Electric vehicles in a smart grid: a comprehensive survey on optimal location of charging station

Mohd Bilal1, Mohammad Rizwan1,2
1Department of Electrical Engineering, Delhi Technological University, Delhi 110042, India
2Department of Electrical Engineering, College of Engineering, Qassim University, Buraidah, Saudi Arabia
E-mail: bilal.zhcet01@gmail.com

Abstract: The burning of fossil fuels and the emission of greenhouse gases motivates policymakers to think about the transition in their approach towards electric vehicles (EVs) from conventional ones. Transportation vehicles’ electrification drives the attention of various researchers and scientists towards the emergence of charging stations (CSs). CS placement is a matter of great concern for large scale penetration of EVs. Old infrastructure causes several challenges in planning the ideal placement of the CS since EVs have not prevailed in recent years. Recently, a lot of studies have been performed on CS placement, which attracts the attention of researchers. Various approaches, objective functions, constraints and range of optimisation techniques are addressed by researchers for optimal placement of CS. This study provides the research outcomes in respect of the placement of CS over the past few years based on objective functions, solution methods, geographic conditions and demand-side management.

1 Introduction

Communities around the world are suffering from the consequence of global warming due to greenhouse gases (GHGs) emissions. The transportation sector of any country produces a considerable amount of GHGs, which has a detrimental effect on the climate of the earth. Fig. 1 shows the typical data of GHGs emissions in different countries of the world.

The total annual greenhouse gas emission in Delhi city is found to be 37.9 million tCO₂. The per capita emission of Delhi city is estimated to be 2.26 tonne per year, which is lower when compared with other cities emitting GHGs. Fig. 2 shows that the amount of GHGs emission in Delhi city is 37.9 million tCO₂, which is about five times lesser than the Beijing city, having a similar population as that of Delhi city. Pollution due to conventional vehicles creates health issues and the life of living beings is deteriorating day by day. Approximately 89% of people in Delhi are feeling sick or not in the comfort zone because of the poor quality of air, and it is believed that conventional vehicles that are based on fossil fuels are the major cause of pollution.

Further, conventional vehicles are becoming one of the causes of the deterioration of air quality.

The demand for electric transportation is growing rapidly. The updated sales of electric vehicles till 2030 have been developed by Edison Electric Institute (EEI) and Institute for Electric Innovation (IEI). It is estimated that by 2030, the number of electric cars that will be plying on the roads will be 18.7 million approximately. To fulfil the fuel requirements of these electric vehicles (EVs), about 9.6 million charging stations (CSs) are required [1]. It requires significant expenses in the development of EV charging infrastructure. Fig. 3 shows the EEI/IEI forecast of EV in 2030. Transition to EVs from conventional vehicles reduces the emission of gases up to some extent to solve the global warming problem. EVs neither harm the environment in a nefarious way, nor do they lead to an increase in prices of oil. EV is a future technology with numerous environmental advantages in various sectors. There are a large number of advantages in the adoption of EVs, but there are certain challenges as well as the optimal placement of CS.

Also, the random placement of electric vehicle CS (EVCS) adversely affects the acceptance of CS, the traffic network layout and EV driver’s convenience. If the placement of CS is not done properly, then fluctuation in voltages and power problems arises. The placing of the CS causes increases in demand for the load on the power grid, which results in an increase in peak demand and a decrease in reserve margin. Numerous studies are being conducted across different countries of the world for developing EVCS.

The paper presents the important aspects of the optimal location of CSs. In the literature, optimal placement of CS is carried out

![Fig. 1 Typical data of GHG emission in different countries (source: World Research Institute (Climate Analysis Indicators Tool (CAIT)))](http://example.com)
based on different approaches such as proper modelling of objective functions, solution techniques and traffic flow consideration. However, over the past few years, a number of papers, including various review studies have been reported on the optimal location of CS. This paper introduces demand response programs (DRPs) as one of the important aspects of the optimal placement of CS. Therefore, it is a timely attempt to conduct the planning of CS based on objective functions, solution techniques, geographic conditions and DRPs.

The remaining paper is categorised into five sections. Section 2 deals with the charging infrastructure planning scenario in India. Section 3 provides a review of the optimal placement of EVCS based on objective functions, solution techniques, geographic conditions and demand-side management (DSM). Summary and a brief discussion is presented in Section 4. Future research directions are discussed in Section 5. The conclusion is provided in Section 6.

2 Charging infrastructure planning scenario in India

Changing the approach to EVs from traditional vehicles is still at an initial stage, as EVs make up a few percents of all the vehicles currently operating in the country (the list of countries per vehicle per capita in 2017), as shown in Fig. 4. However, a large number of electric rickshaws can be witnessed running in not only some small towns and villages but also in many cities of India. The current population of electric vehicles in India is very low. However, electric rickshaws are being operated in many Indian towns and villages. Electric rickshaws are suitable for short-distance travelling and can be charged easily by a normal household socket. Despite a very low EV market, many companies are investing in the development of CS because of the reasons listed below:

(i) The Government of India promulgated in 2013 the progressive ‘National Mission Movement for Electric Mobility Plan (NEMMP) until 2020’ to focus on national energy security, pollution caused by vehicles, and the expansion of domestic production capacity. Taking into account the Paris Agreement, the government plans to introduce EVs into widespread use by 2030 [2].
(ii) An insufficient amount of CSs is the main reason for the smaller number of used EVs. It is, therefore, necessary to develop a sustainable charging infrastructure to make more and more use of EVs.

Thus, the growth of infrastructure for CSs is on the verge of beginning in India. The main landmarks in the development of the charging framework (The Times of India) in India are:

(a) It is being planned by the Indian Government to set-up 206 CSs [2].
(b) TATA Power Delhi has planned to invest 100 crore rupees for establishing 1000 CSs in Delhi [2].

There are some factors that inhibit the establishment of a charging infrastructure. Few of them are listed below:

(a) Bleak in the EV market.
(b) The power grid’s complicated structure.

The EV Industries in India are constantly growing but the lack of CSs and policies made by the Indian government poses difficulty in the growth of the EV industry. The number of EVs sold in the years 2017 and 2018 is 56,000 units as against 25,000 units in the years 2016 and 2017. According to the view held by the Society of Manufacturers of Electric Vehicles (SMEV), in 2017 and 2018, the sales of electric cars decreased to 1200 units from 2000 units in 2016 and 2017, a slump of 40% is recorded. However, the number
of electric two-wheelers for the years 2017 and 2018 is increased to 54,800 units, as shown in Table 1. Electric two-wheelers showed rapid growth of 138% as 54,800 units sold in 2017 and 2018 as compared to 23,000 units in the years 2016 and 2017. The reason for the rapid growth of electric two-wheeler is its affordability and its use for short distances, which reduces the problem of range anxiety.

### 3 Optimal placement and sizing of CS

In the literature, the placement of CS is based on different approaches, i.e. objective functions, solution techniques, geographical conditions and DSM.

#### 3.1 Optimal placement of EVCS considering objective functions

Different objective functions have been considered for the optimal placement of EVCS. Costs, power loss and voltage sensitivity factors are some of the objectives considered for placement of CS. A brief outline of various objective functions has been taken into consideration while defining the problem of CS placement.

##### 3.1.1 Cost

Cost is treated as one of the objectives of the literature. The different types of costs associated with the CS location are indicated in Fig. 5. Installation cost is the cost of installing CSs, which can be divided into charger cost, labour cost, construction cost and land cost, as shown in Fig. 5 [3, 4]. Operating cost deals with the electricity cost required for providing charging services [5]. It includes billing transaction costs, repairing cost and so on. Access Cost refers to the additional cost acquired by EV users to arrive at the CS where the EVs could be charged from the place where the need for charging the EVs arises [6]. Penalty Cost is the cost given by the utility for deviation in voltage [7]. Waiting Time cost refers to the cost earned by the EV users for staying at the CS because of the inaccessibility of charging points [8]. Land cost refers to the cost of land per unit area at the potential site for the CS. The cost of land would include all expenses associated with the acquisition of the property, as well as those needed to get

---

**Table 1** Typical data of electric two-wheelers and electric cars in the years 2016 and 2017, and 2017 and 2018

| Category         | 2016-2017 | 2017-2018 |
|------------------|-----------|-----------|
| electric two-wheelers | 23,000    | 54,800    |
| electric cars    | 2000      | 1200      |
| total EVs        | 25,000    | 56,000    |

Sources: Statista Research Department.
it ready for use by the company [9]. Construction cost refers to all the expenses or costs incurred by a builder or a contractor for material, equipment, services, labour, utilities and so on as well as all the overhead costs [9].

3.1.2 Power loss: Power loss is also the objective function that has been considered in the literature for the optimum placing of the CS. In managing the distribution system with the addition of new units, it is essential that the location selected results in minimum increments in power loss [11]. CS is a heavy load that, when placed on a particular bus in the distribution network, results in increment in power loss [12]. The main goal is to select the optimal location in the distribution system at which the increment in power loss is as low as possible.

3.1.3 Voltage sensitivity factor (VSF): VSF is one of the measures for choosing the optimum location of CS. It is an important factor for measuring system strength or reliability. In general, the sensitivity factor (SF) of a system can be represented as \( F(Z, \mu) \), defined in (1) [13]

\[
SF = \left| \frac{dZ}{dP} \right| \quad (1)
\]

SF's large value ensures that the system is dangerous and ultimately collapsible. In VSF, the voltage of the system is measured by the change in loading as defined in (2) [13]

\[
VSF = \left| \frac{dV}{dP} \right| \quad (2)
\]

Even modest changes in the loading can result in a major change in the magnitude of voltage. High sensitivity can be defined as a large change in voltage, even due to a small change in load. This is an indicator of bus strength.

3.1.4 Constraints: The planning of charging infrastructure considers various constraints in transportation and distribution network as shown in Fig. 6. The power flow equation as defined by (3) and (4) and demand balance equation as in (5), are considered as equality constraints and should be satisfied for charging infrastructure planning [2]. The mathematical representation of the power flow equation is as follows:

\[
P_{gi} = P_{di} + V_i \sum V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) \quad (3)
\]

\[
Q_{gi} = Q_{di} + V_i \sum V_j Y_{ij} \sin(\delta_i - \delta_j - \theta_{ij}) \quad (4)
\]

where \( P_{gi} \) and \( Q_{gi} \) are the active power generation and reactive power generation of the \( i \)th bus, respectively. \( P_{di} \) and \( Q_{di} \) are the active power demand and reactive power demand of the \( i \)th bus, respectively. \( V_i \) and \( V_j \) represent the voltage magnitudes of the starting and ending buses, \( \delta_i \) and \( \delta_j \) are the phase angles of voltage at buses \( i \) and \( j \), respectively, \( \theta_{ij} \) is the angle of \( Y_{ij} \). \( Y_{ij} \) is the magnitude of admittance of \((i, j)\)th term of bus admittance matrix. The demand balance equation is defined as follows:

\[
P_{CS} - P' = 0 \quad (5)
\]

where \( P_{CS} \) is the electricity demand of the \( i \)th CS and \( P' \) is the capacity of the \( i \)th CS. It is essential that limits such as voltage limit, current limit or thermal limit are met after the CS is placed in the distribution network. The number of Cs's required to charge the batteries of the EV shall be appropriately assigned. Also, there must be a considerable separation between each pair of Cs's. The separation between the two Cs's is also considered with the distance is treated as a constraint [2].

A survey of different objective functions, decision variables and constraints considered for CS placement in distribution and transportation network is presented in Table 2. Wang and Wang [29] designed a new model considering set coverage and vehicle refuelling logic. A multipurpose issue was considered to minimise costs and maximise coverage. Baouche et al. [30] presented a charge location model combined with a P-dispersion approach for the locations of CS. This approach aims at lowering the trip energy and the location cost incurred while satisfying the mobility energy demand. Ahn and Yeo [6] introduced an analytical approach, i.e. estimating the required density of EV charging (ERDEC) stations model for determining the optimal location of CS in urban areas. Minimisation of the total cost is done for CS placement. Zhao and Li [31] proposed extensive guidelines for the optimal siting of EVCS. Objective function related to cost, climatic issues and technical factors such as system power loss and power quality problems are being considered in this document. Andrews et al. [32] discussed a methodology to optimise the charging infrastructure with goals considered as the separation between the EVS user and the CS. The location of the CS is chosen so that the path travelled by EV to the charging infrastructure is minimal. Ge et al. [3] discussed the grid partitioning method for the optimisation of the location and sizing of the CS in order to minimise power loss. Jia et al. [4] used graph theory concepts for the modelling of the transportation network to determine the shortest route between the point where they need for charging arises and the allocated CS. Based on charging demand, optimisation of station size at each location is done. The single-objective function of the overall cost is considered in this paper. Hosseini and Hassani [33] have discussed the ‘queue’ theory for the location of CS. Due to the limited size of CS, the vehicle should wait in queues in the case if the whole space is engaged. CS capacity, waiting time and charging time are the factors considered by the author in this paper. Zhu et al. [34] suggested a new model...
Table 2 Various objective functions, decision variables and constraints considered for CS placement [2]

| Attributes                  | Transportation network | Distribution network | Transportation network + distribution network |
|-----------------------------|------------------------|----------------------|-----------------------------------------------|
| objective function          | investment cost [9]    | Y                    | Y                                             |
|                            | installation cost [3]  | Y                    |                                               |
|                            | connection cost [10]   | Y                    | N                                             |
|                            | management cost [15]   | Y                    | Y                                             |
|                            | traveling cost [3]     |                      |                                               |
|                            | charging cost [16]     | Y                    | Y                                             |
|                            | transportation cost [17]| Y                    | N                                             |
|                            | driving range [18]     | Y                    | N                                             |
|                            | waiting time cost [8]  |                      |                                               |
|                            | operating cost [19]    |                      |                                               |
|                            | maintenance cost [7]   | Y                    | Y                                             |
|                            | power loss [20]        | N                    | Y                                             |
|                            | voltage drop [20]      |                      |                                               |
|                            | reliability [21]       | N                    |                                               |
|                            | road construction cost [22]| Y            |                                               |
|                            | land cost [23]         |                      |                                               |
|                            | net benefit of V2G [9] | N                    | Y                                             |
|                            | mobility cost [24]     | Y                    | N                                             |
|                            | EV flow [25]           |                      |                                               |
|                            | transformer loss of life [26]| N           |                                               |
| decision variable           | bus number in distribution network | N                  |                                               |
|                            | node of road network   |                      |                                               |
|                            | CS density             |                      |                                               |
| constraints                 | budget [27]            | Y                    |                                               |
|                            | power flow             |                      |                                               |
|                            | charging demand [2]    | Y                    |                                               |
|                            | number of charging points [28]| Y          |                                               |
|                            | voltage limit [20]     | N                    |                                               |
|                            | thermal limit          |                      |                                               |

for the CS location. The cost of travel, which is carried by users of EV, is considered as one of the goals that need to be minimised, and at the same time solves the problem of the place where the CS should be located and the number of chargers that will be used in each CS. Zihong et al. [15] developed a new model for the CS planning problem considering the daily trips of the EV user. Minimisation of the total cost, which includes CS cost (management cost and installing cost) and cost related to users, i.e. charging cost and station access cost have been performed. Davidov and Pantos [35] discussed an optimised model of the placement of CS with a total cost taken as one of the minimised targets. The author also takes care of reliable charging and quality work as expected by the EV user. Hu and Song [5] suggested a model for the optimal sizing and location of EVCS for the minimisation of cost of operation and the investment cost was made in this document. Liu et al. [7] discussed the optimal planning of EVCS. Mathematical modelling of the EVCS is performed and the objective functions are considered: investment costs, operating costs, maintenance costs, network losses to minimise. Yan et al. [36] proposed a complicated, non-linear and combinatorial optimisation problem for optimal EVCS planning and the distribution system, objectives considered are EVCS investment cost and energy and power loss. Prasomthong et al. [21] effectively determined the optimal location of the CS and its size in order to obtain maximum benefit, which includes increased reliability, reduced power loss and peak power.

3.2 Optimal placement of CS based on solution techniques (optimisation algorithms)

The objectives used for CS placement problems are having more than one variable and are complicated in nature. Studies are conducted based on both an analytical and a nature-oriented algorithm to solve the problem of locating CS. A brief analysis of several optimisation techniques that are utilised by the various researchers to find the best positioning of the CS was searched in this part of this paper.

3.2.1 Classical optimisation algorithm: Classical or analytical methods of optimisation under the influence of differential calculus can be used to determine the optimised value of continuous and differentiable functions [2]. Some of the classic optimisation methods commonly used to determine the location of a CS are integer programming (IP), linear integer programming (LIP), game-theoretic approach and a primal-dual method.

3.2.2 Evolutionary algorithm (EA): EA are the algorithms derived from nature and based on the principle of 'survival of the fittest'. Most of the EA has some central idea. The search process begins with a randomly generated set of population. An increase in the number of iterations leads to the best solution in the consequent generation.

Some of the benefits of an EA are

(i) Simple computation and concept.
(ii) It can be hybridised with a classical technique.
(iii) Fast convergence.

3.2.3 Particle swarm optimisation (PSO): PSO deals with the social behaviour of the number of particles in a swarm, and each particle is presented as a solution to the problem. The PSO is capable to determine high-efficiency solutions in comparison to other techniques. PSO can be implemented easily and has fast convergence when compared with a genetic algorithm (GA) because of the absence of evolution parameters, i.e. mutation and crossover. Zi-fa et al. [9] used the PSO technique for the determination of the best location of the CS. Construction cost, which includes land cost and running cost, which consists of power supply losses, are taken as objective function with geographical
information and the flow of traffic is treated as a constraint. Further modification of the PSO algorithm can be made by changing the coefficient of inertia and then applied to the problem of placing the CS. Tang et al. [22] analysed various factors affecting the CS planning and then the model is developed. Global search capabilities of PSO and Voronoi diagrams are combined for optimal planning of EVCS. First, the weighted Voronoi diagram is used to divide the defined area, and then PSO is utilised to find the best location. In the above case, the author did not discuss the sizing of CS. Kou et al. [26] designed a model based on a cost function for finding the optimal location and capabilities of EVCS. The developed cost model includes cost required for the operation of CS, cost invested on distribution transformer and losses occurred in the network. This model includes several limitations, such as the number of EVs, the distance between the location of the EV and the cost required to install the EVCS. PSO is utilised to tackle the optimisation problem. However, the charging demand forecasting has not been considered for model optimisation. Zhang and Cheng [37] use the PSO to develop a common planning model for charging/exchange facilities. The shortcoming of the PSO technique is that it has low precision value and can be diverted easily. Thus, the non-optimal solution may be obtained for EVCS.

Awasthi et al. [38] presented the siting and sizing of EVCS in Allahabad. In their paper, the authors proposed a hybrid modified version of PSO for finding the CS location in the distribution system of Allahabad. The PSO optimised the sub-optimal solution, i.e. the location as well as the size of the CS, which improves the functionality of the algorithm and improves the quality of the solution. Fan et al. [23] established a mathematical model with optimal siting as well as the sizing of EVCS. The objectives considered in this paper are land cost, construction cost, operation cost, traffic flow, service range and serviceability. The author is aimed at minimising the total cost of EVCS placement and charging ability and distance is taken as a constraint. In this paper, the slight modifications are made in the inertia weight and utilise a modified PSO approach, i.e. chaotic quantum PSO to solve the mathematical model discussed in this paper. The randomness of the chaotic operator increases the accuracy of the algorithm and has good convergence speed. Martins and Trindade [11] utilised time-series analysis approach for the allocation of fast CS in non-rural areas. The variation of load after each hour in a whole day is considered. PSO is used for power loss minimisation occurred in installing fast CS. Prasomthong et al. [21] used the PSO technique in which coefficients are varying in time for vehicle-to-grid (V2G) CS placement and sizing at a peak period in the grid. From the results of the simulation, it is examined that the V2G CS placement maximising the net benefits, reduces the loss of energy, the saving of peak power and the improvement in reliability.

3.2.4 Genetic algorithm: GA is a nature-inspired optimisation technique motivated by the process of natural selection. GA can determine the globally optimised solution in a given search space. Ge et al. [3] utilised GA for minimising transportation costs based on the grid partition method. This paper is aiming at the placement methods of EVCS in city traffic networks. Traffic density and capacity of CS are taken as constraints. However, land cost, fixed cost, cost of operation have not been considered for optimisation of the system. Thus, a global solution is not obtained. Li et al. [39] presented the model of the regional grid of EVCS with the flow of EVs in areas that act as a fixed point of loading of the CS. The total number of EVs and their distribution are predicted and the cost model is developed. In this paper, the authors utilised modified GA to deal with the problem. GA is used to minimise the cost model. Kameda and Mukai [40] presented the CS location, taking into account the data of the taxi and is aimed at the local on-demand bus transportation system. Bendibadeallah et al. [41] developed an algorithm for the placement of EVCS. The algorithm determines the optimal location by optimising the travelling cost and investment cost. Hybrid GA is utilised to determine the optimal number and the size of CS. Xiaojing et al. [42] presented the planning of EVCS placement in which net present value (NPV) and life cycle cost (LCC) are being considered providing a financial benefit to the users. In the developed model, both the power grid as well as traffic flow constraints, are integrated. For determining the flow of traffic and service region, origin-destination (OD) lines and Voronoi diagram are chosen. The quantum GA was employed for the optimisation of the model. Shuangshuang et al. [43] determined the optimal location of EVCS. The location of CS is based on economics, coverage, size and ease. Modified GA is introduced to reduce the cost of investment and the cost of transportation to locate the CS optimally. Yan et al. [36] presented a multi-objective problem, minimising investment cost and feeder energy loss. The presented approach is tested on the IEEE-33 distribution system and a comparison of hierarchical HGA and traditional GA is done. The hierarchical HGA approach is found to be more successful in terms of solving the blind search difficulty.

3.2.5 Ant colony optimisation (ACO): It is also one of the well-known optimisation techniques used in the literature to find the optimum placing of EVCS. Phonnattanasak and Nopbhorn [44] utilised ACO to optimise the total cost, which consists of travelling cost, operating cost, cost of power line loss for finding the CS optimal location in a distribution system while preserving the security of the power system and traffic flow are taken as a constraint. The test is conducted on the IEEE-69 bus to check the results. Joo and Lim [45] developed an energy-efficient routing approach for EVs network and EV battery energy efficiency. Simulation of Energy Routing-ACO (ER-ACO) is compared with other ACO techniques and it is found that the proposed techniques enhance energy efficiency. Prakornchai et al. [46] discussed the minimisation of the cost related to CS as well as the real power loss in the distribution system subjected to traffic conditions as a constraint. Hybrid ACO and bees algorithm are employed to tackle the optimisation problem. Aryapim et al. [47] employed ACO for minimising transmission loss in a power distribution network. Sanchari et al. [48] formulated the CS placement problem in the city of Guwahati, India. The optimal allocation of CS is based on a multi-objective function, which considers several factors such as voltage stability, power loss, reliability, variable road traffic and other economic factors. This optimisation problem is solved using a hybrid optimisation algorithm, i.e. chicken swarm optimisation (CSO) and teaching–learning-based optimisation (TLBO). The test is conducted on the IEEE-10 bus system to verify the technique. The ACO limitations are that it has a slower speed compared to other optimisation methods.

3.2.6 Integer programming: An IP problem is a technique in which few or every variable is treated as an integer. A LIP is a word in which the objective function and constraints are defined linearly [49]. On the other hand, in the case of mixed-IP (MIP), only some variables are defined as an integer [50]. Worley et al. [51] developed an IP model to identify the best sets of routes and CS locations. The goals minimised with the IP approach are transportation costs, the cost of charging and the cost of placing CS. Andrews et al. [32] designed the MIP model to find the CS location, which is a prerequisite for reducing the range anxiety and improving the integration of EVs by reducing the distance travelled to the nearby CS. In this paper, only distance travelled by EV user to selected CS is reduced. Miljancevic et al. [52] presented a systematic approach for EVCS placement. The LIP technique is utilised for finding the best location of CS. The inputs needed are the configuration of the network, the number of EVs and Kockelman et al. [53] solved the problem of EVCS placement using MIP with travelling costs and parking demand as objectives. Ip et al. [54] presented a model comprised of two steps. The first step is regarding gather information on highways in demand clusters using hierarchical clustering analysis. In the second step, LP is used to plan the location, taking into account the constraints and factors related to cost. However, LIP did not incorporate the travelling cost of EV users. Meng and Kang [55] build up the General theory model to solve the problem of EVCS placement and the same was transformed into the LIP problem and later on, the primal dual-path algorithm was used to deal with the problem to make the process easy and viable. However, factors such as network of the road, structure, traffic condition and constraints
related to the capacity of the distribution network are not being considered. Hu and Song [5] suggested a mathematical approach in this paper to tackle the problem of distribution network expansion as well as the siting and sizing of EVCS. A MIP approach is used to solve the problem with voltage limit is treated as a constraint and a requirement of radial network topology. Hongcai et al. in [14] discussed the siting of fast CS for PHEVs based on the coordination between the power and transportation networks. Capacitated flow refuelling location model (CFRLM) is introduced for the estimation of the charging demand of PHEVs with the incorporation of driving range and flow of traffic. MILP is employed for CS planning in coupled transportation and power grid network. This paper deals with the minimisation of investment cost while satisfying the charging demand for PHEVs. The disadvantage of IP is that it is unable to deal with stochastic issues associated with EVCS.

3.2.7 Other techniques: Other techniques are also considered in the literature for finding the ideal site and the size of EVCS. Rastegarfar et al. [24] developed a cost model in which investment cost and operation cost are taken as objectives to be optimised. The model involves traffic conditions, geographic conditions and accessibility for siting of EVCS. MATLAB Programming is done to find out the cost and optimum combination of CS. Lam et al. [56] framed a model based on optimisation for CS placement in the case of potential available and coverage areas. In this paper, the authors proposed a greedy algorithm relies on the network properties of the problem and the problem NP-hardness. Zambrano et al. [57] used flow capturing methodologies to obtain an optimal EVCS site. Firstly, the classical flow-capturing location model (FCLM) is used for maximising the traffic flow. Later, advanced FCLM is utilised for minimising the set-up cost of CS. Siting et al. [58] presented an extended flow location model and refuelling for optimum placement of the CS as well as a charging pad to maximise traffic flow. The charging pad is based on inductive charging technology and also reduces the charging time. Xu et al. [59] described the EVCS planning in coupled transportation and power grid network. For simulating the flow of traffic in the transportation network, the unconstrained traffic assignment model has been proposed. In the case of variable road capacity, the power distribution network and the primal-dual of optimality is utilised to tackle the remedies of the Bureau of Public Roads (BPRs) function. Wirges et al. [60] developed contemporary space models for the EV charging infrastructure in the suburban Stuttgart suburb of Germany. The reason for this study is to find the amount of CS that provides a relatively small quality service. The developed model is based on land use, socio-demographics and traffic flow. Chunyang et al. [61] developed the EVCS model. The developed model is based on three stages, namely, presentation stages, public promotion stage and commercial utilisation stage. Distance ratio, charge capacity and excess of charging power are the factors taken into consideration while developing the model for planning of charging infrastructure. Wang et al. [19] presented a multi-purpose model for planning EVCS. Factors are taken into consideration while planning the model of EVCS are feasibility enhancement of EVs, different aspects of CSs, aspect of charging user, charging demand distribution and public planning. Besides that, an algorithm is designed based on demand choice and the usability of gas stations. Shaojun et al. [62] developed a location of CS in the transportation network, considering different grid constraints while maintaining the balance of charging demand and stability in the power system network. Initially, a spatiotemporal model for charging demand is developed, and a 1−(1/e) algorithm is designed for maximising the charging demand. Then after, a linearised power network model (LPNM) is designed and on the basis of LPNM, an algorithm that involves grid-related constraints are established. Solving et al. [63] framed an optimised model for CS planning in downtown areas. Various factors are considered, such as road structure, the state of traffic and its structure, as well as the transmission capacity of the distribution network. In the designed model, travelling cost and investment cost are taken as objectives for minimisation purposes. The weighted Voronoi diagram is implemented for the distribution of service areas and then queuing theory principles were practiced to optimise the CS capacity. Frade et al. [64] discussed an EVCS deployment model in Lisbon, the capital of Portugal. EVCS placement is a prerequisite for recharging the batteries. The Lisbon city is defined by a strong consolidation of population and employment. Slow charging mode is used in such an area because the EV user parked their vehicle for considerable hours in a day. The approach used in this document to optimisation of demand is based on maximising demand coverage, which also indicates the number of CSs and their capacities. Eisel et al. [65] designed a location-based model for the installation of EVCS, considering user preferences. The developed model is based on considering traffic density and other qualitative factors. For strategic placement of charging infrastructure, Sweda and Klabjan [66] put forward an agent-based decision method that would locate the patterns of ownership of EVs in residential areas. The model is demonstrated in the Chicagoland area as a case study. Changxu et al. [67] utilised multi-agent system (MAS) and evidential reasoning (ER) approach for optimising the EVCS location. In this paper, charging demands of plug-in-electric taxis (PET) and their daily operation is dynamically simulated using the MAS framework. A multi-step Q(λ) learning approach is designed in order to increase the rate of convergence and also maintain the best strategies for operation. Furthermore, a heuristic model involving multi-objective such as charging flow, power loss and voltage deviation are minimised to developed for EVCS location. The model considers constraints related to transportation as well as power networks. He et al. [68] developed a model based on the relationship between the availability of tariffing options, the electricity prices, and targeted and various PHEV routes in transportation and energy networks. In the next phase, the active-set technique is utilised to find the best place for the CS at the highest level of social improvement. Fan et al. [23] presented a new modelling approach for the layout of EVCS. Different factors that have been considered which have effects on the layout of EVCS are charging demand, the performance of the battery, the time required to charge the battery, manner of energy supply and the location of CS. Mainul et al. [69] considered transportation loss (TL) grid power loss (GPL) and build-up costs as the objectives for the optimal location of fast CS. Battery SOC, GPL, Google Map API are taken as constraints in the recommended method. A latest and effective optimisation technique, i.e. binary lightning search algorithm (BLSA) is employed for the optimisation purpose. Masoum et al. [70] described a new intelligent control plan for load management based on peak demand, the improvement in voltage profile and minimisation of power loss to synchronise several chargers, taking into account the daily residential load pattern. Mainul et al. [71] proposed a new approach in which transportation costs, construction costs and substation energy costs are considered as a target function for optimal planning of a fast-CS (RCS). BLSA, a novel optimisation technique, is utilising for solving the objective function. The same optimisation technique is applied to traditional RCS. The test is conducted on the IEEE-34 bus system to validate the results. Zhang et al. [72] presented fast CS planning on coupled power and transportation networks. A closed-form modelling is done for fast CS considering charging demand and driving range of PHEVs. A modified CFRLM based on sub-paths is utilised for capturing charging demand that is varying in nature and the driving range is treated as a constraint. Then, a new approach, i.e. mixed-integer second-order cone programming model, is proposed for the planning of fast CS.

3.3 Optimal placement of CS based on geographic conditions

The location of CS should be chosen such that the charging service can be provided to as many EVs as possible. Thus, the flow of EVs must be maximised while planning EVCS. The objective function which describes EV flow is given as

\[
\max x = \sum_{x} \sum_{y} f_{xy}
\]
where $X$ is the set of the non-zero flow path and $f_x$ is the traffic flow rate. And, $y_{x1} = 1$ if at least one facility is provided on path $x = 0$ otherwise.

In many studies, the flow of EV is assigned as population coverage. Xiang et al. [73] presented an optimised recharge planning strategy for the road network. The developed optimisation model of the system generates the equilibrium of traffic flow and based on that, the queuing theory is introduced to find the CS capacity with the consideration of waiting time. Finally, for the economic analysis, cost functions are made for the selection of cost-effective schemes. Mohammad et al. [74] modelled the optimisation structure to determine the objective design of the CS in order to reduce the total energy consumption and travel distance to the nearby CS from the point where charging is necessary. GA is utilised to solve the problem. Wu and Sioshansi [75] have developed an optimised model to install a public quick CS for EV charges. In this paper, the authors used stochastic FCLM for solving the uncertainty, i.e. where the demand for charging EV appears. For solving the problem, the sample average approximation method and average two replication procedures are utilised. Lin and Hua [76] established an FCLM for the placement of EVCS. Service facilities as well as the electricity of EVCS are considered based on FCLM. Analysed the impact between consumer demand for interception and the number of CSs and balances the increase in the volume of demand interception and increase in the cost of building EVCS due to the increase in CSs and determining the optimal number of EVCS for making decisions about building EVCS in real life. Kuby and Lim [18] used a MIP approach for optimising the locations of CS, given the driving range of EVs and the deviations that the EVs can make from the road the shortest while refuelling their EVs when there is an inadequate fuel station. To maximise the total flows replenished in the bypass paths, Deviation Flow Refuelling Location Model (DFLRM) is used. Yao et al. [77] developed a combined model that minimises that investment cost and energy loss and also assists in traffic flow maximisation. The developed model presents the question of optimal planning in the integrated EV charging and power distribution system. User Equilibrium-based Traffic Assignment Model (UETAM) is employed to determine the maximal traffic flow capturing problem. A multi-objective evolutionary algorithm is utilised to find the non-dominated solutions, i.e. Pareto-Froniter. The aforementioned approach provides the investor with a chance to make an agreement between the total investment cost and the ease of EV payment service. Xiaohong et al. [16] considered the spatial and temporal transportation behaviours for the placement of fast EVCS on a round freeway. The above approach gives an idea of charging points along the highway and takes into account the uncertainties in battery performance and transport behaviour. The shared nearest neighbour (SNN) clustering algorithm is used to determine the EVCS locations on a round freeway. Finally, The Queuing Theory has developed the capacity determination model, which determines the number of chargers required in each CS, which reduces the total cost, i.e. the sum of the cost of the charger and the waiting cost. Chao et al. [78] overcame the problem of locating the CS in such a way that the proposed approach should benefit the EV owner, CS owner and the operator of the network. A Logit Nested Model is used to inspect the load sequence of the owner of EV and judge the total demand at the CS. Competition among CS as a Bayesian Game has been formulated. Wang et al. [25] proposed a planning method considering various objectives for the placement of EVCS, which takes into consideration the minimisation of power loss and maintaining the distribution system's voltage profile. Later, EV FCLM is presented for maximising the flow of EV. To find the optimal solution, the Data Envelopment Analysis Method is utilised. He et al. [79] proposed a bi-level programming model for determining the optimal location of CS with EV. All Electric Range (AER) is taken into consideration. With this approach, the location of the CS is optimised for minimising traffic flow. While in the lower level, EV driving range constraint is defined. Later, the bi-level problem is formulated as a single-level program and later on, the problem is made of linear nature for designing the meta-heuristic algorithm. Arslan and Karas [17] introduced the location problem of CS for charging EVs. The objective is to maximise the AER of these vehicles by minimising total transportation costs. The Bender Decomposition Algorithm is utilised for finding the EVCS location.

3.4 Optimal placement of CS based on DSM

The goal of DSM is to inform consumers that consumers should use less energy during peak times and make the most of it during off-peak hours, i.e. at night and on weekends.

DSM programs comprise planning, executing and controlling activities of electric utilities, which are made to motivate energy users to better their level and electricity usage pattern.

DRPs motivate the electricity user to cut or reduce electricity use during peak hours at the cost of low electricity bills. The DRPs are categorised as Direct Load Control (DLC), Emergency DRP (EDRP), Capacity Market Program, Interruptible/curtailable service, Demand Bidding and Ancillary service programs. Fig. 7 shows the classification of DRPs. In the current scenario, it is essential to consider DSM to find the optimal location of EVCS. Control schemes of battery capacity are essential while considering the DSM for the determination of the optimal location of EVCS. The studies reported in the literature mainly focus on the economic aspect and transportation sector. Shojaabadi et al. [80] have

![Fig. 7 Classification of DRPs](image-url)
presented a mathematical model for the optimal size and location of EVCS in distribution networks. Customer participation is considered for EV charging system planning with some uncertainties related to the load value and market price of electricity are incorporated. TOU programs are employed in modelling of the load. The objectives such as the net benefit of driving range [18] MIP, DFLRM path flows —

| S. no. | Algorithm | Advantages | Disadvantages |
|-------|-----------|------------|---------------|
| 1     | GA        | implementation is easy, more appropriate for placement problems [81] | computational time is large to solve the problem [36] |
| 2     | PSO       | computation is simple and able to determine sub-optimal solution [82] | early convergence [9, 21] |
| 3     | ACO       | has the ability to discover good solutions [44] | convergence time is not certain [46] |
| 4     | greedy algorithm | produce feasible solution in small time | near-optimal solutions are obtained [56] |
| 5     | LIP       | solves distinct combination of problems [54] | not suitable for stochastic problems [83] |

Furthermore, different researchers have considered the different approaches for the optimal location of CS. These approaches are based on the selection of objective functions, solution techniques utilised, consideration of geographic conditions and inclusion of DRPs. In this regard, Table 4 represents numerical-based optimisation techniques for the CS placement problem. An evolutionary and meta-heuristic based optimisation technique for the placement of CS is presented in Tables 5 and 6, respectively. Furthermore, Table 7 gives an insight into other well-known techniques like BLSA, FCLM etc. for the optimal placement of CS.

The chart given in Fig. 8a shows that the available literature predominantly states that the optimal location of CS based on four different approaches. The approaches are (a) objective functions, (b) solution techniques, (c) geographic conditions and (d) DSM.

The literature survey depicts that ~21% of research is based on objective function considered for placing the CS. The literature surveyed also shows that 57% of the research was based on the solution technique for the placement of CS. Similarly, the research based on DSM is 7% and research based on the geographic condition has a proportion of 15% in the literature survey.

As far as the solution techniques are concerned, there are many techniques that are utilised by the researchers. Approximately 20% of the researchers utilised the PSO technique in their research as objective function considered for placing the CS. Similarly, 17% of researchers have used GA, 11% used the ACO technique and 17% utilised LIP technique for the CS placement. It can also be said that 35% of the researchers utilised other techniques like queuing theory, BLSA etc.

Table 4 Analysis of EVCS placement in distribution and transportation system using numerical-based optimisation technique

| Objective function | Solution techniques | Geographic condition | Demand side management |
|--------------------|---------------------|---------------------|------------------------|
| coverage distance and cost [32] | MIP | traffic flow | — |
| trip energy and total location cost [30] | LIP | urban traffic | — |
| coverage distance [32] | MIP | traffic flow | — |
| CS coverage [56] | MIP | — | — |
| travelling cost and parking demand [53] | MIP | road network | — |
| CS placement [55] | game theory model, LIP and primal-dual path algorithm | traffic condition | — |
| operating cost and cost of investment [5] | MIP | distribution network | — |
| transportation cost, charging cost and CS placement costs [61] | IP | traffic flow | — |
| distance travelled [32] | MIP | transportation network | — |
| distance [52] | LIP | road network | — |
| cost [54] | two-step model and LP | transportation network | — |
| driving range [18] | MIP, DFLRM | path flows | — |
| CS cost (management cost and installing cost), charging cost and station access cost [15] | CPLEX Software, MIP | EV user's daily travel | — |
| overall cost [35] | Euclidean distance criterion | road network | — |

Table 3 Analysis of various optimisation methods applied in EVCS sizing and siting problems [2]

| S. no. | Algorithm | Advantages |
|-------|-----------|------------|
| 1     | GA        | implementation is easy, more appropriate for placement problems |
| 2     | PSO       | computation is simple and able to determine sub-optimal solution |
| 3     | ACO       | has the ability to discover good solutions |
| 4     | greedy algorithm | produce feasible solution in small time |
| 5     | LIP       | solves distinct combination of problems |

5 Future research directions

Research on EVCS carries importance and is still in its early stages. As of now, EVs make up a very insignificant percent of the vehicles in the country. The possible research directions in this area are listed below:

(i) Formulation of a problem for the planning of the charging infrastructure: The existing studies related to charging
infrastructure planning point to the diverse behaviour of the problem. Certain limitations have been identified with the problem formulation. The problem formulation needs to incorporate multi-objective functions like operating, installation costs, reliability indices, waiting time cost etc. Reliability indices such as average system interruption duration index, system average interruption frequency index need to be considered while describing the objectives [87]. Furthermore, there are some voltage-based stability indices such as fast voltage stability index, \( L \) index are important for the effective formulation of the problem [88]. Moreover, uncertainties in transportation networks are rarely considered. Certain algorithms like the Bayesian algorithm can be used for road traffic models.

(ii) Optimisation algorithm used to solve the charging infrastructure planning problem: It has been seen that GA and PSO that are applied by most of the researchers in solving the problem of CS placement. Other meta-heuristic techniques such as grey wolf optimisation, teaching-learning based optimisation, grasshopper optimisation, spider monkey optimisation can be employed for the better solution of the CS problem. The classical optimisation techniques can also be combined with meta-heuristic techniques for CS placement.

(iii) Feasibility studies of solar photovoltaic (PV)-based EVCS: The rapid increasing demand of EVs requires many infrastructures before deployments such as charging services etc. As the current CSs are fossil fuels based and causing environmental issues which affects the human health through the emission of various gases such as SOx, NOx, and carbon monoxides particularly in metropolitan cities of India. Thus, the solar PV-based CSs will not only reduce the burden on the existing electrical networks but also provides the sustainable, cost effective and eco-friendly environment. In this regard, the feasibility studies of solar PV-based CS are a new research area for the upcoming years.

### Table 5 Analysis of EVCS placement in distribution and transportation system based on evolutionary algorithm

| Objective function | Solution techniques | Geographic condition | Demand side management |
|--------------------|---------------------|----------------------|------------------------|
| EV user cost, station development cost, grid operator cost [19] | GA | urban traffic | — |
| travel cost [3] | GA | — | — |
| cost of investment, energy loss [36] | GA | — | — |
| power loss and voltage drop [20] | GA | — | DRP |
| energy not supplied (ENS) and CSs related costs [84] | GA | — | — |
| CS cost [39] | GA | traffic flow | — |
| cost of investment, transportation cost [43] | modified GA | traffic flow | — |
| overall energy overhead and driving distance [74] | GA | EV flow | — |
| budget [27] | MIP and GA | maximum coverage | — |
| cost of investment, transportation cost [85] | modified GA | traffic flow | — |
| cost of investment and transportation cost [41] | Modified GA | coverage and convenience to EV user's | — |
| cost of investment and power loss [86] | GA and power flow tracing method | distribution network | — |
| net benefit of discharging programs, day time charging, reliability improvement, investment cost [80] | GA and Monte Carlo simulation | — | DRP |
| cost of investment, operation cost and mobility cost [24] | MATLAB programming | traffic flow | — |

### Table 6 Analysis of EVCS placement in distribution and transportation system based on meta-heuristic optimisation techniques

| Objective function | Solution techniques | Geographic condition | Demand side management |
|--------------------|---------------------|----------------------|------------------------|
| cost of investment, connection cost, grid energy loss and demand response cost [10] | PSO | — | DRP |
| construction cost, cost of investment, running cost [9] | adaptive PSO | traffic flow | — |
| reliability improvement, power loss reduction and peak power [21] | PSO | distribution network | — |
| annual operating income of CSs, investment costs, transmission line investment cost, auxiliary road construction cost, net road costs [22] | PSO and weighted Voronoi diagram | road network | — |
| size of CS [38] | hybrid of GA and PSO | road network | — |
| cost of operation of CS, investment cost of distribution transformer and network losses [26] | PSO | — | — |
| construction cost for charging/exchanging facilities and power network investment [37] | PSO | road network | — |
| land cost, construction cost, operation cost [23] | chaotic quantum PSO | traffic flow | — |
| power loss [11] | time-series analysis and PSO | road network | — |
| power line loss, travelling cost, investment cost and operating cost [44] | ACO | traffic flow | — |
| energy efficiency [45] | ER-ACO | — | — |
| cost, power loss [46] | hybrid ACO and bees algorithm | traffic condition | — |
| transmission loss [47] | ACO | distribution network | — |
Table 7  Analysis of EVCS placement in distribution and transportation system using miscellaneous techniques

| Objective function | Solution techniques | Geographic condition | DSM |
|---------------------|---------------------|----------------------|-----|
| cost, power loss, power quality and harmonics [31] | fuzzy Delphi method, Grey relation analysis – VIKOR | — | — |
| cost [4] | CPLEX Software | — | — |
| charger cost [16] | SNN clustering algorithm | convenience of EV users | — |
| driving range, transportation cost [17] | Bender's decomposition algorithm | — | — |
| cost of investment, maintenance cost, network loss cost and operation cost [7] | MPDIPA | service radius of EVCS | — |
| accessibility and station coverage [56] | greedy algorithm | traffic flow | — |
| set up cost and traffic flow [57] | FCLM | transportation network | — |
| traffic flow [58] | extended flow refuelling location model and charging pad | road network | — |
| demand of charging EV [75] | stochastic SFCLM | traffic flow | — |
| construction cost | FCLM | EV flow | — |
| overall cost of investment, energy loss [77] | UETAM | traffic flow | — |
| charging sequence of EV owner [78] | Nested Logit Model, Bayesian Game | traffic flow | — |
| traveling cost and investment cost [63] | Voronoi Diagram and queuing theory | road network | — |
| social welfare [68] | active-set technique | transportation network | — |
| transportation cost, construction cost and substation loss cost [69] | BLSA | distribution network | — |
| charging cost [28] | heuristic method | — | DRP |
| driving range [79] | bi-level programming | EV flow | — |
| cost functions and waiting time [73] | queuing theory | traffic flow | — |
| power loss, voltage deviation and EV traffic flow [25] | FCLM and cross entropy method | distribution network and transportation network | — |

![Fig. 8](image-url)  
(a) Survey of different approaches considered in literature for optimal siting and sizing of EVCS  
(b) Percentage of approaches used for optimal placement of CS, (b) Different optimisation technique used for optimal placement of CS

6 Conclusion

The growing emission of GHGs due to fossil fuel depletion has detrimental effects on daily life and as a result, the automobile industry is focusing to provide an environment-friendly solution to the above-mentioned problem. EV is one of the emerging solutions to overcome the pollution problem as it causes a negligible amount of pollution. To adopt the EVs in place of conventional transportation systems, adequate charging infrastructure is required. In this context, this work presents the charging infrastructure planning scenario in India. Further, the optimal placement of CS based on different approaches, i.e. objective function, solution technique, geographic conditions and DSM is also discussed in this paper.

7 References

[1] Adam, C., Kellen, S.: ‘Electric vehicle sales forecast and the charging infrastructure required through 2030’, Institute of Electric Innovation, November 2018, pp. 1–16
[2] Sanchini, D., Kari, T., Karuna, K., et al.: ‘Review of recent trends in charging infrastructure planning for electric vehicles’, WIREs Energies Environ., 2018, 7, (6), pp. 1–26
[3] Ge, S., Feng, L., Liu, H.: ‘The planning of electric vehicle charging station based on grid partition method’. Electrical and Control Engineering (ICECE) Int. Conf., Yichang, China, September 2011, pp. 2726–2730
[4] Jia, L., Hu, Z., Song, Y., et al.: ‘Optimal siting and sizing of electric vehicle charging stations’. I.E. Int. Electric Vehicle Conf. (IEVC), Greenville, SC, March 2012, pp. 1–6
[5] Hu, Z., Song, Y.: ‘Distribution network expansion planning with optimal siting and sizing of electric vehicle charging stations’. Universities Power Engineering Conf. (UPEC), London, UK, September 2012, pp. 1–6
[6] Ahm, Y., Yeo, H.: ‘An analytical planning model to estimate the optimal density of charging stations for electric vehicles’. PLoS ONE, 2015, 10, (11), pp. 1–26
[7] Liu, Z., Wen, F., Ledwich, G.: ‘Optimal planning of electric-vehicle charging stations in distribution systems’. IEEE Trans. Power Deliv., 2013, 28, (1), pp. 102–110
[8] Gaozhong, L., Li, K., Zeya, L., et al.: ‘Charging station and power network planning for integrated electric vehicles (EVs)’, Energies, 2019, 12, (2595), pp. 1–22
[9] Zi-Ga, L., Wei, Z., Xing, J., et al.: ‘Optimal planning of charging station for electric vehicle based on particle swarm optimization’. IEEE Innovative Smart Grid Technologies-Asia, Tianjin, China, May 2012, pp. 1–5
[10] Hamid, S., Hasan, D., Hadi, R., et al.: ‘Cost-based optimal siting and sizing of electric vehicle charging stations considering demand response programmes’. IET Gener. Transm. Distrib., 2018, 12, (8), pp. 1712–1720
[11] Martins, M.C., Trindade, F.C.: ‘Time series studies for optimal allocation of electric charging stations in urban area’. I.E. PES Innovative Smart Grid Technologies Latin America (ISGT LATAM), Montevideo, Uruguay, October 2015, pp. 142–147
Xiaohong, D., Yunfei, M., Hongjie, J., et al.

Fan, X., Guo-Qin, Y., Lin-Feng, G., et al.

Pazouki, S., Mohsenzadeh, A., Ardalan, S., et al.

Awasthi, A., Chandra, D., Rajasekar, S.

Kameda, H., Mukai, N.: ‘Optimization of charging station placement by using Kuby, M., Lim, S.: ‘The flow-refueling location problem for alternative-fuel Kuby, M., Lim, S.: ‘An optimized EV charging model considering In the Int. Conf. on Transportation, Mechanical, and Electrical Engineering (TMEE), Changchun, China, December 2011, pp. 1297–1300

Fan, X., Guo-Qin, Y., Lin-Feng, G., et al.: ‘A hybrid heuristic approach to the problem of the location of vehicle charging stations’, Comput. Ind. Eng., 2014, 70, pp. 195–204

Cao, Y., Tang, S., Li, C., et al.: ‘An optimized EV charging model considering TOU price and SOC curve’, IEEE Trans. Smart Grid, 2012, 3, (1), pp. 388–393

Wang, Y.W., Wang, C.R.: ‘Recharging passenger vehicle refueling stations’, Transp. Res. E Logist. Transp. Rev., 2010, 46, (5), pp. 791–801

Bauoche, F., Billot, R., Trigui, R., et al.: ‘Efficient allocation of electric vehicle charging stations using mixed-integer linear programming and bees algorithm for planning of public fast charging stations’. IEEE Int. Smart Grid Communications, Vancouver, BC, 2013, pp. 36–39

Sun, Z., Zhou, X., Du, J., et al.: ‘When traffic flows meet power flow: on charging station deployment with budget constraints’, IEEE Trans. Veh. Technol., 2016, 66, (4), pp. 2740–2756

Shayanuy, G., Liang, F., Hong, L.: ‘Optimal location of electric vehicle charging stations for peak shaving and loss minimization considering voltage constraints’, IEEE Trans. Smart Grid, 2018, 12, (8), pp. 497–507

Masoum, A.S., Deilami, S., Moses, P.S.: ‘Optimal location of charging stations for electric vehicles in a neighbourhood in Lisbon, Portugal’, Transp. Res. Rec., J. Transp. Res. Board, 2011, 2252, pp. 91–98

Eisel, M., Schmidt, J., Kolbe, L.M.: ‘Finding suitable locations for charging stations: implementation of customers’ preferences in an allocation problem’. IEEE Int. Electric Vehicle Conf. (IEVC), Florence, Italy, 2014, pp. 1–8

Sweda, T., Khabaza, M.: ‘Grid-based design of optimal electric vehicle charging infrastructure development’. 7th IEEE Vehicle Power and Propulsion Conf., Chicago, Illinois, 2011, pp. 1–5

Changxu, J., Zhaoxia, J., Tianyao, J., et al.: ‘Optimal location of PEVCS using MAS and ER approach’, IET Gener. Transm. Distrib., 2018, 12, (20), pp. 4377–4387

Frade, I., Ribeiro, A., Gonçalves, G., et al.: ‘Optimal location of charging stations for electric vehicles in a neighbourhood in Lisbon, Portugal’, Transp. Res. Rec., J. Transp. Res. Board, 2011, 2252, pp. 91–98

Eisel, M., Schmidt, J., Kolbe, L.M.: ‘Finding suitable locations for charging stations: implementation of customers’ preferences in an allocation problem’. IEEE Int. Electric Vehicle Conf. (IEVC), Florence, Italy, 2014, pp. 1–8

Sweda, T., Khabaza, M.: ‘Grid-based design of optimal electric vehicle charging infrastructure development’. 7th IEEE Vehicle Power and Propulsion Conf., Chicago, Illinois, 2011, pp. 1–5

Changxu, J., Zhaoxia, J., Tianyao, J., et al.: ‘Optimal location of PEVCS using MAS and ER approach’, IET Gener. Transm. Distrib., 2018, 12, (20), pp. 4377–4387
[72] Zhang, H., Moura, S.J., Hu, Z., et al.: ‘A second-order cone programming model for planning PEV fast-charging stations’, IEEE Trans. Power Syst., 2018, 33, (3), pp. 2763–2777

[73] Xiang, Y., Liu, J., Li, R., et al.: ‘Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates’, Appl. Energy, 2016, 178, pp. 647–659

[74] Mohammad, M.V., Hongmou, Z., Paolo, S., et al.: ‘Optimizing the deployment of electric vehicle charging stations using pervasive mobility data’, Transp. Res. A, Policy Pract., 2019, 121, pp. 1–11

[75] Wu, F., Sioshansi, R.: ‘A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows’, Transp. Res. D, Transp. Environ., 2017, 53, pp. 354–376

[76] Lin, W., Hua, G.: ‘The flow capturing location model and algorithm of electric vehicle charging stations’, Int. Conf. Logistics, Informatics and Service Sciences (LISS), Barcelona, Spain, July 2015, pp. 1–6

[77] Yao, W., Zhao, J., Wen, F., et al.: ‘A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems’, IEEE Trans. Power Syst., 2014, 29, (4), pp. 1811–1821

[78] Chao, L., Yih-Fang, H., Vijay, G.: ‘Placement of EV charging stations—balancing benefits among multiple entities’, IEEE Trans. Smart Grid, 2015, 8, (2), pp. 1–10

[79] He, J., Yang, H., Tang, T., et al.: ‘An optimal charging station location model with the consideration of electric vehicle’s driving range’, Transp. Res. C, Emerg. Technol., 2018, 86, pp. 641–654

[80] Shojaabadi, S., Abapour, S., Abapour, M., et al.: ‘Optimal planning of plug-in hybrid electric vehicle charging station in distribution network considering demand response programs and uncertainties’, IET Gener. Transm. Distrib., 2016, 10, (13), pp. 3330–3340

[81] Mandle, S., Pascoe, S.: ‘An overview of genetic algorithms for the solution of optimization process’, Comput. High. Educ. Econ. Rev., 1999, 13, (1), pp. 16–20

[82] Nyls, K.C., Haesen, E., Driesen, J.: ‘The impact of charging plug-in hybrid electric vehicles on a residential distribution grid’, IEEE Trans. Power Syst., 2010, 25, (1), pp. 371–380

[83] Mohsenzadeh, A., Pang, C., Pazouki, S., et al.: ‘Optimal siting and sizing of electric vehicle public charging stations considering smart distribution network reliability’, North American Power Symp. (NAPS), Charlotte, NC, October 2015, pp. 1–6

[84] Musirin, I., Rahman, T.A.: ‘Novel fast voltage stability index (FVSI) for voltage stability analysis in power transmission system’. Student Conf. on Research and Development, Malaysia, 2002, pp. 265–268