The Effect of Electric Vehicle Charging Stations on Distribution Systems While Minimizing the Placement Cost and Maximizing Voltage Stability Index

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Abstract Greenhouse gas (GHG) emissions from internal combustion (ICE) vehicles, which are reliant on fossil fuels, are one of the problems in major cities. As a result, the electric vehicle (EV) has become the automotive industry's green alternative. Promoting the worldwide adoption of electric vehicles is viewed as a possible solution to energy security, including energy efficiency, reduced noise, and greenhouse emission reduction. Due to its numerous benefits, including their use of flexible fuels, ease, safe charging, high performance, and cost savings, Plug-In Electric Vehicles (PEVs) will soon replace traditional vehicles as the most affordable option for transportation. Despite the benefits indicated above, improper placement and size of aggregated PEVs cause voltage degradation and loss. Therefore, the best location for charging stations (CS) is crucial for the widespread use of EVs. Thus, in order to allocate fast and slow CS as efficiently as possible, this research suggests two optimization technique that takes into account the cost of installation, operation cost, increased line loss cost, and voltage deviation cost. The CS placement approach of Whale Optimization (WO) and Particle Swarm Optimization (PSO) technique is simulated on IEEE-33 radial distribution systems. The results demonstrate that the recommended technique can choose the best location and size for CS, which will benefit EV owners, EVCS creators, and the power grid.

Keywords Distribution system · Electric vehicles · Charging station · Whale optimization · Particle swarm optimization

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1   Introduction

The market for electric vehicles (EVs) is expanding quickly on a worldwide scale. As per EV volumes, the total number of electric vehicles (including battery electric vehicles [BEVs] and Plug-in hybrid electric vehicles [PHEVs]) on the road increased to 6.75 million in 2021 from 4.2% in 2020. As they aid in lowering pollution and reducing resource depletion, EVs are gaining popularity all over the world. As evidence of how quickly the Indian EV industry is developing, close to 0.32 million vehicles, up 168% YoY, were sold in 2021. The ongoing adoption of electric vehicles in India is supported by the Paris Agreement, which aims to reduce carbon emissions, enhance the quality of the air in metropolitan areas, and decrease oil imports [1].

There is an essential need for widely dispersed, publicly available charging stations (CSs) that provide electrical energy for recharging an EV battery since the number of EVs is growing quickly [2]. Therefore, the construction of the charging infrastructure must be prioritized in order to deploy EVs on a big scale. For the EV business to expand sustainably, coordinated EV CS planning is of utmost importance. In response to the recent demand for PEV supplies, researchers have focused on the optimal layout of charging stations [3]. It is possible to broadly divide CS placement into two types: slow and quick. Due to lower charging costs and accessibility at home or the office, slow charging is the most popular approach. The low charging power used by this approach results in a lengthy charge period for an EV battery. However, in order to drive long distances, EV customers also want an urgent charging option. Therefore, it is essential to have a sufficient number of fast CSs (RCSs) for quick charging. However, the widespread use of EVs places an increased demand on a conventional distribution network, which might have a number of negative effects on the network. With consideration for loss and voltage in distribution networks, charging stations are scaled and constructed for maximum efficiency. The distribution network's properties, such as voltage stability, dependability, power loss, etc., must not be compromised by integrating EV CS into the transport network.

The literature describes many strategies and procedures used by researchers from throughout the world to deploy EV CSs in the best possible positions. A Binary Firefly Algorithm (BFA) approach has been proposed by Islam et al. [2] for the optimal allocation of the rapid charging station in the road distribution network of the township of Bangi, Malaysia. A new hybrid algorithm based on Chicken Swarm Algorithm (CSO) and Teaching Learning Based Optimization Algorithm (TLBO) is proposed in Deb et al. [3] to solve the problem of optimal placement of fast and slow CS. In Ge et al. [4], the authors introduced a unique approach to CS placement using the Grid Partition technique, with the aim function of minimizing user loss on the route to the charging station. To minimize the effects of EVCs in the distribution grid, a novel Genetic Algorithm (GA) based approach using capacitor banks is proposed in Pazouki et al. [5]. The authors of Liu et al. [6] used Adaptive Particle Swarm Optimization (APSO) to report the best sites for EV CSs with a single objective cost function. Parking lots with various levels of charging stations are placed and sized in

the best possible way in electric distribution networks is formulated in Mohsenzadeh et al. [7] using Genetic Algorithm (GA). Taking distribution and traffic networks into account [8], the best planning for PEV charging stations and demand response initiatives is done using Genetic Algorithm (GA).

Literature [2–8] describes some of the current research done in the field of EV CSs placement. Additionally, there are a number of restrictions on the objective functions taken into account in the literature, such as a lack of a voltage deviation cost and total line loss cost. In this work, two novel modelling method for the EV CS placement problem is presented that takes into account the superposition of the distribution networks and uses the objective function of installation cost, operating cost, cost of voltage deviation, the extra line lost cost, and Voltage Stability Index (VSI), total line losses. This work proposes a comparison of two metaheuristic algorithms Particle Swarm Optimization (PSO) and Whale Optimization (WO) for the solution of EV CS problem formulation.

The rest of the paper is structured as follows. A brief introduction to EV CS and the work already done is presented in Sect. 1. The concept of the EV CS placement problem is expanded in Sect. 2. Section 3 tells about the optimization technique used in the paper and the flow chart of the optimization technique. The quantitative analysis and simulation result is presented in Sect. 4. The paper is concluded at the end.

2 Objective Problem Formulation

The main goal of the objective function is to minimize the overall cost and maximize the VSI. The overall cost is comprised of the installation cost, the cost of operation, the extra cost for voltage variation, and the total line loss cost. Figure 1 provides a diagrammatic depiction of several objective functions. Equations (1)–(18) in the preceding subsections provide further details on the objective function used for the optimization as well as the various constraints.
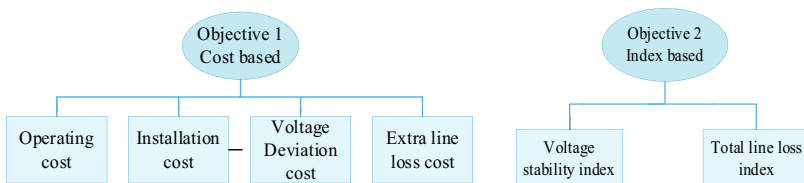

Fig. 1 Objective function of EV CS

2.1 Objective Function 1

The first objective function takes the cost-based approach to find the optimal alloca-
tion of EV CS taking the installation cost, operation cost [3], voltage deviation cost
[9] and extra line loss cost [10]. The objective function is shown by Eq. 1.

$$\text{MinOF1} = \left(C_{\text{installation}}, C_{\textbf{operation}}, C_{\text{deviation}}, C_{\text{extra line loss}}\right) \tag{1}$$

where,

$C_{\text{installation}}$-installation cost of CS

$C_{\text{operation}}$-annual operating cost of CS

$C_{\text{deviation}}$-cost of per unit voltage deviation

$C_{\text{extralineloss}}$-annual cost of extra line loss.

The formulation of different cost function is given below:-

$$C_{\text{installation}} = C_{\text{fast}} + C_{\text{slow}} \tag{2}$$

$$C_{\text{fast}} = n_{\text{fastcs}} * n_{\text{fastcharger}} * n_{\text{fast}_{\text{charger}_{\text{install}}}} + C_{\text{installationfast}} \tag{3}$$

$$C_{\text{slow}} = n_{\text{slowcs}} * n_{\text{slowcharger}} * C_{\text{slow}_{\text{charger}_{\text{install}}}} + C_{\text{installationslow}} \tag{4}$$

$$C_{\text{operation}} = \left(n_{\text{fastcs}} Cp_{\text{fast}} n_{\text{fastcharger}} + n_{\text{slowcs}} Cp_{\text{slow}} n_{\text{slowcharger}}\right) * P_{\text{electricity}} * T \tag{5}$$

where,

n_{fastcs}-no of fast CS

n_{slowcs}-no of slow CS

$C_{\text{installationfast}}$-fast CS installation cost

$C_{\text{installationslow}}$-slow CS installation cost

Cp_{fast}-fast CS consumption power

Cp_{slow}-slow CS consumption power

$P_{\text{electricity}}$-cost of per unit electricity

T-time period of planning

$$C_{\text{deviation}} = P_{\text{VD}} * \sum_{i=2}^{N} \text{VD}_i^2 \tag{6}$$

$$VD_i = V_i^{base} - V_i^{cs} \qquad (7)$$

where,

P_{VD}-cost of per unit voltage deviation

VD_i-voltage deviation at ith bus

V_i^{base}-base case voltage at ith bus

V_i^{cs}-voltage after placing CS at ith bus

$$C_{extra\,line\,loss} = (TPL_{base} - TPL_{cs}) * (k_p + k_e * Lsf * T) \qquad (8)$$

$$Lsf = k * Lf + (1 - k) * Lf^2 \qquad (9)$$

where,

TPL_{base}-total power loss without CS

TPL_{cs}-total power loss after CS

k_p-annual demand power loss cost

k_e-annual loss of energy cost

Lsf-loss factor

Lf-load factor

2.2 Objective Function 2

The second objective function takes the index-based approach to find the optimal allocation of EV CS taking the voltage stability index (VSI) [11] and total real power loss of the distribution system. The objective function is shown by Eq. 10.

$$MinOF2 = \alpha_1 * \frac{TPL_{cs}}{TPL_{base}} + \alpha_2 * \frac{\Delta VSI_{cs}}{\Delta VSI_{base}} \qquad (10)$$

$$\Delta VSI = max\left(\frac{1 - VSI_i}{1}\right) \forall i = 2, 3 \ldots \ldots N \qquad (11)$$

$$VSI_{i+1} = V_s^4 - 4V_s^2(R_iP_{Li} + X_iQ_{Li}) - 4(X_iP_{Li} + R_iQ_{Li})^2 \forall i = 2, 3 \ldots \ldots N \quad (12)$$

where,

α_1, α_2-weighting factors

ΔVSI_{cs}-voltage stability index with CS

ΔVSI_{base}-voltage stability index without CS

N-number of buses

VSI_i-voltage stability index of ith bus

V_s-voltage at sending end

R_i-resistance of the line

P_{Li}-active power load at ith bus

X_i-inductive reactance of the line

Q_{Li}-reactive power load at ith bus

2.3 Constraint Used

Two types of constraints are used in the following proposed objective function.

2.3.1 Equality Constraints

Forward and backward sweep method is used for distribution system load flow analysis and is illustrated in Kazmi et al. [12], Martinez and Mahseredjian [13] and Teng et al. [14]. Power balance equation considering EV CS in the distribution system can be defined as follows:

$$P_{Gi} - P_{CSi} - P_{Di} = \sum_{j=1}^{N} V_i^2 Y_{ij}^2 \cos(\theta_{ij} + \lambda_j - \lambda_i) \forall i = 1, 2, \ldots \ldots N \quad (13)$$

$$Q_{Gi} - Q_{CSi} - Q_{Di} = \sum_{j=1}^{N} V_i^2 Y_{ij}^2 \sin(\theta_{ij} + \lambda_j - \lambda_i) \forall i = 1, 2 \ldots \ldots N \quad (14)$$

2.3.2 Inequality Constraints

Distribution system should be lime by voltage level at each bus by:

$$V_i^{min} \le V_i \le V_i^{max} \quad (15)$$

Maximum and minimum number of fast and slow charging stations can be placed at each bus:

$$0 < n_{fastcs} \leq N_{fastcs\text{max}} \tag{16}$$

$$0 < n_{slowcs} \leq N_{slowcs\text{max}} \tag{17}$$

The total increased load (L) of the network should be less than the maximum load margin (L_{max}) of the system:

$$L \leq L_{\text{max}} \tag{18}$$

3   Optimization Technique Used

Nature-inspired optimization algorithms [15] are metaheuristic algorithms based on biological evolution, swarm behavior patterns, and physical and chemical processes. Nature influenced optimization algorithms are examples of computational intelligence methods that are bioinspired because they contain intelligence. Algorithms influenced by nature are new in their ability to achieve effective solutions with minimal computational resources. Collective intelligence has emerged as a result of biological agents such as ants, bees, crows, bats, cuckoos, and others sharing information and socializing among members of their own species as well as with the environment [16].

In this paper Particle Swarm Optimization (PSO) and Whale Optimization (WO) is used. The social behavior of fish schools and bird flocks served as the basis for the metaheuristic optimization technique known as particle swarm optimization (PSO) [17]. The approach simulates a swarm of particles moving across a search space, each particle standing in for a potential answer to the optimization issue [18]. The flow chart of PSO algorithm is presented in Fig. 2.

Whale Optimization Algorithm (WOA) is a nature-inspired metaheuristic optimization algorithm that was first proposed by Mirjalili et al. in 2016 [19]. It was inspired by the hunting behavior of humpback whales, where the whales work together to encircle their prey and capture it. The algorithm is based on a mathematical model that simulates the behavior of humpback whales, where each whale represents a potential solution to the optimization problem [20]. The flow chart of WO algorithm is presented in Fig. 3.

4   Numerical Analysis

In this study, WO and PSO are used to calculate the ideal CS positions. In this part, test system details and the results of the ideal CS setup are provided. IEEE-33 bus radial distribution system is taken as the test system for this analysis. The bus data

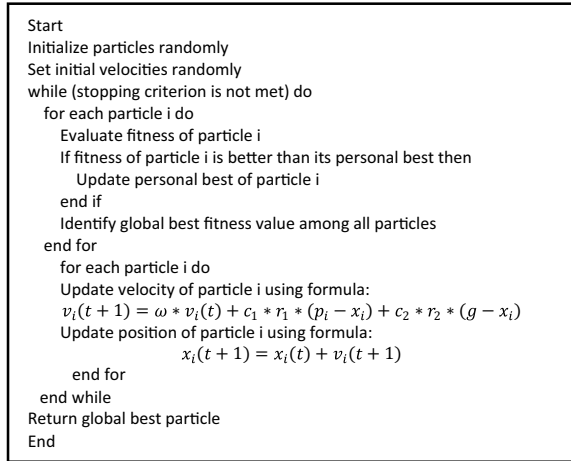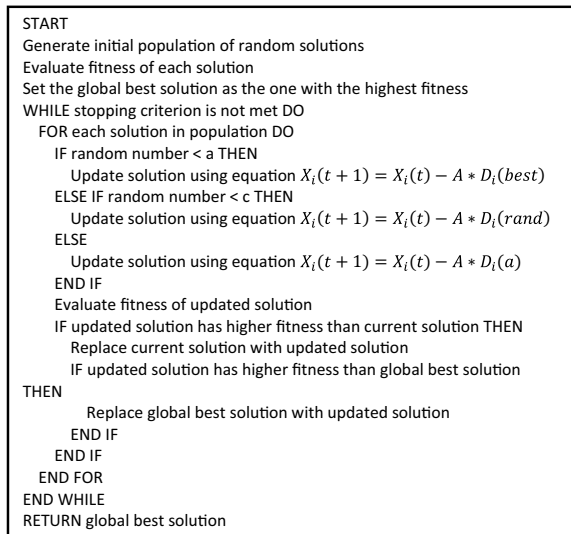**Fig. 2** Flow chart of particle swarm optimization (PSO) algorithm

```
Start
Initialize particles randomly
Set initial velocities randomly
while (stopping criterion is not met) do
  for each particle i do
     Evaluate fitness of particle i
     If fitness of particle i is better than its personal best then
        Update personal best of particle i
     end if
     Identify global best fitness value among all particles
  end for
    for each particle i do
     Update velocity of particle i using formula:
```

$$v_i(t+1) = \omega * v_i(t) + c_1 * r_1 * (p_i - x_i) + c_2 * r_2 * (g - x_i)$$

```
     Update position of particle i using formula:
```

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

```
     end for
  end while
Return global best particle
End
```

Fig. 3 Flow chart of whale optimization (WO) algorithm

```
START
Generate initial population of random solutions
Evaluate fitness of each solution
Set the global best solution as the one with the highest fitness
WHILE stopping criterion is not met DO
  FOR each solution in population DO
     IF random number < a THEN
```
$$\text{Update solution using equation } X_i(t+1) = X_i(t) - A * D_i(best)$$
```
     ELSE IF random number < c THEN
```
$$\text{Update solution using equation } X_i(t+1) = X_i(t) - A * D_i(rand)$$
```
     ELSE
```
$$\text{Update solution using equation } X_i(t+1) = X_i(t) - A * D_i(a)$$
```
     END IF
     Evaluate fitness of updated solution
     IF updated solution has higher fitness than current solution THEN
        Replace current solution with updated solution
        IF updated solution has higher fitness than global best solution
THEN
            Replace global best solution with updated solution
        END IF
     END IF
  END FOR
END WHILE
RETURN global best solution
```

and line data of IEEE-33 bus radial distribution system is taken from [21] and the one-line diagram of the system is shown in Fig. 4. The total demand on the IEEE-33 bus radial test distribution system with a combined real and reactive load demand of 3.715 MW and 2.3 MVAR. All simulations are carried out using an Intel Core I7 7th Gen CPU with 16 GB of RAM with MATLAB 2022a.

Optimal placement is done based on the two different objective functions using PSO and WO optimization algorithms. Different cases have been formed based on the number of EV fast and slow CS, and also based on the number of charging slots present in that EV CS. Different input parameters have been taken from Islam
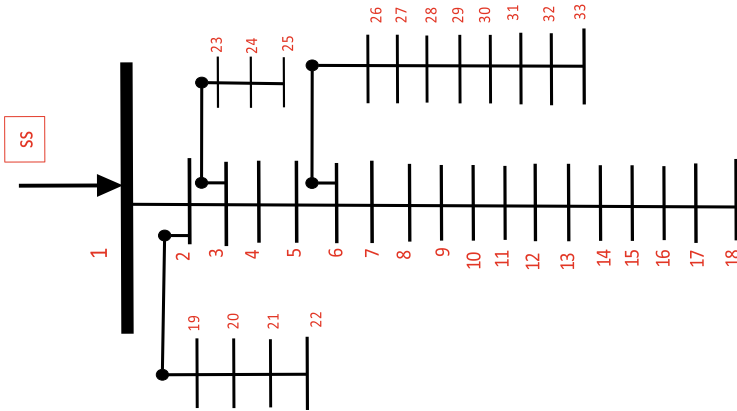
Fig. 4 One line diagram of IEEE-33 bus radial distribution system

et al. [2], Deb et al. [3] and Pazouki et al. [5] are presented in Table 1. On applying distribution load flow analysis to IEEE-33 bus radial distribution the total active and reactive power losses are 202.6771 KW and 135.141 KVAR. The minimum voltage is 0.91306 p.u at bus no 18 and the maximum voltage is 0.99703 p.u at bus no 2.

Two different objective function is compared with two different Optimization algorithm to find the optimal allocation of EV CS. The comparison results of PSO and WO algorithm are tabulated in Table 2. In Table 2 OBJ 1 is the cost-based objective function formulated by adding installing cost, operation cost, extra line loss cost and voltage deviation cost, the second objective function OBJ 2 contains voltage stability index and the line loss index.

The voltage profile curve of both objectives with PSO and WO is presented in Figs. 5 and 6. The Voltage Stability Index (VSI) of objective function 2 is shown in Fig. 7. The respective active and reactive power loss after placing EV CS with different objective functions is shown in Figs. 8, 9, 10 and 11. The convergence graph of both the objective functions is shown in Fig. 12.

Table 1 Input parameters

$C_{installationfast}$	2000 $	Cp_{fast}	50 KW
$C_{installationslow}$	1500 $	Cp_{slow}	19.2 KW
$C_{fast_{charger_{install}}}$	500 $	$C_{slow_{charger_{install}}}$	300 $
$n_{fastcharger}$	8	$n_{slowcharger}$	12
n_{fastcs}	2	n_{slowcs}	2
$P_{electricity}$	0.065 $/kWhr	T	8760
P_{VD}	1000000 $/unit	k_p/k_e	57.693 $ /0.009611 $
k/Lf	0.2/0.43	α_1, α_2	0.5/0.5
Noofpopulation	50	Noofiteration	200

Table 2 Comparison of different results

PARAMETERS	Without EV CS	OBJ 1 with WO	OBJ 1 with PSO	OBJ 2 with WO	OBJ 2 with PSO
Active Power Loss	202.6771	217.1822	221.0593	217.1822	223.9576
Reactive Power Loss	135.141	145.3920	149.0940	145.3920	147.1367
No of fast EV CS/charger	–	2/8	2/8	2/8	2/8
No of slow EV CS/charger	–	2/12	2/12	2/12	2/12
Power factor	–	0.98	0.98	0.98	0.98
Optimal CS Location	–	2/19/21/20	19/20/2/22	2/19/21/20	2/3/20/19
Optimal CS Size P KW	–	400/400/230.4/230.4	400/400/230.4/230.4	400/400/230.4/230.4	400/400/230.4/230.4
Optimal CS Size Q KVAR	–	81.22/81.22/46.78/46.78	81.22/81.22/46.78/46.78	81.22/81.22/46.78/46.78	81.22/81.22/46.78/46.78
Min/Max voltage location	2/18	2/18	2/18	2/18	2/18
Min/Max voltage	0.91306/0.99703	0.91216/0.99622	0.91216/0.99622	0.91216/0.99622	0.91216/0.99622
% Increase in line loss	–	7.156	8.8246	7.156	9.411
Annual extra line loss cost	–	1167.6 $	1439.7 $	1167.6 $	1535.4 $
Computational time	0.0641	90.5961	90.9458	91.6607	90.8697

From Figs. 5 and 6 we can observe that with the placement of EVCS in radial distribution system the voltage profile deviates from the base case. Also, we can see that from Figs. 8,9,10, and 11 that the active and reactive power of the branch and the system increased from the base case. In Fig. 12 whale optimization (WO) algorithm has the better fitness value in both the objective function cases.

The impact on distribution system increases or decreases based on the number of EV CS and number of fast and slow chargers present in the respective CS. The optimal placement of different fast and slow charging stations based on number of chargers presented in Table 3.
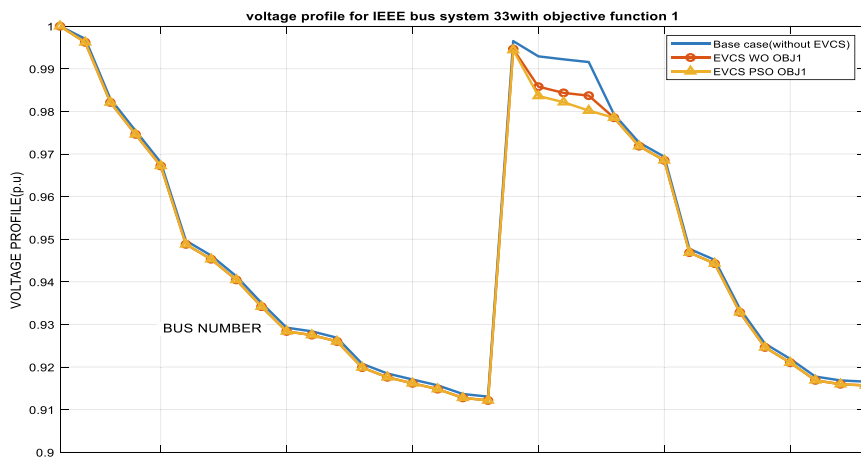
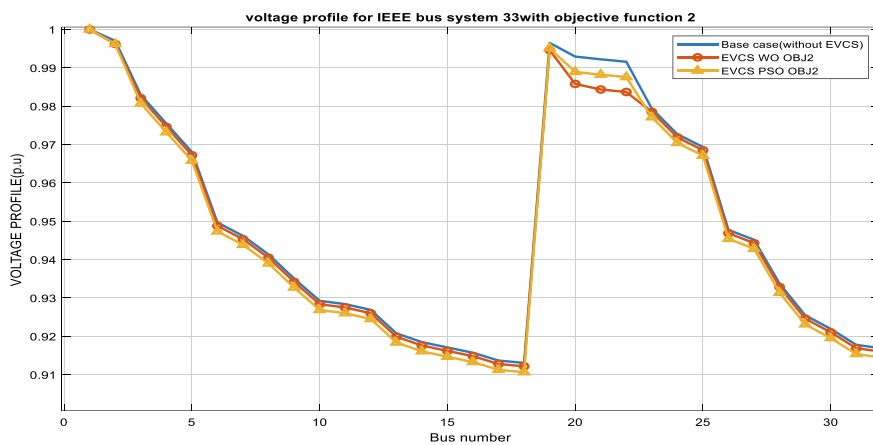**Fig. 5** Voltage profiles of 33-BUS system after placing EV CS with objective 1

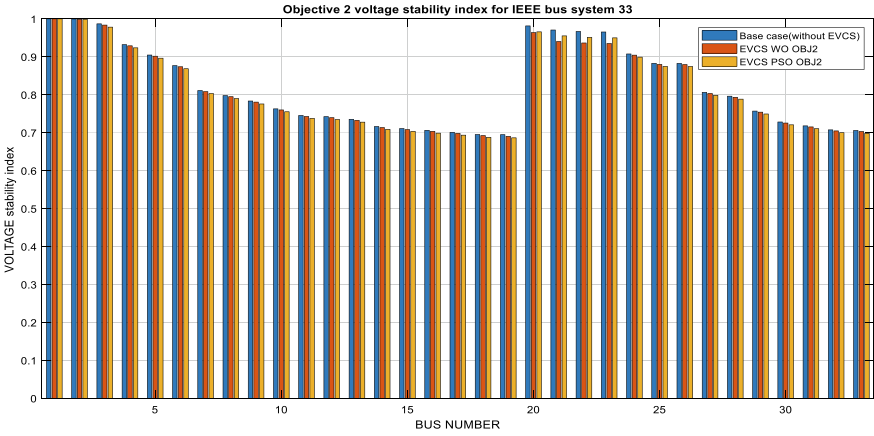**Fig. 6** Voltage profiles of 33-BUS system after placing EV CS with objective 2

Fig. 7   Voltage stability index of objective function 2
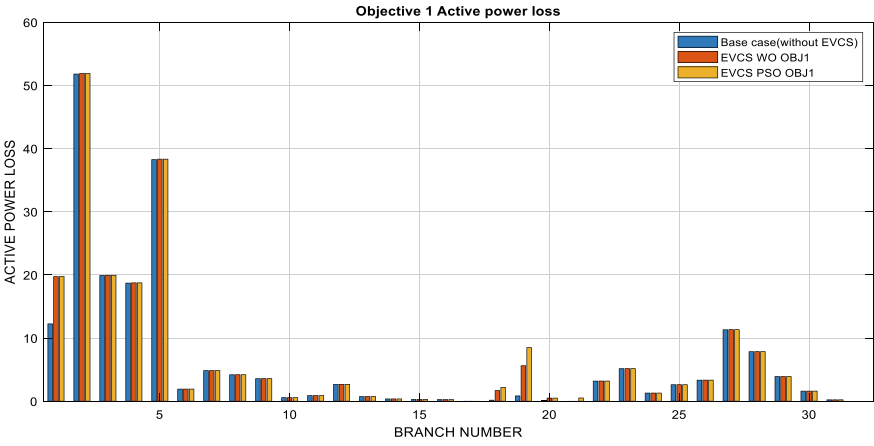

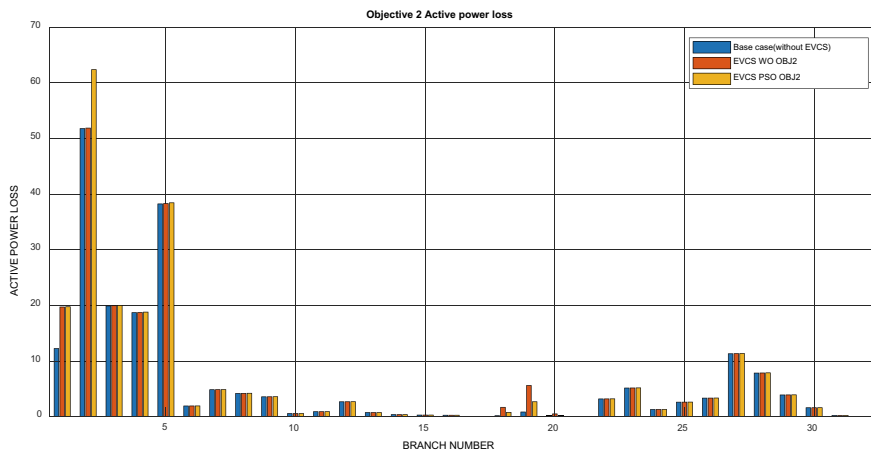**Fig. 8**   Increased active power loss after placing EV CS objective 1

Fig. 9 Increased active power loss after placing EV CS objective 2
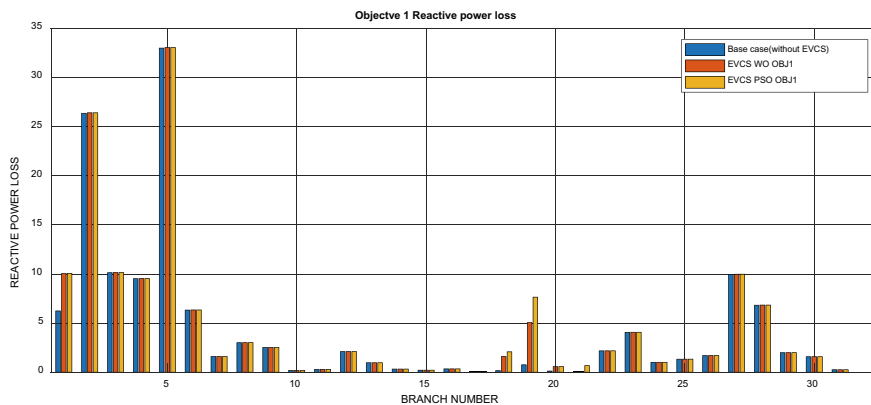

Fig. 10 Increased reactive power loss after placing EV CS objective 1
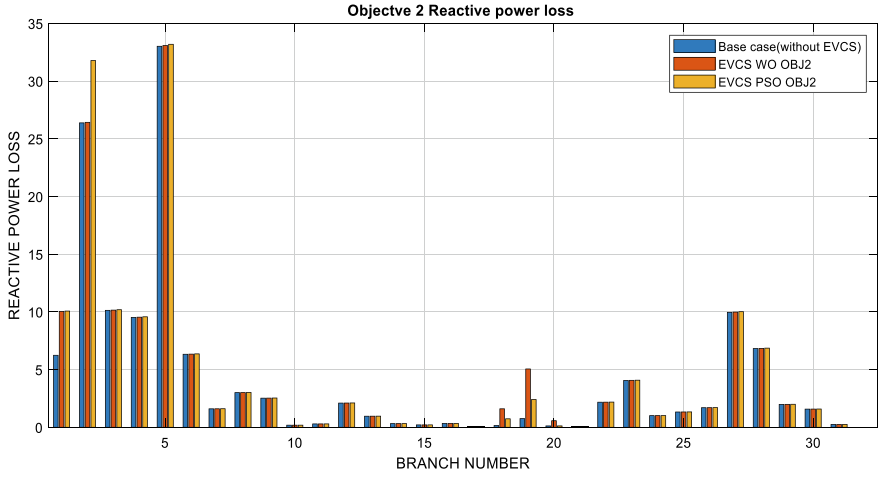
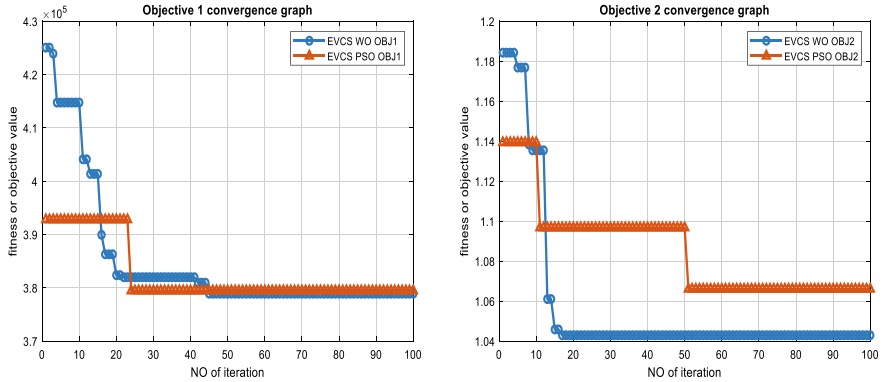**Fig. 11** Increased reactive power loss after placing EV CS objective 2

Fig. 12 Convergence graph of both objective function

Table 3 Different placement locations for different EVCS numbers

EV CS		Optimal placement			
No of fast EV CS/ charger	No of slow EV CS/ charger	OBJ 1 with WO	OBJ 1 with PSO	OBJ 2 with WO	OBJ 2 with PSO
1/8	3/15	2/20/21/19	2/20/21/19	2/21/20/19	21/22/19/2
2/8	2/12	2/19/21/20	19/20/2/22	2/19/21/20	2/3/20/19
3/8	1/10	20/19/2/21	2/22/20/3	2/19/20/21	2/19/20/4
4/8	0/0	2/20/22/19	20/22/19/2	2/19/20/21	21/20/19/2
0/0	4/15	2/19/20/21	2/22/21/19	2/19/21/20	3/2/22/20

5 Conclusion

For the EV business to flourish quickly, the ideal placement of EV CS. This article provides a unique placement approach for EV CS placement considering the economics and the stability of the distribution system. CS is crucial. The modelling of EV CS contains two objective functions, one focuses on the operation, installation, extra losses and voltage deviation cost and the other objective function aims on the voltage stability index and line loss index. Two nature-based optimization algorithm, Particle Swarm Optimization (PSO) and Whale Optimization (WO) is utilized for the resolution of this difficult positioning issue. In this study, the effectiveness of these two algorithms in handling challenging optimization issues is firmly proven. The best optimal location for EV CS in 33 BUS radial distribution system is 2,19, 20, 21. Whale optimization has given the best result of EV CS allocation out of these two optimization techniques. Further adding DGs to improve the system voltage profile is in the further scope of the paper.

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