Green Energy and Intelligent Transportation 2 (2023) 100094

Contents lists available at ScienceDirect

Green Energy and Intelligent Transportation

journal homepage: www.journals.elsevier.com/green-energy-and-intelligent-transportation

Full length article

Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation

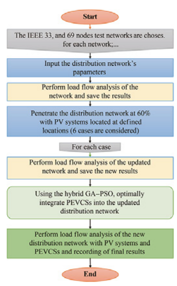
Ebunle Akupan Rene [a,*], Willy Stephen Tounsi Fokui [b], Paule Kevin Nembou Kouonchie [c]

[a] Department of Electrical and Electronic Engineering, University of Buea, P.O Box 63, Buea, Cameroon
[b] Teleconnect GmbH, Am Lehmberg 54, 01157, Dresden, Germany
[c] Department of Electrical Engineering, Pan African University Institute for Basic Sciences, Technology and Innovation, P.O. Box 62000-00200, Nairobi, Kenya

HIGHLIGHTS

- Application of artificial intelligence in electric power system.
- Electric Vehicle integration to the grid power network.
- Using the computational technique to solve power system problem.
- Optimal placement to distributed generation.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Electric vehicles
Charging stations
Distributed generation
Photovoltaic
Genetic algorithm
Particle swarm optimization

ABSTRACT

The transportation sector is characterized by high emissions of greenhouse gases (GHG) into the atmosphere. Consequently, electric vehicles (EVs) have been proposed as a revolutionary solution to mitigate GHG emissions and the dependence on petroleum products, which are fast depleting. EVs are proliferating in many countries worldwide and the fast adoption of this technology is significantly dependent on the expansion of charging stations. This study proposes the use of the hybrid genetic algorithm and particle swarm optimization (GA-PSO) for the optimal allocation of plug-in EV charging stations (PEVCS) into the distribution network with distributed generation (DG) in high volumes and at selected buses. Photovoltaic (PV) systems with a power factor of 0.95 are used as DGs. The PVs are penetrated into the distribution network at 60% and six penetration cases are considered for the optimal placement of the PEVCSs. The optimization problem is formulated as a multi-objective problem minimizing the active and reactive power losses as well as the voltage deviation index. The IEEE 33 and 69 bus distribution networks are used as test networks. The simulation was performed using MATLAB and the results obtained validate the effectiveness of the hybrid GA-PSO. For example, the integration of PEVCSs results in the minimum bus voltage still within accepted margins. For the IEEE 69 bus network, the resulting minimum voltage is 0.973 p.u in case 1, 0.982 p.u in case 2, 0.96 p.u in case 3, 0.961 p.u in case 4, 0.954 p.u in case 5, and 0.965 p.u in case 6. EVs are a sustainable means of significantly mitigating emissions from the transportation sector and their utilization is essential as the worldwide concern of climate change and a carbon-free society intensifies.

* Corresponding author.
E-mail address: ebunleakupanrene@gmail.com (E.A. Rene).

https://doi.org/10.1016/j.geits.2023.100094
Received 14 January 2023; Received in revised form 3 April 2023; Accepted 30 May 2023
Available online 2 June 2023

1. Introduction

Owing to the high greenhouse gas (GHG) emissions from the transportation sector, the adoption of electric vehicles (EVs) is fast increasing in many countries as a replacement for combustion engine-based vehicles to reduce the quantity of GHG emitted into the atmosphere [1]. The fast appropriation of EVs in many countries worldwide also results from the increasing depletion of petroleum resources in addition to its environmental impacts [2]. Hence, the proliferation of EVs, which are noiseless, safer, emission-free, and fuel-efficient are underway [3]. The utilization of EVs in the place of conventional vehicles has environmental benefits and is also advantageous to the electrical distribution network as EVs can aid in frequency/voltage support and serve as spinning reverses [4]. However, the misappropriation of EVs in the distribution network can have a detrimental effect in terms of voltage deviation out of acceptable limits, power quality degradation, and an increase in power loss [5]. This adverse effect can be resolved by incorporating distributed generation (DG) in the distribution network [6]. Photovoltaic (PV) systems are the most prominent DGs owing to the continuous reduction in the prices of PV panels and other accessories [7], as well as the availability of energy from the sunlight [8]. The rate at which PV systems are being installed worldwide is over 70 GW per year [9]. PV systems can mitigate the adverse effect of EVs in the distribution network through voltage support and peak shaving [10].

A major challenge with the adoption of EVs in many communities is the availability of charging facilities [11]. Three types of EV chargers exist: Level 1, Level 2, and Level 3 chargers. Among these EV chargers, Level 3 chargers are the fastest and are usually offboard, followed by Level 2 and then Level 1, which are both onboard chargers [12]. A Level 3 charger can fully charge an EV in less than an hour, whereas Level 1 and Level 2 chargers require a longer time [13]. The proliferation of EVs in the transport sector has led to numerous studies on the strategic placement of EV charging stations (EVCS) in the distribution network. This is because if the EVCSs in a large scale are not carefully integrated into the distribution network, they can endanger the power systems because they have the potential of unbalancing the distribution feeders and increase current levels and bidirectional flow of current [1]. Furthermore, EVs that are charged haphazardly may leave the distribution network to incur power losses and voltage changes that exceed permitted limitations. It is therefore important to optimally allocated EVCS into the distribution network to limit these inconveniences. Most studies have been focused on the use of Heuristic techniques for the optimal allocation of EVCS into the distribution network to limit the impact of the EVCS. The main benefit of using heuristic techniques is that they provide immediate answers that are simple to comprehend and put into practice. Also. heuristic algorithms are useful because they provide quick and workable short-term answers to scheduling and planning issues. In Ref. [14], EVCSs were placed in a distribution network having numerous photovoltaic systems randomly allocated in the network at a high penetration level of 60%. The optimization problem was formulated to minimize power losses and voltage deviation while maximizing the voltage stability index. The hybrid bacterial foraging optimization and particle swarm optimization (PSO) (technique was used to solve the optimization problem. In Ref. [15], an algorithm for the optimal siting and sizing of EVCSs based on demand response incentive-based programs was presented using PSO. The objectives of the optimization were to minimize investment costs, grid losses, and the cost of demand response. Based on an intelligent algorithm and bi-level programming, the authors in Ref. [16] optimally allocated DGs and EVCSs in the distribution network. The objective function was formulated to maximize the annual profit of the utility company and an improved harmonic particle swarm optimization algorithm was utilized to solve the objective function. In Ref. [17], the optimal location for EVCSs combining PV and battery energy storage was determined using a multi-objective whale optimization algorithm. EVCSs were optimally allocated in a commercial distribution network with high penetration of PV panels to increase the PV penetration capability of the distribution network and decrease the effect of the EVCSs on the network [18]. PSO was used to solve the optimization problem, thus minimizing the network voltage deviation and energy loss. Furthermore, EV drivers, the power grid, operators, vehicles, and traffic flow were considered to allocate EV fast-charging stations [19]. Notably, instead of statistical data, which is more scientific and acceptable, the authors used dynamic real-time data for optimal planning of the EV fast-charging stations. In Ref. [20], the placement of EVCS in a commercial distribution network was investigated based on the voltage sensitivity factor of the network. The authors manually placed the EVCS sequentially on every bus of the network and analyzed the voltage sensitivity of the system. EVCSs were placed in the distribution network with capacitors for voltage stability maintenance and power loss improvement using the genetic algorithm (GA) [21]. Based on the simulation results, the simultaneous placement of EVCSs and capacitors decreased the influence of EVCSs on the network's power loss and voltage profile. EVCSs were allocated using a Pareto dominance-based hybrid CSO and TLBO, minimizing the cost of the EVCSs, while ensuring sufficient grid stability and the accessibility of EVCSs to EV users [22].

This study proposes the use of the hybrid genetic algorithm and particle swarm optimization (GA-PSO) for the optimal allocation of plug-in electric vehicle charging stations (PEVCS) in the distribution network with DG in high volumes and suitably placed at selected buses of the network. The optimization problem is formulated as a multi-objective minimization problem that minimizes the active and reactive power losses, as well as the voltage deviation index. The contributions of this study are as follows.

- GA-PSO is used for the allocation of PEVCSs in the distribution network with DGs in high concentration, in which the PEVCSs are modeled to be a combination of loads comprising resistive and reactive parts. EV chargers are modeled at a 0.95 lagging power factor to address the nonlinearity of the converters used in the design of the chargers. In previous studies, EV charging points or stations have been modeled as purely resistive loads, not considering the reactive power demand of the converters used in the design of the chargers.

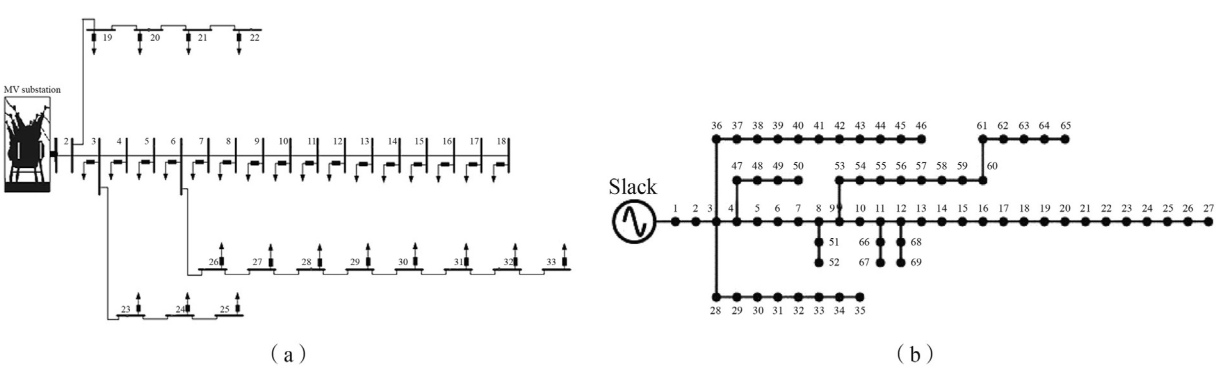


Fig. 1. Networks under investigation. (a) IEEE 33 node. (b) IEEE 69 node.

The rest of this manuscript is structured as follows; The methodology is presented in Section 2. The results and discussions are presented in Section 3. Finally, Section 4 concludes the paper.

2. Methodology

2.1. Networks under investigation

EVs are powered by direct current from chargers connected to the grid. They could as well be discharged into the grid. However, this study focuses on the former. Thus, PEVCSs are seen as direct current loads to the grid's radial distribution network system (RDNS). This study considers two standard IEEE networks, the IEEE 33 node and 69 node test distribution networks whose single line diagrams are shown in Fig. 1. The IEEE 33 node test network is a three-phase balanced network at a voltage of 12.66 kV. This network was considered because it is balanced (not too large nor small). The IEEE 69 node test distribution network is also balanced at a voltage of 12.66 kV similar to the IEEE 33 node network. However, it is larger and incorporates more connections.

The networks supply both commercial and residential loads, with the residential loads accounting for 85% of the total load of each network. Table 1 presents the total power of each network, whereas Table 2 presents the total power demand of the residential loads of each network. The number of homes in the network must be known to properly estimate the total EV population in each network.

Table 1
IEEE 33 bus and 69 bus total power demand.

Bus type	Active power *P* (kW)	Reactive power *Q* (kVar)	Apparent power *S* (kVA)
IEEE 33 bus	3715	2,300	4,369.35
IEEE 69 bus	3,801.85	2,694.6	4,659.93

Table 2
Residential power demand.

Bus type	Active power *P* (kW)	Reactive power *Q* (kVar)	Apparent power *S* (kVA)
IEEE 33 bus	3,157.75	1,955	3,713.9
IEEE 69 bus	3,231.572,5	2,290.41	3,960.9

2.2. Estimation of the number of PEVs and the required number of charging points

Using Eq. (1) and assuming the power demand of each family is 12.7 kVA, the total number of households in the neighborhood can be estimated to be 293 households for the 33 bus RDNS and 312 households for the 69 bus RDNS.

$$n^{\mathrm{H}} = \frac{S^{\mathrm{TH}}}{S^{\mathrm{H}}} \tag{1}$$

where n^{H} is the number of houses in the neighborhood, S^{TH} is the total apparent power in the study area, and S^{H} is the total apparent power per residence in the study area.

The number of PEV (n^{HEV}) in the community may be determined using Eq. (2), assuming the percentage of PEV integration, $\%PEV$ is 63% for IEE 33 bus and 59% for IEE 69 bus networks.

$$\%EV = \frac{n^{\mathrm{HEV}}}{n^{\mathrm{H}}} \times 100 \tag{2}$$

Using Eq. (2), the total number of EVs in the study area is 184.

Seven PEVCSs are strategically located around the radial distribution network to provide an energy bank for the 184 PEVs. Level 1 and Level 2 chargers are used, each with its unique amount of charging points (CPs), outlined in Table 3. PEVCSs with constant capacities are employed at a power factor of 0.95. This has been considered to address the reactive power consumption by the converters at the charging points.

2.3. Allocation of PEVCSs using the hybrid GA-PSO

2.3.1. Problem formulation

The optimization problem is formulated as a minimization problem that minimizes active and reactive power losses, as well as the voltage deviation index. Thus, the multi-objective function is mathematically expressed as follows:

$$f = \mathrm{Min}\{f_1, f_2\} \tag{3}$$

where, f_1 and f_2 are the total power loss and average voltage deviation index, respectively.

The mathematical equation that represents the multi-objective function is shown below.

a. Objective function
   i. Active and reactive power loss minimization (f_1)

Eq. (4) is used to obtain the precise branch loss in each network.

$$\left.\begin{aligned} P_{\mathrm{Loss}(i)} &= I_i^2 * R_i \\ Q_{\mathrm{Loss}(i)} &= I_i^2 * X_i \end{aligned}\right\} \tag{4}$$

where $P_{\mathrm{Loss}(i)}$ and $Q_{\mathrm{Loss}(i)}$ are the total active and reactive powers losses, respectively; R_i and X_i represent the resistance and reactance of the i^{th} branch, respectively; I_i represents the current flowing through the i^{th} branch; i represents the branch number.

Therefore, the function for the minimization of the total power loss is expressed as:

$$f_1 = \mathrm{Min} \sum_{i=1}^{\mathrm{br}} \left[P_{\mathrm{loss}(i)} + Q_{\mathrm{loss}(i)}\right] \tag{5}$$

where br represents the total number of branches.

ii. Average voltage deviation index (f_2)

Eq. (6) describes the required average voltage deviation index equation (AVDI). AVDI defines the deviation of all bus voltage magnitudes about the reference voltage magnitude of 1.00 pu, expressed as follows:

$$f_2 = \frac{1}{N} \sum_{k=1}^{N} [1 - V_k]^2 \tag{6}$$

where V_k represents the voltage at bus k, k represents the bus number, and N represents the overall number of buses.

Consequently, transforming Eqs. (5) and (6) into a minimization function results in the mathematical formulation of a multi-object function shown in Eq. (7).

Table 3
Distribution of the charging points of Level 1 and Level 2 type chargers.

Charger	CP rating (kW)	Number of CPs per PEVCS	PEVCS rating (kW·kVar^{-1})	Number of PEVCS	Total rating (kW·kVar^{-1})
Level 1	11	28	308/101.23	3	924/303.70
Level 2	22	25	550/180.78	4	2,200/723.10
Total number of EVCSs and power consumption				7	3,124/1,026.80

$$f = \text{Min}\left[w_1 f_1 + w_2 f_2\right] \tag{7}$$

where w_1 and w_2 are the weights allotted to the respective individual goal functions.

b. Constraints
 i. Equality constraints
  - The constraints for power requirement:

$$P_{\text{grid}} + \sum_{i=1}^{N_{\text{pv}}} P_{\text{pv}_i} - \sum_{i=1}^{N_{\text{l}}} P_{\text{load}_i} - \sum_{i=1}^{N_{\text{PEVCS}}} P_{\text{PEVCS}_i} - \sum_{i=1}^{\text{br}} P_{\text{loss}\,i} = 0 \tag{8}$$

$$Q_{\text{grid}} + \sum_{i=1}^{N_{\text{pv}}} Q_{\text{pv}_i} - \sum_{i=1}^{N_{\text{l}}} Q_{\text{load}_i} - \sum_{i=1}^{N_{\text{PEVCS}}} Q_{\text{PEVCS}_i} - \sum_{i=1}^{\text{br}} Q_{\text{loss}\,i} = 0 \tag{9}$$

where, P_{grid} and Q_{grid} are the grid's active and reactive power respectively. P_{pv_i} and Q_{pv_i} are the active and reactive power from the i^{th} PV system, respectively. P_{load_i} and Q_{load_i} are the active and reactive power demands at the i^{th} bus, respectively. P_{EVCS_i} and Q_{PEVCS_i} are the active and reactive power demand by a single PEVCS, respectively. P_{loss_i} and Q_{loss_i} are the active and reactive power loss in the i^{th} branch, respectively. N_{pv} is the number of PV systems in the distribution network, N_{l} is the number of load nodes, N_{PEVCS} is the PEVCSs, and br is the number of branches in the network.

$$V_i^{\min} \le V_i \le V_i^{\max}$$

$$0.95 \le V_i \le 1.05$$

where $V^{\min}$ and $V^{\max}$ are the minimum and maximum voltages at bus i, respectively.

$$\theta_i^{\min} \le \theta_i \le \theta_i^{\max}$$

$$P_{\text{pv}_i}{}^{\min} \le P_{\text{pv}_i} \le P_{\text{pv}_i}{}^{\max}$$

$$Q_{\text{pv}_i}{}^{\min} \le Q_{\text{pv}_i} \le Q_{pv_i}{}^{\max}$$

$$I_{\text{r}} \le I_{\text{r}}^{\max}$$

$$S_i \le S_i^{\max}$$

 ii. Inequality constraints
  - **Node voltage constraints:** The voltage of each bus must fall within the predefined limits defined by;
  - **Limits on voltage angles:** The voltage angle of each bus must fall within the predefined limits defined as:
  - **PV power constraints:** The power factor of the PV system is 0.95 and the maximum permissible bus capacity constitutes the bulk of the PV system's power limit. The following equation describes the power limit of the overall PV system;
  - **Current constraints:** The distribution feeder current limit should be maintained within a rated limit;
  - **Line loading constraints:** The maximum volt-amperes rating of the distribution line must not be exceeded.

The aforementioned multi-objective optimization problem is solved using the hybrid GA-PSO technique.

2.3.2. Particle swarm optimization (PSO)

A computational intelligence method for solving issues whose answers can be represented as a point in an n-dimensional solution space is called particle swarm optimization (PSO). In a decision process, each individual particle uses two crucial pieces of information. The first is their experience, in which they observe their own "fitness," and the second is other agents' experiences, in which they are aware of what their neighbors have done and "emulate" successful neighbors by approaching them. The particle swarm method is a straightforward technique and useful in a variety of problem fields. Inspired by Heppner's research on bird flocking behavior, Kennedy et al. created PSO in 1995 [23].

A population of random solutions is used to populate the PSO. Each possible solution, known as a particle (agent), is assigned a random velocity and is flown across the problem space. Each agent has a memory, which allows it to remember its prior best position (called P_{best}) and the related fitness. There are a number of P_{best} in the swarm for each agent and the agent with the greatest fitness is known as the swarm's global best (G_{best}). In an n-dimensional space, each particle is considered as a point. Therefore, the i^{th} particle is represented as $X_i = (x_{i1}, x_{i2}, \ldots x_{in})$ and the best position of the i^{th} particle that offers the greatest fitness value is represented as $P_i = (p_{i1}, p_{i2}, \ldots p_{im})$. The population's best particle is represented as $P_{\text{g}} = \left(p_{\text{g}1}, p_{\text{g}2}, \ldots p_{gn}\right)$ among all the particles. The velocity of the particle determined by the change in location for particle i is denoted as $V_i = (v_{i1}, v, \ldots v_{in})$. The particles are managed using the equations below (the superscripts indicate iterations).

$$v_i^{k+1} = w * v_i^{k} + c_1 * r_1 * \left(P_i - x_i^{k}\right) + c_2 * r_2 * \left(P_{\text{g}} - x_i^{k}\right) \tag{10}$$

$$x_i^{k+1} = x_i^{k} + v_i^{k+1} \tag{11}$$

where $i = 1, 2, \ldots, N$, N denotes the population size; w denotes inertia weight; c_1 and c_2 are two positive constants denoted as the cognitive and social parameters, respectively; r_1 and r are random values uniformly distributed within the range [0, 1]. At each iteration, Eq. (10) is used to calculate new velocity of the i^{th} particle, v_i^{k+1}, whereas Eq. (11) calculates the new location of the i^{th} particle, x_i^{k+1} by adding its new velocity, v_i^{k+1} to its existing position, x_i^{k}.

2.3.3. Genetic algorithm

The search heuristic called a genetic algorithm (GA) was inspired by Darwin's notion of natural evolution [24]. The fittest individuals are chosen for reproduction to produce the children of the next generation, which is how natural selection works. The initial stage of natural selection is the selection of the population's fittest members. They have children who inherit their parents' characteristics and become a part of the next generation. Children born to parents who are physically fitter will perform better and have a better chance of surviving. The constant rounds of this process will finally lead to the emergence of the fittest generation. A search problem can be resolved using this concept.

We consider a number of potential solutions to a problem and choose the most appropriate. A GA considers five stages.

- Initial population: The process begins with a group of individuals known as the population. Genes are a collection of parameters (variables) that characterize an individual. A group of genes make up a chromosome (solution);
- Fitness function: The fitness function gauges an individual's fitness level; that is, the capacity of an individual to compete with others. Each individual receives a fitness rating and based on that, an individual's likelihood of being chosen for reproduction is determined;
- Selection: Here, the fittest individuals are selected and they can pass their genes to the following generation. Selection is based on the fittest scores and individuals with the highest scores are likely to be selected;
- Crossover: The crucial stage of a GA is crossover. A crossover point is picked at random from the DNA for each set of parents to mate;

- Mutation: This aims to maintain diversity in the population and to avoid a situation of premature convertures;
- Termination: The algorithm is terminated when the population converges, that is, the population stops reproducing offspring of significant difference from the later generation.

2.3.4. *Hybrid GA-PSO algorithm*

According to Ref. [25], most evolutionary approaches use the following procedure.

Step 1. Generate an initial population at random;

Step 2. Determine the fitness value for each particle based on the best distance;

Step 3. Fitness values define population reproduction;

Step 4. Stop if optimum solutions are discovered. Otherwise, create a new generation of population and go to Step 2.

Based on the aforementioned process, PSO and GA have some similarities. Both PSO and GA begin with a randomly generated population. These techniques employ fitness values to assess the population. Both modify the population and use random procedures to determine the best solution. However, none of these approaches guarantee success. Particles in PSO update themselves based on their intrinsic velocity. PSO's information-sharing method significantly differs from that of GA, which uses chromosomes for information transfer. In most circumstances, even in the local version, all the particles in PSO rapidly converge to the optimal solution when compared with GA. One of the limitations of GA is that its sampling capacity and efficiency are affected by its limited population size [2]. On the other hand, PSO has the disadvantage of easily falling into the local optimum in high-dimensional space, hence never reaching the global optimum [3]. The proposed hybrid GA-PSO design approach aims to combine the strengths of GA and PSO by merging the two algorithms, with the optimal solution derived from PSO being further improved by GA, employing selection, crossover, and mutation operators. Incorporating PSO in the procedure of GA has the advantage that the number of evaluated agents at each iteration step is high compared to GA or PSO alone. Also, PSO compensates the disadvantage of GA because it has a memory which means that the knowledge of good solutions is stored compared to GA in which the previous solutions are discarded once the population changes [4]. By combining these two algorithms, a hybrid GA-PSO gives a low computational cost and fast convergence [5]. The flowchart of the hybrid GA-PSO is shown in Fig. 2 below.

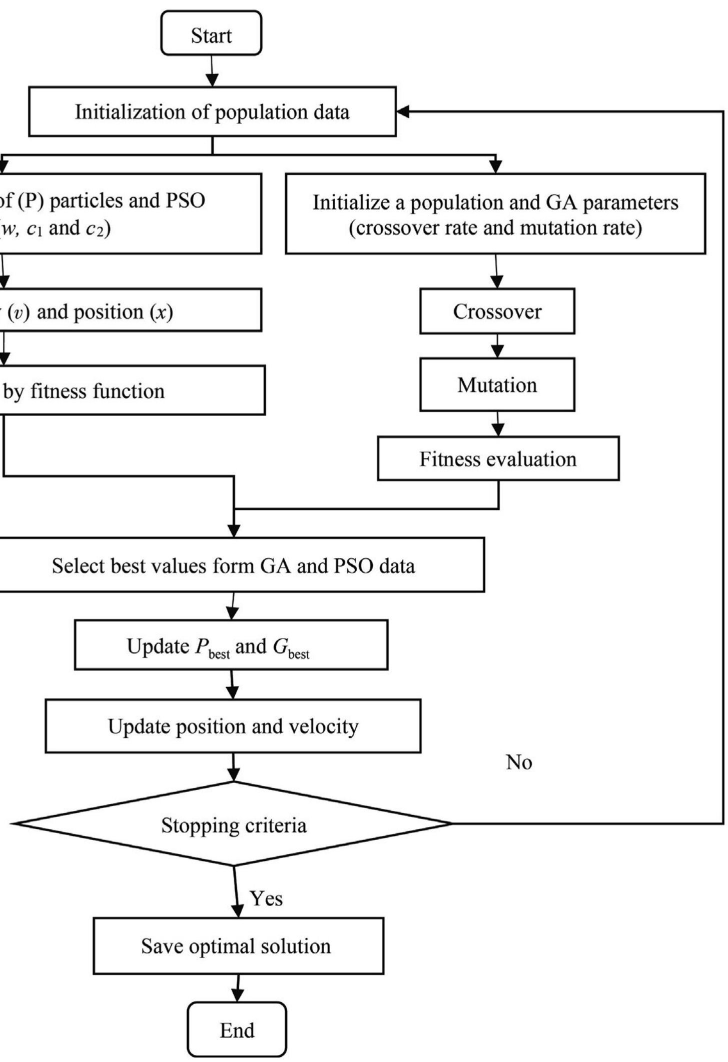


Fig. 2. Hybrid GA-PSO flowchart.

The pseudo-code of the suggested hybrid GA-PSO algorithm used in this study is shown in Algorithm 1.

Algorithm 1: Hybrid GA-PSO algorithm

```
Input:
    Population Size, n
    Max number of iterations, iMAX
Output:
    Global best solution, X_best
start
    Initialize the PSO and GA parameters.
    Randomly initialize the positions of n particles X_i (i = 1, 2, .....n);
    Randomly initialize the velocity of n particles V_i (i = 1, 2, .....n);
    Set iteration counter k = 0;
    Evaluate the fitness of each particle in the search space;
    Set personal best position P_best and global best position G_best;
    Set best solution, X_best;
    Do
        While number of particles ≤ n
            Set and Calculate particle velocity;
            Update particle position;
            Evaluate the fitness function;
            Update personal best position, P_best;
            Update global best position, G_best;
            Go to the next particle;
        End-while
        Update best solution, X_best according to global best position, G_best;
        Rank individuals according to the fitness value.
        Apply crossover operation on the selected pair using crossover probability;
        Apply mutation on offspring using mutation probability;
        Evaluate the fitness of the children;
        Update the best solution, X_best;
        Replace some or all of the population with children;
        Repair the infeasible of the population to be feasible;
        Increment the current iteration, k by 1;
    While k < iMAX or a satisfactory solution has been found
    return the best solution, X_best;
end
```

The parameters used in the optimization problem are shown in Table 4.

Table 4
Hybrid GA-PSO parameter values used.

Parameter	Symbol	Value
Population size	N_p	30
Number of iterations	*it*	20
Inertia coefficient	*w*	1
Damping ratio of the inertia coefficient	*wdamp*	0,99
Personal acceleration coefficient	C_1	2
Social acceleration coefficient	C_2	2
Crossover probability	*p C*	1
Mutation probability	*mu*	0.02

2.4. Simulation

The DGs used in this study are PV systems. To integrate the reactive power injection capabilities of the voltage source inverters utilized in grid-connected PV systems, the PV systems are modeled as negative loads at a power factor of 0.95. The PV systems have a penetration rate of 60% in each study network. The penetration rate is calculated as the ratio of the PV-rated power to the active power demand of the loads. Because this study focuses on the distribution network with PV systems already installed with no predetermined buses designed to harbor the PV systems, six cases of randomly allocated PV systems are considered for optimal PEVCSs placement. For each study network, PEVCSs are optimally placed in each random PV case using the hybrid GA-PSO technique and the results are recorded. The simulations are performed using MATLAB R2019a platform installed in a 16 GB RAM, 2.6 GHz Intel(R) core (TM) i7-6600U CPU laptop.

3. Results and discussions

3.1. Optimal location for the PEVCSs

The optimal locations for the PEVCSs in each simulation case are shown in Tables 5 and 6.

Table 5
Optimal locations of PEVCSs for each random PV (IEEE 33 bus network).

Charger type	PEVCS rating ($kW{\cdot}kVar^{-1}$)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Level 1	308/101.23	19	19	19	19	13	19
	308/101.23	21	20	21	19	19	21
	308/101.23	23	20	23	20	26	23
Level 2	550/180.78	2	19	19	19	19	4
	550/180.78	19	20	19	19	20	19
	550/180.78	20	23	19	21	23	19
	550/180.78	23	23	23	24	23	19

Table 6
Optimal locations of PEVCSs for each random PV (IEEE 69 bus network).

Charger type	PEVCS rating ($kW{\cdot}kVar^{-1}$)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Level 1	308/101.23	10	29	29	32	19	30
	308/101.23	48	37	38	44	33	35
	308/101.23	49	43	46	46	43	38
Level 2	550/180.78	36	39	31	30	30	28
	550/180.78	44	41	33	32	30	29
	550/180.78	45	43	42	37	31	31
	550/180.78	48	47	44	49	34	33

3.2. Network voltage profiles

The network voltage profiles of the IEEE 33 bus and 69 bus networks in all 6 simulation cases of random PV distribution are shown in Figs. 3 and 4, respectively and it can be seen that the random insertion of PV systems into the distribution network at a penetration level of 60% leads to a general improvement in the voltage profile of the two radial distribution networks. This is mainly due to the PVs systems being integrated at load centers where their produced power is consumed. PEVCSs are allocated by the hybrid GA-PSO such that the enhanced voltage profiles are not significantly compromised by the PEVCSs. The GA-PSO algorithm effectively discovers the ideal placements for the PEVCSs that will not significantly alter the network node voltages because of the increased loads from the PEVCSs in all six situations of random size and placement of the PV systems. These simulation results are more accurate than those done [6] where the minimum voltage can be as low as 0.927 p.u, which is below the 0.95 p.u required minimum voltage during the optimization exercise. This is a situation that is not experienced by the hybrid GA-PSO proposed in this study.

3.3. Average voltage deviation index (AVDI)

A node's voltage deviation index (VDI) in a network is the difference between the node's actual voltage and the reference voltage (1.00 p.u). The AVDI is the average VDI of all network nodes. The lower the value, the more stable the network voltage. The AVDI considerably decreased

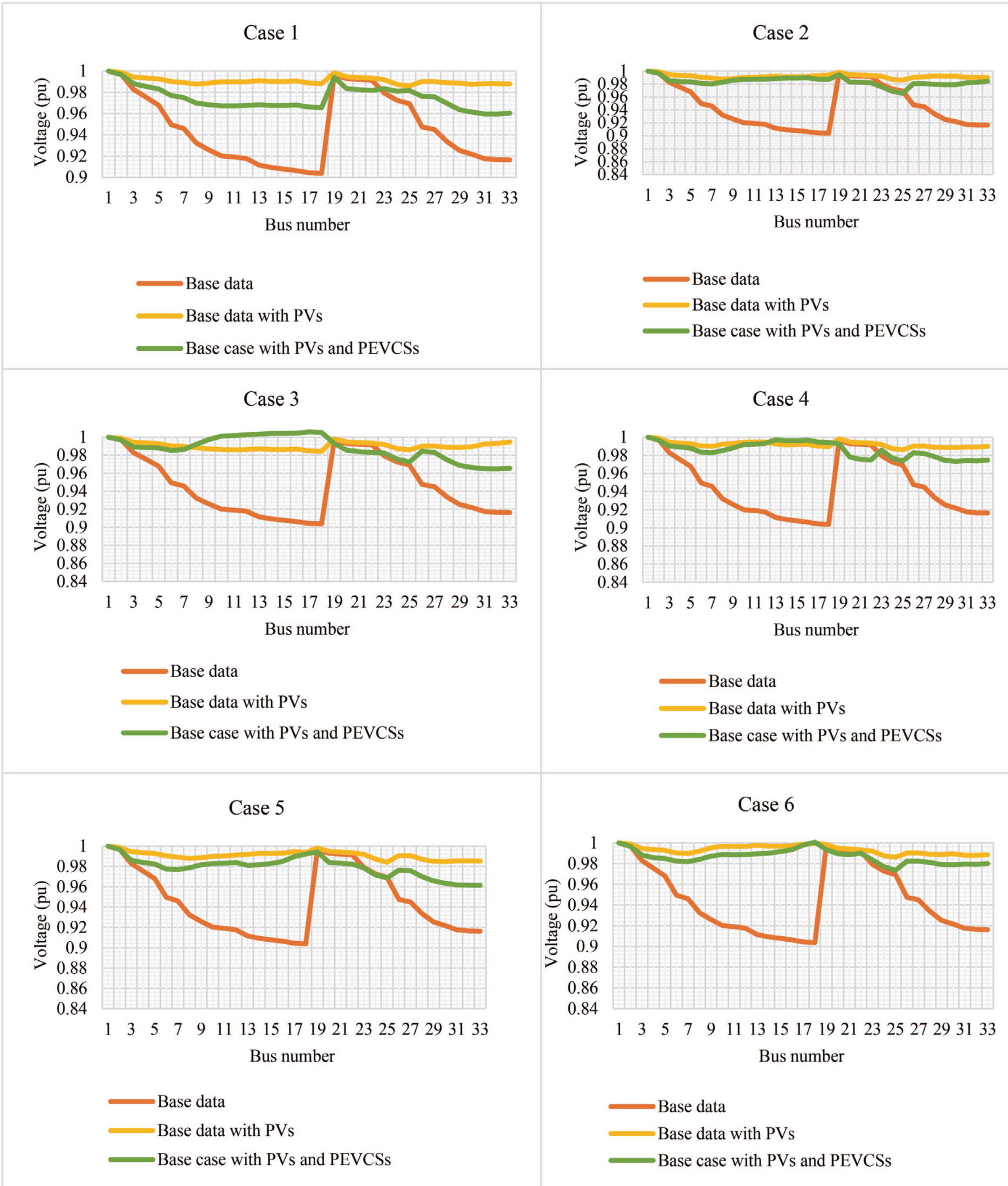


Fig. 3. Voltage profiles of the IEEE 33 bus network in all simulation cases.

with 60% PV penetration, from the base case of 0.004,054,794 and 0.001,439,36 in bus 33 and 69, respectively, to a more improved case, as shown in Figs. 5 and 6. As shown in Fig. 6, the insertion of the PEVCSs had a little effect on the network's AVDI in all simulated instances, with marginal variation compared with the results in Ref. [6].

3.4. Active and reactive power losses

As shown in Figs. 7 and 8, the adoption of PV systems significantly decreases the total active power loss from 210.99 kW in the base scenario for bus 33 and 224.99 kW in the base scenario for bus 69. The total

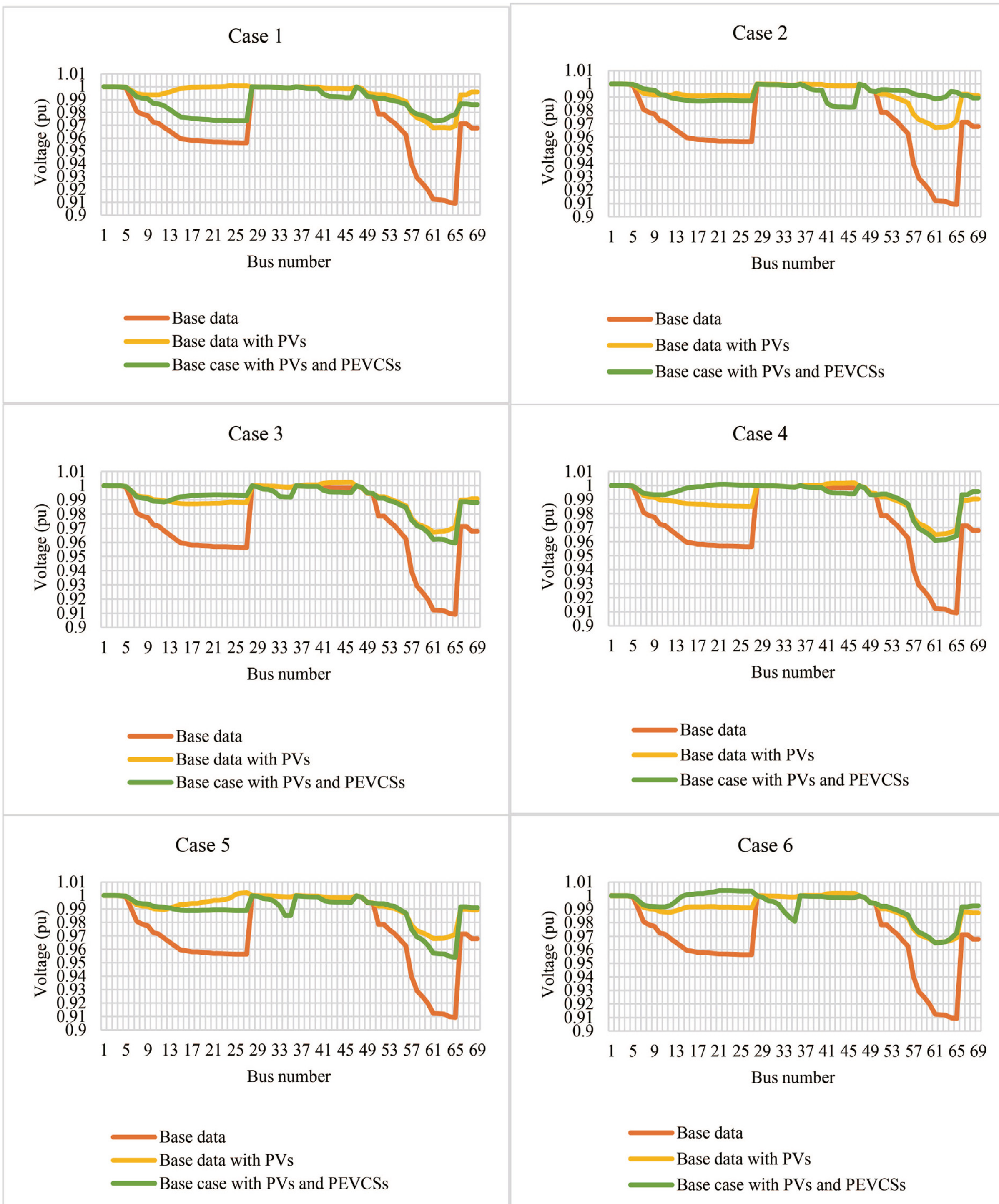


Fig. 4. Voltage profiles of the IEEE 69 bus network in all simulation cases.

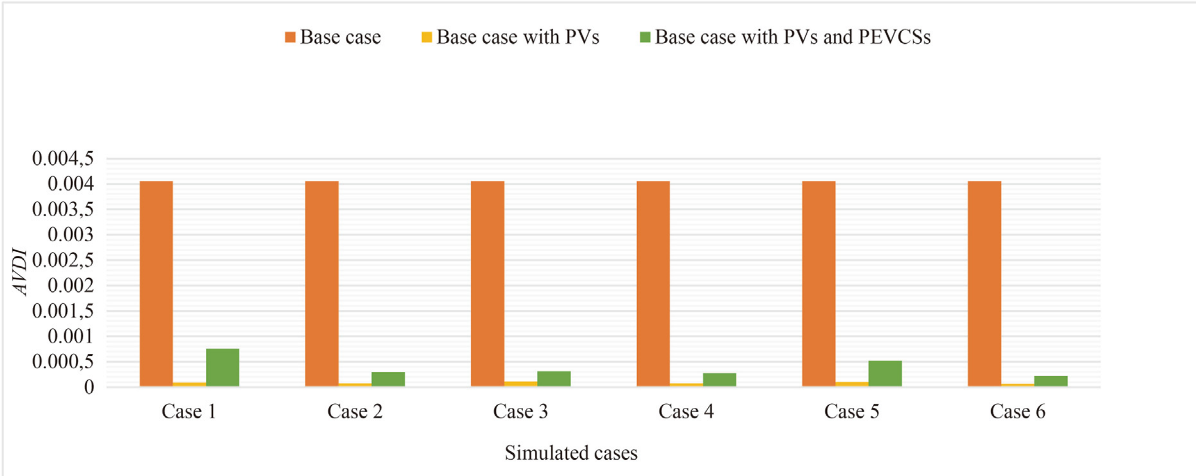


Fig. 5. Average voltage deviation index (IEEE 33 bus network).

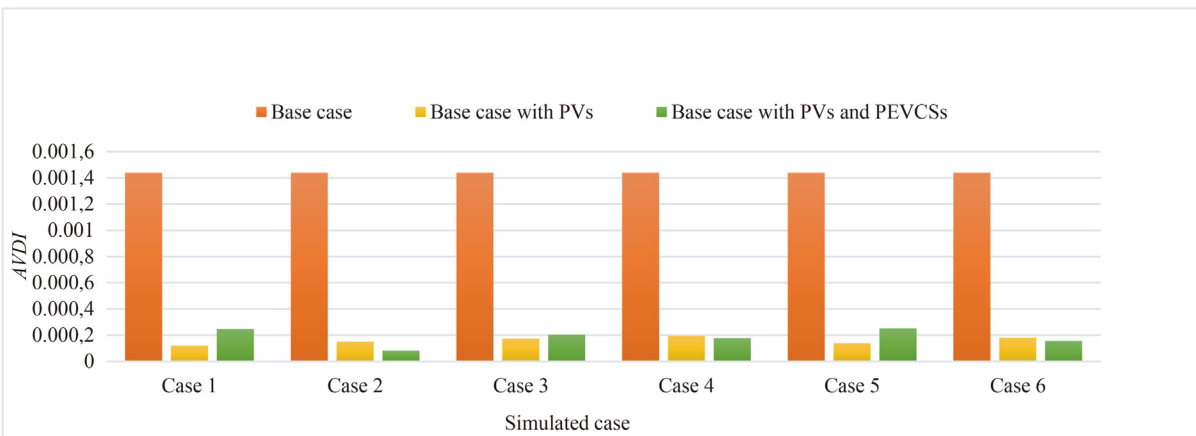


Fig. 6. Average voltage deviation index (IEEE 69 bus network).

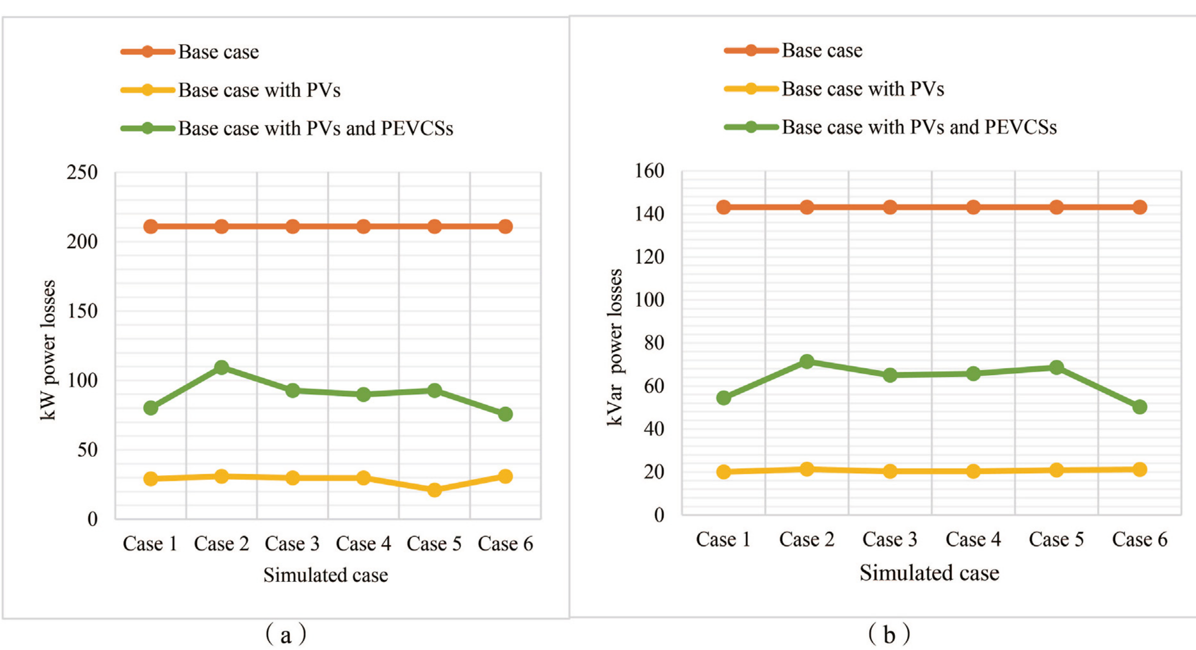


Fig. 7. Total power losses (IEEE 33 bus network). (a) Active power. (b) Reactive power.

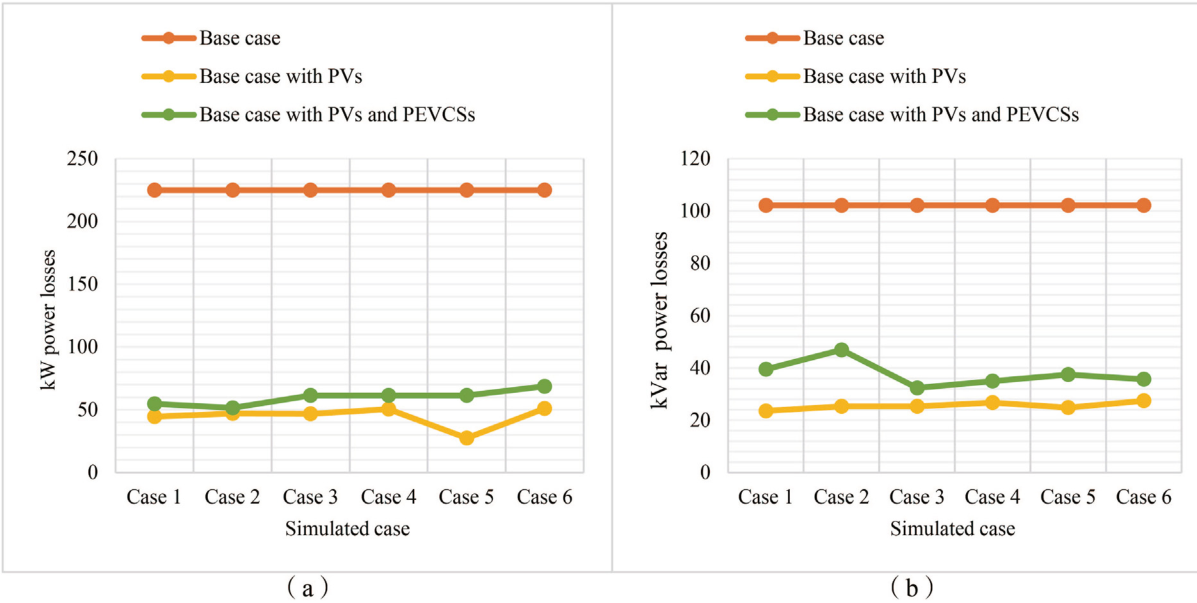


Fig. 8. Total power losses (IEEE 69 bus network). (a) Active power. (b) Reactive power.

reactive power decreases from 143.13 kVar in the base scenario for bus 33 and 102.16 kVar in the base scenario for bus 69. The fall in active and reactive power losses is mainly because as the PV systems are located at load centers, they supply a good portion of the power required by the load, thereby significantly reducing the amount of power flowing in the network feeders. This in turn lead to power losses being reduced as power loss is a function of the square of current flowing through the conductors. In all scenarios, the strategic placement of PEVCSs results in a modest increase in total active and reactive power losses. Obviously, the PEVCS-induced active and reactive power losses are still smaller than in the basic scenario.

3.5. Validation of the results

We compared the proposed hybrid GA-PSO method to place PEVCSs in the distribution network with arbitrarily sized and sited PV systems with that achieved when utilizing GA and PSO independently for the same task. These findings are listed in Tables 7 and 8.

In all six scenarios of PV penetration, the proposed hybrid GA-PSO approach outperforms the component techniques employed separately. First, when PSO is used, the minimum node voltage obtained after placing the PEVCSs using the hybrid technique is 0.959,7 p.u for the IEEE 33 bus and 0.954,1 p.u for the IEEE 69 bus for all simulation cases, which is higher than the minimum node voltage obtained when using the individual techniques separately. Therefore, placing the PEVCSs using both hybridization strategies resulted in a superior network voltage profile. Consequently, a superior AVDI and voltage stability of the networks can be obtained when the hybrid approach is utilized than when GA and PSO are used independently. Hence, employing the hybrid approach to deploy the PEVCSs results in a network with greater voltage stability.

Furthermore, the power losses caused by the PEVCSs inserted in the network using the hybrid approach are often smaller than those caused by the various procedures used independently. The efficiency of the hybrid GA-PSO was validated by comparing its findings to those obtained when GA and PSO were used independently for the deployment of the

Table 7
Comparison of the results obtained using the proposed GA-PSO (IEEE 33 Bus).

Bus type	IEEE 33 bus								
	Cases		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Min values
GA	Location of	Level 1 chargers	19, 21, 22	19, 21, 21	17, 19, 21	6, 10, 19	4, 19, 19	20, 21, 23	
	PEVCS	Level 2 chargers	19, 19, 20, 23	4, 9, 19, 21	19, 20, 21, 23	2, 3, 19, 20	19, 20, 23, 24	4, 19, 19, 20	
	Min voltage		0.971,83	0.957,75	0.965,06	0.961,42	0.969,71	0.961,14	0.957,75
	kWloss		81.944,88	91.495,52	112.124,62	76.013,59	87.921,69	94.573,93	76.013,59
	kVarloss		58.433,20	60.013,57	85.449,67	49.861,21	58.394,14	62.723,33	49.861,21
	AVDI		0.000,32	0.000,59	0.000,45	0.000,63	0.000,47	0.000,45	0.000,32
PSO	Location of	Level 1 chargers	9, 15, 20	3, 16, 19	19, 20, 20	19, 19, 23	4, 20, 22	21, 21, 23	
	PEVCS	Level 2 chargers	19, 19, 20, 23	19, 20, 23, 23	2, 19, 22, 23	19, 19, 23, 23	5, 19, 19 26	19, 19, 20, 23	
	Min voltage		0.962,46	0.968,37	0.973,84	0.947,55	0.961,34	0.972,64	0.947,55
	kWloss		101.386,59	89.247,05	82.685,10	95.836,47	94.498,52	87.929,25	82.685,10
	kVarloss		69.757,75	57.922,95	58.811,66	63.464,23	61.802,18	62.037,18	57.922,95
	AVDI		0.000,60	0.000,52	0.000,31	0.000,70	0.000,55	0.000,41	0.000,31
Hybrid	Location of	Level 1 chargers	19, 21, 23	19, 20, 20	19, 21, 23	19, 19, 20	13, 19, 26	19, 21, 23	
GA-PSO	PEVCS	Level 2 chargers	2, 19, 20, 23	19, 23, 23, 23	19, 19, 19, 23	19, 19, 21, 24	19, 20, 23, 23	4, 19, 19, 19	
	Min voltage		0.959,66	0.965,70	0.964,74	0.973,34	0.961,37	0.973,56	0.959,66
	kWloss		80.298,44	109.425,81	92.773,72	89.908,21	92.773,72	75.677,34	75.677,40
	kVarloss		54.444,97	71.386,99	65.039,90	65.673,20	68.542,68	50.306,55	50.306,55
	AVDI		0.000,75	0.000,30	0.000,318	0.000,28	0.000,51	0.000,22	0.000,22

Table 8
Comparison of the results obtained using the proposed GA-PSO (IEEE 69 Bus).

Bus type	IEEE 69 bus								
	Cases		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Min values
GA	Location of PEVCS	Level 1 chargers	34, 36, 39	22, 33, 42	32, 42, 44	6, 36, 40	22, 32, 51	7, 33, 45	
		Level 2 chargers	30, 32, 32, 37	30, 32, 39, 44	23, 36, 39, 47	32, 38, 43, 44	32, 38, 40, 48	32, 34, 46, 63	
	Min voltage		0.952,94	0.956,92	0.957,84	0.954,24	0.954,53	0.966,18	0.952,94
	kWloss		75.909,63	66.774,64	67.533,74	78.802,52	69.399,95	71.475,23	66.774,64
	kVarloss		37.126,57	33.817,16	34.115,45	41.168,61	36.812,19	42.962,65	33.817,16
	AVDI		0.000,26	0.000,27	0.000,24	0.000,30	0.000,30	0.000,18	0.000,18
PSO	Location of PEVCS	Level 1 chargers	34, 36, 39	22, 33, 42	32, 42, 44	6, 36, 40	22, 32, 51	7, 33, 45	
		Level 2 chargers	30, 32, 32, 37	30, 32, 39, 44	23, 36, 39, 47	32, 38, 43, 44	32, 38, 40, 48	32, 34, 46, 63	
	Min voltage		0.956,24	0.957,43	0.974,68	0.953,32	0.963,20	0.955,33	0.953,32
	kWloss		86.739,67	70.990,49	57.532,26	79.228,82	61.867,36	74.169,57	57.532,26
	kVarloss		40.052,97	35.563,25	40.318,12	44.464,88	36.597,49	40.239,78	35.563,25
	AVDI		0.000,55	0.000,21	0.000,15	0.000,26	0.000,29	0.000,25	0.000,15
Hybrid GA-PSO	Location of PEVCS	Level 1 chargers	10, 48, 49	29, 37, 43	29, 38, 46	32, 44, 46	19, 33, 43	30, 35, 38	
		Level 2 chargers	36, 44, 45, 48	39, 41, 43, 47	31, 33, 42, 44	30, 32, 37, 49	30, 30, 31, 34	28, 29, 31, 33	
	Min voltage		0.973,25	0.982,58	0.959,54	0.960,82	0.954,08	0.965,06	0.954,08
	kWloss		54.811,03	51.532,31	61.511,61	61.273,29	61.511,61	68.712,88	51.532,31
	kVarloss		39.442,54	46.913,61	32.360,71	34.966,24	37.401,21	35.651,60	32.360,71
	AVDI		0.000,25	0.000,08	0.000,20	0.000,18	0.000,252	0.000,16	0.000,08

PEVCSs in the distribution network with arbitrarily sized and sited PV systems.

Based on the simulation results, the proposed hybrid GA-PSO is a viable optimization approach for the deployment of PEVCSs in current distribution networks with randomly dispersed PV systems. The usefulness of hybrid GA-PSO for PEVCS installation will be bolstered as distribution service operators seek to deliver long-term, cost-effective, and dependable services to customers in the short and long term, while ensuring acceptable power quality and voltage within bounds. This is because the algorithm's restrictions are quite similar to the requirement of the planning horizon.

4. Conclusion

The integration of PEVCSs into the distribution network to service the increasing number of PEVs in the present transportation sector should be strategic to reduce the negative impact of PEVCSs on the electrical distribution network. This study proposed the use of a hybrid GA-PSO, which combines the strength of both algorithms to increase the speed of convergence and prevent PSO from being trapped in local minima for the allocation of PEVCSs.

The optimization problem was defined as a multi-objective optimization problem that minimizes the average voltage deviation index as well as active and reactive power losses. The proposed method was tested on two well-known standard IEEE distribution networks, the IEEE 33 and IEEE 69 bus distribution networks. The simulation was performed using MATLAB 2019a and the effectiveness of the hybrid GA-PSO in determining the optimal locations for the PEVCS in both networks was demonstrated. Slight voltage drops were observed owing to the PEVCS. Similarly, the increase in power losses owing to the PEVCS was minimal. For effective planning of PEVCS, the transportation sector and the electricity utility company should collaborate to effectively PEVCS to service EV users [26].

The future scope of this study will include the daytime fluctuation of PV production, EV user driving patterns, distribution network uncertainties, and EV charging time for the optimal placement of EVCSs in the distribution network. This will consider the EV battery state of charge, the EV charging time for the optimal placement of the EVCS, EV user driving patterns, and distribution network uncertainties. In addition, the daily temperature variation and solar insolation will be considered in the modeling of PV systems. These will be used to assess the robustness and effectiveness of the proposed stochastic GA-PSO hybrid method [27].

CRediT authorship contribution statement

Ebunle Akupan Rene and Willy Stephen Tounsi Fokui: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools, or data; Wrote the paper.

Paule Kevin Nembou Kouonchie: Contributed reagents, materials, analysis tools, or data.

Data availability statement

Data included in article/supplementary material/referenced in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This investigation received no financing from any of the funding agencies found in the public, commercial, or nonprofit sectors.

References

[1] Olowu TO, Sundararajan A, Moghaddami M, Sarwat AI. Future challenges andmitigation methods for high photovoltaic penetration: a survey. Energies 2018; 11(7).
[2] El-Shafiey MG, Hagag A, El-Dahshan ESA, Ismail MA. A hybrid GA and PSO optimized approach for heart-disease prediction based on random forest. Multimed Tool Appl 2022:1–25.
[3] Li M, Du W, Nian F. An adaptive particle swarm optimization algorithm based on directed weighted complex network. Math Probl Eng 2014;2014:1–8.
[4] Sharma D, Gaur P, Mittal AP. Comparative analysis of hybrid GAPSO optimization technique with GA and PSO methods for cost optimization of an off-grid hybrid energy system. Energy Technol. Policy 2014;1(1). 06–114.
[5] Anand A, Suganthi L. Hybrid GA-PSO optimization of Artificial Neural Network for forecasting electricity demand. Energies 2018;11(728):1–15.
[6] Tounsi Fokui WS, Saulo MJ, Ngoo L. Optimal placement of electric vehicle charging stations in a distribution network with randomly distributed rooftop photovoltaic systems. IEEE Access 2021;9.
[7] Babu PVK, Swarnasri K, Vijetha P. A three phase unbalanced power flow method for secondary distribution system. Adv Model Anal B 2018:139–44.
[8] Zeb MZ, Imran K, Khattak A, Janjua AK, Pal A, Nadeem M. Optimal placement of electric vehicle charging stations in the active distribution network. IEEE Access 2020;8:68124–34.

[9] Koran WM. Bacterial foraging oriented by particle swarm optimization strategy for PID tuning. Proc. Conf. Companion Genet. Evol. Comput. (GECCO) 2008:1823–6.
[10] Mohanty AK, Babu PS, Salkuti SR. Fuzzy-based simultaneous optimal placement of electric vehicle charging stations, distributed generators, and DSTATCOM in a distribution system. Energies 2022;15.
[11] Pande Sarang, Ghodekar JG. Computation of technical power loss of feeders and transformers in distribution system using load factor and load loss factor. Int J Multidiscip Sci Eng June 2012;3:22–5.
[12] Kashem MA, Ganapathy V, Jasmon GB, Buhari MI. A novel method for loss minimization in distribution networks. London, UK. In: Proceedings of the international conference on electric utility deregulation and restructuring and power technologies; 2000. p. 251–6. 4–7 April.
[13] Baran ME, Wu FF. Optimal capacitor placement on radial distribution systems. IEEE Trans Power Deliv 1989;4:725–34.
[14] Arumugam MS, Rao MVC. On the improved performances of the particle swarm optimization algorithms with adaptive parameters, cross-over operators and root mean square (RMS) variants for computing optimal control of a class of hybrid systems. Appl Soft Comput 2008;8:324–36.
[15] A Kachitvichyanukul V. In: Recent advances in adaptive particle swarm optimization algorithms; 2008.
[16] Goldberg DE. Genetic algorithms in search, optimization and machine learning. Reading, MA: Addison-Wesley; 1989.
[17] Haque MH. Efficient load flow method for distribution systems with radial or mesh configuration. In: Proceedings of IEEE generation transmission and distribution. vol. 143; 1996. p. 8–33. 1.
[18] Suyanto. Algoritma genetika dalam MATLAB. Andi Yogyakarta; 2005.
[19] Shelokar PS, Siarry P, Jayaraman VK, Kulkarni BD. Article swarm and ant colony algorithms hybridized for improved continuous optimization. Appl Math Comput 2007;188:129–42.
[20] Kao Y-T, Zahara E. A hybrid genetic algorithm and particle swarm optimization for multimodal functions. Appl Soft Comput 2008;8:849–57.
[21] Voratas K. Comparison of three evolutionary algorithms: GA, PSO, and de. Industrial Engineering & Management Systems 2012;11:215–23.
[22] Hook JV, Sahin F, Arnavut Z. Application of particle swarm optimization for traveling salesman problem to lossless compression of color palette images. In: Book application of particle swarm optimization for traveling salesman problem to lossless compression of color palette images; 2008. p. 1–5.
[23] Zhang Y, Gong Dw, Cheng J. Multi-objective particle swarm optimization approach for cost-based feature selection in classification. IEEE ACM Trans Comput Biol Bioinf 2017;14:64–75.
[24] Turney PD. Cost-sensitive classification: empirical evaluation of a hybrid genetic decision tree induction algorithm. J Artif Intell Res 1995;2:41.
[25] Min F, Hu Q, Zhu W. Feature selection with test cost constraint. Int J Approx Reason 2014;55:167–79.
[26] Haralick RM, Shanmugam K, Dinstein I. Textural features for image classification. In: IEEE transactions on systems, man, and cybernetic. SMC-3; 1973. p. 610–62.
[27] Haque MH. Efficient load flow method for distribution systems with radial or mesh configuration. In: In proceedings of IEEE generation transmission and distribution. vol. 143; 1996. p. 33–8.