Optimal Placement of Fast Electric Vehicle Charging Station on Radial Distribution Network by using Particle Swarm Optimization Algorithm Technique.

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Abstract – **In recent years, as a result of population growth and the strong demand for energy resources, there has been an increase in greenhouse gas emissions. Thus, it is necessary to find solutions to reduce these emissions. This will make the use of electric vehicles (EV) more attractive and reduce the high dependency on internal combustion vehicles. However, the integration of electric vehicles will pose some challenges. For example, it will be necessary to increase the number of fast electric vehicle charging stations (FEVCS) to make electric mobility more attractive. Due to the high-power levels involved in these systems, there are voltage drops that affect the voltage profile of some nodes of the distribution networks. This paper presents a methodology based on a Particle Swarm Optimization (PSO) algorithm that is used to find the optimal location of fast charging stations that cause the minimum impact on the grid voltage profile so the voltage level will be very close to the base case without the FEVCS and also making the total active power losses in the distribution network very close to that of the base case but with the big load EVCS are added to network. Two case studies are considered to evaluate the behaviour of the distribution grid with different numbers of EV charging stations connected. From the results obtained, it can be concluded that the PSO provides an efficient way to find the best charging station locations, ensuring that the grid voltage profile is within the regulatory limits and that the value of losses is minimized. The proposed methodology is demonstrated with IEEE 33 bus distribution system.**

***Keywords**: Radial Distribution System, Fast Electric Vehicle Charging Station, particle swarm optimization, Optimal location.*

I. Introduction

We are living in a period of transition, with the primary goal of replacing fossil fuels with renewable energy sources. Because the transportation industry is one of the most polluting, releasing enormous amounts of greenhouse gases into the environment, there is a need to develop solutions to address this issue. Furthermore, there is a legislative framework that encourages long-term solutions for the sector. Solutions that can be implemented include the development of urban design and mobility that reduces the demand for transportation, and travel can be done on foot, by bicycle, or by public transportation [1]. However, the transportation component is always present, and it can be powered by electricity or combustion. Since the goal is to lessen reliance on fossil fuels, electric vehicles are a great alternative to combustion vehicles since they use electricity to charge their batteries, which can originate from renewable energy sources [2]. In this regard, fast electric vehicle charging stations (FEVCS) must be built so that owners can charge their vehicles as quickly as possible. These DC-DC FEVCS (Mode 4) directly supply the vehicle's battery [3], and because to the large powers involved (usually greater than 22 kW), voltage drops emerge, impairing the network's voltage profile. According to standard NP EN 50160 [4], the minimum voltage cannot exceed 10% of the maximum voltage in order to keep the network's voltage profile within regulatory limitations.

As a result, it is critical to identify the ideal sites in the network for FEVCS placement in order to reduce the influence on grid voltage. Several scholars are researching various solutions to this challenge. [5] provides a discussion of the most generally utilized optimization algorithms for the optimal placement of FEVCS and their suitability for tackling objective multi-criteria situations. According to [6], GA can be applied to a variety of domains, including the resolution of optimization problems.

In the following publications, two optimization strategies were utilized to find the best placement for FEVCS while minimizing a multi-objective problem. In [7], a GA was utilized, and it was verified that throughout the mutation process, as genes on a chromosome are altered, the diversity of the results is ensured, and with the evolution of generations, the convergence for the minimization of the objective function is impressive. In [8], a PSO is used. [9] employs a graph-based approach to mapping an urban area's streets. A path is built between two nodes, which are weighted using Dijkstra's algorithm before a GA is used to calculate the shortest distance between a FEVCS and a path's reference node. In [10,11], hierarchical GAs are used to find the best site for a substation and the best connections to wind turbines. The substation coordinates are determined using a binary chromosome. In [12], an optimization system called GWO is utilized, which is based on Gray wolves' natural behavior and hunting techniques. This approach can only be used to tackle continuous issues; however, binary integers are required to find the ideal position of FEVCS. In addition to the use of optimization methods, various solutions can be implemented to optimize the grid voltage profile. For example, in [13], a renewable energy source and a storage system were added, and the results were quite promising.

The primary goal of this article is to identify the ideal sites for FEVCS to minimize power losses while keeping the network voltage profile within regulatory limits. To solve the optimization model, a particle swarm optimization (PSO) approach is utilized, which has been applied to a case study of the IEEE 33 bus radial network. The employment of PSO in this optimization problem has various advantages, beginning with the simplification they provide in formulating and solving the problem, which comprises many variables and, as a result, high-dimensional solution spaces. Furthermore, in many circumstances where other optimization algorithms fail to discover a solution, the PSO finds an excellent one. Aside from calculating the voltage drops in the various buses, the novelty of this study is the minimizing of the overall network's power losses.

The paper is organized as follows. In Sect.2, the necessary calculations for the determination of the power losses in the distribution lines are presented, followed by the optimization model, where the objective function focuses on obtaining the minimum value of the power losses, followed by its constraints. Section 3 presents and describes the optimization algorithm that will solve the problem of FEVCS placement. Section 4 presents the case studies, followed by an analysis of the results obtained. Finally, in Sect.5, the conclusions are drawn.

2. **Problem formulation**

2.1. Backward/forward sweep (BFS) algorithm

The BFS algorithm is one of the most common methods used for load flow analysis used for electrical distribution system because of its simplicity, fast, and robust convergence and low memory requirement for processing with very good accuracy. The BFS algorithm involves mainly an iterative three basic steps based on Kirchhoff's current law (KCL) and Kirchhoff's voltage law (KVL). The three steps are named as the nodal current calculation, the backward sweep and the forward sweep and they are repeated until the convergence is achieved. The BFS utilises as a simple and flexible radial distribution system numbering scheme in order to numbering each branch in the feeder, lateral and sub-lateral. The BFS algorithm can be applied to find the load flow results using the following steps:

Step 1: Initialisation

Insert the follows:

- The distribution system line and load data.
- The base power and base voltage.
- Calculate the base impedance.
- Calculate the per unit values of line and load data.
- Take the voltage for all buses flat voltage (1 p.u.).
- Set convergence tolerance Є = 0.0001 and ΔVmax = 0.

Step 2: Radial distribution system numbering scheme

The numbering scheme aims to give a number to each section in the distribution system, where a section is part of a feeder, lateral or sub-lateral that connects two buses in the distribution system. The total number of sections (N_{Sec}^{Total}) of a distribution system can be calculated as:

$$N_{Sec}^{Total} = N_{bus}^{Total} - 1 \qquad (1)$$

where, N_{bus}^{Total} is the total number of buses. Each section will carry a number which is one less than its receiving end bus number, for example, the number of section that connects the sending end p and the receiving end q in Fig. 1 can be calculated as:

$$N_{Sec\,/p-q} = N_{bus\,/q} - 1 \quad (2)$$

where, $N_{Sec\,/p-q}$ is the section number between buses p and q, Nbus/q is the number of bus q.

Now, the radial distribution system numbering scheme should be applied on the distribution system to give a number to each section in the system.

Step 3: Nodal current calculation

At iteration k, the nodal current injection at node i due to loads can be calculated as:

$$I_i^{(k)} = \left(\frac{S_i}{V_i^{(k-1)}}\right)^* \qquad (3\ )$$

where, $I_i^{(k)}$ is the current injection at node i, Si is the specified power injection at node i, $V_i^{(k-1)}$ is the voltage at node i at iteration k − 1.

Step 4: Backward sweep

At iteration k, start from the branches at the end nodes and moving towards the branches connected to the substation. Hence, all branch currents can be calculated by applying the KCL and then the powers through these branches can be determined as:

$$I_L^{(k)} = -I_j^{(k)} - \sum_{m=1}^{M}\left(\frac{S_m}{V_j^{(k)}}\right)^* (4)$$

$$S_L^{(k)} = \left(V_j^k + Z_L * I_L^k\right)\ (I_L^k)^* \qquad (5)$$

where, $I_L^{(k)}$ is the current flow in branch at iteration k, $I_j^{(k)}$is the current injected due to shunt elements at bus j ,M is the number of branches connected to bus j, s_m is the complex power at the sending end of branch m, $V_j^k$is the voltage at bus j, $S_L^{(k)}$ is the power flow in branch Land Z_L is the impedance of branch L.

Step5: Forward sweep

At this iteration (k), the nodal voltages are updated in a forward sweep starting from the branches in the first section toward those in the last by applying the KVL .For a branch connected sending end p and receiving end q, the voltage at receiving end at iteration k can be calculated as:

$$V_q^{(k)} = V_p^{(k)} - Z_L * I_L^{(k)} \quad (6)$$

Where، $V_p^{(k)}$ and $V_q^{(k)}$ are the voltages at sending and receiving ends, respectively.

Step6:at the end of iteration (k) the voltage mismatches at all buses on the distribution network have been computed ،the voltage mismatches for all nodes are calculated from the following equation 7, the voltage mismatch at bus i on iteration k can be calculated as:

$$\Delta V_i^{(k)} = \left| |V_i^{(k)}| - |V_i^{(k-1)}| \right| \quad (7)$$

After calculating the voltage mismatches ،check the convergence of the voltage as:

$$\Delta V_{max} = 0$$

- If $\Delta V_i^{(k)} > \Delta V_{max}$,then make$\Delta V_{max} = \Delta V_i^{(k)}$.
- If $\Delta V_{max} \leq \epsilon$, go to step 8, otherwise increment the iteration number, and go to step3.

Step7:Check for stopping criterion

The program will be terminated when the maximum iteration is reached or the convergence from the voltage mismatches is verified.

Step8:Power loss calculation

After computing the bus voltages and branch currents using the BFS algorithm, the total active in the distribution network have been calculated from equations (8).

The steps of the BFS algorithm can be illustrated by the flowchart shown in Fig2.

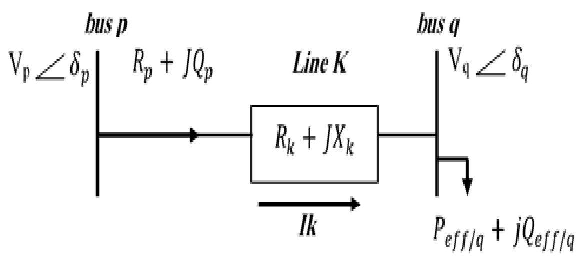

Fig.1 Representation of two nodes in a distribution system.

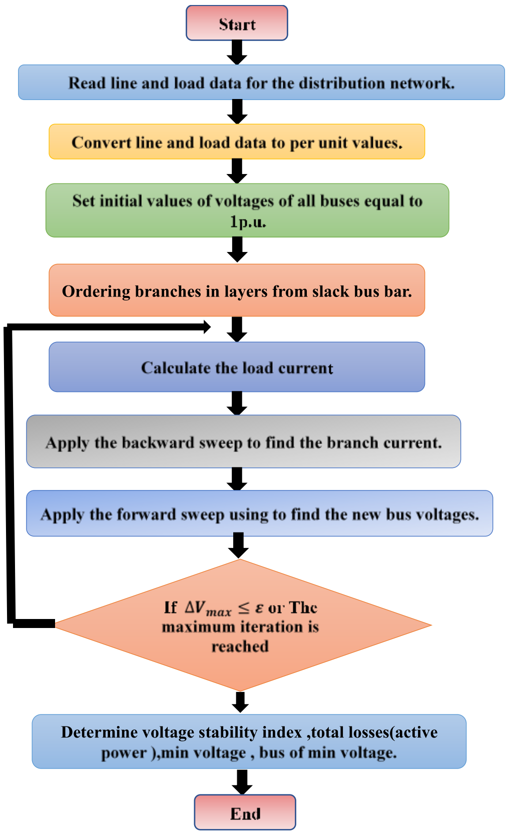

Fig.2. Flow chart of BFS load flow

2.2 Objective Function

The objective function to determine the minimum total power loss resulting from the placement of charging stations in a distribution network is given by Eq. (8)[14]:

$$f_1 = P_{loss} = \sum_{i=1}^{n} I_i^2 R_i \quad (8)$$

In Eq. (8), Ii stands for the current passing through distribution branch number i, n for the total number of branches in the distribution network, and Ri for the resistance of branch i.

The voltage deviation index is chosen as the second objective function, written as f_2. The voltage deviation index, abbreviated *VDI*, is expressed mathematically in Eq. 9 [14].

$$f_2 = \text{VDI} = \sum_{k=1}^{n} |(1 - V_k)|^2 \qquad (9)$$

V_k is the voltage at the *k*th bus. *n* is the number of buses on the networks (IEEE 33-bus test system).

The combination of two objective functions yields the overall objective function (OOF) is developed to minimize power losses, average voltage deviation. Mathematical. The OOF is presented in Eq. (3).

$$OOF = Min(w_1 f_1 + w_2 f_2) \qquad (10)$$

According to Eq. (10), each weighed coefficient (w_n) is accorded equal emphasis in the optimization problem.

2.1.2 System Constraints

Equations (11) – (14) illustrate the constraints for the optimization problem. The electric output active power from the grid is the sum of the load active power and the electric active power losses in the distribution network, as shown in Eq. (4). This configuration represents the original base scenario.

$$P_{grid} = P_L + \sum P_d \qquad (11)$$

Here the Grid power (P_{grid})). P_d is the owner demand supplied to the loads.

The prerequisite for power generation, power losses and load demand on the networks are expressed in Equations 12and 13. The basic idea of power balance is captured by both equations, which ensure that the total amount of active power produced and consumed (active power in Equation 12) and the total amount of reactive power produced and consumed (reactive power in Equation 13) in each system are equal.

$$P_{grid} + \sum P_L = P_d \qquad (12)$$

$$Q_{grid} + \sum Q_L = Q_d \qquad (13)$$

The variables in Equations 12 and 13are defined as follows: Q_L and P_L represent the reactive and real power losses in the network, respectively. The variables P_d and Q_d represent the demands for real and reactive power, correspondingly.

All the buses should have voltage limits of up to 5% to operate within the IEC 60038 margins. The bus voltage is therefore expressed in Equation 8 and applies to both IEEE 33 bus distribution network.

$$V_{min} \le V_i \le V_{max} \qquad i = 1,2,\ldots..n \qquad (14)$$

V_i represents the magnitude of voltage at the *i*th bus., n is the number of system buses.

3:-Particle Swarm Optimisation Algorithm

The PSO algorithm was created by Kennedy and Eberhart in 1995 [15]. The particle location and velocity are denoted by the notations x_i^k and v_i^k, respectively. To get the optimum answer, the current best solution is solved using the prior best solution ($pbest_{id}$). Equations 15 and 16 are utilized iteratively to improve upon the local best in order to get the global best (*gbest*) . Prior to a search, the coordinates of a single particle are stated as follows:

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}\ ,\ i = 1,2,3 \ldots.N_p,\ d = 1,2,3 \ldots.N_g \qquad (15)$$

The population is represented by N_p while the members of the population are N_g. The velocity of the particle is expressed as:

$$v_{id}^{k+1} = w \times v_{id}^{k} + C_1 \times \text{rand}(\quad) \times (pbest_{id} - x_{id}^{k}) + C_2 \times \text{rand}() \times (gbest_d - x_{id}^{k}) \qquad (16)$$

The inertia weight used in updating the particle for each iteration is calculated using the Equation 17.

$$\text{w} = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \qquad (17)$$

4. Analysis of Case Studies Results

In this section, two case studies are considered to analyse the impact of FEVCS on a distribution grid. The key aspects to be considered in each case are the FEVCS locations and the associated voltage profile on the distribution network. In the first case study is the base case that represent the behaviour of the distribution network without charging stations, while the second case study is the analysis of the impact of placing FEVCS on the distribution grid . For this analysis, the IEEE 33-bus network, as shown in Fig.3, is used. The load flow calculations were performed using backward forward sweep method . The total active power of the base case distribution network is 3715 kW, and the total reactive power is 2300 kVar, with base power values of 100 MVA and a base voltage of 12.66 kV. Without FEVCSs, the distribution network has an active power loss of 210.9876 kW. The load values associated with this network, as well as the resistance and reactance values of the lines, can be found in [16].

4.1Scenario 1:Base case distribution network Without FEVCS

In this scenario, the network without FEVCS was considered to understand its behaviour and to facilitate the interpretation of the obtained results in this research. Figure 4 shows the voltage profile, in per unit (p.u.), of the network without FEVCS, clearly showing the minimum voltage is located at bus 18, and The minimum voltage value is displayed in Table1, along with the accepted voltage limit, which is a fixed value that the minimum voltage should not reduced than it in order to comply with the regulatory limits imposed by the NP EN 50160 standard [4]. As the minimum voltage value approaches the limit, it can be concluded that the voltage drops in the distribution lines are significant, indicating that this network is highly constrained and problematic. With the placement of FEVCS that represent large load on the distribution network, due to the high power involved, there will be significant voltage drops, leading to increased losses in the network and a decrease in the minimum voltage value. Determining the optimum locations for these stations is therefore critical to minimizing voltage drops and ensuring that network values remain within regulatory limits.

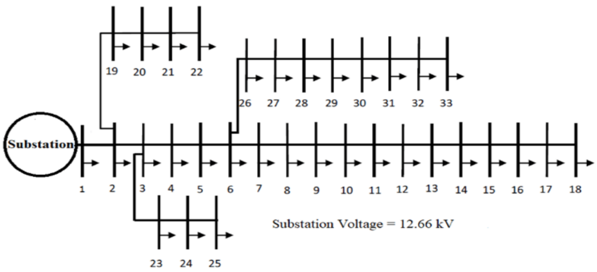

Fig.3. IEEE 33-bus network

Table 1. Characteristics of the IEEE 33-bus network: base case.

Minimum voltage (p.u.)	Accepted minimum voltage limit (p.u.)
0.9038	0.90

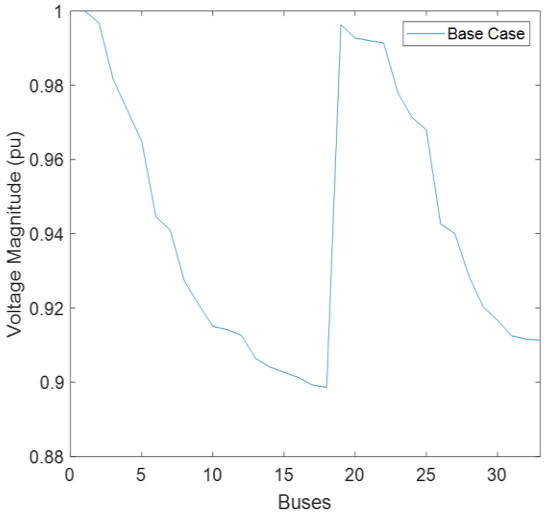

Fig.4. Voltage profile of the IEEE 33-bus network: base case.

4.2 Scenario 2: Placement of FEVCS Using Particle Swarm

In this scenario**,** it was considered that each FEVCS has a power of 100 kW, and using the PSO, the optimal locations of the charging stations are determined. In order to obtain these locations, the PSO was executed five times to find the best possible solutions. As the particle swarm algorithm is not an exact algorithm, it provides a solution that is expected to be close to optimal, so it was decided to run the algorithm 4 times, for each scenario, and then select the best solution according to the objectives set. Tables 2,3 and 4 show the results obtained considering different numbers of FEVCS to be installed. For each of the four runs, the bus location where the FEVCS is to be installed, the minimum voltage at the furthest bus, bus18, and the total power losses obtained are shown. In general, it can be observed that as the number of FEVCS increases, the losses tend to increase and the minimum voltage tends .This is due to the increase in voltage drops in the distribution lines, as the introduction of FEVCS also introduces more power associated with these stations, resulting in an increase in total power losses and a decrease in voltage .Regarding the placement of FEVCS ,it is observed that they are located near the substation as expected. These results show that in networks with a radial structure, in order for the voltage drop values to remain within regulatory limits, the closer the charging stations are to the power injection point in the network, the better the system's performance will be. Figures5,6and7show the grid voltage profile considering the installation of4,5, and 6FEVCS, respectively.

Table2.Placementof 4 FEVCS

Run	Location	Minimum voltage (p.u.)	Losses (kW)
1	2,3,20,22	0.9032	215.5484
2	2,20,23,25	0.9032	216.1584
3	2,3,5,21	0.9023	219.8361
4	3,22,23,24	0.9029	218.8381

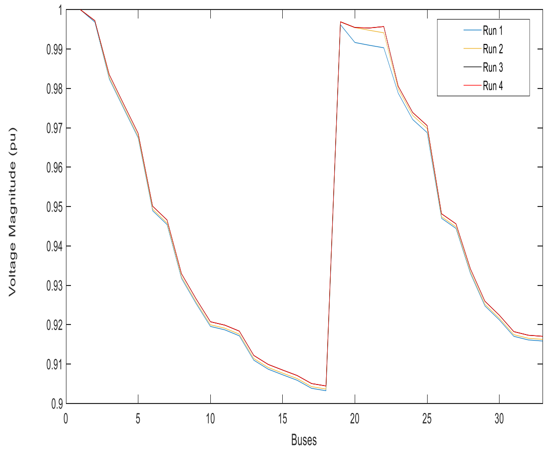

Fig.5.Voltage profile of the 4 runs with 4 FEVCS.

Table3.Placementof 5 FEVCS

Run	Location	Minimum voltage (p.u.)	Losses (kW)
1	2,3,21,24,25	0.9032	215.6706
2	2,3,5,20,25	0.9023	219.8361
3	3,19,21,22,24	0.9032	215.7774
4	2,3,22,23,25	0.9032	215.8000

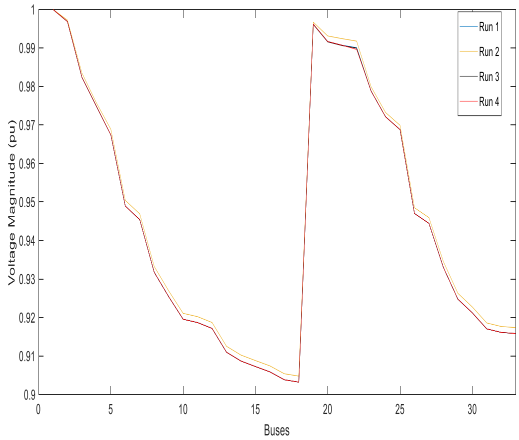

Fig.6.Voltage profile of the 5 runs with 5 FEVCS.

Table4.Placement of 6 FEVCS

Run	Location	Minimum voltage (p.u.)	Losses (kW)
1	2,3,21,23,25,28	0.9032	215.6706
2	4,5,20,21,22,23	0.9021	221.8709
3	2,5,19,24,25,26	0.9027	217.4909
4	2,3,5,8,20,22	0.9023	219.8361

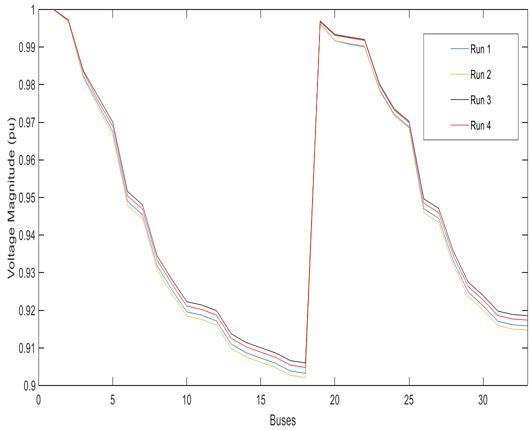

Fig.7.Voltage profile of the 4 runs with 6 FEVCS.

In Table5, the best results obtained are presented. As explained before, with the increase in the number of FEVCS, the installed power associated with these stations also increases, leading to a significant increase in voltage drops at the bus bars where the FEVCS are located. By analysing Fig.8, it is evident that different voltage profiles are generated based on the different locations considered for the charging stations. However, none of the solutions exceed the limit value. It can also be seen in Figs.9, 10 and 11that for the best runs in Table5, the FEVCS are located close to the substation. Based on the obtained results, it can be concluded that the placement of 6 FEVCS differs significantly from the cases with 4 and 5 stations.

Table 5. Best solution for each case of FEVCS number

No. of	Location	Minimum	Losses

FEVCS		**voltage(p.u.)**	**(kW)**
-	**-**	**0.9038**	**210.9876**
4	**2,3,20,22**	**0.9032**	**215.5484**
5	**2,3,21,24, 25**	**0.9032**	**215.6706**
6	**2,3,21,23, 25,28**	**0.9032**	**215.6706**

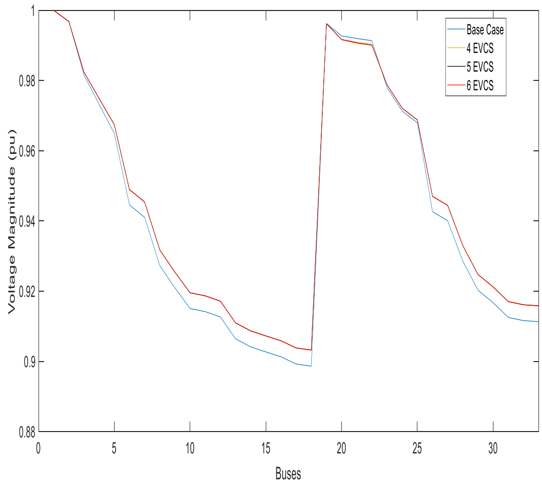

Fig.8. Best voltage profile for the 4 studied scenarios

5. Conclusion

In this article, the used methodology was developed to support the decision-making process in finding optimal locations for FEVCS. The chosen methodology was based on Particle Swarm Algorithms, which were implemented to find the optimal location of the fast electrical vehicle charging stations and to reduce their impacts on the distribution network. One of the conclusions deduced from these studies is that as the number of charging stations increases, so the load added to network increased and consequently there is a corresponding increase in voltage drops on the distribution branches, that make the minimum voltage reduced than that of the base case and also lead to higher active power losses than that of the base case. From the analysis the base case has a minimum voltage of 0.9038 pu and the active power losses of 210.9876 kW, while loading the network with four FEVCS that represent an increased loading of 10.76% leads to make minimum voltage reduced by 0.066% and the losses increased by 2.16% (0.9032 pu), but with five FEVCS connected to network that equal to 13.46% increased loading which gave minimum voltage 0.9032pu and the losses increased by 2.22% and the last analysis is made for six FEVCS connected to network which represent increased loading by 16.15% from the base case total load that make minimum voltage to be 0.9032 pu and the losses increased by 2.22% .Another conclusion from the study is that the specific locations where the charging stations are connected also have a significant impact on the results, both in terms of losses and the voltage profile of the network. It is therefore essential for distribution network operators to determine the optimal configuration to ensure the proper functioning of the network.

Future work could consider the injection of renewable energy sources into the network to mitigate the voltage drops and power losses caused by the charging stations, improving the overall performance of the distribution network.

References

1. F. Fazelpour, M. Vafaeipour, O. Rahbari, and M. A. Rosen, “Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics,” Energy Conversion and Management, vol. 77, pp. 250–261, January 2014, doi: 10.1016/j.enconman.2013.09.006.

2. International energy outlook 2011: energy information administration (EIA), office of integrated analysis and forecasting, U.S. Department of energy, Washington DC, 2011.

3. Gomes, Eduardo, Adelaide Cerveira, and José Baptista. "Optimal Location of Electric Vehicle Charging

Stations in Distribution Grids Using Genetic Algorithms." *International Conference on Optimization, Learning Algorithms and Applications*. Springer, Cham, 2024.

4. CENELEC, ”Voltage characteristics of electricity supplied by public electricity networks, 2010.” 1995, revised in 2010

5. Parah, S.A., Jamil, M.: Techniques for optimal placement of electric vehicle charging stations: a review. In: 2023 International Conference on Power, Instrumentation, Energy and Control (PIECON), pp. 1–5. IEEE (2023)

6. Anwaar, A., Ashraf, A., Bangyal, W.H.K., Iqbal, M.: Genetic algorithms: Brief review on genetic algorithms for global optimization problems. In: 2022 HumanCentered Cognitive Systems (HCCS), pp. 1–6 (2022)

7. Rajendran, A., Kumar, R.H.: Optimal placement of electric vehicle charging stations in utility grid-a case study of Kerala state highway network. In: 2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE), pp. 1–6. IEEE (2022)

8. Singh, D.K., Bohre, A.K.: Planning of EV fast charging station including DG in distribution system using optimization technique. In: 2020 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), pp. 1–6. IEEE (2020)

9. Altundogan, T.G., Yildiz, A., Karakose, E.: Genetic algorithm approach based on graph theory for location optimization of electric vehicle charging stations. In: Innovations in Intelligent Systems and Applications Conference (ASYU), pp. 1–5. IEEE 2021 (2021)

10. Cerveira, A., Baptista, J., Pires, E.: Wind farm distribution network optimization. Integr. Comput. Aid. Eng. 23(1), 69–79 (2016)

11. Cerveira, A., Baptista, J., Solteiro Pires, E.J.: Optimization design in wind farm distribution network. In: Herrero, ´ A., et al. (Eds.) International Joint Conference SOCO 2013-CISIS 2013-ICEUTE 2013. AISC, vol. 239, pp. 109–119. Springer, Cham (2014). https://doi.org/10.1007/978-3-319-01854-6 12

12. Ahmad, F., Iqbal, A., Ashraf, I., Marzband, M., Khan, I.: Placement of electric vehicle fast charging stations using grey wolf optimization in electrical distribution network. In: 2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE), pp. 1–6. IEEE (2022)

13. Ahmad, F., Ashraf, I., Iqbal, A., Khan, I., Marzband, M.: Optimal location and energy management strategy for EV fast charging station with integration of renewable energy sources. In: IEEE Silchar Subsection Conference (SILCON), pp. 1–6. IEEE 2022 (2022)

14. Shuaibu A, Sun Y, Wang Z. Multi-objective for optimal placement and sizing DG units in reducing loss of power and enhancing voltage profile using BPSO-SLFA. Energy Reports [Internet]. 2020;6:1581–9. Available from: https://doi.org/10.1016/j.egyr.2020.06.013

15. Okwu MO, Tartibu LK. Particle Swarm Optimisation. Studies in Computational Intelligence. 2021;927:5–13.

16. M. Z. Zeb et al., “Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network,” IEEE Access, vol. 8, pp. 68124–68134, 2020, doi: 10.1109/ACCESS.2020.2984127.