JTE HCM-UTE
ISSN: 2615-9740

JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Engineering
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

Placement Optimal of Electric Vehicle Charging Stations Considering Location Constraints in Distribution Networks Integrated Distributed Generation

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ARTICLE INFO

Received:	14/01/2025
Revised:	01/02/2025
Accepted:	17/06/2025
Published online:	03/02/2026

KEYWORDS

Electric vehicle;
Symbiotic Organisms Search;
EV charging station;
Land cost index;
Distribution network.

ABSTRACT

Electric vehicles (EVs) are receiving significant attention from countries worldwide due to their outstanding environmental advantages. However, this development has led to the rapid increase and uneven geographical distribution of electric vehicle charging stations (EVCS), which puts pressure on and causes some negative impacts on the power system, particularly the distribution network. Optimizing the placement of EVCS is crucial as it directly affects the efficiency and stability of the power grid, including energy losses, voltage quality, and harmonic distortion. This study focuses on optimizing the placement of EVCS in the distribution network, taking into account cost constraints and EV traffic density, with the objective of minimizing power losses, supporting investment decisions, and ensuring operational indicators of the system. An improved meta-heuristic method combining the Symbiotic Organisms Search (SOS) algorithm and a Chaotic search function (CSOS) is proposed to enhance the search efficiency for solving the problem. The IEEE 34 bus standard distribution network was used to test and evaluate the method through simulations performed in Matlab R2022a. The results from CSOS were assessed and compared with previous studies to demonstrate the superiority and effectiveness of the proposed solution.

Doi: https://doi.org/10.54644/jte.2026.1765

1. Introduction

Energy transition in the transportation sector played a significant role in reducing greenhouse gas emissions and combating climate change. As one of the major sources of carbon emissions, the transportation industry must shift to EV as a potential solution to mitigate environmental impacts. Governments worldwide have introduced various policies and incentives to accelerate this transition, encouraging the adoption of EVs. However, the widespread adoption of EVs has heavily depended on the development of an efficient and extensive charging infrastructure system.

Selecting appropriate locations for EVCS within the power grid has been recognized as crucial, as it significantly impacts efficiency, losses and reliability. However, this remains a complex problem requiring reliable computational models due to the constraints of various factors. Improper placement has resulted in increased losses, voltage fluctuations, harmonic distortion, and serious effects on the efficiency and stability of the power grid [1]. Therefore, determining the optimal placement of EVCS has become a critical issue for achieving efficiency and meeting the growing demand for EVCS infrastructure development, drawing the attention of managers and experts alike.

These issues have been addressed in various studies, which have proposed solutions such as integrating EVCS into distribution networks. For instance, reference [2] explored the application of the Particle Swarm Optimization (PSO) algorithm to identify the most suitable location and capacity for EVCS within power systems integrated with distributed generation (DG). This study was conducted on the IEEE 19 bus and IEEE 25 bus standard test systems, with the primary objective of minimizing power losses across the network while enhancing overall system performance. Another study has leveraged renewable energy sources to optimize EVCS operations by combining PSO with the Bacterial Foraging Optimization Algorithm (BFOA), resulting in a hybrid BFOA-PSO technique [3] that enhances computational efficiency. According to [4], PSO has also been proposed to optimize the placement and size of EVCS based on incentive programs, aiming to minimize investment costs and reduce losses while incorporating load dispatching techniques. This solution has demonstrated high practicality and effectiveness. Furthermore, in [5] the combination of PSO and Genetic Algorithm (GA) has been utilized to evaluate the impact of EVCS placement integrated with DG on voltage deviations, power losses, and operational costs. The results have highlighted the efficiency of the hybrid GA-PSO method. Additionally, the Bat Algorithm (BA) has been applied for simultaneous EVCS placement and DG capacity allocation, maintaining voltage stability and minimizing power losses, which has yielded significant benefits even under fluctuating and increasing EVCS loads [6]. An improvement called the Balanced Mayfly Algorithm (BMA) has also been explored, considering metrics such as Voltage Profile Improvement Index (VPII), Reactive Power Loss Reduction Index (QLRI), Active Power Loss Reduction Index (PLRI), and minimizing installation costs while enhancing power quality [7]. Parallelly, the study [8] has employed the Grey Wolf Optimization (GWO) method to solve a multi-objective optimization problem for determining the optimal EVCS placement. This approach has aimed to maximize the number of EVs served at EVCS while minimizing investment costs and power losses. These findings have provided a critical foundation for planning and developing EV infrastructure in the future.

Although previous studies have proposed effective solutions to mitigate negative impacts on the power grid and address complex constraints, the algorithms applied in these computational models have yet to fully exploit the constraints or ensure high accuracy of the solutions. In this study, we propose an improved CSOS method based on the original SOS algorithm, incorporating a chaotic search function to enhance solution efficiency and accuracy. This method aims to determine the optimal placement of EVCS in distribution networks to improve voltage quality and minimize power losses, considering DG placement. The model has been tested and simulated on the IEEE 34 bus network using Matlab R2022a software under three different scenarios and compared with the previously published hybrid GWOPSO method to evaluate its superiority and accuracy.

The main contributions of this study can be summarized as follows:

- Proposing the application of the improved CSOS algorithm to enhance the efficiency of problem solving.
- Developing a problem model to evaluate construction costs and installation loss costs for EVCS.
- Simulating and solving the problem using Matlab R2022a software.
- Comparing and assessing the superiority of the proposed method and recommending practical applications for EVCS development.

2. Problem Formulation

The cost of land rental for placing EVCS in urban, densely populated areas is much higher than in rural areas, but EV traffic is more concentrated in these urban zones. As a result, investors are cautious and carefully weigh these factors to calculate economic efficiency before committing to EVCS investments. Determining suitable locations for installing EVCS requires an initial assessment of EV traffic, the number of EVCS needed, and the corresponding land rental costs in the proposed area.

2.1. Number of EVCSs

The number of CS is calculated using the following equation [9]:

$$N_{CS} = \frac{P_{EV} \times N_{EV} \times t_c}{t_s \times f_{ch} \times C_{CS} \times d_{lf}} \tag{1}$$

Where: P_{EV} represents the average power consumption of each EV, N_{EV} the total count of EVs charged per day, t_c the time required to fully charge an EV, t_s the service time of the CS, C_{CS} the power capacity of the CS, f_{ch} the charging efficiency, d_{lf} the load demand factor of the CS.

2.2. Formulation of charging station owner decision index

2.2.1. Land cost index (LCI):

Land rental costs vary based on geographical distribution. Therefore, investors need to consider the costs associated with each potential location before deciding to build a CS. To address this, the LCI is introduced to represent land cost factors in the design problem. The LCI is calculated by normalizing the land cost at each bus, dividing it by the maximum land cost in the system.This normalization ensures that the LCI ranges from 0 to 1, reflecting the relative land cost at each bus within the system, as follows:

$$LCI_i^{NB} = \frac{LC_i^{NB}}{\max\left\{LC_i^{NB}\right\}} \tag{2}$$

Where NB the number of bus; LC_i represents the land cost at the i^{th} bus.

2.2.2. Electric vehicle flow index (EVFI):

An investor's profitability is significantly influenced by the quantity of EVs serviced at a charging station (CS). To address this, the EVFI is developed to evaluate and rank potential locations based on the highest EV traffic. EVFI serves as a crucial metric that assists investors in prioritizing installation locations for CS, thereby optimizing the operational performance and profitability of the CS within the distribution system.

$$EVFI_i^{NB} = \frac{EVFI_i^{NB}}{\max\left\{EVFI_i^{NB}\right\}} \tag{3}$$

$$DI_i^{NB} = \alpha \times LCI_i^{NB} - \beta \times EVFI_i^{NB} \tag{4}$$

Finally, the Decision Index *(DI)* is formulated by combining LCI and EVFI. It is represented as follows:

Where α and β are positive parameters used to adjust the relative importance of land cost and the number of EVs in the decision making process. In this study, both α and β are assigned a value of 0.5, indicating that land cost and the number of EVs are given equal weighting.

2.3. Case Study

2.3.1. Objective function:

The primary objective of this study is the minimization of system power loss, which is described as follows:

$$OF = Min(P_L) \tag{5}$$

where

$$P_L = \sum_{k=1}^{N_L} R_k I_k^2 \tag{6}$$

Where N_L represents the total number of lines; R_k denotes the resistance of the k^{th} line, I_k the current of the k^{th} line.

2.3.2. Constraints

- **Power balance constraint:**

$$P_{SS} = \sum_{i=1}^{NB} P_{Di} + P_{loss} + \sum_{i=1}^{N_{CS}} P_{CSi} \tag{7}$$

$$Q_{SS} = \sum_{i=1}^{NB} Q_{Di} + Q_{loss} + \sum_{i=1}^{N_{CS}} Q_{CSi} \tag{8}$$

Where: P_{ss}, P_{Di}, P_{loss} and P_{CSi} the active power from the transformer station, the active power demand at bus i^{th}, the total active power loss the additional load at bus i^{th} due to the placement of CS, respectively; Q_{ss}, Q_{Di} and Q_{loss} are the reactive power from the transformer station, the reactive power demand at bus i^{th}, and the total reactive power loss, respectively.

- **Voltage limit:**

$$V_i^{\min} \le V_i \le V_i^{\max}, i = 1,2,3..., NB \tag{9}$$

- **Branch current limit**

$$I_j^{\min} \le I_j \le I_j^{\max}, j = 1,2,3..., N_L \tag{10}$$

2.4. Chaotic Symbiotic Organisms Search Algorithm

2.4.1. Symbiotic Organisms Search Algorithm

The SOS algorithm has been introduced by Cheng and Prayogo (2014) [10]. It has been a straightforward yet effective method that has employed a population based search approach to guide candidate solutions through iterative exploration of promising optimal areas until a global optimal solution for a given objective function has been identified. The SOS algorithm has drawn inspiration from the concept of symbiosis in biology, where various organisms have coexisted in an ecosystem, either competing for survival or collaborating to thrive.

The SOS algorithm operates with a population of predefined size, referred to as ecosize. Initially, a random ecosystem has been created, similar to other evolutionary algorithms (EAs). Each organism (or individual) X_i within the ecosystem represents a potential solution to the optimization problem at hand. X_i is a D-dimensional vector of real values, where D corresponds to the dimensionality of the optimization problem. The algorithm incorporates symbiotic, mutualistic, and parasitic phases to enhance specific organisms, replacing an organism if its new solution has outperformed the previous one. The process has continued iteratively until a predefined stopping condition has been met.

Mutualism phase

In SOS, a population of organisms has been represented by a set, where each organism $X_i = [x_{i1}, x_{i2}, ..., x_{iD}]$ (i =1,2,…, *Eco_size*; D represents the dimension of the optimization problem; and *Eco_size* denotes the size of the ecosystem. Let X_i denote an organism corresponding to the i^{th} member of the ecosystem. Another organism X_j ($j \neq i$) has been randomly selected from the ecosystem to engage in an interaction with the organism X_i through a mutualistic relationship. New organisms, X_i^{new} and X_j^{new} have been created from this interaction as follows [11]:

$$X_i^{new} = X_i + rand(0,1) \times (X_{best} - MV \times bf_1) \tag{11}$$

$$X_j^{new} = X_j + rand(0,1) \times (X_{best} - MV \times bf_2) \tag{12}$$

$$MV = \frac{bf_1 + bf_2}{2} \tag{13}$$

where *rand* represents a random number in the range [0, 1]; bf_1 and bf_2 are the benefit factors which have been stochastically selected as either 1 or 2; *MV* denotes a mutual vector which is the average of benefit factors, representing for a mutualistic relationship; and X_{best} refers to the best organism in the ecosystem.

New organisms (X_i^{new}, X_j^{new}) are updated only if their fitness values have been found to be better than those of the current organisms (X_i and X_j).

The process of updating new organisms is outlined in the following manner:

$$X_i = \begin{cases} X_i^{new} & if \quad f(X_i^{new}) < f(X_i) \\ X_i & otherwise \end{cases} \tag{14}$$

$$X_j = \begin{cases} X_j^{new} & if \quad f(X_i^{new}) < f(X_i) \\ X_j & otherwise \end{cases} \tag{15}$$

Commensalism phase

In the commensalism phase, organism X_j has been randomly selected from the ecosystem to form a relationship with organism X_i. During this interaction, organism X_i tries to gain a benefit; while organism X_j remains unaffected by the relationship, neither benefiting nor suffering. A new organism, resulting from this commensal symbiotic relationship, has been generated based on the following process [11]:

$$X_i^{new} = X_i + rand(-1,1) \times (X_{best} - X_j) \tag{16}$$

The new organism will be updated only if its fitness value has been determined to be superior to that of the previous organism.

Parasitism phase

In this phase, organism X_i was assigned the role of a parasite, and its primary function was to interact with a randomly selected organism Xj from the current ecosystem, which served as the host. To begin the process, organism X_i created the *Parasite_Vector (PV)* by duplicating itself. The variables of the *PV* were then modified using random numbers, introducing slight changes to differentiate it from the original organism X_i. After these modifications, fitness values were calculated for both the *PV* and the host organism X_j. If the fitness value of *PV* was determined to be better than that of Xj, the *PV* would replace the host organism X_j in the ecosystem. If the fitness value of *PV* was not superior, the *PV* would vanish, and organism X_j would remain in its place within the ecosystem, continuing the process. This phase ensures that only more efficient solutions persist in the ecosystem, contributing to the overall optimization of the system [11].

2.4.2. Chaotic - Symbiotic Organisms Search Algorithm

Although SOS has shown promising results in various problems, its performance can be further enhanced by integrating chaotic functions into the search process. Chaos theory introduces a form of randomness that helps the algorithm avoid local optimal and improves its global exploration capabilities. The Chaotic Local Search (CLS) strategy has been implemented on the current best population of CSOS in order to enhance the optimization process. This technique focuses on exploring the surrounding search space of the best current solutions, aiming to uncover even better solutions by refining the existing ones. By leveraging chaotic dynamics, the CLS strategy creates a more diverse set of candidate solutions, allowing the algorithm to escape local optima and improve the overall quality of the population. From the current best population, a new and potentially better solution is generated through the CLS method, following the equation outlined below [12]:

$$X_{best,k}^{new} = X_{best,k} + (X_k - 0.5) \times (X_{i,k} - X_{j,k}) \tag{17}$$

where X_k is generated using 10 chaotic maps, each contributing to the overall solution by introducing different chaotic behaviors [13].

The process of updating a new solution is carried out in the following manner:

$$X_{best,k} = \begin{cases} X_{best,k}^{new} & if \quad f(X_{best,k}^{new}) < f(X_{best,k}) \\ X_{best,k} & otherwise \end{cases} \tag{18}$$

2.4.3. Implementation of CSOS to the EVCS Problem

Step 1: Begin by identifying the key components of the problem, including the size of the ecosystem, the maximum number of iterations, and the total number of EVCS.

Step 2: Initialize the population for the CSOS algorithm.

Step 3: Use chaotic maps for the initialization process.

Step 4: Commensalism phase: A random individual is selected from the ecosystem to interact with another, and the outcome of this interaction determines if the individual benefits or remains unaffected, as expressed by equation (16).

Step 5: Parasitism phase: Generate parasitic organisms to attack existing individuals and replace less effective solutions with better ones. Use chaotic maps to adjust decision variables during the parasitic phase.

Step 6: The objective function value is recalculated for each individual in the population, and the best individual is selected to continue the search process, as outlined in equation.

Step 7: After each iteration, individuals are updated based on Step 6 results, maintaining or replacing them depending on solution effectiveness.

Step 8: Terminate if the maximum number of iterations is reached or if there is no improvement in the objective function over consecutive iterations, resulting in the optimal solution.

Step 9: Assess the performance of the final solution and extract the results for further analysis.

3. Simulation results

The challenge involves identifying the optimal placement of EVCS within the distribution network of the IEEE 34 bus system. The implementation was carried out using a source code developed on the Matlab platform, with 20 independent trial runs conducted to evaluate the algorithm's effectiveness and stability. Additionally, calculations related to power distribution and electrical flow were performed using Matpower version 6.0, a specialized tool widely used in power system.

The input data for the EVCS planning problem was detailed in [14], which provides the necessary information for calculations and algorithm implementation. Based on equation (1) and the results obtained from the calculation process, the number of EVCS was determined to be three. Consequently, IEEE 34 bus used with three charging stations optimally selected and installed to ensure efficient system operation and meet the charging demands of EV.

Solar photovoltaic generation is a rapidly developing renewable energy source that alleviates the pressure on the power grid caused by EVCS load. However, the rapid increase in EVCS integration into the power grid has led to an imbalance between supply and demand. In this study, the locations of SPDG are randomly distributed across the bus of the distribution network, as shown in Table 1 [14].

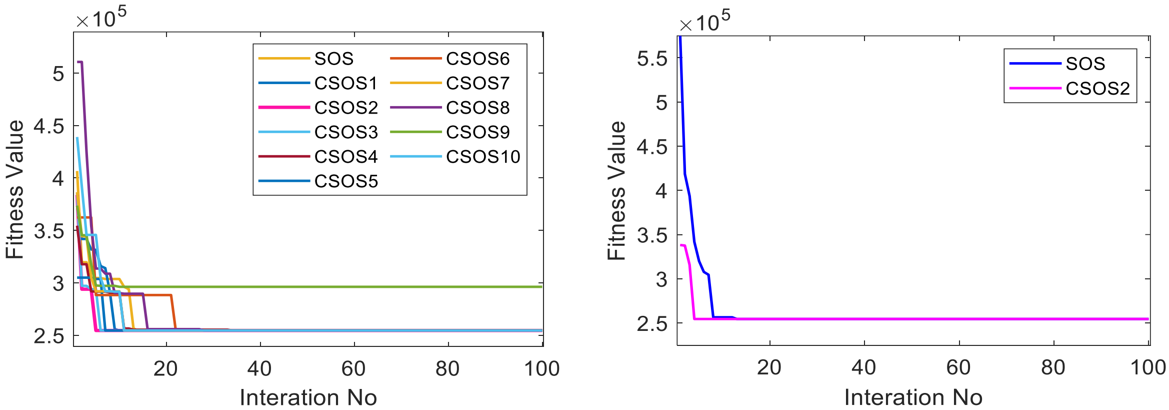
Table 1. *Location and Capacities of DG Units*

Type of DG	Site at Bus	Capacity (kW)

DG_1	22	500
DG_2	6	250
DG_3	11	250

3.1. Testing the CSOS Algorithm

In this section, the enhanced CSOS algorithm has been evaluated using 10 chaotic search functions to assess its effectiveness in solving the optimization problem. After running simulations for 100 iterations, it has been found that CSOS2 outperforms the other algorithms in terms of both convergence speed and the quality of the objective values as shown in Figure 1a. The superior performance of CSOS2 indicates its ability to more efficiently explore the solution space, achieving optimal solutions faster than the alternatives as shown in Figure 1b. This makes CSOS2 a highly effective choice for the EVCS location optimization problem, as it ensures better accuracy and quicker convergence, making it a recommended algorithm for real world applications in distribution networks.



(a) *(b)*

Figure 1. *Convergence Curve Characteristics (a) Curve of CSOS; (b) Curve of CSOS2 and SOS.*

3.2. The results of DI

The value of DI is calculated for each bus in the distribution system. Therefore, LCI for land costs is illustrated for the three proposed scenarios offering insights into how various configurations or conditions have influenced the overall land cost distribution within the system, with some locations marked as having no available land for EVCS installation, represented as infinity, and accompanied by information about the EV population density. Based on these data, three important indices LCI, EVFI, and DI were computed for each bus in the IEEE 34 bus distribution network, corresponding to the three proposed scenarios. The values of DI are then sorted in ascending order to determine the priority for EVCS installation. Among these, the eight locations with the highest DI values are prioritized for deployment, as specifically presented in Table 2.

Based on the results in Table 2, the selected bus locations for EVCS installation have been analyzed and arranged appropriately for each scenario to ensure efficiency, accessibility, and the optimal functioning of the distribution network. Specifically, the selected locations for each scenario are as follows:

- Scenario 1: 19, 17, 18, 13, 10, 28, 30, 4;
- Scenario 2: 17, 18, 19, 9, 5, 31, 2, 6;
- Scenario 3: 18, 15, 19, 17, 28, 21, 32, 25.

Table 2. *Comparative DI bus order for IEEE-34 Distribution Network*

Scenario 1	**Scenario 2**	**Scenario 3**

Bus No	LCI	Bus order	DI	Bus No	LCI	Bus order	DI	Bus No	LCI	Bus order	DI
1	Inf	19	-0.4667	1	Inf	17	-0.3500	1	Inf	18	-0.2583
2	0.8333	17	-0.3500	2	0.0500	18	-0.2583	2	0.5000	15	-0.2250
3	Inf	18	-0.2583	3	Inf	19	-0.1667	3	0.6667	19	-0.1667
4	0.0500	13	-0.1167	4	0.5000	9	-0.0917	4	Inf	17	-0.1250
5	0.6667	10	-0.1000	5	0.0333	5	-0.0583	5	Inf	28	-0.0583
6	0.1667	28	-0.0583	6	0.3333	31	-0.0250	6	0.3333	21	-0.0250
7	0.8333	30	-0.0417	7	0.8333	2	0.0000	7	0.8333	32	-0.0250
8	0.6667	4	-0.0250	8	0.6667	6	0.0917	8	0.6667	25	0.0083

3.3. Results of optimal placement of EVCSs using CSOS

As mentioned in previous sections, the analysis process helped reduce the number of potential locations for EVCS installation from the initial 33 positions to 8 prioritized locations. This is the result of applying specific evaluation criteria, including indices such as land cost, EV density, and energy demand, aimed at optimizing the distribution network. Alternatively, from the 8 identified locations, the top three optimal positions were selected through the process of finding the best locations, focusing on minimizing active power losses, while also ensuring compliance with technical constraints during operation, and finding the most effective solution to the problem.

Table 3 provides a detailed analysis and comparison between two modern optimization algorithms, including the proposed CSOS and GWOPSO [14], this detailed evaluation focuses on their performance in solving the challenging problem of identifying the optimal locations for EVCS under different scenarios, providing insights into the efficiency and accuracy of each algorithm.

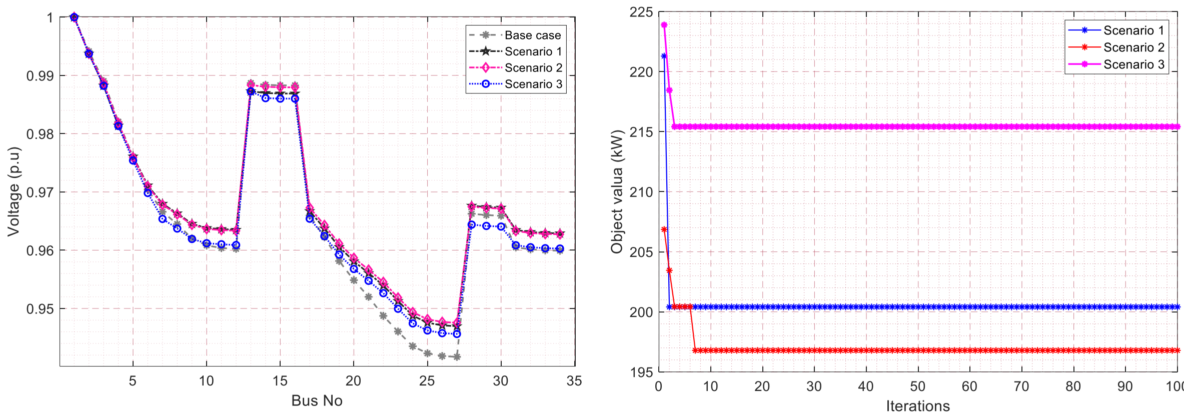
The initial total power loss of the system is determined to be 221.6947 kW, with a minimum voltage of 0.9417 p.u at bus 27 and a maximum voltage of 0.9941 p.u at bus 2. In Scenario 1, the hybrid GWOPSO algorithm reduces the energy loss to 202.74 kW, while improving the minimum voltage to 0.9467 p.u. Meanwhile, the CSOS algorithm achieves better results with a lower energy loss of 200.4092 kW and a higher minimum voltage of 0.9470 p.u. Both algorithms identify the EVCS locations at buses 4, 13, and 17.

Table 3. *Summary of Results for the Proposed Charging Station Techniques*

		Hybrid GWOPSO		
	Base case	**Scenario 1**	**Scenario 2**	**Scenario 3**
Power loss (kW)	221.6947	202.74	198.93	218.55
Min Voltage (p.u)	0.9417	0.9467	0.9473	0.9453
EVCS Location	-	4,13,17	2,5,6	15,7,28
		SOS		
Power loss (kW)	221.6947	200.4092	196.7872	215.4153
Min Voltage (p.u)	0.9417	0.9470	0.9475	0.9456
EVCS Location	-	4,13,17	2,5,6	15,17,28
		CSOS		

Power loss (kW)	221.6947	200.4092	196.7872	215.4153
Min Voltage (p.u)	0.9417	0.9470	0.9475	0.9456
EVCS Location	-	4,13,17	2,5,6	15,17,28

In Scenario 2, the hybrid GWOPSO algorithm continues to demonstrate its ability to reduce energy loss to 198.93 kW, while maintaining the minimum voltage at 0.9473 p.u. However, CSOS proves to be more efficient, with energy loss reduced to 196.7872 kW and a slight improvement in the minimum voltage, reaching 0.9475 p.u. This shows that CSOS not only minimizes energy loss more effectively but also ensures more stable voltage levels within the system. Both algorithms identify the optimal EVCS locations at buses 2, 5, and 6, optimizing the operational performance of the network.



(a) *(b)*

Figure 2. *Voltage characteristic and convergence path of 3 scenarios*
(a) Voltgae profile for scenarios; (b) Convergence curves of scenarios

In Scenario 3, with changing conditions and parameters, the hybrid GWOPSO algorithm reports energy loss at 218.55 kW, with the minimum voltage dropping to 0.9453 p.u. While achieving notable results, CSOS continues to demonstrate its superior performance by reducing energy loss further to 215.4153 kW, with a slight improvement in the minimum voltage, reaching 0.9456 p.u. This difference highlights the effectiveness of the CSOS algorithm in optimizing the system. Notably, CSOS identifies the optimal EVCS locations at buses 15, 17, and 28, unlike GWOPSO, demonstrating better adaptability and resource allocation. This result is clearly illustrated in Figure 2, where CSOS slightly outperforms Hybrid GWOPSO, reinforcing CSOS as a comprehensive and efficient solution in managing and operating distribution networks.

4. Conclusion

The research results proposed a two stage methodology aimed at optimizing the placement of EVCS in the distribution network, effectively combining the economic benefits for CS owners with the operational efficiency goals of the entire system. The first stage reduces the search space by optimizing economic benefits and minimizing investment costs, while the second stage focuses on minimizing power loss and improving bus voltage quality. The improved CSOS2 algorithm was selected and applied to find solutions, and compared with the previously published Hybrid GWOPSO method. Testing on the IEEE 34 bus system showed that CSOS2 consistently outperforms other methods. Specifically, CSOS2 not only reduces power loss but also improves the minimum voltage stability compared to other methods. Furthermore, the algorithm demonstrates robustness and stability, as evidenced by the smallest standard deviation in power loss statistics during the experiments.

The findings of the study have confirmed that CSOS2 is a robust and effective solution for optimizing the placement of EVCS in distribution networks integrated with DG. More importantly, the results not only provide practical value in improving operational performance but also lay the scientific foundation to promote the development of EVCS infrastructure. This is especially significant in the context of the growing number of EVs, reducing carbon emissions, and moving toward a sustainable foundation for the global energy and transportation sectors.

Acknowledgments

We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

Conflict of Interest

The authors declare no conflict of interest.

REFERENCES

[1] H. Zhang, Z. Hu, Z. Xu, and Y. Song, "An Integrated Planning Framework for Different Types of PEV Charging Facilities in Urban Area," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2273–2284, Sep. 2016, doi: 10.1109/TSG.2015.2436069.

[2] M. S. K. Reddy and K. Selvajyothi, "Optimal placement of electric vehicle charging station for unbalanced radial distribution systems," *Energy Sources, Part A Recover. Util. Environ. Eff.*, pp. 1–15, Feb. 2020, doi: 10.1080/15567036.2020.1731017.

[3] W. S. T. Fokui, M. J. Saulo, and L. Ngoo, "Optimal Placement of Electric Vehicle Charging Stations in a Distribution Network With Randomly Distributed Rooftop Photovoltaic Systems," *IEEE Access*, vol. 9, pp. 132397–132411, 2021, doi: 10.1109/ACCESS.2021.3112847.

[4] T. J. Ai and V. Kachitvichyanukul, "A particle swarm optimization for the vehicle routing problem with simultaneous pickup and delivery," *Computers & Operations Research*, vol. 36, no. 5, pp. 1693-1702, 2009, doi: 10.1016/j.cor.2008.04.003.

[5] M. R. Mozafar, M. H. Moradi, and M. H. Amini, "A simultaneous approach for optimal allocation of renewable energy sources and electric vehicle charging stations in smart grids based on improved GA-PSO algorithm," *Sustain. Cities Soc.*, vol. 32, pp. 627–637, 2017, doi: 10.1016/j.scs.2017.05.007.

[6] K. Singh, K. D. Mistry, and H. G. Patel, "Optimal Placement of Electric Vehicle Charging Station and DG in a Distribution System for Loss Minimization," *2023 IEEE 3rd Int. Conf. Sustain. Energy Futur. Electr. Transp. SeFet 2023*, no. February, pp. 1–6, 2023, doi: 10.1109/SeFeT57834.2023.10244845.

[7] L. Chen, C. Xu, H. Song, and K. Jermsittiparsert, "Optimal sizing and sitting of EVCS in the distribution system using metaheuristics: A case study," *Energy Reports*, vol. 7, pp. 208–217, 2021, doi: 10.1016/j.egyr.2020.12.032.

[8] F. Ahmad, M. Marzband, A. Iqbal, I. Ashraf, and I. Khan, "Placement of Electric Vehicle Fast Charging Stations using Grey Wolf Optimization in Electrical Distribution Network," *PESGRE 2022 - IEEE Int. Conf. "Power Electron. Smart Grid, Renew. Energy,"* no. March 2023, 2022, doi: 10.1109/PESGRE52268.2022.9715842.

[9] F. Ahmad, I. Ashraf, and A. Iqbal, "Placement of FCS Considering Power Loss, Land Cost, and EV Population," in *2023 International Conference on Power, Instrumentation, Energy and Control, PIECON 2023*, Feb. 2023, pp. 1–6. doi: 10.1109/PIECON56912.2023.10085898.

[10] A. E. Ezugwu and D. Prayogo, "Symbiotic Organisms Search Algorithm: theory, recent advances and applications," *Expert Systems with Applications*, vol. 119. pp. 184–209, Apr. 2019. doi: 10.1016/j.eswa.2018.10.045.

[11] M. Y. Cheng and D. Prayogo, "Symbiotic organisms search: a new metaheuristic optimization algorithm," *Comput. Struct.*, vol. 139, pp. 98–112, 2014.

[12] J. Ji, S. Gao, S. Wang, Y. Tang, H. Yu, and Y. Todo, "Self-adaptive gravitational search algorithm with a modified chaotic local search," *Ieee Access*, vol. 5, pp. 17881–17895, 2017.

[13] G. G. Wang, L. Guo, A. H. Gandomi, G. S. Hao, and H. Wang, "Chaotic Krill Herd algorithm," *Inf. Sci. (Ny).*, vol. 274, pp. 17–34, 2014, doi: 10.1016/j.ins.2014.02.123.

[14] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. Khan, "Placement of electric vehicle fast charging stations in distribution network considering power loss, land cost, and electric vehicle population," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 44, no. 1, pp. 1693–1709, 2022, doi: 10.1080/15567036.2022.2055233.

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