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Allocation of plug-in electric vehicle charging station with integrated solar powered distributed generation using an adaptive particle swarm optimization

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Abstract

One of the industries that use fossil fuels most frequently worldwide is transportation. Therefore, electrifying the transportation system, such as the creation of plug-in electric vehicles (PEV), has become essential to reducing the effects of carbon dioxide emissions and using less traditional energy supplies that are not ecologically friendly. PEV deployment must be flawless, necessitating a well-developed charging infrastructure. The best location for fast charging stations (FCSs) is a crucial issue. As a result, this article offers a practical method for choosing the best site for FCSs using the east delta network (EDN). When transportation is made electric, the infrastructure of the electrical distribution network may also need to be changed. Therefore, when adopting FCSs, three factors need to be considered: actual power loss, reactive power loss, and investment cost. The energy demand from the electrical grid is also increased by including FCSs in the power distribution network. To lessen the impact of FCSs on the system, this research report suggests integrating photovoltaic distributed generation (PVDG) at certain places in the distribution network. Consequently, the system becomes dependable and self-sustaining. After deploying the FCSs and PVDGs, the distribution system's dependability is also examined. Six case studies (CS) have also been suggested for deploying FCSs with or without DG integration. As a result, the CS-6's active power loss decreased from 1015.38 to 830.58 kW.

Keywords Plug-in electric vehicle · Charging infrastructure · Adaptive particle swarm optimization · Photovoltaic distributed generation · Distribution network

1 Introduction

Rapid system upgrades are necessary to accommodate distributed generation (DG) and electric vehicle charging stations (EVCS) in the current power networks. The size of the PVDGs market is mostly driven by the growing demand for solar-based distributed generation (PVDGs). This is because PVDGs are good for the environment, their costs are going down compared to traditional energy generation, new technology is making them easier to use, and they are getting cheaper. The term "prosumers," which describes people who deliver and consume energy simultaneously, was coined due to the growing usage of PVDGs, wind power generation, and other DGs technologies, which opened the door for small and medium-scale involvements. PVDG has been demonstrated to decentralize the electrical power network, reducing power losses, improving bus voltages, and being environmentally beneficial.

As they support the explosive expansion of PEVs and lower greenhouse gas (GHG) emissions in the transportation system, these distributed renewable energy technologies could help reduce dependency on fossil fuels [1, 2]. Additionally, as PEVs gain popularity, there is growing concerned worldwide regarding the continued use of petroleum-based products in the transportation sector due to their negative environmental effects and depletion [3]. Additionally, PEVs provide benefits like lessened noise pollution, decreased operating costs, and emission-free driving [4, 5].

This extensive use of plug-in electric vehicles (PEVs) in the transportation sector will benefit the environment and improve network stability by enabling frequency and voltage

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regulation and acting as a vehicle-to-grid (V2G) to smooth out any sudden increases in load or grid losses [6]. Contrarily, the integration of EVCSs into the distribution network must be done strategically since it may lead to excessive loads [7], which could worsen power quality, increase power loss, and cause voltage variations to exceed allowed limits [8]. With the widespread penetration of randomly distributed PVDG, the issue worsens as more EVCSs are added to the distribution network. In order to lessen the negative impacts that EVCSs have on the distribution network, it is necessary to deploy EVCSs properly.

Electric vehicle charging infrastructure plays a crucial role in achieving the larger objectives of sustainability and low carbon emissions in several ways. The primary benefit of electric vehicles is that they produce zero tailpipe emissions. By encouraging the adoption of EVs through the availability of charging infrastructure, we can significantly reduce greenhouse gas emissions, particularly in urban areas where transportation is a major contributor to air pollution. EV charging infrastructure can be designed to utilize renewable energy sources like solar and wind power. This means that as the grid becomes cleaner and more reliant on renewables, the carbon footprint of charging EVs decreases further, contributing to overall sustainability. Electric vehicles are quieter than traditional vehicles with internal combustion engines, reducing noise pollution in urban areas. This can lead to improved quality of life and contribute to a more sustainable and livable environment. Electric vehicles are not dependent on fossil fuels, reducing a country's reliance on oil imports and vulnerability to oil price fluctuations. This enhances energy security and economic stability.

1.1 Related works

The authors in [9] obtained the charging station's optimal location and capacity by optimizing the transportation cost value. The problem is handled by the whale optimization algorithm. Furthermore, the power loss of the electrical network, voltage deviation, and EV charging costs are offered in the literature as objective functions for the problem formulation to obtain the optimal location of CSs and RESs [10]. Additionally, minimizing electrical power loss and charging zone center is the objective function for placing CS in [10], which is solved using the bat optimization algorithm. In [11], investment cost and operational cost for charging stations are set as the objective function for determining the optimal location of charging stations with renewable energy sources, and the formulated optimization problem is solved by a genetic algorithm. In [12], the authors considered transportation cost for traveling to charge the EV, active power loss cost of the electrical system, and investment cost for installing the charging station as the objective functions, and the formulated optimization problem is solved by the hybrid technique

using gray wolf optimization and particle swarm optimization. Furthermore, the uncertainties related to electric vehicle power demand and photovoltaic power generation are handled using the Monte Carlo method.

A power loss of an unbalanced radial distribution network was proposed as an EVCS deployment goal in [13], and the outlined optimization problem was solved using the particle search optimization technique. Additionally, [14] investigated where parking lots should be placed in order to maximize parking lot revenues. The genetic algorithm (GA) produced the best results while using the cost of power loss, reliability, voltage variation, and parking lot as the objectives. Similar issues are covered in [15], which also uses the gray wolf optimization algorithm to solve an optimization problem while accounting for installation and active power loss costs for placement. The focus of [16] was on the best CS deployment for sustainable cities, and they proposed a multi-objective issue. Additionally, the annualized time opportunity cost, trip expense, construction expense, and operation expense are purportedly objective functions, and GA addressed the suggested issue. The quantum-behaved and Gaussian mutational dragonfly algorithm is used to address the defined problem [17] discovered the ideal location of CSs and capacitors while accounting for power loss costs.

The overall cost is lowered in [18] by the optimal placement and size of the CSs in the IEEE 123 distribution system, which results in decreased power loss and an enhanced voltage profile. Furthermore, without considering the traffic network, [19] identifies the optimal sites for CS in Allahabad city of India distribution network to reduce active power loss and development costs. The authors of [20] explore the yearly profit maximization for allocating distributed generation (DG) and customer service (CS) in 33 and 69 distribution systems. Again, in [21], CS and DG are optimally allocated in a microgrid and distribution network, respectively, while cost minimization is considered. In [22], the placement of rapid charging stations for electric buses takes into account the routes and distribution system of the buses. To reduce power loss and voltage variation, the authors of [23] place the CS in a distribution network that overlaps with the traffic network. Moreover, power loss of the electrical network and voltage stability index is formulated as objective functions for the optimal location of charging stations with distribution generations and proposed problem handed by the new nature-inspire meta-heuristic technique known as future search algorithm [24] and further this problem is solved by Coyote optimization algorithm, and also highlights the computational efficiency of the proposed technique with PSO and gray wolf optimizer [25]. The authors in [26] obtained the optimal location of the capacitor with EV load at the distribution network by considering the voltage stability index and power losses of the distribution network and the for-
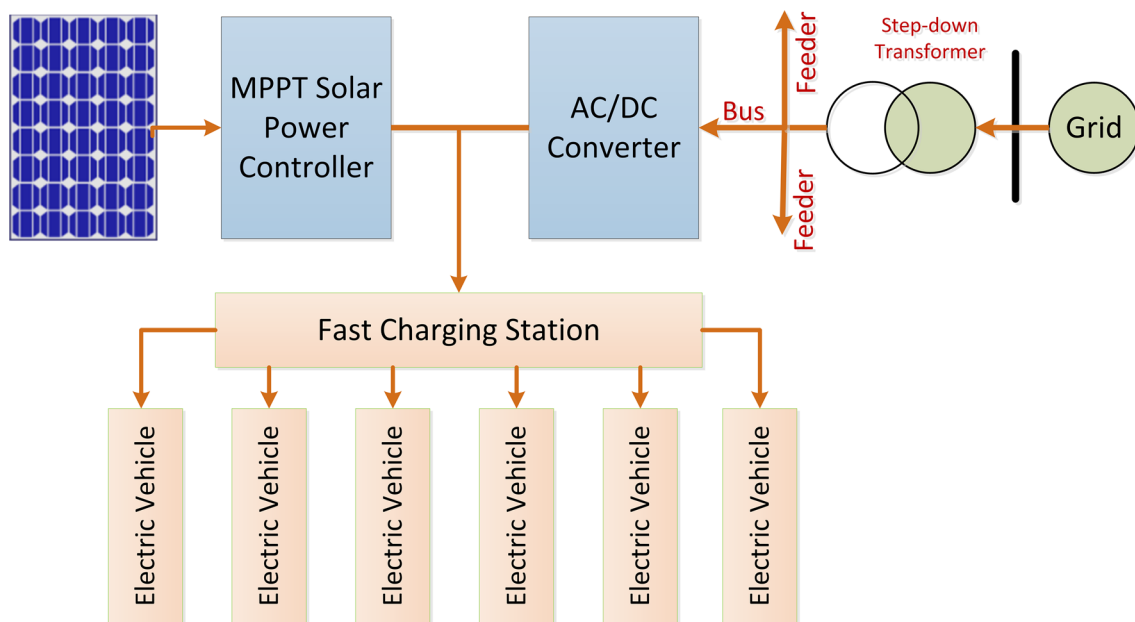
Fig. 1 Single line diagram of the charging station [32]

mulated problem is handled by improved flower pollination algorithm. Furthermore, active power loss and voltage deviation of the IEEE-33 and IEEE-69 bus systems are used to place the charging stations and renewable energy sources, and the multi-objective optimization problem is solved by modern meta-heuristic Aquila optimizer [27].

After installing the charging station and DGs in [28], the dependability of the distribution system was examined. In contrast, the suggested problem is tackled using the hybrid gray wolf optimization particle swarm optimization technique, which uses the cost of voltage variation and power loss as objective functions. Moreover, in [29], the authors categorized the objective functions under the three approaches for deploying charging stations in electrical and transportation networks: the distribution system operator approach, charging station investor approach, and electric vehicle driver approach.

1.2 Findings and contributions

This study enhances the adaptive particle swarm optimization approach for placing FCS in the proposed EDN network with integrating PVDG. Furthermore, the PVDGs are randomly scattered and positioned at the electrical node of the suggested electrical system. The following are the esoteric contributions of this paper:

1. A adaptive particle swarm optimization approach is proposed for optimizing the location for proposed FCSs in the given EDN system. According to the authors, an

APSO has never been used for positioning the charging station.
2. Consider an electrical network with PVDG that is arbitrarily sized and positioned to mimic consumer-based decentralized penetration. Most studies involve scattered generations to account for the impact of FCSs on the electrical system. In contrast, this investigation comprises FCSs and PVDG over the proposed distribution system.
3. Under the charging station investor approach, one objective is modeled and under the distribution system operator approach, two objectives are modeled for the placement of FCS. Therefore, the multi-objective optimization problem is formulated under the two approaches.

2 Problem formulation

The appropriate positioning of the FCSs is one of the primary focuses of this study. This multi-objective issue includes various economic elements, including operating costs, and costs related to the required equipment and land. Furthermore, the multi-objective optimization problem is formulated for the placement of the proposed charging infrastructure to enhance the distribution system's performance and reduce the costs related to the charging station installation. Figure 1 displays a block diagram with a single line.

2.1 Photovoltaic distributed generations

As noted previously, integrating EV charging demand from the grid is inadvisable for decreasing carbon emissions if

Table 1 PVDGs randomly generated location at respective nodes

Distributed PVs	Active power in kW	Reactive power in kVAR	Node number
PVDG-1	840	275	5
PVDG-2	1119	368	16
PVDG-3	560	184	22

the electricity is produced using commercial fuels. Consequently, including PVDG in the grid is strongly advised to achieve the same advantages. In addition, the PVDG should be spread throughout the system to decrease losses and maintain voltage stability. In addition, our approach identifies areas for deploying PVDGs with sufficient space and favorable atmospheric conditions. In [30], the authors alleviate the grid strain due to charging demand for PEV at the distribution system. In addition, 1/10 of the energy demand of the east delta network (EDN) is generated from renewable energy sources for the actual benefits of the electric vehicle to reduce carbon emission [31]. Therefore, three units of PVDG are proposed with different capacities as shown in Table 1 with total active power generation is 2519 kW, whereas total reactive power is 827 kVAR using 0.95 power factor.

2.2 Buildup cost reduction objective

The variance in land prices depends on the investigated locality. In addition, the buildup cost contributes substantially to the project's entire investment. However, this cost will decrease in the future as technology advances. Hence, FCS investors must study the land price of each potential FCS location. Therefore, the buildup cost (BC) is computed using the land cost, equipment development cost, and fixed cost for the charging connectors, as shown in Eq. (1). They estimated for installing FCS is 100 m^2 approximately. Hence, the cost of the land required is determined for the five-year land leasing. In addition, the buildup cost reduction objective (BCRO) at the ith bus is formulated as total buildup cost in a normalized manner, as shown in Eq. (2).

$$BC_i = \text{Cost}^{fix} + 100 \times N_{\text{days}} \times \text{Cost}_i^{lan} + (N_c - 1)$$
$$\times \text{Con}_p \times \text{Con}_{\text{dev}} \tag{1}$$

$$BCRO_i = \frac{BC_i}{\max(BC_i)} \tag{2}$$

where price rate per m^2 per day is expressed by Cost_i^{lan} for the 5 years duration at ith node, N_c is the proposed number of connectors at the charging station, Con_p represents the power capacity of the charging point, Con_{dev} represent the total cost for the development of every charging connector, and N_{days} represent the total days required for proposed planing.

2.3 Real power loss reduction objective

For the optimal distribution of the proposed charging station in the EDN system, real power loss and reactive loss are modeled as objective functions. Therefore, the real power loss reduction objective (PLRO) is modeled for the reduction of the real power loss of the system. The PLRO assesses potential increases in grid power losses upon connection of FCSs. This is shown in Eq. (3).

$$PLRO = 1 - \frac{PL^{\text{Base}}}{PL^{\text{FCS}}} \tag{3}$$

where PL^{Base} and PL^{FCS} represent the distribution system's total active power loss without and with interesting charging stations, respectively. In addition, the real power loss for the proposed EDN system is calculated by Eq. (4).

$$PL = \sum_{b=1}^{Nb} \left(\frac{P_b^2 + Q_b^2}{V_b^2} \right) R_b \tag{4}$$

where P_b is the real power flow in bth line, Q_b is the reactive power in bth line of the proposed system, R_b represents bth line resistance, and V_b represents the voltage of sending node of the respective line.

2.4 Reactive power loss reduction objective

The reactive power loss reduction objective (QLRO) offers a predetermined threshold for preserving grid voltage stability. This indication is represented using Eq. (5).

$$QLRO = 1 - \frac{QL^{\text{Base}}}{QL^{\text{FCS}}} \tag{5}$$

where QL^{Base} and QL^{FCS} are the reactive loss for the proposed network without integrating the charging station and with integrating the charging stations as suggested, respectively. Moreover, the reactive loss of the power for the proposed network can be determined using Eq. (6).

$$QL = \sum_{b=1}^{Nb} \left(\frac{P_b^2 + Q_b^2}{V_b^2} \right) X_b \tag{6}$$

where X_b is the bth line reactance, and V_b represents the voltage of sending node of using line.

3 Multi-objective function

For the optimal placement of FCS, three objectives are modeled as suggested in the paper. Therefore, multi-objective optimization problems have been formulated using the proposed objective to reduce the buildup cost of the charging station and enhance the performance of the EDN system. Furthermore, there are different approaches available to handle the multi-objective problem but the easiest method is to use the weighted coefficient method. Therefore, three weighted coefficients for each objective are assigned to the problem. By using this approach, the multi-objective optimization problem can be handled as single objective problem as denoted by the eq. (7).

$$\text{Objective} = \alpha \times \text{PLRO} + \beta \times \text{QLRO} + \delta$$
$$\times \sum_{i=1}^{N}(\text{BCRO}_i \times X_i)/N_{\text{FCS}} \tag{7}$$

where N is the nodes of the proposed electrical network, and X_i is the variable which can have the value of 0 or 1. *If $X_i =$ 0, it shows that no charging station at the given node, if $X_i =$ 1, it shows that charging station must be integrated at given node.* where α, β, and δ are the weighing coefficient that decides the value of particular objectives function for finding the optimal deployment of the charging station, expressed in Eqs. (8) and (9), respectively.

$$\alpha + \beta + \delta = 1 \tag{8}$$
$$0 \leq \alpha, \beta, \delta \leq 1 \tag{9}$$

α, β, and δ are the weighted coefficients, and the value of these coefficients depends on the participation of the respective objective in the final decision for the placement of charging stations (Table 2).

3.1 Constraints

Some limits are proposed for the proper solution of the proposed optimization problem to place the charging station in the distribution network, these limits are given in detail below.

Node voltage constraint The upper and lower voltage limits are set for all given nodes of the EDN electrical network, defined in Eq. (10).

$$V^{\text{lower}} \leq V_i \leq V^{\text{upper}} \tag{10}$$

Table 2 Used parameters

Parameters	Value	Unit
N^{EV}	2000	–
$\text{Ch}_{\text{time}})$	0.33	Hours
N^C	10	–
st	18	Hours
Cost_{fix}	21900	$
Con_{dev}	109.5	$
pf	0.95	–
p^{EV}	96	kW
C_p	100	kVA
C_E	0.11	$/kWh
N_{days}	1825	–

where V^{lower} is the lower node voltage, V^{upper} represents the upper node voltage, and V_i is the ith node voltage.

Active power limit constraints In Eq. (11), the lower limit and upper limits of the active power are imposed for each line of the proposed electrical network.

$$P^{\text{lower}} \leq P_j \leq P^{\text{upper}} \tag{11}$$

where P^{lower} is the lower limit of the active power in lines, P^{upper} is the upper limit of the active power in lines, and P_j is the active power at jth line.

Reactive power constraint Reactive power limits are imposed for each line for the stability and reliability of the electrical system, which is formulated as given in Eq. (12).

$$Q^{\text{lower}} \leq Q_j \leq Q^{\text{upper}} \tag{12}$$

where Q^{lower} represents the lower limit, Q^{upper} represents the upper limit, and Q_j represents the line reactive power at jth.

Power balanced constraints The power required of the electrical network with EV demand should be balanced by the PV generation and power taken from the grid, formulated in (13).

$$P_{\text{EV}} + P_{\text{sys}} = P_{\text{PV}} + P_{\text{grid}} \tag{13}$$

where P_{sys} represents the power required of the EDN without EV charging demand, P_{grid} represents the grid power, P_{EV} represents the EV charging demand, and P_{PV} is the power produced from PVDGs.

Number of FCSs constraints: The total required FCSs is computed using (14); hence, the number of FCS is restricted to the bare minimum to reduce the cost function.

$$N_{\text{FCS}}^{\text{min}} \leq N_{\text{FCS}} \tag{14}$$

where $N_{\text{FCS}}^{\min}$ is the minimal number of charging stations required in the planned region; each FCSs have a set number of 100 kVA connections.

4 The proposed adaptive particle swarm optimization algorithm

The particle swarm optimization is driven by modeling social behavior instead of population-based evolutionary algorithms, and each possible outcome is connected with the velocity. The outcome, often known as "particles," then "fly" through the search space. Therefore, at the beginning, a particle-sized population is generated. Then, the velocity of each particle is continuously changed based on that particle's experience and the experiences of its partners. The particles are anticipated to travel toward locations with more effective solutions. Furthermore, according to the objective of an optimization issue, each particle's fitness may be evaluated. During each iteration, each particle's velocity will be computed as follows:

$$v_i^{k+1} = wv_i^k + c_1 r_1 (pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k) \tag{15}$$

where x_i^k represents the particle i position at kth iteration, $pbest_i^k$ represents the particle's best previous location, $gbest^k$ represents all particle's best previous location at the kth iteration, w denotes the inertia weight, c_1 represents a cognitive parameter, c_2 shows social parameters, and r_1 and r_2 both are randomly generated integers inside the interval [0, 1]. After computing the velocity, each particle's new location may be determined using Eq. (16).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{16}$$

The PSO method applies the update equations many times until the predetermined number of generations G is attained.

Although adaptive particle swarm optimization (APSO) has demonstrated significant advancements by providing rapid convergence in specific problems, it does have some deficiencies. Lacking a velocity control mechanism, APSO is found to be incapable of searching at a fine-grain level. Numerous attempts exist to enhance APSO's performance through variable inertia weight. The inertia mass is crucial to the performance of PSO, which balances the swarm's global exploration and local exploitation capabilities. A large inertia weight facilitates exploration but prolongs particle convergence. In contrast, a small inertia weight causes the particle to converge rapidly but can also result in local optima [33]. The step-by-step implementation of adaptive PSO is shown in Fig. 3 by the flowchart.

Although these methods increase the performance of PSO, they cannot accurately depict the actual search process when the true ideal value is known in advance, and no feedback is gathered from how distant the particle's fitness is from the estimated optimal value. A high velocity is still required to explore the solution space worldwide for a particle whose fitness is distant from the genuine optimal value. Hence, its inertia weight must be adjusted to bigger values. To permit more precise local investigations, inertia weight must be adjusted to a modest value when only a tiny amount of movement is required. In addition, by adopting the same inertia weight for all particles and disregarding variances in particle performance, a rough animal backdrop was reproduced rather than a more detailed biological model. Throughout the search, each particle's position varies dynamically. Thus, each particle locates in a complicated environment and faces a unique circumstance. Hence, each particle may have unique trade-offs between global and local search capabilities.

In this research, the inertia weight is dynamically adjusted for each particle based on the adjacency index (AI), which represents the closeness of individual fitness to the actual ideal solution. Based on this index, every particle might determine how to change the values of its inertia weight. In this regard, the proposed APSO specifies the velocity update rules as given in Eq. (17):

$$v_i^{k+1} = w_t^k v_i^k + c_1^k r_1 (pbest_i^k - x_i^k) + c_2^k r_2 (gbest^k - x_i^k) \tag{17}$$

To compute the inertia weight for the ith particle in the kth iteration, given by x_i^k in Eq. (18), the adjacency index (AI) must first be established.

$$AI_i^k = \frac{F(pbest_i^1) - F_{KN}}{F(pbest_i^k) - F_{KN}} - 1 \tag{18}$$

where $F(pbest_i^1)$ is the fitness of the particle's best prior location and F_{KN} is the known genuine ideal solution value. It may be inferred that the AI varies with the number of particles and is configured based on the best recollections of the particles' responses. A tiny AI_i indicates that the fitness of the ith particle is far from the true ideal value, necessitating a vigorous global search and a high inertia weight. A large AI_i, on the other hand, indicates that the ith particle is in close proximity to the true optimum, necessitating strong local exploitation and, therefore, a low inertia weight. Thus, the value of inertia weight for each particle in the kth iteration is determined dynamically using the following Eq. (19).

$$w_i^k = \frac{1}{1 + exp(-\alpha \times AI_i^k)^{-1}} \tag{19}$$

where α is a constant in the range [0, 1]. Using the preceding assumptions and definitions, it is possible to deduce that

$0.5 \leq w_i < 1$. The value of inertia mass for each particle in the kth iteration depends on the value of parameter α. The value of parameter α determines the rate of decrease of inertia weight. The greater the rate of increase of inertia weight, the lower the parameter α value. The particle swarm size chosen is 50. Adaptive PSO algorithms can dynamically adjust parameters like the inertia weight, cognitive, and social coefficients during the optimization process. This adaptability allows the algorithm to respond to the changing behavior of the swarm, potentially speeding up convergence by balancing exploration and exploitation more effectively. This adaptability helps prevent premature convergence to suboptimal solutions and encourages exploration when necessary. Conventional PSO requires careful tuning of parameters like the inertia weight and learning coefficients for different problem types. Adaptive PSO algorithms automate this process to some extent, reducing the sensitivity to parameter tuning and making them more user-friendly.

Throughout the search, according to Eqs. (18) and (19), the particles encounter various fitness; as a result, their inertia weight values and AI vary. Furthermore, while particle fitness is distant from the true global optimum, AI of the given particle has a low value, and inertia weight value will be high, consequently in more global search capabilities and the identification of interesting search regions.

5 Results and discussions

The suggested multi-stage solution addressed the optimal FCS placement problem for east delta network (EDN) electrical system. The EDN distribution system is a component of the unified Egyptian network (UEN) [31]. The EDN single-line representation is depicted in Fig. 2. 11 kV is the rate line voltage, 27.22 MVA is the rated capacity, and 0.854 is the power factor of the EDN system. Table 1 presents the location and size of the distributed renewable generation. The proposed FCS includes ten 100 kVA connections with a power factor of 0.95 (Fig. 3).

This research was employed for the allocation of FCSs in the 30-bus EDN system to demonstrate the effectiveness of the proposed APSO algorithm. Moreover, the esoteric APSO technique was also employed to compare the fitness value supplied in the objective Eq. (7) to the variable α, β, and δ for the FCSs placement in the network. This technique gives ideal placements for FCSs with randomly placed PVDGs and reduces investment cost, actual power loss, and reactive power loss. The optimal necessary number of FCSs was five. Nevertheless, six scenarios were shown for the placement of FCSs by varying the α, β, and δ values. In addition, six case studies, including the placement of FCSs alongside renewable-based distributed power were provided to address
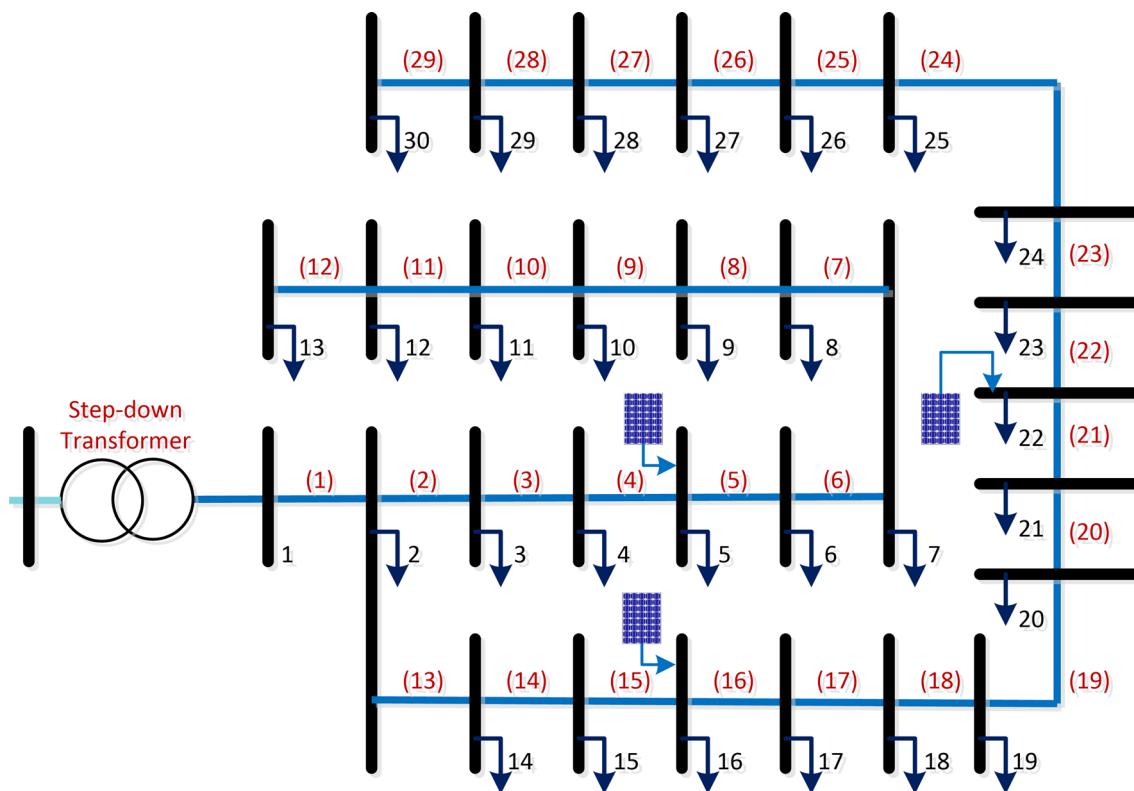

Fig. 2 Single line diagram of the EDN [5]

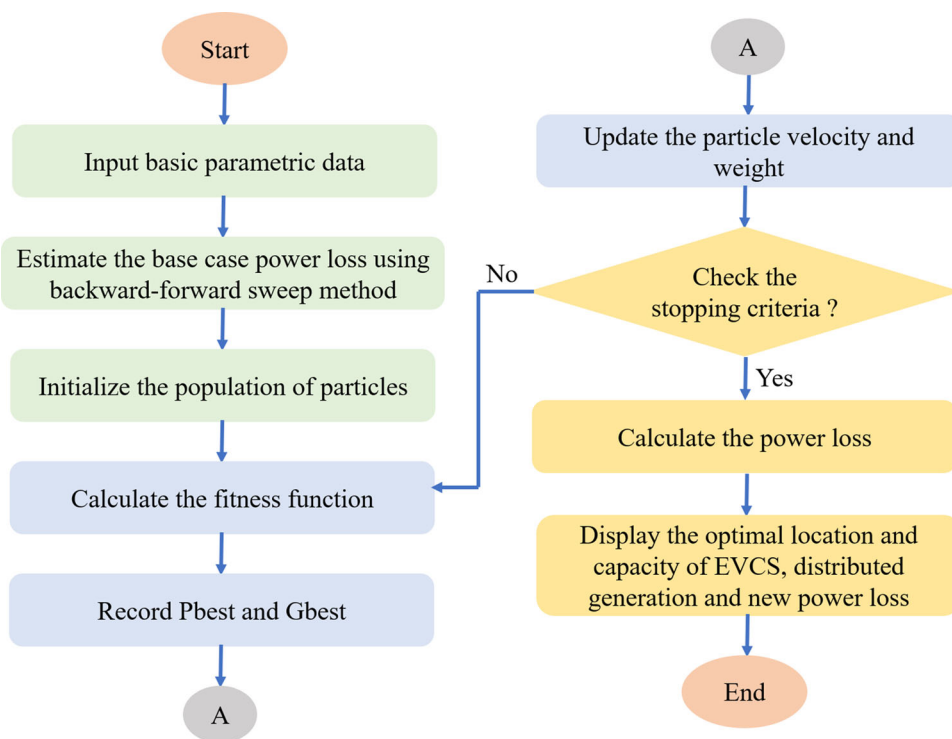**Fig. 3** Flowchart of adaptive particle swarm optimization algorithm

Table 3 Results with FCSs placement

Cases	α	β	δ	Ploss (kW)	Qloss (kVAR)	Norm. IC	Cost Fun	Optimal locations
Base	–	–	–	807.63	362.13	–	–	–
Case-1	0	0	1	1278.83	563.36	0.4736	0.4736	11,14,18,25,28
Case-2	0.1	0.1	0.8	1278.83	563.36	0.4736	0.4513	11,14,18,25,28
Case-3	0.2	0.2	0.6	1194.49	532.23	0.4888	0.4217	7,11,14,18,28
Case-4	0.3	0.3	0.4	1055.51	481.01	0.5587	0.3755	2,4,11,14,15
Case-5	0.4	0.4	0.2	1048.85	478.31	0.5762	0.3037	2,4,7,11,14
Case-6	0.5	0.5	0.0	1015.58	466.35	0.7201	0.2128	2,3,4,5,14

the sensitivity analysis for optimizing the FCS site by modifying the weight constant.

5.1 Results analysis of the obtained location of FCSs without PVDGs

In Case-1, the buildup cost is factored into the optimization issue, with neither active nor reactive power losses addressed. For Case-2, however, the ideal placements are determined by including 10% of real power loss and 10% of reactive power loss, together with 80% of the buildup cost, into the optimization issue. Because of the minimal power loss, the ideal placement of FCSs is identical to that of the preceding example. In addition, for Case-3 20% part of real power loss reduction objective, 20% part of the reactive power loss reduction objective, and 60% buildup cost participate for the decision of FCS location. In Case-4, the active and reactive power losses rise from 20 to 30%, while the investment cost

decreases from 60 to 40%; hence, power losses are the most important element in determining the appropriate position of the FCS. Similarly, in Case-5, the incorporation of power loss is increased and the investment cost is decreased while determining the ideal position of the FCS. Lastly, in Case-6, only power losses are evaluated for the placement of FCS; hence, the best position of FCSs derived in this example has lower power losses than previous proposed cases. Due to the growing power losses in the objective function, the losses obtained from Case-1 through Case-6 continue to decrease. Table 3 provides the findings acquired for the FCSs sites with real power losses, reactive power losses, and cost function values for the relevant scenarios. In addition, the actual and reactive power flows for the EDN lines are obtained for each of the given situations.

Table 4 FCS with PVDG results Analysis

Cases	α	β	δ	P_{loss}(kW)	Q_{loss}(kVAR)	Norm. IC	Cost Fun	Optimal locations
Base case	–	–	–	550.46	247.90	–	–	–
Case-1	0	0	1	1068.13	470.23	0.4736	0.4736	11,14,18,25,28
Case-2	0.1	0.1	0.8	1068.13	470.23	0.4736	0.4746	11,14,18,25,28
Case-3	0.2	0.2	0.6	992.03	442.67	0.4888	0.4698	7,11,14,18,28
Case-4	0.3	0.3	0.4	882.02	402.10	0.5338	0.4488	2,7,11,14,15
Case-5	0.4	0.4	0.2	862.49	395.01	0.5762	0.4079	2,4,7,11,14
Case-6	0.5	0.5	0	830.28	383.14	0.7201	0.3441	2,3,4,5,14
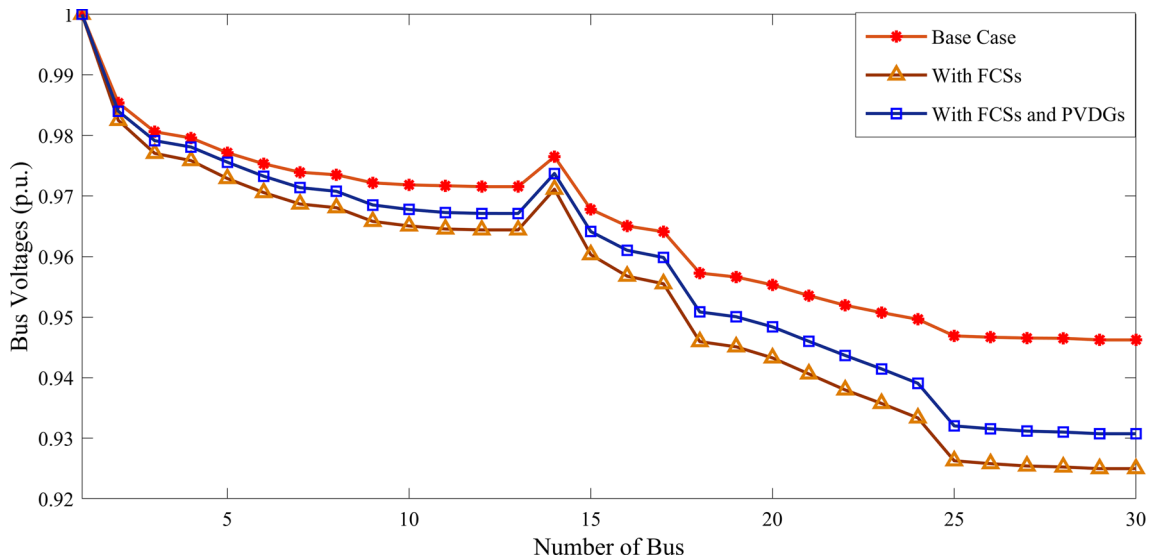
Fig. 4 Obtained bus voltage for Case-1

5.2 Results analysis of the obtained location of FCS with PVDG

For Case-1, the total power loss is not factored into the charging station placement determining criteria. As demonstrated in Table 3, this results in greater power losses than other cases. Moreover, in Case-2, the ideal placement of CSs is found by factoring in 10% of real power loss. On the other side, reactive power loss participates 10% and the buildup cost of the charging station participates 80% for the decision to find the optimal location of the FCSs; due to low power losses, the optimal location of FCSs remains unchanged. In addition, in Case-3, 20%, 20%, and 60% of the real power loss, reactive power loss, and investment cost were considered while determining the location of the FCS. In Case-4, power loss concerns increase from 20 to 30%, while investment cost decreases from 60 to 40%, resulting in power losses being the dominant factor in determining the appropriate site of FCS. Similarly, while calculating the ideal position of the FCS in Case-5, the power loss factor is increased, but the investment cost factor is decreased. In Case-6, however, only power losses are evaluated for FCS placement. Thus, the ideal

placement of FCSs results in the lowest power losses. Due to the rising power losses in the objective function, the losses accumulated from Case-1 through Case-6 continue to rise. Table 3 displays the findings obtained for the placements of FCSs with actual power losses, reactive power losses, and cost function values for all analyzed cases. As demonstrated in Table 3, the normalized value of investment cost increases from Case-1 to Case-6 for deploying FCSs. In contrast, as shown in Table 4, the arrangement of charging stations with PVDGs reduces the installation cost.

5.3 The node voltage profile results analysis

The voltage profile of the respective nodes is depicted in Figs. 4, 5, 6, 7, 8, and 9 for proposed cases. Figure 4 illustrates the node voltage of the system after the integrating EV charging load without and with PVDG for FCS placements and FCS deployments with PVDG in Case-1. The findings indicate that in Case-1, FCS deployment drops while FCS placement with PVDG sites rises. Figure 5 demonstrates the voltages in Case-2 during FCS placement and FCS placement with PVDG. Furthermore, adding FCSs with PVDGs
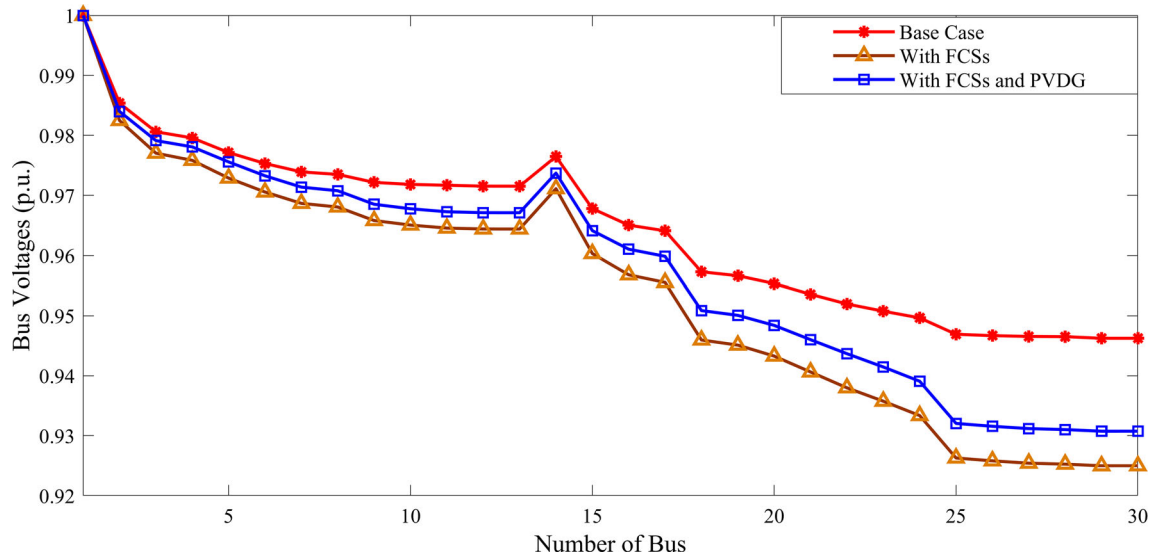
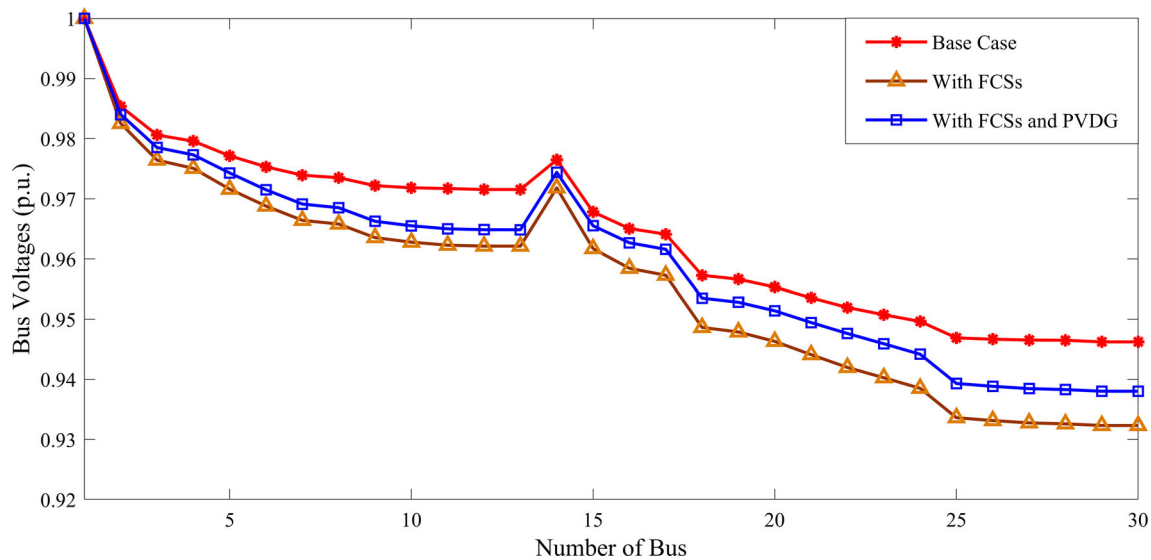**Fig. 5** Obtained bus voltage for Case-2

Fig. 6 Obtained bus voltage for Case-3

improves the voltages in Case-3, as shown in Fig. 6. Voltages in the deployment of FCS with PVDG are equal to the basic scenario depicted in Fig. 7. After the installation of FCS with PVDG, the obtained voltage profile is improved as compared to base case in Case-5 and Case-6, as demonstrated in Figs. 8, 9. In addition, Fig. 10 depicts the performance of all the methods with the proposed APSO technique.

5.4 Total power loss results analysis

With the deployment of the fast charging station in the suggested EDN system, the actual power loss decreased by 20.6% in Case-6 compared to Case-1, the reactive power loss decreased by 17.28% in Case-6 compared to Case-1, and the

investment cost decreased by $ 34.23. Figure 11 illustrates the actual and reactive power loss while placing CSs with and without PVDG addition. In addition, the placement of FCSs with PVDGs in the proposed EDN network reduced the power loss by 22.23% for Case-6 compared to Case-1, the reactive power loss by 18.64% for Case-6 compared to Case-1, and the investment costs by 34.23% for Case-1 compared to Case-6.

6 Conclusion

The paper suggests a novel model to strategically position rapid EV charging stations while integrating solar-based
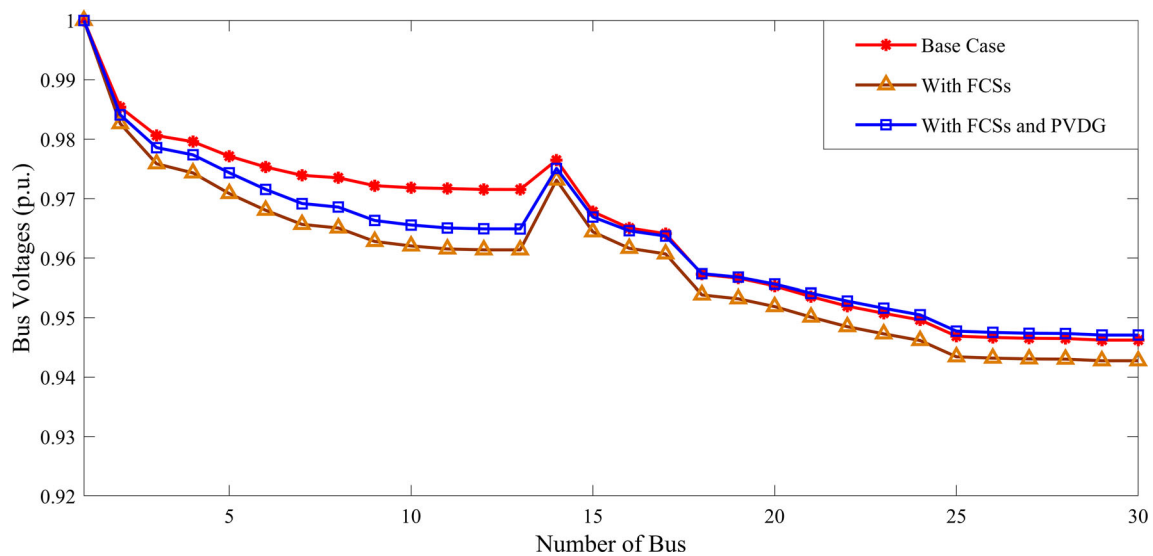
Fig. 7 Obtained bus voltage for Case-4
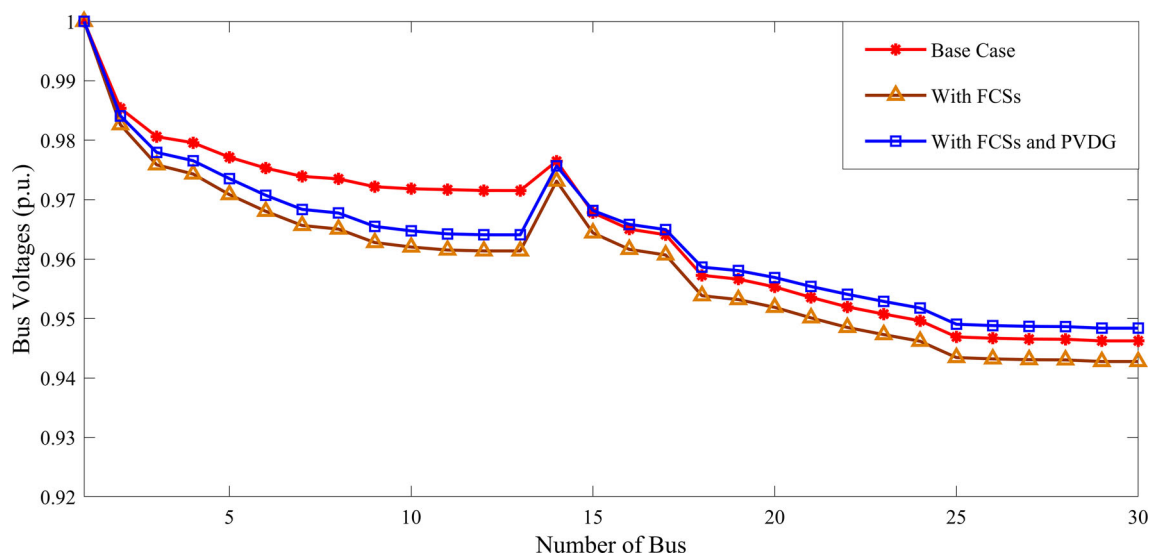
Fig. 8 Obtained bus voltage for Case-5

distributed generation. This model revolutionizes the implementation of fast charging stations (FCSs) by significantly reducing investment needs and minimizing power loss within the system, all while maintaining power quality and voltage stability. An adaptive particle swarm optimization method is presented for effectively locating charging stations with distributed photovoltaic (PV) generation in the electrical system. Furthermore, the paper compares the performance of this proposed algorithm with several other available techniques. It also outlines six cases illustrating the establishment

of FCSs based on charging infrastructure costs, considering real and reactive power loss for station construction. The paper additionally evaluates the distribution system's reliability for deploying fast charging stations, both with and without PV integration, within the proposed electrical system. Six specific case studies (CS) were proposed to explore the deployment of fast charging stations (FCSs), with or without distributed generation (DG) integration. Notably, in the sixth case study (CS-6), the active power loss was reduced from 1015.38 to 830.58 kW.
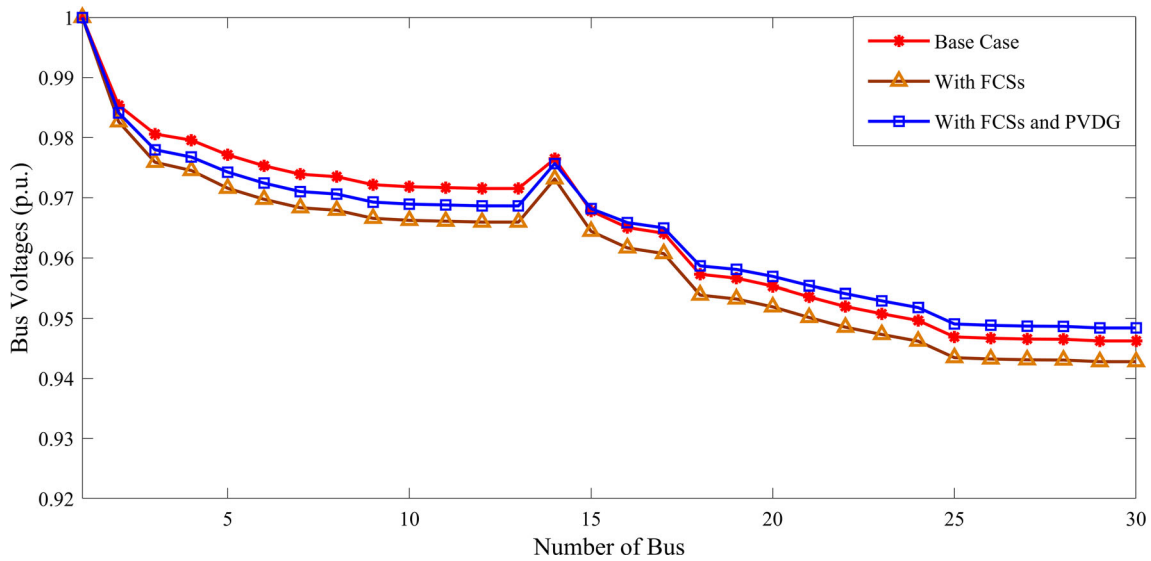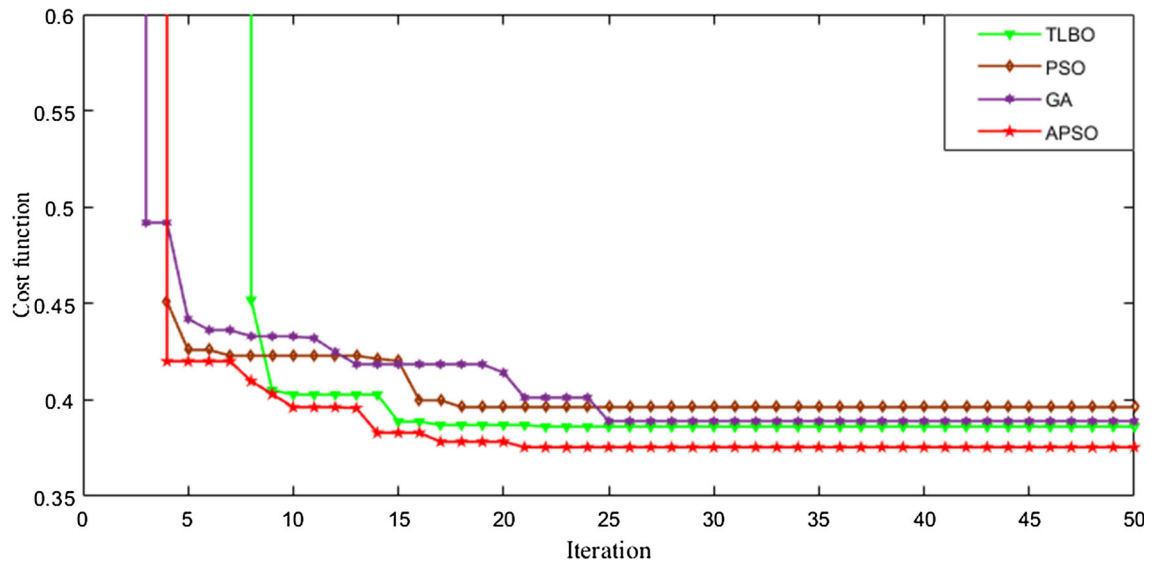
Fig. 9 Obtained bus voltage for Case-6

Fig. 10 Performance analysis of the proposed APSO with other techniques

The researchers expect that their study will streamline the incorporation of plug-in electric vehicles into the power grid, reducing CO_2 emissions and incentivizing investors to develop charging infrastructure. Moreover, advancements in research and technology are essential for effectively identifying optimal locations for charging stations. Future research could explore diverse energy management approaches, integrating electric vehicles, grid functionality, and the potential for charging stations to power homes to enhance the efficiency of the distribution network.
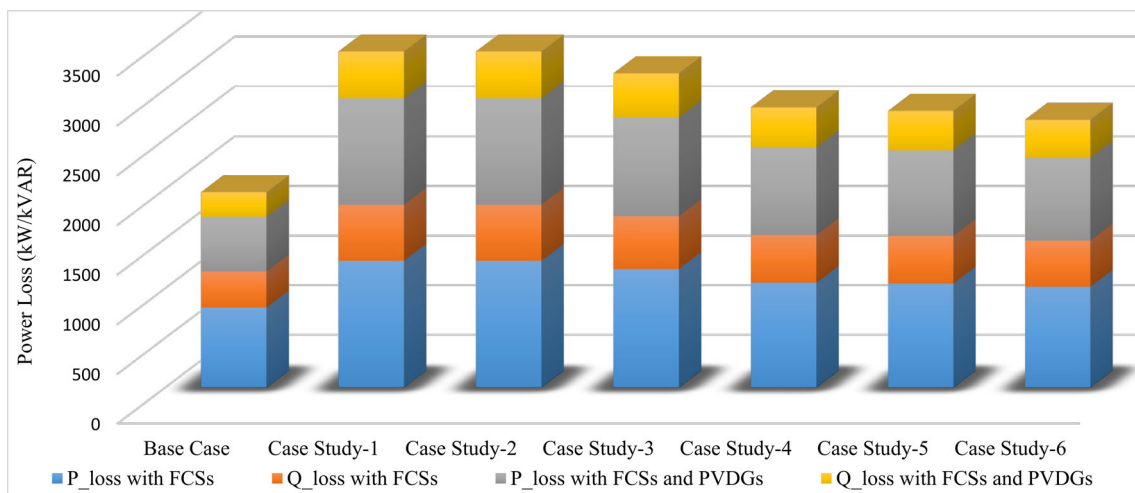
Fig. 11 Active and reactive power losses for proposed case studies

Declarations

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