of DGs with a minimum state of 0.96076 p.u and will decrease slightly in the integration of EVCS with DGs to 0.94759 p.u at bus 65. where the best state occurs when the integration of EVCS with DGs is carried out after network reconfiguration with a value of 0.9695 p.u at bus 61. The voltage profiles decrease as DGs penetration increases and that network reconfiguration also helps reduce power losses.

Figure 7 shows under fixed conditions, WOA achieves the lowest loss value within 30 iterations, indicating its high efficiency in finding optimal solutions in fewer iterations. Particle swarm optimization (PSO) achieves the lowest loss value within 50 iterations. Although slower than WOA, PSO still shows good convergence and can reach optimal solutions relatively quickly. Genetic algorithm (GA) achieves the lowest loss value within 60 iterations, which is the slowest compared to WOA and PSO. With the same conditions as the previous IEEE-33 bus simulation in IEEE-69 bus, the factors that affect the performance of the algorithm in obtaining the solution are due to the randomness of the system value so that each algorithm obtains different results. Based on the IEEE-69 bus simulation, it is concluded that the WOA algorithm itself is still capable of handling problems with medium complexity and is better than PSO or GA which are usually often used in solving light to medium numerical problems.

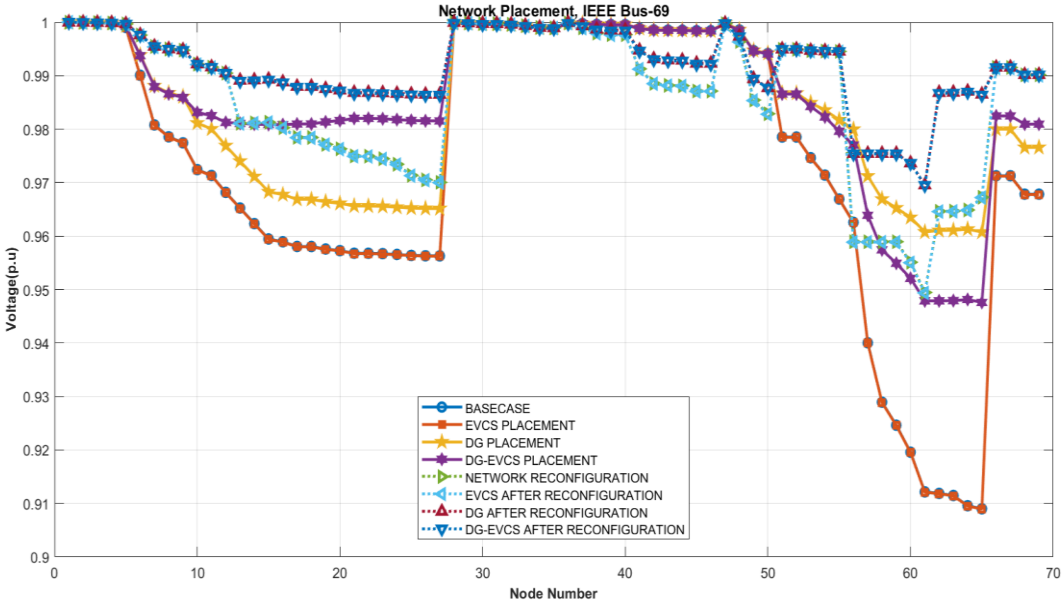

Figure 6. Voltage profile of All IEEE-69 bus scenarios with WOA

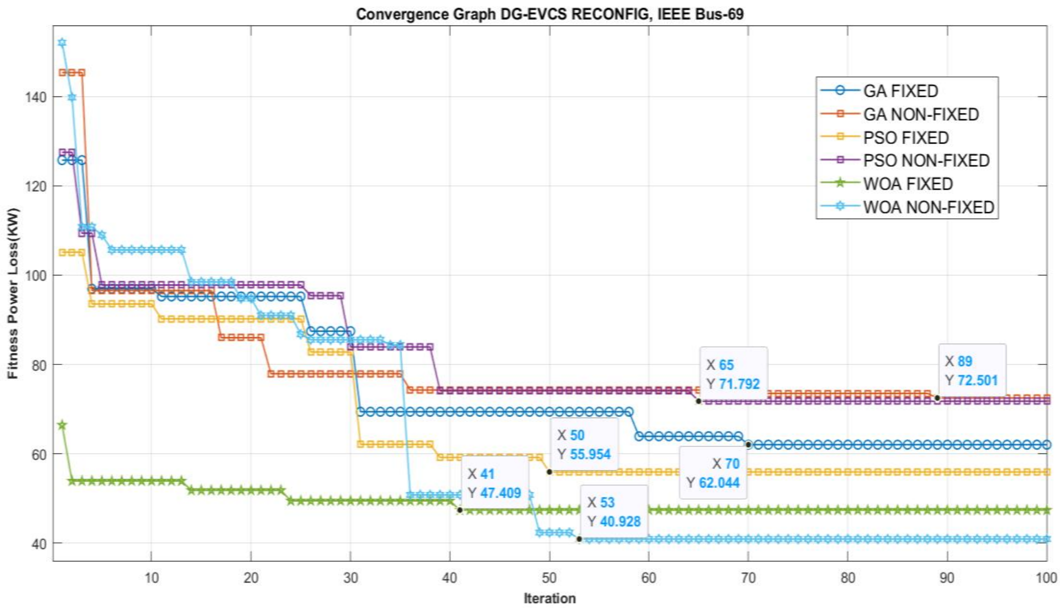

Figure 7. Convergence characteristics simulation IEEE-69 bus

Figure 8 shows the IEEE-69 bus simulation data indicates that the integration of EVCS and DGs with network reconfiguration provides the optimal solution. In the base case, all optimization algorithms yield identical results, with WOA, PSO, and GA showing active power losses of 234.96 kW and reactive power losses of 102.15 kVar. However, when EVCS is introduced, slight increases in losses are observed across all algorithms. The addition of DGs decreases losses, with WOA achieving 67.11 kW and 34.51 kVar, PSO with 69.11 kW and 36.35 kVar, and GA with 78.74 kW and 38.75 kVar. Combining DGs and EVCS leads to increased losses, with WOA, PSO, and GA showing losses of 83.73 kW and 42.41 kVar, 108.18 kW and 49.88 kVar, and 115.82 kW and 59.68 kVar, respectively. However, network reconfiguration significantly reduces losses across all scenarios and algorithms, with WOA achieving the lowest losses of 47.41 kW in active power and 40.07 kVar in reactive power, followed closely by PSO and GA. Therefore, it is confirmed that the integration of EVCS and DGs with network reconfiguration is the optimal solution.

The data presented in Table 4 compares the results of different optimization techniques applied to the IEEE-69 bus system. The techniques compared include PSO, GA, and WOA in both fixed and non-fixed scenarios. The analysis shows that the non-fixed WOA proposed method achieved the best results, with a significant 76.13% reduction in power losses.

Table 5 compares the performance of the whale optimization algorithm (WOA) under various load variations for the IEEE-69 bus system. As the load increases from 100% to 200%, the placement of electric vehicle charging stations (EVCS) and distributed generators (DGs) changes accordingly. Notably, at 100% load, EVCS and DGs are located at nodes 3, 28, 36 and 60, 61, 64, while at 200% load, they shift to nodes 2, 2, 2 and 2, 28, 4. Similarly, the tie switch numbers alter with load variations. Despite the increase in load, WOA consistently achieves a significant reduction in power losses, ranging from 65.06% to 76.13%, demonstrating its effectiveness in optimizing the system under varying load conditions.

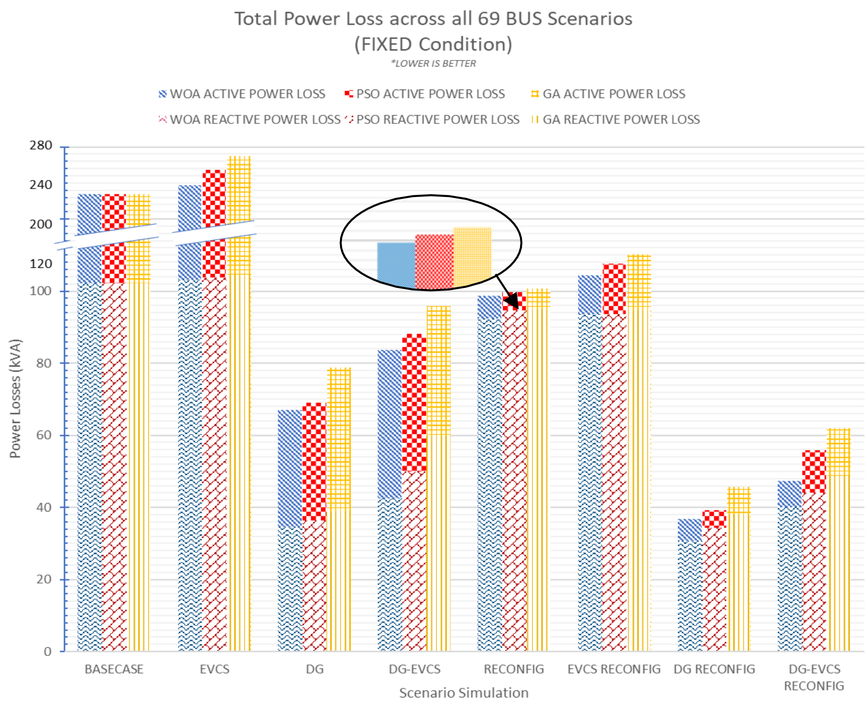

Figure 8. Comparison of performance of optimization methods across IEEE-69 bus scenarios

Table 4. Comparisons WOA under load variations IEEE-33 bus

IEEE-69 BUS	PSO fixed	GA fixed	WOA fixed (Proposed)	WOA non-fixed (Proposed)
Best Solution	Case-8	Case-8	Case-8	Case-8
EV and DGs Location	28, 47, 5 and 59, 61, 2	29, 2, 36 and 51, 59, 27	3, 28, 36 and 60, 61, 64	2, 2, 2 and 61, 2, 27
Tie Switch Number	70, 12, 56, 69, 62	69, 61, 56, 13, 70	61, 70, 55, 12, 69	61, 19, 55, 12, 69
Existing Ploss (KW)		224.9606+ j102.147		
Ploss (KW)	55.954+ j41.0745	62.0442+ j58.7458	47.4094+ j40.0745	40.9285+ j43.1065
% Reduction in Ploss	72.73%	68.24%	76.13%	78.23%
Total DGs Size (KW)		1050+j508.54		1200+j581.19
Total Number EV (unit) and EVCS Size (KW)		90 and 4500+j2179.5		114 and5700+j2760.63
Execution Time (s)	1527.4631	1863.6383	1001.5101	1092.3372

Table 5. Comparisons under load variations IEEE-69 bus

WOA IEEE-69 BUS	100% load	125% load	150% load	200% load
EVCS and DGs Location	3, 28, 36 and 60, 61, 64	53, 47, 47 and 61, 60, 65	2, 2, 2 and 2, 2, 3	2, 2, 2 and 2, 28, 4
Tie Switch Number	61, 70, 55, 12, 69	70, 14, 61, 69, 58	24, 44, 48, 3, 15	53, 14, 60, 5, 70
Existing Ploss (KW)	224.9606+ j102.147	368.9939+ j167.0894	560.4328+j253.0384	1130.1818+j506.9546
Ploss (KW)	47.4094+ j40.0745	114.3148+j97.6085	177.2092+j138.1335	282.9246+j197.0004
% Reduction in Ploss	76.13%	65.17%	65.06%	72.83%
Existing minimum voltage (p.u)	0.90901	0.88315	0.85557	0.79356
Minimum voltage (p.u)	0.9695	0.95646	0.90009	0.89384

4. CONCLUSION

Findings from simulation results on IEEE 33-bus and 69-bus test systems show the advantages of optimal allocation of EVCS, DGs and network reconfiguration, especially under varying loading conditions. In simulations to minimize power losses with network reconfiguration and placement of EVCS and DGs, the WOA algorithm performed better than PSO and GA. The optimal placement of EVCS, DGs as well as network reconfiguration can improve the voltage profile and reduce 56.22% and 76.13% of power losses at IEEE-33 and 69 buses, respectively.

REFERENCES

[1] S. Bouzaid, L. El Mehdi, and A. El Ballouti, "A fast charge algorithm for Li-ion battery for electric vehicles," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 3, pp. 2457–2465, Jun. 2024, doi: 10.11591/ijece.v14i3.pp2457-2465.
[2] F. Ahmad, L. Al-Fagih, S. A. Qadir, and M. Khalid, "EV charging station placement using nature-inspired optimisation algorithms," in *2023 International Conference on Power, Instrumentation, Energy and Control (PIECON)*, IEEE, Feb. 2023, doi: 10.1109/piecon56912.2023.10085885.
[3] A. K. Mohanty and S. B. Perli, "Fuzzy logic based multi-objective approach for optimal allocation of charging stations for electric vehicles," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 2, p. 100089, 2022, doi: 10.1016/j.prime.2022.100089.
[4] M. M. Islam, H. Shareef, and A. Mohamed, "A review of techniques for optimal placement and sizing of electric vehicle charging stations," *Przeglad Elektrotechniczny*, vol. 91, no. 8, pp. 122–126, Aug. 2015, doi: 10.15199/48.2015.08.29.
[5] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Charging station placement for electric vehicles: A case study of Guwahati City, India," *IEEE Access*, vol. 7, pp. 100270–100282, 2019, doi: 10.1109/ACCESS.2019.2931055.
[6] B. T. Geetha, P. A., S. Jeyasudha, and K. P. Dinakaran, "Hybrid approach based combined allocation of electric vehicle charging stations and capacitors in distribution systems," *Journal of Energy Storage*, vol. 72, p. 108273, Nov. 2023, doi: 10.1016/j.est.2023.108273.
[7] M. Bilal, M. Rizwan, I. Alsaidan, and F. M. Almasoudi, "AI-based approach for optimal placement of EVCS and DG with reliability analysis," *IEEE Access*, vol. 9, pp. 154204–154224, 2021, doi: 10.1109/ACCESS.2021.3125135.
[8] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Advances in Engineering Software*, vol. 95, pp. 51–67, May 2016, doi: 10.1016/j.advengsoft.2016.01.008.
[9] T. Naidu, G. Balasubramanian, and B. Venkateshwar Rao, "Optimal power flow with distributed energy sources using whale optimization algorithm," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 5, pp. 4835-4844, Oct. 2023, doi: 10.11591/ijece.v13i5.pp4835-4844.
[10] S. Kumar, K. K. Mandal, and N. Chakraborty, "Comparative performance study of various PSO techniques for multiple allocations of DG units in radial distribution system," in *2015 IEEE Power, Communication and Information Technology Conference (PCITC)*, IEEE, Oct. 2015, doi: 10.1109/pcitc.2015.7438120.
[11] N. Dharavat *et al.*, "Optimal allocation of renewable distributed generators and electric vehicles in a distribution system using the political optimization algorithm," *Energies*, vol. 15, no. 18, p. 6698, Sep. 2022, doi: 10.3390/en15186698.
[12] I. Prempeh, R. A. El-Sehiemy, A. K. Awopone, and P. N. Ayambire, "Optimal allocation and sizing of distributed generation and electric vehicle charging stations using artificial bee colony and particle swarm optimization algorithms," in *2022 23rd International Middle East Power Systems Conference, MEPCON 2022*, IEEE, Dec. 2022, doi: 10.1109/MEPCON55441.2022.10021807.
[13] Y. Siregar, T. S. Jaya Tambun, S. P. Panjaitan, K. Tanjung, and S. Yana, "Distribution network reconfiguration utilizing the particle swarm optimization algorithm and exhaustive search methods," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 2, pp. 821–831, Apr. 2024, doi: 10.11591/eei.v13i2.6206.
[14] M. S. K. Reddy and K. Selvajyothi, "Optimal placement of electric vehicle charging stations in radial distribution system along with reconfiguration," in *2019 IEEE 1st International Conference on Energy, Systems and Information Processing, ICESIP 2019*, IEEE, Jul. 2019, doi: 10.1109/ICESIP46348.2019.8938164.
[15] Y. Siregar, Z. Pane, F. R. Astianta Bukit, and E. Gunanta Sembiring, "Network reconfiguration of distributed generation for reduced power loss and increasing voltage profile by using artificial bee colony," in *Proceedings - 2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering: Applying Data Science and Artificial Intelligence Technologies for Global Challenges During Pandemic Era, ICITISEE 2021*, IEEE, Nov. 2021, pp. 235–240, doi: 10.1109/ICITISEE53823.2021.9655826.
[16] F. R. A. Bukit, N. Mubarakah, and D. M. Nasution, "Minimizing the electrical power distribution cost by optimizing the distributed generation placement," in *2019 3rd International Conference on Electrical, Telecommunication and Computer Engineering, ELTICOM 2019 - Proceedings*, IEEE, Sep. 2019, pp. 60–65, doi: 10.1109/ELTICOM47379.2019.8943868.
[17] S. Lamontagne, M. Carvalho, E. Frejinger, B. Gendron, M. F. Anjos, and R. Atallah, "Optimising electric vehicle charging station placement using advanced discrete choice models," *INFORMS Journal on Computing*, vol. 35, no. 5, pp. 1195–1213, Sep. 2023, doi: 10.1287/ijoc.2022.0185.
[18] A. A. Saleh, A. A. A. Mohamed, A. M. Hemeida, and A. A. Ibrahim, "Multi-objective whale optimization algorithm for optimal allocation of distributed generation and capacitor bank," in *Proceedings of 2019 International Conference on Innovative Trends in Computer Engineering, ITCE 2019*, IEEE, Feb. 2019, pp. 459–465, doi: 10.1109/ITCE.2019.8646352.
[19] A. Slowik, *Swarm intelligence algorithms*. CRC Press, 2020, doi: 10.1201/9780429422614.
[20] Y. T., D. K.R., S. B. Thanikanti, B. Aljafari, and N. Nwulu, "Minimizing the electric vehicle charging stations impact in the distribution networks by simultaneous allocation of DG and DSTATCOM with considering uncertainty in load," *Energy Reports*, vol. 10, pp. 1796–1817, Nov. 2023, doi: 10.1016/j.egyr.2023.08.035.
[21] K. Kathiravan and P. N. Rajnarayanan, "Application of AOA algorithm for optimal placement of electric vehicle charging station to minimize line losses," *Electric Power Systems Research*, vol. 214, p. 108868, Jan. 2023, doi: 10.1016/j.epsr.2022.108868.
[22] S. Rout and G. R. Biswal, "Integration of distributed generations by coordinating electric vehicle charging station in medium voltage network by Swarm intelligence," *World Journal of Engineering*, vol. 20, no. 6, pp. 1097–1111, Jun. 2022, doi: 10.1108/wje-03-2022-0105.

[23] S. H. Dolatabadi, M. Ghorbanian, P. Siano, and N. D. Hatziargyriou, "An enhanced IEEE 33 bus benchmark test system for distribution system studies," *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 2565–2572, May 2021, doi: 10.1109/TPWRS.2020.3038030.
[24] Y. Sun, X. Kong, Z. Yang, L. Zheng, J. Qin, and Y. Wang, "Optimize the placement of measurement and remote control switch in distribution network to improve the network observability after network reconfiguration: A bilevel coordinated optimization approach," in *2022 25th International Conference on Electrical Machines and Systems (ICEMS)*, IEEE, Nov. 2022, doi: 10.1109/icems56177.2022.9983157.
[25] J. Blanco-Solano, J. F. Petit-Suarez, and G. Ordonez-Plata, "Optimal placement of voltage sag monitors in smart distribution systems: Impact of the dynamic network reconfiguration," in *2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM)*, IEEE, Oct. 2015, doi: 10.1109/isgt-la.2015.7381182.

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