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Optimal Integration of Electric Vehicle Charging Stations and Compensating Photovoltaic Systems in A Distribution Network Segregated into Communities

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Abstract. *This paper proposes a method of optimally utilizing electric vehicles (EVs) in the distribution network. The method is firstly based on segregating the distribution network into communities and then optimally placing an EV charging station (EVCS) in each community using the backward forward sweep (BFS) technique. The Second phase uses particle swarm optimization (PSO) to size and allocates photovoltaic systems in the network for power loss minimization and voltage improvement. The proposed method is tested on an IEEE 33 node test feeder and simulation results showed the effectiveness of the BFS in finding the best nodes for the placement of EVCS in each community as well as the effectiveness of the PSO in allocating the photovoltaic systems. To validate the effectiveness of the BFS technique, its results obtained are compared with those obtained when the EVCSs are placed on some nodes other than those chosen by the BFS technique.*

Keywords

Charging station, Electric vehicle, Photovoltaic, Communities.

1. Introduction

Electric vehicles (EVs) are fast gaining ground in today's transport sector as they are a promising technology to reduce greenhouse gases (GHG) in the atmosphere [1]. Research has shown that to achieve the target of reducing global warming pollution to less than 80 percent of that of 1990 (22.4 billion metric tons of carbon dioxide) by 2050 [2], the transport sector needs to be completely revolutionized by EVs and powered by renewable as well as other zero-carbon emission energy sources [3]. This, coupled with the continuous depletion of crude oil has led to the future of petroleum-based vehicles being overshadowed. The fast deployment of EVs in today's transport sector greatly depends on the fast expansion of charging facilities where consumers live, play, and work. This, therefore, means that the electricity sector needs to be upgraded and made robust to accommodate strategically placed electric vehicle charging stations (EVCS). The Increased penetration of EVs into the distribution network will necessitate solutions to compensate for the effects they have on the network such as increased power loss, voltage and frequency instability due to random charging, and network overloads [4]. A potential solution is the installation of distributed generation (DG) such as photovoltaic (PV) systems.

Owing to the extended length of distribution networks and the high R/X ratio of transformers, minimizing power loss, improving the reliability of the network and the power factor, and improving the voltage profile of the network are also big challenges [5]. The installation of distributed PV systems close to load centers has been a potential solution to this challenge. The penetration of PV systems in the distribution network is fast increasing as the war against GHG emissions, the restructuring of the distribution network, and the deregulation of the electricity market are implemented [6]. The distribution network can benefit from the fast penetration of PVs such as in ancillary services, network voltage improvement, network reliability enhancement, reduced power loss, and distribution feeders congestion [7]. Nevertheless, this technology needs to be strategically deployed to reduce harmful fault current increase in the network [8], and reverse power flow at a certain time of the day which can result in excess power loss or malfunctioning of protective devices [9], frequency excursion in the case of loss in load or generation [10], voltage rise, and power factor degradation [11].

Due to the challenges that EVs bring to the distribution network, several techniques have been used for their optimal integration into the distribution network alongside PV systems. In [12], the authors optimally placed PV systems and EVCSs simultaneously in the distribution network for a reduction in power loss and improvement in the network voltage profile using Artificial Bee Colony (ABC) taking into consideration the uncertainty of the loads. The authors in [13] focused on optimally placing EVCSs by striving to minimize the distance traveled by the EVs using fuzzy C-means and K-means clustering techniques. Testing the techniques on a modified IEEE 123 node test feeder rendered satisfactory results. The work presented in [14] proposed a strategy to optimally size and place different types of EVCSs (Level 1, Level 2, and Level 3) in a distribution network that comprised commercial and residential buildings with PV systems, considering the effect of the PV systems using particle swarm optimization (PSO). The objective was to reduce the cost of installation of the EVCSs and the cost of power losses. The results demonstrated a reduction in the cost of the EVCS by 75% and network losses by 82%. In [15], EVCSs were optimally placed in the distribution network using PSO for minimal power loss. The work went further to propose the reconfiguration of the network to reduce the increase in power loss as a result of the EVCSs. A strategy for the optimal sizing of EVCSs by minimizing system losses and augmenting the utilization factor of the EVCSs was solved using a non-dominated sorting Genetic Algorithm in [16]. Simulation results demonstrated the ability of the proposed algorithm in reducing power losses as well as achieving economic benefits for the EVCSs. The researchers in [17] optimally sized and placed EVCSs in an unbalanced distribution network using PSO. To increase the sustainability and reliability of their test networks, type one DGs which compensate only for reactive power were incorporated into the distribution systems. The research elaborated in [18] proposed an optimization technique based on scenarios for the optimal sizing of EVCSs in a commercial distribution network with the aim of increasing the PV penetration level and also reducing the effect of the EVCSs on the network. The objective function was solved using PSO for power loss and voltage deviation minimizations. The authors in [19] proposed a multi-objective index-based approach to determine the size and site of more than one DG considering the distribution network to have various load models and obtained the optimal location and sizes of DGs were significantly affected by load models. PSO was used to solve the multiobjective function.

This paper proposes a new approach for the optimal placement of EVCSs and distributed PV systems in the distribution network wherein the distribution network is segregated into communities using an improved spectral clustering technique and in each community, an EVCS is optimally placed using the backward forward sweep (BFS) power flow method. The distributed PV systems are then optimally sized and placed in the distribution network using Particle Swarm Optimization (PSO) to compensate for the extra power loss and voltage drops as a result of the EVCSs. The rest of this paper is organized as follows; the next section is the methodology, followed by results and discussions, and then the conclusion.

2. Methodology

2.1. Test Network

The IEEE 33-node test feeder is used as a test network in this research work. The IEEE 33-node test distribution network is a balanced distribution network with a system voltage of 12.66 kV. This network is chosen because this research aims to expand on the work done in [20] wherein the test network is divided into communities based on an improved spectral clustering technique as shown in Fig. 1 with the aim of maximizing the usage of flexible resources. The division of the network into communities permits each community to have an electric vehicle charging station (EVCS) with a number of charging points to serve that particular community.

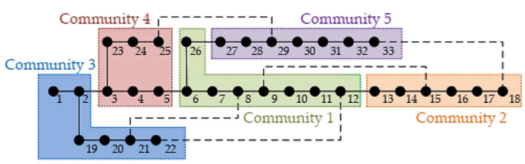

Fig. 1: Division of the test network into communities [20].

2.2. Estimation of the Number of Electric Vehicles in Each Community

The number of EVs in each community is estimated based on the estimated number of households in each community. The number of households is estimated based on the total load demand of that community. In this research, it is assumed that all the households have the same three-phase power demand of 12.7 kVA. From that, it is possible to calculate the number of households in each community. However, not all households are considered to own an EV. An EV penetration of 20 percent is considered in this study. The percentage EV calculation is done using (1).

$$\%EV = \frac{\text{Households with EVs}}{\text{Total Number of Households}} * 100 \tag{1}$$

From equation (1), it is possible to know the number of EVs in each community and the required number of charging points in each EVCS. The number of households and EVs in each community is shown in Tab. 1.

Tab. 1: Estimation of the number of households in each community

Community	Total Load Demand (kVA)	Power demand of a single household (kVA)	Number of Households	Number of EVs
1	829.60	12.7	66	14
2	523.93	12.7	42	9
3	411.47	12.7	33	7
4	1341.64	12.7	106	22
5	1263.02	12.7	100	20

2.3. EV Charging Station Modelling Using ETAP

Electric vehicles nowadays are manufactured by a good number of motor companies such as Nissan, Tesla, Chevrolet, and Renault among others. The EV considered in this study is the 2018 Nissan Leaf (Leading which is environmentally friendly, affordable, and a Family Car) battery electric vehicle which has a battery capacity of 40 kWh with 36 kWh useable to cover a distance of up to 220 km [21]. The 2018 Nissan Leaf model has a Lithium-ion battery pack with the specifications shown in Tab. 2 below.

Charging the 2018 Nissan Leaf can be done using its 6.6 kW onboard charger. Depending on the country, the Nissan Leaf could be charged as per the options shown in Tab. 3.

In this study, the 5th charging option is used wherein the EV charger draws 32 A from the

Tab. 2: 2018 Nissan Leaf battery specifications [22].

	Characteristics
Manufacturer	AESC
Battery type	Lithium ion
Number of cells	192
Number of modules	24
Battery pack Nominal voltage	360 V
Battery pack capacity	40kWh
Useable Battery Capacity	36kWh
Energy Density	224 Wh/kg

Tab. 3: Nissan Leaf charging options using the 6.6kW onboard charger [2].

Opt	Charging Point	Max. Power	Power	Charging time
1	Wall plug (2.3kW)	230V/1x10A	2.3 kW	18h30m
2	1-phase 16A (3.7kW)	230V/1x16A	3.7 kW	11h30m
3	1-phase 32A (7.4kW)	230V/1x29A	6.6 kW	6h30m
4	3-phase 16A (11kW)	230V/1x16A	3.7 kW	11h30m
5	3-phase 32A (22kW)	230V/1x29A	6.6 kW	6h30m

main supply through a 230 V three-phase charging socket. Since the voltage of the test network is 12.66 kV, a 12.66/0.23 kV step-down transformer is used to supply the EV charger. As per the international standard IEC 61851, an EV charger taking a maximum current of 32 A from the mains is categorized as a mode 2 (Level 2) charger [23]. Level 2 chargers are faster than Level 1 chargers and have an average efficiency of 89.4, which is higher than that of level 1 chargers [24].

A battery is used to model the EV using ETAP. ETAP has a large library of batteries of various specifications. The YUASA-EXIDE CX battery model is used here. It is a 65 AH battery with each cell having a voltage of 2.06 V. To have a battery pack of 360 V like that of the Nissan Leaf, 175 cells are used as shown in Fig. 2. The EV charger rating required to draw a maximum of 32 A from the mains to charge the Nissan Leaf is calculated using basic power calculation and its specifications are shown in Fig. 3.

The modeled Nissan Leaf and the charging system were tested and the result shows the Nissan Leaf charger taking 32 A from the 12.66/0.23 kV stepdown transformer as shown in Fig. 4.

The power demand of a single charging point is calculated and verified from the simulation, is

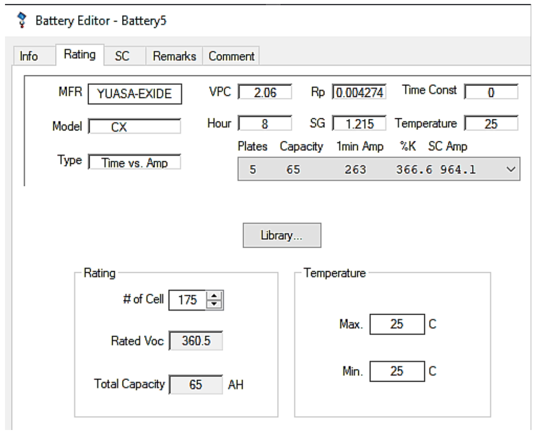

Fig. 2: Nissan Leaf Model in ETAP.

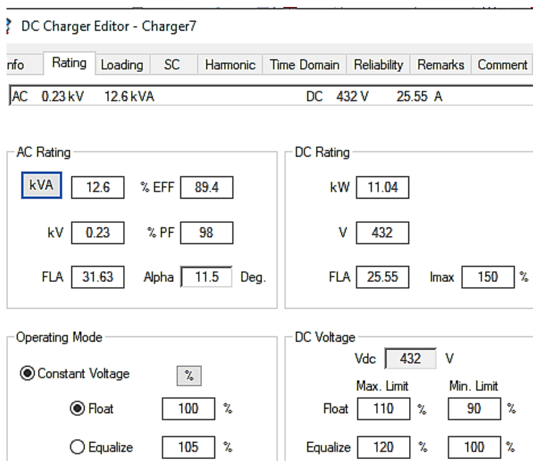

Fig. 3: Modeled Nissan Leaf Charger Characteristics.

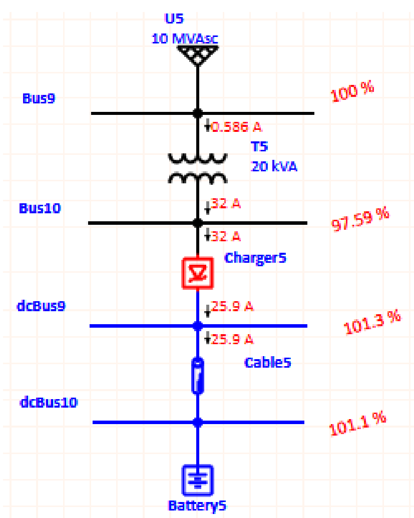

Fig. 4: Testing the Modeled Nissan Leaf.

used to obtain the total power of each EVCS as shown in Tab. 4.

Tab. 4: Power Demand of Each EVCS.

Community	No of CP	EVCS rating (kVA)	
		kW	kVAR
Community 1	14	172.872	35.103
Community 2	9	111.132	22.566
Community 3	7	86.24	18.49
Community 4	22	271.656	54.148
Community 5	20	246.96	50.147

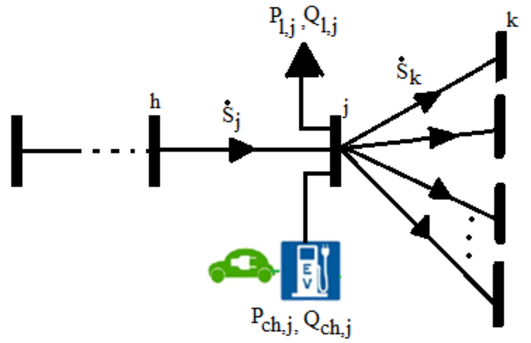

Fig. 5: Simple Network with an EV charging point.

2.4. Optimal Placement of EVCSs in the Communities

The backward forward sweep load flow method is used for the optimal placement of the EVCSs to serve the various communities. Since there are five communities, five EVCSs are to be placed in the network with each community having one EVCS. The number of charging points in the charging stations matches the number of EVs in the given community.

The backward-forward sweep (BFS) is an iterative method of load flow calculation wherein two computational stages are done at each iteration. The first set of equations of the BFS is for power flow calculation through the network's branches beginning from the last branch and moving backward toward the source bus, and the second set of equations is the calculation of the voltage magnitude and angle of every bus beginning from the source bus to the end bus [25].

In the forward direction, the objective is simply to calculate the voltage drops at every bus and update the current and power flow in the network while in the backward direction, the aim is simply power or current flow solution while updating the bus voltages. With reference to Fig. 5, the apparent power flowing into bus j is given by

$$\dot{S}_j = \dot{S}_{lj} + \sum_k \dot{S}_k \tag{2}$$

where $\dot{S}_{lj}$ is the apparent power consumed at bus j, and $\dot{S}_k$ is the apparent power flowing to bus k.

With an EVCS installed on node j, the power $\dot{S}_{lj}$ consumed at bus j is given by

$$\dot{S}_{lj} = (\dot{P}_{lj} + \dot{P}_{ch}) + j(\dot{Q}_{lj} + \dot{Q}_{ch}) \tag{3}$$

where $\dot{P}_{lj}$ is the load active power, $\dot{P}_{ch}$ is the EVCS active power, $\dot{Q}_{lj}$ is the load reactive power and $\dot{Q}_{ch}$ is the charging station reactive power.

The current $\dot{I}_j^{i+1}$ injected into the load bus j at the $i+1$ iteration is given by

$$\dot{I}_j^{i+1} = \left(\frac{\dot{S}_{lj}}{\dot{V}_j^i}\right)^* \tag{4}$$

where $\dot{V}_j^i$ is the voltage at node j at the i^{th} iteration.

In the backward sweep, the current, $\dot{I}_{h,j}^{i+1}$ in the branch $h-j$ at the $i+1$ iteration is calculated as

$$\dot{I}_{h,j}^{i+1} = \dot{I}_j^{i+1} + \sum_k \dot{I}_{j,k}^{i+1} \tag{5}$$

where $\dot{I}_j^{i+1}$ is the current consumed by the loads on bus j, and $\dot{I}_{j,k}^{i+1}$ is the current leaving bus j.

On the other hand, in the forward sweep, the $h-i$ branch current $\dot{I}_{h,j}^{i+1}$ is utilized to calculate the voltage at bus h as shown in (6)

$$\dot{V}_h^{i+1} = \dot{V}_j^{i+1} - (\dot{I}_{h,j}^{i+1})(Z_{h,j}) \tag{6}$$

where $Z_{h,j}$ is the impedance of branch $h-j$.

Upon satisfaction of the convergence criterion given by (7) for all the buses, the BFS power flow is ended. At that instant, the voltage at node j is equal to $\dot{V}_k^{i+1}$, and the current in the

$j-k$ branch is equal to $\dot{I}_{j,k}^{i+1}$. The convergence factor is the scaler ε shown in equation (7).

$$\left|\dot{V}_k^{i+1} - \dot{V}_k^{i}\right| \leq \varepsilon \tag{7}$$

The BFS has been used in the past by researchers for the optimal placement of DGs in the distribution network [26] as well as the optimal placement of capacitors in the distribution network [27]. In this research, it is used for the optimal placement of EVCSs.

2.5. Problem Formulation for the Optimal Placement of EVCSs

The problem is formulated as a minimization problem. The power loss is to be minimized as shown in (8)

$$F_{loss} = min \sum_{j,k=1}^{n} g_{j,k}\left[V_j^2 + V_k^2 - 2V_jV_k cos(\theta_j - \theta_k)\right] \tag{8}$$

where F_{loss} is the total active power loss in the network, $g_{j,k}$ is the conductance of branch $j-k$, n is the total number of lines in the network, V_j is the voltage magnitude at node j and V_k is the voltage magnitude at node k, θ_j and θ_k are the voltage angles at nodes j and k, respectively.

Equation (8) is subject to the following constraints

a) Voltage constraint

$$V_j^{min} \leq V_j \leq V_j^{max} \tag{9}$$

where V_j^{min} is considered as 0.95pu and V_j^{max} as 1.05pu.

Current constraint

$$I_a \leq I_a^{max} \tag{10}$$

The current flowing through the conductors is limited to the maximum current capacity of the conductors.

2.6. Proposed algorithm

In each community, all the nodes are candidate nodes for the placement of the EVCS as shown in Tab. 5.

Tab. 5: Candidate nodes for the optimal placement of EVCS in the various Communities.

Community 1	Community 2	Community 3	Community 4	Community 5
6	13	1	3	27
7	14	2	4	28
8	15	19	5	29
9	16	20	23	30
10	17	21	24	31
11	18	22	25	32
12				33

For each community, the BFS technique locates the node with the least network power loss when its EVCS is placed and considers it a suitable place for the installation of the EVCS. For a particular community, the BFS determines the best node for the placement of its EVCS in the following steps:

- Step 1: Place the EVCS on the first candidate node
- Step 2: Run power flow calculation using BFS while observing the constraints
- Step 3: Record the network power loss
- Step 4: Place the EVCS on the next candidate node
- Step 4: Run power flow calculation using BFS while observing the constraints
- Step 5: Record the network power loss
- Step 6: Have all the candidate nodes been tested? Go back to step 4 if NO, otherwise go to step 7
- Step 7: Compare the power losses from all the candidate nodes
- Step 8: Select the node with the least power loss as the best position

2.7. Optimal Sizing and Placement of PV Systems Using PSO

The aim of the optimal sizing and placement of PV systems is to compensate for the extra power losses as a result of the EVCSs and also enhance the network voltage profile. Two cases of PV sizing and placement are considered. Case 1 deals with the sizing and placement of a single PV system and case 2 deals with the sizing and placement of two PV systems. The utilization of PV systems is to assist the network to service the EVCSs without violating its operating constraints.

1) Problem Formulation

The objective of this optimization problem is to minimize the network's total power loss and the average voltage deviation index of the network. In other words, enhance the voltage profile of the network.

2) Objective function

A. Active and reactive power loss minimization

$$f_1(j) = min\sum_{i=1}^{br}(R_i * I_i^2 + X_i * I_i^2) \qquad (11)$$

where $f_1(j)$ is the total power loss, br is the number of branches in the network, R_i is the branch resistance, I_i is the branch current and X_i is the branch reactance.

B. Minimize average voltage deviation

$$f_2(j) = \frac{1}{N_b}\sum_{j=1}^{N_b}|1 - V_j|^2 \qquad (12)$$

where $f_2(j)$ is the average voltage deviation of the network, N_b is the number of nodes in the network, V_j is the voltage at bus j.

Therefore, the objective function is written as

$$F(j) = min\{f_1(j) + f_2(j)\} \qquad (13)$$

3) Constraints

i. Equality constraints

Power balance constraints

$$P_{Grid}+\sum_{i=1}^{N_{pv}} P_{pv} = \sum_{i=1}^{N_{bus}} P_{load}+ \sum_{i=1}^{N_{EVCS}} P_{EVCS}+\sum_{i=1}^{N_{br}} P_{loss} \qquad (14)$$

where P_{Grid} is the grid active power, P_{pv} is the PV systems active power, N_{pv} is the number of installed PV systems, P_{load} is the load active power demand, N_{bus} is the number of load nodes, P_{EVCS} is the active power demand by the EVCS, N_{EVCS} is the number of EVCS, P_{loss} is the total active power loss in the network, and N_{br} is the number of branches in the network.

$$Q_{Grid}+\sum_{i=1}^{N_{pv}} Q_{pv} = \sum_{i=1}^{N_{bus}} Q_{load}+ \sum_{i=1}^{N_{EVCS}} Q_{EVCS}+\sum_{i=1}^{N_{br}} Q_{loss} \qquad (15)$$

where Q_{Grid} is the grid reactive power, Q_{pv} is the PV systems reactive power, Q_{load} is the load reactive power demand, Q_{EVCS} is the reactive power demand by the EVCS, and Q_{loss} is the total reactive power loss in the network.

ii. Inequality Constraints

a. Voltage constraints

$$V_j^{min} \leq V_j \leq V_j^{max} \qquad (16)$$

where V_j^{min} is considered as 0.95pu and V_j^{max} as 1.05pu.

b. Current constraints: Current flow should not exceed the feeder's capacity

$$I_j \leq I_j^{max} \qquad (17)$$

The current flowing through the conductors is limited to the maximum current capacity of the conductors.

c. PV power constraints

$$P_{pv}^{min} \leq P_{pv} \leq P_{pv}^{max} \qquad (18)$$

where $P_{pv}^{min} = 0$ KW and $P_{pv}^{max} = 5000$ kW.

PSO is used to solve the optimization problem. It is a metaheuristic algorithm with great capabilities for optimizing nonlinear functions and it was developed by Kennedy and Eberhart in 1995 [28]. PSO algorithm equation has two optimum concepts; the global optimum, g_{best} and the local optimum p_{best}. The global optimum g_{best} is the optimum solution obtained by the particle swarm while the local optimum, p_{best} is the optimum solution obtained by each particle. Formulating the equations of PSO are as follows; For a swarm with particles, P, there exists a position vector $X_i^t = (x_{i1}x_{i2}x_{i3}...x_{in})^T$ and a velocity vector $V_i^t = (v_{i1}v_{i2}v_{i3}...v_{in})^T$ at t iteration for each of the i particles making up the swarm. The above vectors are updated through dimension j in accordance to the following equations:

$$V_{ij}^{t+1} = wV_{ij}^t + c_1 r_1^t (p_{best_{ij}} - X_{ij}^t) + c_2 r_2^t (g_{best_{ij}} - X_{ij}^t) \tag{19}$$

$$X_{ij}^{t+1} = X_{ij}^t + V_{ij}^{t+1} \tag{20}$$

where $i = 1, 2, 3, ..., P$ and $j = 1, 2, 3, ..., n$, c_1 and c_2 are learning factors, r_1^t and r_2^t are random numbers between 0 and 1, the parameter w is an initial weight constant, usually positive for classical PSO, and serves to balance the global search (known as exploration in the case of being set with higher values) as well as the local search (known as exploitation when being set with lower values).

Equation (19) updates the velocities of the particles while equation (20) updates the positions of the particles. To optimally size and place the PV systems using PSO, the following stages are followed:

- Stage 1: Input the network data with the EVCSs placed at optimal locations
- Stage 2: Run load flow calculation and record the power losses at all the branches as well as node voltages
- Stage 3: Set the desired number of iterations, the number of particles, the initial weights, and the acceleration vectors
- Stage 4: Randomly generate the initial population of the swarm with initial velocities and positions
- Stage 5: Run power flow calculation for each particle while checking the network constraints
- Stage 6: Compare the result of the individual best of all particles and select the particle with the lowest individual best (p_{best}) and set its value as the global best (g_{best})
- Stage 7: Update the particle's velocity and position using equation (18) and equation (19)
- Stage 8: Check if the maximum number of iterations has been reached. If YES, go to the next stage, else go back to stage 4 for the $k = k + 1$ iteration
- Stage 9: Output the results which are the optimal PV size and location. Also, record the active and reactive power losses and node voltages.

The PSO parameters used in the simulation are shown in Tab. 6.

Tab. 6: PSO parameter values.

Parameter	Symbol	value
Population size	pop_size	33
Number of iterations	iteration	30
Maximum inertia	wmax	0.9
Minimum inertia	wmin	0.4
Acceleration vectors	c1	2
	c2	2

The optimization problem is solved using MATLAB. PSO was run five times and the best results were recorded.

3. Results and Discussion

Simulation is done for peak load conditions, all EVCSs have EVs connected and charging, and the PV systems are also at their peak production. The IEEE 33 node test feeder which is our test network is divided into communities and an EVCS is optimally placed in each community using the BFS load flow method.

3.1. Optimal location for the EVCSs and the optimal allocation of the compensating PV(s)

The best nodes among the candidate nodes in each community obtained from the BFS load flow method are shown in Tab. 7. The rating of each EVCS is also shown.

Tab. 7: EVCS Best Location Using BFS.

Community	EVCS rating (kVA)		Best locations
	kW	kVAR	
Community 1	172.872	35.10	6
Community 2	111.132	22.57	13
Community 3	86.24	18.49	2
Community 4	271.656	54.15	3
Community 5	246.96	50.15	27

Two scenarios of PV sizing and placement using PSO were simulated. The first case was the sizing and siting of a single PV system and the second case was the sizing and siting of two PV systems. The best PV sizes and locations as obtained by PSO in both scenarios are shown in Tab. 8.

Tab. 8: Best Size and Position for the two cases of PV integration.

1 PV system		2 PV systems	
Size (kW)	Node	Size (kW)	Node
3235.35	4	1257.36	13
		1294.15	29

The effects of the placement of the EVCS on the test network and the compensation by the PV systems are shown in the following sections.

3.2. Network Voltage profile

The optimal placement of the EVCSs in the network results in a drop in the voltage profile of the network with the minimum voltage dropping from 0.913 p.u. with no EVCSs to 0.899 p.u. as observed on node 18 shown in Fig. 6. For case 1 where a single PV system is optimally sized and placed, an improvement in the voltage profile of the network is noticed. The new voltage profile is even better than when there was no EVCS with the minimum voltage being 0.93 p.u. compared to 0.913p.u. with no EVCSs and 0.899 p.u. with EVCSs at node 18. In the second case of simulation where two PV systems are used, the network voltage profile is substantially improved with all the nodes having voltages above the minimal (0.95 p.u.). The optimal sizing and location of the two PV systems lead to a minimum voltage of 0.96 p.u. noticed at node 18. The network voltage profiles in all the scenarios are shown in Fig. 6.

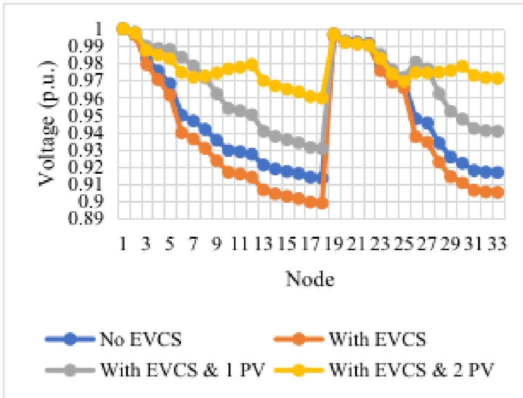

Fig. 6: Network Voltage Profile without EVCS, with EVCS, with EVCS+1PV, and with EVCS+2PV.

3.3. Average Voltage Deviation Index

The voltage deviation index (VDI) is an indicator of a bus voltage drift from the reference voltage which is usually 1 p.u. The smaller the VDI the closer the bus voltage is to the reference voltage and the larger the VDI, the further the bus voltage is from the reference voltage and the more vulnerable the bus is exposed to voltage stability issues. The average voltage deviation index is the average of all the VDI of the network. The smaller it is, the greater the voltage stability of the network. It is seen that the introduction of the EVCSs led to an increase in the AVDI of the network from 0.05149 to 0.06024 as the EVCS serve as extra loads to the network as shown in Fig. 7.

The introduction of 1 PV leads to a drop in the AVDI to 0.03411 and the insertion of a second PV system further improves the AVDI to 0.02288.

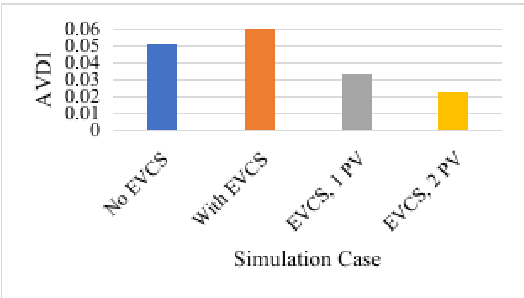

Fig. 7: AVDI without EVCS, with EVCS, with EVCS+1PV, and with EVCS+2PV.

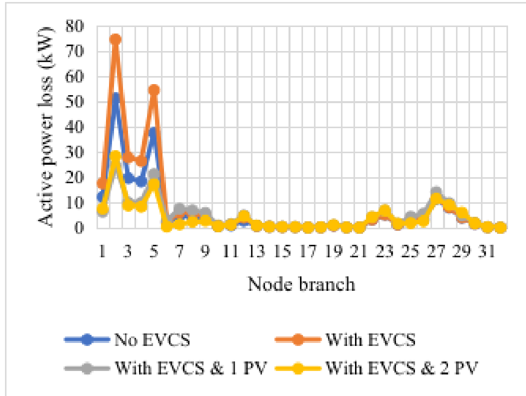

Fig. 8: Network active power loss profile.

3.4. Network Active and Reactive Power Losses

As expected, an increase in the network's active and reactive power loss with the installation of the EVCSs is noticed and this is a result of the extra stress the EVCSs introduce into the network. It is realized that both active and reactive power losses have a greater percentage increase from nodes 1 to 5 as compared to other nodes as shown in Fig. 8 and Fig. 9. The optimal installation of the PV systems reduces the active and reactive power losses at each node and the overall active and reactive power losses of the network as shown in Fig. 10 and Fig. 11. The reduction in the active and reactive power losses upon introduction of the PV systems is a result of the reduction in the current flow through the distribution network feeders as the PV systems supply parts of the power that was to be gotten from the main substation.

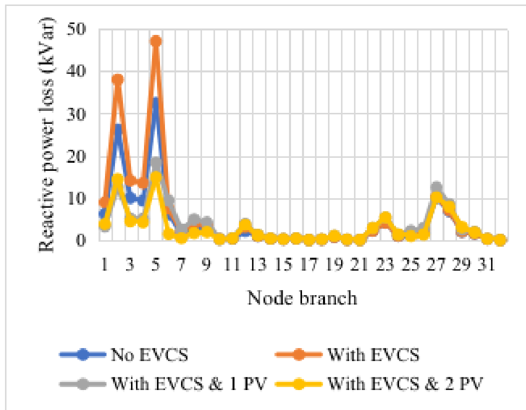

Fig. 9: Reactive power loss profile.

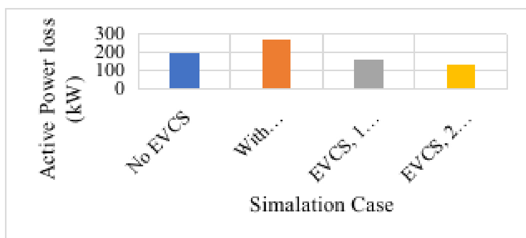

Fig. 10: Total active power loss with no EVCS, with EVCS, with EVCS and 1 PV, and, with EVCS and 2PV.

3.5. Validation of the effectiveness of the BFS technique in finding the best nodes for the EVCSs

To validate the effectiveness of the BFS technique in finding the best nodes for the placement of the EVCS in each community, its results are

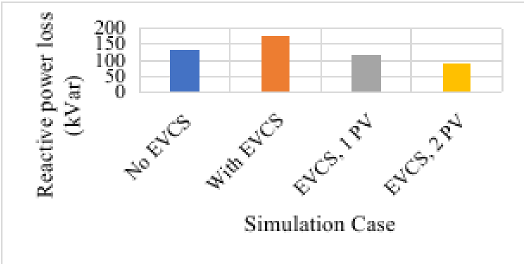

Fig. 11: Total reactive power loss with no EVCS, with EVCS, with EVCS and 1 PV, and, with EVCS and 2PV.

compared with those obtained when randomly choosing a node for the placement of an EVCS in each community. The random choice of nodes for the placement of the EVCSs is done thrice and for each case, the load flow results with the EVCSs placed are recorded. Table 9 shows the optimal location of the EVCSs as obtained by the BFS technique versus the three cases of randomly allocating the EVCSs in the communities. It is reminded that each community is expected to have one EVCS of a predetermined size as depicted in Tab. 9. For a given community, the random allocation of an EVCS is done by choosing any other node among the candidate nodes of that community other than the node chosen when the BFS technique. For each case of random placement of an EVCS in each community, the compensating PV(s) is(are) sized and placed using PSO; firstly 1 PV system, then after 2 PV systems as shown in Tab. 10.

Tab. 9: Optimal location of the EVCSs using BFS vs randomly locating the EVCSs.

Community	EVCS rating (kVA)		Best locations by BFS	Random allocations		
	kW	kVAR		Case 1	Case 2	Case 3
1	172.872	35.10	6	8	11	12
2	111.132	22.57	13	15	18	17
3	86.24	18.49	2	20	19	22
4	271.656	54.15	3	4	23	25
5	246.96	50.15	27	30	29	33

As shown in Tab. 10, it is seen that for all three random cases of integrating the EVCSs, a greater compensation is required to cater for the adverse effects of the EVCSs compared to when the EVCSs are placed using the proposed BFS technique. When 1 PV is used for compensation, the required PV capacity is 3235.35kW, and this is lower compared to the required compensation PV in random case 1 (3351.077 kW), case 2 (3324 kW), and case 3 (3349.67 kW). In the scenario of installing 2 PVs for compensation, the total PV capacity when using the BFS is 2551.36 kW, and it is again lower compared to 2894.968 kW in case 1, 2763.279 kW in case 2, and 2749.916 kW in case 3. This, therefore, means that more costs will be incurred for compensation if the EVCSs are not installed on the designated node obtained by the BFS technique in each community. This demonstrates the strength of the BFS in choosing the best nodes for the installation of the EVCSs.

Looking at the convergence curves of PSO in each scenario of PV sizing and siting (1 PV and 2 PVs), it is seen that PSO convergences faster when the EVCSs are integrated into the network using BFS compared to when integrated randomly as shown in Fig. 12 and Fig. 13. This demonstrates that the BFS places the EVCSs in every community so well that, PSO does not find it very difficult to size and place the appropriate compensating distributed PV system(s) to compensate the adverse effects of the EVCSs.

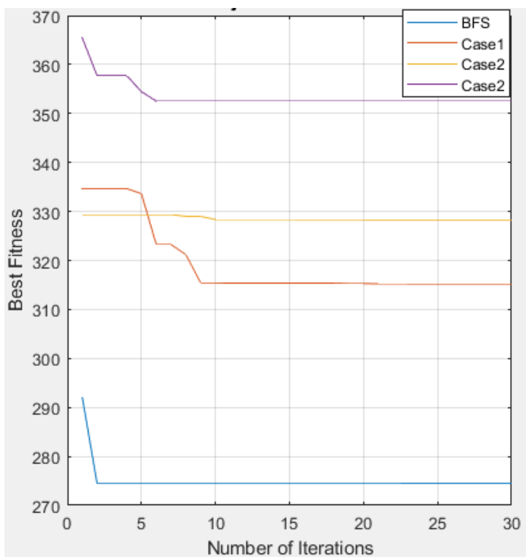

Fig. 12: Convergence Curve of PSO in the placement of 1 PV.

The network parameters are compared when the EVCSs are placed using the BFS against

Tab. 10: Optimal Sizing and Siting of the PV systems in each case of EVCS placement.

Best locations by BFS	When EVCSs are placed using BFS		When EVCSs are random allocated					
			Case 1		Case 2		Case 3	
	Size (kW)	Node	Size (kW)	Node	Size (kW)	Node	Size (kW)	Node
1 PV	3235.35	4	3351.077	4	3324	4	3349.67	4
2 PVs	1257.36	13	1397.21	13	1382.911	30	1387	12
	1294.15	19	1497.759	12	1380.368	11	1362.916	12

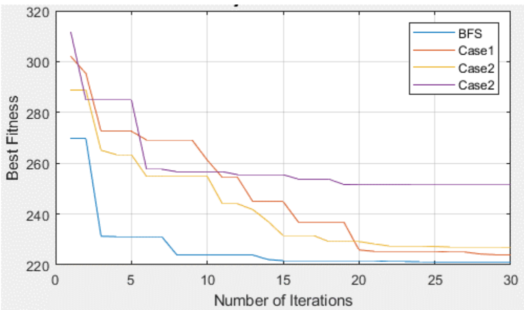

Fig. 13: Convergence Curve of PSO in the placement of 2 PVs.

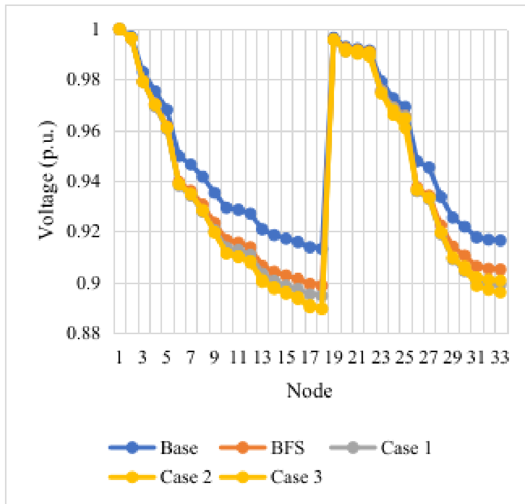

Fig. 14: Comparison of the network voltage profile when the EVCSs are placed using the BFS technique with when they are randomly placed.

when randomly placed as shown in the following sections.

1) Network voltage profile comparison

From Fig. 14, it is observed that the network voltage profile upon placing the EVCSs using the BFS method is better than those when randomly choosing other nodes for the placement of the EVCSs. The minimum node voltage when the EVCSs are placed using the proposed BFS method is 0.8987 p.u. and this is greater than the minimum node voltage of random case 1 (0.8946 p.u.), case 2 (0.8896 p.u.), and case 3 (0.8895 p.u.).

2) Comparison of the average voltage deviation indices

It can be observed in Fig. 15 that the network's AVDI is 0.060242 when the EVCSs are placed using the BFS. When other nodes are chosen for the placement of the EVCSs, this results in a higher network AVDI (0.062724 in case 1, 0.0631576 in case 2, and 0.0640606 in case 3). This means that when the EVCSs are placed on the nodes chosen by the BFS technique, the network has better voltage stability compared to when the EVCSs are placed on other nodes. It is noticed that, even when 1 PV system is used for compensation and of the lowest value when the BFS technique is used, the AVDI of the network is still better (smaller) compared to the AVDI when the EVCSs are randomly placed. In the scenario of 2 PVs compensation, the resulting AVDI of the random cases is lower than that of the BFS, and this is because the sum of the 2 compensating PVs in all three random cases is much higher (2894.968 kW in case 1, 2763.2785 kW in case 2, and 2749.916 kW) than those of the BFS technique (2551.36 kW). The higher the

PV wattage, the more the amelioration of the AVDI.

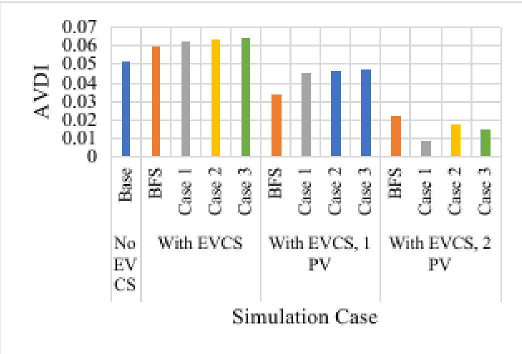

Fig. 15: Comparison of the network AVDI when the EVCSs are placed using the BFS technique with when they are randomly placed.

3) Power loss comparison

Looking at the total active and reactive power losses of the network when the EVCSs are placed using the BFS technique and when they are not placed using the BFS technique as shown in Fig. 16 and Fig. 17, it is seen total active and reactive power losses of the network upon installing the EVCSs using the proposed BFS technique is lesser than when randomly installing the EVCSs on other nodes. Even the total power losses upon inserting 1 compensating PV system are lower compared to case 1, case 2, and case 3. Nevertheless, in the scenario of 2 compensating PVs, the resulting active and reactive power losses in case 2 are lower than those when the BFS is used.

4. Conclusion

Despite electric vehicles (EVs) being the way forward to reducing greenhouse gases from the transport sector, the fast deployment of this technology will critically depend on the fast upgrading of the distribution network to accommodate large numbers of charging facilities in our communities. The increasing integration of this technology also necessitates solutions to compensate for their effect on the distribution

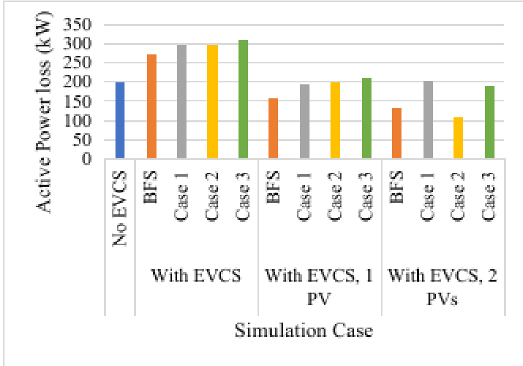

Fig. 16: Comparison of the network active power loss when the EVCSs are placed using the BFS technique with when they are randomly placed.

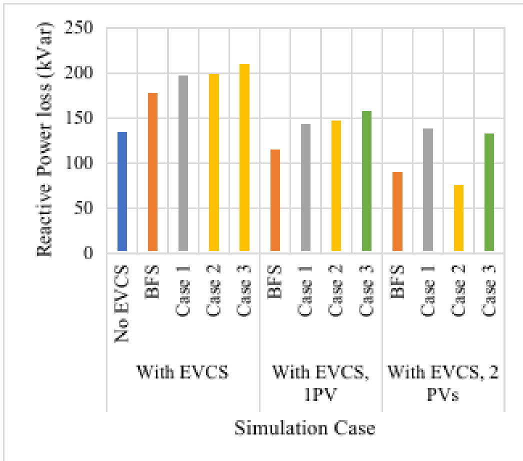

Fig. 17: Comparison of the network reactive power loss when the EVCSs are placed using the BFS technique with when they are randomly placed.

network. PV systems have been proposed by several researchers as the DG of choice to minimize the effect of EVs on the distribution network. This research aimed at utilizing the work of Huizi Gu and X. Chu who divided the IEEE 33 node test distribution network into communities based on an improved spectral clustering technique with the aim of maximizing the usage of flexible resources [20]. The segregation of the network into communities is utilized for the placement of EVCSs into the distribution network using a new approach and later on integrating compensating PV systems to remedy the effect of the EVCSs.

The new approach for the placement of the EVCSs used here is the backward forward sweep (BFS) technique of power flow calculation considering that each community needs a single EVCS. Using PSO, two scenarios of PV integration were used to compensate for the effects of the EVCSs in the distribution network. The first case was the optimal sizing and siting of a single PV system and the second case was the optimal sizing and placement of 2 PV systems. In both scenarios, the optimization problem was aimed at minimizing the real and reactive power losses and enhancing the network voltage profile. Simulation results showed the effectiveness of the BFS in obtaining the best node for the placement of an assigned EVCS in each community. The compensation was also properly done using PSO. The effectiveness of the BFS in the placement of the EVCSs was validated by randomly placing the EVCSs on nodes other than the ones chosen by the BFS. Three random cases were simulated and it was seen that the resulting active and reactive power losses, minimum network node voltage, and the AVDI of the network were all better when the EVCSs were placed using the proposed BFS technique. This demonstrated the efficacy of the proposed BFS in finding the best node for the installation of a given EVCSs in every community. The proposed BFS technique for the integration of EVCSs in a distribution network segregated into communities necessitates that the transport sector and the utility company work hand in glove to ensure the proper segregation of the network into communities.

As a future scope of this study, the driving distance of the EVs and the state of charge of the EV batteries will be considered in the allocation of the EVCSs.

Acknowledgement

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