Electric Power Systems Research 214 (2023) 108868

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Application of AOA algorithm for optimal placement of electric vehicle charging station to minimize line losses

K. Kathiravan, P.N. Rajnarayanan *

Department of Electrical and Electronics Engg., Theni Kammavar Sangam College of Technology, Koduvilarpatti P.O, Theni Dt, Tamilnadu, India

ARTICLE INFO

Keywords:
Integrated electric vehicle charging station with distributed generation
Loss sensitivity factor
Real power loss
Arithmetic optimization algorithm
Radial network

ABSTRACT

The conventional transportation system uses fossil fuels and it emits greenhouse gases which affect the environment. A new kind of transportation must be created immediately because of the growing population. Electric Vehicles (EVs) have less impact on environmental pollution and they will become the base for future transport systems. The battery's specific energy is very low and it needs frequent charging. The long-distance transportation using EVs needs charging stations and it leads to placing Electric Vehicle Charging Station (EVCS) in the power grid. The placement of EVCS in the grid increases network losses which have an adverse impact on the grid. In this research work, network loss minimization by the optimum placement of EVCS along with Distributed Generation (DG) is considered. The proposed approach has been validated on the IEEE 33 bus system. The analysis was carried out using the Loss Sensitivity Factor (LSF) approach considering the variable network parameters in the Radial Distribution Network (RDN). The EVCS optimal placement was resolved by Arithmetic Optimization Algorithm (AOA). The results are compared with Particle Swarm Optimization (PSO) and Harris Hawks Optimization (HHO) approaches. The findings show that the optimal placement of EVCS along with DGs reduces network losses considerably.

1. Introduction

The excessive use of conventional vehicles has an adverse impact on the environment since it causes a significant rise in temperature and emits CO2. It leads to global warming and affects the ecological system. The majority of people in the world commute using gasoline-powered vehicles [1]. An alternative mode of transportation is encouraged by a number of issues, including rising oil prices and environmental pollution. The usage of EVs will save fossil fuels and reduces the problems associated with the conventional transportation system [2]. To reduce pollution, a lot of nations throughout the world are switching to battery-powered transportation. For the purpose of battery charging, EVs are in need to connect to the power network. The rapid growth of EVs is posing considerable challenges in grid operations. Additionally, as more EVs are produced, more dependable electric vehicle charging station (EVCS) systems are needed. The connection of EVs to the grid increases the system load and affects the generation-demand balance. The inappropriate placement of charging stations leads to voltage fluctuations, greater power loss, and harmonics, which might all severely affect the power grid's capacity to operate smoothly [3].

The perfect location for connecting EVCS and its load demand on the grid have both grown in importance as research topics during the past decade [4]. Taking into account the accessibility of charging stations and the comfort of drivers, the EVCS placement problem was formulated. The advantages of EVCS distribution on various buses are discussed. The arrangement of different types of EVCS and optimizing the size of industrial and residential entities, offices, and houses within the grid were discussed in [5]. The authors employed the Particle swarm optimization (PSO) algorithm. Additionally, parking restrictions due to geography were taken into account while modelling the ambiguous behaviour of the vehicle owner using probability distributions fitted on actual data. Various EV scenarios and charge management techniques are used to study the impact of EVs on electricity distribution systems [6]. Three sorts of EV charge management techniques are presented. The importance of centralized EV charge control, which calls for a strong communications network, is emphasized. The subject of decentralized charge control, which requires less communication, is then covered. Also investigated is communication-free, autonomous EV charge control. An analysis of the effects of placing the EVCS was reported in [7]. The IEEE 33 bus system was considered a test system. To maintain

* Corresponding author.
E-mail addresses: rndkathiravan@gmail.com (K. Kathiravan), pnrajnarayanan@gmail.com (P.N. Rajnarayanan).

https://doi.org/10.1016/j.epsr.2022.108868
Received 1 July 2022; Received in revised form 19 September 2022; Accepted 4 October 2022
Available online 29 October 2022
0378-7796/

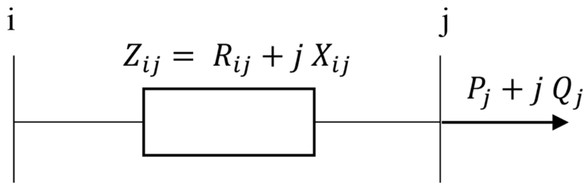

Fig 1. Equivalent circuit.

constant voltage, the authors suggest using a distributed generation (DG) system with E-bus charging. The Newton-Raphson method was used to compute the power flow, and the voltage deviation index was used to determine the size and placement of the DG. A comprehensive study on several techniques utilized to address the placement and sizing issues with EVCS was provided in [8]. The application of Genetic Algorithm (GA), PSO, and Integer Programming (IP) methods to solve the optimization problem was elaborated. The quick and effective method for the location of EVCS was reported in [9]. The optimization problem is formed as combinatorial optimization with the objective of minimizing the location for EVCS placement. The optimization based on integer linear programming is considered. A method for placement and sizing an EVCS based on grid partition was discussed in [10]. Traffic density and charging station capacity restrictions are the key considerations. The optimization mechanism used is the genetic algorithm (GA). For finding the suitable placement for EVCS, minimization of real power loss was chosen as an objective function and the PSO method was used to solve it [11]. The allocation of Distributed Generations (DG) was optimized using the PSO method in [12]. The DG optimal placement, sizing, and contract pricing may all be determined simultaneously and the problem formulated as a multi-objective optimization problem.

From the literature review, it is found that the integration of a DG along with EVCS into the optimal node has not been discussed. Connecting the DG-powered EVCS in the same location of a distribution network provides better reliability in operation and autonomous operation is also possible and no need to depend on other distributed power producers in some other location as well as power Grid.

This research demonstrates a unique method for placing integrated EVCS-DG. For the validation of the results, the IEEE 33 bus system is considered. In order to determine the best location for EVCS placement with regard to equality and inequality constraints on the buses, the AOA approach is employed for finding suitable buses for integrated EVCS-DG. The results are compared with other approaches reported in the literature.

2. Problem formulation

For any power system network, line loss minimization is the main objective function. The primary goals of this research work are to reduce the real power loss, first by optimal placement of EVCS and integrating EVCS with DG. The fitness function is taken into account to minimize overall active power losses given by

$$Min\ P_{Loss} = \sum_{i=1}^{N_B} I_i^2 R_i \tag{1}$$

where,

N_B- Number of buses in the system

2.1. Equality constraints

Power flow equations serve as equality constraints, which look for a set of voltages that satisfy the system requirements.

$$0 = P_i - V_i \sum_{j\in N_i} V_j\left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right),\ i \in\ N_{B-1} \tag{2}$$

$$0 = Q_i - V_i \sum_{j\in N_i} V_j\left(G_{ij}cos\theta_{ij} - B_{ij}sin\theta_{ij}\right),\ i \in\ N_{PQ} \tag{3}$$

where,

N_{PQ}- Number of load buses in the system

The grid-supplied electric energy, as well as that from connected DGs and EVs, should be sufficient to meet system losses and load demands.

$$P_{Grid} + \sum_{i=1}^{N} P_{DGi} = P_{loss} + \sum_{i=1}^{N}\left(P_{Load\ i} + P_{EVCS\ i}\right) \tag{4}$$

2.2. Inequality constraints

2.2.1. Voltage limit

Bus voltage constraints are intended to keep buses running within specified per unit voltage limits.

$$V_i^{min}\ \le\ V_i\ \le\ V_i^{max},\ i\ \in\ N_B \tag{5}$$

2.2.2. DG power limit

The DGs are designed to operate within the power limits.

$$P_{DGi}^{min}\ \le P_{DGi} \le\ P_{DGi}^{max} \tag{6}$$

2.2.3. Battery SoC limit

To prevent battery deterioration, EV batteries' State-of-Charge (SoC) are to be kept within the bounded limits.

$$EV_{SoC}^{min} \le EV_{SoC} \le EV_{SoC}^{max} \tag{7}$$

2.3. Loss sensitivity factor approach

In this research work, candidate buses for the installation of EVs are identified using LSF procedure. By adopting LSF, the search area is significantly reduced, as is the amount of time needed for optimization [13]. The power network line "l" connected to the buses "i" and 'j" and the equivalent circuit of distribution system is represented in Fig. 1.

The system line losses is given by

$$P_{loss} = \frac{\left(P_j^2 + Q_j^2\right)R_{ij}}{V_j^2} \tag{8}$$

$$Q_{loss} = \frac{\left(P_j^2 + Q_j^2\right)X_{ij}}{V_j^2} \tag{9}$$

The LSF can be determined from

$$\frac{\partial P_{loss}}{\partial Q_j} = \frac{2Q_j{}^*\ R_{ij}}{V_j^2} \tag{10}$$

$$\frac{\partial Q_{loss}}{\partial Q_j} = \frac{2Q_j{}^*\ X_{ij}}{V_j^2} \tag{11}$$

The LSF values are obtained by running power flow and which are rearranged for all transmission lines in descending order. The base case voltages are then divided by 0.95 to get normalised voltages. These voltages can be considered potential candidate buses for placing EVs if their values are less than 1.01 [14].

3. Arithmetic optimization algorithm

The initial search points of population-based algorithms are

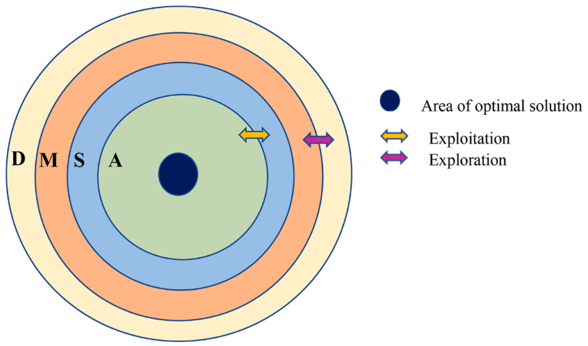

Fig 2. Arithmetic operators hierarchical order.

generated randomly. The core of optimization methods is the gradual improvement of this created set of solutions by a set of optimization rules and iterative evaluation by a particular objective function. Due to its stochastic nature, the population-based algorithms will not provide the solution in a single run [15]. The population-based optimization process involves two basic stages: exploration and exploitation. In the first stage, local solutions are avoided by deploying search agents that cover a large portion of the search field. The latter is an enhancement in the precision of the answers discovered during the first stage.

The AOA is a method that is based on the concepts of contemporary mathematics, geometry, and algebra and is inspired by the distribution behaviour of the primary math operators. The four basic math operations such as, addition, subtraction, multiplication, and division are used in arithmetic to explore numerical techniques used in mathematical optimization to solve any problem. The exploration vs exploitation mechanism using the basic arithmetic operators: Addition (A, "+"), Subtraction (S, "-"), Multiplication (M, " × ") and Division (D, "÷") [16] are shown in Fig. 2.

3.1. Initial population generation

The initial population, $X_{i,j}$ is created using the Eq. (12)

$$X_{i,j} = ((ub - lb) \times rand) + lb \tag{12}$$

where,

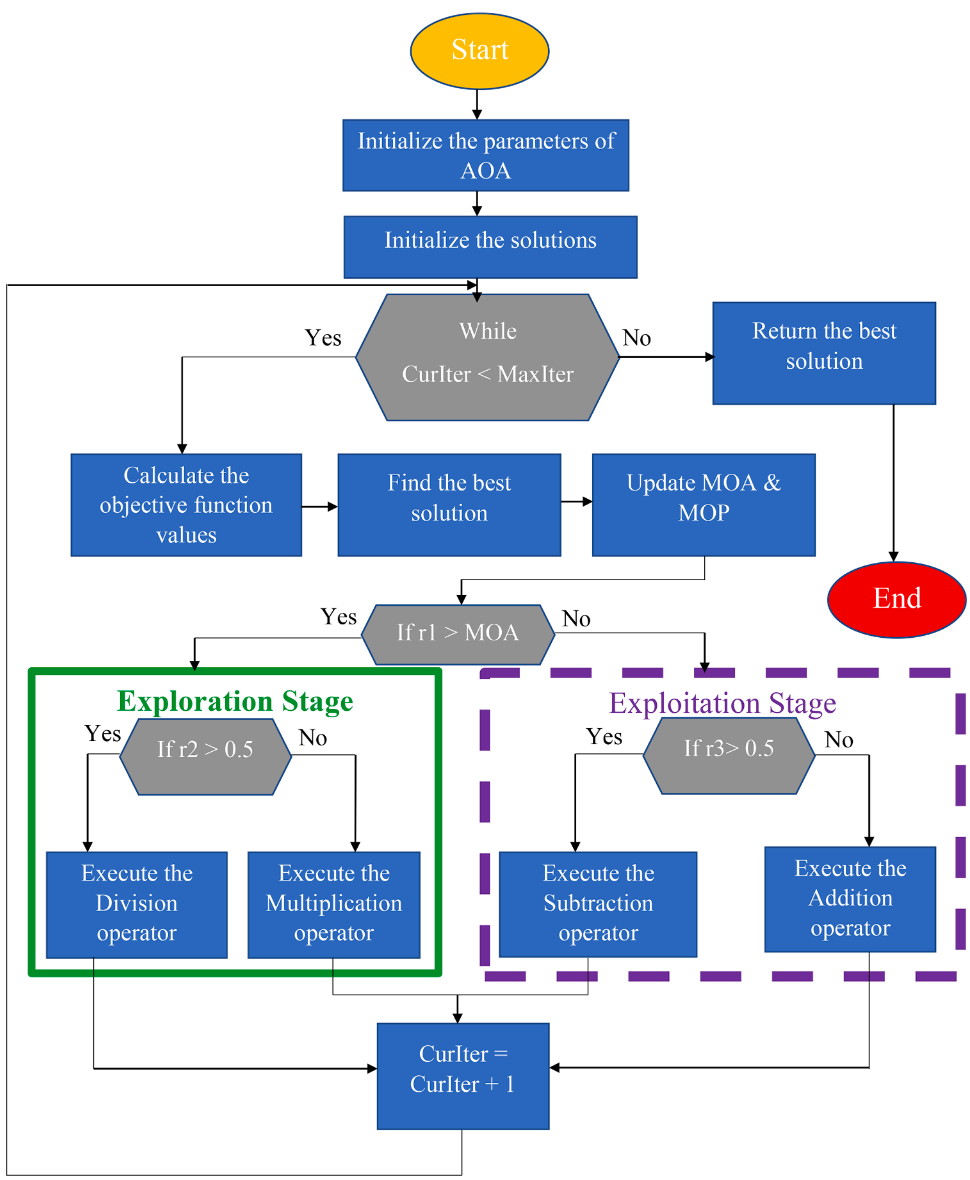

Fig. 3. Flowchart of AOA.

Table 1
Parameters of IEEE 33 radial distribution bus network.

Parameters	Value
Base MVA	100
Base voltage in kV	12.66
Real power load in kW	3715
Reactive power load in kVAR	2300
Initial power loss in kW	255

X – population
i - i^{th} individual in the initial population
j – dimension of the problem.

The Eq. (11) determines the values of individuals i in dimension j. To cover more ground in the search space, the first population is created using random numbers (rand) in the [0 1] range. The distribution of individuals throughout the search space is made possible by multiplying them by the difference between the bounds [16].

The AOA should choose the search stage before it begins to work. A coefficient calculated using Math Optimizer Accelerated (MOA) function is used in the search i.e. exploration and exploitation stages.

$$MOA\ (Iter) = Min + CurIter\ \times\ \left(\frac{Max - Min}{MaxIter}\right) \tag{13}$$

where,

CurIter- Current iteration starting with a value of 1 and going up to MaxIter
MaxIter- Maximum number of iterations
Min, Max- Represents operating limits.

3.2. Exploration stage

Here, two primary search methods (Division (D) search strategy and Multiplication search strategy), which are modelled in Eq. (14), are used by the exploration operators of AOA to randomly explore the number of regions as well as attempt to find an improved solution [16]. However, due to their high dispersion, operators D & M cannot easily reach the target. The MOA function in Eq. (14) conditions this stage of the search i.e. executing D or M on the fact that r1 > MOA (r1 is a random number).

$$X_{i,j}(Iter+1) = \begin{cases} best(x_j) \div (MOP+ \in) \times \left((ub_j - lb_j) \times \mu + lb_j\right), & r2 < 0.5 \\ best(x_j) \times MOP \times \left((ub_j - lb_j) \times \mu + lb_j\right), & r2 > 0.5 \end{cases} \tag{14}$$

where,

$X_{i,j}$ (iter+1)- i^{th} solution in the next iteration
best(x_j)- j^{th} position of the improved solution
$\in$ *and* μ- integer number and control parameter

In this stage, the primary operator “D” is conditioned by r2 < 0.5, and the secondary operator “M” will be disregarded until the first operator completes its present task. Here, Math Optimizer Probability (MOP) is a coefficient and is defined in eq, (15)

$$MOP\ (Iter) = 1 - \frac{CurIter^{\frac{1}{\alpha}}}{MaxIter^{\frac{1}{\alpha}}} \tag{15}$$

where,

∝- sensitivity parameter

Table 2
Load ratings of various cases of IEEE 33 bus system.

Case No	Detail	Active Power (kW)	Reactive Power (kVAR)
1	Case 1 - Base Load	3715	2300
2	Case 2 – Increase in load	3900	2430
3	Case 3 – Increase in load	4105	2580
4	Case 4 – Increase in load	4230	2680
5	Case 5 – EVCS as load	4735	2295
6	Case 6 - EVCS along with DG	4735	2295

Table 3
Voltage and DG power limits.

Parameter	Minimum Limit	Maximum Limit
Voltage in p.u	0.95	1.1
DG 1 Power in kW	240	528
DG 2 Power in kW	150	330
DG 3 Power in kW	220	484
DG 4 Power in kW	250	550

Table 4
Parameters for AOA.

Parameter	Value
Control Parameter (μ)	0.5
Sensitive Parameter (α)	5
Maximum Iteration	200

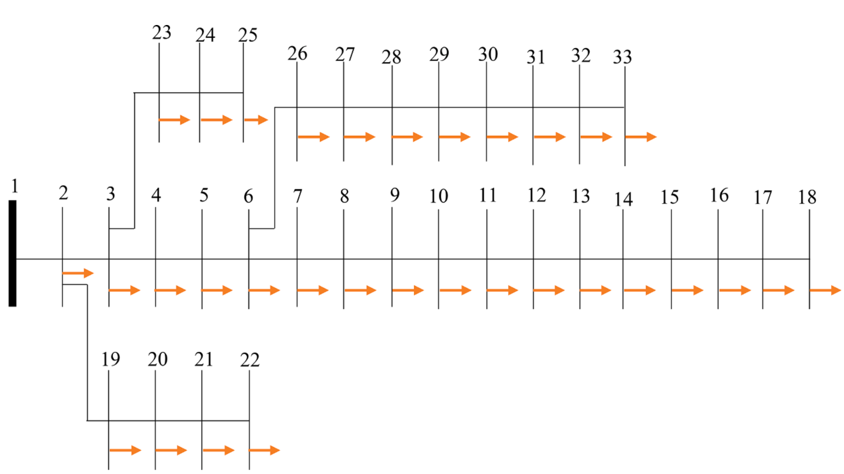

Fig. 4. One-line diagram of IEEE 33 bus system.

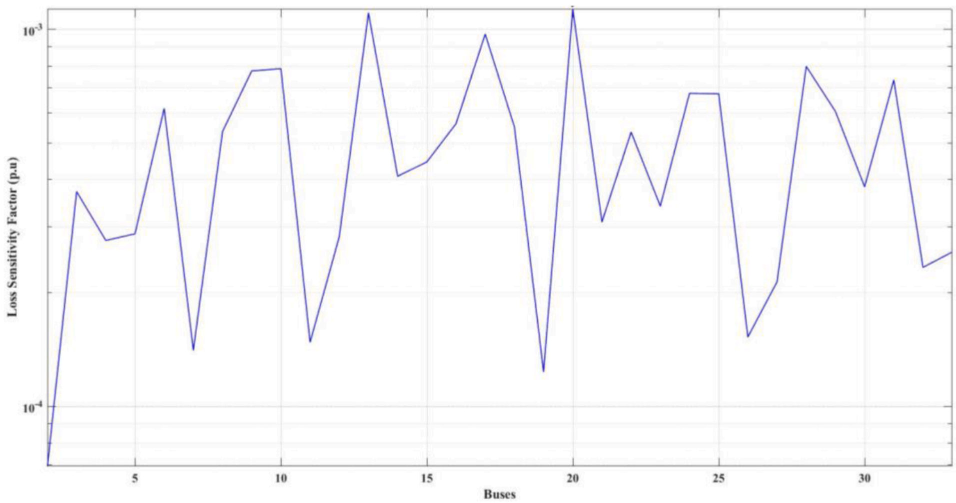

Fig 5. LSF values for IEEE 33 radial distribution bus network.

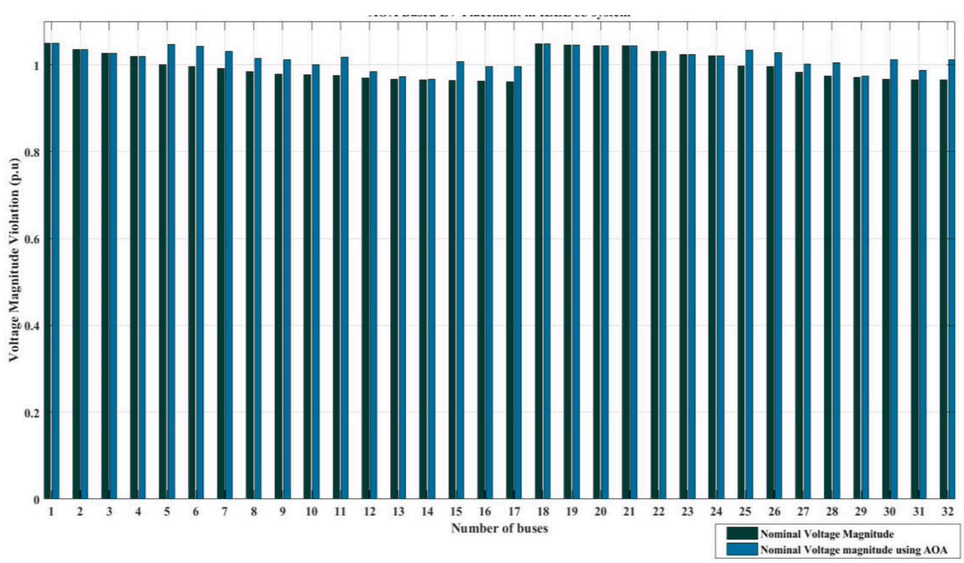

Fig 6. Nominal voltage levels of all buses except slack bus.

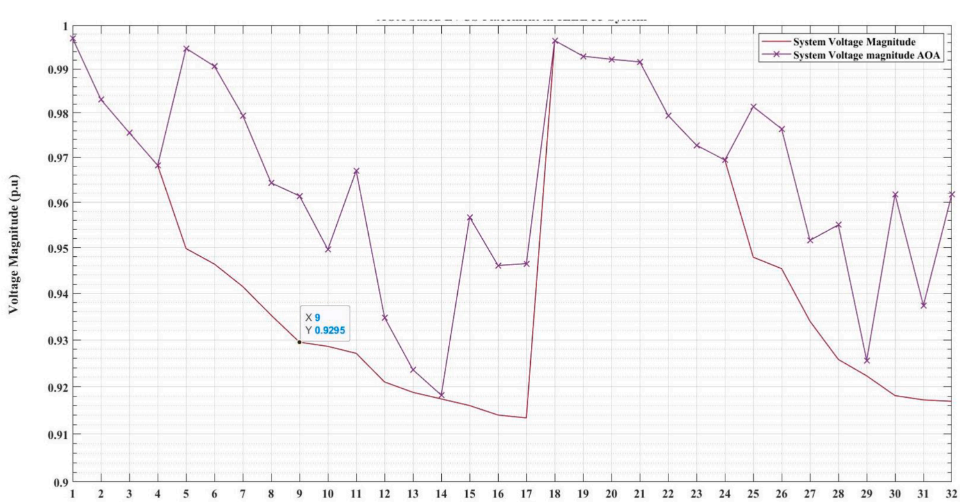

Fig. 7. System voltage levels of all buses except slack bus.

Table 5
Values of Bus Voltages for Different Cases.

Bus No	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
1	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
2	1.00045	1.00029	1.00009	0.99998	0.99978	1.00089
3	0.98638	0.98558	0.98437	0.98376	0.98214	0.98919
4	0.97891	0.97770	0.97585	0.97489	0.97203	0.98346
5	0.97152	0.96990	0.96747	0.96613	0.96189	0.97790
6	0.95314	0.95044	0.94655	0.94425	0.93754	0.96348
7	0.94963	0.94671	0.94249	0.93980	0.93376	0.96021
8	0.93603	0.93221	0.92660	0.92292	0.91813	0.94849
9	0.92972	0.92537	0.91894	0.91485	0.91170	0.94227
10	0.92387	0.91899	0.91199	0.90749	0.90573	0.93650
11	0.92301	0.91804	0.91096	0.90642	0.90484	0.93565
12	0.92150	0.91646	0.90922	0.90459	0.90330	0.93416
13	0.91535	0.90995	0.90190	0.89687	0.89703	0.92809
14	0.91307	0.90751	0.89926	0.89403	0.89470	0.92585
15	0.91165	0.90594	0.89752	0.89213	0.89325	0.92445
16	0.91027	0.90440	0.89578	0.89038	0.89185	0.92309
17	0.90823	0.90234	0.89329	0.88787	0.88976	0.92108
18	0.90762	0.90173	0.89249	0.88706	0.88914	0.92048
19	0.99992	0.99974	0.99955	0.99938	0.99925	1.00037
20	0.99636	0.99599	0.99580	0.99518	0.99568	0.99680
21	0.99566	0.99529	0.99510	0.99434	0.99498	0.99610
22	0.99502	0.99466	0.99446	0.99360	0.99435	0.99547
23	0.98281	0.98190	0.98054	0.97993	0.97855	0.98563
24	0.97616	0.97504	0.97335	0.97275	0.97187	0.97900
25	0.97285	0.97173	0.96972	0.96911	0.96855	0.97570
26	0.95122	0.94843	0.94438	0.94205	0.93481	0.96208
27	0.94867	0.94576	0.94149	0.93915	0.93160	0.95989
28	0.93728	0.93377	0.92853	0.92616	0.91998	0.94864
29	0.92909	0.92524	0.91927	0.91687	0.91164	0.94055
30	0.92555	0.92152	0.91518	0.91276	0.90803	0.93705
31	0.92140	0.91696	0.91038	0.90796	0.90380	0.93296
32	0.92049	0.91591	0.90925	0.90683	0.90287	0.93206
33	0.92021	0.91562	0.90888	0.90645	0.90258	0.93178

3.3. Exploitation stage

The mathematical calculations utilising either addition “A” or subtraction “S” produced highly dense results during the exploitation process. Due to their low dispersion values, the subtraction “S” and addition “A” operators can quickly reach the target. When searching for a better solution, the exploitation operators “S & A” thoroughly examine a number of dense locations in the search area [16]. The exploitation search process is conditioned by the fact the r1 value is not higher than the curIter value of MOA. The exploitation strategy is given in Eq. (16)

$$X_{i,j}(Iter+1) = \begin{cases} best(x_j) - MOP \times ((ub_j - lb_j) \times \mu + lb_j), & r3 < 0.5 \\ best(x_j) + MOP \times ((ub_j - lb_j) \times \mu + lb_j), & r3 > 0.5 \end{cases} \tag{16}$$

The operator (A) will not be considered until the first operator (S) in this stage completes its present task, which is conditioned by r3 < 0.5. The process of AOA is given in Fig. 3.

4. Experimental results

This suggested approach is evaluated for the appropriate EVCS placement on the IEEE 33 bus radial distribution system. The LSF for all buses are calculated with six different load levels, system voltage and the nominal voltages are obtained. The simulation was performed in MATLAB-R2021a software.

4.1. IEEE 33 radial distribution bus network

It consists of 33 buses including slack bus and 32 transmission lines and the system’s bus data, line data, and load flow solution are obtained from [17]. The details of various parameters are given in Table 1. The one-line diagram is given in Fig. 4.

The load ratings for different cases are given in Table 2 and the voltage and DG power limits are given in Table 3. The instantaneous EVCS load values are 300 kW, 150 kW, 250 kW, and 320 kW. The SoC minimum and maximum limits are 0.2 and 0.9 p.u respectively.

4.2. Parameters for AOA

The chosen values of various parameters in AOA algorithm [17] are given in Table 4.

4.3. Result analysis

The LSF values for all the buses of IEEE 33 bus system are calculated and given in Fig. 5.

The nominal voltages and system voltages for all buses except slack bus are shown in Fig 6 and Fig. 7. It is clearly seen that, both system

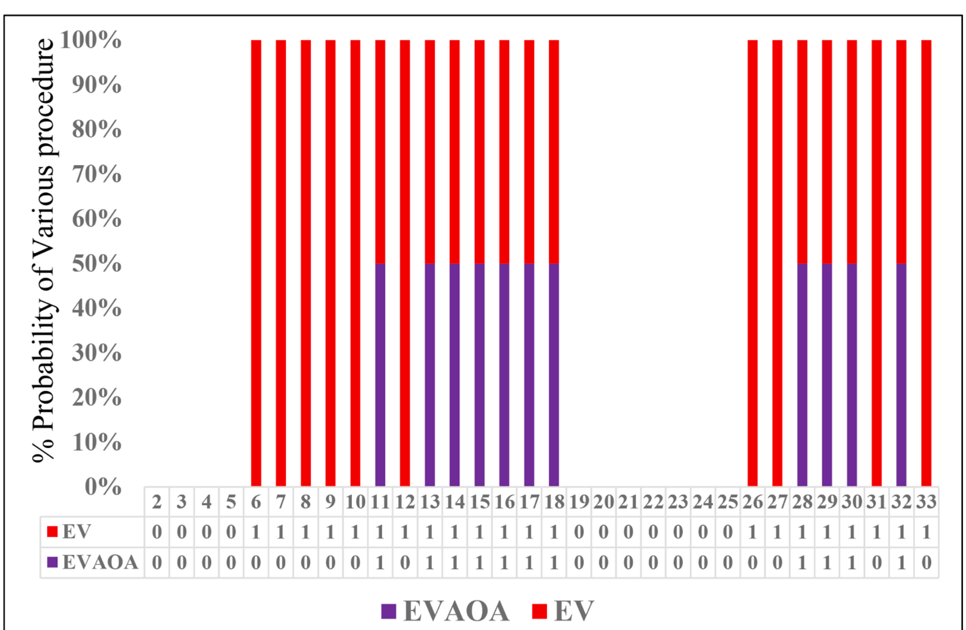

Fig 8. Probability of EVCS location.

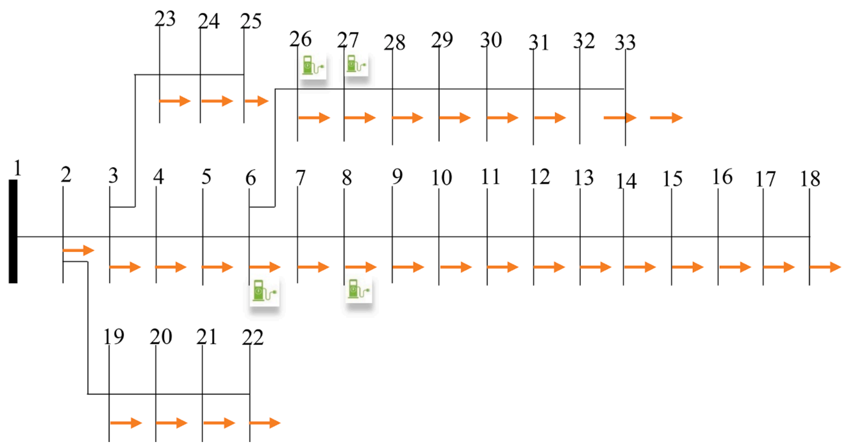

Fig 9. EVCS placement on IEEE 33 bus system.

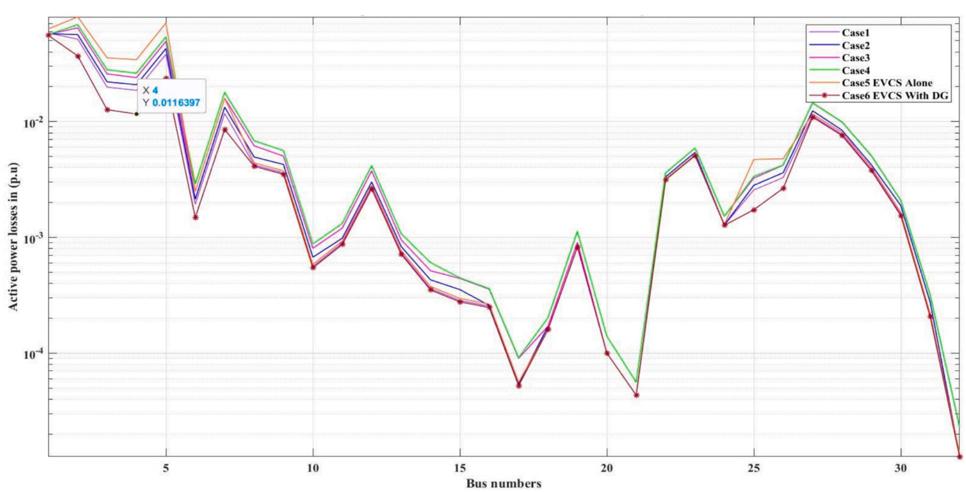

Fig. 10. Comparison of active power losses of all buses for different load cases.

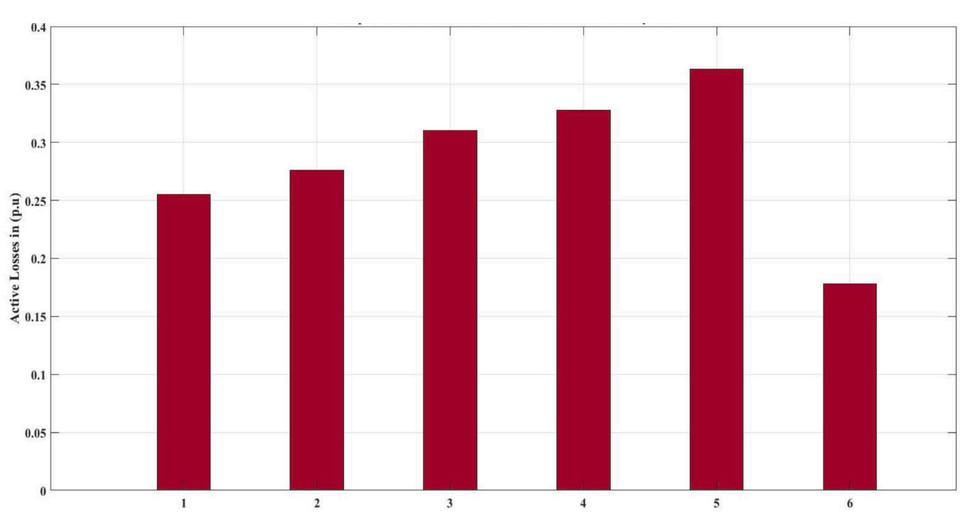

Fig 11. Comparison of active power losses of different cases.

voltage and nominal voltage profiles are increased in AOA approach than the conventional approach.

The bus voltage values for different cases are given in Table 5. It is clearly seen that, whenever EVs are placed along with DGs, the system voltage profile has been increasing considerably.

Based on LSF values, the location for where to place the EVCS is identified. By employing the AOA approach, more buses were identified for placing EVCS (6, 7, 8, 9, 10, 12, 26, 27, 31 & 33) and are given in Fig. 8. The probability analysis was performed and, it is evident that buses 6, 8, 26, and 27 were selected to place the EVCS, and it is shown in

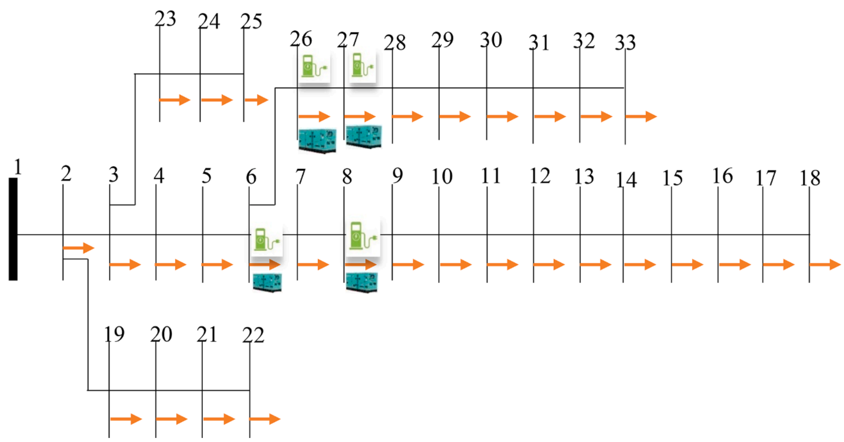

Fig 12. Placement of DGs along with EVCS of IEEE 33 bus system.

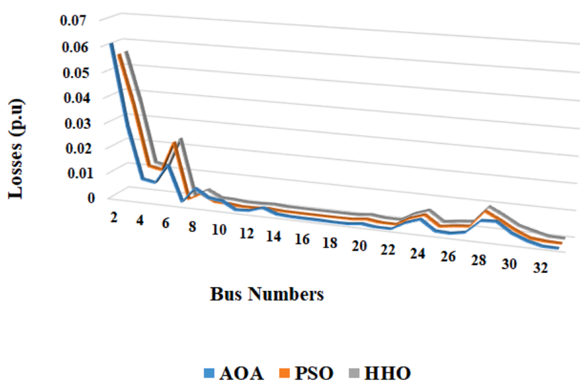

Fig 13. Comparison of Individual buses loss using PSO, HHO and AOA methods.

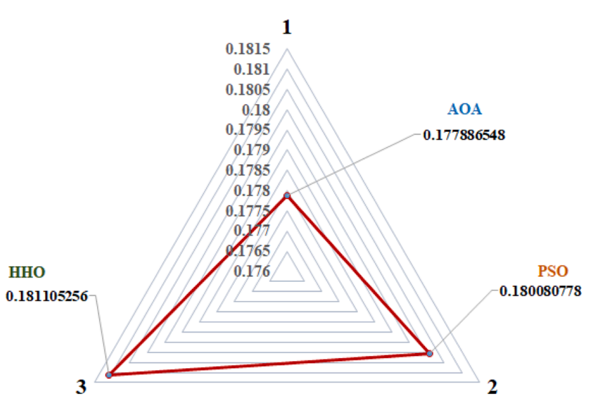

Fig. 14. Comparison of real power loss by PSO, HHO and AOA methods.

Fig. 9.

For analysis, different cases of loads are considered and the line losses of all the buses are calculated and shown in Fig. 10.

The active power losses for all cases are determined and shown in Fig. 11. Case 1 is considered a base case load and cases 2, 3, and 4 are increasing in percentage of loads. In case 5, the EVCS is placed at the optimal bus and is considered as an additional load, so the losses are increased by 30% more than in case 1. In case 6, the EVCS are placed at suitable buses along with DGs. From Fig. 11, it is implied that, whenever the EVs are placed along with DGs, the system active power losses are considerably minimized. The placement of DGs along with EVCS reduces the real power losses by 51% more than in case 5 and 30% more than in case 1.

The DGs are placed along with EVCS at buses 6,8, 26 & 27 determined by the AOA approach and given in Fig. 12.

4.4. Comparison of results

The placement of EVCS using meta-heuristic techniques is reported in [18]. The authors proposed the PSO approach and Harris Hawks Optimization (HHO) for finding the buses for placing EVCS in IEEE 33 bus system. Buses 7, 12, 17, and 31 were selected for placing the EVCS [18]. The PSO and HHO methods were implemented. For comparing the results of the proposed AOA approach, the DGs are placed on buses 7, 12, 17, and 31 and the loss values for all the buses are calculated and given in Fig. 13.

The total real power losses of the IEEE 33 bus system are calculated using PSO, HHO, and AOA methods and represented in Fig. 14. Obviously, the AOA method reduces the line losses by approximately 2% more than PSO and HHO methods. The AOA method took 0.46 s to find the optimal solution, whereas PSO took 0.55 s and HHO took 0.58 s. The AOA method finds the optimal solution with less computation time than the PSO and HHO methods.

5. Conclusion

Electric vehicles are the only option to reduce the pollution caused due to transportation. The inappropriate connection of EVCS creates the effect on network losses as well as voltage profile. This research work proposed a new technique to identify the location for placing the integrated EVCS-DG. The LSF approach is employed. The AOA approach was chosen for the optimal placement of EVCS. For analysis, six different load profiles were taken into consideration. The AOA approach identifies a greater number of buses for placing the EVCS than the conventional Approach. The probability analysis gives the best possible location of the buses (bus 6, 8, 26, and 27) for the optimal placement of EVCS. From the experimental results, it is found that, whenever the EVCS is added to the system as a load, it will increase the system losses. To minimize the losses, EVCS is integrated with DGs. If the EVCS is integrated along with DGs, the line losses are reduced considerably and it enhances the voltage profile of the system also. It is evident that the placement of DGs reduces the line losses almost by 1/3rd of system initial losses and reduces 51% of loss when the EVCS alone are placed on the system. The results are compared with the PSO and HHO methods and it is concluded that the AOA approach reduces the line losses considerably when EVCS is placed along with DGs. This research work is further extended with power management along with EV patterns for 24 h horizons such as Grid to Vehicle and Vehicle to Grid by integrating renewable energy sources like solar, wind, etc. along with EVCS in the same node.

Authorship statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the *Electric Power System Research*.

CRediT authorship contribution statement

Conception and design of study: **K Kathiravan;** acquisition of data: **P.N Rajnarayanan;** analysis and/or interpretation of data: **K. Kathiravan & P.N. Rajnarayanan.**

Drafting the manuscript: **P.N. Rajnarayanan;** revising the manuscript critically for important intellectual content: **K. Kathiravan**

Declaration of Competing Interest

We have no conflicts of interest to disclose.

Data availability

Data will be made available on request.

Acknowledgements

All persons who have made substantial contributions to the work reported in the manuscript (e.g., technical help, writing and editing assistance, general support), but who do not meet the criteria for authorship, are named in the Acknowledgements and have given us their written permission to be named. If we have not included an Acknowledgements, then that indicates that we have not received substantial contributions from non-authors.

References

[1] S. Deb, K. Tammi, K. Kalita, P. Mahanta, Impact of electric vehicle charging station load on distribution network, Energies Multidisciplinary Digital Publishing Institute 11 (1) (2018) 01–25, no, 178.
[2] Z. Liu, F. Wen, G. Ledwich, Optimal planning of electric-vehicle charging stations in distribution systems, IEEE Trans. Power Delivery 28 (1) (2013) 102–110.
[3] S. Deb, K. Kalita, P. Mahanta, Review of impact of electric vehicle charging station on the power grid, Int. Conf. Advance. Power Energy (2017) 01–06.
[4] A.Y. Lam, Y.W. Leung, X. Chu, Electric vehicle charging station placement: formulation, complexity, and solutions, IEEE Trans. Smart Grid 05 (06) (2014) 2846–2856.
[5] M.Z. Zeb, K. Imran, A. Khattak, A.K. Janjua, A. Pal, M. Nadeem, S. Khan, Optimal placement of electric vehicle charging stations in the active distribution network, IEEE Access 8 (2020) 68124–68134.
[6] S. Faddel, A. Al-Awami, O. Mohammed, Charge control and operation of electric vehicles in power grids: a review, MDPI (Energies) 11 (4) (2018) 701–714.
[7] T. Boonraksa, A. Paudel, P. Dawan, B. Marungsri, Impact of electric bus charging on the power distribution system-a case study IEEE 33 bus test system, in: IEEE PES GICEA, GTD Asia, 2019, pp. 819–823.
[8] M.M. Islam, H. Shareef, A. Mohamed, A review of techniques for optimal placement and sizing of electric vehicle charging stations, Przegl. Elektrotech. 91 (8) (2015) 122–126.
[9] M. Zoran, R. Vladan, L. Budimir, Efficient placement of electric vehicles charging stations using integer linear programming, AECE 18 (2) (2018) 11–16.
[10] S. Ge, L. Feng, H. Liu, The planning of electric vehicle charging station based on Grid partition method, in: International Conference on Electrical and Control Engineering, Yichang, China 6057636, 2011, pp. 2726–2730, https://doi.org/10.1109/ICECENG.2011.
[11] M.S.K. Reddy, K. Selvajyothi, Optimal placement of electric vehicle charging station for unbalanced radial distribution systems, Taylor Francis-Energy Sources (Part A: R,U,and E effect (2020) 1–15.
[12] A. Ameli, S. Bahrami, F. Khazaeli, S. Haghifam, A multi-objective particle swarm optimization for sizing and placement of DGs from DG owner's and distribution company's viewpoints, IEEE Trans. Power Deliv. 29 (4) (2014) 1831–1840.
[13] A.Y. Abdelaziz, E.S. Ali, S.M. Abdul Elazim, Flower Pollination Algorithm and Loss Sensitivity Factors for optimal sizing and placement of capacitors in radial distribution systems, Int. J. Electr. Power Energy Syst. 78 (2016) 207–214.
[14] P. Das, S. Banerjee, Optimal sizing and placement of capacitor in a radial distribution system using loss sensitivity factor and firefly algorithm, IJECS 3 (4) (2014) 5346–5352.
[15] S. Mirjali, SCA-A sine cosine algorithm for solving optimization problems, Knowledge based System 96 (2016) 120–133.
[16] Abualigaha L., Diabat A., Mirjali S., Elazizf M.D., and Amir HG, "The arithmetic optimization algorithm, computer methods in applied mechanics and engineering", No. 376, 2021.
[17] M.E. Baran, F.F. Wu, Network reconfiguration in distribution systems for loss reduction and load balancing, IEEE Trans. Power Deliv. 4 (1989) 1401–1407.
[18] G. Naresh Kumar, S. Suresh Kumar, V. Suresh, Optimal Placement of Electrical vehicle charging station in distribution system using meta-heuristic techniques, Mathem. Modell. Eng. Problems 9 (1) (2022) 60–66.

K. Kathiravan has obtained his Bachelor degree in Electrical and Electronics Engineering from Anna University, India in 2006 and Master degree in Power Systems Engineering from Anna University Trichy, India in 2011 and Ph.D in Faculty of Electrical Engineering from Anna University, Chennai, India in 2020. He has 15 years of teaching and Research Experience. His research topics includes Artificial Intelligence adoption in Power System problems, Renewable energy System and Power system Planning and reliability.

P.N. Rajnarayanan has obtained his Bachelor degree in Electrical and Electronics Engineering from Madurai Kamaraj University, India in 2002 and Master degree in Power Systems Engineering and Ph.D in Power System Operation and Control from Anna University, Chennai, India in 2005 and 2010 respectively. He has 17 years of teaching and research experience. He is currently working as Professor in Electrical and Electronics Engineering at Theni Kammavar Sangam College of Technology, Theni, Tamilnadu India. His research topics includes evolutionary computation, soft computing, renewable energy system and power system operation and control.