# Set cover model-based optimum location of electric vehicle charging stations

**Binal Vansola[1], Minal[2,*] and Rena N. Shukla[1]**

[1]Civil Engineering Department, L.D. College of Engineering, Ahmedabad 380 015, India
[2]CSIR-Central Road Research Institute, Transportation Planning and Environmental Division, New Delhi 110 025, India

**The adoption rate of electric vehicles (EVs) is affected by the availability of charging stations (CS). The optimum location of CS in a city is a major part of the charging infrastructure for EVs. Factors like charging demand, charging time, investment cost, etc. affect the location decision of CS. This study presents a set cover problem-based methodology to optimally locate fast-charging stations for mixed traffic flow in NCT-Delhi, India, by maximizing the coverage range of CS. The study area was divided into grid-like zones and geographical information system (GIS) was used to analyse the distance matrix of the study-area grid map. For mixed traffic flow, different EV penetration rates were assumed to calculate the charging demands. We used origin and destination data, distance matrix and mixed traffic flow data of NCT-Delhi. The different vehicle categories considered from the mixed traffic flow in this study were two-wheelers, three-wheelers, four-wheelers and commercial vehicles (CVs). The results show that when each CS has a coverage range of 3 km, a total of 62 CS are required. Further, a decrease in the coverage range by 1 km leads to an increase in the number of required CS by 72%. This study shows the exact location of these CS on the GIS map of the study region.**

**Keywords:** Charging station, coverage range, electric vehicles, optimum location, set cover method.

AIR and noise pollution due to the usage of fossil fuel-based automobiles for transportation adversely affect the quality of life in all cities[1]. As fossil fuels are a non-renewable source of energy, the drive towards adopting alternative and clean energy transport modes has increased. The use of electric vehicles (EVs) in the transport sector is a much cleaner alternative than internal combustion engine vehicles (ICEVs)[1]. The transition from ICEVs to EVs is taking place gradually with the wider support of state policies worldwide. EV take-up rates (percentage of new vehicle sales) vary significantly from one country to another, ranging from 60% of new passenger vehicles in Norway[1], to 4.7–8% in other Scandinavian countries, 1.6–7% in western European countries, 4.4% in China, 2.2% in Canada, 2.1% in the USA, 2% in South Korea[2] and 1% in Japan[1]. Currently, the EV penetration rate in India is less than 1% for the four-wheelers (4Ws) segment[3]. This can be attributed to various issues like EV purchasing cost, insufficient public charging infrastructure, uninterrupted electricity supply, longer charging time of affordable cars and related infrastructure development, as identified by Chandra and Minal[4]. To encourage people to adopt EVs, it is imperative to develop an infrastructure which boosts the usage and trust in EVs. Inaccessibility to requisite infrastructure facilities like public charging stations (CS; apart from the private CS at home) will discourage the potential buyers of EVs. Therefore, installing readily available public fast-charging stations is essential to give an impetus to the EV penetration rate in India.

Several studies have been conducted worldwide on the optimization framework for deploying CS[1,5,6]. These studies mostly focused on uniform traffic conditions, where the traffic fleet was uniform in nature and mostly composed of cars. The studies have used constraints like maximizing profit, minimizing cost, minimizing waiting time, minimizing drag distance and the number of CS by different optimization techniques[1,5,6]. The novelty of the present study lies in the fact that it considers mixed traffic flow, which is a typical feature of Indian cities. The traffic flow data were obtained from the origin and destination (OD) data of NCT-Delhi, with a multimodal fleet comprising two-wheelers (2Ws), three-wheelers (3Ws) and 4Ws to provide a unique solution for mixed traffic fleet as observed on Indian roads.

This study aims at developing a methodology to optimize the location of CS for mixed traffic flow according to Indian traffic conditions for NCT-Delhi (Figure 1 *a*). The set cover methods were used to maximize coverage range of a CS. This method gives a local optimum solution, and the result obtained is optimal enough to locate CS in the study area as it covers the demand of all zones within permissible distance. Different EV penetration rates were chosen for different vehicle classes. The CS are distributed in the study area according to the demand in each zone. Also, each zone has at least one CS within the coverage range to satisfy the demand.

## Literature review

The literature on the optimization of EV CS locations is vast. Several studies have been carried out on optimization worldwide using different techniques, datasets, models

*For correspondence. (e-mail: minal.crri@nic.in)

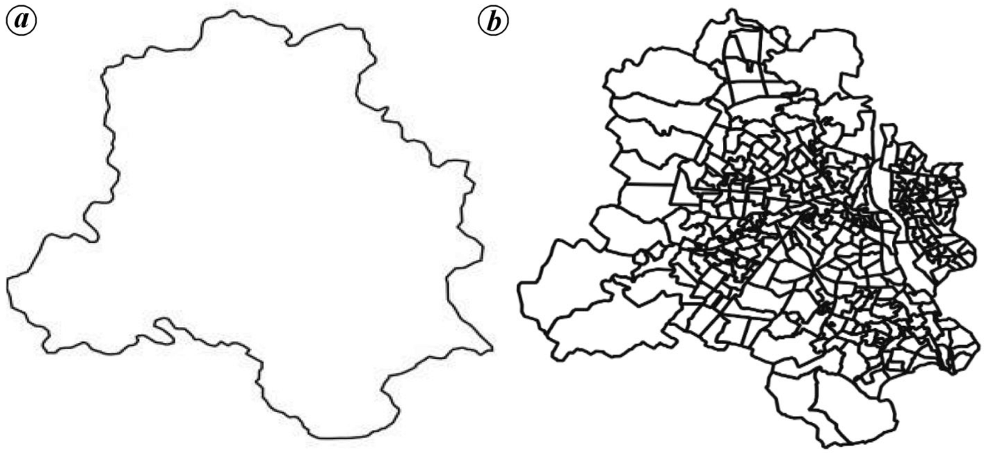


**Figure 1.** Study area NCT-Delhi, India. ***a***, Boundary map. ***b***, Zone map.

and perspectives like demand representation, demand coverage approaches, objective functions, side constraints, decision variables, model structure as well as time dependency and uncertainty on the problem parameters[7].

In the context of locating CS in the urban road network, few studies have used multi-day data to cluster the activity–travel pattern of trip makers using the *k*-medoids algorithm. A study further developed grid charging strategies for an efficient grid energy management[5]. For congested intra-city travel, Bao and Xie[8] developed a bi-level mixed, nonlinear integer programming model, where the upper level of the model focused on construction budget and the lower level on the equilibrium flow pattern to locate CS. Geographical information system (GIS) has been extensively used in some studies for optimum location of CS. The study by Morro-Mello *et al.*[9] located fast-charging stations in an urban area for taxis, resulting in the development of spatial database that can be visualized in GIS by the agencies such as urban planning department or the electrical service concessionaire. Bian *et al.*[10] used a GIS-based mixed-integer linear programming (MILP) model to maximize profits of CS. A recent study by Li *et al.*[11] introduced a new service mode, viz. valet charging service and a risk-averse two-stage stochastic mixed-integer model (RTSMIP). For inter-urban roads, Bräunl *et al.*[1] determined the locations of CS by taking six different values of EV penetration rate, viz. 1%, 5%, 10%, 20%, 50% and 100%. The analysis considered energy demand, peak demand and charging times in the model. Xu *et al.*[12] located CS at the intercity route by minimizing accumulated range anxiety in the study area of Texas highways, USA.

Artificial intelligence and machine learning techniques find prolific use in determining the location of CS. Deb *et al.*[13] used the nature-inspired optimization algorithm (NIO) and compared the different NIO methods like genetic algorithm (GA), particle swarm optimization (PSO), firefly algorithm (FA), chicken swarm optimization (SWO), ant colony optimization (ACO), lightening search algorithm (LSA) and teaching–learning-based optimization. Efthymiou *et al.*[14] attempted to locate CS by using GA for an urban area. Fredriksson *et al.*[15] focused on a practical approach to finding the optimum location of CS for a large-scale network, where they considered limited driving range and minimized driving range anxiety by route node coverage problem. Ouyang and Xu[16] located CS by considering vehicle user's travel pattern and determined the optimum location of multi-type EV CS.

Instead of using travel data, a call detail record (CDR) was utilized by Vazifeh *et al.*[5] to extract the trip pattern for optimizing the location of CS was made. The study done by Vazifeh *et al.*[5] determined the fast-charging station location by optimizing the drag distance and minimizing the number of CS using the set cover method. Charging demand was calculated by pervasive mobility data using CDR, while the optimization problem was solved by the greedy algorithm and GA[6]. Zhang *et al.*[17] conducted a study on shared autonomous EVs and charging demand. They developed an agent-based simulation model, BEAM and *K*-means algorithm was used to optimize CS location. Iacobucci *et al.*[18] aimed to optimize CS location for shared autonomous EVs. The optimization problem was solved by the MILP method.

Most of the studies reported in the literature are for homogeneous traffic, primarily consisting of cars. The biggest gap the present study fills is that it considers the prevalent Indian traffic scenario, which consists of mixed traffic with 2Ws, 3Ws and 4Ws. Also, this study combines the two methods of set cover problem model for optimization and GIS to visualize the results.

## Methodology

The set cover model mainly depends upon the distance between non-overlapping zones to maximize coverage of the CS. Maximum coverage of a CS is the maximum number of zones it can cover within the coverage distance limit or the driver's willingness to drive from the demand point to the CS. One CS can serve more than one zone if the zones are within the coverage distance limit. The study methodology was divided into three steps to locate fast charging for mixed traffic flow (see Figure 2).

## *Data collection and analysis*

*Zone map and distance matrix:* We divided the study area into $n$ non-overlapping grids or traffic analysis zones to obtain a distance matrix. The centroid of each non-overlapping zone was used to calculate the shortest distance between each zone. The distance matrix $n \times n$ was generated using network analysis tools in QGIS (an open-source software). The distance matrix was further used to analyse the coverage range of zones.

*Demand modelling:* The study area was divided into $n$ number of non-overlapping zones in QGIS, according to eq. (1). Single-day OD data for each zone were collected to calculate charging demand. The charging demand was computed by considering three factors, viz. EV penetration rate $\delta$, the percentage of public charger users and peak traffic flow. Based on previous studies, Table 1 shows the EV penetration rates for different vehicle classes[19]. Two-wheelers were divided into four categories: (a) scooters, (b) B2B (business to business), (c) B2C (business to consumer) and (d) motor-cycles. B2B vehicles are used for

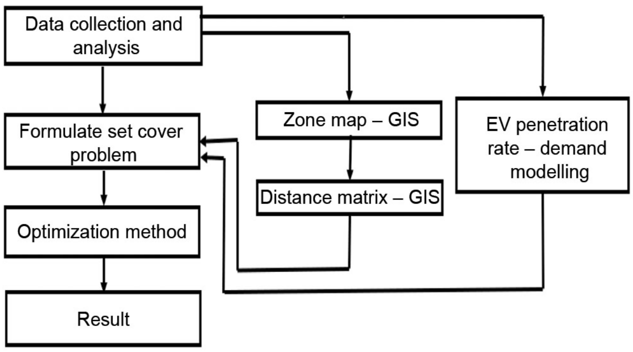


**Figure 2.** Study methodology – flowchart.

**Table 1.** Segment-wise analysis – electric vehicle (EV) penetration rate

| Vehicle segment | Vehicle sub-segment | EV penetration rate (%)[20] 2025 | 2030 |
|---|---|---|---|
| 2Ws | Scooters | 10–25 | 50–70 |
| | B2B | 40–60 | 60–80 |
| | B2C | 13–18 | 40–60 |
| | Motorcycles | 1–2 | 10–20 |
| | Overall | 7–10 | 25–35 |
| 3Ws | Overall | 35–45 | 65–75 |
| 4Ws | Private | 1–3 | 10–15 |
| | Commercial | 8–10 | 20–30 |

commercial purposes, whereas 2Ws are used for food delivery, grocery delivery, courier, etc. from one business to another. While B2C considers all 2Ws which cater directly to consumers. Four-wheelers were divided into two different categories, viz. commercial vehicles (CVs) and private vehicles (PVs). It is assumed that the penetration rate for 2Ws, ($\delta_{2\mathrm{w}}$) is 7–10% by 2025 and 25–35% by 2030. $\delta_{3\mathrm{w}}$ is 35–45% by 2025 and 65–75% by 2030, and $\delta_{4\mathrm{w}}$ is 1–3% and 5–10% by 2025 for a PV and CV respectively. It will reach up to 10–15% and 20–30% for private vehicle and commercial vehicle respectively. Different types of EVs have different range capacities. In the private vehicle category, 2Ws have a lower range compared to 4Ws. In the recently launched EVs, the range of 2Ws is 150–250 km. Therefore, if any user has a home charging facility, they will not use public CS and the vehicle minimum range capacity is sufficient for single-day intercity travel. According to the literature, 60–80% of EV users will charge their vehicles at home using a private charger; therefore, public CS can be located for the rest of the EV users[1]. For commercial vehicles, the trip length is different from person to person and most of the time it is much higher than the range of EVs. Therefore, while calculating charging demand, we assume that 100% of commercial vehicles will require charging at public CS. The OD matrix gives the value of travelling vehicles throughout the day, but while computing charging demand we consider vehicles during peak hours alone, as it will give the maximum charging demand of the zone on a day. Thus, we consider this maximum charging demand (during peak hours) to avoid a waiting queue. Charging at any other time during the day will be less than the peak hour demand and will not lead to queue formation.

$$Z = \{z_1, z_2, z_3, \ldots, z_n\}. \tag{1}$$

## *Formulation of set cover problem*

To develop zone network $Z_n$ in zone partitioning of the study area, first we need to locate the centroid of each zone, denoted as 'node', such that $z_i \in Z$. A link is created by connecting the origin zone $z_i$ and destination zone $z_j$ by the shortest route. The link starts from origin node zone (origin of the trip) to the node of the destination zone. To develop the zone network, the nodes of a zone must be connected to the nodes of all the zones adjacent to it (in all directions, i.e. north, south, east and west) through an available road segment in the road network. We established parameter $L$, which is the maximum distance the driver is willing to drive to reach a CS. Suppose $z_j$ is the adjacent zone of $z_i$ within the proximity of $L$. If we locate CS at $z_i$ then it will cover the charging demand of $z_j$. To maximize the coverage of the CS, we need to determine the location for stations which cover the maximum zones within distance $L$. Here, we introduce a universe set, which is a set of zones that needs to be covered as well as the set of zones where CS can be

**Table 2.** Notations used in this study

| | |
|---|---|
| $z_i \in Z$ | Partitioned zones in the study area and the corresponding zones in the zone network |
| $z_n$ | Zone network |
| $Z$ | Set of non-overlapping zones |
| $z_i$ | Zone $i$ |
| $z_j$ | Zone $j$ |
| $L$ | Distance which the driver is willing to drive to reach the charging station |
| $U$ | Universe set which denotes all the zones in the study area |
| $S$ | Set of $S_i$ which is a subset of $U$ |
| $s_i$ | Set of nodes that zone $z_i$ can cover within permissible distance |
| $c_{i(L)}$ | Index set of cells which can be covered by zone $z_i$ within distance $L$ |
| $c_i$ | Number of stations available within distance $L$ from $z_i$ |
| $x_i$ | Decision variable which indicates whether the charging station will be located at $z_i$ (or not) |
| $m_z$ | Maximum number of electric vehicles (EVs) at charging station (CS) that can be charged at a time |
| $Scp_{ij}^h$ | Binary matrix denoting whether $z_i$ covers $z_j$ within distance $L$ |
| $D_{i,t}$ | Number of trips destined in zone $I$ during time $t$ |
| $f_i$ | Minimum number of charging stations required to built at $z_i$ to cover charging demand within $L$ proximity of $z_i$ |

located. $S$ is a subset of $U$, which denotes the zones which are within distance $L$ from $z_i \in Z$. The sets are defined as follows:

$$U = \{z_1, z_2, z_3, ..., z_n\}, \tag{2}$$

$$S = \{s_1, s_2, s_3, ..., s_n\}, \tag{3}$$

$$s_i = \{z_j / j \in c_{i(L)}\}, \tag{4}$$

where $c_{i(L)}$ is the set of zones in $L$ proximity of zone $z_j$.

$s_i$ is a subset of $U$ and it is a set of zones which contains zones which are at $L$ distance from $z_i$. Here, we need to find $s_{\text{opt}}$ such that all the elements of $U$ are covered by CS within permissible distance by maximizing the total covered zone by CS. Maximization of the covered zone is done by choosing the location of CS, which can cover maximum zones within $L$ proximity. If $s_i$ is maximized, then ultimately, the number of CS required to be installed will be minimized. If the number of required CS is minimum, then eventually, its cost will also be minimized. If we consider $L = 0$, then we need to locate a CS at every zone. If $L = \infty$, then it is required to locate only one CS as it covers the demand of all zones. Therefore, the value of $L$ (distance the driver is willing to drive) lies between 0 and $\infty$. Here, considering the Delhi Government's EV policy of maximum distance between two CS should not exceed 3 km, $h = 3$ km was chosen. We considered different values of $L$, i.e. 3 and 2 km to determine $s_{\text{opt}}$. The objective function used for optimization by the set cover method is presented in eq. (5), subject to the constraints in eqs (6) and (7).

$$\text{Maximize} \sum_{1}^{n} s_i \cdot x_i. \tag{5}$$

Subject to:

$$c_i = \sum_{j \in c_{i(L)}} x_j \geq 1 \quad (i = 1, 2, ..., N), \tag{6}$$

$$x_i \in \{0, 1\}. \tag{7}$$

$c_i$ is defined as the number of stations available within distance $L$ from $z_i$. The number of CS that can handle the finite capacity of EVs at a time are denoted by $m_z$. If we require that the capacity not be exceeded, then we need to ensure that the following condition is satisfied for every zone.

$$c_i \geq \text{ceiling}\left[\frac{\max(D_{i,t})}{m_z}\right] = f_i, \tag{8}$$

where $\max(D_{i,t}) = \max D_{i,t}$ is the maximum value of $D_{i,t}$. To modify inequality constraint, put $\geq f_i$ instead of $\geq 1$.

$$\text{Maximize} \sum_{1}^{n} s_i \cdot x_i. \tag{9}$$

Subject to

$$c_i = \sum_{j \in c_{i(L)}} x_J \geq f_i \quad (i = 1, 2, ..., N), \tag{10}$$

$$x_i \in \{0, 1\}. \tag{11}$$

It was assumed that the capacity of a CS was large enough to satisfy all the charging demand in the coverage equivalent to $f_i = 1$ for all zones.

To solve the optimization problem, the distance matrix $n \times n$ was set as a binary matrix. In the binary matrix rows indicate the zones that need to be covered and columns indicate the CS at various zones. Now, the $(i, j)$ elements of distance matrix SCP is either 1 or 0. If zone $j$ covered zone $i$ because zone $i$ is at $L$ distance from zone $j$ then it denotes as 1 or else it will be 0.

$$\text{SCP}_{ij}^{h} = \begin{cases} 1 & j \in c_{i(L)} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

Each configuration of CS in this binary representation is a binary vector in which the indices of non-zero elements correspond to those of the cells which have CS in them.

### *Optimization method*

First, we converted the distance matrix $n \times n$ to a binary matrix by setting parameter $L$. The binary matrix shows zones covered by CS at $z_j$. To optimize $s_i$, we selected the first zone $z_1$ as a CS and then added that zone in the final CS set. The covered zones from that CS will be added to the set of covered zones by CS. Thereafter, we selected $z_2$ as CS. If $z_2$ covered more CS than $z_1$ and consisted all the zones covered by $z_1$ then $z_1$ was replaced by $z_2$ in the final best CS set. The zones covered by the CS at $z_1$ is replaced with zones covered by CS at $z_2$. This process was repeated till we evaluated all the zones up to $z_n$ and members of the covered zones became equivalent to the universe zone $U$. The final station was a set of CS obtained after completion of the optimization. Figure 3 shows the optimization done in Python. The methodology was adapted from Abdelazeem[20].

After analysing the generated data, it was found that some zones overlapped with more than one CS. Therefore, while calculating the charging demand, one needs to eliminate overlapping covered zones in CS. For this, we first set the data in descending order of area of zones. Then we eliminated repeatedly covered zones from larger area to smaller area to get minimum charging demand in smaller zones. In the elimination process, we did not consider the host zones of CS, because the zones which consist of CS will cover their demand.

## Case study

The set cover-based optimization model was implemented in NCT-Delhi, which has an area of 1484 sq km. The entire study area was divided into 360 zones (Figure 1 *b*). The set cover model was performed on 360 zones. The most important parameter to perform the set cover method is the

```
#a set to hold the final set of stations
finalStations = set()

#loop until statesNeeded is empty
while statesNeeded:
    bestStation = None
    statesCovered = set()
    for station, states in stations.items():
        covered = statesNeeded & states              #union between statesNedded amd states
        if len(covered) > len(statesCovered):        #check if this station covers more states than the best one so far
            bestStation = station                    #change the best station to that station
            statesCovered = covered                  #change statsesCovered to these states
    statesNeeded -= statesCovered                    #remove these states from the statesNeeded set
    finalStations.add(bestStation)                   #add the station to the finalStation set

print(finalStations)
```

**Figure 3.** Optimization in Python.

distance matrix. The GIS map of the study area was divided into 360 zones in QGIS (Figure 4). The centroid of each zone was located by QGIS, which is the node of each zone. The network analysis was performed in QGIS to generate a $360 \times 360$ distance matrix. The distance between two zones was calculated from the centroid of one zone to the centroid of the other.

Further, OD data of each zone for different vehicle classes were used analyse the charging plugs required to be installed. Charging demand was computed by considering the three assumptions of EV penetration rate, rate of public charger users and peak hour flow discussed earlier. The EV penetration rate was taken according to segment-wise analysis for 2025 (Table 3) as the average range for different vehicle classes[20]. According to a study in Australia, 60–80% of EV users will charge their vehicles at home[1]; therefore, only 20–40% of EV users will use the public CS. Based on these factors, it was assumed that 40% of EV users (private EV owners) would charge their vehicles at public CS in the study area (Table 3). However, all (100%) commercial vehicle owners will use public chargers at least once a day because their trips are longer compared to private vehicle trips. A CS should have the capacity to satisfy peak-hour charging demands.

Therefore, peak-hour vehicle traffic was computed assuming that 60% of public charger users will charge their vehicles during peak hours.

## Results

When $h$ (the distance a driver is willing to drive to reach a CS) is taken as 3 km, we obtain the location of 62 CS (Figure 5 *a*). As discussed earlier, the above value was taken

**Figure 4.** Delhi traffic zone map created in QGIS.

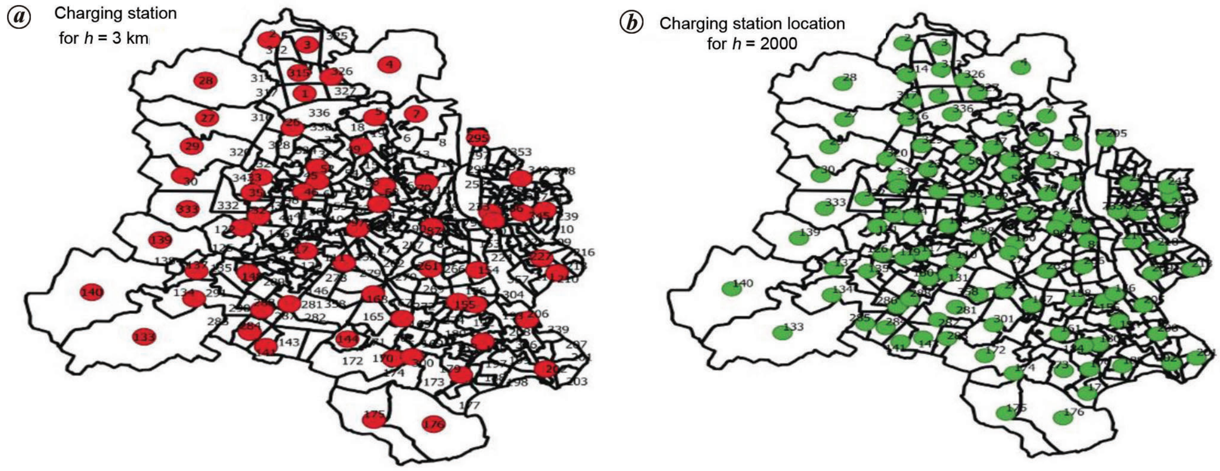


**Figure 5.** Estimated optimum locations for (***a***) 62 charging stations (at $h = 3$ km) and (***b***) 107 charging stations (at $h = 2$ km).

**Table 3.** Assumptions: EV penetration rate, public charger users and peak hour traffic flow[15]

| Vehicle category | Average EV penetration rate (%) by 2025 | Public charger users (%) | Peak hour traffic flow (%) |
|---|---|---|---|
| 2Ws | 8.5 | 40 | 60 |
| 3Ws | 40 | 100 | 60 |
| 4Ws (PV) | 2 | 40 | 60 |
| 4Ws (CV) | 7.5 | 100 | 60 |

**Table 4.** Charging plugs required to be installed in one zone

| Zone number | 2W | 3W | 4W – PV | 4W – CV | Total number of charging stations |
|---|---|---|---|---|---|
| 2 | 16 | 8 | 5 | 1 | 29 |
| 4 | 27 | 13 | 8 | 1 | 49 |
| 5 | 26 | 13 | 8 | 1 | 49 |
| 7 | 25 | 12 | 8 | 1 | 46 |
| 27 | 16 | 8 | 5 | 1 | 29 |
| 28 | 40 | 20 | 12 | 2 | 74 |
| 29 | 21 | 10 | 6 | 1 | 39 |
| 30 | 24 | 12 | 7 | 1 | 43 |
| 133 | 34 | 17 | 10 | 2 | 63 |
| 134 | 27 | 13 | 8 | 1 | 49 |
| 139 | 33 | 16 | 10 | 2 | 61 |
| 140 | 27 | 13 | 8 | 1 | 50 |
| 175 | 36 | 18 | 11 | 2 | 66 |
| 176 | 30 | 15 | 9 | 1 | 55 |
| 333 | 8 | 4 | 2 | 1 | 16 |

by considering the Delhi Government's EV policy of maintaining the maximum distance between two charging stations to less than 3 km. The estimated average distance between the CS was obtained as 3.24 km. Zones which have a smaller area (less than 9 sq. km) cover more adjacent zones (approximately 3–29 zones). While if the area of a zone where the CS is located is greater than 9 sq. km, then it covers less than two zones. There are 13 CS at 13 zones which do not cover the demand of any other zones because the area of these zones is greater than 19 sq. km.

With decreasing $h$, the number of CS should increase. For $h = 2$ km, the number of charging stations obtained is 107 (Figure 5 *b*). The average distance between CS is 2.53 km for the 107 CS. We assume that the capacity of each CS is sufficient to cover all the charging demand in the coverage range. If the CS cannot satisfy all the charging demands, then more chargers need to be provided. Assuming that a CS in a zone can handle $m$ EVs at a time, if in future there is an increase in the overall charging demand, then that zone will require more CS.

Table 4 shows the number of charging plugs required for different vehicle classes in 15 zones. Charging plugs are calculated for peak hours. In Table 4, it is assumed that the time taken to charge (up to 80% charge) EVs by fast chargers is 10 minutes. Therefore, if one EV can be charged in 10 min by one fast charger, then in 60 min, six EVs can be charged by a single charger. In this study, peak hour traffic is the traffic during rush hour, which is taken as 2 h. Therefore, we divide the charging demand by 12, as one charger can charge 12 EVs in 2 h.

Figure 6 shows a combination graph of zone area, charging demand and estimated total CS for each category of vehicles versus zone number and CS location. As seen from the figure, the minimum demand for charging is 76 vehicles during peak hours (2 h) in zone no. 326. The area of this zone is 2.33 sq. km and the estimated number of CS is 6. The maximum charging demand is 11,197 EVs in zone no. 88. The area of this zone is 0.76 sq. km and the estimated number of CS is 933, which is very large compared to the area. There are totally eight zones which have an area less than 1 sq. km. However, the charging demand is low in all the smaller zones. Zone no. 234 is the smallest

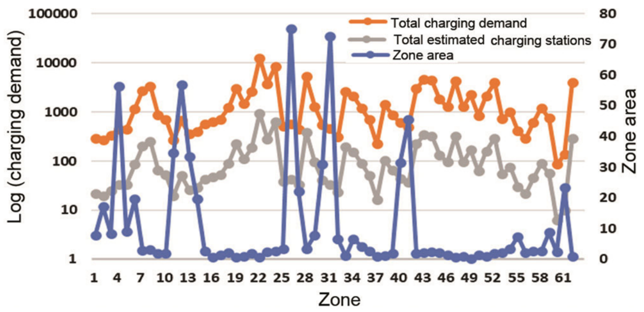


**Figure 6.** Total demand and estimated number of charging stations versus area of zones for the study region.

zone in Delhi which has an area of 0.31 sq. km with a charging demand of 2011 EVs and an estimated number of CS as 168.

## Conclusion

Locating EV CS is a complex and multi-objective problem. CS location depends on various factors like drag distance, construction cost, operating cost, power grid, profit, drag distance, coverage of CS, charging demand and waiting time. Optimizing fast-charging station location by maximizing its coverage simultaneously minimizes the number of CS required.

This study locates a fast-charging station for mixed traffic flow using the set cover method. The distance matrix of a zone is the key to find the optimum location by set cover method to maximize coverage of CS. As the parameter *h* (distance the driver is willing to drive to a CS) increases, the number of CS locations will decrease. The results show that for a covering range of 3 km, 62 CS are required. Further, a decrease in the coverage range by 1 km leads to an increase in the number of CS required by 72%. The location of CS obtained by this method covers all zones. Therefore, the charging demand of zones is covered by at least one CS.

To conclude, the EV penetration rate is important for installing charging plugs. Calculating charging demand specifically for mixed traffic is a complex problem. EV penetration rate gives the value of energy demand. The present study locates CS for a mixed traffic flow; therefore, the study refers to EV penetration rate for the individual vehicle classes. Since EV penetration rate differs for different classes of vehicles, this study will be useful for locating CS in mixed traffic conditions. It will also help locate CS in different cities across India.

*Conflict of interest:* The authors declare that there is no conflict of interest.


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