

Coordinated optimal planning of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility

Mohd Bilal (✉ bilal.zhcet01@gmail.com)

Delhi Technological University

Mohammad Rizwan

Delhi Technological University

Research Article

Keywords: Electric vehicle charging infrastructure, Optimization techniques, Distribution network, Vehicle to grid, Reactive power compensation

Posted Date: May 5th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-281250/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Coordinated optimal planning of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility

Mohd Bilal and M. Rizwan

Department of Electrical Engineering, Delhi Technological University, Delhi 110042, India

E-mail: bilal.zhcet01@gmail.com

Abstract: Deployment of electric vehicles as a future mode of transport is essential to lower the greenhouse gas emissions and other harmful gases instigated by conventional engine driven vehicles. Installation of electric vehicle charging stations are one of the prominent aspects for the widespread use of electric vehicles. Improper positioning of electric vehicle charging station creates challenges which in turn affect the electrical network and utility operator. This paper presents a new hybrid approach for investigating the optimal location of electric vehicle charging stations. Reactive power compensation is also provided along with charging station to deal with power loss issues and retain the distribution network's reliability. Moreover, vehicle to grid facility has been comprehensively considered in this paper. The proposed algorithm is the hybrid of grey wolf optimization and particle swarm optimization. The hybridization of two algorithms combines the desirable attributes of both algorithms and maintains a strong balance between the exploration and exploitation capability. The proposed hybrid approach is applied on IEEE-33 bus and 34-bus distribution system for minimizing the active power loss and maximizing the net profit. Furthermore, the outcome attained using the anticipated technique is equated with conventional grey wolf optimization (GWO). For 33-bus system, the proposed technique results in loss reduction of 30.67% and maximizing the net profit by 1142.91\$ as compared to GWO. Likewise, power losses have been reduced to 27.6% and maximized net profit by 4111.74\$ for 34-bus network. The obtained results prove the supremacy of the proposed approach over grey wolf optimization to evaluate locations of charging stations' and reactive power source in radial distribution network.

Keywords: Electric vehicle charging infrastructure, Optimization techniques, Distribution network, Vehicle to grid, Reactive power compensation

1. INTRODUCTION

One of the primary concerns of metropolitan cities is the reduction of greenhouse gas emissions due to the internal combustion engine-based vehicles. Excessive usage of such vehicles leads to health issues not only in humans but also worsens the ecological system of earth (Golpîra H & Khan S. A. R. 2019). The release of various toxic oxides like CO₂, NO₂, SO₂ etc. is one of the key factors for global warming and climate change. Researchers and policymakers around the world advocate the implementation of alternative mode of transport in the form of electric vehicles (EVs) to minimize the content of greenhouse gases. The technological advancement from internal combustion engine-based vehicles to EVs has numerous environmental and economic advantages which includes flexibility in fuels, easy charging, decent performance, and less reliance on fossil fuel (Vayá M. G, & Andersson G. 2015). For the broad adoption of EVs, electric vehicle charging stations (EVCS) are inevitable. Charging stations are the energy source to the increasing number of EVs globally. Energy is transferred from charging station to EVs through a safe communication path. Inappropriate locations of EVCS impose negative impact on the efficiency of electric grid. Therefore, researchers emphasized on improving the performance of grid by enhancing its reliability, maximizing the benefit of EV users and reducing the station development cost. These objectives can be realized by investigating the optimum locations and sizing of EVCS in the electrical grid network.

1.1 Related works

Many previous research studies in the domain of EVs allocation, operation management in the distribution network along with capacitors are summarized as follows:

EVCS allocation in electric distribution networks causes challenges for grid operators if proper planning procedure is not considered (Deng B, & Wang Z. 2011). Researchers and academicians are looking for the appropriate planning of EVCS in power systems (Han. S et.al. 2010). Various researches have been conducted on integrating EVCS into the electric power network. In this context, the influence of integrating EVCS to the electric power networks based on

power loss and voltage profile is addressed (Singh M. et.al. 2013). The EVCS has been optimally planned for the IEEE 30-bus system (Dharmakeerthi C. H. et.al. 2015). Allocation of distributed generations and EVCS have been performed for IEEE 30-bus and IEEE 69-bus system (Liu. L. et.al. 2020). A hybrid algorithm based optimal planning of EVCS has been carried out in electric power network of Allahabad city (India) with installation cost minimization and power quality improvement are the objective function taken under consideration (Awasthi. A. et.al. 2017). (Mehta R. et.al 2019) have used a two-layer optimization strategy for integrating EVCS to IEEE 33- bus distribution network. (Liu. Z. et.al 2012) have considered power loss and different cost-based functions for the optimal EVCS allocation in IEEE 123-bus system. (Bilal and Rizwan 2020) have performed a qualitative survey for optimal planning of EVCS in distribution network and transportation networks. (Reddy et.al 2020) utilized PSO for the EVCS and DGs allocation in unbalanced radial DS. (Aljaidi M. et.al. 2019) minimized station development cost, EV energy loss cost, and operation cost for the suitable placement of EVCS in the distribution network. (Wang X. et.al. 2016) discusses the EVCS placement at bus stoppage to reduce the development cost of the charging station. Optimal planning of EVCS infrastructure has been performed by minimizing the cost of installation, cost of operation, and maintenance cost by taking care of system reliability (Davidov and Pantos 2019). (Lin X. et.al. 2014) have tried to place EVCS in the Beijing district by minimizing the system's overall cost and power loss. The transportation network and distribution network for the EVCS placement is considered by utilizing cross-entropy and particle swarm optimization to optimize the objective (Wang Z. et.al. 2013). (Arnab P. et.al. 2021) have planned the EVCS placement problem in superimposed distribution network and road network. Uncertainties related to EVs are considered using 2m point estimation method. Also, differential evolution and Harris Hawks optimization techniques are used for optimization purposes. A new methodology has been adopted for the optimal location and sizing of parking lots by enhancing network reliability and minimizing the cost (Fathy A. et.al. 2020). Several cost functions are taken into consideration, including the cost for improving reliability, cost of improving power loss, etc. competition over resources (COR), have been utilized for optimization purposes.

In fact, the addition of EVCS to the electric distribution network causes an increase in power loss and degrades the voltage profile. In previous studies, the benefits of adding capacitor in distribution network along with EVCS have not been addressed for the reduction in power loss and improvement in voltage profile. Numerous techniques have been applied in literature for the optimal capacitor placement considering power loss minimization and voltage profile improvement. The addition of capacitors to the distribution network has many advantages such as power loss reduction, power factor correction, etc. Hence, it is necessary that the capacitor needs to be sized and optimally placed in the distribution network. A wide variety of heuristic methods have been modeled for the optimal placement of capacitors. (Prakash and Sydulu 2007) performed particle swarm optimization-based capacitor placement in the radial distribution network. Initially, the authors used the concept of loss sensitivity factor for locating the capacitors. A comprehensive analysis based on intelligent algorithms for determining the optimal size and location of the capacitor is explained (Sirjani et.al. 2012). (Raju et.al. 2012) discussed the direct search algorithm to determine the size and site of fixed and switched capacitors in radial distribution systems by minimizing the power loss and maximizing the energy savings. (El. Fergany et.al. 2014) have found the optimal location for capacitor using an artificial bee colony algorithm. Authors proposed the two-step procedure for the optimal locations and sizes of capacitors in radial distribution network. Ant colony optimization has been used for minimizing the power loss (Abou El-Ela A. A et.al. 2016). The proposed approach is tested in 34-bus and 85-bus radial distribution system. (Sachan and Amini 2020) introduced a new strategy for the proper positioning of the EVCS, which focuses on congestion management and the compensation for reactive power to allocate parking lots and capacitors. Sensitivity analysis is performed in this work by determining the inverse Jacobian matrix. To prove the proposed algorithm's effectiveness, the biogeography-based optimization approach was considered for the optimum size of the parking lot and contrasted with particle swarm optimization. Authors presented the grasshopper optimization algorithm based on two stage fuzzy multi-objective approach for optimum sizing and placement of EVCS, distributed generations and capacitors in the electrical distribution network (Gampa S. R. et.al 2020). A new comprehensive strategy for the allocation of parking lots and capacitor is presented with the consideration of congestion management (Rajesh and Shajin 2021). Quantum-Behaved and Gaussian Mutational Dragonfly Algorithm is utilized to optimize real and reactive power loss.

1.2 Motivations

There is a limited literature available on the EVCS allocation as the research work on EVCS is in the commencement phase so far. Very few researches addressed the vehicle to grid mode of EVCS. Also, considerable literature is available on the placement of capacitor and EVCS individually. However, the placement of EVCS in the presence of capacitor has rarely been considered in all these prior works. The benefits of capacitor allocation for minimizing power loss and improving the voltage profile of integrating EVCS into distribution networks have not been adequately

addressed in previous planning studies. The joint placement of capacitor and EVCS can reduce power loss, enhancing power factor correction, and many more. Furthermore, most of the previous metaheuristic algorithm-related approaches discussed are complex in construction, involve broad control parameters, and trap local optima. In addition, based on analytical methodologies, some works used a very complex mathematical model that required excessive details. Unlike analytical procedures, metaheuristic methods are simple to implement, consume less time, have reduced parameter control and appropriate solutions can be achieved.

1.3 Contribution

Motivated by the existing research in the optimal allocation of EVCS, a hybrid intelligent technique for the optimal planning of EVCS is proposed. The proposed technique utilizes capacitors to maintain voltage profile, reduces the active power loss and maximize the net profit. The proposed technique is the amalgamation of grey wolf optimizer and particle swarm optimizer. Installation costs and operating costs of EVCS and capacitors have been applied on the objective function. The allocation of EVCS and capacitors acts as an additional demand which varies the power loss of the system. A direct approach for load flow analysis is utilized for the calculation of current and voltage of each node and hence provides the active power loss. Thereafter, the effectiveness of the proposed technique is implemented in MATLAB and the performance is evaluated with the current methods.

The major contribution of this work can be summarized as follows:

- The addition of EVCS has been performed in radial distribution network with different percentage of EVs participating in the vehicle to grid mode. Incorporation of EVCS with vehicle to grid facility reduces the active power loss as well as maintaining the healthy voltage profile at all buses of the distribution network. Also, vehicle to grid idea is beneficial to balance the loads by valley filling and peak shaving.
- The operating cost and installation cost of EVCS as well as capacitors have been included for the estimation of net profit.
- A new technique entitled advanced grey wolf particle swarm optimization is proposed. In this technique, exploitation is based on grey wolf optimization, while particle swarm optimization is used for exploration. This is assumed to be the novelty of this article.
- The proposed hybrid approach is selected to solve the optimization problem because of its high convergence rate and capability of handling discrete as well as integer variable problem involving a smaller number of control parameters. Also, the hybridization of the two algorithm takes the advantages of both techniques simultaneously. Hence, the optimal solution can be easily achieved even for large complicated system. The same problem is solved using grey wolf optimization and compared with proposed hybrid approach. The effectiveness and efficiency of the proposed hybrid algorithm is validated by implementing AGWOPSO algorithm on selected benchmark functions and then applied on 33-bus, and 34-bus radial distribution networks.

The remaining of the article is organized as follows: The problem formulation is discussed in Section 2. Section 3 describes the sensitivity calculations. Section 4 discusses the application of the proposed algorithm for the optimal placement of the EVCS and capacitor. Section 5 provides the brief overview of the test system. Simulation results and insights are provided in Section 6. Finally, Section 7 concludes about this article.

2. MATHEMATICAL MODELING OF RADIAL DISTRIBUTION SYSTEM

The two-bus model for the analysis of distribution system is discussed in this section. The single line diagram of two bus radial distribution system is shown in Fig.1.

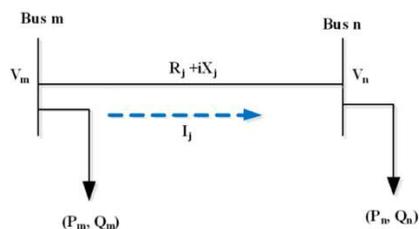


Fig.1. Representation of two nodes and one branch of distribution system

From Fig.1

$$V_n = V_m - I_j Z_j \quad (1)$$

$$|V_n| \delta_n = |V_m| \delta_m - |I_j| - \theta_j * |Z_j| \phi_m \quad (2)$$

$$|V_n| \cos \delta_n + |V_n| \sin \delta_n = |V_m| \cos \delta_m + |V_m| \sin \delta_m - |I_j| (\cos \theta_m - j \sin \theta_m) (R_j^2 + X_j^2) \quad (3)$$

By separating real and imaginary terms

$$|V_n| \cos \delta_n = |V_m| \cos \delta_m - |I_j| (R_j \cos \theta_m + X_j \sin \theta_m) \quad (4)$$

$$|V_n| \sin \delta_n = |V_m| \sin \delta_m - |I_j| (X_j \cos \theta_m - R_j \sin \theta_m) \quad (5)$$

Squaring and adding Eqns. (4) and (5)

$$|V_n|^2 = |V_m|^2 - 2 * |V_m| * |I_m| * \cos \delta_m \{(R_j \cos \theta_m + X_j \sin \theta_m)\} + |I_j|^2 \{(R_j^2 + X_j^2)\} - 2 * |V_m| * |I_m| * \sin \delta_m \{(X_j \cos \theta_m - R_j \sin \theta_m)\} \quad (6)$$

After mathematical rearrangement Eq. (6) can be written as

$$|V_n|^2 = |V_m|^2 - 2 * |V_m| * |I_m| \{(\cos(\delta_m - \theta_m)) + X \sin(\delta_m - \theta_m)\} + |I_j|^2 \{(R_j^2 + X_j^2)\} \quad (7)$$

$$|V_n|^2 = |V_m|^2 - 2 * |V_m| * |I_m| * |Z_j| \cos(\delta_m - \theta_m - \phi_m) + |I_j|^2 \{(R_j^2 + X_j^2)\} \quad (8)$$

Since $\delta_m - \theta_m - \phi_m$ is negligible hence, $\cos(\delta_m - \theta_m - \phi_m) = 1$

Because variation in voltage angle from source bus to end bus is very small.

Therefore, Eq. (8) can be written as

$$|V_n|^2 = |V_m|^2 - 2 * |V_m| * |I_m| * |Z_j| + |I_j|^2 \{(R_j^2 + X_j^2)\} \quad (9)$$

$$|V_n|^2 = [|V_m| - |I_m| * |Z_j|]^2 \quad (10)$$

$$|V_n| = |V_m| - |I_j| |Z_j| \quad (11)$$

Where

$$|I_m| = \frac{(P_m^2 + Q_m^2)^{1/2}}{|V_m|} \quad (12)$$

It can also be written as Eq. (13)

$$|I_n| = \frac{(P_n^2 + Q_n^2)^{1/2}}{|V_n|} \quad (13)$$

$$|V_n| = |V_m| - \frac{(P_n^2 + Q_n^2)^{1/2}}{|V_n|} * |Z_j| \quad (14)$$

$$|V_n|^2 = |V_m| * |V_n| - (P_n^2 + Q_n^2)^{1/2} * (R_j^2 + X_j^2) \quad (15)$$

$$|V_n|^2 - |V_m| * |V_n| - (P_n^2 + Q_n^2)^{1/2} * (R_j^2 + X_j^2) = 0 \quad (16)$$

Positive root of Eqn (16) is given as

$$|V_n| = \frac{|V_m| \pm (|V_m|^2 - 4((P_n^2 + Q_n^2)^{1/2})(R_j^2 + X_j^2))^{1/2}}{2} \quad (17)$$

Voltage at the receiving end can be calculated using Eq. (17).

The active power loss in the line connected between m and n bus can be calculated as

$$P_{loss}(m, n) = |I_j|^2 * R_j \quad (18)$$

Hence, the active and reactive power loss in the line connecting m and n bus can be calculated as

$$P_{loss}(m, n) = \frac{(P_n^2 + Q_n^2)}{|V_n|^2} * R_j \quad (19)$$

$$Q_{loss}(m, n) = \frac{(P_n^2 + Q_n^2)}{|V_n|^2} * X_j \quad (20)$$

The total active power loss i.e., $P_{T,loss}$ can be evaluated by adding the individual power loss of all branches which can be expressed as

$$P_{T,loss} = \sum_{j=1}^{N_{br}} P_{loss,j}(m, n) \quad (21)$$

Where, N_{br} represents the number of branches (line) in the distribution system.

2.1 Formulation of the Problem

For EV users and electric utilities, EVCS deployment at the proper position plays a major role. Due to the limitation of all electric range, EV must be recharged several times during a ride. EVCS often serves as a heavy load which, when put in the distribution network incorrectly, induces increases in power loss. Therefore, for a minimal increase in power loss, the optimum location of EVCS is necessary. Installing capacitors overcomes the effect of incorporating EVCS into the distribution network as it lowers the power loss and strengthens the voltage profile. The proposed methodology is depicted in Fig.2.

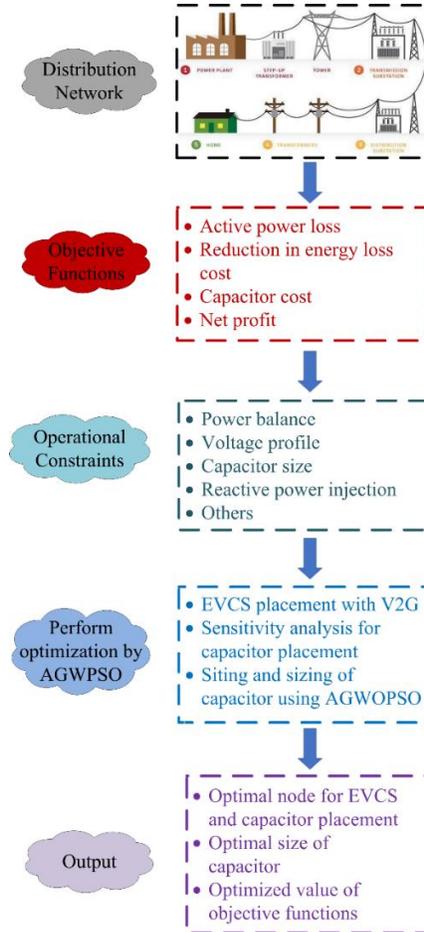


Fig.2. Layout of the proposed methodology

2.1.1 Modelling of EVCS load

EVCS's act as an extra load for the distribution network. The total load in the distribution system after integrating EVCS can be evaluated using Eq. (22).

$$T_{load} = \sum_{bs=1}^{N_{bus}} P_{avail,bs} + P_{EVCS}^{bs} \quad (22)$$

Where, T_{load} represents the total load in the system, N_{bus} is the total number of bus, $P_{avail,bs}$ is the already available load at bs^{th} bus and P_{EVCS}^{bs} is EVCS load connected to bs^{th} bus.

EVCS load depends on several factors which includes number of vehicles operating in G2V mode, V2G mode, charging rate (C_R), and discharging rate (DC_R).

Thus, the capacity of EVCS can be expressed as:

$$P_{EVCS}^{bs} = [N_{EV}(G2V) * C_R - N_{EV}(V2G) * DC_R] \quad (23)$$

Simply, the additional load of EVCS will be applied only on that bus where the CS is expected to be placed. That bus number i.e., CS location is the decision variable for which the optimization is performed. Fig.3. shows the addition of EVCS into the distribution system.

2.1.2 Modeling of Integrated Capacitor into the Distribution Network

The installation of capacitor units at suitable locations in the distribution system has many advantages which includes line loss reduction, voltage profile enhancement, power factor correction, etc. The governing equations for integrating capacitor into the distribution network are shown below.

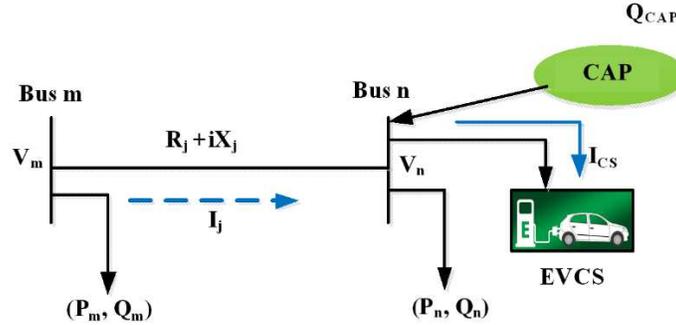


Fig.3. Representation of integrated EVCS and capacitor in distribution system

The net reactive power after injecting capacitor at bus n can be defined as

$$Q_N^{inj} = Q_n - Q_{cap} \quad (24)$$

The active power loss after connecting the capacitor at bus n is shown in Fig.3 is expressed as

$$P_{loss(m,n)}^{cap} = \frac{P_n^2 + Q_N^{inj^2}}{|V_n|^2} * R_j \quad (25)$$

$$P_{loss(m,n)}^{cap} = \frac{(P_n^2 + (Q_n - Q_{cap})^2)}{|V_n|^2} * R_j \quad (26)$$

$$P_{loss(m,n)}^{cap} = R_j * \frac{(P_n^2 + Q_n^2)}{|V_n|^2} + \frac{Q_{cap}^2 - 2 * Q_n * Q_{cap}}{|V_n|^2} * R_j \quad (27)$$

The reduction in power loss i.e., $\Delta P_{loss(m,n)}^{cap}$ is the difference between the power loss before and after capacitor placement and can be given as

$$\Delta P_{loss(m,n)}^{cap} = \frac{Q_{cap}^2 - 2 * Q_n * Q_{cap}}{|V_n|^2} * R_j$$

Increasing the number of capacitors is effective in decreasing power losses of the distribution network.

2.1.3 Assumptions

Following points have been presumed for the research to be carried out:

- The electric distribution network is balanced in nature.
- No EVCS load and capacitor are located on substation bus.
- Installed EVCS and capacitors are assumed to supply active and reactive power respectively.
- The voltage angle difference is believed to be constant as there is a change of a few degrees in the voltage angle from the source to the tail end.

2.1.4 Explanation of the Objective Functions

The primary objective of carrying out this research work is to optimally place the EVCS and capacitor in the distribution network. The location of EVCS in the distribution network causes an increase in system power loss and degradation in the voltage profile. Capacitors are located at optimum nodes in the distribution to mitigate increased power losses. The voltage profile is also preserved within desired limits by this capacitor allocation process. Therefore, the objective function is designed to minimize the loss of power, which eventually leads to a decrease in overall annual energy loss costs and maximizes net profit without violating the subject constraints. The objective functions of the proposed problem can be mathematically written as below.

$$\text{Total active power loss} \quad P_{T,loss} = \sum_{j=1}^{N_{br}} P_{loss,j}(m,n) \quad (29)$$

$$\text{Maximize net profit} = \text{energy loss reduction benefit} - \text{installation cost of system components} - \text{operating cost of system components}$$

$$\text{Energy loss reduction benefit} = K_{ep} * (P_{T,loss} - P_{T,loss}^{cap}) * T \quad (30)$$

$$\text{Installation cost of system components} = \beta \left[C_i^{cap} * N_{cap} + C_i^{EVCS} * N_{EVCS} + K_{cp} * \sum_{i=1}^{N_{cap}} Q_{cap}(i) \right] \quad (31)$$

$$\text{Operating cost of system components} = C_o^{cap} * N_{cap} + C_o^{EVCS} * N_{EVCS} \quad (32)$$

Here, $P_{T,loss}^{cap}$ represents the total active power loss after integrating capacitors, K_{ep} is the cost of energy paid per kWh, T is time period in hours, β is the depreciation factor, C_i^{cap} and C_i^{EVCS} are the installation cost of capacitor and EVCS per location respectively, N_{cap} and N_{EVCS} are the number of capacitors and charging stations, K_{cp} denotes the cost of purchase of capacitor per kVAR, C_o^{cap} and C_o^{EVCS} are the operating cost of capacitors and EVCS respectively, $Q_{cap}(bs)$ is the amount of reactive power injected at bs^{th} bus.

2.1.5 Explanation of Operational Constraints

The modeled objective functions are optimized taking into consideration the following constraints.

1) Load flow constraints

The constraints related to load flow in distribution network can be stated as follows

$$P^{substation} = \sum_{j=1}^{N_{br}} P_{loss}^j(m,n) + \sum_{bs=1}^{N_{bus}} P_{avail,bs} + P_{EVCS}^{bs} \quad (33)$$

$$Q^{substation} + \sum_{bs=1}^{N_{bus}} Q^{cap}(bs) = \sum_{j=1}^{N_{br}} Q_{loss}^j(m,n) + \sum_{bs=1}^{N_{bus}} Q_{avail,bs} \quad (34)$$

2) Bus voltage tolerance

Voltage at each bus i.e., $V(bs)$ must lie within the minimum V_{bs}^{min} and maximum V_{bs}^{max} limits.

$$V_{bs}^{min} \leq V(bs) \leq V_{bs}^{max} \quad bs = 1, 2, 3 \dots N_{bus} \quad (35)$$

3) Transmission line tolerance

The power flow in each line $PF(j)$ should not exceed the maximum specified limit of PF_j^{max} .

$$PF(j) < PF_j^{max} \quad (36)$$

4) Limit on number of capacitors

This restriction is proposed to decrease the number of capacitor placement. Hence, number of capacitor installed N_{cap} should be either less than or equal to maximum number of capacitor N_{cap}^{max} .

$$N_{cap} \leq N_{cap}^{max} \quad (37)$$

5) Limit on capacitor sizing

The reactive power to be injected Q_{cap} should be within the allowable minimum Q_{cap}^{min} and maximum Q_{cap}^{max} limits.

$$Q_{cap}^{min} \leq Q_{cap} \leq Q_{cap}^{max} \quad (38)$$

6) Limit on maximum compensation provided by capacitor

The total reactive power injected by capacitor Q_{cap}^{total} must be either less than or equal to total reactive power load $Q_{avail,bs}^{total}$.

$$\sum_{p=1}^{N_{cap}} Q_{cap}(p) \leq \sum_{bs=1}^{N_{bus}} Q_{avail,bs} \quad (39)$$

3. SENSITIVITY CALCULATIONS

The primary objective of the positioning of capacitors is to reduce the system losses that are increased by the integration of EVCS. Since capacitor placement in the distribution network at each node leads to different power loss values. Therefore, it is desirable to select the node that gives the least power loss. To achieve this goal, sensitivity analysis is carried out to identify those nodes that have the greatest effect on the active power loss of the system with respect to the reactive power of the node (Abou El-Ela A. A et.al. 2016). The preferred location for capacitor placement would be nodes that show high sensitivity values. Sensitivity analysis also decreases the search space for optimization, helping to reach a precise solution for identifying the location.

3.1 Loss Sensitivity Indexes (LSI)

The load buses are graded for capacitor placement on the basis of two loss sensitivity indexes. LSI is capable to predict which bus will have the maximum loss reduction when a capacitor is located (Abou El-Ela A. A et.al. 2016). Fig.1. shows the section of radial distribution system comprise of two buses linked by a branch, where bus m is the sending end bus and bus n is the receiving end bus.

The first loss sensitivity index LSI (1) and second loss sensitivity index LSI (2) can be calculated by taking the first derivative of $P_{loss}(m,n)$ with respect to V_n and Q_n respectively. Therefore, LSI (1) and LSI (2) can be expressed as:

$$LSI (1) = \frac{\partial P_{loss}(m,n)}{\partial V_n} = -2 * R_j * \frac{P_n^2 + Q_n^2}{V_n^3} \quad (40)$$

$$LSI (2) = \frac{\partial P_{loss}(m,n)}{\partial Q_n} = 2 * R_j * \frac{Q_n}{V_n^2} \quad (41)$$

The LSI (1) list is organized in such a way that the highest negative value is at the top and the lowest negative value is at the bottom. The LSI (1) values at the top of the list are considered to be more sensitive for installing the capacitors. As that of LSI1, the same procedure is applied to arrange LSI (2) values with the highest positive value are indexed at the top of the list while the lowest positive value occupies the bottom position. The LSI (2) values at the top of the list are considered to be more sensitive for capacitor placement.

In this way, up to approximately 50 percent to 55 percent of the total number of system buses are selected for capacitor placement based on the LSI (1) and LSI (2) listings starting from the top of these lists. The common buses from both lists will be preferred for capacitor placement.

4. APPLICATION OF PROPOSED APPROACH FOR EVCS AND CAPACITOR PLACEMENT

The proposed approach is the hybrid in which Grey Wolf Optimizer is amalgamated with Particle Swarm Optimizer. It is inspired by the attacking movement of grey wolves to capture their prey and swarming action of group of birds to achieve the target i.e., food. In GWO, the pack is categorized into four main groups of different hierarchical levels such as alpha, beta, delta and omega. Alpha holds the highest positions in hierarchy and believed to be the key decision-makers and the rest follows the decision made by alpha. The process of surrounding, searching and attacking the prey is managed by optimization techniques using mathematical equations (Mirjalili S. et.al. 2014).

$$\vec{m} = |\vec{c} \cdot \vec{x}_p(t) - \vec{x}(t)| \quad (42)$$

$$\vec{x}(t+1) = \vec{x}_p(t) - \vec{a} \cdot \vec{m} \quad (43)$$

Here, \vec{m} represents the surrounding behavior of grey wolf, \vec{x} defines the present location of grey wolf, \vec{x}_p is the position of target that has to be attacked, the coefficient vectors \vec{a} and \vec{c} can be expressed as

$$\vec{a} = 2\vec{p} \cdot \vec{r}_{GWO}^1 - \vec{p} \quad (44)$$

$$\vec{c} = 2 \cdot \vec{r}_{GWO}^2 \quad (45)$$

\vec{p} decreases linearly from two to zero during the complete passage of iteration, \vec{r}_{GWO}^1 and \vec{r}_{GWO}^2 are random variables whose values lies between 0 and 1. The hunting behavior of grey wolf are defined by Eq. (46)-(52). The position vectors of alpha, beta and delta are represented by \vec{x}_α , \vec{x}_β and \vec{x}_δ respectively.

$$\vec{m}_\alpha = |\vec{c} \cdot \vec{x}_\alpha - \vec{x}(t)| \quad (46)$$

$$\vec{m}_\beta = |\vec{c} \cdot \vec{x}_\beta - \vec{x}(t)| \quad (47)$$

$$\vec{m}_\delta = |\vec{c} \cdot \vec{x}_\delta - \vec{x}(t)| \quad (48)$$

$$\vec{x}_1 = \vec{x}_\alpha - \vec{a} \cdot \vec{m}_\alpha \quad (49)$$

$$\vec{x}_2 = \vec{x}_\beta - \vec{a} \cdot \vec{m}_\beta \quad (50)$$

$$\vec{x}_3 = \vec{x}_\delta - \vec{a} \cdot \vec{m}_\delta \quad (51)$$

$$\vec{x}(t+1) = \frac{\vec{x}_1 + \vec{x}_2 + \vec{x}_3}{3} \quad (52)$$

The exploitation of AGWOPSO is based on grey wolf optimization, while particle swarm optimization is used for exploration. The proposed approach is the amalgamation of grey wolf optimization and enhanced particle swarm optimization. The improved equations for alpha, beta and delta wolves are updated using Eqn. (53)- (55). The velocity and updated equation of PSO is improved to Eqn. (56)- (58).

$$\vec{m}_\alpha = |\vec{c} \cdot \vec{x}_\alpha - w_{PSO} * \vec{x}(t)| \quad (53)$$

$$\vec{m}_\beta = |\vec{c} \cdot \vec{x}_\beta - w_{PSO} * \vec{x}(t)| \quad (54)$$

$$\vec{m}_\delta = |\vec{c} \cdot \vec{x}_\delta - w_{PSO} * \vec{x}(t)| \quad (55)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (56)$$

$$w_{PSO}(t) = w_{max} - \frac{(w_{max} - w_{min})}{T} * t \quad (57)$$

$$v_i(t+1) = w_{PSO}(t) * v_i(t) + c_1 r_{PSO}^1 (x_1 - x_i(t)) + c_2 r_{PSO}^2 (x_2 - x_i(t)) + c_3 r_{PSO}^3 (x_3 - x_i(t)) \quad (58)$$

For the performance assessment of AGWOPSO, it has been tested on specific benchmark functions. Compared with GWO, the efficacy of the proposed AGWOPSO has been proven. AGWOPSO has a faster convergence rate and is more reliable. The proposed algorithm was run 50 times on every benchmark function. Without being stuck in local minima and maxima, AGWOPSO converges to an optimal solution, thereby achieving a quicker convergence. Table.1.

shows that the output of the proposed algorithm for standard benchmark functions in terms of the number of iterations for convergence and the optimum solution.

The methodology adopted for solving the optimization problem under consideration is described with flowchart shown in Fig.4. The complete process can be categorized into four stages: the initialization stage, evaluation stage, updating stage, and termination stage. Initially, the constant parameters required to compute active power loss and net profit, etc., are given as input and the initialization of AGWOPSO parameters, which includes maximum iteration, number of runs, number of search agents in GWO, number of particles in PSO, etc. Then load flow analysis is performed to calculate the active power losses and hence, the net profit calculation. In the first run, the most feasible solutions regarding the location and sizing of EVCS and capacitor are chosen from the random population and installed in the grid network. The load flow analysis is carried out after installing EVCS and capacitor and then determine the objective functions. The steps displayed in the flowchart are executed with taking care of operational constraints. In each iteration, the sizes and location of EVCS and capacitors are sent to the evaluation stage of the flowchart to minimize the active power loss and maximize the net profit. The steps are repeated until the termination criteria is achieved.

Table.1. Comparison of results obtained from AGWOPSO and GWO applied on standard benchmark functions

Function	Mathematical Formulation	(D) Dimension	Search Range	Techniques Applied			
				AGWOPSO		GWO	
				Maximum Iterations	Optimal Solution	Maximum Iterations	Optimal Solution
Sphere	$f(x) = \sum_{p=1}^D x_p^2$	30	[-100,100]	1000	$1.55*10^{-22}$	1000	$7.25*10^{-19}$
Rosenbrock	$f(x) = \sum_{p=1}^D [100 * (x_p^2 - x_{p+1})^2 + (1 - x_p)^2]$	30	[-2.048,2.048]	425	$2.72*10^{-2}$	548	$4.57*10^2$
Rastrigin	$f(x) = \sum_{p=1}^D [x_p^2 - 10 \cos(2\pi x_p) + 10]$	30	[-5.12,5.12]	343	$7.57*10^{-13}$	495	$2.53*10^{-2}$
Greiwank	$f(x) = \frac{1}{4000} \sum_{p=1}^D x_p^2 - \prod_{p=1}^D \cos\left(\frac{x_p}{\sqrt{p}}\right) + 1$	30	[-600,600]	1000	$4.25*10^{-2}$	1000	$2.87*10^{-1}$
Schewefel	$f(x) = \sum_{p=1}^D \left(\sum_{q=1}^p x_q \right)^2$	30	[-100,100]	1000	8592.7	1000	6985.8
Ackley	$f(x) = -20e \left(-0.2 \sqrt{\frac{1}{D} \sum_{p=1}^D x_p^2} \right) - e \left(\frac{1}{D} \sum_{p=1}^D \cos(2\pi x_p) \right) + 20 + e^1$	30	[-32.76,32.76]	1000	$7.74*10^{-9}$	1000	$8.54*10^{-3}$
Alpine	$f(x) = \sum_{p=1}^{D-1} x_p \sin x_p + 0.1 x_p $	30	[-10,10]	1000	-192.55	1000	-192.50

5. TEST SYSTEM

5.1 Input parameter related to the study area

In this work, IEEE 33-bus system and 34-bus radial distribution network have been considered for testing the effectiveness of the proposed hybrid algorithm. The line parameters and existing load demand of respective network are mentioned in (Quadri I. et.al. 2019) and (Chis M. J. S et.al. 1997).

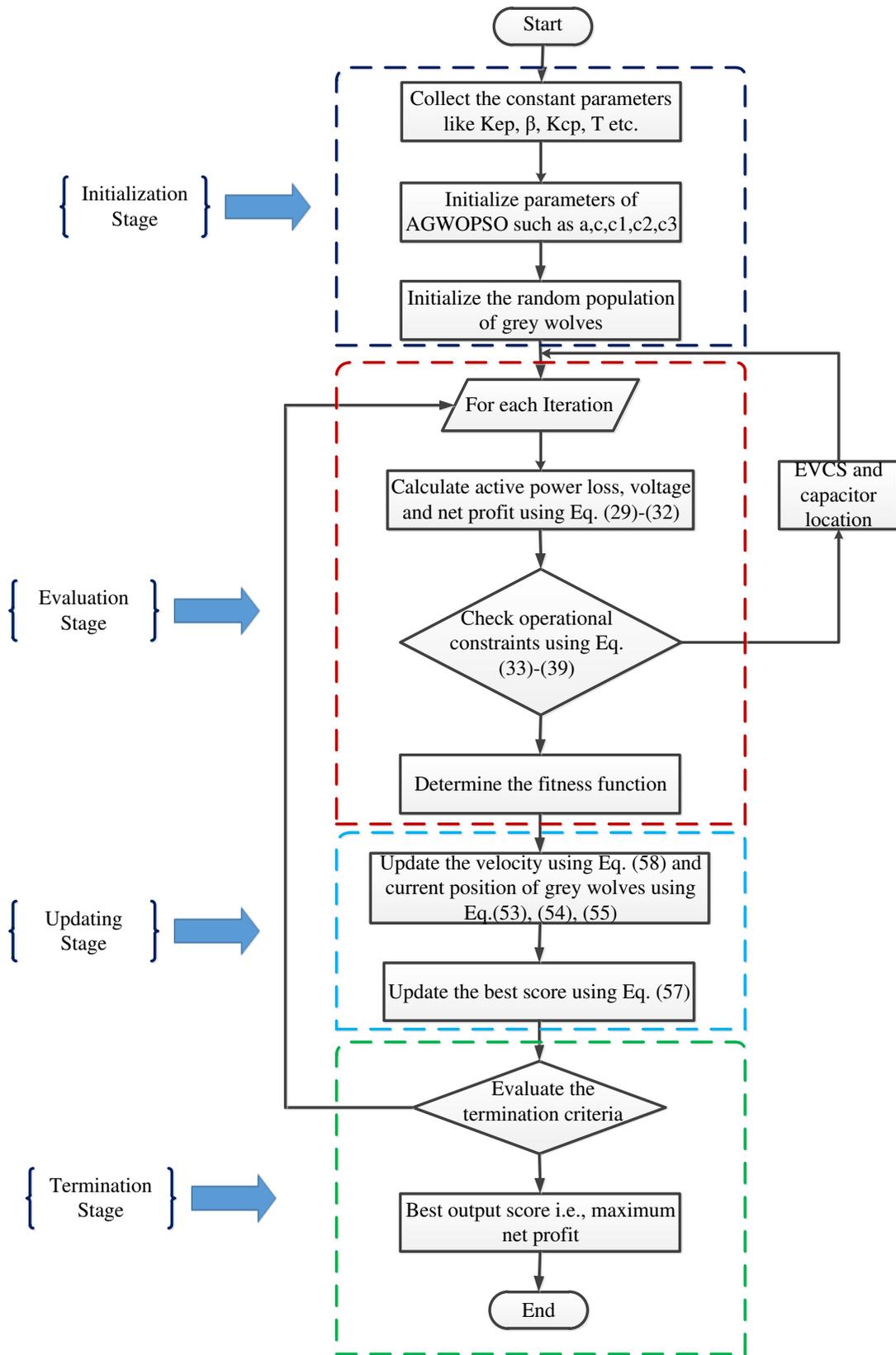


Fig.4. Flow chart of the proposed approach

5.2 Input data related to EVs, EVCS and Capacitors

This research work involves 100 EVs, 2 EVCS with multiple charging points, and a maximum of four capacitors to be optimally positioned. The EVCS load is determined by the number of EVs involved in the grid to vehicle, vehicle-to-grid mode, charging, and discharge rates. In this research analysis, charging rate of 19 kW for grid to vehicle mode and discharge rate of 8 kW for vehicle to grid mode are taken into consideration (Mohamed A. et.al. 2013). Moreover, charging and discharge efficiencies vary from around 80 percent to 95 percent. This research assumes that grid to vehicle mode efficiency is 95 percent while vehicle to grid mode efficiency is 80 percent.

The overall number of potential positions for the capacitor placement is presumed to be 4 for both the 33-bus and 34-bus networks. The voltage restriction on each bus is considered between 0.95 and 1.05 p.u. The maximum active power flow limit is taken to be 5000 kW for both test network (Abou El-Ela A. A et.al. 2016). EVCS and capacitor are not expected to be located on bus 1, since it is a substation bus for all test networks with a constant voltage of 1 p.u. Furthermore, the reactive power to be injected for compensation purposes is set within the range of 150 and 1200 kVAR.

6. SIMULATION RESULTS AND DISCUSSIONS

The performance and efficiency of the proposed hybrid algorithm have been certified on 33-bus and 34-bus radial distribution system with the objective of minimizing the active power loss and maximizing the net profit of the network. The suggested approach focuses on the optimum positioning of EVCS, assuming that EVs are 100 percent penetrated, and then capacitors are optimally installed to compensate for the increased losses incurred by the integration of EVCS and thus, increase the resilience of the electric network. For both test systems, the constants considered for net profit calculation are given in the Table.2. In order to assess the active power losses, direct approach-based load flow analysis of the distribution network is performed (Teng J. H. 2003). All loads are considered as constant power loads and the inclusion of tap-changing transformers is not considered to prevent complexity. A number of trials have been carried out on the considered test network to verify the efficacy of the proposed algorithm. The tuned parameters of AGWOPSO are mentioned in Table.3. The entire simulation is executed in MATLAB R2016a on an Intel i7, 3.2 GHz, 4 GB RAM, desktop PC.

Table.2. Constant parameters required for the computation of net profit

Parameter	Value	Unit
Cost of energy paid per kWh (K_{ep})	0.06	\$/kWh
Depreciation factor (β)	20%	-
Hours per year (T)	8760	Hours
Cost of purchase of capacitor per kVAR (K_{cp})	25	\$/kVAR
Installation cost of capacitor (C_i^{cap})	1400	\$/location
Installation cost of charging station (C_i^{CS})	6070	\$/location
Operating cost of capacitor (C_o^{cap})	300	\$/year/location
Operating cost of charging station (C_o^{CS})	8400	\$/year/location

6.1 Implemented simulation results and discussion for 33-bus, 12.66 kV system

The 33-bus radial distribution network comprise of 33 nodes and 32 branches as depicted in Fig.5. The line data and bus data of such system is taken from [29]. The total active power and reactive power demand of the network is 3715 kW and 2300 kVAR respectively. The distribution network operates at rated voltage of 12.66 kV. Initially, direct approach method for performing load flow analysis is implemented to investigate the active power losses which comes out to be 201.87 kW. In this case, the minimum voltage is 0.9132 p.u and maximum voltage is 0.9972 p.u. The annual energy loss cost incurred for 201.87 kW is \$106102.87. To certify the effectiveness of the proposed hybrid algorithm, results attained using AGWOPSO are compared with that of Grey wolf optimization. Using the proposed algorithm, the optimal nodes for EVCS placement comes out to be node 2 and 19 which results in minimum power loss of 213.06 kW and 221.49 kW respectively. The results indicate that optimum EVCS placement strategy increases the loss of power and disturbs the voltage profile in electrical power networks, though EVCS are positioned near to the substation bus. In order to improve the voltage profile and loss, capacitors are placed closer to EVCS and the end of feeders by delivering some reactive power. In this respect, the optimal location and capacities of EVCS and capacitors utilizing the proposed approach and its comparison with GWO are displayed in Table.4.

Table.3. Tuned parameters of the proposed algorithm

Algorithm	Parameter	Description	Value
GWO	maxitr	Maximum number of iterations	100
	NSA	Number of search agents	30
PSO	Npop	Swarm size	50
	w _{min}	Minimum value of inertia weight	0.4
	w _{max}	Maximum value of inertia weight	0.9
	c ₁	Cognitive acceleration coefficients	2.01
	c ₂	Social acceleration coefficients	2.02
	Nruns	Number of runs	50

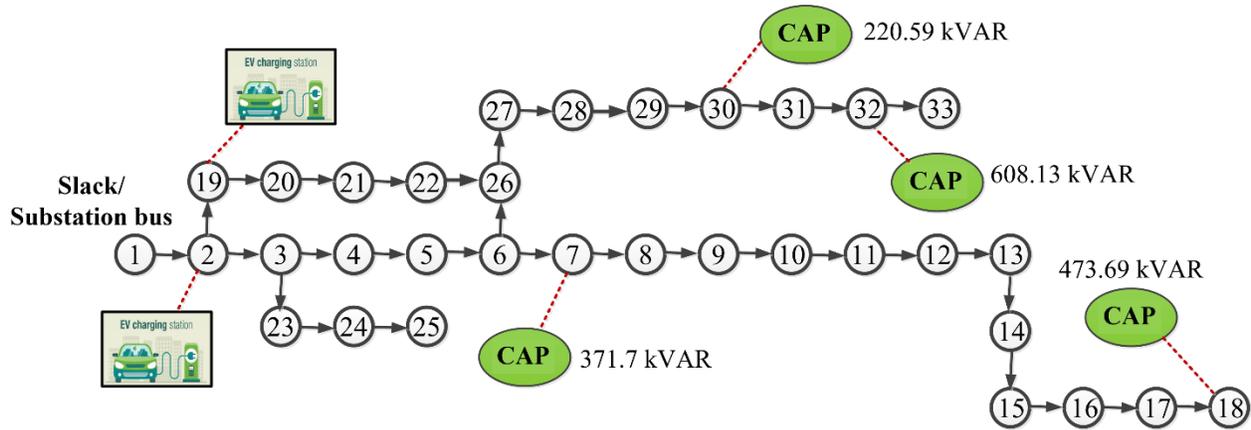


Fig.5. Typical configuration of 33-bus system with two EVCS and four capacitors

The optimal locations are initially filtered by performing the sensitivity analysis. Furthermore, the proposed algorithm AGWOPSO is applied to select the optimal nodes based on LSIs. When the capacitors of rating 371.7, 473.79, 220.59 and 608.13 kVAR are placed at optimal nodes 7, 18, 30 and 32 respectively leads to significant drop in active power loss of 139.94 kW from the base case active power loss of 201.87 kW, thus obtaining 30.6 % loss reduction benefit in annual energy loss cost. The minimum voltage of 0.9515 p.u. is registered at 15th bus which is satisfying the voltage restriction limit. In this article, the percentage of loss reduction in annual energy loss cost is 30.67% using the proposed AGWOPSO which is better than that of GWO i.e., 29.74%. Also, the amount spent on the installation of capacitors using AGWOPSO is comparatively small when compared with GWO as shown in Table.4. In addition to this, the net profit obtained after integrating EVCS and capacitors to the 33-bus distribution system utilizing AGWOPSO is 13358.55 \$ whereas GWO provides less net profit of 12215.64 \$. The above analysis proves the supremacy of AGWOPSO algorithm over GWO. The comparison of the attained results using the proposed algorithm against GWO approach for 33-bus system is presented in Table.4.

Also, the computational time and convergence time for the AGWOPSO and GWO are determined and mentioned in Table.4. The computational time refers to the time needed to perform the total number of runs, while the time required by the specific algorithm to reach the termination criterion is the convergence time. The computational time for the proposed AGWOPSO is 2054.7 sec while it attains the optimum solution after 378.9 sec. The other approach is GWO which takes 2391.3 sec for computation and converge in 594.2 sec. The efficiency of the proposed approach can be investigated by the ratio of difference between the computational time and convergence time to the computational time. The efficiency of the proposed approach is 81.5 % while for GWO it is 75.1 %.

Fig.6. shows the voltage profile of 33-bus system after the optimal placement of EVCS and capacitor. It is shown that the voltage profile is enhanced by the installation of the capacitor. Thus, the proposed AGWOPSO technique is successful for maintaining the healthy voltage profile of the 33-bus distribution system. Fig.7. depicts the flow of active power in all branches of distribution system after incorporating EVCS as well as capacitor. The active power flow jumps to higher value due to increased loading of EVCS but it is managed by capacitor placement at optimal nodes and bringing it to the allowable limits.

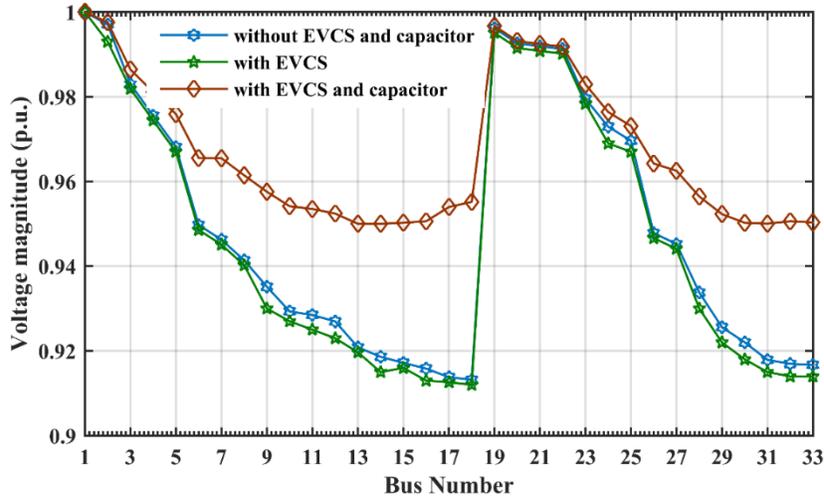


Fig.6. Improvement in voltage profile based on capacitor placement

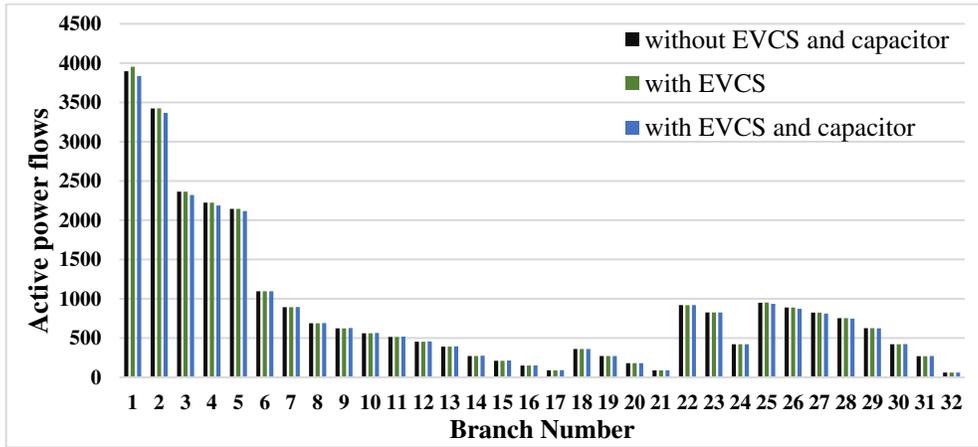


Fig.7. Improvement in flow of active power based on capacitor placement

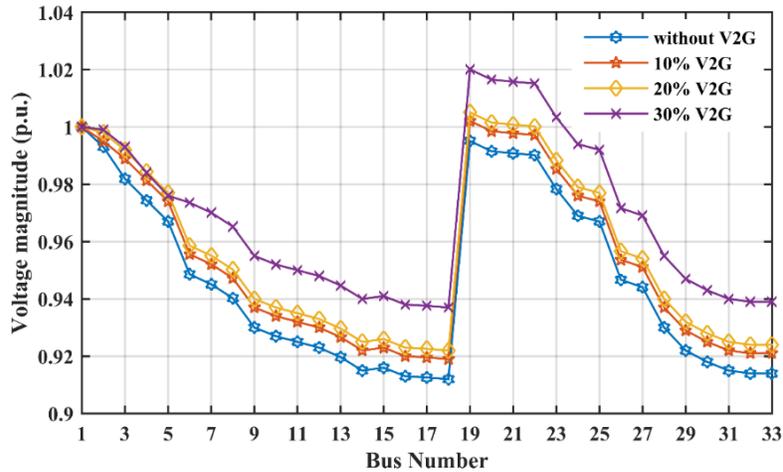


Fig.8. Voltage profile improvement due to participation of EVs in V2G

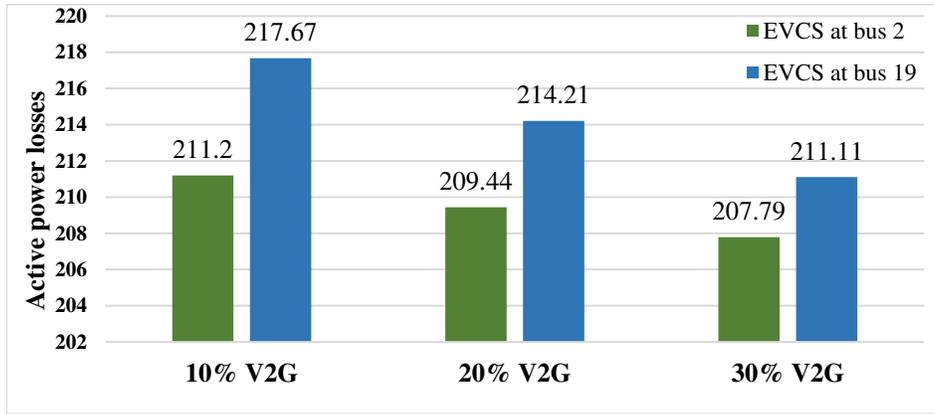


Fig.9. Reduction in active power losses with increase in EVs participation in V2G for 33-bus system

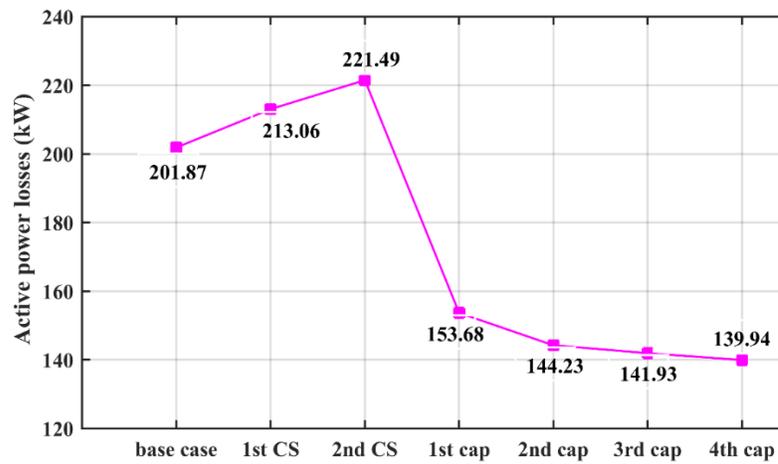


Fig.10. Variation of active power losses on integrating EVCS and capacitor for 33-bus system

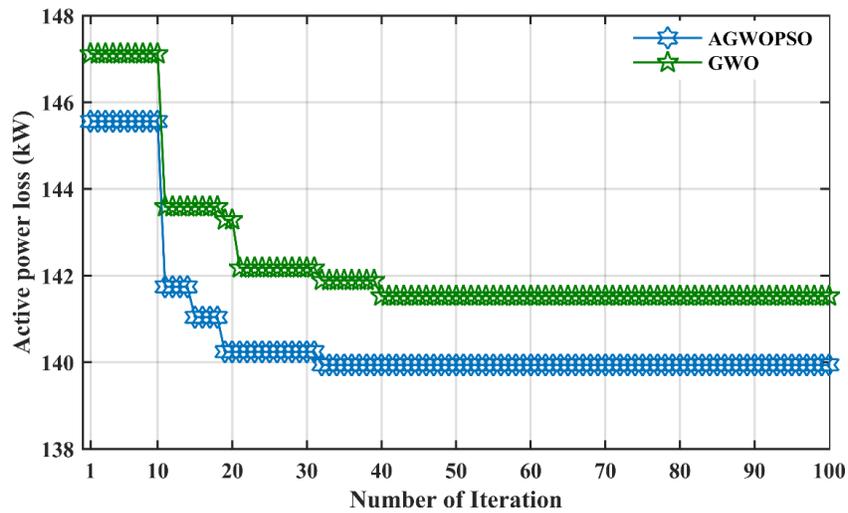


Fig.11. Response of AGWOPSO and GWO for 33-bus distribution system

When EVs are having surplus energy, the extra energy is fed to the grid for maintaining the reliability of the system. Hence, EVs participation in vehicle to grid mode assist the grid operator for keeping the acceptable voltage profile and also decreases the power losses of the system. In this regard, Fig.8. shows the improvement in voltage profile when different percentage of EVs participates in vehicle to grid mode. In this paper, three different cases have been considered which comprises of 10%, 20% and 30% of the vehicles takes part in inverting mode i.e., vehicle to grid. Moreover, vehicle to grid facility not only improves the voltage profile but reduces the active power losses as well. In 34-bus network, the active power losses for optimal EVCS nodes i.e., 2 and 19 are calculated to be 213.06 kW and 221.49 kW respectively when vehicle to grid facility is not incorporated. As the EVs participation in vehicle to grid mode increases, active power losses come down. Fig.9. shows the active power losses of 33-bus system for different percentage of EVs operation in V2G mode. Furthermore, Fig.10. reflects the variation of power losses on integrating the EVCS and capacitor. It can be realized that power losses reduce as the quantity of capacitors increases. But reduction in power loss is marginal on further increasing the capacitors and also it creates economic issues. The efficacy of proposed algorithm i.e., AGWOPSO can be verified by comparing the results with GWO. The convergence characteristics of the proposed algorithm and GWO are shown in Fig.11. and found that proposed algorithm has faster convergence towards the optimal solution as compared with GWO.

Table.4. The optimal results obtained via AGWOPSO in comparison with GWO for 33-bus system

Parameter	Base Case	EVCS and capacitor placement	
		AGWOPSO	GWO
Active power losses (kW)	201.87	139.94	141.82
Optimal nodes for EVCS	–	2, 19	2, 19
Total number of EVs	–	100	100
Optimal nodes for capacitor	–	7, 18, 30, 32	7, 18, 30, 32
Capacitor sizes (kVAR)	–	371.7, 473.7, 220.59, 608.13	425.18, 494.5, 353.8, 710.2
Total kVAR	–	1674.12	1983.68
Energy loss cost (\$)	106102.87	73552.46	74540.59
% loss reduction in energy loss cost	–	30.67	29.74
Total capacitor cost (\$)	–	41853	49592
Net profit (\$)	–	13358.55	12215.64
Convergence time in seconds	–	378.9	594.2
Computational time in seconds	–	2054.7	2391.3
Efficiency	–	81.5	75.1

6.2 Implemented simulation results and discussion for 34-bus, 12.66 kV system

The 34-bus system comprises of 33 branches and 34 nodes as represented in Fig.12. The line data and bus data of such system is taken from [30]. The overall active power and reactive power demand of the network is 4636.5 kW and 2873.5 kVAR respectively. The distribution network operates at rated voltage of 12.66 kV. The active power losses come out to be 163.45 kW using the direct approach method of load flow. In this case, the minimum voltage is 0.9561 p.u and maximum voltage is 0.9952 p.u. The annual energy loss cost incurred for 163.45 kW is 85909.32 \$. To confirm the effectiveness of the proposed hybrid algorithm AGWOPSO, obtained results are compared with results obtained via Grey wolf optimization.

The optimal nodes for EVCS placement for 34-bus system are nodes 2 and 13 using the proposed algorithm, resulting in a lowest power loss of 180.01 kW and 199.42 kW, respectively. Concerning this, the optimal location and capacities of EVCS and capacitors using the proposed approach and its comparison with GWO are displayed in Table.5.

In 34-bus system, when the capacitor of sizes displayed in Table.5 are placed at optimal nodes 5,9,21 and 24 results in least power loss of 118.21 kW from the base value of 163.45 kW thus, achieving 27.6 % reduction in active power loss. The minimum voltage of 0.9627 p.u. is registered at 27th bus which is satisfying the voltage restriction limit. The percentage of loss reduction in annual energy loss cost is 27.67% using the proposed AGWOPSO which is better than that of GWO i.e., 25.74%. Also, the amount spent on the installation of capacitors using AGWOPSO is comparatively small when compared with GWO as shown in Table.5. In addition to this, the net profit gained in 34-bus distribution system utilizing AGWOPSO is 4111.74 \$ whereas GWO provides less net profit of 2384.78 \$.

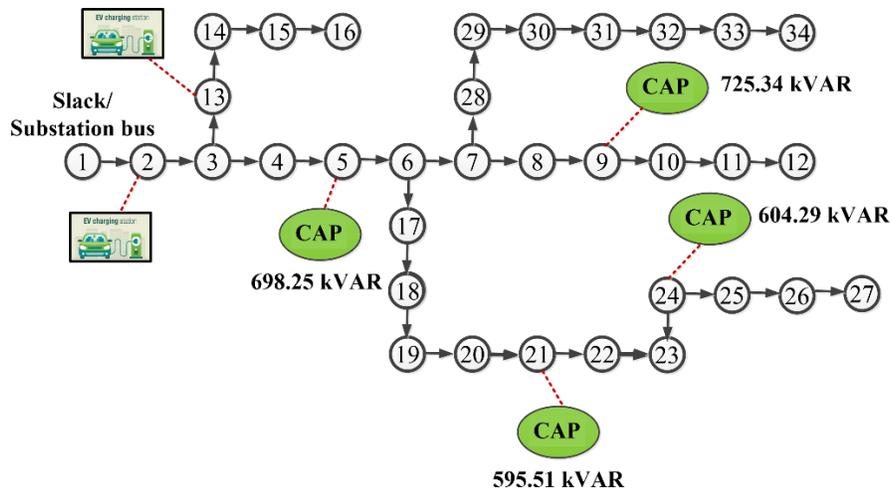


Fig.12. Typical configuration of 34-bus system with two EVCS and four capacitors

Compared to GWO, the proposed algorithm has better performance. The comparison results using proposed algorithm with GWO for 34-bus system have been tabulated in Table.5.

The computational time for the proposed AGWOPSO is 2246.9 sec while it attains the optimal solution after 422.5 sec. The other approach is GWO which takes 2578.3 sec for computation and converge in 685.1 sec. The efficiency of the proposed approach is 81.1 % while for GWO it is 73.4 %. Fig.13. shows the voltage profile of 34-bus system after the optimal placement of EVCS and capacitor. Fig.14. depicts the flow of active power in all branches of distribution system for 34-bus system after incorporating EVCS as well as capacitor.

Fig.15. shows the enhancement in voltage profile for 34-bus system when different percentage of EVs participates in vehicle to grid mode. In 34-bus network, the active power losses for optimal EVCS nodes i.e., 2 and 13 are calculated as 180.01 kW and 199.42 kW respectively when vehicle to grid facility is not incorporated. Active power losses decrease as EVs operation in V2G mode increases. Fig.16. displays the variation of power losses on integrating the EVCS and capacitor in 34-bus system. It can be observed that power losses reduce with increasing number of capacitors. Fig.17. shows the active power losses of 34-bus system for different percentage of EVs operation in V2G mode. Furthermore, the efficacy of proposed algorithm i.e., AGWOPSO is validated by comparing with GWO. The convergence plot of the proposed algorithm and GWO is shown in Fig.18. and found that, compared to GWO, the proposed algorithm converges more quickly towards the optimal solution.

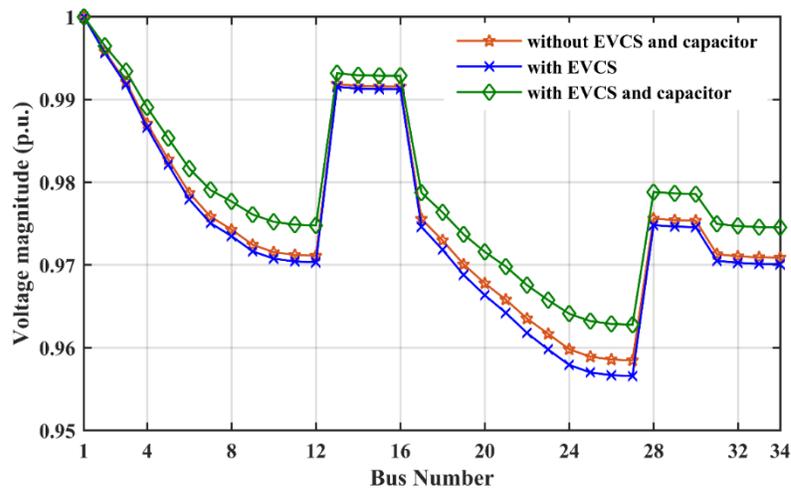


Fig.13. Improvement in voltage profile based on capacitor placement for 34-bus system

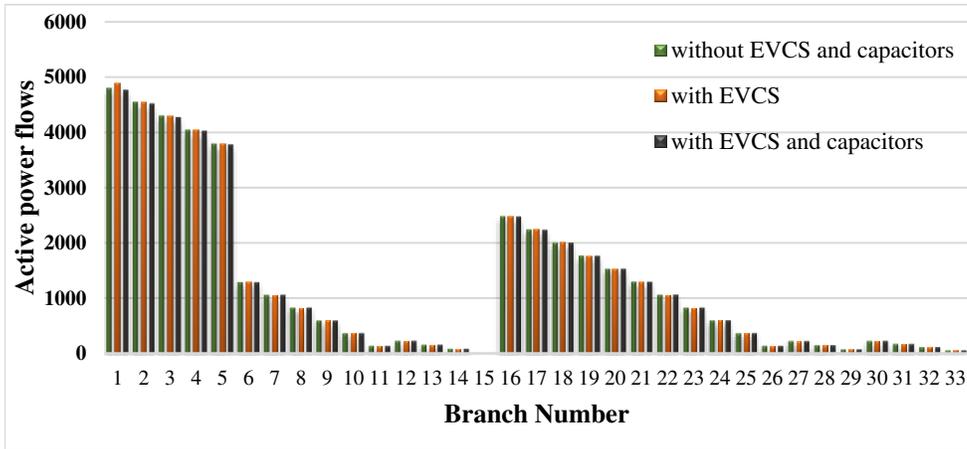


Fig.14. Improvement in flow of active power based on capacitor placement

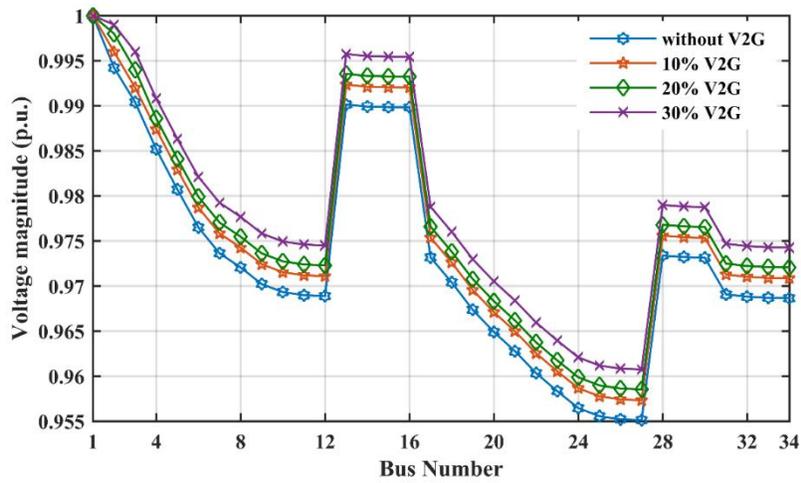


Fig.15. Voltage profile improvement due to participation of EVs in V2G

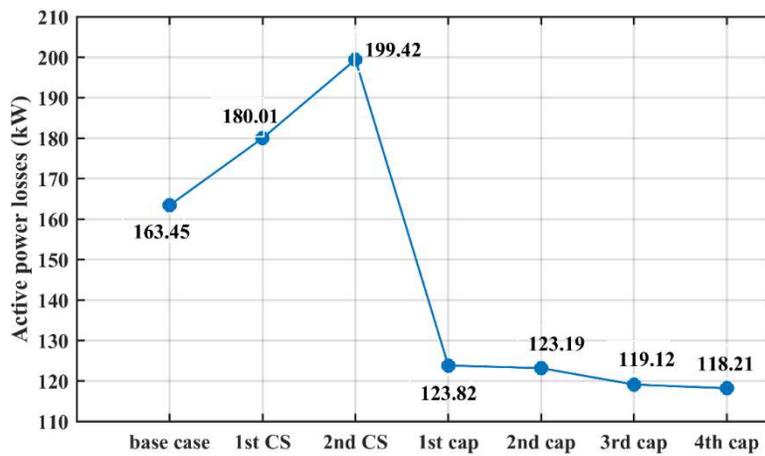


Fig.16. Variation of active power losses on integrating EVCS and capacitor

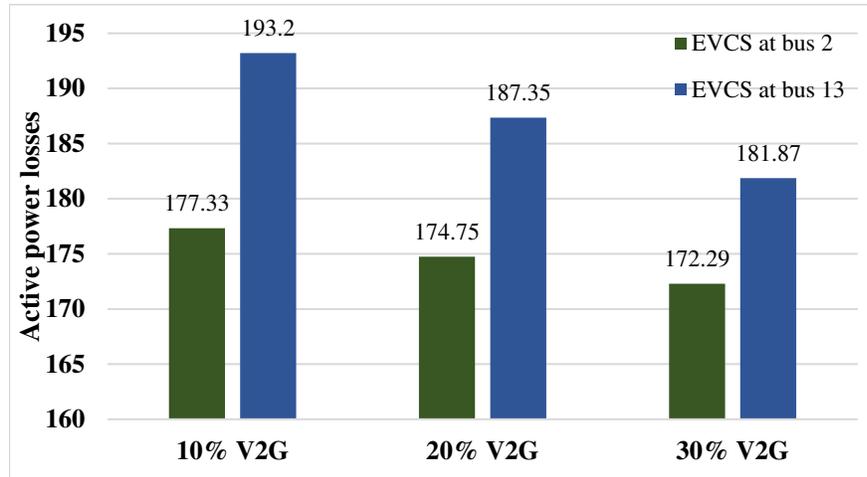


Fig.17. Reduction in active power losses with increase in EVs participation in V2G

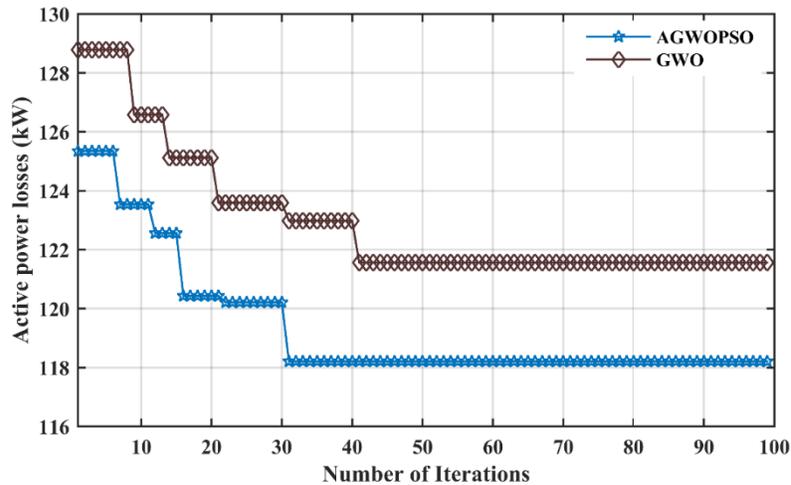


Fig.18. Response of AGWOPSO and GWO for 34-bus distribution system

Table.5. The optimal results obtained via AGWOPSO in comparison with GWO for 34-bus system

Parameter	Base Case	EVCS and capacitor placement	
		AGWOPSO	GWO
Active power losses (kW)	163.45	118.21	121.56
Optimal nodes for EVCS	—	2, 13	2, 13
Total number of EVs	—	100	100
Optimal nodes for capacitor	—	5, 9, 21, 24	5, 9, 21, 24
Capacitor sizes (kVAR)	—	698.2, 725.3, 595.5, 604.2	713.5, 797.6, 628.1, 656.9
Total kVAR	—	2623.2	2796.1
Annual energy loss cost (\$)	85909.32	62131.17	63891.93
% loss reduction in energy loss cost	—	27.6	25.7
Total capacitor cost (\$)	—	65580	69902.5
Net profit (\$)	—	4111.74	2384.78
Convergence time in seconds	—	422.5	685.1
Computational time in seconds	—	2246.9	2578.3
Efficiency	—	81.1	73.4

7. CONCLUSION

This research work has been performed to minimize the real power losses and maximizing the net profit, keeping the healthy voltage profile at each node using AGWOPSO algorithm. The results have revealed that the optimal planning of EVCS increases power loss and voltage drop in electrical power networks. In this specific case, CSs are placed close to the substation bus. Further, the results have demonstrated that the optimal planning of capacitor after optimal planning of CS in the network improves power loss and voltage profile. Capacitors are employed closer to EVCS and end of feeders for the enhancement of voltage profile and loss by contributing some reactive power. It is also shown that, different percentage of EVs participated in vehicle to grid mode thereby improving the active power flows, voltage profile and reduces the active power loss of the network. The algorithm considered in this work is the amalgamation of grey wolf optimization and particle swarm optimization, for determining the optimal nodes for EVCS and capacitor placement and hence, optimizing the objectives. The proposed hybrid algorithm is capable of extracting best features of the both methods and achieve improved results as compared to the separate application of the two methods. The proposed algorithm is tested on selected benchmark functions and then applied on 33-bus and 34-bus system. The attained results using the proposed hybrid algorithm reveals the preeminence of the algorithm over other techniques discussed in literature. Additionally, as a future extension of this work, the impact of distributed generation on the EVCS placement can be considered which has not been examined here. Furthermore, the system reliability and expansion of network has not been checked in the proposed work. So, based on these findings, these open problems can be studied.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Author contribution statement

Mohd Bilal: Conceptualization, Methodology, Software, Writing - original draft. **Mohammad Rizwan:** Supervision, Conceptualization, Methodology, Software, review & editing.

REFERENCES

- [1] Golpîra H, & Khan S. A. R. (2019) A multi-objective risk-based robust optimization approach to energy management in smart residential buildings under combined demand and supply uncertainty. *Energy* 170: 1113-1129.
- [2] Vayá M. G, & Andersson G. (2015) Self scheduling of plug-in electric vehicle aggregator to provide balancing services for wind power. *IEEE Transactions on Sustainable Energy* 7(2):886-899.
- [3] Deng B, & Wang Z. (2011) Research on electric-vehicle charging station technologies based on smart grid. In 2011 Asia-Pacific Power and Energy Engineering Conference (pp. 1-4). IEEE.
- [4] Han S, Han S, & Sezaki K. (2010) Development of an optimal vehicle-to-grid aggregator for frequency regulation. *IEEE Transactions on smart grid* 1(1):65-72.
- [5] Singh M, Kumar, P, & Kar I. (2013) A multi charging station for electric vehicles and its utilization for load management and the grid support. *IEEE Transactions on Smart Grid* 4(2):1026-1037.
- [6] Dharmakeerthi C. H, Mithulananthan N, & Saha T. K. (2015) A comprehensive planning framework for electric vehicle charging infrastructure deployment in the power grid with enhanced voltage stability. *International Transactions on Electrical Energy Systems* 25(6): 1022-1040.
- [7] Liu L, Zhang Y, Da C, Huang Z, & Wang M. (2020) Optimal allocation of distributed generation and electric vehicle charging stations based on intelligent algorithm and bi-level programming. *International Transactions*

on Electrical Energy Systems 30(6), e12366.

- [8] Awasthi A, Venkitesamy K, Padmanaban S, Selvamuthukumar R, Blaabjerg F, & Singh A. K. (2017) Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm. *Energy* 133:70-78.
- [9] Mehta R, Verma P, Srinivasan D, & Yang J. (2019) Double-layered intelligent energy management for optimal integration of plug-in electric vehicles into distribution systems. *Applied energy* 233:146-155.
- [10] Liu Z, Wen F, & Ledwich G. (2012) Optimal planning of electric-vehicle charging stations in distribution systems. *IEEE transactions on power delivery* 28(1):102-110.
- [11] Bilal M, & Rizwan M. (2020) Electric vehicles in a smart grid: a comprehensive survey on optimal location of charging station. *IET Smart Grid* 3(3):267-279.
- [12] Reddy M. S. K, & Selvajyothi K. (2020) Optimal placement of electric vehicle charging station for unbalanced radial distribution systems. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* 1-15.
- [13] Aljaidi M, Aslam N, & Kaiwartya O. (2019) Optimal Placement and Capacity of Electric Vehicle Charging Stations in Urban Areas: Survey and Open Challenges. In 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT) (pp. 238-243). IEEE.
- [14] Wang X, Yuen C, Hassan N. U, An N, & Wu W. (2016) Electric vehicle charging station placement for urban public bus systems. *IEEE Transactions on Intelligent Transportation Systems* 18(1):128-139.
- [15] Davidov S, & Pantoš M. (2019) Optimization model for charging infrastructure planning with electric power system reliability check. *Energy* 166:886-894.
- [16] Lin X, Sun J, Ai S, Xiong X, Wan Y, & Yang D. (2014) Distribution network planning integrating charging stations of electric vehicle with V2G. *International Journal of Electrical Power & Energy Systems* 63:507-512.
- [17] Wang G., Xu, Z., Wen, F., & Wong, K. P. (2013) Traffic-constrained multiobjective planning of electric-vehicle charging stations. *IEEE Transactions on Power Delivery* 28(4):2363-2372.
- [18] Pal A, Bhattacharya A, & Chakraborty A. K. (2021) Allocation of electric vehicle charging station considering uncertainties. *Sustainable Energy, Grids and Networks* 25:100422.
- [19] Fathy A, & Abdelaziz A. Y. (2020) Competition over resource optimization algorithm for optimal allocating and sizing parking lots in radial distribution network. *Journal of Cleaner Production* 264:121397.
- [20] Prakash K, & Sydulu M. (2007) Particle swarm optimization based capacitor placement on radial distribution systems. In 2007 IEEE power engineering society general meeting (pp. 1-5). IEEE.
- [21] Sirjani R, Mohamed A, & Shareef H. (2012) Heuristic optimization techniques to determine optimal capacitor placement and sizing in radial distribution networks: a comprehensive review. *Przełąd Elektrotechniczny (Electr. Rev.)* 88(7a):1-7.
- [22] Raju M. R, Murthy K. R, & Ravindra K. (2012) Direct search algorithm for capacitive compensation in radial distribution systems. *International Journal of Electrical Power & Energy Systems* 42(1):24-30.
- [23] El-Fergany A. A, & Abdelaziz A. Y. (2014) Capacitor placement for net saving maximization and system stability enhancement in distribution networks using artificial bee colony-based approach. *International Journal of Electrical Power & Energy Systems* 54:235-243.
- [24] Abou El-Ela A. A, El-Sehiemy R. A, Kinawy A. M, & Mouwafi M. T. (2016) Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. *IET Generation, Transmission & Distribution* 10(5):1209-1221.
- [25] Sachan S, & Amini M. H. (2020) Optimal allocation of EV charging spots along with capacitors in smart distribution network for congestion management. *International Transactions on Electrical Energy Systems*

30(9):e12507.

- [26] Gampa S. R, Jasthi K, Goli P, Das D, & Bansal R. C. (2020) Grasshopper optimization algorithm based two stage fuzzy multiobjective approach for optimum sizing and placement of distributed generations, shunt capacitors and electric vehicle charging stations. *Journal of Energy Storage* 27:101117.
- [27] Rajesh P, & Shajin F. H. (2021) Optimal allocation of EV charging spots and capacitors in distribution network improving voltage and power loss by Quantum-Behaved and Gaussian Mutational Dragonfly Algorithm (QGDA). *Electric Power Systems Research* 194:107049.
- [28] Mirjalili S, Mirjalili S. M, & Lewis A. (2014) Grey wolf optimizer. *Advances in engineering software* 69:46-61.
- [29] Quadri I. A, Bhowmick S, & Joshi D. (2019) A hybrid teaching–learning-based optimization technique for optimal DG sizing and placement in radial distribution systems. *Soft Computing* 23(20):9899-9917.
- [30] Chis M. J. S, Salama M. M. A. (1997) Capacitor placement in distribution system using metaheuristic search strategies. *IET Generation Transmission Distribution* 144(3):225–230.
- [31] Mohamed A, Salehi V, Ma T, & Mohammed O. (2013) Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy. *IEEE Transactions on Sustainable Energy* 5(2);577-586.
- [32] Teng J. H. (2003) A direct approach for distribution system load flow solutions. *IEEE Transactions on power delivery* 18(3):882-887.

Figures

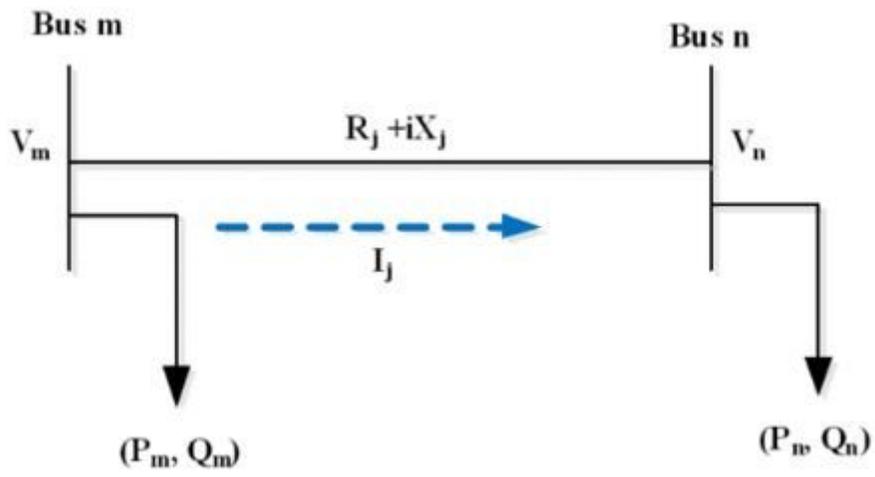


Figure 1

Representation of two nodes and one branch of distribution system

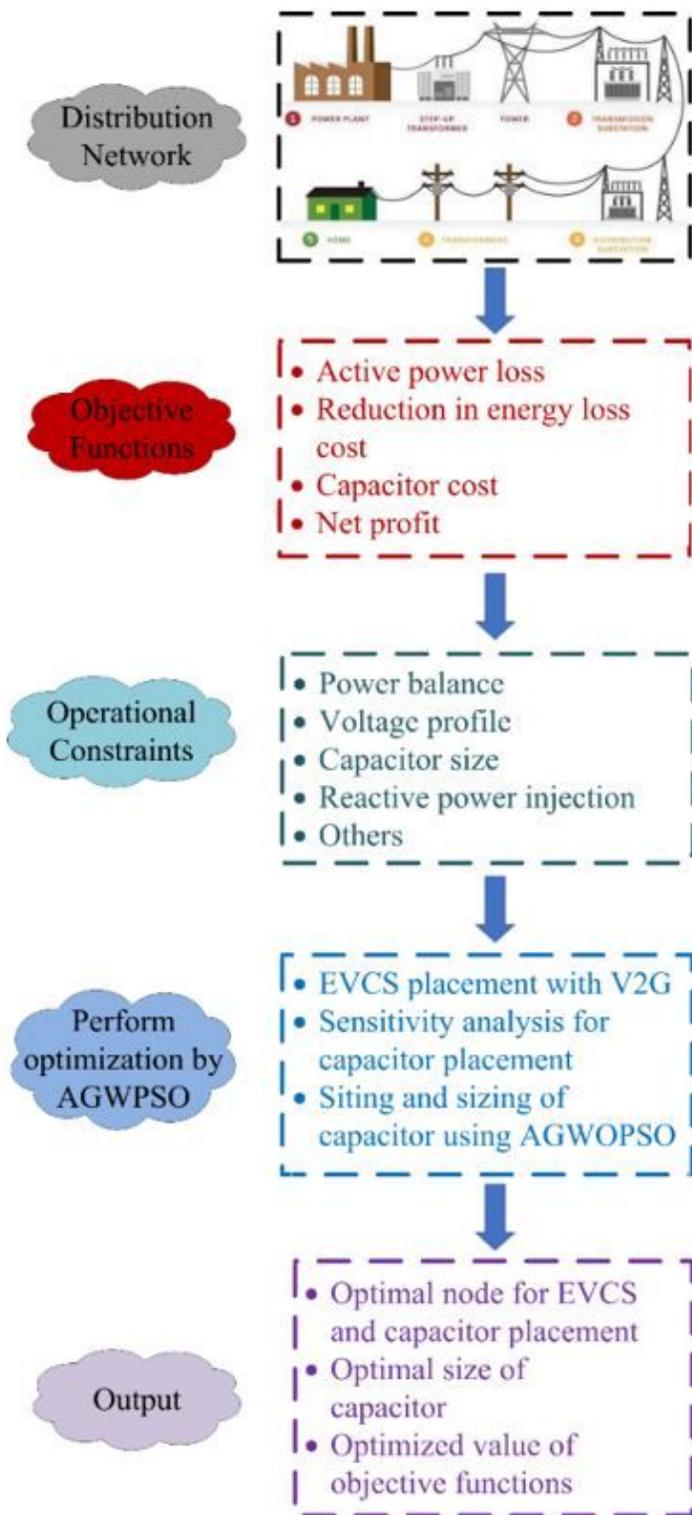


Figure 2

Layout of the proposed methodology

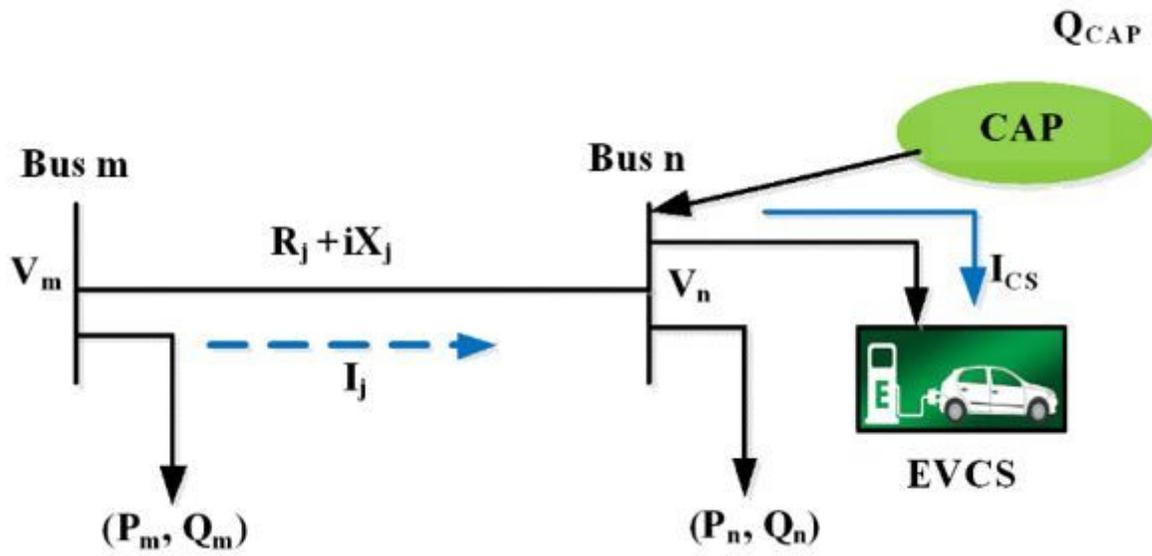


Figure 3

Representation of integrated EVCS and capacitor in distribution system

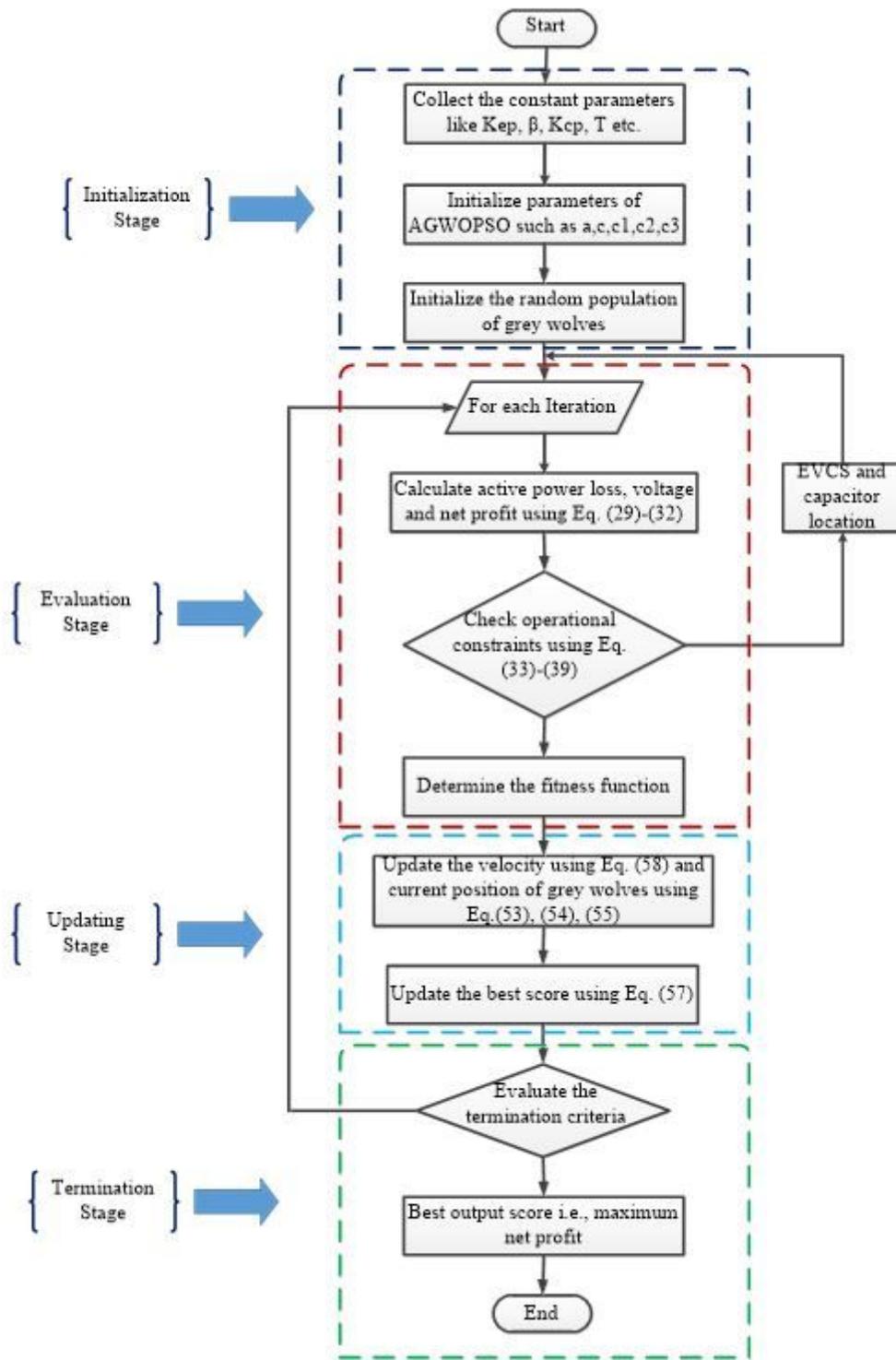


Figure 4

Flow chart of the proposed approach

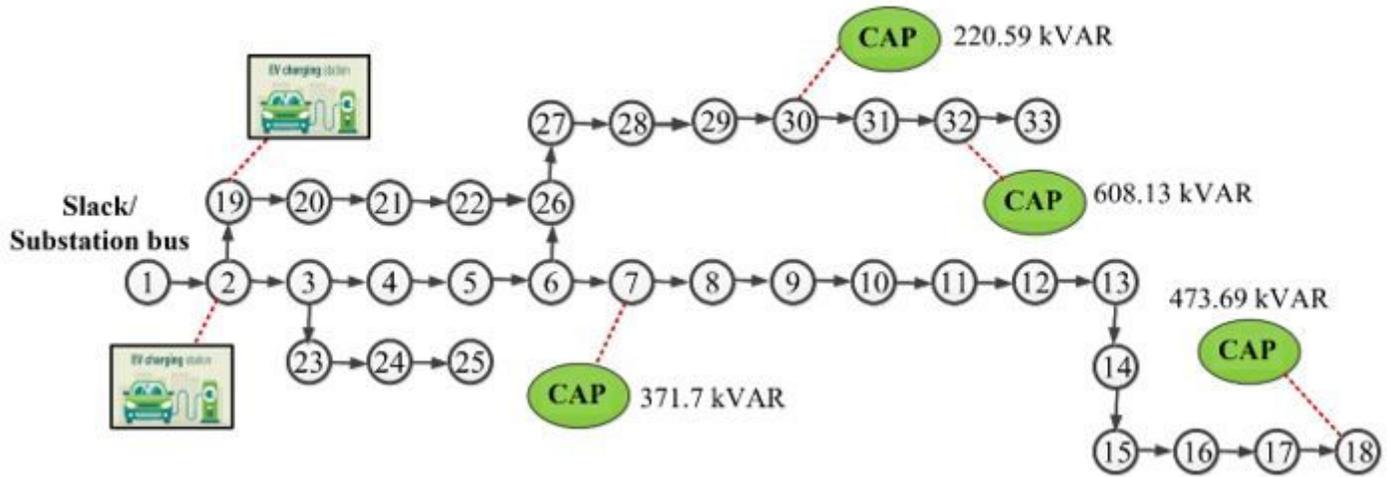


Figure 5

Typical configuration of 33-bus system with two EVCS and four capacitors

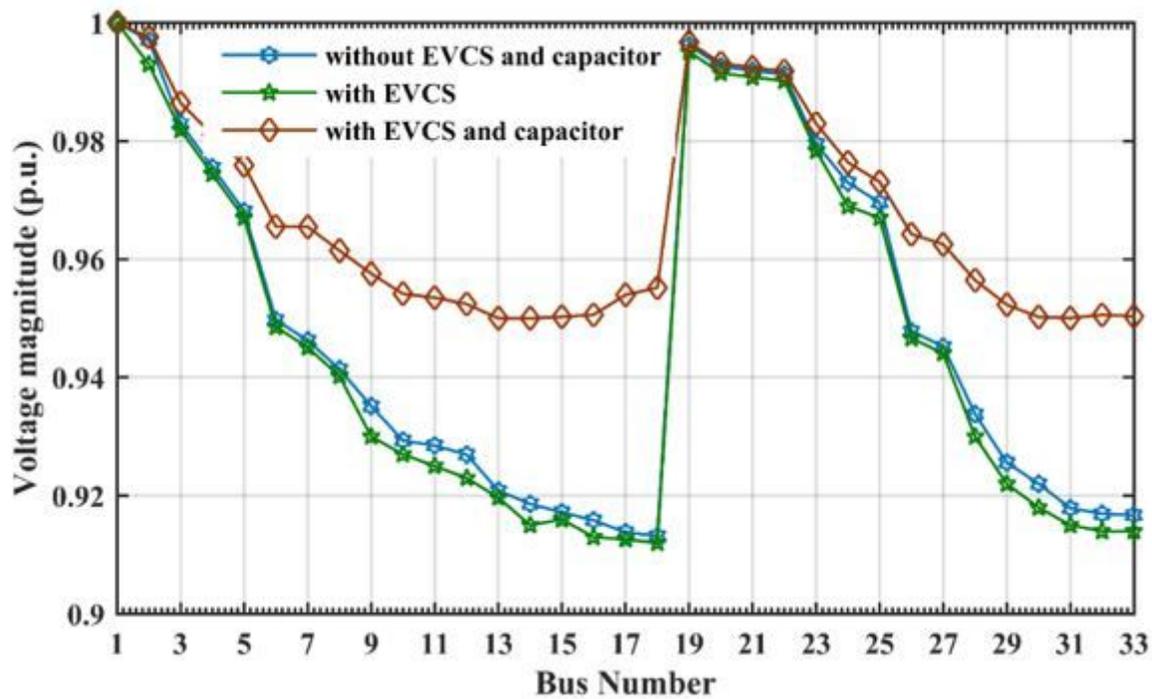


Figure 6

Improvement in voltage profile based on capacitor placement

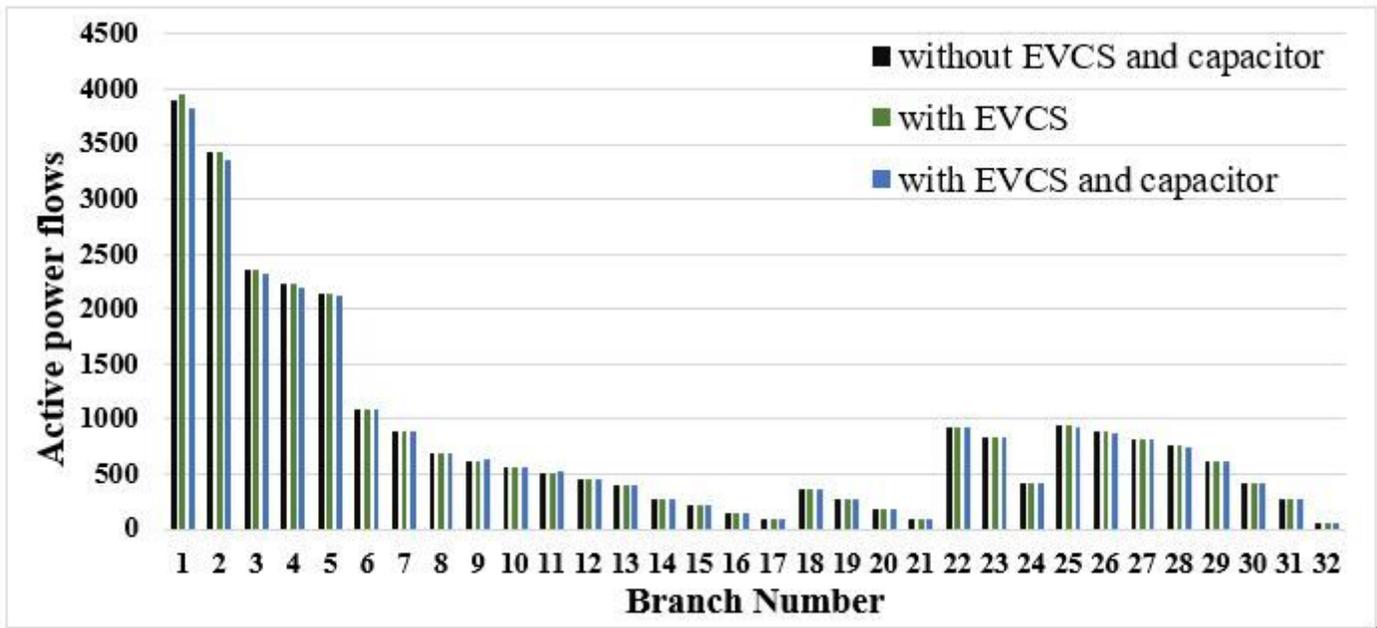


Figure 7

Improvement in flow of active power based on capacitor placement

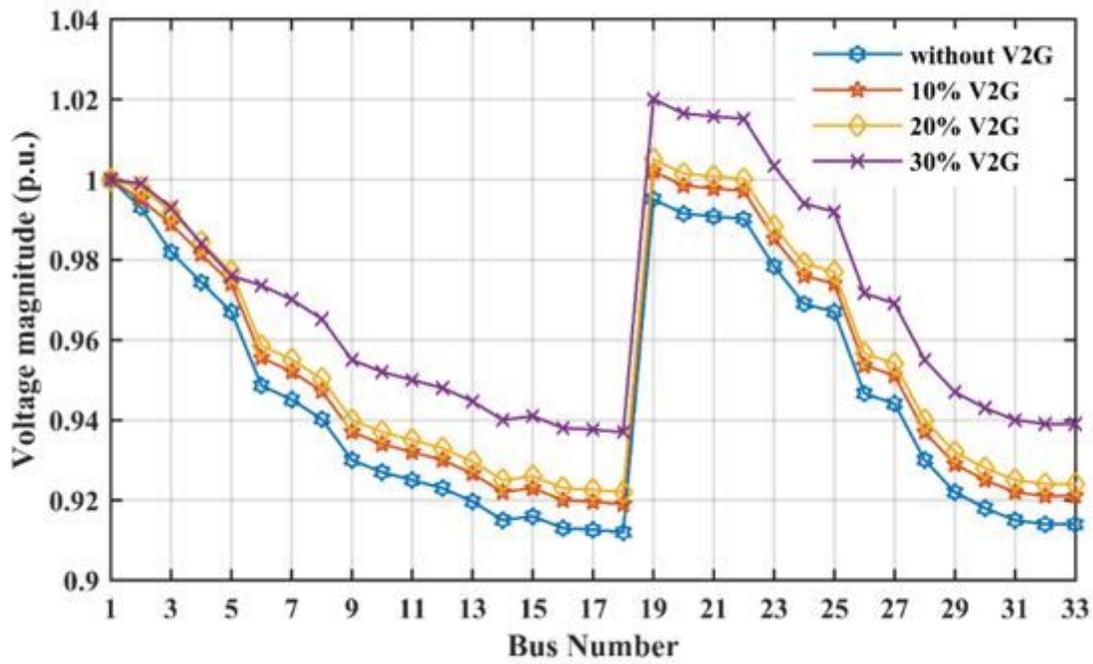


Figure 8

Voltage profile improvement due to participation of EVs in V2G

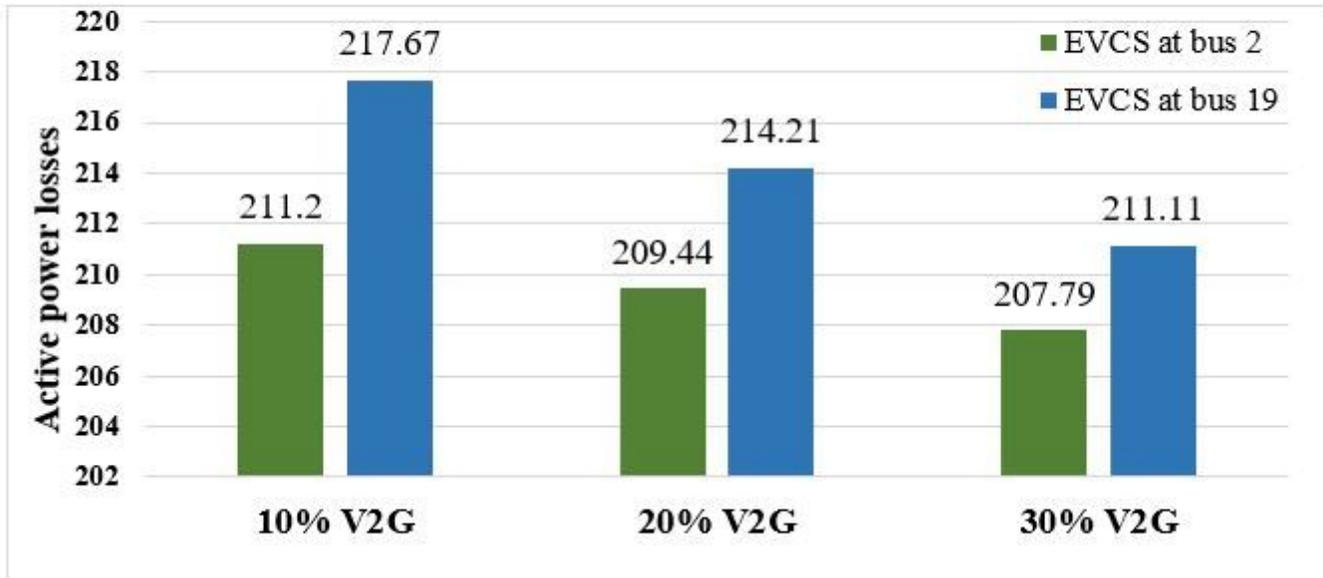


Figure 9

Reduction in active power losses with increase in EVs participation in V2G for 33-bus system

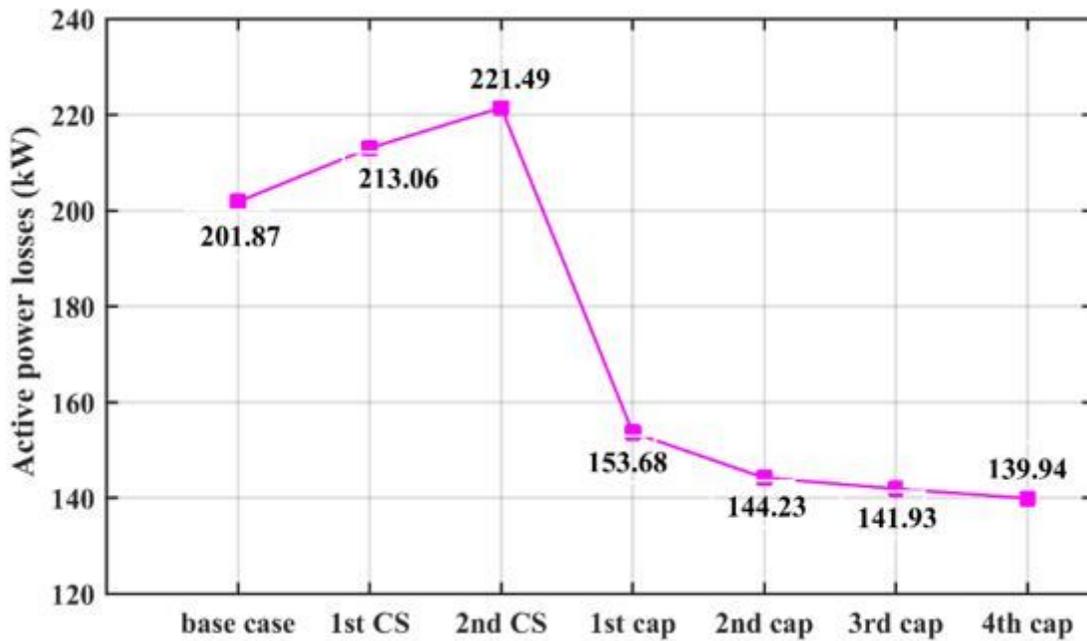


Figure 10

Variation of active power losses on integrating EVCS and capacitor for 33-bus system

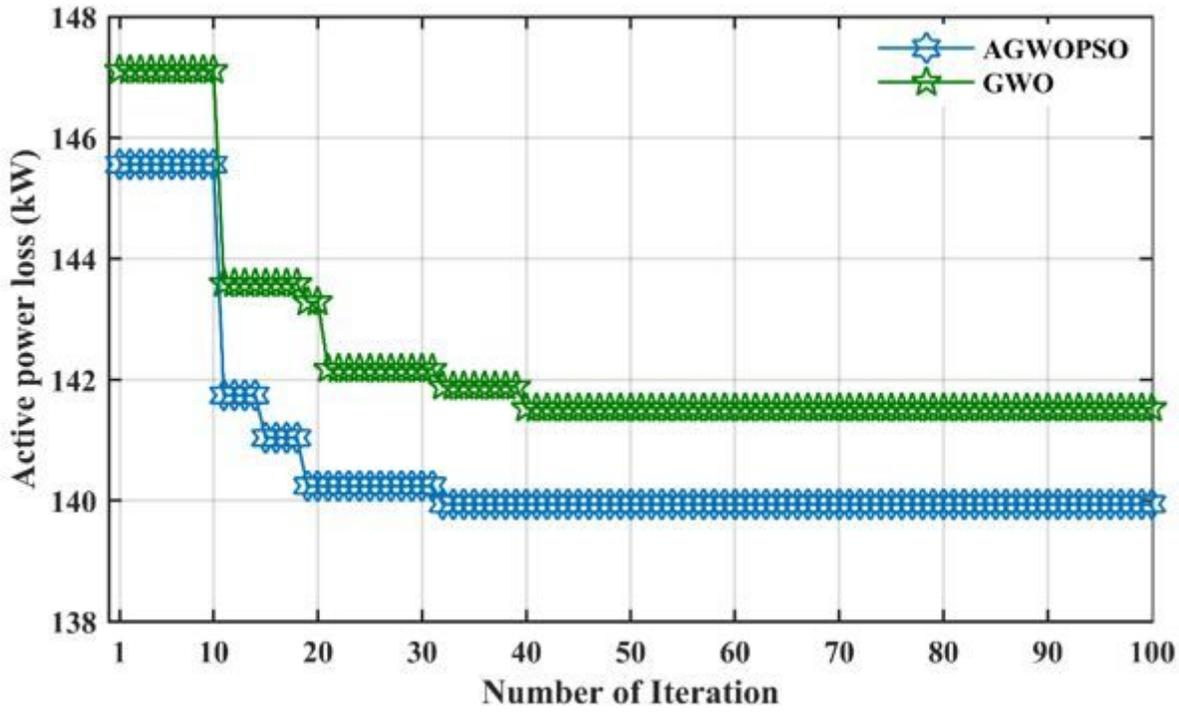


Figure 11

Response of AGWOPSO and GWO for 33-bus distribution system

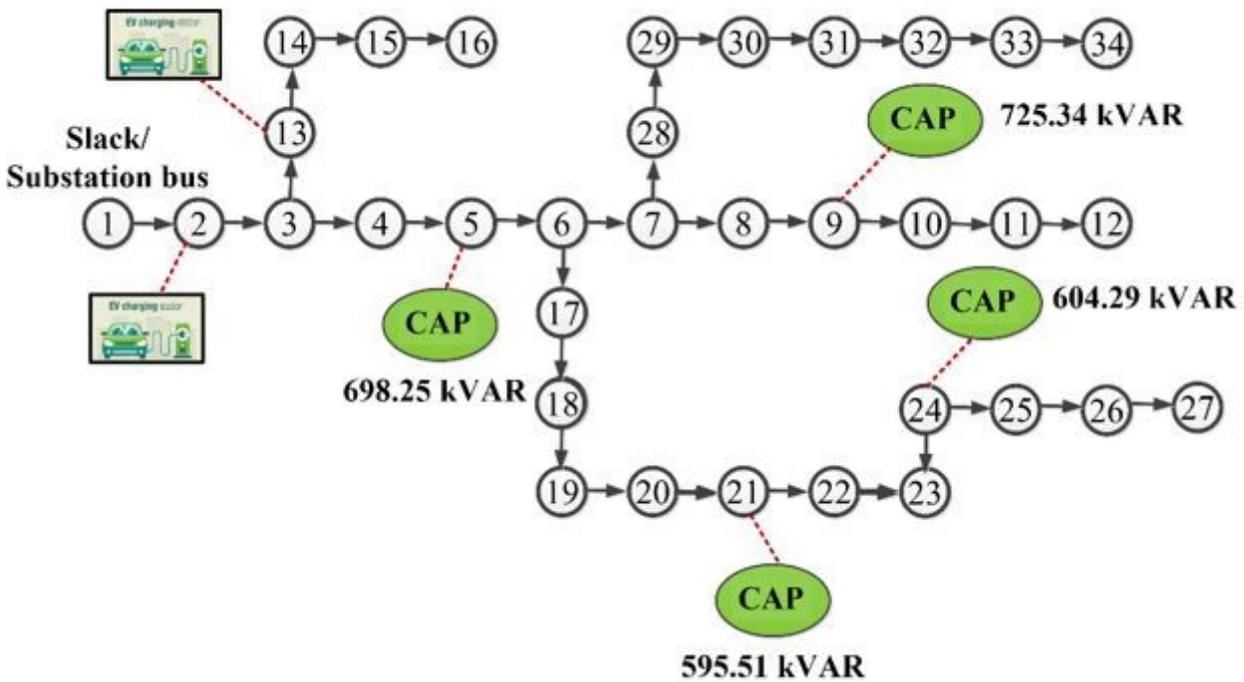


Figure 12

Typical configuration of 34-bus system with two EVCS and four capacitors

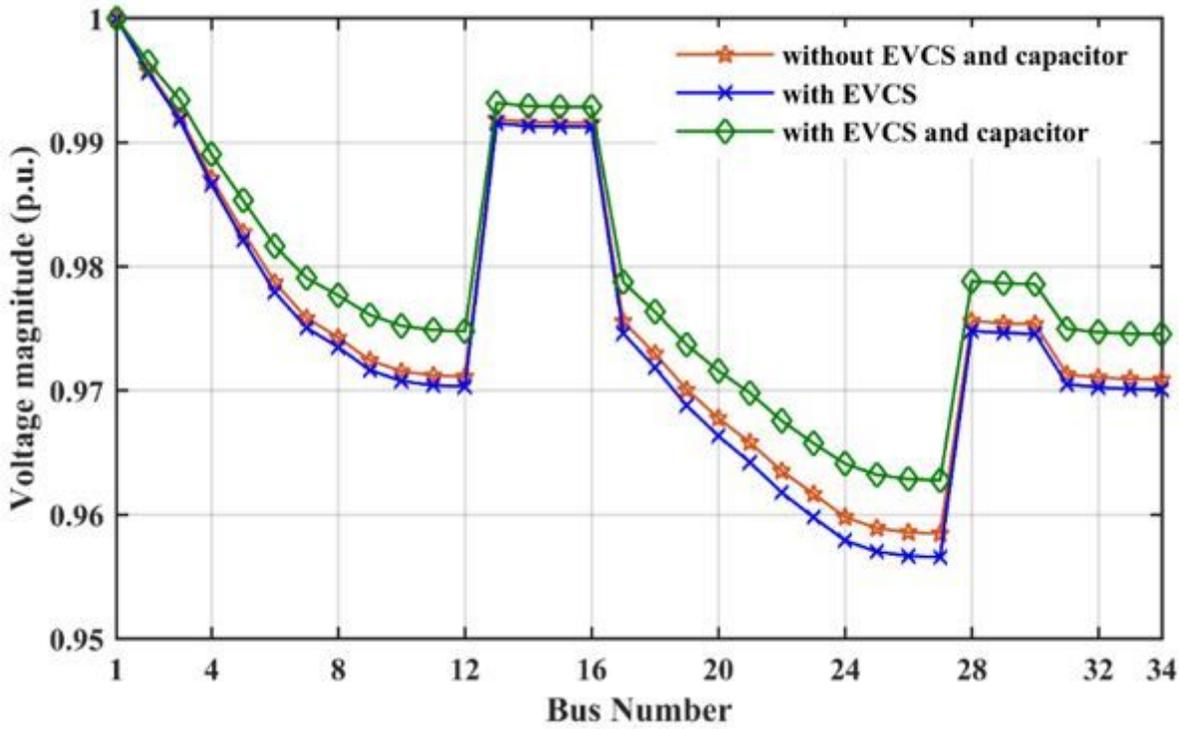


Figure 13

Improvement in voltage profile based on capacitor placement for 34-bus system

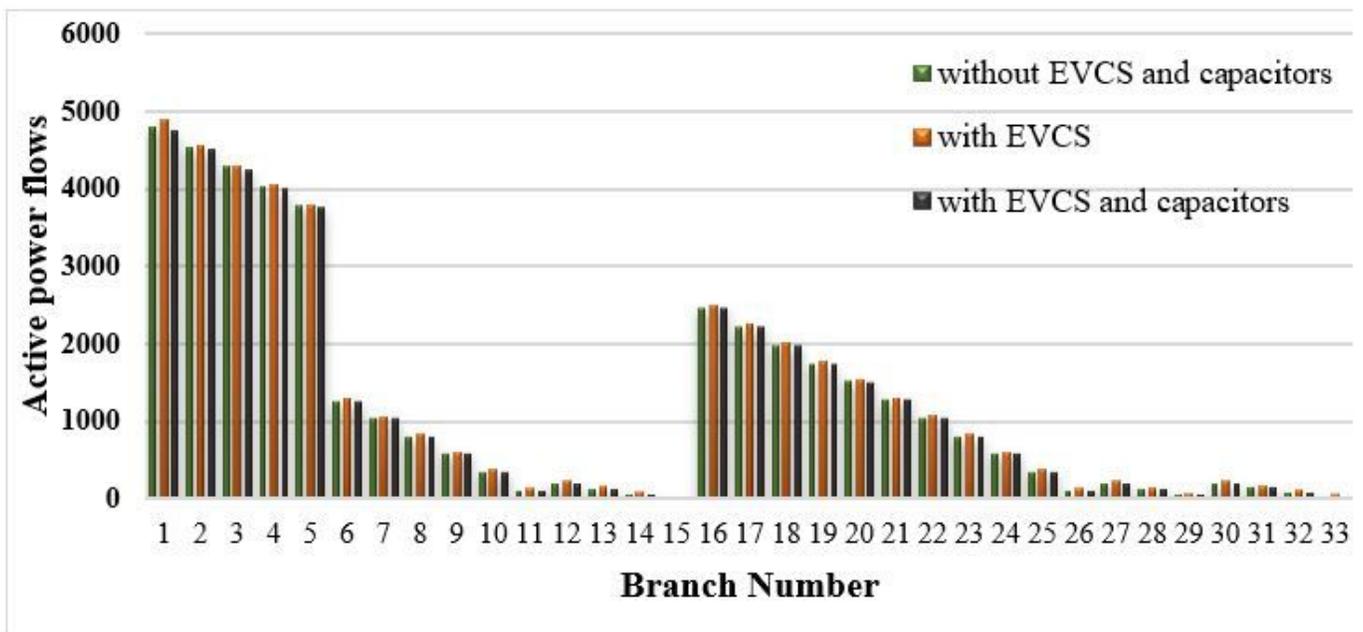


Figure 14

Improvement in flow of active power based on capacitor placement

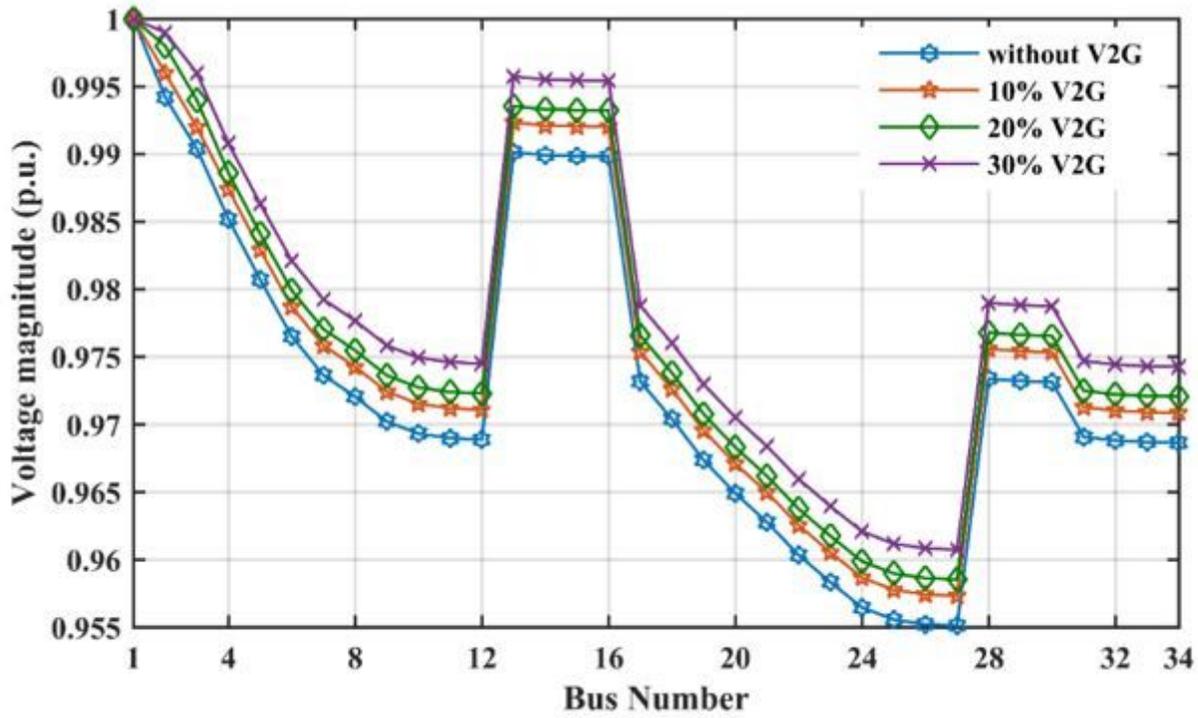


Figure 15

Voltage profile improvement due to participation of EVs in V2G

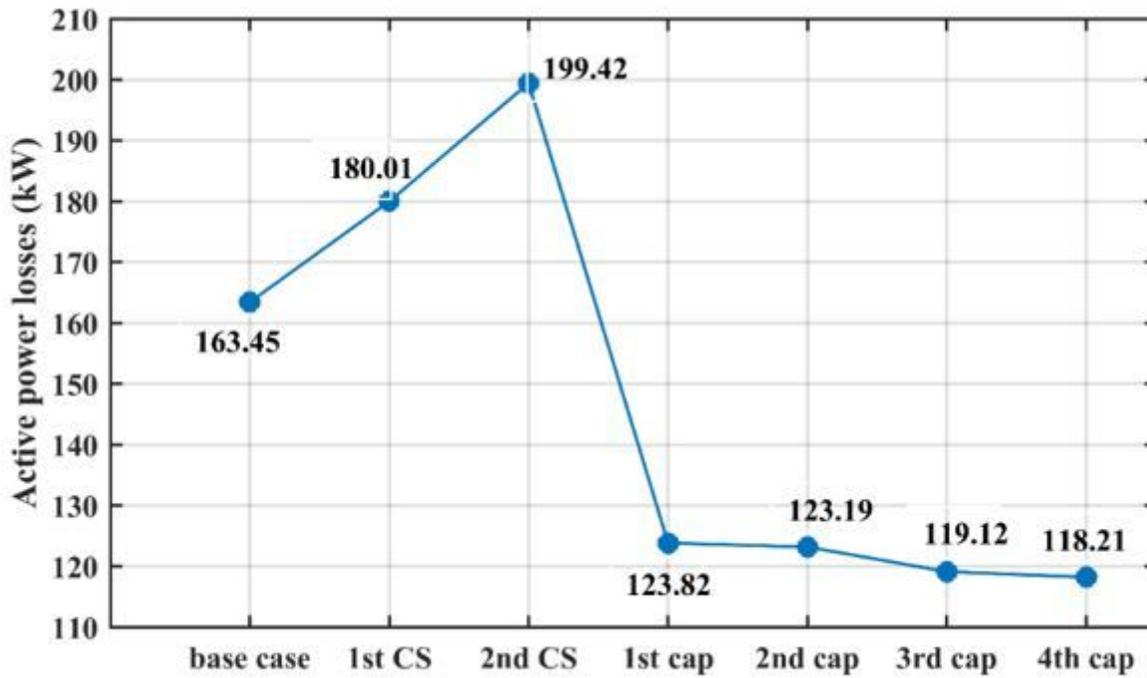


Figure 16

Variation of active power losses on integrating EVCS and capacitor

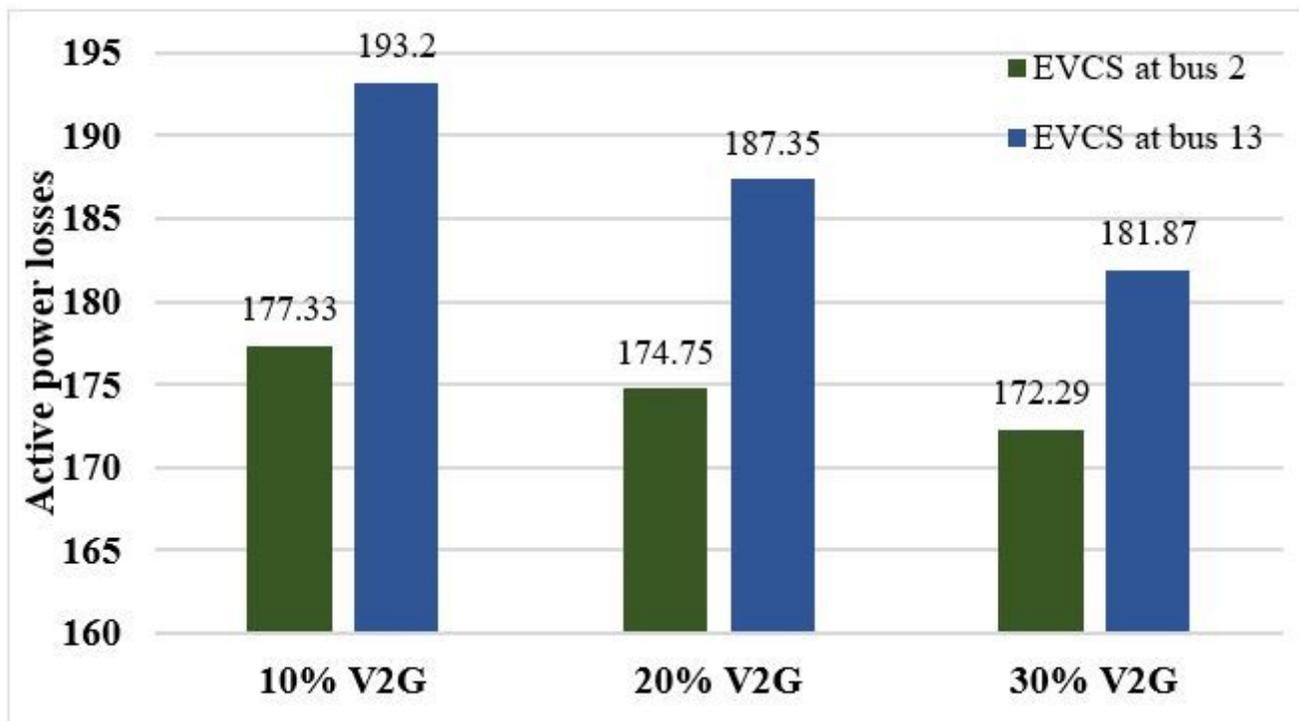


Figure 17

Reduction in active power losses with increase in EVs participation in V2G

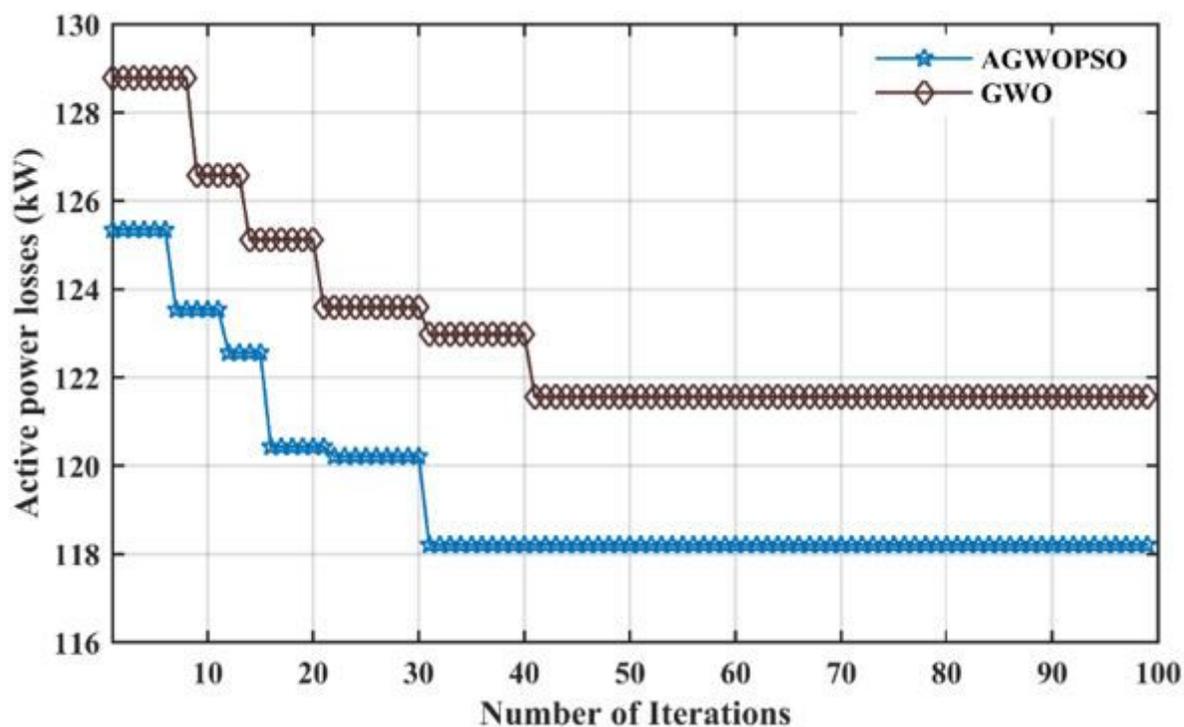


Figure 18

Response of AGWOPSO and GWO for 34-bus distribution system