



Optimal siting and sizing of electric vehicle charging stations in distribution network considering load uncertainty: An optimization framework

Seyed Alireza Hosseini¹, Alireza Askarzadeh^{1*}, Farshid Keynia¹

¹. Department of Energy Management and Optimization, Institute of Science and High Technology and Environmental Sciences, Graduate University of Advanced Technology, Kerman, Iran.

ARTICLE INFO

Article type:

Research Paper

Article History:

Received 31 August 2025

Accepted 7 September 2026

Keywords:

Electric vehicles,
Charging stations,
Optimization framework,
Optimal siting and sizing,
Load uncertainty.

ABSTRACT

Utilization of electric vehicles (EVs) is rapidly increasing in power systems. Due to the impact of EVs on the system performance, from the distribution network's point of view, it is vital to optimally site and size electric vehicle charging stations (EVCSs). This paper establishes an optimization framework for optimal allocation of EVCSs in distribution network. For this goal, development cost of EVCSs and network losses are included in the objective function and the planning problem is solved considering load flow calculation. To effectively solve the problem, crow search algorithm (CSA) and differential CSA (CSA_{dif}) are applied and the results are compared. Furthermore, impact of the load uncertainty is investigated on the planning problem. Over the IEEE-33 bus distribution network with photovoltaics (PVs) and wind turbines (WTs) penetration, it can be drawn that it is beneficial to install EVCSs near renewable resources to simply charge batteries. On the other hand, by consideration of the load uncertainty, it is preferred to install more connectors in the stations. Furthermore, compared to CSA, CSA_{dif} finds more promising results in terms of accuracy.

Cite this article: Hosseini, S.A., Askarzadeh, A., Keynia, F. (2026). Optimal siting and sizing of electric vehicle charging stations in distribution network considering load uncertainty: An optimization framework. *Energy Systems: Technology and Management*, 2 (1), 23-40. DOI: <http://doi.org/10.48306/estm.2026.544366.1012>



© Seyed Alireza Hosseini, Alireza Askarzadeh, Farshid Keynia / **Publisher:** Graduate University of Advanced Technology.
DOI: <http://doi.org/10.48306/estm.2026.544366.1012>

* Corresponding author.

Email: a.askarzadeh@kgut.ac.ir, askarzadeh_a@yahoo.com.

1. Introduction

In recent years, due to various reasons such as economic affordability and environmental concerns, using electric vehicles (EVs) is rapidly increasing in many countries as an alternative to internal combustion engines (ICEs)-based vehicles. In terms of air pollutant emissions, EVs are far better than ICEs since they are typically powered by rechargeable lead-acid or lithium-ion batteries charged by electricity (most often produced by renewable resource) while an ICE needs fossil fuels. In addition to the environmental impacts, the rapid adoption of EVs originates from the ever-increasing depletion of petrol or diesel sources. Furthermore, compared to ICEs, EVs are quieter and more relaxing to drive and have fewer moving parts.

To satisfy their electric need, EVs require charging stations (CSs). In general, the capacity of an EV battery varies from 20 to 60 kWh and there are three standard charging levels: charging level 1 which refers to employ a single-phase AC system with up to 3 kW charging power, charging level 2 which refers to employ a 3-phase AC with up to 24 kW charging power and charging level 3 (known as fast charging level) which provides power to entirely charge an EV battery in 20 to 30 min [1]. Fast charging stations which are mostly suitable for public and commercial applications are directly connected to the electricity grid. In these stations, to produce DC voltage, a set of equipments (transformer, rectifier, etc) are installed. Moreover, to use DC voltage for charging EV battery in less than 20 min, charge connectors should be installed.

Because of vehicle-to-grid (V2G) and grid-to-vehicle (G2V) interactions, EVs can affect the power system performance. In V2G mode, energy flows from the EVs batteries toward the grid to supply the loads during peak hours. In G2V mode which is usually utilized during off-peak periods, energy flows from the electricity grid toward the EVs batteries to charge them. This bidirectional power flow between EVs and the grid can be used to improve the power system performance. If

EVs are properly utilized, they can reduce power losses and increase voltage stability and reliability of the distribution network. For this aim, it is important to optimally plan EV charging stations (EVCSs). If large-scale EVCSs are not carefully planned in distribution networks, they can endanger power system performance since they cause the imbalance of the distribution feeders and also increase the current density.

In recent years, different studies have focused on EVs operation and planning aspects. In [2], authors have minimized total cost including station development and electrification costs as well as EV and electric grid energy losses cost due to charging EV. Moreover, in order to find candidate station points and calculate EV energy losses, urban roads have been considered. The problem has been formulated as a mixed-integer non-linear programming (MINLP) problem and has been solved by genetic algorithm (GA). In [3], a partitioning-based method has been used to optimally locate CSs by minimization of the traffic loss. In [4], an analytical method has been introduced to optimally locate CSs considering driving patterns. In [5], graph theory has been employed to determine optimal size and location of CSs. In [6], a methodology has been introduced to optimally allocate EVCS and FACTS devices in power system. In [7], authors have focused on analyzing the impact of CS location considering traffic network. In [8], internet of things (IoT) technique has been suggested for real time load prediction of EVs. Also, a technique has been proposed for allocation of EVCSs. In [9], GA has been suggested to determine size of EVCSs considering many factors related to EVs and EVCS like economic, safety and power availability. In [10], a novel approach has been proposed to integrate EVCSs and EV battery swapping stations (EVBSSs) into radial distribution network by minimizing the unfavorable impact on various performance parameters. In [11], the impact of EVCS load, DG uncertainties and load variations have been analyzed. Also, renewable energy-based distributed generation (DG) units have been

allocated to mitigate the impact of EVCS load. In [12], the main objective is to minimize power losses and harmonic distortion of EVs by optimal placement of CSs. In [13], optimal location of EVCSs have been determined from the perspective of the private investors. In [14], a new technique has been proposed to identify the location of EVCSs and DGs by arithmetic optimization algorithm (AOA). In [15], operation of an EV fleet with V2G capability has been investigated where EV users decide when and where they exchange energy with the grid. A mixed-integer linear programming (MILP) formulation has been presented to jointly perform the routing of EVs and scheduling of their charge/discharge operation. In [16], simultaneous scheduling of EVs and responsive loads has been investigated in a micro-grid (MG) to reduce the operation cost and emissions in the presence of wind turbines (WTs) and photovoltaics (PVs). In [17], an EV charging scheduling model has been developed based on the real-time traffic data and the shortest path scheduling algorithm. A methodology has been proposed to optimize the charging time and balance the load of the CSs. There are other studies which focus on energy storage sizing of EVs [18], estimation of EV battery capacity [19], allocation of EVCSs by whale optimization algorithm (WOA) [20] and allocation of charging infrastructure considering information-sharing [21].

Due to the high penetration of EVs in distribution network and consequently, their significant impact on the network performance, planning of EVCSs is one of the most important and challenging issues for power system planners. As a result, it is vital to optimally site and size EVCSs in distribution networks. The present paper proposes a straightforward optimization framework to optimally site and size EVCSs in distribution network. For this goal, in the optimization framework, development cost of EVCSs and distribution network losses cost are considered and the planning problem is solved with respect to load flow and other constraints. Furthermore, to define a more realistic condition, load uncertainty is included

and modelled by normal distribution function and the impact of the uncertainty is investigated on the planning problem.

In the literature, various approaches such as analytical methods [4], graph theory [5], GA [2,9], AOA [14] and WOA [20] have been applied to plan EVCSs. However, since the planning problem is complex for medium- and large-sized networks (the dimension is high) and the probability of trapping into local optima is high, heuristic algorithms have a more chance to find optimal (or close-to-optimal) solution. As a result, in this paper, to effectively and efficiently solve the planning problem, crow search algorithm (CSA) and differential CSA (CSA_{dif}) are applied. CSA is a population-based stochastic search method which has shown a promising performance for solving difficult optimization problems. CSA has several merits such as simplicity of concept, ease of implementation, fast convergence speed and simple control of diversification and intensification [22]. A comprehensive review of CSA variants and applications can be found in [23]. Briefly, the main contributions of the present paper are as follows:

- Introduction of a straightforward optimization framework to optimally site and size EVCSs in distribution network considering development cost and power losses
- Evaluation of load uncertainty on the planning problem of EVCSs in distribution network
- Assessment of CSA performance for optimal allocation of EVCSs in distribution network

This paper is organized in five Sections. Section 2 models the planning problem by definition of the objective function and constraints. Section 3 explains the optimization algorithms in detail. Evaluation of the proposed framework is conducted in Section 4 and conclusion is given in Section 5.

2. Modeling EVCS allocation problem

2.1. Optimization model

2.1.1. EVCS cost

The costs related to an EVCS originates from equipment, operation and maintenance and land costs. In general, it is assumed that the equipment cost linearly changes with the station capacity which it is a function of the number and capacity of the connectors installed in the station. For each connector, a minimum width of 2.7 m and a length of 5.5 m are needed. If there are more than one connector, it is essential to consider a minimum clearance around 0.9 m between the connectors. Mathematically, total cost of station i (TSC_i) is calculated as follows [2]:

$$TSC_i = SFC_i + N_{c,i} \times \alpha_{c,land} \times C_{land} + (N_{c,i} - 1) \times P_c \times C_c \quad (1) \\ \times + C_{OM,npv}$$

where SFC_i is the fixed cost of station i (\$), $N_{c,i}$ is the number of connectors in station i , $\alpha_{c,land}$ is the land area needed for each connector, C_{land} is the land rental cost during the lifetime (here 10 years), P_c is the connector rated power (kW), C_c is the connector cost (\$/kW) and $C_{OM,npv}$ is the net present value (npv) of the operation and maintenance cost (\$). In Eq. (1), the station fixed cost shows the costs associated with the basic equipment and facilities which are used to establish a charging station and pay employees. More or less, this type of cost is similar in different countries. Furthermore, the land rental cost highly depends on the land quality and varies in different locations.

The capacity of station i (SC_i) is obtained as follows:

$$SC_i = N_{c,i} \times P_c \quad (2)$$

2.1.2. Power losses cost

In power system, the highest power loss belongs to the distribution lines. In fact, since the electrical current which passes through the distribution conductors is high and power loss is proportional to the square of this current, distribution network power loss is considerable. For this aim, to keep the power system performance in a desired level, distribution network planning should be done with respect to power losses. Since the site and size of EVCSs can considerably influence the network losses, in the defined objective

function, there is a term which takes into account the cost of power losses. During a year, total cost of power losses ($TCPL$) is defined as follows:

$$TCPL = 365 \times \alpha_{loss} \times \sum_{t=1}^{t_{max}} P_c(t) \quad (3)$$

where α_{loss} is the cost of power losses (\$/kW) and $P_c(t)$ is the network power losses at hour t (kW).

2.1.3. Objective function and constraints

In this paper, in order to optimally site and size EVCSs, an objective function is defined which considers the annual costs related to EVCSs and power losses. Mathematical expression of the objective function (OF) is defined as follows:

$$Min. OF = \sum_{i=1}^{N_{EVCS}} TSC_{i,annual} + TCPL \quad (4)$$

where N_{EVCS} is the number of EVCSs allocated in the distribution network, $TSC_{i,annual}$ is the total annual cost related to EVCS i and $TCPL$ is the annual power losses cost.

To calculate annual cost of EVCS i , capital recovery factor (CRF) is used as follows:

$$TSC_{i,annual} = CRF \times TSC_i \\ = \frac{r \times (1 + r)^n}{(1 + r)^n - 1} \times TSC_i \quad (5)$$

where r is the interest rate and n is the project lifetime.

The objective function value should be minimized subject to the power flow limitations. Here, balance equation, thermal capacity of the network lines, network minimum voltage and network maximum voltage should be satisfied.

2.2. Energy management

In the distribution network, there should be a strategy for energy management issue. For this goal, at hour t , net power (P_{net}) is obtained by calculation of the difference between the total generation (sum of PVs power (P_{PV}) and WTs power (P_{WT})) and the load (P_L) as follows:

$$P_{net}(t) = P_{PV}(t) + P_{WT}(t) - P_L(t) \quad (6)$$

According to the sign of P_{net} , there are two operating conditions: V2G and G2V. These operating modes are defined as follows:

Operating mode 1: G2V

In this operating mode, total generation of PVs and WTs is more than the load and power losses. In this case, the excess power is sent to the EVCSs to charge the batteries of EVs. As a result, state of charge (SOC) of each EV battery is obtained as follows:

$$SOC(t+1) = SOC(t) + \eta_{inv} \times \eta_{bat,c} \times P_{ex,each}(t) \quad (7)$$

where $P_{ex,each}$ is the excess power sent to each battery, η_{inv} is the inverter efficiency and $\eta_{bat,c}$ is the charging efficiency of EV battery. In this case, if the batteries are fully charged and the excess power remains available, the surplus energy is fed into the upstream grid. However, in an isolated network, this energy must be dumped.

Operating mode 2: V2G

In this operating mode, summation of load and power losses is more than the total generation of PVs and WTs. As a result, there is deficit power which should be provided by EVCSs. In this case, SOC of each EV battery is obtained as follows:

$$SOC(t+1) = SOC(t) - \frac{P_{dis,each}(t)}{\eta_{inv} \times \eta_{bat,d}} \quad (8)$$

where $P_{dis,each}$ is the discharging power of each battery and $\eta_{bat,d}$ is the discharging efficiency of EV battery.

It should be noted that charging and discharging of the EV battery is conducted with respect to the constraint defined by Eq. (9) as follows:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (9)$$

where SOC_{min} and SOC_{max} are the minimum and maximum values of SOC. Here, the initial value of SOC is assumed to be 50% of the rated capacity of the EV battery. Furthermore, SOC_{min} is considered 20 percent of the rated capacity.

2.3. Load uncertainty

In power system studies, load is not considered as a deterministic parameter. Most

often, stochastic behavior of load is modelled by a Gaussian probability density function (PDF) whose mean is equal to the predicted value. It can be expressed as follows [24]:

$$PDF(S) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(S-\mu)^2}{2\sigma^2}\right] \quad (10)$$

where S is the load's apparent power, μ is the mean of the apparent power (predicted value) and σ is the standard deviation of the apparent power. Fig. 1 illustrates a Gaussian PDF for a typical load with mean of 500 kW and standard deviation of 50 kW.

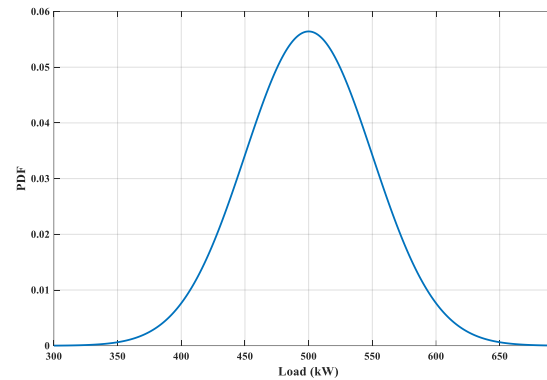


Fig. 1. A Gaussian PDF for a typical load with mean of 500 kW and standard deviation of 50 kW.

3. Methodology

Among optimization methods, heuristic algorithms have more chance of escaping local optima since they utilize stochastic patterns to seek search space. Using random behavior increases population diversity and in optimization theory, diversity control is one of the main reasons of escaping local optima. In recent years, CSA has been promisingly applied to many optimization problems with different degrees of complexity [23]. CSA works based on a population and tries to seek the search space iteration by iteration until optimal (or close-to-optimal) solution is found. This algorithm is user-friendly, easy to code, simple to understand and efficient. In CSA, each solution (so-called crow) is characterized by two vectors: position and memory. Position vector (x) is the momentary location of a crow in the search space and memory vector (m) is the best position found by that crow in the previous iterations. To update its position, each crow tries to follow the memory of another

crow. However, it should be noted that if a crow finds that it is being followed by another crow, the following crow will be cheated by the followed crow. Mathematically, at iteration

$$x^{k,iter} = \begin{cases} x^{k,iter-1} + rand^1 \times fl \times \begin{pmatrix} m^{j,iter-1} \\ -x^{k,iter-1} \end{pmatrix}, & AP \geq rand^2 \\ a \text{ random position}, & otherwise \end{cases} \quad (11)$$

where $x^{k,iter}$ is the position of crow k at iteration $iter$, $x^{k,iter-1}$ is the position of crow k at iteration $iter - 1$, $m^{j,iter-1}$ is the memory position of crow j at iteration $iter - 1$ (crow j is selected randomly), fl is flight length, AP is awareness probability and $rand^1$ and $rand^2$ are random numbers with uniform distribution from $[0 \ 1]$.

The new position is accepted if it satisfies the problem constraints. Otherwise, it is ignored. If the new position is feasible, it is evaluated in terms of the objective function value. Then, it is compared with the

$$x^{k,iter} = \begin{cases} x^{k,iter-1} + rand^1 \times fl \times \begin{pmatrix} m^{pqs,iter} \\ -x^{k,iter-1} \end{pmatrix}, & AP \leq rand^2 \\ a \text{ random position}, & otherwise \end{cases} \quad (12)$$

Where

$$m^{pqs,iter} = m^{p,iter-1} + rand^3 \times (m^{q,iter-1} - m^{s,iter-1}) \quad (13)$$

$iter$, crow k generates a new position as follows:

memorized position. If the new position outperforms the memory position in terms of the objective function value, the memory is updated by the new position. Otherwise, the memory does not change.

To enhance search power of CSA, authors in [25] have introduced differential variant of CSA, named CSA_{dif}. In CSA_{dif}, instead of using the memory of one crow, the memories of three random crows are utilized. If the memory of the random crows is shown by m^p , m^q and m^s , new position of crow k is obtained by Eq. (12). Flowchart of CSA_{dif} implementation is shown in Fig. 2.

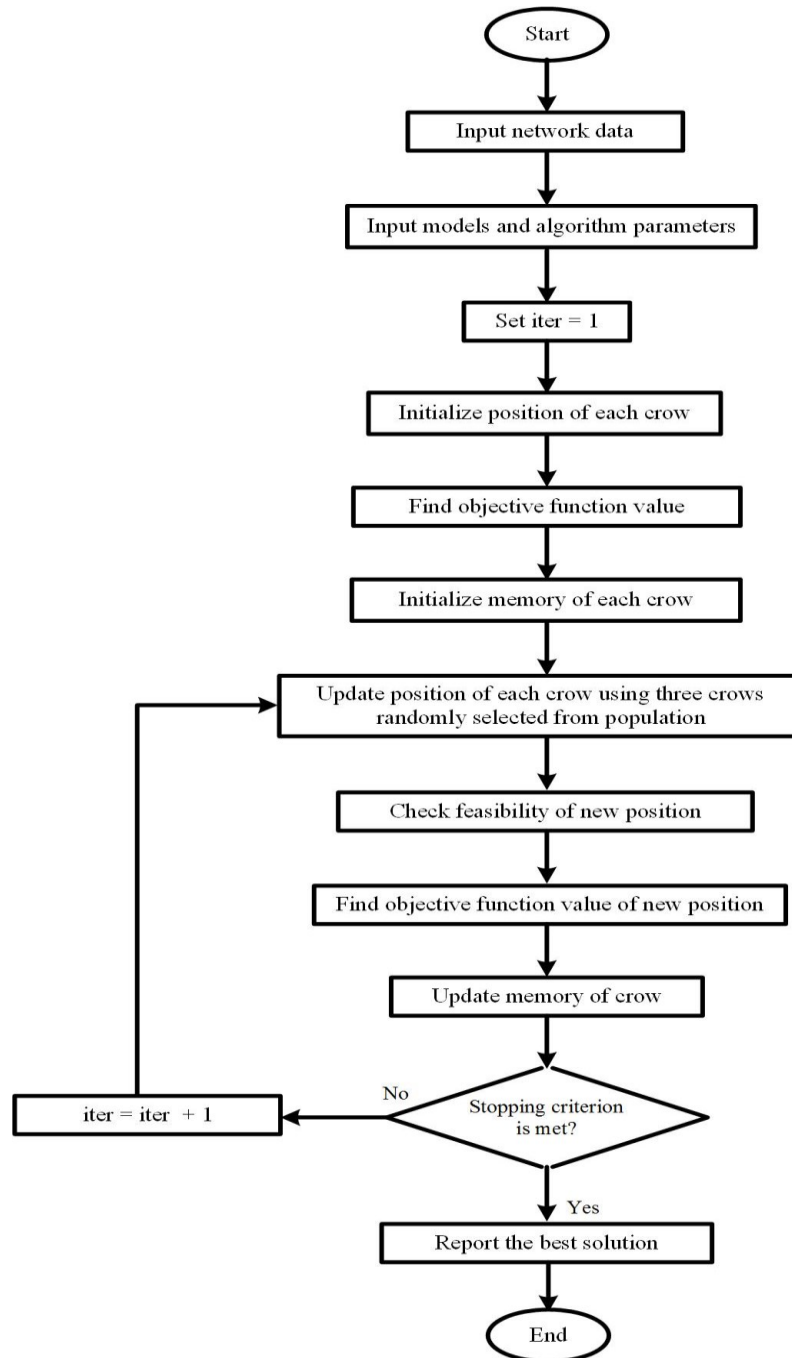


Fig. 2. Flowchart of CSA_{dif} implementation.

4. Simulation results

In order to evaluate the usefulness of the proposed framework, optimal allocation of EVCSs is investigated on IEEE 33-bus distribution network incorporated with PVs and WTs [26-28]. Schematic of the network is shown in Fig. 3. In this 12.66 kV network, active and reactive load values are 3.715 MW and 2.3 MVar, respectively. It is assumed that there are three PVs and six WTs. PV systems

are located on buses 5 (400 kW), 8 (500 kW) and 21 (400 kW). Size of the WTs is 1 MW and they are located on buses 12, 18, 24, 28, 31 and 33. A 24-h time period is considered for the allocation problem. Fig. 4 shows scaling factor of the load, PVs generation and WTs production. Moreover, the parameters are given in Table 1 [2].

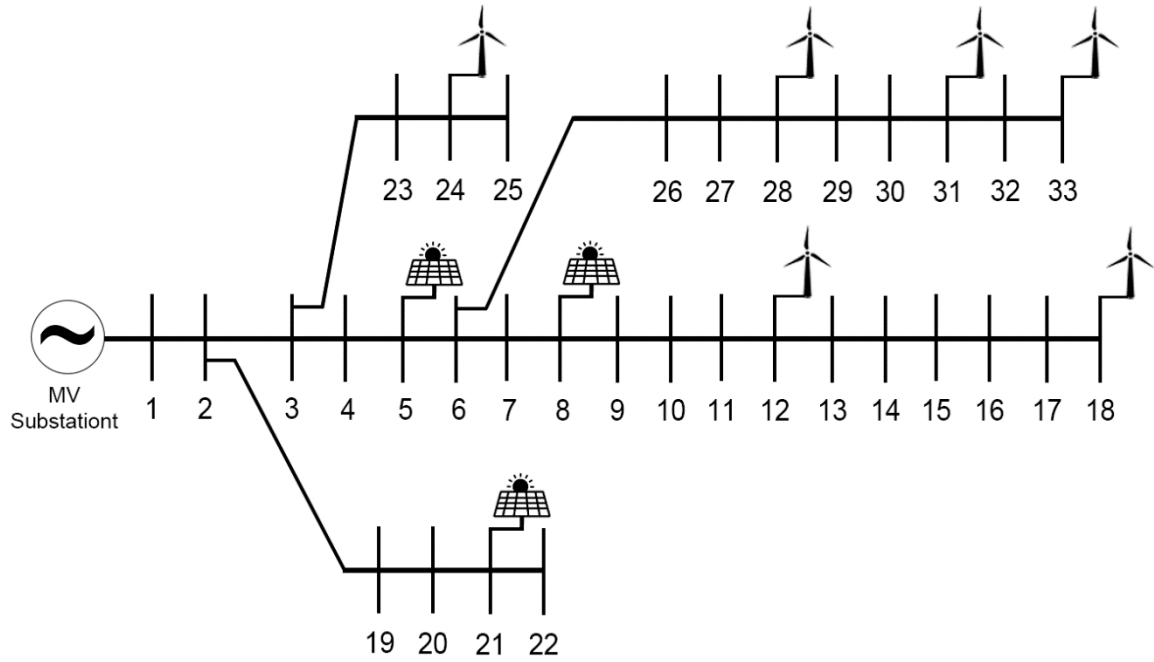


Fig. 3. Schematic of IEEE 33-bus network including PVs and WTs.

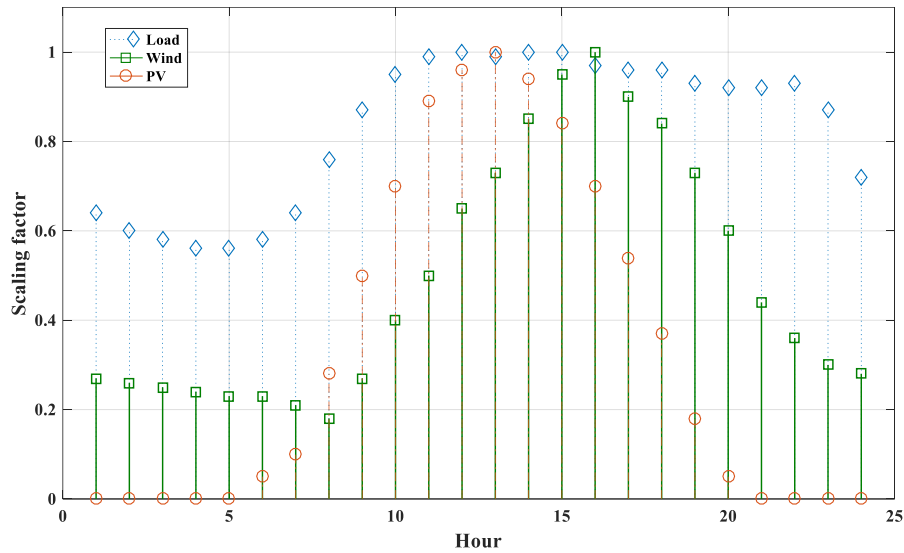


Fig. 4. Scaling factor of load, PVs and WTs during each hour.

Table 1. Parameters of the models used in this study.

Parameter	Value
SFC	70000 \$
$\alpha_{c,land}$	25 m ²
C_{land}	8000 \$/m ²
P_c	96 kW
C_c	208.33 \$/kW
C_{OM}	2160 \$/year
α_{loss}	0.284 \$/kWh
r	6%
$\eta_{bat,c}$	95%
$\eta_{bat,d}$	95%
η_{inv}	94%

The allocation problem is coded in MATLAB environment. Since the optimization algorithm has a stochastic nature, a number of independent runs (here 30) is conducted and the best result is considered as the final solution. Table 2 shows parameter setting of the optimization algorithm. The problem is solved in two scenarios with/without considering the load uncertainty and the results are compared.

Table 2. Parameter setting of CSA for solving the allocation problem.

Parameter	Value
Population size	30
Awareness probability	0.2
Flight length	2
Maximum number of iterations	2000
Number of runs	30

Scenario 1: Allocation of EVCSs without considering load uncertainty

In the first scenario, allocation of EVCSs is investigated when the load uncertainty is ignored. Table 3 shows the optimization results found by CSA and CSA_{dif}. As previously mentioned, due to the random nature of the algorithms, 30 independent runs are conducted and the stochastic results are compared. In Table 3, four indices have been reported: (1) the best performance of the

Table 3. Final results found by the optimizers for scenario 1.

Algorithm	Min (\$)	Mean (\$)	Max (\$)	Median (\$)
CSA	16539466.20	16552662.65	16561497.95	16552469.22
CSA _{dif}	16539145.16	16550394.53	16556978.76	16551403.74

Table 4 lists details of the final solution found by the algorithms. It is observed that the optimal buses for installing EVCS found by CSA are 12 (60 connectors), 16 (30 connectors), 19 (30 connectors), 24 (60 connectors) and 33 (120 connectors). 40% of the connectors are installed on bus 33 where there is a 1 MW WT. Moreover, it is seen that most of the connectors (80%) are installed on buses with WT (buses 12, 24 and 33).

Based on the result found by CSA_{dif}, five locations are suggested for installing EVCS (buses 8, 9, 18, 24 and 33). Among the suggested locations, there is a WT at three locations (buses 18, 24 and 33) and there is a

algorithm over the runs (Min), (2) average of the objective function values over the runs (Mean), (3) the worst performance of the algorithm over the runs (Max) and (4) median of the objective function values over the runs (Median). As table indicates, the best performance (Min index) belongs to CSA_{dif}. However, the difference between Min index found by CSA and CSA_{dif} is trivial. In this case, the minimal objective function value found for the allocation problem is 16539145.16 \$. In terms of the other indices (Mean, Max and Median), CSA_{dif} finds better results than CSA. As Mean index shows, the average of the objective function values obtained by CSA_{dif} is 16550394.53 \$ while the value found by CSA is 16552662.65 \$.

500 kW PV system at one location (bus 8). Total number of the connectors installed by CSA and CSA_{dif} is 300. Fig. 5 depicts schematic of the designed network. Fig. 6 shows the charging and discharging of EVs in an EVCS including 30 connectors. In such a station, when there is excess power (PVs and WTs produces power more than load), SOC starts to increase. On the other hand, when there is deficit power, SOC decreases to satisfy the load. In other words, SOC curve decreases when the load curve exceeds the generation curve and increases when the load curve falls below the generation curve.

Table 4. Final results found by the optimizers for scenario 1.

Algorithm	Bus number for installing EVCSs (number of connectors)	Total number of installed connectors
CSA	12 (60), 16 (30), 19 (30), 24 (60) and 33 (120)	300
CSA _{dif}	8 (60), 9 (30), 18 (30), 24 (60) and 33 (120)	300

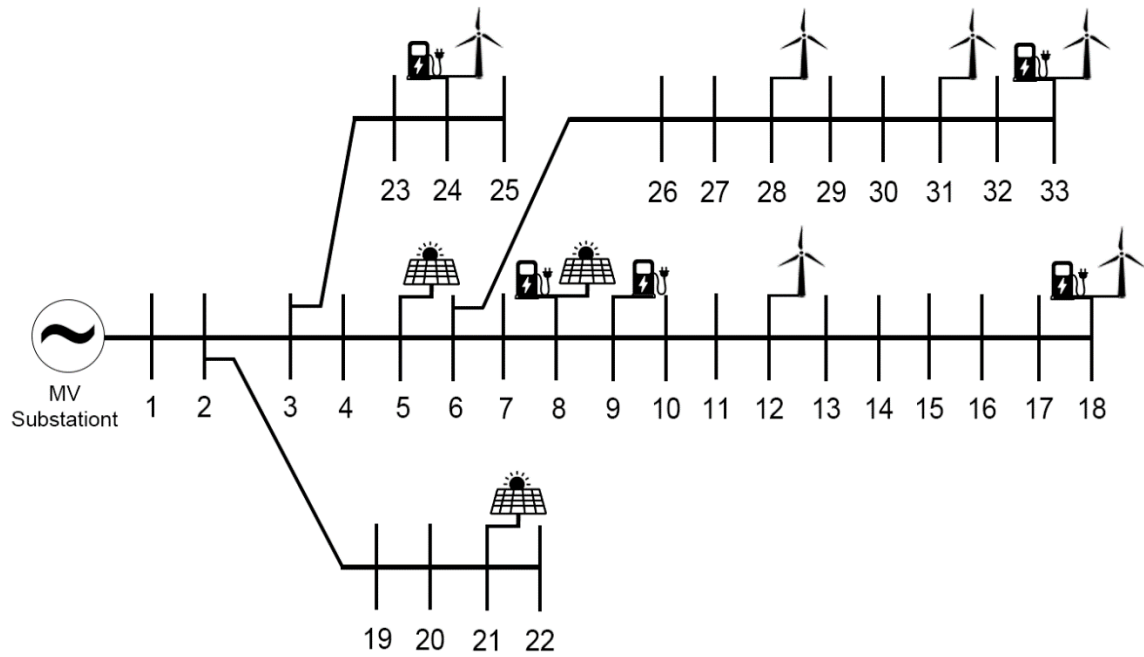


Fig. 5. Schematic of the designed network in scenario 1 found by CSA_{diff}.

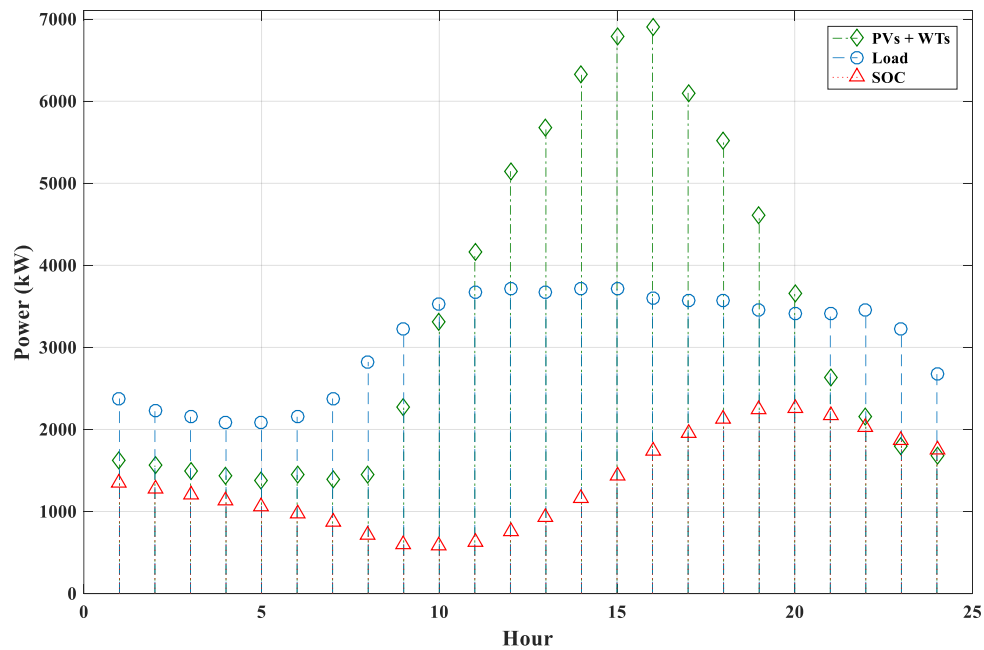


Fig. 6. Status of SOC at different hours with respect to load and renewable generation without considering load uncertainty obtained by CSA_{diff}.

Table 5 compares the network parameters before and after allocating EVCSs. Before allocation of EVCSs, the network power loss is 2503.88 kW. In this network, minimum and maximum voltages are 0.967 and 1.071 p.u. which belong to buses 32 and 18, respectively. It is obvious that the maximum voltage

(occurred on bus 18) exceeds the limit of 0.95 p.u. As table indicates, in the designed network by CSA_{diff}, power loss reduces to 1562.85 kW and maximum voltage is 1.0132 p.u. which belongs to bus 18. In this network, minimum voltage is 0.9835 p.u. which is related to bus 33. Figs. 7 and 8 show voltage of the network

buses at different hours for base case and the designed network, respectively. In the

designed network, all the voltages are in the allowable range.

Table 5. Comparison of the network parameters before and after allocation of EVCSs.

Parameter	Network before EVCSs allocation	Network after EVCSs allocation	
		CSA	CSA _{diff}
Network power losses (kW)	2503.88	1565.05	1562.85
Bus with minimum voltage	32	30	33
Minimum voltage (p.u.)	0.967	0.9859	0.9835
Bus with maximum voltage	18	18	18
Maximum voltage (p.u.)	1.071	1.0144	1.0132
Total capacity of EVCSs (kW)	-	2880	2880

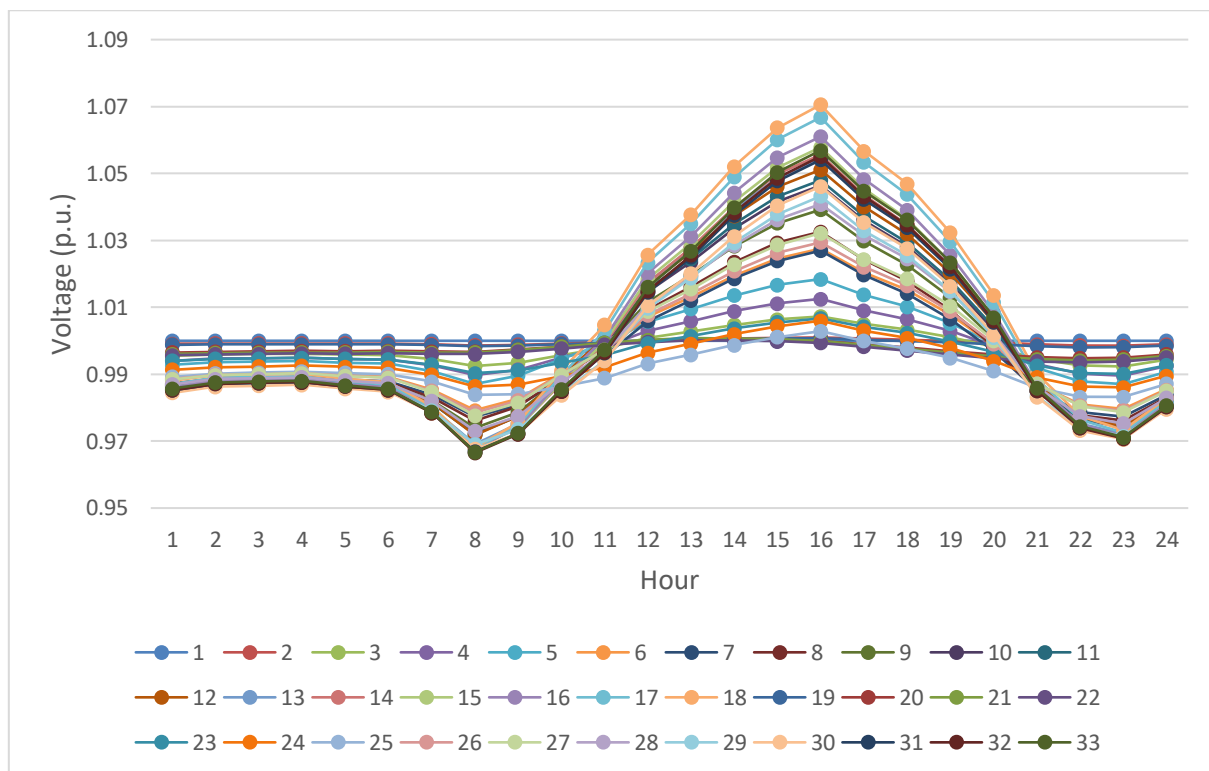


Fig. 7. Voltage of the network buses at different hours before allocation of EVCSs.

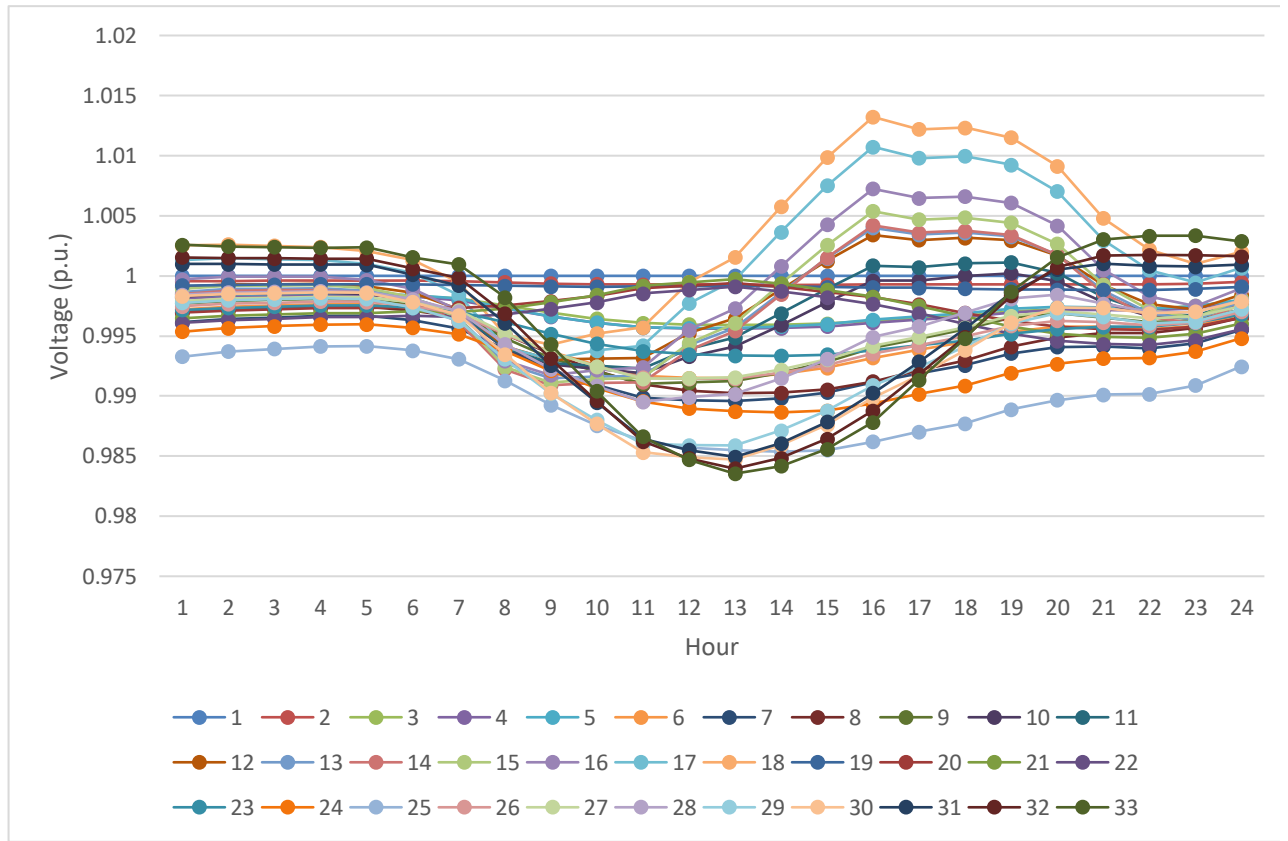


Fig. 8. Voltage of the network buses at different hours after allocation of EVCSs in scenario 1.

Fig. 9 shows a comparison between the convergence process of CSA and CSA_{dif} over the allocation problem. Convergence process shows the objective function value related to the best-so-far solution at each iteration. Based

on the figure, it is seen that CSA_{dif} has a more promising convergence rate than CSA. This algorithm converges to the final solution around iteration 200.

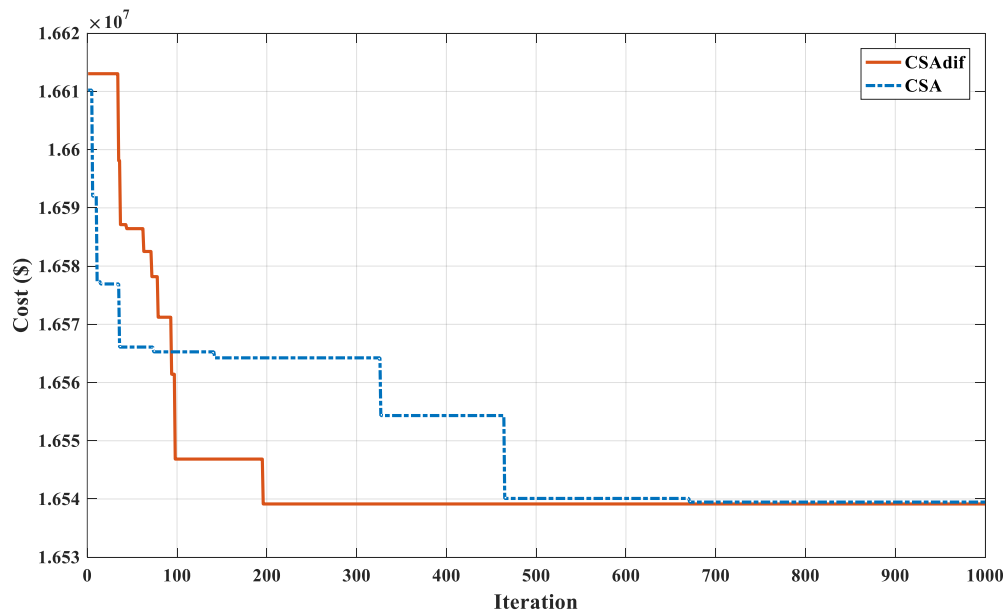


Fig. 9. Comparison of convergence rate between CSA and CSA_{dif} for solving the allocation problem without considering load uncertainty.

Scenario 2: Allocation of EVCSs considering load uncertainty

In the second scenario, the impact of the load uncertainty is investigated on the optimal allocation of EVCSs in the distribution network. In power systems, most studies include load uncertainty by default because it directly affects the system balance while wind/solar uncertainty is sometimes ignored for simplicity, especially in planning studies where their variability can be approximated deterministically. However, to increase the

accuracy, wind and solar uncertainties can be incorporated into the planning problem.

Table 6 shows the optimization results found by CSA and CSA_{dif}. In terms of Min index, the solution found by CSA_{dif} is more accurate than that of CSA. When the load uncertainty is included, the minimum value of the objective function is 17071848.02 \$ which increases around 3.2% compared to the first scenario (16539145.16 \$). In terms of the other indices, CSA_{dif} finds more promising results than CSA. On average, the objective function value found by CSA_{dif} is 17084613.97 \$.

Table 6. Final results found by the optimizers for scenario 2.

Algorithm	Min (\$)	Mean (\$)	Max (\$)	Median (\$)
CSA	17080668.52	17090720.26	17101335.33	17090743.25
CSA _{dif}	17071848.02	17084613.97	17093640.07	17086098.31

Table 7 shows the details of the final solution obtained by the algorithms where 310 connectors are suggested for installation. Compared to the first scenario, the number of connectors increases from 300 to 310. CSA suggests five locations for EVCS installation while CSA_{dif} suggests four locations. According to the final solution found by CSA_{dif}, the optimal buses for installing EVCSs are 8 (62 connectors), 10 (93 connectors), 23 (62 connectors) and 33 (93 connectors). Fig.

10 shows schematic of the designed network. In this case, 60% of the connectors are installed on buses 10 and 33. Parameters of the designed network are listed in Table 8. By comparing the results with the results found in the first scenario, it is seen that inclusion of the uncertainty not only will increase the network cost (from 16539145.16 to 17071848.02 \$) and losses (from 1562.85 to 1610.61 kW) but also increases the total capacity of the installed connectors (from 2880 to 2976 kW).

Table 7. Final results found by the optimizers for scenario 2.

Algorithm	Bus number for installing EVCSs (number of connectors)	Total number of installed connectors
CSA	4 (31), 9 (93), 18 (31), 23 (62) and 33 (93)	310
CSA _{dif}	8 (62), 10 (93), 23 (62) and 33 (93)	310

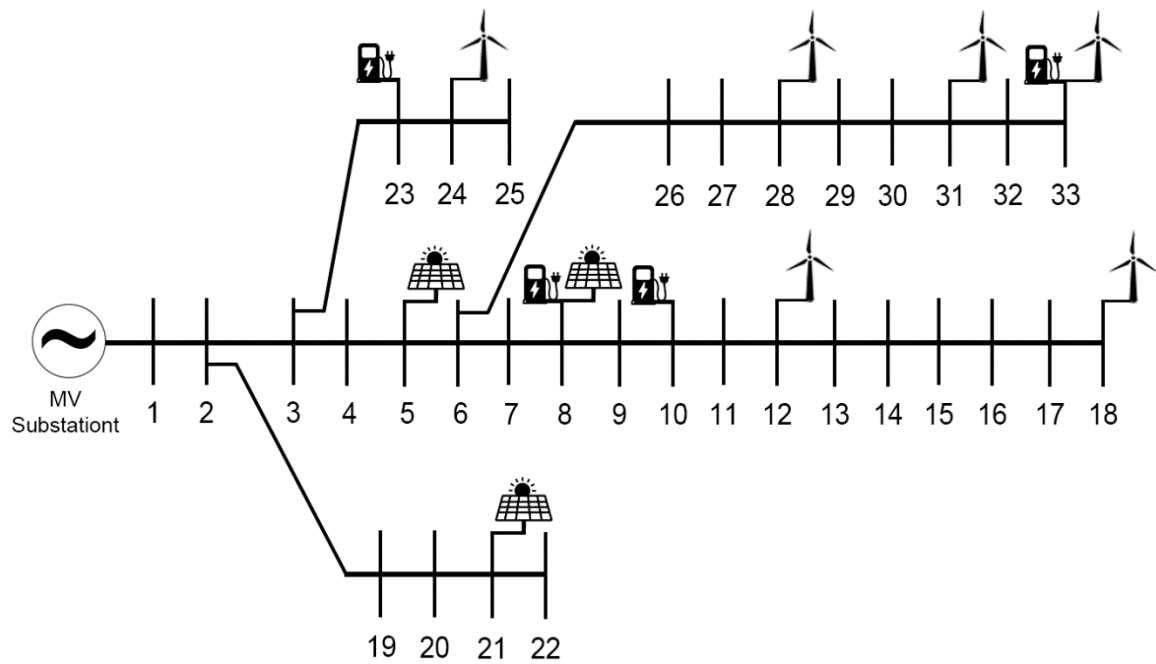


Fig. 10. Schematic of the designed network in scenario 2 found by CSA_{dif}.

Table 8. Comparison of the network parameters after allocation of EVCSs obtained by the algorithms considering the uncertainty.

Parameter	Network parameters after EVCSs allocation	
	CSA	CSA _{dif}
Network power losses (kW)	1580.19	1610.61
Bus with minimum voltage	30	30
Minimum voltage (p.u.)	0.9865	0.9861
Bus with maximum voltage	18	18
Maximum voltage (p.u.)	1.0113	1.0160
Total capacity of EVCSs (kW)	2976	2976

Fig. 11 shows charging and discharging processes of a typical station. Fig. 12 shows voltage of the network buses when the load uncertainty is considered in the planning problem. Compared to the first scenario,

voltage of the network buses does not change considerably. Fig. 13 illustrates the convergence process of the algorithms. In this case, CSA_{dif} reaches to the final solution around iteration 500.

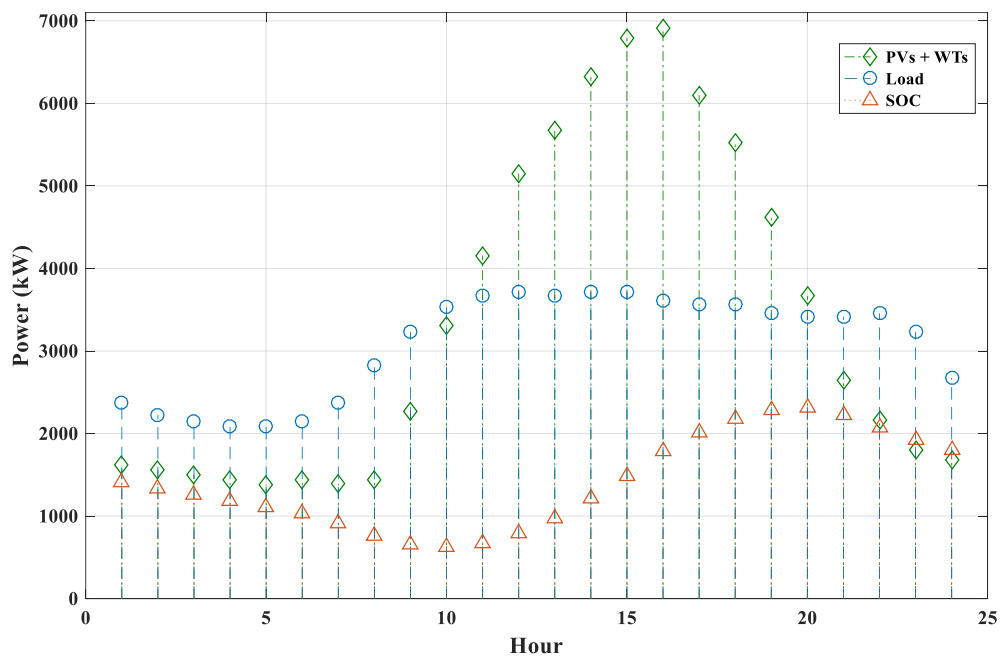


Fig. 11. Status of SOC at different hours with respect to load and renewable generation without considering load uncertainty obtained by CSA_{diff}.

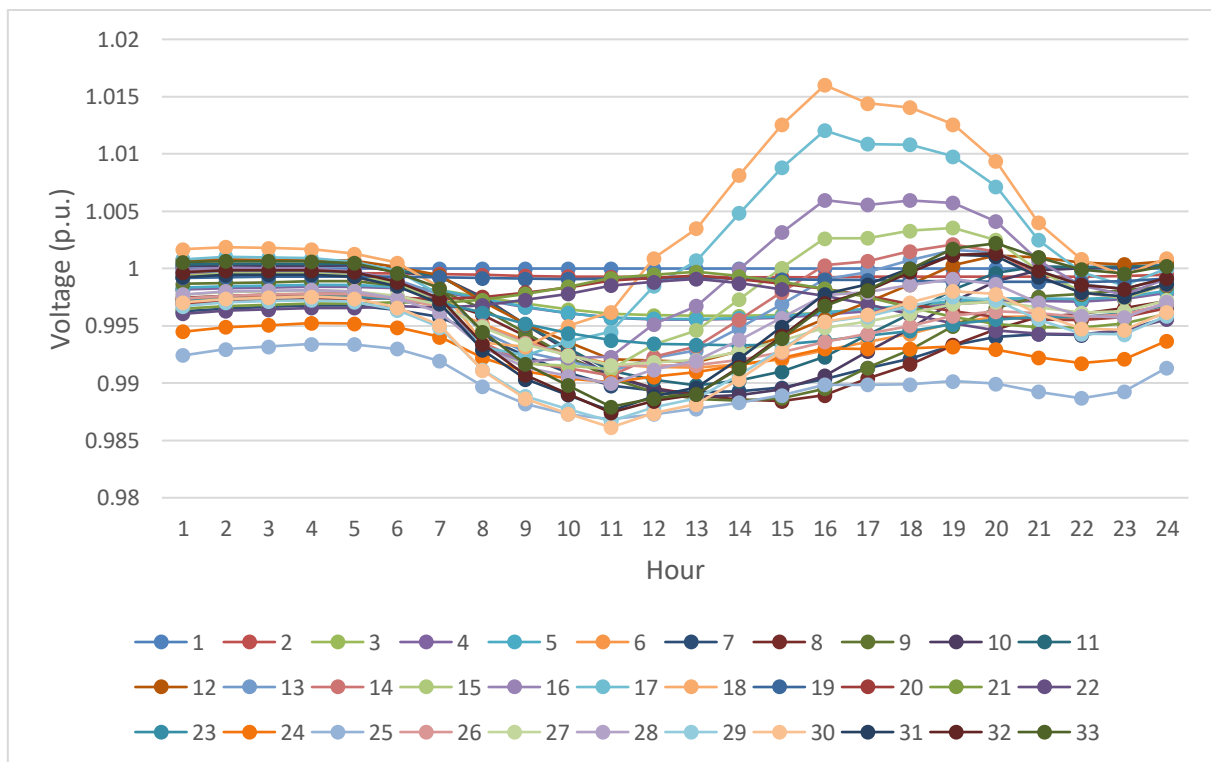


Fig. 12. Voltage of the network buses at different hours after allocation of EVCSs in scenario 2 obtained by CSA_{diff}.

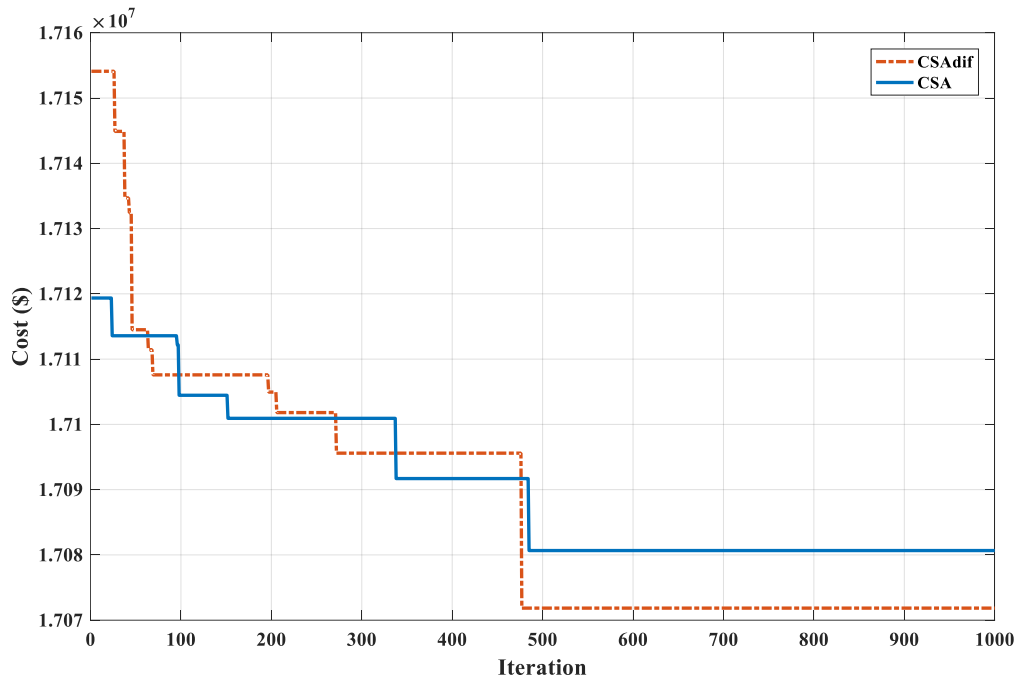


Fig. 13. Comparison of the convergence rate between CSA and CSA_{dif} for solving the allocation problem when there is load uncertainty.

5. Conclusion

In distribution networks, optimal allocation of EVCSs is an important and challenging issue. Because siting and sizing of EVCSs can significantly influence power system performance, this paper proposes an optimization scheme to optimally allocate EVCSs. In the allocation problem, load uncertainty is included and CSA-based algorithms are used to effectively solve the problem. Over the case study, it can be concluded that

(1) When load uncertainty is ignored, 300 connectors with the total capacity of 2880 kW are suggested for installation on five buses. EVCSs are installed next to or near renewable resources. In this case, compared to the base case, network losses decrease around 38%.

(2) When load uncertainty is included, 310 connectors with the total capacity of 2976 kW are suggested for installation on four buses. Compared to the base case, network losses decrease around 36%.

(3) By considering the load uncertainty, optimization algorithm prefers to install more connectors. In this case, total capacity of the installed connectors increases around 3.3%.

(4) Compared to CSA, CSA_{dif} produces more promising results in terms of accuracy.

References

- [1] A. Sheikhi, S. Bahrani, A.M. Ranjbar, H. Oraee, "Strategic charging method for plugged in hybrid electric vehicles in smart grids; a game theoretic approach," *Int J Electr Power Energy Syst* 2013;53:499–506.
- [2] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," *Appl Energy*, vol. 125, pp. 289–299, 2014, doi: <https://doi.org/10.1016/j.apenergy.2014.03.077>.
- [3] S. Ge, Liang Feng, and Hong Liu, "The planning of electric vehicle charging station based on Grid partition method," *International Conference on Electrical and Control Engineering*, pp. 2726–2730, 2011.
- [4] H. Hanabusa and R. Horiguchi, "A Study of the Analytical Method for the Location Planning of Charging Stations for Electric Vehicles," vol. 6883. 2011. doi: 10.1007/978-3-642-23854-3_63.
- [5] L. Jia, Z. Hu, Y. Song, and Z. Luo, "Optimal siting and sizing of electric vehicle charging stations," *IEEE International Electric Vehicle Conference*, Mar. 2012, doi: 10.1109/IEVC.2012.6183283.
- [6] K. Pal, K. Verma, and R. Gandotra, "Optimal location of FACTS devices with EVCS in power system network using PSO," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 7, p. 100482, 2024, doi: <https://doi.org/10.1016/j.prime.2024.100482>.
- [7] M. A. Abdelaziz, A. A. Ali, R. A. Swief, and R. Elazab, "A reliable optimal electric Vehicle charging

- stations allocation,” *Ain Shams Engineering Journal*, p. 102763, 2024, doi: <https://doi.org/10.1016/j.asej.2024.102763>.
- [8] G. F. Savari, V. Krishnasamy, J. Sathik, Z. M. Ali, and S. H. E. Abdel Aleem, “Internet of Things based real-time electric vehicle load forecasting and charging station recommendation,” *ISA Trans*, vol. 97, pp. 431–447, 2020, doi: <https://doi.org/10.1016/j.isatra.2019.08.011>.
- [9] W. Kong, Y. Luo, G. Feng, K. Li, and H. Peng, “Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid,” *Energy*, vol. 186, p. 115826, 2019, doi: <https://doi.org/10.1016/j.energy.2019.07.156>.
- [10] K. Balu and V. Mukherjee, “Optimal deployment of electric vehicle charging stations, renewable distributed generation with battery energy storage and distribution static compensator in radial distribution network considering uncertainties of load and generation,” *Appl Energy*, vol. 359, p. 122707, 2024, doi: <https://doi.org/10.1016/j.apenergy.2024.122707>.
- [11] K. Balu and V. Mukherjee, “Optimal allocation of electric vehicle charging stations and renewable distributed generation with battery energy storage in radial distribution system considering time sequence characteristics of generation and load demand,” *J Energy Storage*, vol. 59, p. 106533, 2023, doi: <https://doi.org/10.1016/j.est.2022.106533>.
- [12] S. P. R. S. Polisetty, R. Jayanthi, and M. Sai Veerraju, “An intelligent optimal charging stations placement on the grid system for the electric vehicle application,” *Energy*, vol. 285, p. 129500, 2023, doi: <https://doi.org/10.1016/j.energy.2023.129500>.
- [13] Y. Li, J. Wang, W. Wang, C. Liu, and Y. Li, “Dynamic pricing based electric vehicle charging station location strategy using reinforcement learning,” *Energy*, vol. 281, p. 128284, 2023, doi: <https://doi.org/10.1016/j.energy.2023.128284>.
- [14] K. Kathiravan and P. N. Rajnarayanan, “Application of AOA algorithm for optimal placement of electric vehicle charging station to minimize line losses,” *Electric Power Systems Research*, vol. 214, p. 108868, 2023, doi: <https://doi.org/10.1016/j.epsr.2022.108868>.
- [15] A. Triviño-Cabrera, J. A. Aguado, and S. de la Torre, “Joint routing and scheduling for electric vehicles in smart grids with V2G,” *Energy*, vol. 175, pp. 113–122, 2019, doi: <https://doi.org/10.1016/j.energy.2019.02.184>.
- [16] A. Rabiee, M. Sadeghi, J. Aghaei, and A. Heidari, “Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and PV units uncertainties,” *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 721–739, 2016, doi: <https://doi.org/10.1016/j.rser.2015.12.041>.
- [17] Y. An, Y. Gao, N. Wu, J. Zhu, H. Li, and J. Yang, “Optimal scheduling of electric vehicle charging operations considering real-time traffic condition and travel distance,” *Expert Syst Appl*, vol. 213, p. 118941, 2023, doi: <https://doi.org/10.1016/j.eswa.2022.118941>.
- 1-1- [18] S. Bansal, S. Dey, M. Khanra, “Energy storage sizing in plug-in Electric Vehicles: Driving cycle uncertainty effect analysis and machine learning based sizing framework,” *Journal of Energy Storage*, vol. 41, September 2021, 102864.
- [19] M. Etxandi-Santolaya, L. C. Casals, C. Corchero, “Estimation of electric vehicle battery capacity requirements based on synthetic cycles,” *Transportation Research Part D: Transport and Environment*, vol. 114, January 2023, 103545.
- [20] J. Cheng, J. Xu, W. Chen, B. Song, “Locating and sizing method of electric vehicle charging station based on Improved Whale Optimization Algorithm,” *Energy Reports*, vol. 8, November 2022, Pages 4386–4400.
- [21] C. A. Vandet, J. Rich, “Optimal placement and sizing of charging infrastructure for EVs under information-sharing, Technological Forecasting and Social Change,” vol. 187, February 2023, 122205.
- [22] A. Askarzadeh, “A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm,” *Comput Struct*, vol. 169, pp. 1–12, 2016, doi: <https://doi.org/10.1016/j.compstruc.2016.03.001>.
- [23] Y. Meraihi, A. B. Gabis, A. Ramdane-Cherif, D. Acheli, “A comprehensive survey of crow search algorithm and its applications,” *Artificial Intelligence Review*, vol. 54, pp. 2669–2716, 2020.
- [24] A. R. Jordehi, “How to deal with uncertainties in electric power systems? A review,” *Renew Sustain Energy Rev*, vol. 96, pp. 145–155, 2018.
- [25] S. Makhdoomi and A. Askarzadeh, “Optimizing operation of a photovoltaic/diesel generator hybrid energy system with pumped hydro storage by a modified crow search algorithm,” *J Energy Storage*, vol. 27, p. 101040, 2020, doi: <https://doi.org/10.1016/j.est.2019.101040>.
- [26] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401–1407, 1989, doi: 10.1109/61.25627.
- [27] C. K. Das et al., “Optimal allocation of distributed energy storage systems to improve performance and power quality of distribution networks,” *Appl Energy*, vol. 252, p. 113468, 2019, doi: <https://doi.org/10.1016/j.apenergy.2019.113468>.
- [28] A. Ghaffari, A. Askarzadeh, R. Fadaeinedjad, “Optimal allocation of energy storage systems, wind turbines and photovoltaic systems in distribution network considering flicker mitigation,” *Appl Energy* 2022;319:119253.