SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I4P118

Volume 12 Issue 4, 241-251, April 2025

Original Article

Optimizing Electric Vehicle Charging Station Placement: Comparative Analysis

Amalina Izzati[1], Hasmaini Mohamad[1]*, Kanendra Naidu[1], Norazliani Md Sapari[2], Lilik Jamilatul Awalin[3], Zuhaila Mat Yasin[4]

[1]*Power System Planning and Operation Research Group (PoSPO), School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia.*
[2]*Faculty of Electrical Engineering, University Technology Malaysia, Skudai, Johor, Malaysia.*
[3]*Department of Electrical Engineering Faculty of Advanced Technology and Multidiscipline, Airlangga University, Surabaya, Jawa Timur, Indonesia.*
[4]*Solar Research Institute (SRI), Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia.*

**Corresponding Author : hasmaini@uitm.edu.my*

Received: 13 February 2025 Revised: 15 March 2025 Accepted: 16 April 2025 Published: 29 April 2025

Abstract *- Internal Combustion Engine (ICE) vehicles are gradually being replaced by Electric Vehicles (EVs), propelling the shift to environmentally friendly transportation. The environmental impact of ICE vehicles has accelerated the adoption of EVs to mitigate Carbon Dioxide (CO_2) emissions, necessitating the optimal planning of Electric Vehicle Charging Stations (EVCS). This study explores strategies to improve power generation and voltage stability in distribution networks by integrating EVCS with distributed solar Photovoltaic (PV) systems. To minimize power losses and identify the optimal placement of EVCS in IEEE 33-bus and 69-bus systems, Evolutionary Programming (EP), Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) are three optimization techniques that have been compared. To reduce the dependency on the grid and accommodate additional charging demand, the EVCS is being integrated with PV systems. The results demonstrate that GWO outperforms PSO and EP. GWO achieved the lowest power losses and the highest voltage profile improvements. These findings provide valuable insights into efforts to optimize EVCS placement, integrate it with sustainable energy systems, and improve power system efficiency.*

Keywords *- Grey Wolf Optimization, Particle Swarm Optimization, Evolutionary Programming, Optimal placement of electrical vehicle charging station, Photovoltaic.*

1. Introduction

There is a shift among automotive producers from fossil fuels to green energy due to the environmental issues associated with fossil fuels. The ability to cut greenhouse gas emissions, enhance air quality and reduce the dependency on fossil fuels has led to the increasing popularity of Electric Vehicles (EVs) as an environmentally friendly transportation option [1-3]. Electric-powered passenger cars accounted for 9% of global sales in 2021, with projections estimating an increase to 75% by 2040 [4]. Many policies and initiatives have been introduced to promote EV adoption and expand charging infrastructure to satisfy charging needs. To accommodate widespread EV adoption, it is essential to establish the appropriate number and capacity of EV Charging Stations (EVCS). There are three types of EVCS: level 1 (120V) for standard outlets, level 2 (240V) for faster public or residential charging, and DC fast charging for high-speed charging during long-distance travel [5]. The function of these chargers installed at these stations is to deliver DC power to EVs for recharging. For instance, a 50-kW charger usually takes about 30 minutes to fully recharge an EV's 28kWh battery to 80% capacity. Slower chargers took around 1 to 2 hours to charge the same battery capacity, while FCs provided quicker charging, significantly reducing waiting times and offering greater convenience. However, it poses significant challenges for the distribution network [6]. Chargers installed at these stations deliver DC power to EVs for recharging, and the time required for charging depends on the delivered power [7]. The placement and capacity of EVCSs directly impacted the performance and stability of the electrical grid. The placement and capacity of EVCSs directly influenced grid performance, affecting bus voltage, system load, and energy losses as more vehicles charge simultaneously [8, 9]. To preserve grid stability and prevent excessive load stress on the power system, proper installation and strategic placement of EVCSs were essential [10]. EV charging stations caused significant disruptions in the distribution network, which include voltage deviations, severe harmonic distortions, higher peak demands, and reduced overall system stability without proper planning [11]. To minimize the effect on the distribution network, careful consideration of the placement and the size of EVCSs was crucial. Effective placement strategies may enhance user accessibility and charging convenience, which helps mitigate grid instability, making them the key aspect of sustainable EV infrastructure development.

Different optimization strategies to locate the optimal location for EVCS have been conducted in several research. In Indonesia, a robust model for EVCS planning using the Control Variates (CV) technique was adopted to select the optimal location for EVCSs at Surabaya [12]. The model using this technique resulted in 13% better and 10 times faster than the non-robust method. This was beneficial for designing EVCS in areas with unstable power supply. There was another study that estimated EVCS location by spectral clustering and Gaussian Mixture Model (GMM) based on the total number of charging stations in [13]. The location used for the study was in Ankara, Turkey, and it considered EV density, road and traffic flow to increase accuracy.

These factors were concluded to guide efficient EVCS for urban planning. In the other research, a multi-objective optimization methodology using the Bat Algorithm and Pareto Frontier was used to identify the optimal placement of semi-fast EVCS within a distribution network [14]. The methodology comprised EV penetration levels, user behavior uncertainties, and Geographic Information System (GIS) data. Hierarchical clustering defined charging station zones, while scenario reduction techniques enhanced computational efficiency. The mid-term and long-term planning strategies were compared and analyzed.

A real-time modelling and integration approach for Electric Vehicle Charging Stations (EVCS) in distribution networks was introduced in [15]. This method considered important factors such as Voltage Stability Indices (VSI), Voltage Sensitivity Factor (VSF), and current limitations. Using topography-based distribution load flow analysis and Typhoon HIL simulations, the best bus locations for charging stations were identified, network performance was accessed, and system stability and reliability were ensured. A study in [16] proposed an optimal way to size and place solar-powered EVCS using the Artificial Bee Colony (ABC) algorithm.

The approach integrated Photovoltaic (PV) location modelling and EV modelling with voltage-dependent characteristics to find the most efficient and effective solution. To determine the best locations and capacities for fast-charging stations, further research in [17] explored the use of the Grey Wolf Optimization (GWO) algorithm. The objective was to cut down transportation costs and inefficiencies. The algorithm also aimed to minimize energy losses and maintain stable voltage and power quality. On the other hand, research in [18] applied the Particle Swarm Optimization (PSO) algorithm to optimize the size and placement of Distributed Generation (DG). Different Durgapur city, India zones have been chosen as the study samples. The result showed that integrating DG with EV infrastructure improved energy efficiency and enhanced the overall performance of charging stations.

Apart from the strategic placement of EVCSs challenge, increasing grid stress has remained a significant challenge as the popularity of EVs increases. One possible solution has been integrating Renewable Energy (RE) sources into charging infrastructure. Integrating RE with EVCS charging stations would be a more sustainable and efficient solution. PV systems could generate clean electricity, reducing dependence on the grid and lowering emissions [19]. Several studies have explored PV-powered charging stations to resolve the issues of grid overloading while enhancing station profitability and decreasing user charging costs [20]. In addition, incorporating PV panels, batteries, and transformers has been proven to relieve the grid burden by balancing high EV loads with local energy generation and storage [21].

An energy management framework for PV-EVCS using a PV Distributed Generator (PV-DG) and an Energy Storage System (ESS) in a radial distribution network was proposed in [22]. The study demonstrated that the approach enhances energy stability and reduces grid dependency. The MATLAB simulation confirmed improved voltage profiles and reduced power line stress. Similarly, a study in [23] investigated the capacity optimization of PV and Battery Storage (BS) for EVCS across multiple locations. The variations in charging behavior were considered. Using a robust optimization model, the study highlighted behavioral dispersion affecting PV-BS integration. It showed that the location-specific charging patterns significantly impact economic efficiency. The study also demonstrated improvements in voltage stability and reduced annual operational costs.

The author in [24] analyzed PV-EVCS performance under different solar irradiation conditions in India, emphasizing the role of solar availability in affecting the economic feasibility of PV-powered charging stations. The research in [25] introduced an optimal dispatch model for PV-assisted EVCS, optimizing charging schedules to minimize costs while ensuring efficient battery utilization. Moreover, [26] proposed a hybrid approach to further enhance PV-EVCS performance. Although significant advancements have been made in optimizing EVCS placement and integrating RE sauces, most existing studies address these aspects separately. Limited research has addressed the simultaneous optimization of EVCS placement and RE integration within distribution networks. This creates a research gap, as neglecting the combined impact of location, sizing and energy source integration may result in suboptimal grid performance and increased operational costs.

This research introduces a novel approach that simultaneously optimizes EVCS placement and integrates PV systems within the distribution network, bridging the gap in the existing literature. Unlike prior studies that separately tackle either placement or renewable integration, this work considers the dual impact on grid dependability, voltage stability, and power losses. The study evaluates the effectiveness of GWO, PSO, and EP in determining optimal EVCS locations across IEEE 33-bus and 69-bus systems, exploring various scenarios with and without PV integration.

These algorithms were selected due to their proven effectiveness in handling complex, nonlinear optimization problems, adaptability to multi-objective functions, and balance between exploration and exploitation. The proposed approach mitigates grid stress, reduces energy losses, and enhances voltage profiles by strategically placing PV systems at weak buses. The methodology also takes into consideration crucial technical limitations, which include voltage limits, current flow restrictions and power balance requirements, which are often overlooked in isolated optimization models. The comparative analysis of GWO, PSO and EP provides a deeper insight into the trade-offs between computational efficiency and solution accuracy. With thorough testing, the study aims to provide useful information for grid operators and policymakers to facilitate the development of resilient and sustainable distribution networks. The findings will not only support the growth of EV infrastructure but also encourage the use of clean energy sources. This will expedite the shift to a future with reduced carbon emissions.

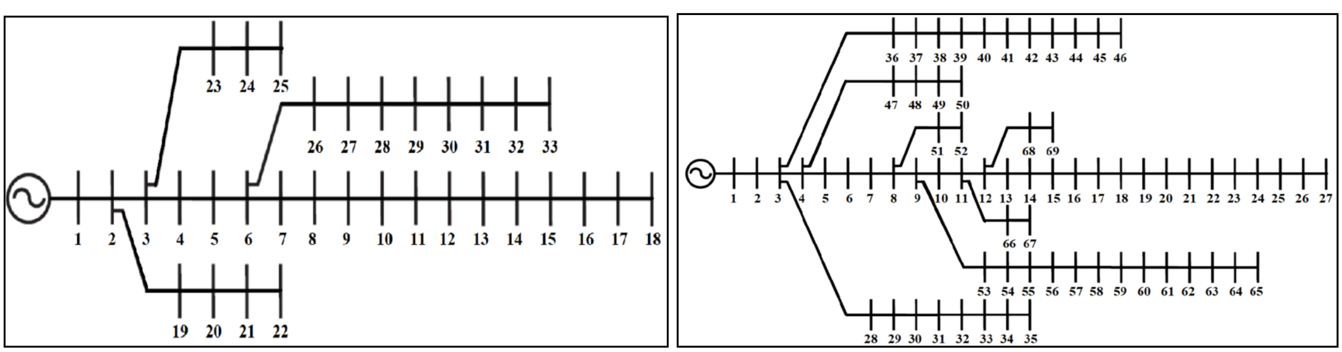
The approach of EVCS placement and PV system integration marks a major advancement in tackling the difficulties associated with modern power systems, which have extensive implications for sustainable energy management and smart grid development. The remaining content of this paper is organized as follows: The methodology, which comprises problem formulation, case study specifics and methods of optimization applied, is presented in Section II. The results are discussed in Section III, and a summary of the conclusions and suggestions is provided in Section IV.

2. Methodology

This section presents the comprehensive methodology for determining the optimal placement of EVCS with integrated PV systems in IEEE 33-bus and 69-bus distribution networks. The methodology is structured into five main parts: system modelling, optimization techniques, proposed method, number of EVCS, and load modelling of EVs.

2.1. System Modelling

In order to identify the optimal location for EVCS in this investigation, the distribution network was modelled using the IEEE 33-bus and IEEE 69-bus test systems. The 33-bus system serves as a smaller-scale test, while the 69-bus system provides insights into a larger and more complex network. In order to determine the baseline power losses and voltage profiles without the use of EVCS or PV integration, the Newton Raphson Load Flow (NRLF) technique was utilized to perform the initial load flow study.



(a) **(b)**

Fig. 1 Single line diagram, (a) IEEE 33-bus system, and (b) IEEE 69-bus system.

The overall active power demand of the IEEE 33-bus distribution system, as illustrated in Figure 1, is 4.58 MW, whereas the reactive power demand is 2.839MVar. The lowest voltage magnitude, recorded at bus 18, is 0.952 p.u., with total power losses amounting to 0.13482 MW in the base case scenario. Likewise, Figure 2 displays the IEEE 69-bus distribution system's total active power consumption of 3.802 MW and the reactive power demand of 2.695 MVar. The power flow analysis demonstrates that bus 65 has the lowest voltage magnitude, roughly 0.909 p.u., while the total power loss for the base case is 0.22463 MW.

2.2. Optimization Technique

Optimization techniques are essential for solving complex problems in power system optimization. Three optimization techniques, namely Evolutionary Programming (EP), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO), are used in this study to identify the best placement of EVCS in the distribution system.

2.2.1. Particle Swarm Optimization (PSO)

Kennedy and Eberhart created the early PSO methods a stochastic optimization technique based on swarming behavior [27]. It provides solutions to complex numerical issues involving the maximization or minimization of nonlinear limits [28]. Due to the numerous advantages PSO offers over alternative heuristic optimization methods, it was selected to minimize the optimization problem in this work.

In this method, particles traverse a multi-dimensional problem field at a specific speed. Every particle has the ability to interact, changing its speed in response to the patterns of movement of other particles and itself. This dynamic motion prevents the swarm from getting stuck in local minima. Throughout PSO iterations, each particle preserves its position within the solution space. During each iteration, if a particle's current position surpasses previous values, it is stored as its personal best $\boldsymbol{P_{Best,i}}$. The variable $\boldsymbol{G_{Best,i}}$ holds the best value for the objective function. Positions and velocities are updated in each iteration. The equations of motion and velocity update in the PSO algorithm are formulated as in Equations (1), (2), and (3):

$$\mathbf{X}_i^{k+1} = \mathbf{X}_i^{k} + \mathbf{V}_i^{k+1} \tag{1}$$

$$\mathbf{V}_i^{k+1} = \boldsymbol{\omega}^{k} \times \mathbf{V}_i^{k+1} + \boldsymbol{C_1} \times \boldsymbol{rand_1} \times \left(\boldsymbol{P}_{Best,i}^{k} - \mathbf{X}_i^{k}\right) + \boldsymbol{C_2} \times \boldsymbol{rand_2} \times \left(\boldsymbol{G}_{Best,i}^{k} - \mathbf{X}_i^{k}\right) \tag{2}$$

$$\boldsymbol{\omega}^{\mathbf{k}} = \boldsymbol{\omega}_{\mathbf{max}} - \left(\frac{\boldsymbol{\omega}_{\mathbf{max}} - \boldsymbol{\omega}_{\mathbf{min}}}{\mathbf{k}_{\mathbf{max}}}\right) \times \mathbf{k} \tag{3}$$

Where $\boldsymbol{\omega}$ stands for the inertia weight, the $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ stand for the acceleration coefficients, respectively. The local best of particle $\boldsymbol{i}$ is indicated by $\boldsymbol{P_{Best,i}}$, and the $\boldsymbol{G_{Best,i}}$ represents the particle group's global best position. The random variables $\boldsymbol{rand_1}$ and $\boldsymbol{rand_2}$ are evenly distributed between 0 and 1. The objective is to minimize power outages by iteratively updating the positions of particles, which represent the potential locations for EVCS.

2.2.2. Grey Wolf Optimization (GWO)

GWO algorithm introduced in [29] is inspired by wolves' cooperative behavior and communication strategies within a pack to address complex optimization problems. The algorithm represents potential solutions as wolf individuals, and their positions are updated iteratively by simulating the hunting process. The alpha, beta, and delta wolves represent the best solutions discovered so far, and their movements have an impact on the search space's exploration and exploitation. The algorithm is intended to converge towards the optimal solution by balancing exploration and exploitation by imitating wolf pack dynamics. There are binary GWO and non-binary GWO [30]. The non-binary GWO is used in this work. The solutions to the optimization problems can be better presented as continuous values.

In this study, the initial values for the GWO algorithm in terms of the number of search agents (SearchAgents_no) is set to 20, the maximum number of potential iterations ($\boldsymbol{Max\_iter}$) is set to 100, for Test System 1, the dimension ($\boldsymbol{dim}$) is 4, and for Test System 2, it is 8. The upper ($\boldsymbol{ub}$) and lower ($\boldsymbol{lb}$) boundaries are set to 33 and 2, respectively. The initial iteration ($\mathbf{1}$) is set to 0. The objective function ($\boldsymbol{fObj}$), each wolf positions and convergence ($\mathbf{convergence\_curve}$) are initialized. The random positions of bus locations ($\boldsymbol{positions}$) are also generated. The power loss function is then used to determine each wolf's fitness value. The algorithm continuously refines the wolves' positions by mimicking the haunting behavior, effectively balancing exploration and exploitation. Adjusting the change rate parameter (a) is performed iteratively, following the expression in Equation (4).

$$\mathbf{a} = \mathbf{2} - \mathbf{l}\left(\frac{\mathbf{2}}{\mathbf{Max\_Iter}}\right) \tag{4}$$

The alpha, beta and delta wolves, which signify the most optimal solutions, lead the population's movement throughout the optimization process. This process continues until it meets the maximum iteration. The final positions of the wolves, particularly the alpha wolf, provide the optimized solution for minimizing power loss.

2.2.3. Evolutionary Programming

EP is derived from the fundamental concepts of natural evolution and starts with the population's initialization of potential solutions, each representing different configurations of EVCS. This population is subjected to iterative mutation, evaluation, and selection processes to evolve towards optimal solutions. The mutation step introduces random variations in the solutions, allowing exploration of the solution space. The EP algorithm simulates power flows and accesses the performance of each solution. Each solution is then evaluated using a fitness function aimed at minimizing power losses while ensuring voltage profiles remain within permissible limits.

The fitness function F is formally defined as:

$$\mathbf{F} = \mathbf{w_1} \times \mathbf{P_{loss}} + \mathbf{w_2} \times \sum_{\mathbf{i=1}}^{\mathbf{n}} |\mathbf{V_i} - \mathbf{V_{ref}}| \tag{5}$$

Where $\mathbf{P_{loss}}$ denotes the total power losses, $\boldsymbol{V_i}$ denotes the voltage at bus $\boldsymbol{i}$, $\boldsymbol{V_{ref}}$ is the reference voltage, and $\boldsymbol{w_1}$ and $\boldsymbol{w_2}$ are weighting factors. The selection process involves the selection of the best-performing solutions based on their fitness values. This is to ensure that only high-quality solutions propagate to subsequent generations. The iteration proceeds until a predefined stopping condition, such as achieving the convergence criterion or the maximum number of generations, is satisfied.

2.3. Proposed Method

The proposed method employs PSO, GWO, and EP optimization techniques to determine the most suitable locations for EVCS within the IEEE 33-bus and 69-bus systems. These techniques were selected for their proven capability in solving optimization challenges in the electricity distribution power distribution network. The main intention is to lower power losses while maintaining voltage levels within ±10% of the permissible range. The study compares the effectiveness of EP, PSO and GWO by evaluating their effectiveness in enhancing voltage stability, cutting down on power losses and improving voltage stability. Each technique follows a common framework but incorporates specific parameters and strategies to enhance performance and maintain solution diversity.

For PSO, a swarm of 20 particles is initialized, with each particle representing a potential solution. The parameters include an inertia weight of 0.5 and acceleration coefficients (c_1 and c_2) set to 1.5. Particle positions and velocities are iteratively updated within the defined search space, ensuring solution uniqueness. The GWO method uses 20 search agents, constantly shifting their positions up to 100 times under the direction of alpha, beta, and delta wolves. A penalty term is applied to avoid duplicate locations. EP starts with 20 individuals undergoing Gaussian mutation to generate offspring, followed by a selection process to retain the best individuals for subsequent iterations. By standardizing these parameters and maintaining search space boundaries from buses 2 to 33 in the IEEE 33 bus system and from buses 2 to 69 in the IEEE 69 bus system, this study establishes a robust and uniform optimization framework across all methods. This approach enables a comparative analysis of PSO, GWO, and EP, highlighting their strengths and suitability for optimizing EVCS placement in power distribution networks.

2.3.1. Objective Function

This proposal of this study is that the EVCS will be positioned thoughtfully across the distribution network to attain minimal objective function values as defined in Equation (6), which represents the total active power losses ($\boldsymbol{P_{loss}}$) accumulated across all branches within the network.

$$\boldsymbol{f = \sum_{j=1}^{N} Ploss_j} \tag{6}$$

Where in the $\boldsymbol{j^{th}}$ branch, $\boldsymbol{P_{loss}}$ represents the active power loss, $\boldsymbol{j}$ represents the branch index, and $\boldsymbol{N}$ represent the network's total number of branches. This formulation allows for assessing the impact of EVCS locations on network performance, emphasizing the importance of minimizing losses and maintaining voltage stability.

2.3.2. Constraints

There are three constraints were considered in this study, i.e voltage, current and active/ reactive power.

i. Voltage constraint: To keep the voltage of the bus within limits. Voltage has minimum and maximum restrictions on each bus, as stated in (7).

$$\boldsymbol{V^{min} < V_i < V^{max}} \quad \text{where i= 1, 2, 3, …N} \tag{7}$$

ii. Current flow limit: Every branch within the distribution system is subject to defined maximum and minimum current limits. To keep the current within limitations, Equation (8) is applied.

$$\boldsymbol{I^{min} < I_j < I^{max}} \quad \text{where j= 1, 2, 3, …N} \tag{8}$$

iii. The necessity of equality of active power and reactive power: Equations (9) and (10) represent the active power and reactive power equality limitations for the distribution system.

$$\boldsymbol{P_{GRID} = \sum_{i=1}^{NB} P_i + Ploss} \tag{9}$$

$$\boldsymbol{Q_{GRID} = \sum_{i=1}^{NB} Q_i + Qloss} \tag{10}$$

2.3.3. Number of EVCS

The suitable numbers of EVCS installations for the test system are determined using Equation (11).

$$\boldsymbol{N_{CS} = \frac{p \times N_{EV} \times ch_{time}}{st \times C_{EVCS}}} \tag{11}$$

Where the number of EVCS is denoted by $\boldsymbol{N_{CS}}$, $\boldsymbol{p}$ presents an EV's average power, $\boldsymbol{N_{EV}}$ denotes the total units of EVs that need to be charged and $\boldsymbol{C_{EVCS}}$ indicates the charging station's capacity; additionally, $\boldsymbol{st}$ refers to the CS serving time and $\boldsymbol{ch_{time}}$ represents the charging time. The calculated number of EVCS is rounded up.

2.3.4. Load Modelling of EVs

The entire distribution system load, which includes both the existing distribution load and the is modelled using Equation (12).

$$\mathbf{P_{total} = \sum_{i=1}^{NB} Pi_{ext} + Pi_{CS}} \tag{12}$$

Where P_{total} is the total power demand, the number of busses is indicated by NB, $\boldsymbol{Pi_{ext}}$ is the existing load at the i^{th} bus, *and* Pi_{CS} is the EVCS load at the i^{th} bus, which is determined using Equation (13).

$$\boldsymbol{Pi_{cs} = N_{EV} \times P_{charger} \times \eta_{eff}} \tag{13}$$

Where N_{EV} is the number of charging ports, $P_{charger}$ is the power rating of each individual charger, and η_{eff} is the efficiency of the charging station.

3. Results and Discussion

A thorough examination of the simulation results is provided in this section for optimal EVCS placement in IEEE 33 bus and IEEE 66 bus systems through the utilization of three different algorithms: PSO, GWO, and EP. In this work, every bus has the possibility to locate the EVCS except for bus 1 (slack bus). The optimal number of EVCS units is determined as 4 and 8 for the IEEE 33-bus and 69-bus systems, respectively, depending on optimization limitations and system load needs.

3.1. Case Studies and Simulation Setup

This research introduces the following four case studies:

Case 1 : IEEE-33 bus system without PV integration
Case 2 : IEEE-33 bus system with 0.1 MW PV integration at the weakest bus, bus 18
Case 3 : IEEE-69 bus system without PV integration
Case 4 : IEEE-69 bus system with 0.1 MW PV integration at weakest busses 27, 61 and 65

The system's performance under these conditions is analyzed based on power loss, voltage profile, and algorithmic efficiency.

Table 1. Comparative results across case scenarios

Case	Test System	Algorithm	EVCS Location	Ploss (MW)	Vmax (p.u)	Vmin (p.u)
1	33	Base	-	0.135	0.993 (Bus 2)	0.952 (Bus 18)
		PSO	2, 3, 19 and 20	0.148	0.992 (Bus 2)	0.951 (Bus 18)
		GWO	2, 3, 19 and 20	0.148	0.992 (Bus 2)	0.951 (Bus 18)
		EP	2, 19, 22 and 23	0.160	0.992 (Bus 2)	0.949 (Bus 18)
2	33	Base	-	0.127	0.993 (Bus 2)	0.955 (Bus 18)
		PSO	2, 3, 19 and 20	0.139	0.992 (Bus 2)	0.954 (Bus 18)
		GWO	2, 3, 19 and 20	0.139	0.992 (Bus 2)	0.954 (Bus 18)
		EP	2, 19, 22 and 23	0.151	0.992 (Bus 2)	0.952 (Bus 18)
3	69	Base	-	0.224	1.000 (Bus 2)	0.909 (Bus 65)
		PSO	2, 5, 31, 39, 43, 47, 48, and 49	0.227	1.000 (Bus 2)	0.909 (Bus 65)
		GWO	2, 4, 28, 29, 30, 36, 39 and 47	0.225	1.000 (Bus 2)	0.909 (Bus 65)
		EP	2, 3, 9, 28, 34, 40, 42 and 48	0.234	1.000 (Bus 2)	0.908 (Bus 65)
4	69	Base	-	0.187	1.000 (Bus 2)	0.919 (Bus 65)
		PSO	4, 29, 33, 36, 38, 39, 40 and 47	0.189	1.000 (Bus 2)	0.919 (Bus 65)
		GWO	2, 4, 29. 31, 36, 37, 38 and 47	0.188	1.000 (Bus 2)	0.919 (Bus 65)
		EP	2, 4, 6, 28, 29, 32, 33 and 45	0.192	1.000 (Bus 2)	0.919us 65)

3.2. Selection of Weakest Busses and Stability Assessment

The weakest buses were identified based on voltage magnitude and sensitivity analysis. Buses with the lowest voltage magnitudes in the base case were selected to assess the effect on the system stability of PV integration and EVCS location. The integration of EVCS introduces additional load, influencing voltage profiles and power losses. To mitigate these impacts, PV generation is incorporated at the weakest buses to counterbalance the increased demand and maintain system stability. A power flow analysis under different load conditions was conducted, revealing that the weakest buses exhibited higher voltage drops and were more susceptible to stability issues. Integrating PV at these buses provided local generation support, reducing dependency on upstream supply and improving voltage regulation. This strategy ensures a balanced load distribution, minimizing adverse effects on the grid.

3.3. Comparative Performance Study

The comparative analysis demonstrates that GWO generally outperforms PSO and EP in reducing power losses and sustaining higher voltage profiles. Optimal locations obtained by GWO, PSO and EP are shown in Table 1. These findings demonstrate that the GWO algorithm exhibits higher effectiveness in optimizing EVCS placement, including scenarios involving PV integration, across both IEEE 33-bus and 69-bus power systems. The base cases without any EVCS or PV-EVCS integrations show the lowest power losses, which is used as a basis to identify the impact when an additional load from EVCS is introduced into the system. However, integrating PV systems into EVCSs helps mitigate some of these impacts by providing additional power generation, improving voltage profiles, and enhancing overall system stability.

In case 1, buses 2, 3, 19 and 20 are identified as the best locations for EVCS for both GWO and PSO, while the EP determined the optimal placements at busses 2, 19, 22 and 23. The power analysis is implemented with the existing loads by allocating the EVCS in the 33-bus system. Additionally, the system showed the highest voltage profile at 0.951 p.u, and its power losses were lowest at 0.135 MW. However, the integration of EVCS led to an increase in power losses.

Among the optimization algorithms, PSO and GWO are equally effective in achieving a power loss of 0.148 MW, and both maintain voltage levels within acceptable limits. However, the EP algorithm shows a marginally lower minimum voltage, indicating slightly less favorable voltage stability. Notably, as shown in Figure 2(a), the GWO algorithm is the most efficient, converging in 19 iterations compared to PSO with 29 iterations.

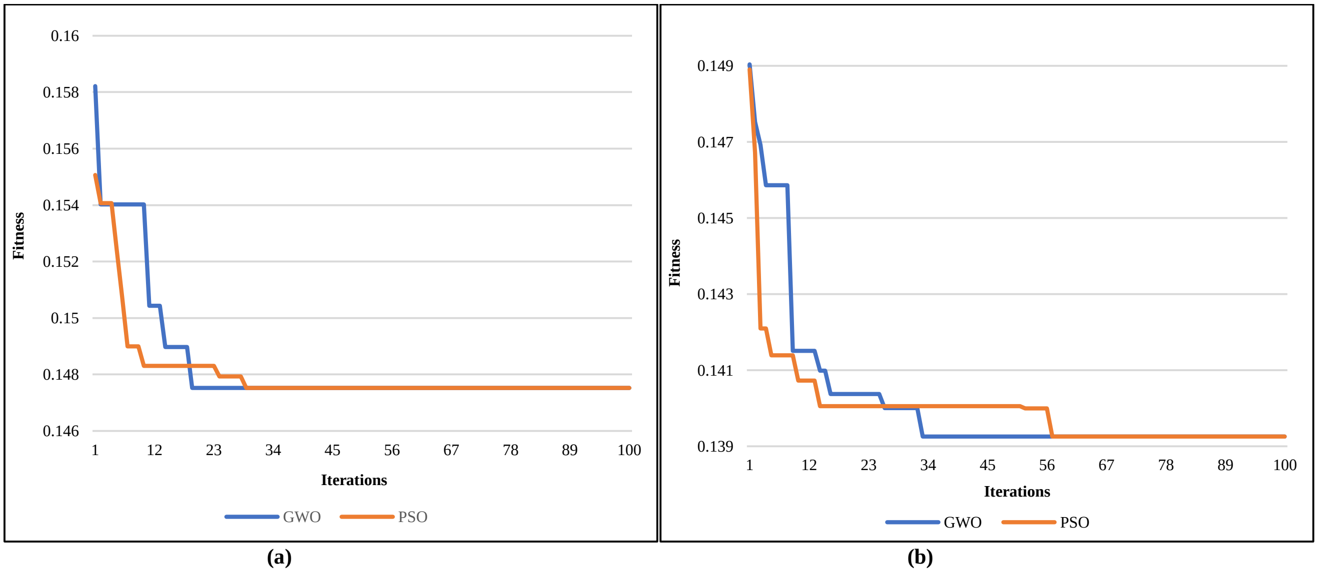


Fig. 2 Convergence curve for minimizing power losses in the IEEE 33-bus system, (a) Without PV integration, and (b) With PV integration.

In case 2, the integration of PV systems on weak buses within the 33-bus system is investigated. The GWO and PSO exhibit similar power losses of 0.139MW and maintain acceptable voltage levels at bus 18. In contrast, the EP algorithm shows higher power loss and lower minimum voltage. GWO demonstrated good performance by converging in 33 iterations, while PSO requires 57 iterations, as shown in Figure 2(b). Thus, the GWO algorithm provides a good balance between minimizing power loss and faster convergence. Figure 3 illustrates the 33-bus system's voltage profile for cases 1 and 2 using four different algorithms, i.e., base, GWO, PSO and EP. The results indicate that the voltage profile improved significantly for all cases by introducing a 0.1 MW PV capacity at the weakest bus, bus 18.The lowest power loss of 0.225 MW is achieved by GWO in Case 3, and voltage levels are kept within allowable limits. PSO has a slightly higher power loss of 0.227 MW but maintains the same voltage stability. The EP algorithm, with a power loss of 0.234 MW and a marginally lower minimum voltage, shows less favorable performance.

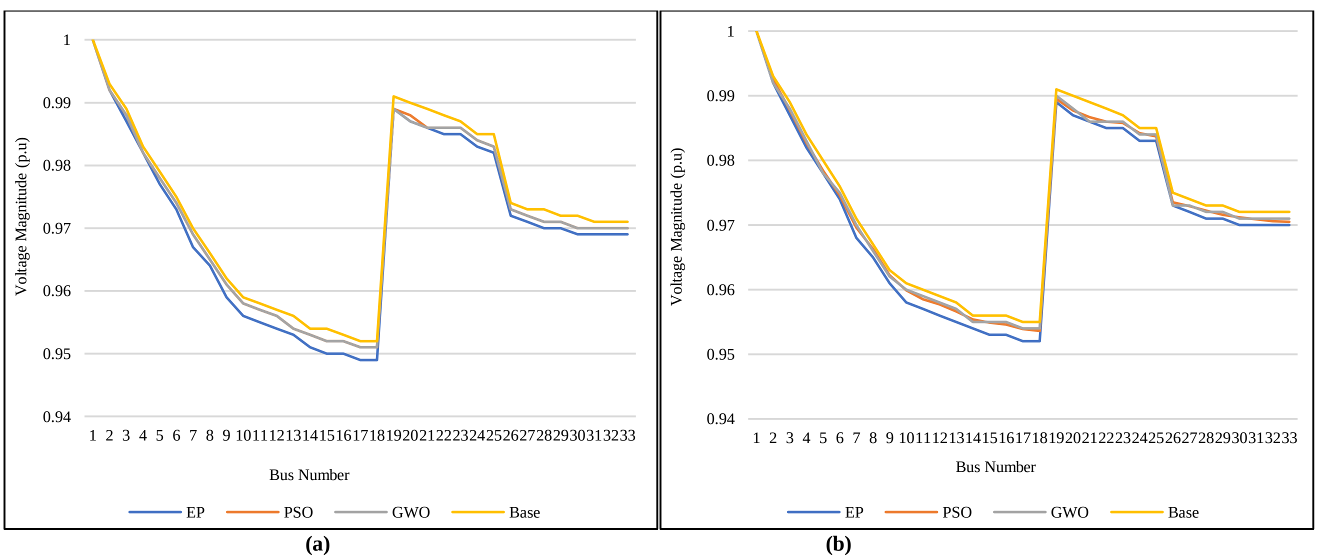


Fig. 3 Network voltage profile within the 33-bus system, (a) Without PV integration, and (b) With PV integration on week busses.

Lastly, in case 4, the GWO algorithm demonstrates the most effective performance, achieving the lowest power loss of 0.188 MW, followed by PSO with a power loss of 0.189 MW. The EP algorithm again shows the highest power losses, indicating the lowest optimization performance compared to PSO and GWO. In order to optimize the location of EVCSs within the 69-bus system, the GWO algorithm proves to be the most effective method, achieving the ideal balance between preserving voltage stability and reducing power losses.

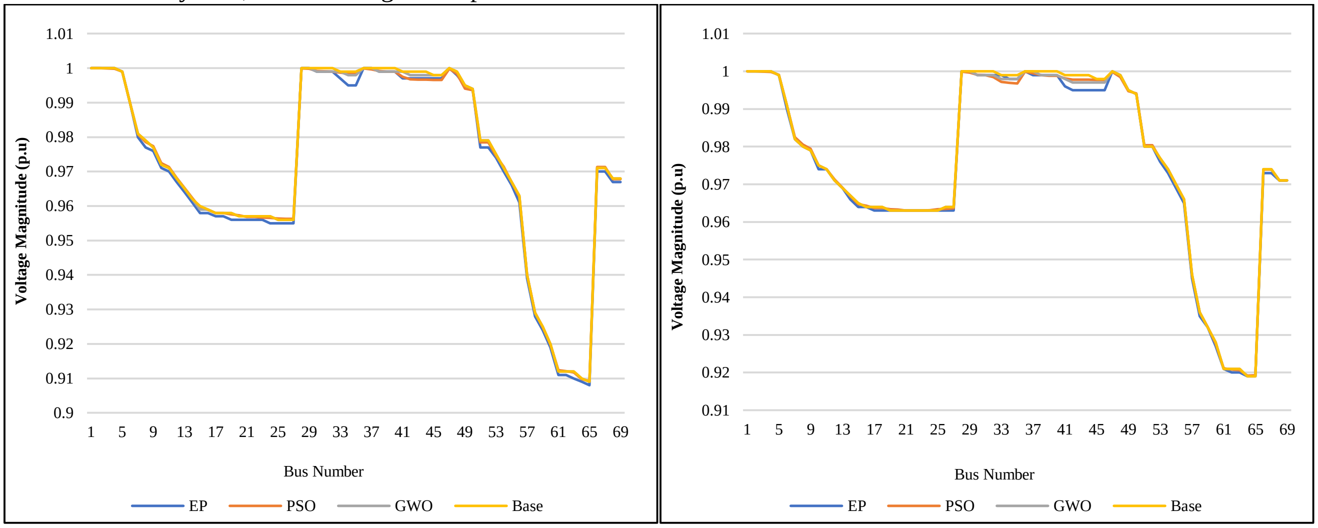


Fig. 4 Network voltage profile for 69-bus system, (a) Without PV integration, and (b) With PV integration on week busses.

Figure 4 depicts the voltage profile of 69- the bus system for case 3 and case 4, considering PV integration at the weakest busses of 27, 61 and 65, each with a capacity of 0.1 MW. The improved voltage profile in the network is contributed by the integration of PVCS. This enables these generators to dispatch power to a portion of the load, reducing dependence on the main grid. The GWO algorithm demonstrates proficiency in pinpointing optimal positions for EVCS and effectively maintaining voltage stability following the additional loads introduced by the EVCS.

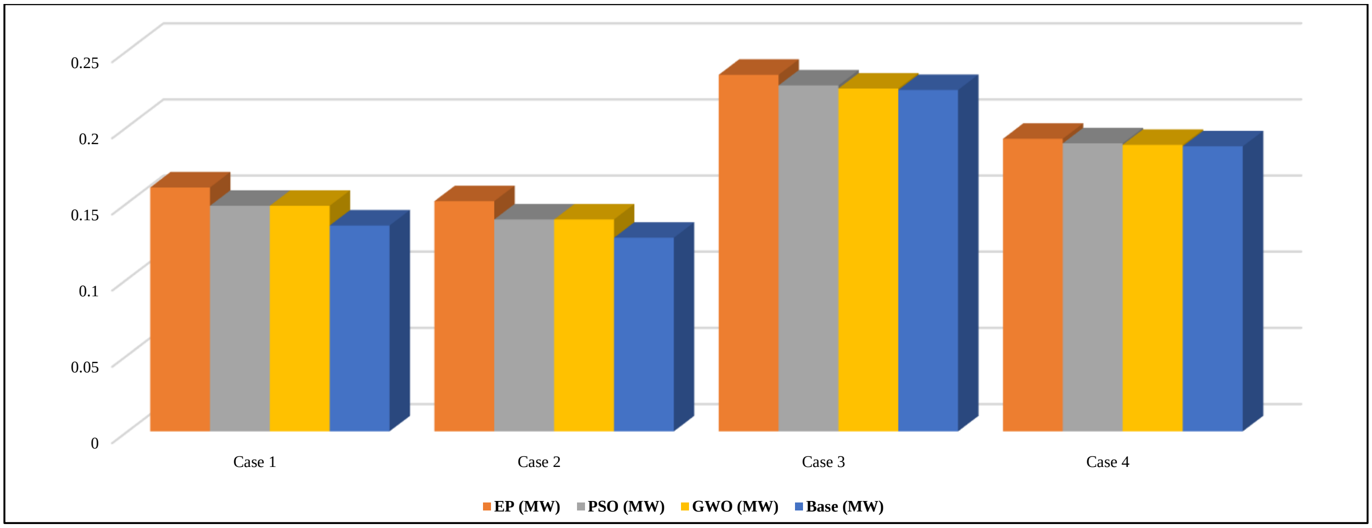


Fig. 5 Power losses difference

Figure 5 illustrates the power losses across four different cases, analysed using GWO, PSO and EP optimization techniques, in comparison to the base case for both the 33-bus and 69-bus test systems. Table 2 shows that in both Cases 1 and 2, PSO and GWO show increases in a power loss of 9.63% and 9.45%, respectively, significantly outperforming the EP algorithm. In Case 3, GWO demonstrates the lowest increment in power loss at 0.45%, followed by PSO at 1.34% and EP at 4.46%, highlighting GWO's superior performance. Similarly, in Case 4, GWO again has the lowest increment in power loss at 0.53%, with PSO at 1.07% and EP at 2.67%. The GWO consistently showed the least increase in power losses among the optimization techniques, promoting its effectiveness in minimizing losses.

3.4. Ethical Considerations and Practical Implications of PV-EVCS Integration

The integration of PV with EVCS has significant ethical and practical implications. From an environmental standpoint, this approach promotes sustainability by reducing reliance on fossil fuel-based power generation. This aligns with global initiatives to encourage the use of RE sources and lower carbon emissions. From a socio-economic perspective, strategically placed EVCS enhances accessibility and encourages EV adoption. However, a well-spread distribution must be ensured to prevent an imbalance in EVCS availability, particularly in rural areas. Policymakers and grid operators need to establish regulatory frameworks that promote the well-spread and efficient deployment of PV-EVCS infrastructure. These frameworks should ensure fair access to charging facilities while supporting the integration of RE sources into the grid. By adopting comprehensive regulations, stakeholders can address technical challenges, create more sustainability and promote an accessible energy ecosystem.Besides the strategic EVCS location, addressing grid stability is crucial to prevent excessive strain on existing networks. By integrating demand-side management and real-time monitoring within smart grid technologies, the PV-EVCS system's performance can improve significantly. This approach helps to maintain a balance between load demand and supply capacity.

Table 2. Comparative analysis of the increment power losses for all algorithms and base case

Case	Base (MW)	EP (MW)	Increase	PSO (MW)	Increase	GWO (MW)	Increase
1	0.135	0.16	18.52%	0.148	9.63%	0.148	9.63%
2	0.127	0.151	18.90%	0.139	9.45%	0.139	9.45%
3	0.224	0.234	4.46%	0.227	1.34%	0.225	0.45%
4	0.187	0.192	2.67%	0.189	1.07%	0.188	0.53%

4. Conclusion

This research offers a comprehensive comparison of the performance of PSO, GWO, and EP in determining the optimal placement of EVCS, improving voltage profiles and reducing power losses in IEEE 33-bus and IEEE 69-bus power systems. The results showed that the GWO algorithm outperformed PSO and EP in terms of performance by effectively reducing power losses and enhancing voltage profiles. This established it as the most efficient optimization technique for determining the optimal placement of EVCS. Additionally, integrating PV systems into the EVCS effectively mitigated some of the power losses associated with the charging loads, contributing to better voltage stability and overall system performance. By combining both strategic EVCS location and integration with PV systems, this approach will subsequently attract users to use EVs and, in the long run, contribute to sustainable development goals. For future research, hybrid optimization techniques that combine the strengths of multiple algorithms to enhance power system optimization shall be investigated to further increase the efficiency. Additionally, testing these techniques in larger and more complex power networks is crucial to validate their effectiveness and scalability. Consideration of real-world applications is also suggested, which includes optimizing EVCS placement in urban and suburban areas by segmenting networks into zones that reflect actual EV usage patterns. This approach would ensure a more accurate representation of charging demand, supporting the development of resilient and efficient charging infrastructure in diverse geographical settings.

Acknowledgements

Authors acknowledge the Ministry of Higher Education (MOHE) for funding under the Fundamental Research Grant Scheme (FRGS) (FRGS/1/2022/TK07/UITM/02/3) and College of Engineering, Universiti Teknologi MARA.

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