Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

International Journal of Electrical and Intelligent Engineering

Plug-in Electric Vehicle Charging Station Placement using Hybrid Genetic Algorithm-Particle Swarm Optimization

Ardhito Primatama[1]* **Hadi Suyono[2]** **Rini Nur Hasanah[3]**

[1]*Universitas Islam Negeri Maulana Malik Ibrahim Malang,Indonesia*
[2,3]*Universitas Brawijaya, Indonesia*
* Corresponding author's Email: ardhitop@uin-malang.ac.id

Abstract: The increasing penetration of plug-in electric vehicles (PEVs) introduces significant challenges to distribution networks, particularly in terms of power losses, voltage deviation, and transformer loading. Proper planning of fast charging station locations is therefore essential to ensure reliable and efficient grid operation. This paper proposes a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) method to determine the optimal placement of level-3 PEV charging stations in a radial distribution network. The proposed approach combines the global search capability of Genetic Algorithms with the fast convergence characteristics of Particle Swarm Optimization to balance exploration and exploitation while avoiding premature convergence. The optimization objective considers minimization of real and reactive power losses and voltage deviation, subject to system constraints such as bus voltage limits and transformer capacity. The method is validated using a real 20 kV distribution feeder from PLN in South Surabaya. Simulation results demonstrate that the HGAPSO method outperforms conventional GA and PSO approaches by achieving lower power losses while requiring fewer charging heads. These results indicate that the proposed HGAPSO provides an effective and practical solution for optimal PEV charging station planning in distribution systems.

Keywords: Charging Station Placement, Distribution Network, Hybrid Optimization, Plug-in Electric Vehicle, Power Loss

1. Introduction

An electric vehicle, commonly referred to as a plug-in electric vehicle (PEV), is powered by an electric motor that draws energy from an onboard battery. The global adoption of electric vehicles has increased significantly in recent years, driven by environmental concerns and energy transition policies. Previous studies reported that electric vehicles were expected to account for approximately 10% of global vehicle sales by 2020 [1]. In Indonesia, the acceleration of electric vehicle adoption is formally regulated under Presidential Regulation No. 55 of 2019, which emphasizes not only vehicle deployment but also the development of public charging infrastructure [2]. These policy initiatives highlight the growing importance of reliable and well-planned charging systems to support large-scale PEV penetration.

According to the International Electrotechnical Commission (IEC), electric vehicle charging systems are categorized into three main levels based on voltage, current, and charging speed. Level 1 charging utilizes single-phase AC supply, typically rated at 120 V/16A in North America and 230 V/16A in Europe and Southeast Asia. Level 2 charging employs single-phase or three-phase AC supply with voltage levels ranging from 208 V to 240 V and current ratings up to 80 A. Level 3 charging, commonly referred to as fast or rapid charging, operates using high-voltage DC supply in the range of 300–500 V with current levels between 125 A and 250 A, enabling significantly reduced charging times [3].

Charging at home or in workplace parking facilities using Level 1 or Level 2 chargers is suitable for long-duration parking; however, such charging methods are impractical for users traveling long distances due to extended charging times, which may range from two to eight hours. In contrast, Level 3 fast charging technology can typically recharge an electric vehicle battery within 30 minutes, making it more attractive for public and highway charging applications. The widespread acceptance of electric vehicles is therefore closely linked to the availability of strategically located fast charging stations that align with user travel patterns. Nevertheless, fast charging stations impose substantial power demands on the electrical grid and must be carefully planned to ensure adequate supply and system reliability [4].

The integration of fast charging stations introduces new technical challenges for distribution networks, including increased power losses, voltage deviations, and potential overloading of network

Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

International Journal of Electrical and Intelligent Engineering

components. Consequently, determining the optimal placement of fast charging stations with minimal adverse impacts on the existing distribution infrastructure has become an important research topic. Several studies have investigated charging station placement at substations to minimize network losses and voltage violations [5]. Other works have incorporated transportation factors such as driving distance and traffic flow into the placement strategy [6], while some studies have explored the co-optimization of charging stations and renewable energy sources to enhance system sustainability [7]. In addition, various heuristic and metaheuristic optimization techniques, including Particle Swarm Optimization (PSO), have been widely applied to address this complex planning problem [8]. More recently, hybrid optimization approaches that combine multiple algorithms have been proposed to improve solution quality and convergence performance [9].

In this study, the focus is placed on the optimal placement of Level 3 fast charging stations on a single feeder within a distribution system network. A Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) method is employed to determine the optimal charging station locations while minimizing power losses and maintaining acceptable voltage profiles.

2. Problem Formulation

Finding the best location for charging stations while reducing power losses and voltage deviation is the primary goal of this study.

Fig. 1 shows a representation of the electrical power system with the voltage drop calculation shown in equation (2).

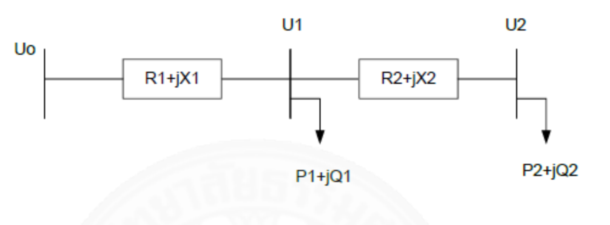

Figure 1. Simple Distribution System

$$\Delta U_f = \frac{P_i R_i + Q_i X_i}{U_N} \quad (1)$$

From Eq. (1) when we add the electric vehicle charging system to the electric power system then the equation will become the Eq. (2)

Fig. 2 depicts a power system with a charging station load.

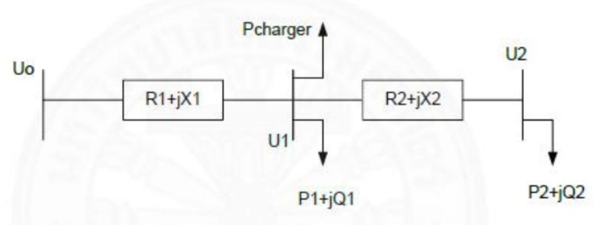

Figure 2. Power System with Charging Station Load

$$\begin{aligned} U_2 &= U_0 - (\Delta U_1 + \Delta U_2) \\ &= U_0 - \left[\left(\frac{(P_1 + P_{charger})R_1 + Q_1 X_1}{U_N}\right) + \left(\frac{(P_2 R_2 + Q_2 X_2}{U_N}\right)\right] \quad (2) \end{aligned}$$

Calculations of power losses and voltage deviation shown on Eq. 3 and Eq. 4

$$P_{loss} = \sum_{i=1}^{N_b} |I|^2 R_i \quad (3)$$

$$V_d = Max_{i=2}^{m} \left(\frac{V_{rated} - V_i}{V_{rated}}\right) \quad (4)$$

The system's rated voltage, denoted by $Vrated$, is 1.0 pu. The voltage on the bus, denoted by i, and the total number of buses on the system, denoted by m. The goal of this study is

$$Min(f) = \sum_{i=1}^{Nb} (P_{loss} + V_d) \quad (5)$$

Then the second objective of optimizing the placement of charging stations is to maximize the coverage area for PEVs to charge their batteries on the network. The more charging stations installed on the system, the easier it will be for PEV users to charge, but the more charging stations will increase the load on the system beyond the maximum capacity of the installed transformer.

$$Max(N_{fast}) = P_{charger} + \sum_{i=1}^{n} P_{existing} \quad (6)$$

Some restrictions or limitations on the system must also be taken into account during the entire optimization process. Among these limitations are maximum load and bus voltage shown in equation (7) and (8).

$$p_{demand}^{max} \geq \sum_{i=2}^{n} (P_{load} + P_{charger})_i \quad (7)$$

Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

IJEIE International Journal of Electrical and Intelligent Engineering

$$V_{min} \leq V_i \leq V_{max} \quad (8)$$

3. Research Method

Finding the issue that forms the foundation of the research background is the first stage in this process. Additionally, literature studies are carried out by looking through relevant books and periodicals. To ascertain the state of the system both prior to and following PEV penetration, load flow analysis is performed. The Newton Raphson method is employed to determine the power flow of the 20 kV distribution system. The Newton-Raphson technique of power flow analysis seeks to determine the channel's voltage drop and power losses.

In order to meet the demand of plug-in electric vehicle users to charge on the highway without experiencing a battery drain during the journey, the number and location of charging stations on the electricity distribution system network must not surpass the installed distribution transformer's maximum capacity. The process of placing a charging station involves first randomly positioning it on one of the buses, followed by a power flow analysis using the Newton-Raphson method. If the placement of the charging station is found to be out of constraint, the next iteration will be carried out at random and power flow analysis will be used again until the results converge.

This problem has a local minimum since the allocation mechanism is discrete. A heuristic method is a suitable option for this problem in order to optimize this objective function. This paper proposes particle swarm optimization and genetic algorithms. The objective function and the fitness function are regarded as identical. Which bus stops will have charging outlets placed depends on the chromosomes. In order to display the optimal choice, the GA and PSO algorithms work together to prevent the algorithm from becoming stuck in a local minimum. The HGAPSO method's parameters are provided to determine the ideal charging station position and size. GA will then compute a number of suboptimal solutions and forward them to PSO for additional improvement, enhancing the traditional PSO algorithm's operational capability. The ideal solution is obtained by further fine-tuning the solution set using the suggested HGAPSO approach. To enable the algorithm to strike a balance between exploration and exploitation, the particle speed limit prevents the suggested HGAPSO from becoming stuck in a local minimum.

4. Solving Algorithm

4.1 Genetic Algorithm

The following is a description of the steps involved in optimizing PEV charging coordination.

a. Step 1:
   The software receives all input data. These data include PEV data, network data, bus data, line data, and existing load data.
b. Step 2:
   Setting the maximum number of iterations and GA optimization parameters.
c. Step 3:
   Use the Newton-Raphson approach to analyze load flow and create random charging station locations on the network.
d. Step 4:
   Use a roulette wheel to select parents
e. Step 5:
   To obtain the most recent answer, perform crossover and mutation.
f. Step 6:
   Use Newton-Raphson to do power flow analysis once more, then show the network's power loss data.

Repeat the Step 4 through Step 6 optimization phases until an ideal solution is identified if the optimization results deviate from the constraints.

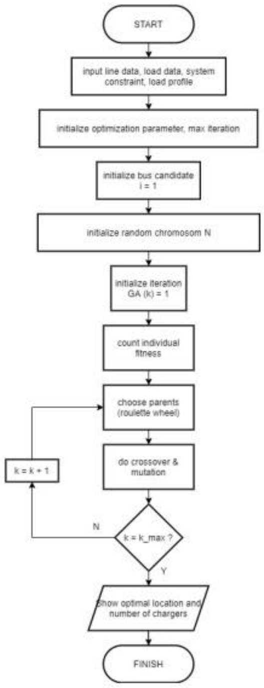

Figure 3. Genetic Algorithm-Based Charging Station Placement Optimization Flowchart

Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

IJEIE International Journal of Electrical and Intelligent Engineering

4.2 Particle Swarm Optimization

The following outlines the procedures for placing the PEV charging station as efficiently as possible.

a. Step 1:
   The software receives all input data. These data include PEV data, network data, bus data, line data, and existing load data.
b. Step 2:
   Enter the maximum iteration settings and initialize the PSO optimization parameters.
c. Step 3:
   Setting up the iteration for the PSO algorithm i = 1 to determine the best place for a charging station.
d. Step 4:
   Determine network losses and conduct power flow analysis for the current load network using the Newton-Raphson method.
e. Step 5:
   Update the velocity and position of the particles using Eq.7.

$$vel_{i,d}^{t} = w^{t} vel_{i,d}^{t} + c_1 r_1 \left(pbest_{i,d}^{t} - x_{i,d}^{t}\right) + c_2 r_2 \left(gbest_{i,d}^{t} - x_{i,d}^{t}\right) \quad (7)$$

   Where the weight of the particle determined by Eq. 8.

$$W = Wmax - \frac{(Wmax - Wmin)}{(n-1)} \times (iter - 1) \quad (8)$$

f. Step 6:
   Perform load flow analysis again with Newton-Raphson and show the network losses
g. Step 7:
   If the losses violate the allowed network constraints, repeat the iteration until an optimal solution is found.

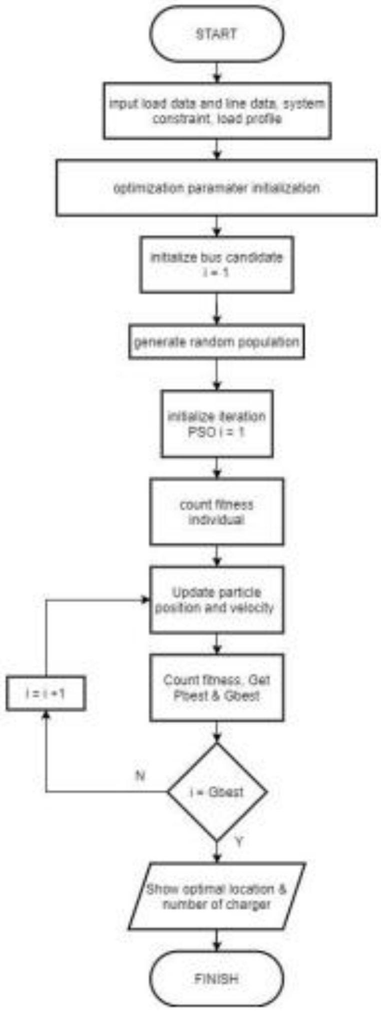

Figure 4. Particle Swarm Optimization-Based Charging Station Placement Optimization Flowchart

4.3 Hybrid Genetic Algorithm-Particle Swarm Optimization

The following outlines the procedures for placing the PEV charging station as efficiently as possible.

a. Step 1:
   The software receives all input data. These data include PEV data, network data, bus data, line data, and existing load data.
b. Step 2:
   Type in the optimization parameters for GA and PSO.
c. Step 3:
   Use the Newton-Raphson method to analyze load flow and determine the network's power losses.
d. Step 4:

Set up a random solution for the network's charging station locations.

e. Step 5:
Use the roulette wheel to choose the parents.

f. Step 6:
To find a solution, perform crossover and mutation.

g. Step 7:
Link the GA's best results to the PSO operator

h. Step 8:
Rerun the Newton-Raphson load flow analysis based on the less-than-ideal outcomes.

i. Step 9:
Particle position and velocity updates from the PSO operator

j. Step 10:
Next, select parents and perform crossover and mutation.

k. Step 11:
Repeat the Newton-Raphson power flow analysis until you obtain Pbest and Gbest.

l. Step 12:
Continue iterating until you find the ideal charging station position.

m. Step 13:
Repeat until you find the best option if the outcome still deviates from the limitation.

5. Result & Discussion

5.1 Load Flow Analysis

This study optimizes the coordination of plug-in electric vehicle (PEV) charging stations in a 20 kV distribution network using real system data obtained from PT. PLN APJ South Surabaya, which consists of 18 substations. The Basuki Rahmat feeder, interconnected with the Simpang and Kupang substations, is selected as the case study.

The Basuki Rahmat feeder is supplied by Transformer 1 at GI Kupang with a capacity of 60 MVA and a current limit of 360 A. The feeder employs All Aluminum Alloy Conductor (AAAC) cables and has a total length of 2.901 km with 30 buses. Each distribution line is characterized by resistance and reactance values, which are converted into per-unit (p.u.) values to facilitate load flow calculations.

The single-line diagram of the Basuki Rahmat feeder is shown in Fig. 5.

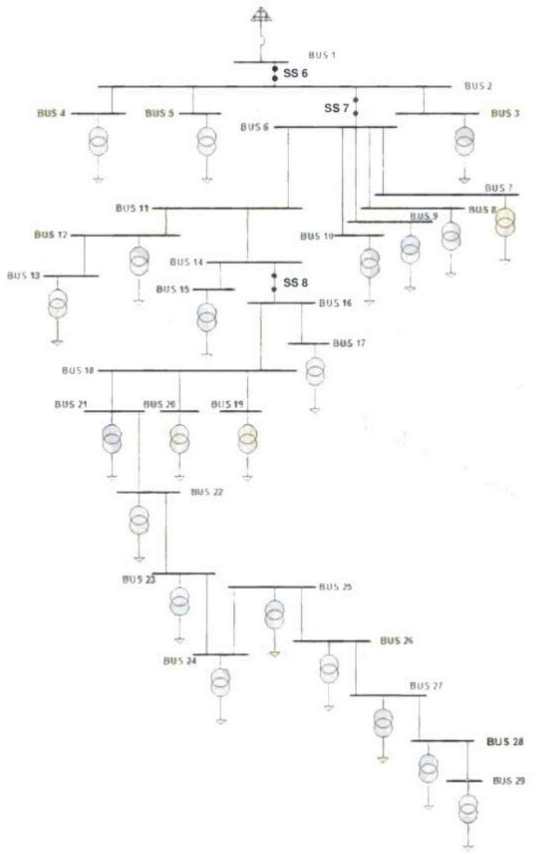

Figure 5. Basuki Rahmat Feeder Single Line Diagram

Load flow analysis of the existing system, without the integration of charging stations, is performed using the Newton–Raphson method. The analysis results indicate that the total real power loss is 0.009 MW, while the reactive power loss is 0.005 MVAR. The voltage magnitudes at all buses remain within acceptable operating limits, as summarized in Table 1.

Table 1. Load Flow Analysis Results

Bus no.	Voltage Magnitude	Angle Degree	Load	
			P (MW)	Q (Mvar)
1	1.000	0	0	0
2	0.995	0.059	0	0
3	0.994	0.069	0	0
4	0.994	0.070	0.095	0.129
5	0.994	0.069	0.010	0.001
6	0.994	0.069	0.001	0.003
7	0.993	0.077	0	0
8	0.993	0.076	0.111	0.016
9	0.993	0.080	0.198	0.243
10	0.993	0.077	0.022	0.004
11	0.993	0.077	0.009	0.003

Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

International Journal of Electrical and Intelligent Engineering

12	0.992	0.081	0	0
13	0.992	0.080	0.009	0.003
14	0.992	0.083	0.151	0.188
15	0.991	0.079	0	0
16	0.991	0.079	0.003	0
17	0.991	0.078	0	0
18	0.991	0.079	0.104	0.135
19	0.991	0.075	0	0
20	0.991	0.075	0.034	0.005
21	0.991	0.075	0.022	0.006
22	0.991	0.072	0.035	0.005
23	0.990	0.069	0.029	0.009
24	0.990	0.068	0.050	0.007
25	0.990	0.067	0.043	0.009
26	0.990	0.066	0.026	0.004
27	0.990	0.066	0.030	0.004
28	0.990	0.065	0.029	0.004
29	0.990	0.065	0.010	0.001
30	0.990	0.065	0.012	0.003

5.2 Genetic Algorithm Based Charging Station Location Optimization

Using the optimization framework described in the previous section, the Genetic Algorithm (GA) is applied to determine the optimal placement of charging stations within the distribution network. After several iterations, the voltage profile for each bus is obtained, as illustrated in Fig. 6.

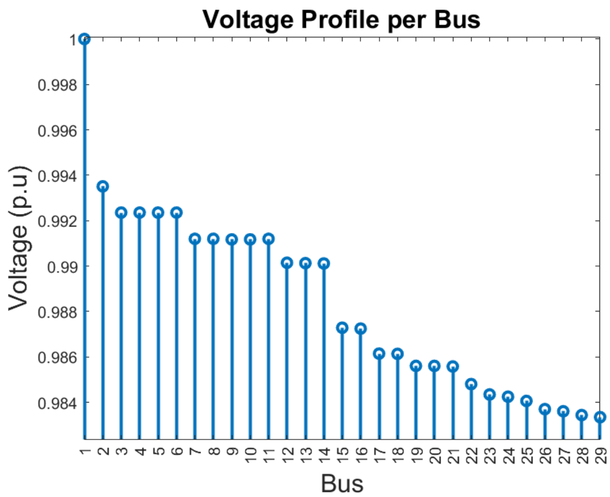

Figure 6. Voltage Profile Each Bus After Optimization with Genetic Algorithm

The GA-based optimization results in a real power loss of 0.015 MW and a reactive power loss of 0.007 MVAR. The charging stations are optimally placed at buses 6, 14, 21, 23, 24, 26, 27, and 28. Among these, buses 14 and 23 are allocated two charging heads each, while the remaining buses are assigned one charging head. In total, ten charging heads are installed, as shown in Fig. 7.

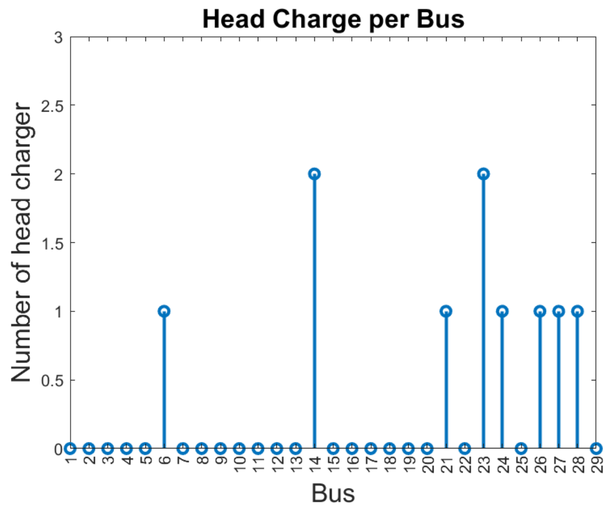

Figure 7. Number of Head Chargers Installed on The Grid After Genetic Algorithm Optimization Performed

Although the GA successfully identifies feasible charging station locations while satisfying system constraints, the resulting power losses and the number of installed charging heads indicate that further improvement is possible.

5.3 Particle Swarm Optimization Based Charging Station Location Optimization

The Particle Swarm Optimization (PSO) algorithm is subsequently employed to solve the charging station placement problem using the same system configuration. The resulting voltage profile after optimization is presented in Fig. 8.

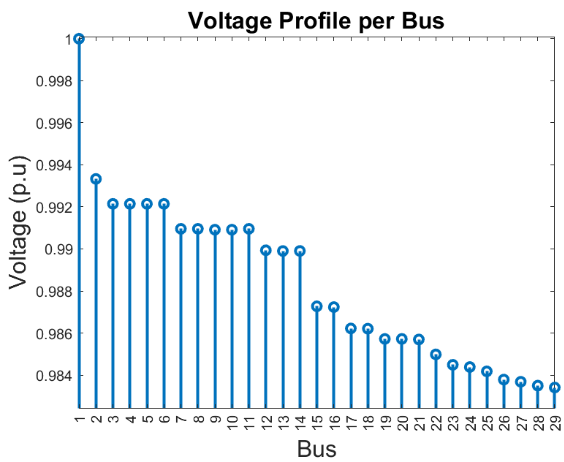

Figure 8. Voltage Profile Each Bus After Optimization with Particle Swarm Optimization

Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

International Journal of Electrical and Intelligent Engineering

The PSO-based solution yields a real power loss of 0.013 MW and a reactive power loss of 0.006 MVAR. Charging stations are optimally located at buses 5, 8, 10, 14, 21, 23, 25, and 26. Buses 14, 23, and 26 are assigned two charging heads each, while the remaining buses are equipped with one charging head. Consequently, a total of eleven charging heads are installed, as depicted in Fig. 9.

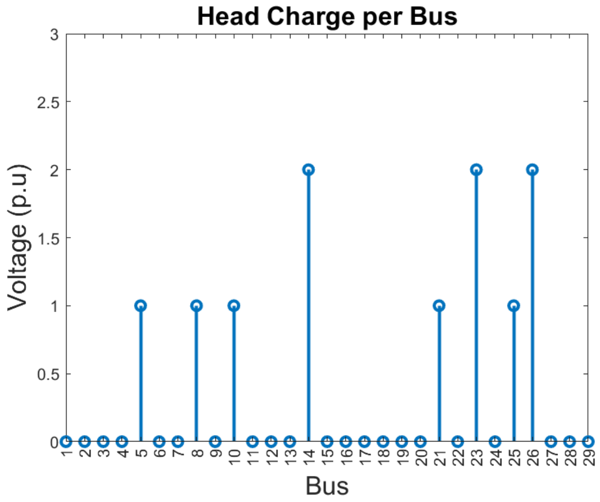

Figure 9. Number of Head Chargers Installed on the Grid After Particle Swarm Optimization Performed

Compared to the GA approach, PSO achieves lower real power losses. However, this improvement is accompanied by an increased number of charging heads, which may impose higher infrastructure and operational costs.

5.4 Hybrid Genetic Algorithm-Particle Swarm Optimization Charging Station Location Optimization

The proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) method is then applied to determine the optimal charging station placement. This hybrid approach integrates the global search capability of GA with the fast convergence characteristics of PSO.

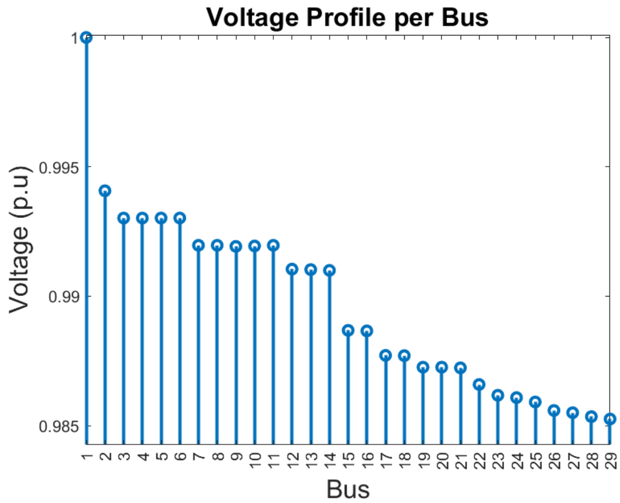

Figure 10. Voltage Profile Each Bus After Optimization with Hybrid Genetic Algorithm-Particle Swarm Optimization

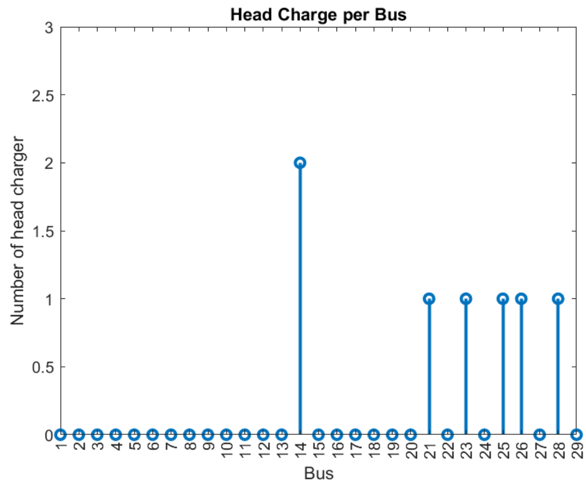

Figure 11. Number of Head Chargers Installed on the Grid After Hybrid Genetic Algorithm-Particle Swarm Optimization Performed

The voltage profile obtained after HGAPSO optimization is shown in Figure 10. The results indicate a real power loss of 0.012 MW and a reactive power loss of 0.006 MVAR. Charging stations are optimally placed at buses 14, 21, 23, 25, 26, and 28. Bus 14 is allocated two charging heads, while the remaining buses are assigned one charging head each, resulting in a total of seven charging heads, as illustrated in Fig. 11.

Compared to both GA and PSO, the HGAPSO method achieves the lowest real power loss while utilizing the fewest charging heads. This demonstrates that HGAPSO provides a more

Volume 01, Issue 02, December 2025 : 22-29 Received: June 11, 2025. Revised: December 29, 2025.

International Journal of Electrical and Intelligent Engineering

efficient trade-off between system performance and infrastructure requirements.

A comparison of the three optimization techniques indicates that the proposed HGAPSO method outperforms the conventional GA and PSO approaches. While GA offers strong global exploration capabilities, it converges more slowly and results in higher power losses. PSO improves convergence speed and reduces losses but tends to allocate a larger number of charging heads.

The superior performance of HGAPSO can be attributed to its ability to combine the strengths of both algorithms. GA effectively explores diverse solution spaces, while PSO refines promising solutions through local exploitation. This synergy enables HGAPSO to avoid local optima and premature convergence, leading to improved voltage profiles, reduced power losses, and a more economical charging station deployment.

6. Conclusion

Improper placement of fast charging stations in distribution systems can lead to increased power losses and unacceptable voltage deviations. This study proposed a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) approach to optimally determine the locations and number of level-3 PEV charging stations in a 20 kV radial distribution network. The proposed method was tested on the Basuki Rahmat feeder using real system data and compared with conventional Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) techniques. Simulation results show that HGAPSO achieves lower real power losses while utilizing fewer charging heads, indicating a more efficient and reliable charging station allocation. Specifically, the HGAPSO method results in a real power loss of 0.012 MW with only seven charging heads, outperforming both GA and PSO solutions. The improved performance is attributed to the complementary strengths of GA and PSO, which enhance global search capability and convergence behavior. The findings confirm that HGAPSO is a promising optimization tool for practical PEV charging station planning in distribution networks. Future work will focus on extending the proposed approach to multiple feeders, dynamic load conditions, and the integration of renewable energy sources.

References

[1] P. Prakornchai, "Development of Fast Charging Station for Thailand", *International Journal of Innovation, Management and Technology, Vol. 3, No. 6*, Thailand, 2012

[2] Kementrian ESDM, "Kesiapan dan Kecukupan Pasokan Listrik untuk Mendukung Pengembangan Kendaraan Bermotor Listrik", *Focus Group Discussion Menyongsong Era Kendaraan Listrik di Indonesia di Badan Pengkajian dan Penerapan Teknologi (BPPT)*, Jakarta 2019

[3] IEA, "Global EV Outlook 2018: towards cross-modal electrification", International energy agency, 2018.

[4] C. H. Dharmakeerthi, "A Comprehensive Planning Framework for Electric Vehicle Charging Infrastructure Deployment in the Power Grip with Enhanced Voltage Stability", *International Transactions on Electrical Systems Volume 25*, 2014

[5] Z. Liu, "Optimal Planning of Charging Station for Electric Vehicle Based on Particle Swarm Optimization", *IEEE*, 2012

[6] S. Saelee, "Optimal Placement of EV Charging Station Considering the Road Traffic Volume and EV Runnning Distance", *Sirindhorn International Institute of Technology*, 2012

[7] M. Mozafar. "A Simultaneous Approach for Optimal Allocation of Renewable Energy Sources and Charging Stations based on Improved GA-PSO Algorithm", *Islamic Azad University*, 2017

[8] M. Satish, "Optimal Placement of Electric Vehicle Charging Station for Unbalanced Radial Distribution", *Indian Institute of Information Technology, Design & Manufacturing*, India, 2020

[9] A. Awasthi, "Optimal Planning of Electric Vehicle Charging Station at the Distribution System using Hybrid Optimization Algorithm", *19th National Power Systems Conference*, India, 2016

[10] W.D. Stevenson, J.J. Granger, *Power System Analysis*, McGraw-Hill International Edition, New York. 1994