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# Optimal Placement of Electric Vehicle Charging Stations in a Distribution Network With Randomly Distributed Rooftop Photovoltaic Systems

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**ABSTRACT** The increasing number of electric vehicles (EVs) in today's transport sector is gradually leading to the phasing out of petroleum-based vehicles. However, the rapid deployment of EVs largely depends on the coordinated and fast expansion of EV charging stations (EVCSs). The integration of EVCSs in the modern distribution network characterized by increased penetration of randomly distributed photovoltaic (PV) systems is challenging as they can lead to excessive power losses and voltage deviations beyond acceptable limits. In this paper, a hybrid bacterial foraging optimization algorithm and particle swarm optimization (BFOA-PSO) technique is proposed for the optimal placement of EVCSs into the distribution network with high penetration of randomly distributed rooftop PV systems. The optimization problem is formulated as a multi-objective problem minimizing active and reactive power losses, average voltage deviation index, and maximizing voltage stability index. The IEEE 69 node distribution network is used as the case network. The simulation is done using MATLAB to integrate the EVCSs in five cases of randomly sized and placed PV systems in the distribution network. For all five cases, a minimal increase in power losses is recorded with minor changes in the voltage deviation and stability indices due to the placement of the EVCSs. But for the voltages of nodes 29 to 48, the other node voltages remain unchanged upon placement of the EVCSs. The largest increase in power losses due to the EVCSs being brought into the network with PVs was noticed in case 3 (from 142.27kW, and 62.90kVar to 147.65kW, and 72.48kVar).

**INDEX TERMS** Electric vehicle, charging station, photovoltaic, hybrid BFOA-PSO, optimal placement.

## I. INTRODUCTION

Modern power systems are fast changing with the introduction of photovoltaic (PV) systems and electric vehicle charging stations (EVCSs). Distributed PV penetration is increasing in many countries as the prices of PV modules and their accessories continue to decrease [1]. The penetration of PV systems and other distributed generation (DG) technologies has led to the introduction of the term prosumers that describes the simultaneous production and consumption of electricity [2]. PV technology has not only proven to be beneficial to the environment as green energy, but has also been demonstrated to be essential to the electrical distribution

network in terms of reduced power losses, and network voltage profile improvement [3]. To the consumers (prosumers), they lead to a reduction in electricity bills paid to the utility company [4].

On the other hand, the rapid proliferation of electric vehicles (EVs) in the transport sector is revolutionary and the integration of this technology together with DGs is the most promising way to cut down the dependency on fossil fuels and reduce greenhouse gases (GHG) emissions [5]. Furthermore, as crude oil keeps being depleted in addition to its environmental impact, the future of petroleum-based vehicles around the world is becoming darker following the uprise of EVs [6]. Moreover, EVs come with advantages such as being noiseless, fuel-saving, in addition to being emission-free [7].

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The fast adoption of EVs heavily depends on the rapid expansion of charging facilities [8]. There are three categories of EV chargers; Level 1, Level 2, and Level 3, and these could be onboard or offboard. Level 1 and level 2 chargers are onboard chargers with level 2 being faster, having an average efficiency of 89.4%, and this is higher than that of their counterpart [9]. Both chargers are limited by power density, weight, and size, while level 3 chargers are usually offboarded and are the fastest [10]. Level 1 chargers supply the EV with a current between 12-16A maximum from the mains, level 2 with 32-70A, and level 3 with 167A [11]. Level 3 chargers make use of AC/DC power electronics converters. Level 1 and 2 chargers require a longer time to fully charge an EV, while level 3 chargers require less than an hour [12]. In the attempt of saving EV charging time, EV battery swapping stations (EVBSS) are being developed wherein the flat battery of the EV is replaced with a fully charged battery. Compared to charging the EV at the charging stations, EVBSS offers quick and effortless power solutions to EV users as the battery replacement is done automatically at the EVBSS [13]. A few EV manufacturing companies such as Tesla have already begun utilizing battery swapping and this shows to be faster than even refueling a petroleum-based vehicle [14].

Just like PV systems, the fast integration of EVs into the transport sector will not only be helpful to the environment but will also benefit the electrical distribution network as they could help provide frequency and voltage support while being used as spinning reserves to cater for sudden load increase or loss in some generators [15]. Nonetheless, the installation of EV charging stations (EVCSs) into the distribution network has to be carefully done because they can result in excessive loading of the distribution network leading to increased power loss [16]. The issues of power quality degradation and increased voltage deviation beyond acceptable limits could also be experienced as well [17]. The situation becomes even more complicated when integrating the EVCSs in a distribution network with high penetration of randomly placed photovoltaic (PV) systems. This calls for optimal placement of the EVCSs in the distribution network to limit the negative impact of EVCSs on the network power losses and voltage stability.

## II. RELATED WORKS

Several related works have been published on the optimal placement of EVCSs while considering the challenges of power systems, urban traffic, EV battery state of charge, among others. The authors in [18], did the optimal placement of EVCSs in the distribution network using Harries Hawk Optimization (HHO) and Teaching-Learning Based Optimization (TLBO) techniques to minimize the multi-objective function of the problem that aimed at minimizing real power loss and average voltage deviation index while maximizing voltage stability index. They went further to optimally size and place DGs so as to minimize the effects of the EVCSs on the network. In [19], R. Mehta *et al.* proposed the optimal placement of EVs into the distribution network

based on a double-layered intelligent energy management approach. This strategy was based on two layers: one for real power management at the nodes to minimize the daily total cost incurred in EV charging/discharging, and the other layer for reactive power management at the level of the system that was to minimize the power loss in the system using the capacity of the reactive power of the EVs. The authors in [20] proposed a method to optimally locate EV fast-charging stations considering drivers, operators, vehicles, the power grid, and traffic flow. Nash bargaining theory was proposed in [21] for the optimal allocation of EV fast-charging stations with the theory used for the analysis of the interaction between the distribution companies and the owners of the fast-charging stations. Using Guwahati city in India as a case study, the authors in [22] formulated a multi-objective optimization problem for the optimal planning of charging infrastructures while considering power loss, voltage stability, economic factors, random road traffic, the convenience of the EV user, and economic factors. A hybrid chicken swarm optimization (CSO) and TLBO were used to solve the problem. Non-dominated sorting genetic algorithm II (NSGA-II) was used in [23] to solve a multi-objective optimization problem for the simultaneous siting and sizing of fast-charging stations and DGs in the distribution network. The number of EVs, and the number of fast-charging stations on the road, and the distribution network were considered as constraints. The authors in [24] used a hybrid multi-objective CSO and TLBO for the allocation of EVCSs to minimize the cost of the EVCSs while guaranteeing adequate grid stability, and accessibility of the EVCSs by the EVs. The authors in [25] proposed the use of an improved CSO to optimally place EVCS in an IEEE 33 node test distribution network. They first investigated the impact of the predicted EV load demand at the EVCSs on the network in terms of voltage profile, average voltage deviation index, voltage stability index and power loss; and using a feed-forward neural network they evaluated the solar power needed to power the EVCSs. In [26], the authors proposed an optimization scheme for the optimal placement of all three types of EV chargers to efficiently manage EV loads while keeping the installation charging stations cost, loading of distribution transformers, and losses minimal.

This paper proposes a novel hybrid bacterial foraging optimization algorithm and particle swarm optimization (BFOA-PSO) that was developed by W. Korani in [27] to optimally place EVCSs in a distribution network with randomly distributed rooftop PV systems. The PV systems are randomly sized and distributed at the load nodes of the IEEE 69 test network feeder which is used as the case study network. The contributions of this paper are:

- The use of the hybrid BFOA-PSO for the optimal placement of EVCSs in the distribution network. To the best of our knowledge, the hybrid BFOA-PSO has never been used for the placement of EVCSs.
- Considering the distribution network to have randomly sized and sited PV systems that represent real-life consumer-based distributed PV penetration.

Most researches incorporate PV systems after having placed the EVCSs in the network to compensate for the effects of the EVCSs on the distribution network. Whereas this research places the EVCSs in the distribution network with the PVs already randomly scattered across the network.

The rest of this paper is organized as follows; the next section is the methodology and this is followed by the results and discussions, and then the conclusion and recommendations.

### III. METHODOLOGY

This section describes the methodology used in this research.

#### A. EVCS MODEL, STUDY AREA, AND EV POPULATION ESTIMATION

From the power systems point of view, EVs according to [28] are seen as:

- i. Simple loads that absorb constant power when charging. This is known as the grid to vehicle (G2V).
- ii. Complex loads with the possibility of adjusting their charging period.
- iii. Storage devices that are charged (G2V) and discharged (vehicle to grid (V2G)) based on the condition of the network.

In this research, the EVs are considered as per the first option above. Thus, the EVCSs are seen by the distribution network as loads (G2V). V2G is not considered in this research.

The IEEE 69 Node Test Feeder is used as the study network in this research work. This distribution network is large and balanced at a voltage of 12.66kV as shown in figure 1.

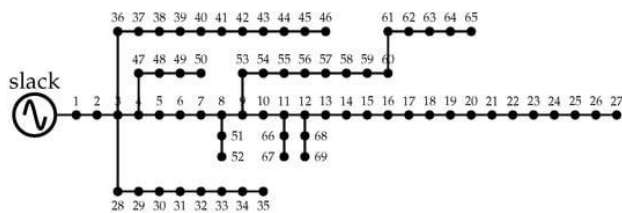


FIGURE 1. IEEE 69 node test feeder.

To estimate the EV population in the study area, the number of households in the area is needed. The network is considered to be a residential/commercial network with 85% of the load being residential loads. The power demand of the IEEE 69 node network is shown in table 1 while the power demand of residential loads is calculated and shown in table 2.

TABLE 1. Network power demand.

Active Power (kW)	Reactive Power (kVar)	Apparent Power (kVA)
3801.4	2693.6	4658.98

TABLE 2. Residential power demand.

Active Power (kW)	Reactive Power (kVar)	Apparent Power (kVA)
3231.19	2289.56	3960.133

Assuming each household has a power demand of 12.7kVA, the number of households in the community is calculated to be 312 households using equation (1).

$$N_h = \frac{S_{Th}}{S_h} \tag{1}$$

where  $N_h$  is the number of households in the study area

$S_{Th}$  is the total power demand of residential loads

$S_h$  is the power demand of a single household

Considering a percentage EV integration of 59%, the number of EVs in the community is calculated using equation (2)

$$\%EV = \frac{N_{hEV}}{N_h} * 100 \tag{2}$$

From equation (2), the number of EVs in the study area is 184.

Five models of EVs are considered in this work. The characteristics and charger specifications of the five models of EVs are shown in table 3 including the quantities. These EVs can be charged using level 1 or level 2 chargers.

TABLE 3. Selected EVs and their charging characteristics [26].

EV Model	EV Specs	Charging Type			
		Level 1 (11kW)		Level 2 (22kW)	
		Charging Time	Qty	Charging Time	Qty
Nissan Leaf 2018	36kWh, 220km	11h30m	20	6h30m	21
Renault Zoe R110	53kWh, 315km	5h45m	20	3h	21
Honda e	28.5kWh, 170km	9h15m	20	5h15m	21
MG ZS EV	42.5kWh, 220km	13h30m	20	7h45m	21
Mazda MX-30	30kWh, 170km	9h45m	20	5h30m	21
<b>TOTAL Number of EVs</b>			<b>100</b>		<b>84</b>

#### B. EVCSs CHARACTERISTICS

A total of seven EVCSs are optimally placed in the network to service the 184 EVs. Both level 1 and level 2 chargers are used, but having a different number of charging points (CPs) shown in table 4. Out of the seven EVCSs, three are made up of level 1 chargers, and four are made up of level 2 chargers.

TABLE 4. Repartition of level 1 and level CPs in the EVCSs.

Charger	Rating of CP (kW)	No CP per EVCS	Rating of EVCS (kW)	No of EVCS	Total Rating (kW)
Level 1	11	28	308	3	924
Level 2	22	25	550	4	2200
Total number of EVCSs and power demand				7	3124

C. PV SYSTEMS PENETRATION; RANDOM SIZING, AND PLACEMENT

The PV systems are modeled in MATLAB in negative PQ modes at a power factor of 0.95 so as to incorporate the reactive power injecting capabilities of the voltage source inverters used in grid-connected PV systems. The PV systems have a 60% penetration level. Although several ways of calculating PV penetration levels exists, the PV penetration percentage could be obtained as the ratio of [27]:

- The total production of the PV systems to the total generation
- The peak PV capacity to the loads' peak apparent power
- The PV rated power to the loads' active power demand

The last option of calculating the percentage PV penetration is used to calculate the total PV rated power required at 60% penetration which is 2274.72kW. Therefore, with a power factor of 0.95, the PV systems inject a reactive power of 747.66kVar into the network.

The random sizing and siting of the distributed PV systems are done using Microsoft Excel. It should be noted that, since the study considers randomly distributed rooftop PV systems, only the load nodes of the study network are randomly assigned PV systems. Nodes without loads are not considered. Every PV system consists of 280W PV modules. With this, it is possible to randomly size and site the PV systems across the network. The rand() function is used to generate random numbers between 0 and 1 which are used to determine the number of 280W PV modules to be placed on each target nodes using equation (3) such that the total PV power rating across the network equals 2274.72kW.

$$n_a = \frac{rand(a)}{\sum_{a=6}^{69} rand(a)} * k \tag{3}$$

where: -  $n_a$  is the number of PV modules on node  $a$

- $a$  is the load node number, with  $a = 6$  being the first load node in the network
- $rand(a)$  is the random generation function in charge of generating random numbers between 0 and 1 and assigning to node  $a$
- $k$  is a carefully chosen number such that the network's total PV capacity equals 2274.72kW

From equation (3), the PV capacity on each load node is obtained using equation (4)

$$P_{PVa} = n_a * P_{PVm} \tag{4}$$

where:

- $P_{PVa}$  is the PV capacity at node,  $a$
- $n_a$  is the number of PV modules on node  $a$
- $P_{PVm}$  is the rating of a single PV module (280W)

Therefore, the total power rating,  $P_T$  of the distributed PV systems is given by

$$P_T = \sum_{a=6}^{69} P_{PVa} \tag{5}$$

D. OPTIMAL PLACEMENT OF THE EVCS USING HYBRID BFOA-PSO

The problem is to optimally place the 7 EVCSs into the test distribution network penetrated with randomly distributed PV systems at 60%.

1) PROBLEM FORMULATION

The objective of this optimization problem is to minimize the network's active and reactive power losses, and the average voltage deviation index, while maximizing the network average stability index as the EVCSs are allocated in the network.

$a$ : OBJECTIVE FUNCTION

i) ACTIVE AND REACTIVE POWER LOSS MINIMIZATION

The active and reactive power losses ( $P_{loss(a,a+1)}$  and  $Q_{loss(a,a+1)}$ ) in a branch  $a - a + 1$  of the network are given by

$$P_{loss(a,a+1)} = \left( \frac{P_{a+1}^2 + Q_{a+1}^2}{|V_{a+1}|^2} \right) * R_{br} \tag{6}$$

$$Q_{loss(a,a+1)} = \left( \frac{P_{a+1}^2 + Q_{a+1}^2}{|V_{a+1}|^2} \right) * X_{br} \tag{7}$$

where  $P_{a+1}$  and  $Q_{a+1}$  are the receiving end active and reactive powers respectively,  $V_{a+1}$  is the receiving end voltage,  $R_{br}$  is the branch resistance, and  $X_{br}$  is the branch reactance.

Therefore, the total power loss minimization function is given by

$$f_1(j) = \min \sum_{b=1}^{br} [P_{loss(b)} + Q_{loss(b)}] \tag{8}$$

where  $br$  is the number of branches.

ii) MINIMIZATION OF AVERAGE VOLTAGE DEVIATION INDEX (AVDI)

The AVDI is the voltage deviation with respect to 1.0pu which is the reference voltage. It is defined in terms of the voltage magnitudes at all the nodes and it is given by;

$$f_2(j) = \frac{1}{N_a} \sum_{a=1}^{N_a} |1 - V_a|^2 \tag{9}$$

where  $N_a$  is the number of nodes in the network,  $V_a$  is the voltage at node,  $a$ .

iii) MAXIMIZATION OF THE VOLTAGE STABILITY INDEX (VSI)

At a receiving node,  $b$ , the VSI is given by

$$f_3(j) = [|V_b|^4 - 4(P_b x_{ab} + Q_b r_{ab})^2 - 4(P_b r_{ab} + Q_b x_{ab}) |V_b|^2] \quad (10)$$

where  $V_b$  is the voltage at node  $b$ ,  $P_b$  is the active power demand at node  $b$ ,  $Q_b$  is the reactive power demand at node  $b$ ,  $r_{ab}$  is the resistance branch a-b, and  $x_{ab}$  is the reactance of branch a-b.

Therefore, converting equation (10) into a minimization function and combining it with the former two equations give a multi-object function shown in equation (11).

$$F(j) = \min \left\{ w_1 f_1(j) + w_2 f_2(j) + w_3 \left( \frac{1}{f_3(j)} \right) \right\} \quad (11)$$

where  $w_1, w_2, w_3$  are weights assigned to the individual objective functions.

b: CONSTRAINTS

The multi-objective function for this optimization problem is subject to the following constraints.

i) EQUALITY CONSTRAINTS

- Power balance constraints

$$P_{st} + \sum_{j=1}^{N_{pv}} P_{pv} = \sum_{j=1}^{N_{al}} P_{load} + \sum_{j=1}^{N_{EVCS}} P_{EVCS} + \sum_{j=1}^{N_{br}} P_{loss} \quad (12)$$

where  $P_{st}$  is the active power from the grid,  $P_{pv}$  is the active power from a single PV system,  $P_{load}$  is the active power demand of the load on a said node,  $P_{EVCS}$  is the active power demand of a single EVCS,  $P_{loss}$  is the active power loss in the  $j^{th}$  branch,  $N_{pv}$  is the number of PV systems in the network,  $N_{al}$  is the number of load nodes,  $N_{EVCS}$  is the number of EVCSs, and  $N_{br}$  is the network's number of branches.

$$Q_{st} + \sum_{j=1}^{N_{pv}} Q_{pv} = \sum_{j=1}^{N_{al}} Q_{load} + \sum_{j=1}^{N_{EVCS}} Q_{EVCS} + \sum_{j=1}^{N_{br}} Q_{loss} \quad (13)$$

where  $Q_{st}$  is the reactive power from the grid,  $Q_{pv}$  is the reactive power from a single PV system,  $Q_{load}$  is the reactive power demand of the load on a said node,  $Q_{EVCS}$  is the reactive power demand a single EVCS, and  $Q_{loss}$  is the reactive power loss in the  $j^{th}$  branch

ii) INEQUALITY CONSTRAINTS

- Voltage constraints: The voltage magnitude at every node has to be kept within acceptable margins.

$$\begin{aligned} V_a^{min} &\leq V_a \leq V_a^{max} \\ 0.95 &\leq V_a \leq 1.05 \end{aligned} \quad (14)$$

- Current constraints: The distribution feeder's capacities must not be exceeded.

$$I_r \leq I_r^{max} \quad (15)$$

- Charging power constraints: The EVCS power must be within margins

$$P_{EVCS}^{min} \leq P_{EV} \leq P_{EVCS}^{max} \quad (16)$$

$P_{EV} = P_{EVCS}^{min} = P_{EVCS}^{max}$  as the power rating of each EVCS is fixed.

The hybrid BFOA-PSO is used to solve this optimization problem.

2) BACTERIAL FORAGING OPTIMIZATION ALGORITHM (BFOA)

Bacterial foraging optimization was developed by K. M. Passino inspired by the "chemotaxis" activity exhibited by foraging bacterial behaviors such as E. Coli [29]. E. Coli present in the human intestine forage in four processes; chemotaxis, swarming, reproduction, and elimination dispersal [30].

**i. Chemotaxis:** It is the swimming and tumbling action of the bacteria through the movement of the flagella. If  $\theta^i(j, k, l)$  represent a bacterium at  $j^{th}$  chemotactic,  $k^{th}$  reproductive, and  $l^{th}$  elimination-dispersal step, the run-length unit parameter  $C(i)$  represents the chemotactic step size during each run, then the computation chemotactic movement of the bacterium is given by

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i) \Delta(i)}} \quad (17)$$

where:  $\Delta$  is a vector in the random direction with its elements lying in  $[-1, 1]$ .

**ii. Swarming:** The bacteria communicate with each other in an attractive or repulsive manner. The signal between bacteria cells in E. Coli is given by

$$\begin{aligned} J_{cc}(\theta, P(j, k, l)) &= \sum_{i=1}^S J_{cc}(\theta, \theta^i(j, k, l)) \\ &= \sum_{i=1}^S [-d_{attractant} \exp(-w_{attractant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2)] \\ &\quad + \sum_{i=1}^S [h_{repellant} \exp(-w_{repellant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2)] \end{aligned} \quad (18)$$

where  $J_{cc}(\theta, P(j, k, l))$  is the objective function value to be minimized to present a time-varying objective function,  $S$  is the total number of bacteria,  $p$  is the number of variables present in each bacterium to be optimized,  $\theta = [\theta_1, \theta_2, \dots, \theta_p]^T$  is a point on the  $p$ -dimensional search domain,  $d_{attractant}, w_{attractant}$  are parameters of depth and width of attraction and  $h_{repellant}, w_{repellant}$  are parameters of height and width of repulsion (repellent).

**iii. Reproduction:** This is the process wherein the healthier bacteria reproduce asexually, which is split into 2 while the less healthy bacteria die due to insufficient nutrients



hence keeping the swarm constant. This occurs after  $N_C$  Chemotaxis steps and it is given mathematically by

$$J_{health}^i = \sum_j^{N_c+1} J(i, j, k, l) \quad (19)$$

**iv. Elimination and Dispersal:** This occurs after  $N_{re}$  steps of reproduction wherein a situation may come up and cause the sudden elimination of the bacteria or dispersal of the bacterial to a new location. The probability  $P_{ed}$  is the probability for a bacterium to be subjected to elimination and dispersal wherein some bacteria are killed based on a probability  $P_e$  and others dispersed to a new environment where the process starts all over. The number of elimination and dispersal is given by  $N_{ed}$ .

The dependence of the BFOA on random search directions to find the global best solution makes the optimization problem take a long time to converge [31].

### 3) PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a metaheuristic optimization algorithm that was developed by Kennedy and Eberhart in 1995, inspired by the behavior of animals like birds and fish, and is very much adapted to solving nonlinear optimization problems [32]. It is an evolutionary algorithm that is based on swarm intelligence. Since its development, PSO has been used for many engineering applications and it has also undergone tremendous mutations due to the tuning of the PSO parameters and has led to variants of the algorithm such as Binary PSO, Stochastic inertia weight (Sto-IW) PSO, Hierarchical PSO (HPSO), Self-organizing hierarchical PSO with time-varying acceleration coefficients (HPSO-TVAC), amongst other [33]. These new variants of PSO have been developed to solve the technique's problem of being trapped in the local optimum solution instead of obtaining the global best solution [34]. That notwithstanding, PSO has been successful in solving optimization problems due to its [35];

- Few parameters that need to be tuned
- Fast convergence
- Convergence not roughly being affected by the initial solution
- Simple concept and ease of coding

There are two concepts in PSO equations; the global optimum  $g_{best}$  and the local optimum  $p_{best}$ . The former is the optimum solution gotten by the particle swarm, while the latter is the optimum solution acquired by each particle in the swarm. For a swarm of  $P$  particles, there is a position vector  $X_j^t = (x_{j1}x_{j2}x_{j3} \dots x_{jn})^T$  as well as a velocity vector  $V_j^t = (v_{j1}v_{j2}v_{j3} \dots v_{jn})^T$  at iteration  $t$ , for every particle  $j$ , constituting the swarm. These vectors are updated at every iteration through  $k$  dimension as per the following equations;

$$V_{jk}^{t+1} = wV_{jk}^t + c_1r_1^t (p_{best_{jk}} - X_{jk}^t) + c_2r_2^t (g_{best_k} - X_{jk}^t) \quad (20)$$

$$X_{jk}^{t+1} = X_{jk}^t + V_{jk}^{t+1} \quad (21)$$

where:

$j = 1, 2, 3, \dots, P$ ,  $k = 1, 2, 3, \dots, n$ ,  $c_1$  and  $c_2$  are the acceleration factors,  $r_1^t$  and  $r_2^t$  are random numbers between 0 and 1,  $w$  is an initial weight constant whose purpose is to balance the global and the local searches

Optimization with PSO is begun by a set of potential solutions being initialized randomly and then performing the search for the optimum solution. The velocities and positions of the particles keep being updated using equations (20) and (21) respectively.

### 4) HYBRID BFOA-PSO

The hybrid BFOA-PSO was developed in 2008 by Korani to make use of PSO's ability to exchange information between particles and the ability of BFOA to look for new solutions through elimination and dispersal [36]. The hybrid BFO-PSO uses the strength of both BFOA and PSO to solve each of the optimization technique's limitations. The problem of BFOA taking a long time to achieve the global optimum is solved by giving the bacteria (E. Coli) the ability to communicate with each other which is obtained from PSO, while on the other hand, PSO's limitation of being stuck in the local optimum is solved by utilizing the chemotaxis steps of BFOA [37]. The inheritance from BFOA and PSO makes the hybrid BFOA-PSO robust and effective in obtaining the optimum solution. In the hybrid BFOA-PSO, the global best position and the local best position of each bacterium can be used to decide the unit length direction of tumble behavior [38]. During chemotaxis, equation (22) is used to determine the update of the tumble direction.

$$\emptyset(j+1) = w.\emptyset(j) + c_1.r_1(P_{lbest} - P_{current}) + c_2.r_2(g_{lbest} - P_{current}) \quad (22)$$

where  $P_{lbest}$  is the best position of each bacterium,  $g_{lbest}$  is the global best bacterial.

The basic flowchart of the hybrid BFOA-PSO obtained from [39] is shown in figure 2 below.

The Optimal placement of the EVCSs using the hybrid BFOA-PSO is done using the following steps,

**Step 1:** Input the network data

**Step 2:** Run load flow calculation and record the results (power losses, node voltage, AVDI, VSI)

**Step 3:** Randomly sizing and place PV systems at load nodes

**Step 4:** Run load flow calculation and record the results

**Step 5:** Initialize BFOA parameters

- The search space dimension,  $d$
- Total number of bacteria,  $s$
- Number of chemotaxis steps,  $N_c$
- number of swarming,  $N_s$
- Number of reproduction steps,  $N_{re}$
- Number of elimination-dispersal occasions,  $N_{ed}$
- Elimination-dispersal probability,  $P_{ed}$
- Step size,  $C(l)$
- Inertia weight,  $\omega$

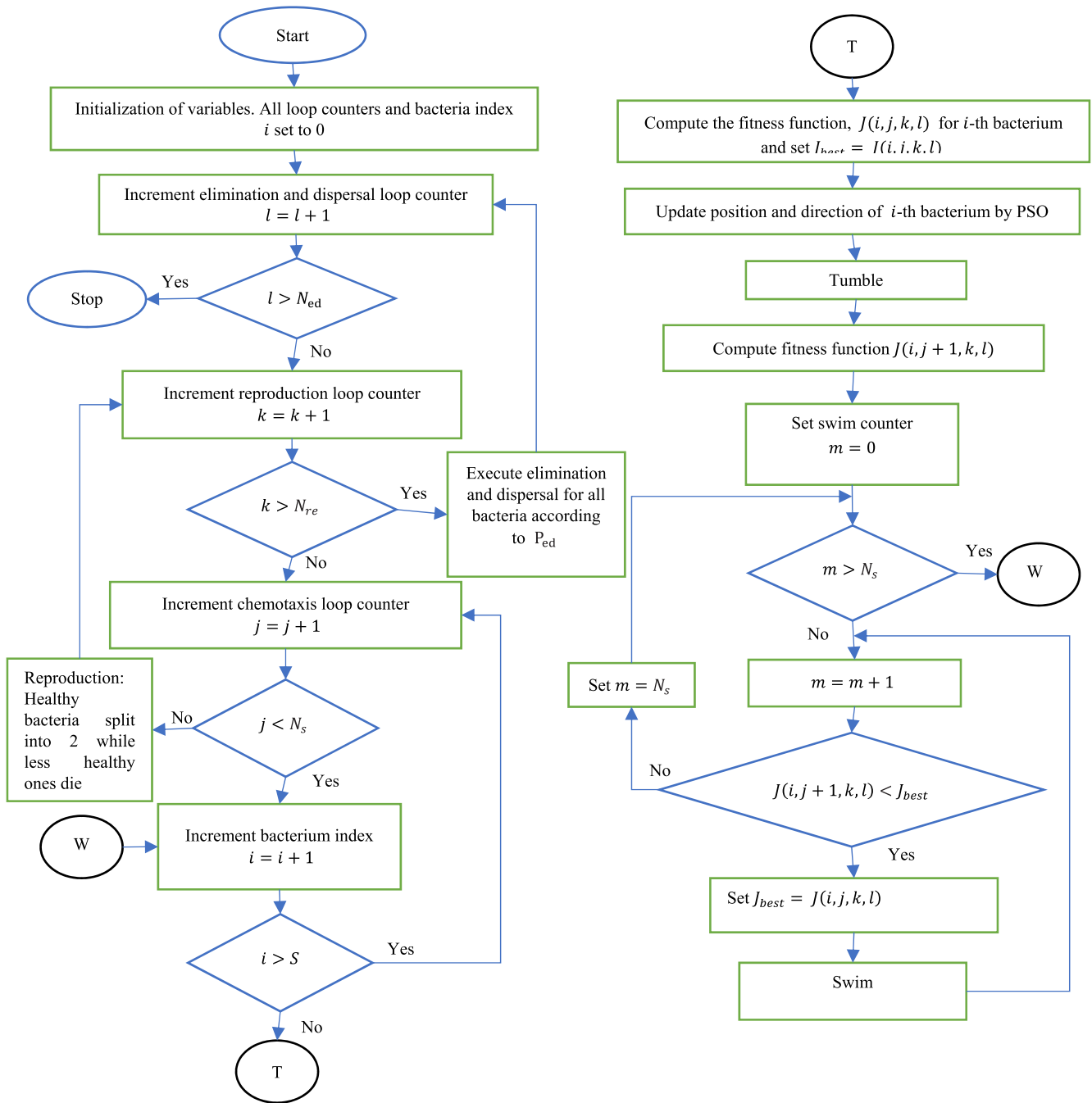


FIGURE 2. Flowchart of hybrid BFOA-PSO.

- Position vector,  $\theta^i(j, k, l)$  of  $i^{th}$  bacterium, at  $j^{th}$  chemotactic,  $k^{th}$  reproductive, and  $l^{th}$  elimination-dispersal step
- The velocity,  $V^i$  of  $i^{th}$  bacterium

**Step 6:** Update

- The fitness function  $J(i, j, k, l)$  of  $i^{th}$  bacterium, at  $j^{th}$  chemotactic,  $k^{th}$  reproductive, and  $l^{th}$  elimination-dispersal step
- The best position vector  $\theta\_gbest$  found by all the bacteria

- The best fitness function based  $J_{best}(\theta, P(j, k, l))$  based on the best position found so far

**Step 7:** Reproduction loop,  $k = k + 1$

**Step 8:** Chemotaxis loop  $j = j + 1$

For every bacterium,  $i$ , in the search space,

- Compute the fitness function  $J(j, k, l)$
- Save the computed fitness function,  $J_{final} = J(j, k, l)$  as there is the possibility of finding a better one as through the run

- (c) Tumble: Generate a random vector  $\Delta(i)$  in such a way that  $1 \leq \Delta(i) \leq -1$
- (d) Move: Let

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta^T(i) * \Delta(i)}}$$

- (e) Compute  $J(i, j+1, k+1)$  and  $J(i, j+1, k+1) = J(i, j+1, k+1) + J_{cc}$

- (f) Swim: It is considered that only the  $i^{th}$  bacterium is swimming while the others are static Initialization of swim length counter,  $m$  that is  $m = 0$

- 1) While  $m < N_s$
- 2) Let  $m = m + 1$
- 3) If  $J(i, j+1, k+1) < J(i, j, k) + J_{cc}$   
 Let  $J_{final} = J(i, j+1, k+1)$  and  
 $\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta^T(i) * \Delta(i)}} \theta^i(j+1, k, l)$   
 $(j+1, k, l)$  is used to compute the value  $\theta^i(j, k, l)$  as depicted in step 8(e).  
 Else  $m = N_s$  (End of the while loop)

**Step 9: Alteration with PSO**

For  $d = 1, 2, 3, 4, \dots, S$

- Update  $\theta_{gbest}$  and  $J_{best}(\theta, P(j, k, l))$
- Update the velocity and position of the  $i^{th}$  bacterium in the  $q^{th}$  coordinate as per the following equations

$$V_{iq}^{new} = wV_{iq}^{new} + C_1\phi_1(\theta_{bestiq} - \theta_q^{old}(j+1, k, l))$$

$$\theta_q^{old}(j+1, k, l) = \theta_q^{old}(j+1, k, l) + V_{iq}^{new}$$

**Step 10:** Let  $Sr = S/2$ . The  $Sr$  bacteria with the largest cost functions die and the other half bacterial population reproduce (split into two) and new bacteria are placed at the same position as their parent.

**Step 11:** If  $m < N_{re}$ , meaning the number of specified reproduction steps has not yet been reached, go back to step 5 and restart the process with the new generation of bacteria. Else

**Step 12:** Output load flow results (power losses, node voltage, AVDI, VSI) and the optimal locations for the EVCSs.

The BFOA-PSO parameters used in the simulation are shown in table 5. The parameters are an adjustment of the

**TABLE 5. Hybrid BFOA-PSO parameter values.**

Parameter	Symbol	value
Total number of bacteria	S	10
Number of iteration	iter	20
Chemotaxis steps	$N_c$	4
Swim steps	$N_s$	4
Reproduction steps	$N_{re}$	4
Number of elimination-disposal	$N_{ed}$	2
Elimination-disposal probability	$P_{ed}$	0.5
Maximum inertia	wmax	4.3
Minimum inertia	wmin	-4.3
Acceleration vectors	c1	0.02
	c2	0.02

empirical values of the hybrid BFOA-PSO parameters aiming at ensuring speed and accuracy of the solution process as employed in [36].

**E. SIMULATION CASES**

Since the study is concerned with randomly sized and placed rooftop PV systems, five cases of randomly sized and sited PV systems are considered for the optimal placement of the EVCSs. For each case, the EVCSs are optimally placed using the hybrid BFOA-PSO optimization technique, and the results are recorded. Also, for each case, the EVCSs are optimally placed using BFOA and PSO separately. This is essential to validate the effectiveness of the proposed hybrid BFOA-PSO in finding the best locations for the EVCSs in the distribution network with randomly sized and placed distributed rooftop PV systems.

**IV. RESULTS AND DISCUSSIONS**

The optimal placement of the EVCSs in the distribution network with randomly distributed PV systems was simulated using MATLAB 2019a. Load flow analysis is performed without PV systems and EVCS for the base case and with PV systems and EVCSs for other cases. The simulation results are shown in figures 3 to 11.

**A. OPTIMAL EVCSs LOCATIONS**

For every simulation case, the optimal locations for the 7 EVCSs found by the hybrid BFOA-PSO are shown in table 6.

**TABLE 6. Optimal locations of the EVCSs for each simulation case.**

Charger Type	Charger rating (kW)	Case 1	Case 2	Case 3	Case 4	Case 5
Level 1	308	47	40	50	45	69
	308	45	33	34	30	4
	308	38	32	40	5	43
Level 2	550	28	2	2	2	5
	550	29	4	37	39	28
	550	31	29	38	49	29
	550	32	37	43	4	47

**B. NETWORK VOLTAGE PROFILE**

The network voltage profiles for all five cases of simulations are shown from figure 3 to figure 7. It is observed that the introduction of the random introduction of the PV systems at 60% penetration level into the distribution network leads to a general improvement in the voltage profile of the network. The improvement is noticed in all five cases of random penetration of the PV systems. This improvement in the network voltage profile is a result of the PV systems being connected at load centers. Hence supplying part of the loads that were otherwise suppose to be supplied by the grid. It is required to allocate the EVCSs in such a way that the improved voltage profile is not dramatically degraded by the EVCSs. It is



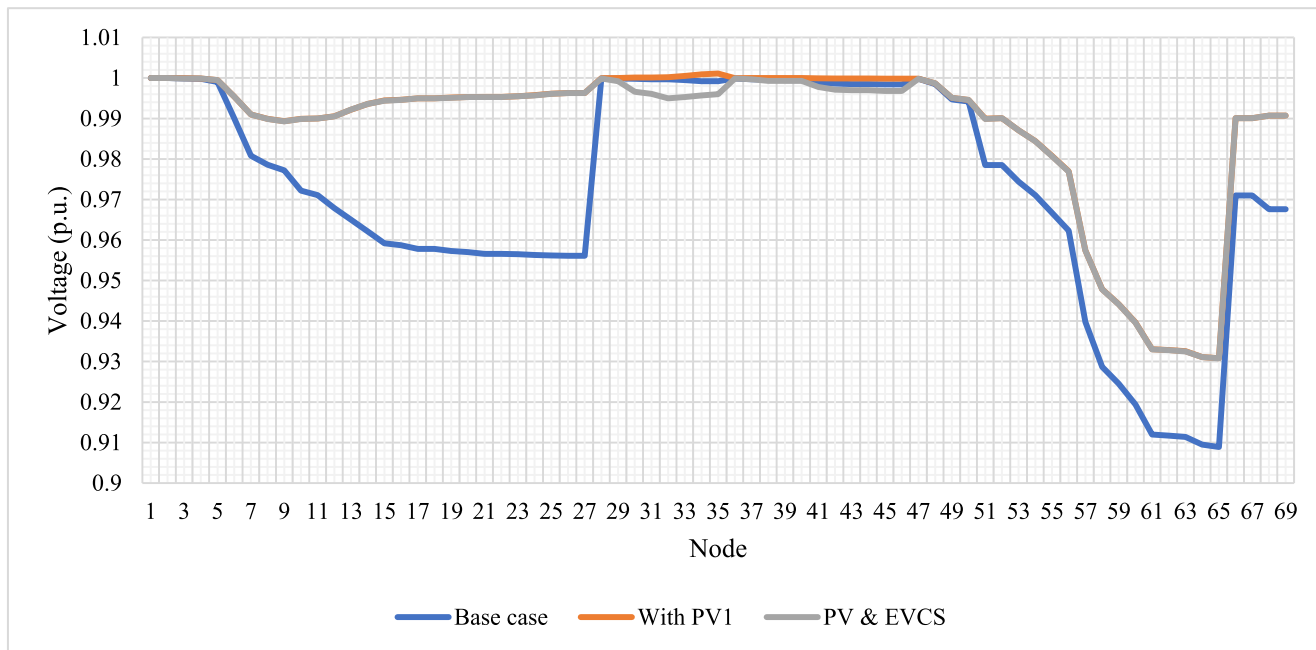


FIGURE 3. Network voltage profile (case 1).

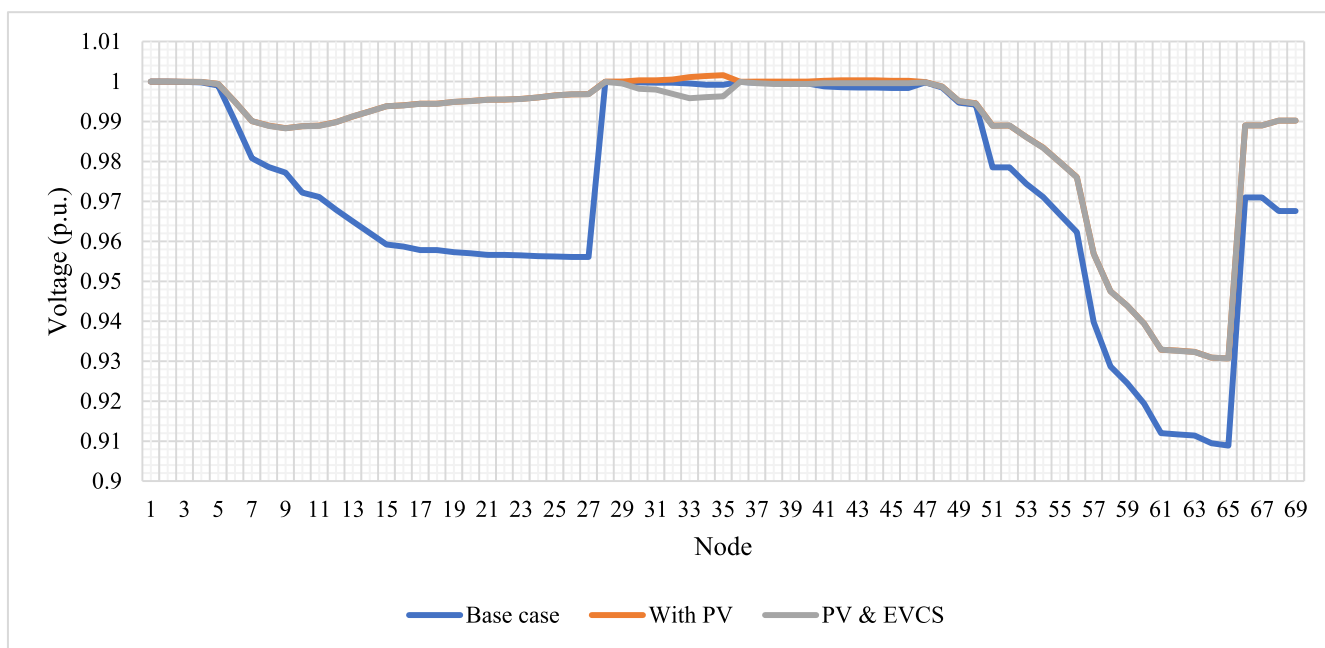


FIGURE 4. Network voltage profile (case 2).

noticed that for all five cases of random sizing and siting of the PV systems, the BFOA-PSO algorithm successfully determines the best positions for the EVCSs that will not much affect the network node voltages as a result of the additional loads from the EVCSs. For all cases, only the node voltages between nodes 29 and 48 are slightly affected by the EVCSs as they experience slight drops compared to when there are no EVCSs.

**C. AVERAGE VOLTAGE DEVIATION INDEX (AVDI)**

The voltage deviation index (VDI) of a node in the network is the difference between the actual voltage of the node and the reference voltage (1p.u). The AVDI is the average of the VDI of all nodes in the network. The lower the value, the more stable the voltage of the network is. From the simulations results in figure 8, the AVDI of the base case is significantly reduced at 60% PV penetration from 0.02665 in the base

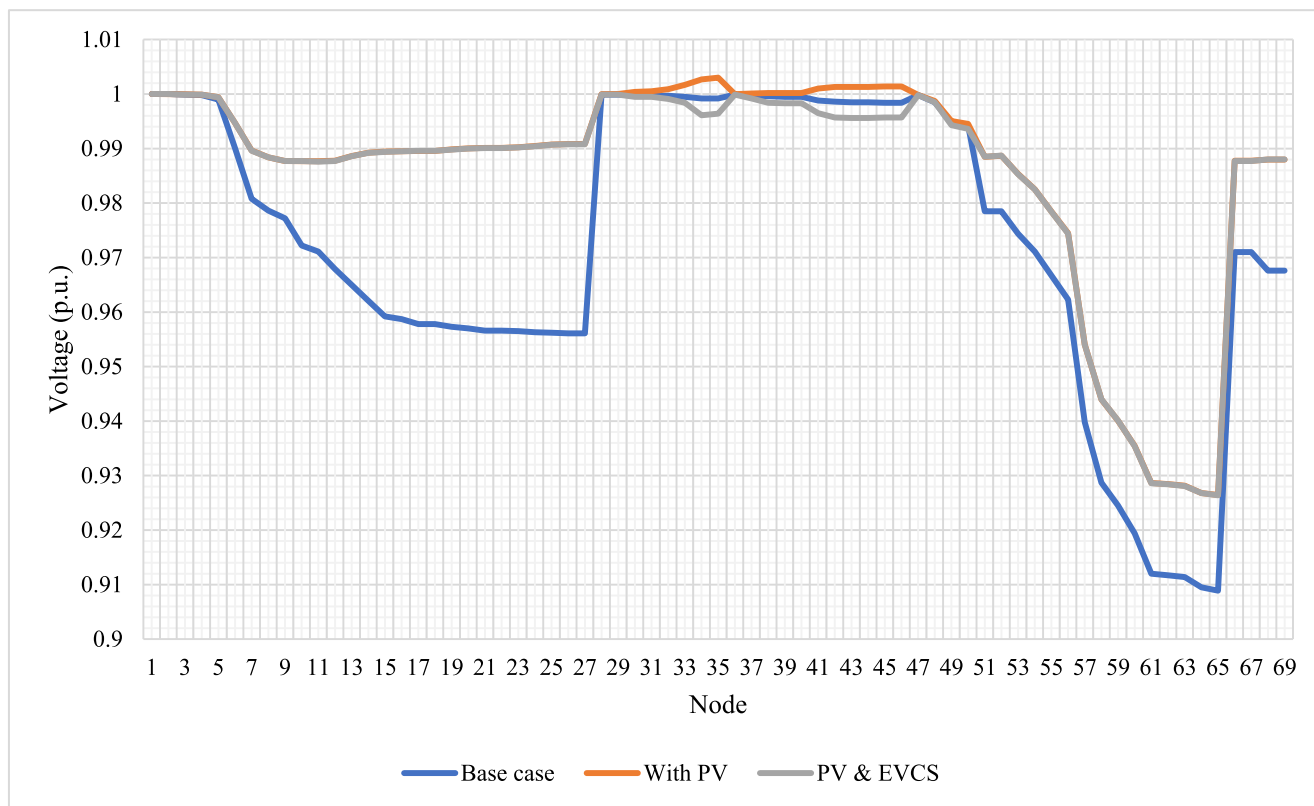


FIGURE 5. Network voltage profile (case 3).

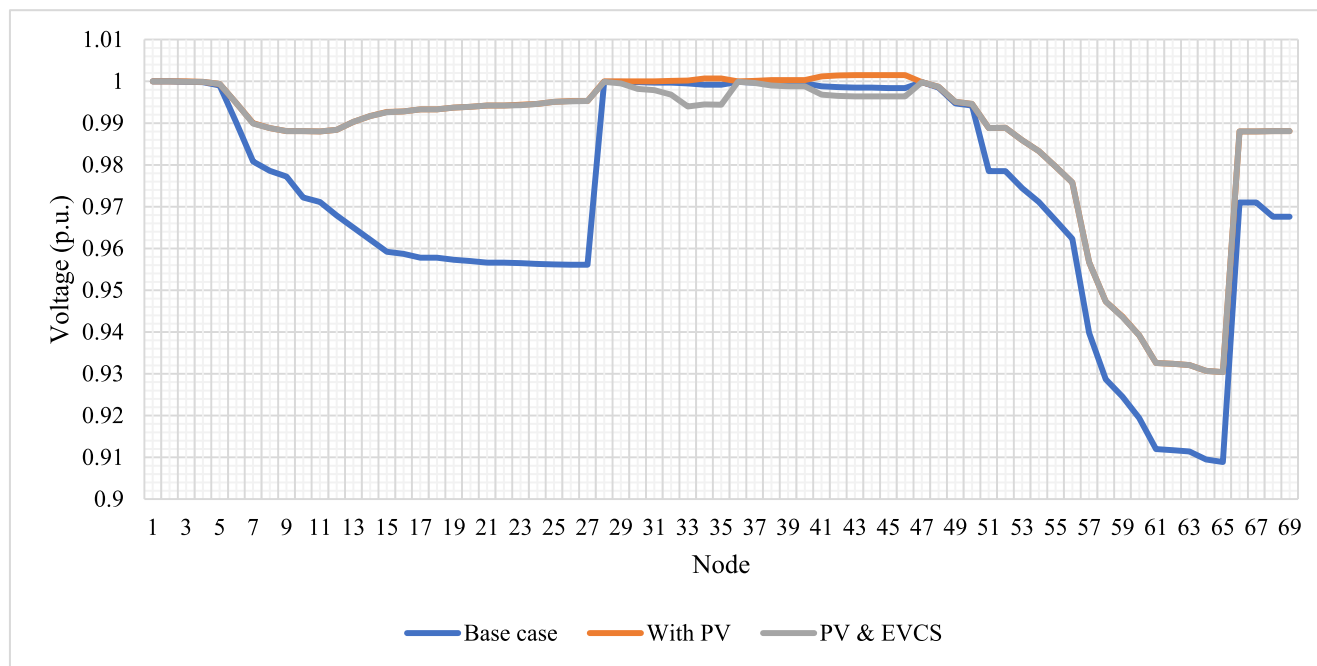


FIGURE 6. Network voltage profile (case 4).

case to 0.01208 in case 1, 0.01242 in case 2, 0.01444 in case 3, 0.01294 in case 4, and 0.01426 in case 5. The results

shown in figure 7 indicate the AVDI of the network is not affected much by the introduction of the EVCSs in all the

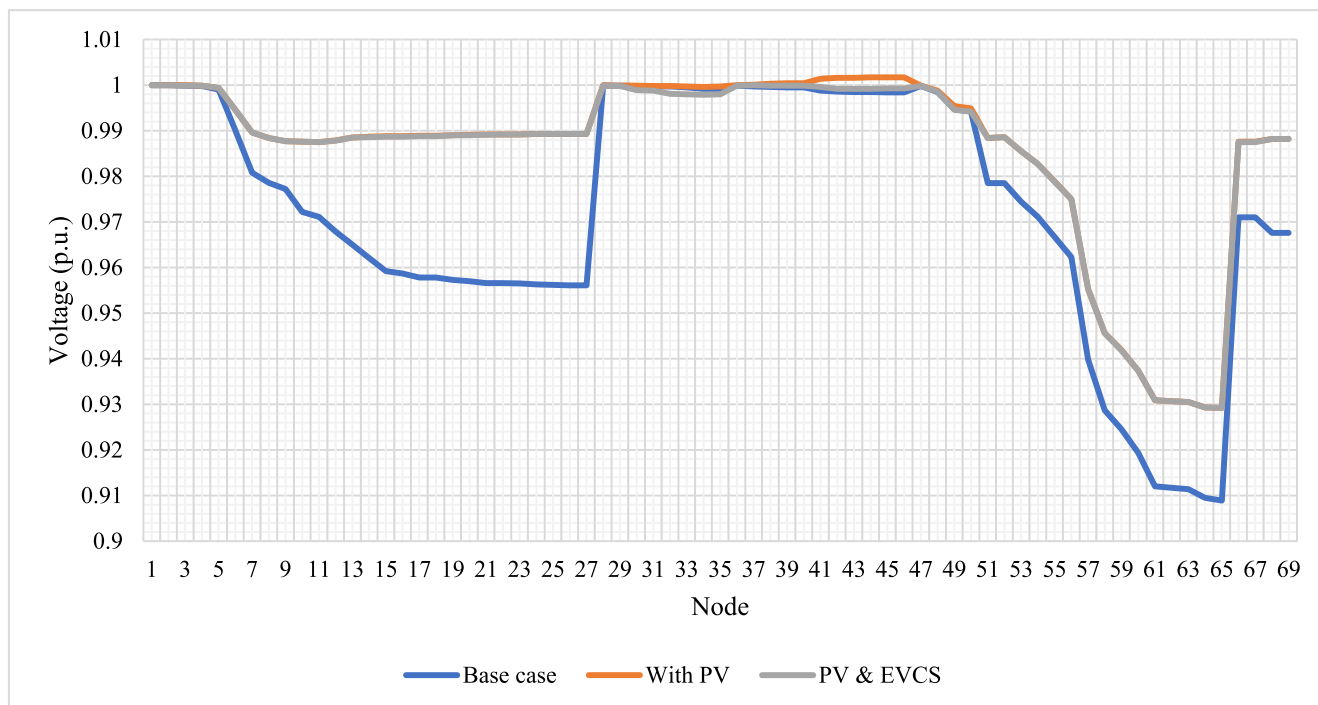


FIGURE 7. Network voltage profile (case 5).

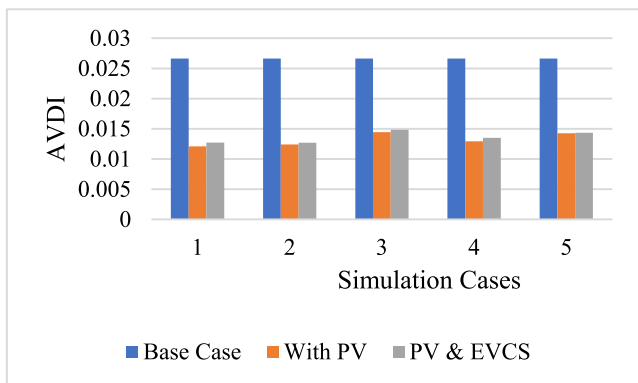


FIGURE 8. Average voltage deviation index.

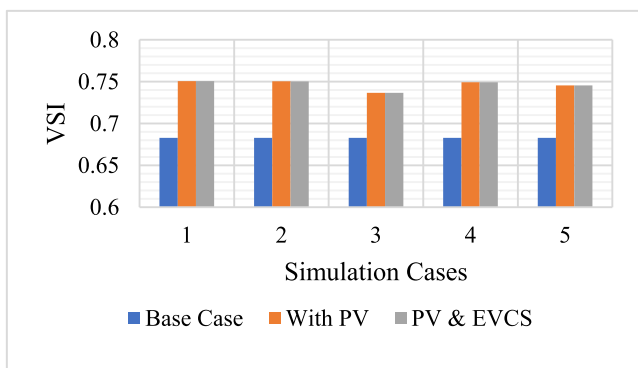


FIGURE 9. Minimum voltage stability index.

simulation cases with it slightly increasing to 0.01271 in case 1, 0.01268 in case 2, 0.01484 in case 3, 0.01351 in case 4, and 0.01434 in case 5.

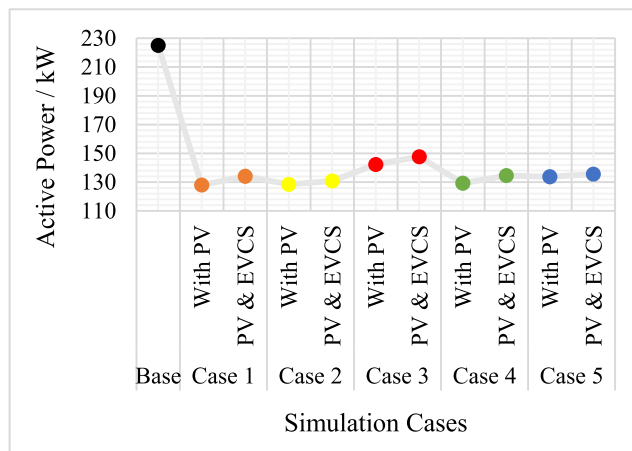


FIGURE 10. Total active power loss.

**D. VOLTAGE STABILITY INDEX**

The voltage stability index (VSI) is another indication of network stability. It is driven based on the magnitudes of the voltage and current of the network in order to obtain the distance between the operating point of the current and the collapse point of the voltage [40]. The smaller the value, the more sensitive the network is to voltage collapse. Unlike VDI, the larger the value of VSI, the more stable the network. The Minimum VSIs from the simulation of all the cases are shown in figure 9. The introduction of the PV systems increases the minimum VSI of the network with the poorest increase being in case 3, that is from 0.68276 to 0.73673 (case 3) compared to 0.75068 in case 1, 0.75033 in case 2, 0.74935 in case 4,

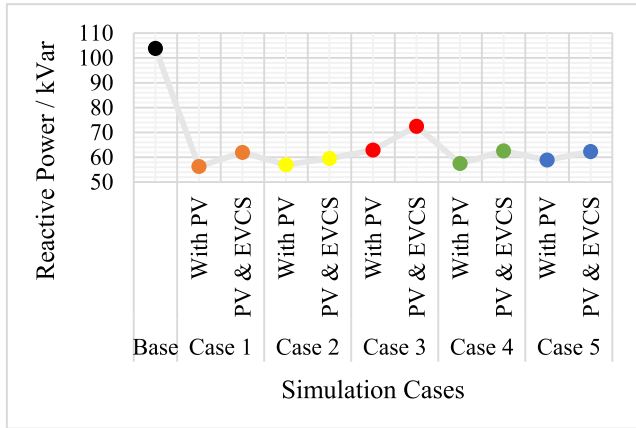


FIGURE 11. Total reactive power loss.

and 0.74553 in case 5. The placement of the EVCSs in all cases does not significantly affect the VSI of the network. This demonstrates the effectiveness of the hybrid BFOA-PSO in placing the EVCSs while ensuring the maximization of the VSI of the network.

**E. ACTIVE AND REACTIVE POWER LOSSES**

In all the simulation cases, the introduction of the PV systems leads to a considerable decrease in total active power loss from 225.06kW in the base case to 127.99kW in case 1, 128.43kW in case 2, 142.27kW in case 3, 129.23kW in case 4, and 133.75kW in case 5 as shown in figure 10. There is a decrease in total reactive power from 103.85kVar in the base case to 56.27kVar in case 1, 56.98kVar in case 2, 62.90kVar in case 3, 57.51kVar in case 4, and 58.89kVar in case 5 as seen in figure 11. The judicious placement of the EVCSs in all cases leads to a slight increase in both total active and reactive power losses. The largest increase in power losses is in case 3 where the active power loss is incremented by 3.78% (from 142.27kW to 147.65kW), and the reactive power loss is elevated by 15.23% from 62.90kVar to 72.48kVar. The smallest increase in active and reactive power losses are observed in case 5 with the active power increasing by 1.35% from 133.75kW to 135.55kW while the reactive power

increased from 58.89kVar to 62.29kVar giving an increase of 5.77%. It is clear, that the resulting active and reactive power losses due to the EVCSs are still lower than those in the base case.

**F. VALIDATION OF THE PROPOSED HYBRID BFOA-PSO**

The results of the proposed hybrid BFOA-PSO for the placement of the EVCSs in the distribution network with randomly sized and sited rooftop PV systems are compared with results obtained when using BFOA and PSO separately for the same task. These results are shown in table 7, table 8, and table 9. For all five cases of PV penetration, it is seen that the proposed hybrid BFOA-PSO performs better than the individual techniques used standalone. Firstly, it is seen that when using PSO, the resulting locations for the EVCSs are mostly clustered on the same network nodes especially the level 2 chargers which have a higher power rating. This can be as a result of PSO being trapped in the local optimum and hence never obtain the global best solution. Indeed, hybridizing BFOA and PSO solves this problem and the results are better locations for the placement of the EVCSs. Secondly, the minimum node voltage obtained after placing the EVCSs using the hybrid technique in all five cases are 0.931p.u. in case 1, 0.931p.u. in case 2, 0.926p.u. in case 3, 0.920p.u. in case 4, and 0.929p.u. in case 5, which are higher than what is obtained when using the individual techniques separately; that is 0.927p.u. in case 1, 0.926p.u. in case 2, 0.925p.u. in case 3, 0.925p.u. in case 4, and 0.924p.u. in case 5 for BFOA, and 0.926p.u. in case 1, 0.926p.u. in case 2, 0.913p.u. in case 3, 0.927p.u. in case 4, and 0.919p.u. in case 5 for PSO. This means that the placement of the EVCSs using both techniques hybridized results in a better network voltage profile. Therefore, as will be expected the AVDI and the minimum VSI of the network when the hybrid technique is use are healthier than when BFOA and PSO are used separately. This shows that the placement of the EVCSs using the hybrid technique leads to a network with superior voltage stability. Furthermore, the power losses as a result of the EVCSs placed in the network using the hybrid technique in cases are lower than the resulting power losses when using the individual techniques separately. This shows the

TABLE 7. Comparison of the results obtained using the proposed (case 1 and case 2).

Algo.	EVCS	Case 1					Case 2						
		Opt. location	Min Volt (p.u.)	kW loss	kVar loss	Min VSI	AVDI	Opt. location	Min Volt (p.u.)	kW loss	kVar loss	Min VSI	AVDI
BFOA	Level 1	7, 25, 5	0.927	142.275	70.154	0.73916	0.01702	49, 15, 38	0.925	146.925	69.994	0.73384	0.01757
	Level2	2, 38, 31, 50					2, 3, 37, 51						
PSO	Level 1	5, 6, 7	0.926	135.696	61.29	0.74233	0.01355	6, 8, 9	0.926	146.412	68.4704	0.73452	0.01584
	Level2	4, 4, 4, 5					5, 5, 5, 5, 5						
Hybrid	Level 1	47, 45, 38	0.931	134.091	61.966	0.75061	0.01271	40, 33, 32	0.931	130.832	59.501	0.75025	0.01268
	Level2	28, 29, 31, 32					2, 4, 29, 37						

**TABLE 8. Comparison of the results obtained using the proposed (case 3 and case 4).**

Algo.	EVCS	Case 3						Case 4					
		Opt. location	Min Volt (p.u.)	kW loss	kVar loss	Min VSI	AVDI	Opt. location	Min Volt (p.u.)	kW loss	kVar loss	Min VSI	AVDI
BFOA	Level 1	21, 48, 31	0.925	158.264	75.642	0.73056	0.01879	16, 50, 56	0.924	151.421	73.530	0.73033	0.01794
	Level2	2, 33, 41, 42					2, 5, 37, 43						
PSO	Level 1	13, 19, 25	0.913	230.111	106.514	0.69388	0.02974	3, 11, 22	0.926	144.533	66.755	0.73609	0.01848
	Level2	5, 6, 7, 8,						4, 5, 5, 5					
Hybrid	Level 1	50, 34, 40	0.927	147.653	72.481	0.74928	0.01351	45, 30, 5	0.930	134.568	62.550	0.74928	0.01351
	Level2	2, 37, 38, 43						2, 39, 49, 4					

**TABLE 9. Comparison of the results obtained using the proposed (case 5).**

Algo.	Case 5						
	EVCS	Opt. location	Min Volt (p.u.)	kW loss	kVar loss	Min VSI	AVDI
BFOA	Level 1	11, 40, 55	0.924	153.931	70.862	0.72842	0.01748
	Level 2	4, 5, 44, 47					
PSO	Level 1	11, 16, 19	0.919	196.510	90.825	0.71273	0.02563
	Level2	5, 6, 6, 6					
Hybrid BFOA-PSO	Level 1	4, 43, 69	0.929	135.549	62.289	0.74542	0.01434
	Level2	5, 28, 29, 47					

effectiveness of the proposed hybrid BFOA-PSO in finding the best nodes for the EVCSs that will result in minimal power losses.

In all, the proposed hybrid BFOA-PSO proves its effectiveness in the placement of EVCSs in the distribution network with randomly sized and placed rooftop PV systems compared to using BFOA and PSO separately for the same task. This also validates the ability of the proposed technique to use the strength of one algorithm to solve the weakness of the other.

**V. CONCLUSION AND RECOMMENDATIONS**

This study focused on the integration of electric vehicle charging stations (EVCSs) into a distribution network with randomly distributed rooftop photovoltaic (PV) systems using a hybrid BFOA-PSO optimization technique. MATLAB 2019a was used for the simulation of the optimization problem. The objective was to optimally place the EVCSs in such a way that they do not impede the quality of the network. The objective function was formulated as a multi-objective function that minimized active and reactive power losses and the average voltage deviation index while maximizing the voltage stability index. The random distribution of the PV systems mimicked real-life consumer-based integration of PV systems. The random sizing and siting of the PV systems were done using Microsoft Excel and transferred into MATLAB. The simulation results showed the effectiveness of the hybrid BFOA-PSO in finding the best positions for the installation of the EVCSs across the network in all five cases of randomly sized and sited PV systems. Small voltage drops on some nodes and a minimal increased in power losses were

noted following the integration of the EVCSs. The effectiveness of the hybrid BFOA-PSO was validated by comparing its results with the results obtained when using BFOA and PSO separately for the placement of the EVCSs in the distribution network with randomly sized and sited PV rooftop PV systems. The results from the simulation demonstrate that the proposed hybrid BFOA-PSO is an effective optimization technique for the placement of EVCSs in modern distribution networks that are characterized by randomly distributed PV systems. As the distribution service operators plan to provide long-range, cost-effective, reliable, and affordable services to consumers in the short and long term future, while maintaining adequate power quality and voltage within boundaries, the effectiveness of hybrid BFOA-PSO for EVCSs placement will be further enhanced. This is because the algorithm’s constraints are much in line with the constraints of the planning horizon.

The future scope of this research will consider the daytime variation of PV production, the driving pattern of EV users, the distribution network uncertainties, as well as the charging time of the EVs for the optimal allocation of the EVCSs in the distribution network. These will be used to test the robustness of the hybrid BFOA-PSO algorithm.

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