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Cost-based optimal siting and sizing of electric vehicle charging stations considering demand response programmes

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Abstract: Here, the optimal placement and sizing of electric vehicle charging stations (EVCSs) are presented. High penetration of electric vehicles (EVs) and resulted losses in network would consequently impose more complexity to solution of application problem of EVCSs. To overcome this problem, the model would consider the incentive-based demand response programmes (DRPs), which is handled by particle swarm optimisation algorithm. Minimising investment cost, connection cost, total cost of losses, and demand response (DR) cost are the objective functions of this problem here. Finally, the proposed model is applied to a test system and results are discussed. By comparing the results obtained through different scenarios, it is concluded that the application of DRP results in a distinct reduction in grid losses and total costs.

Nomenclature

$\rho(i)$	elasticity price after implementing DRP
$\rho_0(i)$	elasticity price before implementing DRP
A	area requirement per connector
c_1	cognitive learning factor
c_2	social learning factor
$C_{\rm con}$	connector development cost
$C_{\rm fixed}$	station fixed-cost
$C_{\rm lan}$	land rental cost for 5 years
$\mathrm{CR}(i)$	amount of the incentive for each unit of load reduction
$d(i)$	demand after implementing DRP
$d_0(i)$	demand before implementing DRP
D_i	distance of ith charging station from the closest substation
DE	maximum number of EVs that can be charged by a connector
$E(i)$	elasticity of the demand
i	index of candidate charging station
j	index of electric vehicle
k	index of particle
L_j	trajectory length to the charging station
$l_{i,j}$	trajectory length of jth EV to ith candidate station and $X_i = 1$
n	index of substation
$N_{\rm Bus}$	number of buses
$N_{\rm CS}$	number of candidate charging stations
$N_{\rm DR}$	number of responsive demands
$N_{\rm EV}$	number of electric vehicles
P	electricity price
PC	connector rated power
$\mathrm{pen}(i)$	penalty factor
r_1	random number in the range of [0,1]
r_2	random number in the range of [0,1]
ref	amount of the demand which the customer is responsive to reduce it
S	cross-section area of the line
SEC	EV-specific electricity consumption
t	current iteration number
TC_i	transmission cost of the ith overhead line
TD	total number of days in 5 years
w	inertia factor
X_i	binary decision variable to status of ith charging station
x_{S_n}	longitude of the nth substation
x_{CS_i}	longitude of the ith charging station
x_{EV_j}	longitude of the jth EV position
Y_i	number of connectors in ith charging station
y_{S_n}	latitude of the nth substation
y_{CS_i}	latitude of the ith charging station
y_{EV_j}	latitude of the jth EV position
Z_k	binary decision variable to status of kth responsive load

1 Introduction

1.1 Motivation

Most attention over the past few years has focused on electric vehicles (EVs). EVs can decrease the fossil fuel consumptions but increase the demand in power sector [1, 2]. EVs can be summarised into two categories: battery EV and hybrid EV [3, 4]. Standard EV charging levels have been defined and three of them are currently used for EVs [5]. In levels 1 and 2, EV requires hours to fully be recharged, while charging level 3, named direct current (DC) fast charging, provides the possibility to fully charge an EV battery in less than half an hour. Therefore, it is expected that public DC fast charging stations (CSs) play a key role in distribution systems in near future [6, 7], especially when many EVs are loading their accumulators simultaneously. Consequently, the topic of electric vehicle charging stations (EVCSs) has attracted attention from point of view of distribution system operator and EV users [8, 9]. A CS is usually in the form of a fixture connected directly to an electrical distribution panel, or sometimes to an electrical outlet. It has one or more charging cables equipped with a connector that is similar to a gas-pump nozzle and is used in the same way: it simply connects to the EV's charging socket to charge the battery. Overload in substations may occur due to non-optimal placement of CSs. Their optimal placement and sizing can result in reduction in energy losses, improvement of voltage profile, better controllability of system loading, and economic benefits for distribution network operators [10].

Nowadays, it is necessary to considering demand-side management to determine optimal EVCS location. A successful demand response programme (DRP) enables end-users to receive a revenue stream for reducing electricity consumption when wholesale prices are high. Providing that a demand response (DR) is successful in a power market several valuable events will occur; commercial and industrial facilities will reduce their electricity consumption in response to either price or system reliability events; commercial and industrial facilities will be paid for performance based on wholesale market prices; participating in DR can empower people to negotiate more attractive retail prices with competitive electricity suppliers; participation helps an end-user to control peak demand for electricity. This paper presents a new approach for optimal placing and sizing of EVCSs using DRP [11].

The DRPs are usually classified into time-based and incentive-based programmes. In the former, the electricity price changes for different periods according to the electricity supply cost. These programmes can be categorised such as time of use (TOU), real-time pricing, and critical peak pricing programmes. Whereas in the latter, incentives are paid to the customers to reduce or cut their consumption during peak hours. Incentive-based programmes can be categorised such as direct load control (DLC), emergency demand response programme (EDRP), capacity market programme, interruptible/curtailable service, demand bidding, and ancillary service programme. The main focus of the present paper is on EDRP and DLC.

In this paper, DRP is modelled considering incentives and penalty factors. These factors would lead to optimal control on DR resources. In addition, applying DRP can reduce the electric losses due to EV charging. So, both grid losses and DRP are critical in determining CS location.

1.2 Literature review

Problem of optimal placement of CSs has been investigated from different viewpoints in the literature, objective functions, various solution methods, geographic conditions, and considering demand-side management.

In the traditional EVCS location problem, CSs should be installed at the least investment cost. Multi-objective functions are introduced in new strategies of EVCS location problem. Minimisation of network losses, environmental impacts, and sustainable criteria as well as reliability of power system are other objectives used in the literature [12].

In [13], the problem of the optimal placement of CSs to get maximum coverage at minimum cost has been analysed. Their approach was based on consideration of a graph of all possible locations of CSs and finding the optimal subgraph of this graph that has complete coverage of all areas in the network.

In [14], the optimal siting and sizing of the fast CS, considering both electric grid losses and construction cost, have been solved by genetic algorithm (GA). In [15], the site of EVCS has been selected based on sustainable criteria such as environmental, economic, and social criteria. The fuzzy technique for order of preference by similarity to ideal solution method has been used for the selection of the EVCS site alternatives.

In [16], a cost-based placement of fast EVCS has been presented considering the effect of control of state of charge on reliability of network.

From the solution method point of view, several papers have been focused on the use of evolutionary algorithms [17].

In [18], an improved particle swarm optimisation (PSO) algorithm by changing the inertia factor proposed to determine an optimal location of a CS based on construction and maintenance costs. However, in [19], game theory has been used to solve the price competition problem among EVCSs with renewable energy source (RES), considering relevant physical constraints.

In [20], to determine the optimal EVCSs location considering environmental factors and service radius, a two-step model has been proposed and then the EVCS size has been determined.

In the literature, there are a number of publications on the optimal placement of CSs, considering geographic conditions. In [21], the placement of EVCSs to minimise the total installing cost in the public transportation system has been proposed. In the paper, there was a trade-off between the battery capacity and the number of CSs needed. In [22], planning of the EVCS placement problem to easily access a CS within its driving range has been presented.

In [23], a novel planning method has been developed for fast EVCSs location on a round freeway, considering the spatial and temporal transportation behaviours based on the origin–destination analysis.

In [24], the impact of the placement of EV charging on power grid, considering traffic flow of EVs, has been proposed. In the paper, a Bayesian game framework has been applied to analyse the strategic interactions among service providers such as EV owner, station owner, and power grid operator.

A DC fast CS, considering the integration of RESs and effects of city roads for full EV and plug-in hybrid electric vehicle, has been proposed in [25].

In [26], a cost model to find the optimal locations considering geographic conditions, traffic, and local access is proposed. In the paper, transportation cost is important to accurately model the cost function.

Considering the effect of demand-side management in placement of CSs, battery capacity control schemes are needed. While existing researches have mainly put their emphasis on economic dimensions and transportation sector, few researches are available to study the load demand due to considerable EV charging behaviours and their influence over load characteristics of distribution network. A strategy to model the charging power demand on a residential power distribution system has been proposed in [27]. This strategy can ensure a high utilisation of the battery capacity, and the aggregated charging demand resulted is more rational and credible. In [28], control mechanisms for charging demand of EVs to avoid charging during peak hours are presented. A stochastic modelling for aggregated EVs and their impact on the optimal load profile of the network has been discussed in [29]. In [30], TOU price has been utilised for finding optimal charging loads and minimising charging cost in a regulated market. Stochastic model for aggregated EVs and their impact on the optimal load profile of the network has been presented in [31]. In [32, 33], a coordination charging control between EVs and energy storage system (ESS) has been proposed. The goal of the paper is to minimise the total cost of investment and charging cost. From the above existing research work on the optimal placement of CSs, it is clear that it is difficult to simultaneously address all important parameters. This paper presents cost-based model to determine optimal location and size of EVCS, considering DRPs.

Table 1 shows the comparison of our placement of EVCS problem with other models investigated in the published papers.

1.3 Contribution and paper organisation

As a result, the main contributions of the present paper are summarised as follows:

- modelling the EVCS location problem with DRP as a cost-based model;
- investigating the effects of DRPs on grid losses reduction.

To show these contributions, the paper is organised as follows: Section 2 formulates the optimal placement and sizing of EVCS problem. In Section 3, implementation of the optimisation method is proposed. Section 4 presents the simulation results. Section 5 concludes the paper.

2 Problem of optimal placement and sizing of EVCS

The problem of optimal siting and sizing of the EVCSs is a binary integer problem, which seeks for the minimum of newly added CS costs, total losses of network, and DR cost considering equality and inequality constraints. Its mathematical model can be described as follows.

2.1 Investment cost

The investment include three parts, first part is the cost associated with basic equipment and facilities used to establish a CS; second

Table 1 Comparison of the proposed placement of EVCS problem with other published papers

	Objective function	Solution method	Geographic conditions	Demand-side management
[33]	EV user/station development/ grid operator cost	GA	urban traffic	—
[14]	station development cost grid/EV loss	GA	—	—
[22]	construction cost	iterative mixed integer linear programming greedy method	—	—
[24]	profit of EV charging	repeat simphony	traffic flow	—
[23]	charger cost	shared nearest neighbour clustering algorithm	travelling convenience of EV users	—
our paper	investment/ connection/grid energy loss/DR cost	PSO	—	DRP

part is the land rental cost; and the other part is the connector development cost, which can be formulated as follows:

$$\mathrm{Cost}_1 = \sum_{n=1}^{N_{\mathrm{CS}}} (C_{\mathrm{fixed}} + A\,.\,C_{\mathrm{lan}}\,.\,Y_i + \mathrm{PC}\,.\,C_{\mathrm{con}}\,.\,(Y_i - 1))\,.\,X_i \tag{1}$$

The cost of equipment can be estimated by the type, number, and size of the charging connectors, which are considered fixed and predetermined. The land cost depends on the number of the charging connectors and is considered as yearly rental cost of the land for 5 years.

For each candidate CS, binary variables (X_i) are used. The number of binary variables is equal to the number of CS (N_{CS}), which can be added by optimisation problem. Whenever a binary variable is equal to zero, the candidate CS will be completely removed.

Additionally, the capacity of the selected CS (when $X_i = 1$) greatly depends on the number of connectors (Y_i) and the connector rated power (PC).

Then, the capacity of the ith CS is calculated as follows:

$$C_i = \mathrm{PC} \times Y_i \tag{2}$$

2.2 Connection cost

The connection cost depends on the distance of the station from the connection point to the grid, i.e. closest substation as well as the connection technology. It is assumed that the station is directly connected to the substation via dedicated overhead line. According to (4), transmission cost of the overhead line (TC) can be calculated as a function of cross-area of the line (S)

$$\mathrm{Cost}_2 = \sum_{i=1}^{N_{\mathrm{CS}}} (\mathrm{TC}_i \times D_i) \times X_i \tag{3}$$

$$\mathrm{TC}_i = 8000 + 65.7 \times S \tag{4}$$

2.3 Active power losses

The active power losses should be considered for the distribution network and EVs. Therefore, the total active power losses can be presented as follows:

$$P_{\mathrm{loss}} = P_{\mathrm{loss-Dist}} + P_{\mathrm{loss-EV}} \tag{5}$$

The steps of alternating current (AC) power flow to obtain the distribution network losses due to added EVCS are described as below [14]:

Step 1. The input data including AC bus, as well as branch data, real power flow constraints, and load data should be given by user.
Step 2. The total power losses are calculated when there is no CS in the grid. This is the base case of the existing system.
Step 3. The additional power losses are calculated after selection of a CS, connected to bus n. Then, store the results. Added power losses (APL) due to connection of CS i to bus n is obtained, as follows:

$$P_{\mathrm{loss-Dist}} = \sum_{n=1}^{N_{\mathrm{Bus}}} \mathrm{APL}_n \tag{6}$$

Step 4. In this step, the cost of grid energy losses is finally calculated by considering the electricity price (P) and the total number of days in 5 years (TD) as follows:

$$\mathrm{Cost}_3 = P_{\mathrm{loss-Dist}} \times P \times \mathrm{TD} \tag{7}$$

A station near to electric substation can be far from the main urban roads or vehicle position, which results in an increase in EV energy losses. Therefore, not only the reduction in distribution network losses but also EV energy losses is important in determining EVCS location. The EV should follow a certain trajectory to reach the closest station (L) and charge its batteries. EV losses by the EV-specific electricity consumption (SEC) are calculated as follows:

$$P_{\mathrm{loss-EV}} = \sum_{j=1}^{N_{\mathrm{EV}}} \mathrm{SEC} \times L_j \tag{8}$$

Similarity to (7), the EV energy loss cost is finally calculated by the following equation:

$$\mathrm{Cost}_4 = P_{\mathrm{loss-EV}} \times P \times \mathrm{TD} \tag{9}$$

2.4 DR modelling

DRPs can be defined as the changes in normal consumption patterns of end-user customers due to the incentive payments over the time in response to the changes in the price of electricity.

To obtain the optimal consumption at the demand side, the elasticity is defined as the sensitivity of the demand respect to the price [34]. The load change at the ith bus arising from DR can be expressed as follows:

$$\Delta d(i) = d_0(i) - d(i) \tag{10}$$

The total payment, as incentive to the customer for participating in DRP, is calculated as follows:

$$C_1(\Delta d(i)) = \mathrm{CR}(i) \times \Delta d(i) \tag{11}$$

where $\mathrm{CR}(i)$ is the amount of incentive for each unit of load reduction.

If the customers participating in the DRP do not respond to the minimum load reduction as required in the contract, the customers should pay the penalty which is determined by the aggregator, i.e.:

$$C_2(\Delta d(i)) = \mathrm{pen}(i) \times [\mathrm{ref} - \Delta d(i)] \tag{12}$$

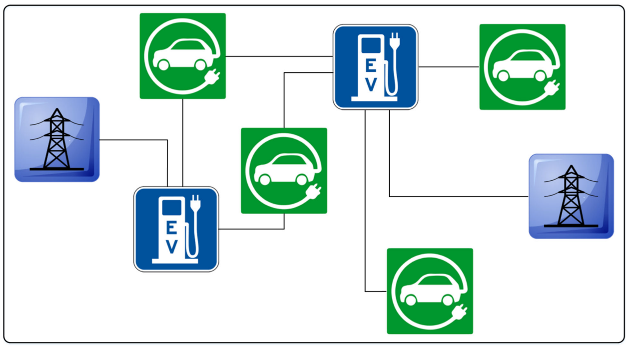

Fig. 1 *Substations, CSs, and EVs interactions*

where pen(i) is the penalty factor; and ref is the amount of the demand which the customer is responsive to reduce their demand.

Therefore, the DR model can be achieved as follows:

$$d(i) = d_0(i) \times \left(\frac{\rho(i) - \rho_0(i) + \mathrm{CR}(i) - \mathrm{pen}(i)}{\rho_0(i)}\right)^{E(i)} \tag{13}$$

The DR cost is finally calculated by the following equation:

$$\mathrm{Cost}_5 = \sum_{k=1}^{N_{\mathrm{DR}}} (\Delta d(i) \times \mathrm{CR}(i)) \times Z_k \tag{14}$$

where Z_k is the binary decision variable to status of kth responsive load.

For each candidate responsive load, binary variables are used. The number of binary variables is equal to the number of responsive load.

Finally, the total cost can be presented as follows:

$$\mathrm{Cost}_{\mathrm{total}} = \sum_{i=1}^{5} \mathrm{Cost}_i \tag{15}$$

2.5 EVCS selection constraint

The problem of optimal siting and sizing of the EVCSs is subject to existing and candidate substations, CSs and EVs constraints, as follows:

- Number of CSs: For number of CSs, we have:

$$\sum_{i=1}^{N_{\mathrm{CS}}} X_i > 0 \tag{16}$$

- Number of connectors: For number of connectors in selected CS, we have:

$$Y_i \geq X_i; \quad i = 1, 2, \ldots, N_{\mathrm{CS}} \tag{17}$$

- Maximum capacity of connector: The maximum capacity of connector for charging all EVs is limited by the following inequality:

$$\sum_{i=1}^{N_{\mathrm{CS}}} (X_i \times Y_i \times \mathrm{DE}) > N_{\mathrm{EV}} \tag{18}$$

where DE is the maximum EV that can be charged by a connector during 24 h.

- Distance between EVCS and EV location: For distance between EVCS and EV location, we have:

$$L_i = \min(l_{i,j}); \quad i = 1, 2, \ldots, N_{\mathrm{CS}}, \quad j = 1, 2, \ldots, N_{\mathrm{EV}} \tag{19}$$

where $l_{i,j}$ is the trajectory length of EV (j) to station candidate (i) that $X_i = 1$.

- Number of charging EVs: The number of charging EVs in each station is limited, as follows:

$$X_i \times Y_i \times \mathrm{DE} > N_{\mathrm{EV}_i} \tag{20}$$

- Number of EVs: For number of EVs connected to each station, we have:

$$N_{\mathrm{EV}_i} = \sum_{j=1}^{N_{\mathrm{EV}}} X_i \times \frac{1 + \mathrm{sign}(L_j - l_{i,j})}{2} \tag{21}$$

Constraint (16) ensures that when CS is installed, its search state will be 1 in the following optimisation procedure. Therefore, the status of installation is considered as fixed for that particle. Based on constraint (17), for each selected station, at least one connector must be considered.

Additionally, in this paper, the problem of optimal siting and sizing of the EVCSs problem is subject to constraints set related to the power flow equations such as voltage profile and existing transmission line flows.

2.6 Assumptions

Several assumptions are taken in this study, as follows:

- The candidate EVCSs and EV positions are considered to have normal distribution function.
- The number of candidate EVCSs is proportional to the total number of EVs in that area.
- EV users are assumed to charge their vehicles in a fixed CS.

3 Methodology

3.1 Calculation of L&D matrices

According to the above section, we model two matrices based on distance among substation, candidate CS and position of EV shown in Fig. 1.

Path 1 presents the distance between ith CS and nth substation using matrix $\boldsymbol{D}$, as follows:

$$\boldsymbol{D} = [d_{i,n}]_{N_{\mathrm{CS}} \times N_S} \tag{22}$$

where

$$d_{i,n} = \sqrt{(x_{\mathrm{CS}_i} - x_{S_n})^2 + (y_{\mathrm{CS}_i} - y_{S_n})^2} \tag{23}$$

i and n are the set of candidate CSs and the set of substations, respectively, as follows:

$$i = 1, 2, \ldots, N_{\mathrm{CS}} \tag{24}$$

$$n = 1, 2, \ldots, N_S \tag{25}$$

Path 2 presents the distance between jth EVs and ith CS using matrix $\boldsymbol{L}$, as follows:

$$\boldsymbol{L} = [l_{i,j}]_{N_{\mathrm{EV}} \times N_{\mathrm{CS}}} \tag{26}$$

where

$$l_{i,j} = \sqrt{(x_{\mathrm{CS}_i} - x_{\mathrm{EV}_j})^2 + (y_{\mathrm{CS}_i} - y_{\mathrm{EV}_j})^2} \tag{27}$$

j is the set of EVs, as follows:

$$j = 1, 2, \ldots, N_{\mathrm{EV}} \tag{28}$$

The x and y in (23) and (27) are gained based on geographic information in the study area.

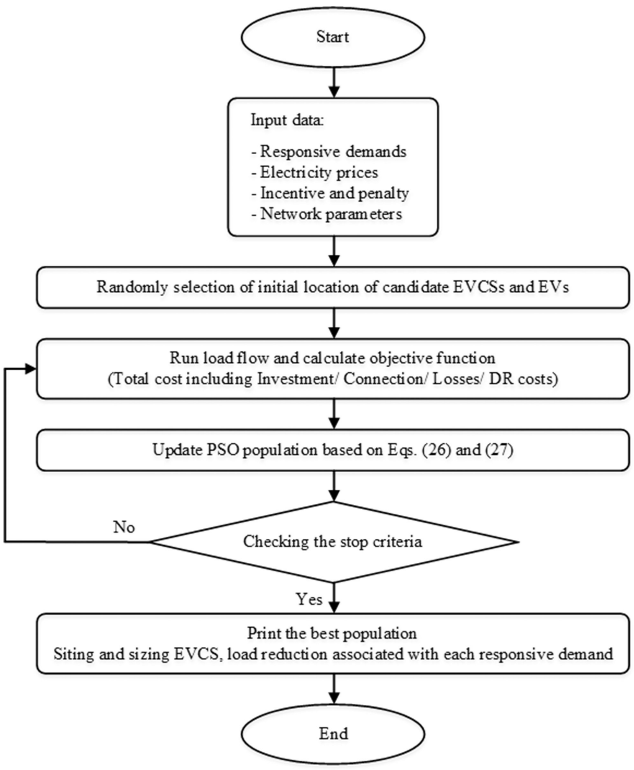

Fig. 2 *Flowchart of siting and sizing of EVCS*

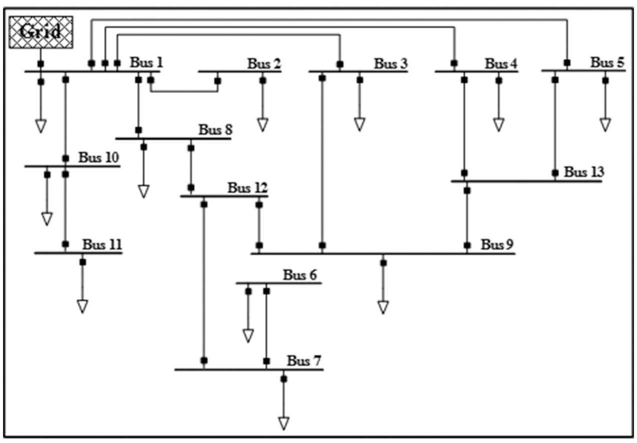

Fig. 3 *Single-line diagram of test system*

3.2 PSO algorithm

PSO algorithm is an evolutionary algorithm which was inspired by social behaviour of bird flocking or fish schooling and improved by Kennedy and Eberhart. The salient features of PSO algorithm compared to mathematical and other evolutionary algorithms are: simple implementation mechanism, controllability of parameters to maintain the diversity of the solution, and ability to explore the global and local minimum point.

In this paper, the PSO algorithm is used for determining the optimal location and capacity of CSs. The PSO algorithm is a population-based evolutionary algorithm, which each solution is known by its position and velocity. Each particle adjusts its new position by changing its velocity based on its own/neighbour's experience ($P_{\text{best}_k}/G_{\text{best}}$) as follows [35]:

$$V_k^{t+1} = wV_k^t + c_1r_1(P_{\text{best}_k} - X_k^t) + c_2r_2(G_{\text{best}} - X_k^t) \quad (29)$$

$$X_k^{t+1} = X_k^t + V_k^{t+1} \quad (30)$$

where k is the index of each particle, t the current iteration number, and r_1 and r_2 are two random functions in the range of [0,1].

To start the PSO algorithm, an initial population as binary string with a fixed length (depends on the amount of candidate CSs) is created, and the number and capacity of the connectors installed in the station are determined. Also, the amount of DR participation based on the solution of the optimisation problem is achieved.

In this paper, there are two kinds of variables in the problem: binary and discrete variables. The former refers to the location of EVCSs and responsive demands and the second one is related to the size of selected EVCSs.

Therefore, the binary/discrete decision variables associated with the location and size of EVCS have been considered as particle.

3.3 Implementation of proposed method

The optimal siting and sizing of the EVCSs of problem aims at determining where and how many CS should be installed at the least total cost including (i) investment and connection costs, (ii) minimisation of losses of network and losses generated by EV user, and (iii) DR costs due to applying DR programmes, to meet a set of technical constraints.

The flowchart of determining the optimal siting and sizing of the EVCSs is shown in Fig. 2, based on the following steps.

Step 1. Define the input data: The initial data such as the responsive demands, electricity prices, incentive and penalty factors, and network parameters should be known.

Step 2. *Generate an initial population:* The candidate locations for EVCSs and EVs placement are determined with two subproblems:

- Candidate locations for EVCSs have been considered to be placed along the main urban roads with minimum 3 km distance between them.
- The EV locations are generated randomly based on normal distribution function (random place).

Step 3. Run load flow and calculate objective function: For each population, the total cost and grid losses will be analysed. The total cost is calculated by solving (1) and the active power losses is calculated by solving AC power flow and the constraints are checked. Then the augment objective functions are calculated using the values of objective functions and constraints.

Step 4. Optimisation: To update the position and velocity of each individual, it is necessary to calculate these in the next stage which is obtained from (29) and (30).

Step 5. Check the termination criteria: If the current iteration number reaches the predetermined maximum iteration number, the search process is stopped.

Step 6. Print the best solution: The best solution found in the search process is considered as the output results including 'siting and sizing EVCSs' and 'load reduction associated with each responsive demand'.

4 Simulation results

The proposed method has been applied to an area with length of ~17.5 km and width of 1 km. The siting and sizing of EVCS problems are performed in MATLAB environment applying the PSO algorithm and the AC power flow by MATPOWER operation functions. It should be noted that the performance is verified through computer-based simulation.

The single-line diagram of test system is shown in Fig. 3. The base case of the test system consists of 11 buses and 15 lines. The technical data of this test system are tabulated in Tables 2 and 3. The required data of the EVCS location problem are listed in Table 4.

The location of candidate EVCSs are shown in Fig. 4. It should be mentioned that 15,000 vehicles have been assumed to be EVs in the studied zone. Three per cent of the EV population has been assumed to be charged on each day and as a result, 500 EVs have been assumed to be daily charged.

In addition, EV location with a certain dissipation probability is randomly produced based on normal distribution function.

Table 2 Line data of test system

Line	From	To	Length, km	*R*, p.u.	*X*, p.u.
1	bus 1	bus 2	5.6	0.02	0.06
2	bus 1	bus 3	4.4	0.02	0.04
3	bus 1	bus 4	5.3	0.02	0.05
4	bus 1	bus 5	0.3	0.001	0.0027
5	bus 1	bus 8	4.8	0.0181	0.048
6	bus 1	bus 10	8	0.03	0.0794
7	bus 10	bus 11	3.7	0.0084	0.0251
8	bus 9	bus 13	4.2	0.035	0.0574
9	bus 5	bus 13	1.5	0.035	0.0574
10	bus 6	bus 7	2.8	0.01	0.0303
11	bus 9	bus 12	6.35	0.0328	0.0871
12	bus 7	bus 12	2.8	0.0328	0.0871
13	bus 3	bus 9	6.7	0.03	0.07
14	bus 4	bus 13	3.6	0.01361	0.0365
15	bus 8	bus 12	6	0.0246	0.0655

Table 3 Bus data of test system

ID	Type	PG, MW	QG, Mvar	PD, MW	QD, Mvar
bus 1	swing	–	–	34.001	13.998
bus 2	load	0	0	36.001	9.394
bus 3	load	0	0	71.501	21.995
bus 4	load	0	0	54	11.997
bus 5	load	0	0	37.998	8.009
bus 6	load	0	0	43	11
bus 7	gen	66	—	66	11.483
bus 8	load	0	0	38	10
bus 9	gen	47.298	—	47.298	20.405
bus 10	load	0	0	48.499	19.502
bus 11	gen	34.998	—	34.998	15.004

Table 4 Required parameters

Parameter	Value	Unit
N_{EV}	500	—
N_{CS}	20	—
N_S	11	—
SEC	7	km/kW h
P	87.7	$/MW h
C_{lan}	1200	$/m^2
C_{fixed}	70,000	$
C_{con}	208.33	$/kW
PC	96	kW
DE	30	—
TD	1825	days
S (PARTRIDGE)	156.9	mm^2
CR	100, 200	$/kW

For validation of performance of the proposed method, the five scenarios listed in Table 5 are studied.

In Table 5, the elements that have been considered in each scenario have been shown with (×) mark and otherwise have been shown with (−) mark.

In scenario 1, the EVCS location problem is considered without using any DRP. In scenarios 2–5, to show the effect of the DR, it is assumed that responsive demand are located at buses 3, 5, 6, 8, and 10.

In scenarios 2 and 3, it should be noted that the penetration of the DR is assumed to be 10% of all the selected load buses.

Also, to show the effect of the DR penetration on EVCS location problem, it is assumed that the penetration of the DR is considered to be 20% of all the selected load buses, in scenarios 4 and 5. The amount of price for DRP are considered as fixed values which are $100 and 200 $/MW h, for scenarios 2–5 as indicated in Table 5.

The results of the proposed method including the number of EVs and capacity of each CS are listed in Table 6. Results of objective functions are tabulated in Table 7 in detail.

It can be seen in these tables that the total cost of the obtained solutions for the scenario 1 is larger than that of other scenarios. However, the grid losses in scenario 1 are greater than others. It is evident that the application of DRP results in a distinct reduction in grid losses and total costs. In scenarios 2–5, the optimisation procedure searches and selects CSs with much lower total cost. Thus, the need for EVCSs are lower. So, application of DRP are utilised to find optimal EVCS. In scenarios 4 and 5, due to the increase in penetration of DRP, minimisation of losses is the major priority of planners.

Investigation of above five scenarios reveals that by using DRP in addition to decrease in total cost, the EV energy losses cost is improved.

The load reduction in the responsive demand at mentioned buses are listed in Table 8. It can be seen in Table 8 that by changing the price of the DRP, the load reduction associated with each responsive demand is significantly reduced.

To show the impact of the proposed method on the grid losses with and without CS, Table 9 is provided. In Table 9, results for each scenario are shown. As listed in Table 9, from the viewpoint of losses, when there are no CS, the losses are reduced. Also, as can be seen, the grid losses in scenario 4 are clearly decreased in comparison with other ones by employing DRP with low price and 20% penetration of DRP.

4.1 Discussion

In the literature, the problem of optimal placement and sizing of EVCS is not presented as it is formulated in this paper. Therefore, no direct comparison is possible.

The constraints of 'distance between EVCS and EV location' and 'number of charging EVs in each station' are two important factors that must be investigated to evaluate the performance of the proposed method.

Therefore, in order to show the merits of the proposed method, the siting and sizing of EVCS problem has been considered in the following two cases:

Case 1. EVCS problem without considering the constraint of distance between EVCS and EV location.

Case 2. EVCS problem without considering the constraint of number of charging EVs in each station.

To investigate the sensitivity of EVCS problem to mentioned cases, Table 10 is provided for scenario 2. The results of the number of EVs, capacity of each CS, and objective functions are illustrated in Table 10.

By investigating the results of Table 10, the following conclusions can be achieved.

The results of case 1 in this table emphasise that without considering the constraint of distance between EVCSs and EV locations, the total cost of investment and EV loss are 1.05 and 1.7447 M$, respectively. As can be seen, the EV losses for optimal results in case 1 are clearly increased in comparison with scenario 2. However, also the investment cost are reduced significantly. In

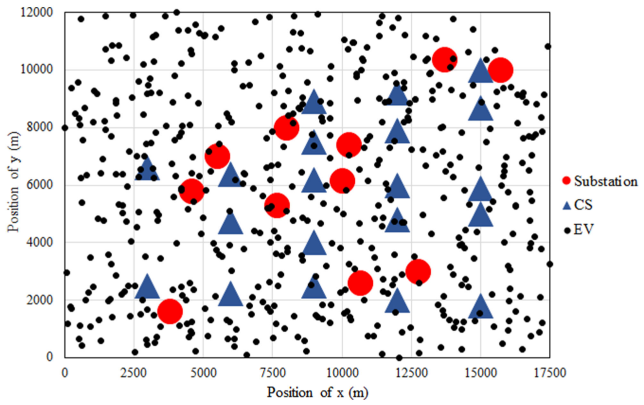

Fig. 4 *Position of substation/candidate CS/EV location*

Table 5 Studied scenarios

Scenario	DR	DR price, $	DR penetration, %
1	—	—	—
2	×	100	10
3	×	200	10
4	×	100	20
5	×	200	20

Table 6 Results of siting and sizing of CS by different scenarios

	Number of electric vehicles (N_{EV})				
Station	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
1	66	81	0	81	0
2	0	0	118	0	118
3	61	0	0	0	0
4	84	109	0	109	0
5	0	0	82	0	82
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	103	103	115	103	115
11	0	0	0	0	0
12	0	0	0	0	0
13	0	0	0	0	0
14	0	0	0	0	0
15	100	114	0	114	0
16	0	0	0	0	0
17	0	0	104	0	104
18	0	0	0	0	0
19	0	93	81	93	81
20	86	0	0	0	0
Total	500	500	500	500	500

Capacity of the charging station (*C*)					
1	288	288	0	288	0
2	0	0	384	0	384
3	288	0	0	0	0
4	288	384	0	384 0	—
5	0	0	288	0	288
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	384	384	384	384	384
11	0	0	0	0	0
12	0	0	0	0	0
13	0	0	0	0	0
14	0	0	0	0	0
15	384	384	0	384	0
16	0	0	0	0	0
17	0	0	384	0	384
18	0	0	0	0	0
19	0	384	288	384	288
20	288	0	0	0	0
total	1920	1824	1728	1824	1728

Table 7 Total cost obtained by different scenarios

Scenario	1	2	3	4	5	
investment, $	1.3	1.2	1.15	1.2	1.15	—
connection, $	0.1416	0.12518	0.1731	0.12518	0.1731	—
EV loss, $	1.4277	1.4947	1.478	1.4947	1.478	—
grid loss, $	0.75753	0.61507	0.56242	0.56765	0.53666	—
DR, $	0	0.044	0.03	0.057	0.045	—
total cost, $	3.6268	3.4789	3.3936	3.4445	3.3828	—
—	—	—	—	—	—	$\times 10^6$

Table 8 Load reduction due to DRP

Scenario	1	2	3	4	5
bus 3, MW	0	15	0	22.5	0
bus 5, MW	0	6	0	0	0
bus 6, MW	0	7	7	10.5	10.5
bus 8, MW	0	8	0	12	0
bus 10, MW	0	8	8	12	12
total cost, MW	0	44	15	57	22.5

this case, four CS are installed. Additionally, the total capacity of selected CSs is reduced.

In Table 10, for case 2, the optimisation procedure is following to search candidates with the much lower investment cost. Thus, the need for new connectors in each CS have been reduced.

Simulation results demonstrate that the performance of a proposed method is significantly affected by these constrains.

5 Conclusion

In this paper, a cost-based method has been presented to solve siting and sizing of EVCS problem by considering the effect of DRPs. The DRPs can be classified into incentive-based and time-based programmes. In this paper, DRP is modelled by incentive-based such as EDRP and DLC programme. The DRPs play an important role in a distinct reduction in grid losses and total costs. The performance of the proposed model has been tested on a test system by considering different scenarios. The results show that the application of the DRP could result in a distinct reduction in power losses and total cost.

Table 9 Comparison of losses by different scenarios

Scenario	Without stations, kW	With stations, kW
1	5.4324	5.4674
2	3.9405	3.9696
3	4.5845	4.6091
4	3.3162	3.3429
5	4.2094	4.2328

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Table 10 Results of the proposed method for scenario 2 for different cases

Station	Case 1		Case 2	
	N_{EV}	C	N_{EV}	C
1	0	0	81	192
2	118	384	0	0
3	0	0	0	0
4	0	0	109	192
5	117	384	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	115	384	103	192
11	0	0	0	0
12	0	0	0	0
13	0	0	0	0
14	0	0	0	0
15	0	0	114	192
16	0	0	0	0
17	150	480	0	0
18	0	0	0	0
19	0	0	93	192
20	0	0	0	0
total	500	1632	500	960
investment, $	1.05×10^6		0.75×10^6	
connection, $	0.14607×10^6		0.12518×10^6	
EV loss, $	1.7447×10^6		1.4947×10^6	
grid loss, $	0.4416×10^6		0.61491×10^6	
DR, $	0.03×10^6		0.038×10^6	
total, $	3.4123×10^6		3.0228×10^6	

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