Optimal Infrastructure Planning and Placement of Charging Station for Electric Vehicles -A review

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Abstract. In the present scenario, global warming and climate change are the major concerns that can severely affect the environment and life on earth, so the World is going towards sustainability. Due to environmental pollution and the ever-growing energy demand, there has been a shift from conventional vehicles toward electric vehicles (EVs). Public acceptance of EVs and their large-scale deployment raises the requirement for a fully operational charging infrastructure. Charging station (CS) planning for electric vehicles (EVs) for a region has become an important concern for urban planners to meet the escalating demand for EVs. There are diverse challenges and parameters concerned with finding an optimal placement and infrastructure planning for setting up charging stations for electric vehicles in a smart city.
Research is going on all over the globe to reach optimal solutions to this problem by meeting those challenges. This paper aims to provide a comprehensive review of some recent state-of-the-art proposals on this emerging research field. The core proposal presented in techniques are elaborated and the advantages and disadvantages of the proposals are unveiled. A comparison of the reviewed techniques is also depicted and light is flashed on the future direction of research in this field.

Keywords: Electric vehicle(EV) · Charging station placement · Infrastructure planning · Genetic algorithm · Machine Learning

1 Introduction

Attention to the environment in consideration with sustainable development has become an utmost necessity for the survival of humans and other species. The rise in greenhouse gas emission from diverse sectors is not only the driving factor for global warming, but it also has damaging effects on human health related to cardiovascular and respiratory diseases [1] [2]. Research have found its adverse impact on pregnancy, such as premature birth, reduced birth weight, and physical and mental disabilities [3].

According to current research [4], the transport sector is the miscreant of committing 27% of global greenhouse gas emissions. To reduce the use of fossil fuel, the policymakers of several countries are leaning towards the use of electric vehicles, and their improved performance, hassle-free, and less maintenance cost also gains public acceptance with a sharp positive slope.

For accommodating more electric vehicles (EVs) to the battle against fossil fuel consumption, the problem of charging station placement in an urban area is an inevitable issue and could be found costly if done improperly. Incorporating EVs into an existing self-contained transportation system is a tedious and challenging task. With the increase of EV the transportation network must be equipped with sufficient number of charging stations and at suitable locations for mass accessing. As there exists home charging facility mainly to the smaller units like cars, improper placement of charging station in the transportation network may lead to financial loss to both the vehicle and charging station owner.

Charging of electric vehicles is a time taking process (even if a fast charging facility is used) than refueling at some oil pump. For this reason, the driver or the owner generally chooses the parking time for getting charged. It causes heavy demand for charging at some points of interest (like offices, malls, restaurants, and places with religious or tourist attractions) while some places face lesser demand. Often it is found that vehicles roaming on the road may need immediate charging and heavy traffic flow some portions of the transport access network also increases the demand. Thus demand plays an important role in the placement of charging stations.

Several factors related to infrastructure must be in consideration while setting up a charging station. Area required for establishing a charging station is inversely proportional to the budget constraints. From general convention the cost of land is high in a developed area like a tourist place, official area, an area with a dense population, or having more infrastructure setup. Already it is mentioned that the demand of charging is generally more is those areas. Thus to accommodate more vehicles for charging, the station must be equipped with more charging points or must be accompanied by a lengthy waiting queue. So there is a trade-off between area and budget constraints.

Setting up a charging station requires an uninterrupted electricity supply with stable voltage. Electricity cost is also a contributing factor. Thus electricity cost must be included within the infrastructure cost for setting a charging station.

Placing charging stations in locations where there is no proper road connectivity to surrounding areas, placing them without considering traffic issues in that area, no proper queue length planning, and not satisfying electric demand in that grid leads to financial loss to charging station owners.

Solely expanding the population of EVs in a city without enough road connections and corresponding charging and parking infrastructure will suppress the practicability of EVs due to their limited driving ranges. Planners are focused on providing an adequate charging infrastructure to a planning area. To supply the area, vehicles driving ranges have to be enlarged and electricity suppliers will need to constraints with power grid around charging stations. The locations of charging stations are critical. An EV should always be able to access a charging station within its capacity anywhere in the city. They should not only be pervasive enough such that an EV anywhere can easily access a charging station within its driving range. It can be extended to every corner of the city by having the EV recharged at a charging station available nearby.

The large-scale adoption of EVs requires a fully operational charging infrastructure. Charging infrastructure planning involves interactions between both the road and power distribution network. The location preference and setting up of charging stations in a city should minimize the construction cost with coverage extended to the whole city and fulfillment of drivers' convenience. Based on these perspectives, this paper has assessed the proposed techniques available in some state-of-the art proposals on EV charging station placement and infrastructure planning.

2 Literature review

With the increased adoption of electric vehicles (EV) in the transport sections of different developed and developing countries the need to set up charging stations is at utmost priority to keep the transport section in flow. A number of factors like road network, traffic flow, population density, point of interest, and infrastructure have influence in taking the decision of setting up a charging station. Research is going all over the globe [5] [6] [7] [8] [9] [10] to find an optimal location for setting up a charging station for EV.

A pioneering proposal for finding the optimal location for charging station setup is found in [11]. The proposal is developed on two main factors; the demand covered with a threshold level of service provided and the number of charging stations with service capacity. Simulation–optimization model is used in [12] to compare different possible locations such as universities, shopping malls, working places, etc. with different levels of charging infrastructure for possible consideration of charging stations setup location. A type of work is noticed in [13] which has used whale optimization algorithm to find optimal locations as well as service capacity for an EV charging station.

Lam et. al. [14] have designed the problem of placing a charging station with two conditions- i)accessing it from anywhere within its driving range by an EV and ii) spreaded widely such that each EV can roam in the city without range anxiety. They have also proved that the problem is a NP-hard problem. Four solutions employing a mixed-integer linear program, greedy approach, effective mixed-integer linear program, and Chemical Reaction Optimization are used in the research to find a solution for the problem. Optimal planning for setting up a charging station is presented in [15]. The proposed method first finds the service radius of the proposed charging station using Voronoi diagram. Service radius is dependent on several factors like driving range, state of charge, depth of discharge etc. An objective function is derived for the optimal size of the charging station and its associated cost for setting it up. A modified primal-dual interior point algorithm (MPDIPA) is employed to solve the optimization problem. Several optimization approaches like ant colony optimization [16] [17] [18] [19], particle swam optimization [20] [21], arithmetic optimization algorithm (AOA) [22], antlion optimization algorithm [23], etc. are used to address effective solutions for charging station placement problem.

Charging demand is one of the major deciding factors for the optimal placement of a charging station. The proposal for the placement of a fast charging EV station is addressed in [24] which has taken urban traffic data as a deciding factor into consideration. The model has divided the whole city into several non-overlapping areas (districts) and hourly traffic circulation data comprising of inward, outward, and within the area are collected for each district. A mixed-integer nonlinear (MINLP) problem aiming to minimize the EV charging cost is framed using traffic circulation data, user behavior related to charging demand and an increase in the cost of charging in peak hours. The application of the genetic algorithm finds the suitable location of the charging station as well as its capacity. Some notable works for finding suitable placement locations of charging stations considering traffic flow are available in literature [25] [26] [27] [28] [29].

One of the influential factors in choosing a suitable location for setting up a charging station is the behavior of the drivers of EVs. This has a direct impact on charging demand at any charging station. A recent work [30] is done over the placement location strategy of charging stations based on driver behavior. Here the planning area is divided into non-overlapping zones each having a charging station. An EV driver may visit to some other zones for charging by deriving a charging cost function containing travel time, travel distance, charging fare, and queuing duration as parameters. To minimize the charging cost function k-Level nested Quantal Response Equilibrium (k-Level QRE) is used. This charging behavior model is used to develop a social cost function (total time for waiting in queue) with the objective to minimize the latter within a budget constraint. The algorithm for finding a location for setting the charging station is implemented based on multi-start point searching, derivative approximation, and gradient descent method. Pan et al. [31] technique has taken the recent activities of EV drivers', availability of home and public infrastructure, range anxiety, and the battery power consumption of remaining trips into consideration to model the charging behavior of EV drivers. Some related notable works considering charging station choice behavior are found in [32] [33] [34] [35] [36].

Cost is an important deciding factor for setting up a charging station. The cost contains fixed costs (land cost, structural setup cost) and operation costs (cost of electricity, workers' salary, maintenance cost). For finding the cost function for setting up the charging stations, different types of cost functions may be calculated. The aim is to minimize the cost function so that the charging station owners can be benefited. Land acquisition cost, installation cost, maintenance cost, and protection cost with the objective of charging station deployment are been derived in [37]. Some electrical parameters like a substation power grid, voltage regulation, line capacity, and sensitivity validation are also taken into account. Awasthi .et.al [38] have derived an equation for cost function with parameters like development cost, charging point cost, land cost, and maintenance cost(real power reduction index, reactive power reduction index, voltage profile improvement index). The decision of selecting a suitable location for the charging station is done by using the GAIPSO algorithm, a hybrid method of genetic algorithm, and particle swarm optimization. A modified primal-dual interior point algorithm (MPDIPA) based technique [39] is used to solve the optimization problem aiming to decrease the cost of the charging station. The total cost includes land, charging facility, electrification cost, electric grid loss, and electric vehicle loss due to the charging travel. Some notable works related to cost function are given in [40] [41], [42], [43].

Machine learning is taking its way and providing great contributions in different research areas. A large number of recent research works related to the optimal placement of charging stations in a smart city have used machine learning algorithms successfully. A machine learning-based approach for suitable placement of charging stations is available in [44]. The research work has taken a data set containing parameters like location, type of point of interest, population density, etc. for possible consideration of setting up a charging station. Logistic regression, SVM, K-nearest neighbor(KNN), and Neural network are applied over the dataset. The validation accuracy is received as 89% for KNN. Several notable research works on placement issues have used different supervised and unsupervised learning algorithms like logistic regression [45], K-means [46], clustering [47], hierarchical clustering [48] etc. A wide use of reinforcement learning for charging station deployment problem are addressed in different literature [49] [50] [51].

3 Anatomization of some state-of-the-art techniques

A proposal for the optimal placement of a charging station in a smart city is available in [52]. The paper has framed a mobility model for priority-based charging for EV with low battery power. Genetic programming is used to determine the optimal placement of the charging station based on the mobility model. According to the assumptions taken by the authors

i) The average state of charge (SOC) used by an EV is linear and follows Eqn 1 (let an EV travels distance d in $(t_2 - t_1)$ time)

$$SOC_{avg} = \frac{SOC_{t_1} - SOC_{t_2}}{d} \tag{1}$$

ii) The charging time (t) of an EV is linear in nature and follows Eqn 2 (let battery of an EV is charged at a rate $r\%$)

$$t = \frac{SOC_2 - SOC_1}{r} \tag{2}$$

The mobility model introduced in the paper is a combination of different mobility models in vehicular ad-hoc networks (VANETs) [53] [54] addressing issues like a random selection of road topology according to its characteristics (origin–destination, railway crossing), traffic of different level at different sections, behavior of the car driver etc. The mobility model has two states namely a) Basis and b) attraction. When an EV reaches a certain threshold limit of its charge SOC^{th}, it enters into the attraction state which may minimize the trip length or trip duration, and trying to reach the nearest charging station- may be in cost of more waiting (queueing) time. To deploy p charging stations, each with maximum k charging points, with a total serving capacity of X kWh for each, m distinct locations are selected according to the model. Genetic programming is used for modeling the deployment of charging points to individual charging stations (aim is to map total p charging stations to m distinct location) using algorithm 1.

Algorithm 1:

Input: Populate solution '*Sol*' with P random values, Number of iterations G, fraction value f

Output: Set of feasible solutions along with their fitness values.

I. **for** *i=1 to G* **do**

  i) Compute fitness values for each solution
  ii) Sort *Sol* according to the fitness value to get Soc_{sort}, the sorted state of charge.
  iii) Discard the least $f \times P$ number of solutions from *Sol*.
  iv) Populate *Sol* with new values by pairwise combining the existing solutions

The whole process is repeated for the target number G of generations. The outcome of the process is a set of feasible solutions, along with their fitness values. The best among such solutions is, with statistical certainty, very close to the actual optimal solution.

For the performance of the algorithm 1 some data like area size, number of e-vehicles, number of charging stations, the total number of charging plugs, average battery capacity of each vehicle, average driving range, the average threshold value of SOC, etc. related to the smart city are provided. Simulation is done for the city of Vienna with 720 existing vehicles and 720 inserted vehicles per hour. SUMO simulator is used to perform the simulation.

A big data analysis-based model for finding the optimal locations for the charging station of EV is presented by Wagner and Götzinger [55]. According to their proposal, first some important locations (point of interest, PoI) are determined. Those are categorized into different types (P^{type})- then the optimal locations for setting up the charging station are derived based on the charging infrastructure used by the EVs. Finally, Big data analysis is applied to compute the charging station infrastructure based on urban economics like land uses.

The location is determined by two ways i) Maximum coverage optimization and ii) Iterative optimization using penalties. Those are discussed below.

i) Maximum coverage Optimization (MCO):

The city area (M) is divided into some blocks (B_i) each having an equal area. Each block is defined by triple tuples $\{B_i^{latitude}, B_i^{longitude}, B_i^{rank}\}$, where B_i^{rank} is found using Equation 3

$$B_i^{rank} = \sum_{j=1}^{n}(pt_j^{rank}) \tag{3}$$

where pt denotes an individual member of some particular type of PoI and the distance between the central point of each block to point of interest is less than 100 meter.

Each block can be considered as a potential location for the placement of a charging point. The demand of a charging station is contributed by the demands of its neighboring blocks. The method has used linear programming to select the charging station subject to maximize the demand covered by a charging station. The researchers have used the maximum coverage facility location model available in [56].

Algorithm 2:

I. **Computation of the rank of charging station**

i)Consider a set of charging stations

$C = \{c_i\}$, each having attributes

$c_i^{latitude}$: Latitude,$c_i^{longitude}$: Longitude,

c_i^{freq}: number of EVs getting charged in a day,

$c_i^{duration}$: Average daily service period

ii)The rank of the charging station is derived as

$c_i^{rank} = \sum_{day=1}^{n} \frac{C_{day,i}^{freq} . C_{day,i}^{duration}}{n}$

II. **Computation of the rank of points of interests(POI)**

i)Consider a set of point of interests

$P = \{P_i\}$, each having attributes

$P_i^{latitude}$: Latitude,$P_i^{longitude}$: Longitude,

P_i^{type}: Type of the point of interest (bank, restaurant, park etc.)

ii)The rank of the POI is derived as

$P_i^{rank} = \sum_{j=1}^{n} c_j^{rank}\ where\ dist(C_j, P_i) <= \rho$

where, $dist(C_j, P_i)$ is derived using Haversine formula [57] and ρ is some preset distance.

III. **Computation of the rank of each type of points of interest**

i)Let $P_j^{type} \in pt_i^{type}$ (Let, all restaurants)

ii)The rank of each p_j^{type} is computed as

$pt_i^{rank} = \frac{\sum_{j=1}^{n} p_j^{rank}}{n}$, where $p_j^{type} = pt_i^{type}$

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ii) Iterative optimization using penalties (IOP): The influence of a charging station is inversely proportional to the distance between the charging point and its surrounding point of interest (POI). The general practice of an EV owner is to get charged from a neighboring charging point of its destination;-which finally contributes to the demand of a charging station. Thus a penalty function can be defined to recalculate pt_j^{type} surrounding a possible charging point placed as in Eqn 4 .

$$\Delta(B_i) = \sum_{j=1}^{n} \frac{dist(B_i, P_j)}{\delta_{dist}.\delta_{fac}} \tag{4}$$

The basic difference between MCO and IOP is that the first one is a static one where the rank of POI does not change at any time (even after placing a charging station in a neighbor location) but, on the contrary in IOP that rank is determined at the runtime based on the position of a charging station. If there are more POIs in a block and if a charging station is unable to cover the demand then IOP facilitates to setup of more charging points in the block.

For the experimental purpose, the researchers have taken the cities Amsterdam and Brussels. Amsterdam city (which already has a working CP system with more than 230 stations in total) performed with the optimization scheme with p = 230 to produce a comparable output. At first, Amsterdam city is divided into grids with an edge length of 100 meters for each box and an overall planning area of approximately 9 square kilometers. For each grid, the box factor is calculated using Equation 3. The maximum coverage problem is determined by a radius of 100 meters around the grids for Amsterdam. For the iterative optimization using penalties techniques, they have considered penalty distance value $\delta_{dist} = 0.5$ and a penalty factor $\delta_{fac} = 1$. The case study for Brussels showed that this approach is applicable to planning a charging infrastructure for any city, even if there is not a single charging station available currently. (Since In this case study the author assumed that currently there is no active charging infrastructure available in Brussels) The results for both Amsterdam and Brussels are computed using statistical and computational analysis.

In [58], the authors examine the impact of different deployment levels of public charging infrastructure in a smart city. Two terms 'Missed trip' and 'Missed miles' associated with range anxiety (maximum range an EV can travel) are considered to propose the charging station deployment model. If the destination distance of some trip k is larger than the range of the EV, then the particular trip and its subsequent trips are treated as missed trip until the EV is recharged. The total distance associated with the missed trips is considered as missed miles. An EV will only take charge from some charging stations after completing $(k-1)^{th}$ trip and if the distance in k is more than the range of its battery's SOC.

Travel patterns of drivers D_i, $i = 1, \cdot, n$ are framed by some parameters like

The following factors influence the setup of charging stations

$TD^d_{i(k)}$:Travel distance of D_i on k^{th} trip on day d (mile).
$IT^d_{i(k)}$:Idle time of D_i between k^{th} and $(k+1)^{th}$ trip on day d (hour).
$L^d_{i(k)}$: Destination in k^{th} trip on day d of D_i.
$P_{L^D_{i(k)}}$: Available power at the destination in k^{th} trip on day d of D_i.
R_i :Range of the EV D_i is driving with (mile).
C_i :Electricity consumed per mile travel by the EV, D_i isving with (kWh/mile).

CS : Site for installing charging station
x_i : $\in$ {0,1,2,3} if charging station is placed at CS_i
0 means no charging station, 1,2 and 3 are type of chargers
P_i : Charging power of CS_i
CT_i : Cost of installing charging station at CS_i

Algorithm 3:

Input: R_i: Driving range , $R^d_{SOC,i(0)}$: Initial SOC , C_i: Electricity consumption per mile, P_L :Power at all charging station where $x_j \neq 0$
Output: Destination point j to setup a charging station

I. Set missed trip $T_{miss} = 0$
II. **Computation of available charging power**
while $(k \neq 0)$ **do**
  if $(L^D_{i(k)} \in CS$ && $x_j == 0)$ **then**
    Available power $P_{L^D_{i(k)}}$ =0
  else
    $P_{L^D_{i(k)}} = f(x_j)$
  Energy increase in battery if $P_{L^D_{i(k)}} \neq 0$
    /* (Measured in increase of range) */

  i) Compute $R_{charge} = \frac{P_{L^D_{i(k)}} \times t^d_{i(k)}}{C_i}$
    /* Increase of charge (in range) of EV of D_i from charging station having power $P_{L^D_{i(k)}}$ for $t^d i(k)$ time */

  ii) Find the charge of EV (in range) as
  $R^d_{i(k)} = min(R_i, R_{charge} + R^d_{SOC,i(k)})$
  Calculate
  i) $R^d_{SOC,i(k)} = R^d_{SOC,i(k-1)} + R^d_{i(k-1)} - T^d_{i(k)}$
    /* The SOC of EV after k^{th} trip */

  ii) $R^{d_{plan}}_{SOC,i(k)} = R^d_{SOC,i(k)} - T^d_{i(k)}$
    /* Checking whether it can afford $(k+1)^{th}$ trip */

III. Find total number of missed trip as $T_{miss} = T_{miss} +$ subsequent trips on day d +1
IV. Set up a charging station at some destination point j subject to minimize $\sum_i \sum_d T_{miss}$ and $\sum_j C_j \leq B$
Where B is the budget constraint.

A generic algorithm based technique for the localization of charging stations is presented in [59]. The authors have considered a multi-agent system for data collection from different sources such as population census information, traffic data, amount of time spent at some place, geo-tagged locations etc. A variety of agents are employed to gather the information as given in Table 1.

Table 1. Types of agents

Name of Agent	**Information Collected**	**Source**
PoI agent	Points of interest	based on city development plan
Urban agent	Population information	Census data
Traffic agent	Amount of traffic	Traffic Department
Popularity agent	Marking popular places	Number of visitors and amount of time spent over a time span
Social network agent	Geo tagged location	Social media

It is to be noted that except PoI agent the remaining agents are grouped under data processing agent.

The presented model contains six stages. In the first stage, the PoI agent selects some point of interest (PoI) based on importance (number of visitors) to possible set up of charging stations. To find the area of influence (service area covered) by taking the PoI as centroid, in the second state the PoI agent constructs the Voronoi diagram which in fact divides the city area into non-overlapping polygons. In the third and fourth stages the data processing agent, working on the polygonally divided city area collects data on population density, traffic flow information, degree of popularity, and geo-tagged in the social network for each polygon. The emplacement optimizer agent working in the fifth stage analyzes a set of possible configurations for setting a charging station and selects the optimal configuration using genetic algorithm. In the final stage, the user interface agent publishes the results on a website in such a way that the intended users can easily search and use the information as required. The block diagram of the technique (in [59]) is presented in Fig. 1.

The prime part of the method is to determine the pertinent location for setting up a charging station- the responsibility of which is given to the emplacement optimizer agent.

The emplacement optimizer agent selects some possible locations $P = \{p_1, p_2, \cdots, p_n\}$ for setting up charging stations, where each p_i has six attributes namely $a_{population}$, $a_{traffic}$, a_{time}, a_{social}, $cost_{area}$, $cost_{per-charger}$ and p_i is a PoI of the city under study.

The agent also considers the number of charging points in each charging station as $S = \{s_1, s_2, \cdots, s_n\}$, where $0 < s_i \leq max - charger - per - POI$.

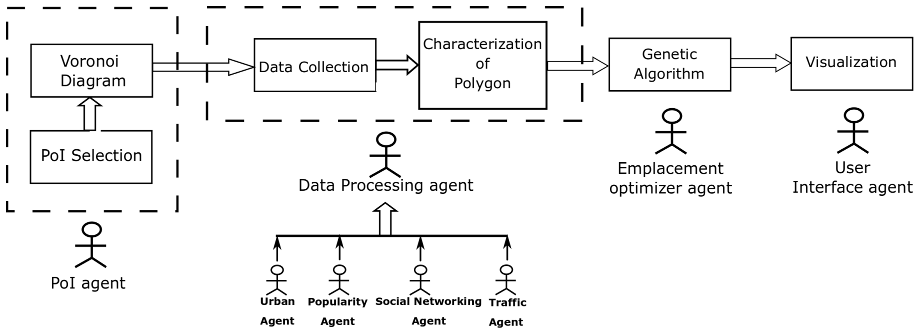

Fig. 1. Block diagram of Jordán et. al scheme [59]

From these above two considerations, a configuration $C_i = \{p_i, s_i\}$ can be provided which is treated as chromosome for the Genetic algorithm program. For each configuration, the fitness value is computed by Eqn. 5.

$$V(C_i) = \sum((w_p.a_{population} + w_{tr}.a_{traffic} + w_t.a_{time} + w_s.a_{social}) \\ - (w_a.cost_{area} + w_c.cost_{per-charger}.|S_i|)) \tag{5}$$

The tournament selection method over the chromosome creates various random agents of individuals, called tournaments - from which the best one of each group is picked. A genetic algorithm is applied over these selected chromosomes and mutation among the chromosomes generates the best configuration for setting up the charging stations.

For the experimental purpose, the researchers have taken Valencia city of Spain as a testing bed. For their experiment, they used an initial population of 250 individuals, which evolve in the GA through 200 generations. There are 926 PoIs in the city of Valencia after performing the clustering. Their goal is to locate 100 charging points in the provided PoIs, considering a max charger per poi of 4. They have taken the weights for the different parameters for the city are $w_p = 0.4$; $w_t r = 0.3$; $w_t = 02$; and $w_s = 0.1$ which represents the population, traffic, time spent in a place and social activity, respectively. The weights for the costs cost area and cost per charger are $w_a = 0.5$ and $w_c = 0.5$, respectively. Finally, they have taken the probability of performing a crossover operation as 0.5, while the probability of performing a mutation operation is 0.05.

For their first crossover mutation, the crossover consists of a series of tests to evaluate the maximum fitness of the best individual that the GA can achieve using different values of g and n. Therefore, they have used an approximation of the maximum values of g and n depending on the values of the problem to solve. g and n are the parameters of the graph crossover corresponding to the number of subgraphs and the depth level of neighbors. Finally, their proposed algorithm incorporates a new crossover method which is specially designed for geolocated domains. Experiments have also shown a good performance of the newly proposed crossover method.

In a smart city, the charging stations must be placed in such a way that any EV operating in the road transportation network will find a charging station before its charge is fully exhausted. Given a road transportation network and a set of routes, the aim is to place a minimum number of charging stations in the network such that any EV will get a charging station before its charge is fully exhausted. This is known as route node coverage problem (RNC). Fredriksson et. al. [60] have taken into consideration the RNC problem and have proposed an iterative approximation approach to find optimal locations for charging stations placement. The first phase of the proposal is the problem formation consisting the items as given in Table 2.

Table 2. Notations used in Fredriksson et. al. [60] scheme

N	Set of nodes
A	Set of links
R	Set of routes δ_{ij} =1 if $j \in R$ and $i \in N$
d	Number of nodes in the network
x_i	Allocation of charging station at node i $x_i = 1$ means allocates, otherwise 0
c(j)	Travel cost of route $j \in R$ (length of the route)
c	Maximal route cost; It must be less than the driving range of an EV

The route $j \in R$ is considered to be covered if $\sum \delta_{ij} x_i \geq 1$. Thus the route node optimization problem can be framed as

“For a given road transportation network with N nodes and having R number of routes to setup minimum number of chargimg station x_i such that each route $j \in R$ is covered by a charging station. " and mathematically it can be denoted as Equation 6

$$min \left\{ \sum_{i \in N} x_i | \sum_{i \in N} \delta_{ij} x_i \geq 1, \forall j \in R_k, x \in \{0,1\}^d \right\} \quad (6)$$

In this paper [60], the author proposed an approach to optimally allocate charging stations in large-scale transportation networks for electric vehicles. They have described the Root Node Coverage (RNC) Problem where they have found the minimum number of charging stations and their locations in order

to cover the most probable routes in the transportation road network. They have proposed an iterative approximation technique for RNC where the associate integer problem is solved by exploiting a probabilistic random walk route selection and thereby taking advantage of the numerical stability and efficiency of the standard IP software packages.
The paper also proposes a methodology based on self-avoiding random walks along the links in the network, combined with a probabilistic rule applied at each node (intersection) in the network. The optimal location of charging stations in the network is selected by solving a pruned integer problem.

Their main idea is to iteratively solve small sub-problems of the RNC problem, and continuously further extend the current subproblem to a slightly larger problem. This will continuously strive for a solution with a minimal number of charging stations. Their procedure ensures coverage and localizes interesting common junctions within the given transportation network. The purpose of this procedure is to ensure that a charging station is placed in an environment that is of mutual interest to several of the found routes.

The proposed method to solve our RNC problem is based on integer programming, and the outline of the method can be described in Algorithm 4 with the following basic steps:

Algorithm 4:

Step 1: Initialization: Set $R_k = \phi$. Fix $x_i = 1$ if a charging station is already allocated at node $i \in N$, and fix an upper route length bound C.
Step 2: Given a reference set $R_k \subset R$, solve the subproblem.

$$\left(P^{(k)}\right)\left(z^{(k)}\right) = min\left\{\sum_{i \in N} x_i : \sum_{i \in N} \delta_{ij} x_i \geq 1, \forall j \in R_k, x \in \{0,1\}^d\right\}$$

yielding the solution vector x(k).
Step 3: Define the entering index R_e by route j with $c(j) \leq c$. Stop, if a new R_e cannot be found according to some termination criteria.
Step 4: Define the new reference set by $R_{k+1} = (R_k R_e)$ and go to step 2.

In their work, they emphasized the simplicity and efficiency to find a minimal number of charging stations as well as an approximate solution that covers each found route of this hard problem. Since the procedure is based on a controlled selection of constraints, there are opportunities to add and fulfill requirements that make the procedure of selecting routes to model the transportation network even more realistic.

Optimization is a core part of machine learning. Optimization guides the machine learning algorithms to minimize their loss function. Setting up a suitable location for the placement of charging station contains several issues like accessibility, serving the demand, budget constraints and overall making profit, etc. These issues are governed by several parameters; for some of the cases, there are some common intersected regions. Thus solving the optimization problem for all the nodes with the contribution of all the parameters is a tedious task. Here machine learning algorithms, mainly reinforcement learning is a better choice.

A recent proposal [50] has exercised reinforcement learning techniques for the optimal placement of charging stations in urban areas. An optimization problem is framed from several data sources and reinforcement learning forms a charging plan in each iteration. The block diagram of the proposed model is presented in Fig. 2.

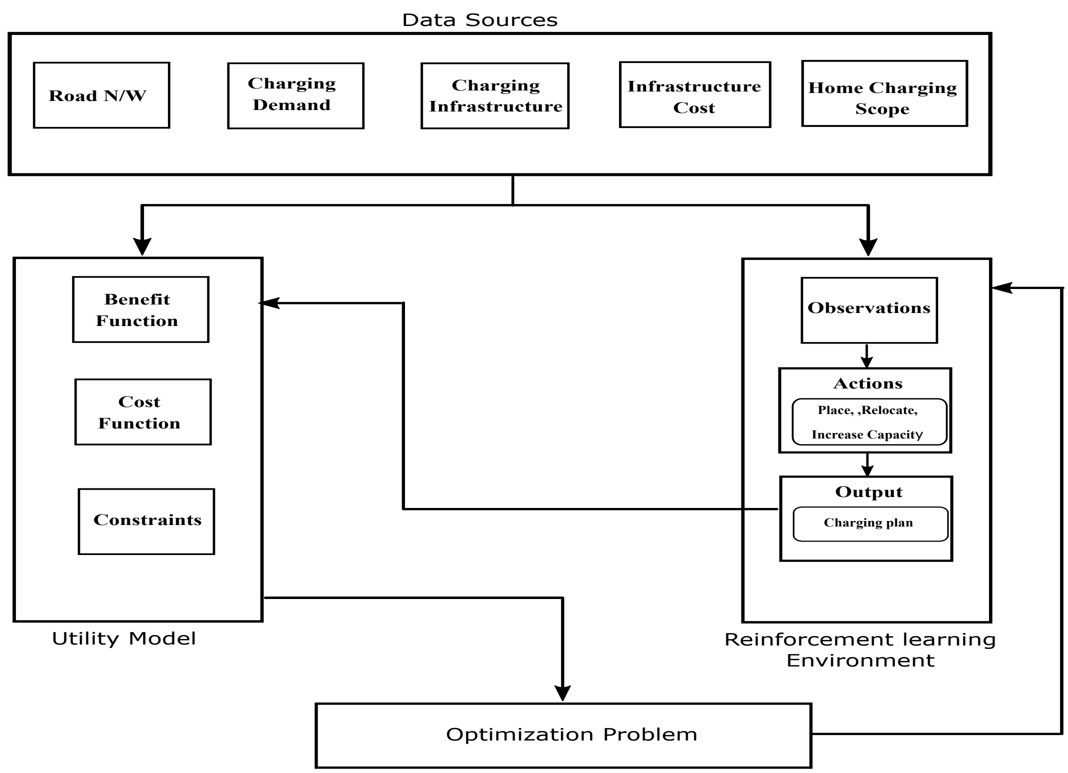

Fig. 2. Block diagram of Wahl et. al. proposal [50]

The technique has partitioned the contributing parameters into two broad classes i) Benefit function and ii) Cost function. Influential radius and coverage area are grouped under benefit function; whereas cost function contains travel

Algorithm 5:

I. **Initial considerations**

i Represent road network as $G = (V, E)$
where V=vertices , E=Directed edges with assigned weights

ii Represent charging station as $S = (v, t)$
where $v \in V$ and t represents type of charging point with following condition.
$\sum_{i=1}^{m}(s.t_i) \leq K$ (Some predefined integer constant)

iii Charging plan(p) is defined as at most one charging station per node and each node must be covered by a charging station.
P=$\{Set\ of\ charging\ plans\}$

II. **Computation of benefit function**

i Calculation of CS capacity $C(S)$
$C(S) = \sum_{i=1}^{m} t_i.C_i$
where C_i is charging power at t_i

ii Finding Coverage
a) Find max(C(s))for all charging stations
Consider maximum influential radius as r_{max}
b) Calculate $\overline{C}(S) = \frac{C(s)}{max(C(s)}$
c) Compute influential radius
$r(s) = r_{max}.\frac{1}{1+e^{-\overline{C}(s)}}$
d) Find coverage of vertex
$cov(v) = \{S \in P|$d(v,s) $\leq r(s)\}$

iii Find $home(v) \in [0, 1]$ for area with home charging facilities

iv Compute $benefit(p) = \frac{1}{|V|}\sum_{v\in V}\left(\sum_{i=1}^{cov(v)}\frac{1}{i}\right)(1 - \omega.home(v))$
where w is some weighted parameter

III. **Computation of Cost function**

i Find weakened demand of a node with CS as
$dem_{weak}(v) = dem(v)(1 - \omega.home(v))$
where $dem(v) \in [0, 1]$ is the normalized charging demand at vertex v.

ii Calculate travel time of a vehicle to reach to that CS as
$travel(p) = \sum_{v\in V}\sum_{s\in p}.i(s, v)\frac{dist(s,v)}{V}$
where V is the average velocity of a vehicle in that area.

iii Find overall charging time of a CS
$charging(p) = \sum_{s\in P}\frac{D(s)}{\mu(s)}$
where $D(s) = \sum_{v\in V}\frac{i(s,v)}{dis(s,v)}.dem_{weak}(v)$
D(s) is the number of vehicles approaching to the CS.
and $Service\ rate\ \mu = \frac{C(S)}{E}$

iv Compute expected waiting time using the Pollaczek-khintchine formula
$waiting(p) = \sum_{s\in P} W(s)D(s)$
with $W(s) = \frac{\rho(s)}{2\mu(s)(1-\rho(s)}$ for $\rho(s) \leq 1$ and $\rho = \frac{D(s)}{\mu(s)}$

v Compute $cost(p) = \alpha travel(p) + (1 - \alpha)(charging(p) + waiting(p))$
where $\alpha \in [0, 1]$ is a weighting parameter

IV.**Optimal charging placement**

i $P^* = \arg max_{p\in P}\lambda.benefit(p) - (1 - \lambda)cost(p)$

ii $\sum_{s\in P^*} = fees(s) \leq B$

iii $\sum_{i=1}^{m} s.t_i \leq K \quad \forall s \in p*$

iv $\rho(s) \leq 1 \quad \forall s \in p*$

V. **Finding installation cost**
$fee(s) = estate_{cost}(s.v) + \sum_{i=1}^{m} s.t_i.charger_{cost}(i)$

time, waiting time and charging time. The objective is to choose a charging station placement plan which maximizes the benefit but minimizes the cost function. The computation of objective function for a charging station placement plan is sketched in Algorithm 5.

Values of the objective function for a charging station placement plan found from Algorithm 5 are set as $Score$. The reinforcement learning starts with the placement of one charging station (CS) at each node with some random assignment of different types of charging points to each CSs. In each epoch of the learning process charging point/s from CS with the lowest benefit is shifted to some CS with the highest waiting and charging time with some condition satisfied. The reward/penalty for the reoriented charging station placement plan is computed from old and new $Score$ values. The iteration comes to a halt when for some CS (to which a charging point is relocated) the budget exceeds and some other conditions are satisfied. The reinforcement learning process is elaborated in Algorithm 6.

Algorithm 6: Finding Optimal charging placement using Reinforcement learning

I Set action as
- a $a^i \in$ {Create by benefit, Create by demand, Increase by benefit, Increase by demand, relocate}
- b Create by benefit is chosen for the node with low coverage
- c Create by demand is chosen for node with high $dem_{weak}(v)$

II In each iteration
- a) Find CS S_{old} having lowest benefit.
- b)Relocate one of its charging points to the CS with highest waiting time and charging time with condition $\sum_{i=1}^{m} s.t_i \leq K$ satisfied.
- if $K = 0$ for S_{old} then remove it from P

III Compute $Score(p) = \lambda.benefit(p) - (1 - \lambda)cost(p)$ for a charging plan P.

IV Set reward/penalty as $r^i = Score(p^{i+1}) - Score(p^i)$.

V Stop if any of below criteria do not satisfy
- a) $\sum_{s \in P*} = fees(s) \leq B$
- b) $\sum_{i=1}^{m} s.t_i \leq K \quad \forall\, s \in p*$
- c) $\rho(s) \leq 1 \quad \forall\, s \in p*$

4 Comparison of the techniques

A variety of techniques are used in the state of the art proposals reviewed in this scope. All of the proposals are simulated by different simulation techniques and simulation is performed over reallife data taken from some urban area. A brief comparison of the reviewed techniques is presented in Table 3.

Table 3. A comparison of the state of the art proposals reviewed in the article

Author	**Year**	**Technique used**	**Type of Simulation**	**City**
Hess.et.al [52]	2012	Genetic Algorithm	Sumo Simulator	Vienna
Wagner and Götzinger [55]	2014	i)Maximum Coverage Optimization ii)Iterative Penalty using optimization	CPLEX	Amsterdam and Brussels
Jing Dong.et.al [58]	2015	Genetic Algorithm	@Risk software	Seattle (Washington DC)
Fredriksson.et.al [60]	2019	i)root node coverage optimization ii)Integer programming model	MATLAB & Gurobi	Sioux-Falls network Southern Sweden Transportation Network
Jordan.et.al [59]	2020	Genetic Algorithm	Python programming	Valencia
Leonie Von.et.al [50]	2022	Reinforcement Learning	Machine Learning	Hanover (Germany) Dresden (Germany)

5 Discussion: some reflections

From the detailed study of the presented approaches in the discussed research articles in section 3 some advantages and drawbacks of the methods are pointed out in this section. These advantages and drawbacks help to propose some new techniques for optimal placement of charging stations in a smart city.

The Hess et. al technique [52] is a priority based model based on genetic algorithm and aims to find an optimal solution for the placement of p charging stations, each with upto X kWh and having maximum k charging points. This is a very basic model and has following advantages and drawbacks.

I. Advantages
   a) Considered vehicles' state of charge and based on that switches from basis and attraction model.
   b) Priority based charging for EV with low battery power in cost of waiting time. (Enter into attraction state)

c) Use of genetic algorithm helps in trying more potential solutions.
d) Use of VANET gives real-time data.

II. Drawbacks
a) Lack of infrastructure planning like distinct number of different types of charging points in a charging station.
b) No queue length is taken into account. (Have considered queue length is infinite)
c) Each EV are considered with same battery capacity and driving range.
d) Have not considered the demand as a factor for setting up a CS.
e) Cost for setting up a charging station is not taken into account.

The Wagner and Götzinger technique [55] is a big data analysis based model where location of a charging station is determined by maximum coverage optimization followed by iterative optimization using penalties. Following advantages and drawbacks of the model are pointed out.

I. Advantages
a) More importance is provided to popular places while computing rank. (point of interests).
b) Target is to perform maximum coverage using minimum number of charging stations.
c) Penalty is applied in iterations if the distance between point of interest and charging station is more.
d) Rank for both PoI and charging stations are considered.

II. Drawbacks
a) Airtime distance (Haversine formula), not driving route distance is taken into account.
b) No waiting queue length is taken into account.
c) Types of charging points and number of charging points are not considered for a CS.
d) Model is silent about the charging capacity of a CS.

The Dong et al. model [58] is based on two parameters 'missed trip' and 'missed miles' related to range anxiety. Some destination point j is selected for setting up a charging station subject to minimize the number of missed trip and within the budget constraints. Following advantages and disadvantages of the proposed model are noted in this current discussion.

I. Advantages
a) SOC of EVs in taken into consideration for the proposal.
b) Provision of three types of chargers are provided depending on SOC of the EV and user preferences.
c) Location of charging station is based on user travel pattern.
d) Setting up a charging station should abide by the budget constraints.

II. Drawbacks
a) Setting up a CS at some destination point have not considered the coverage area to be served by the CS. Have taken only amount of 'missed trips' occurs at that destination point before starting a new trip.

b) The proposal has not pointed to the queue length. (size of CS)
c) For setting up a CS, the budget is same for all places. But this will fail in real time implementation.
d) 'missed trip' is computed after finishing a trip and before starting a new trip. Thus charging in the midway is not allowed. Thus longer trip distances starting from a location will contribute always to 'missed trip'.

In [59] first, the data related to the smart city is collected from different sources. Some point of interest based on importance are selected for possible setup of CS. Then the coverage area in form of non-overlapping polygon for each CS is determined. For each polygons different parameters are fetched and based on those the possible configuration of each CS is determined. The observed advantages and disadvantages of the proposed model are mentioned below.

I. Advantages
   a) Proposed model is a layered approach and the activity of each layer is clearly mentioned.
   b) The models sets the locations to set up CSs and the possible configuations (number of charging point) are determined based on fitness values found from genetic algorithm.
   c) Use of genetic algorithm helps to find more potential solution.
II. Drawbacks
   a) Model is silent about types of charging points, and the capacity of each CS.
   b) In the model there is no specific mention of waiting for queue length.
   c) The proposal has not considered home charging coverage.

In [60],the author has proposed an optimization technique for optimal placement of charging stations. The problem is solved by solving a sequence of subproblems and are iteratively extended by adding routes that are generated using probabilistic self-avoiding random walks in the transportation network

1. Advantages
   (a) The model performs maximum coverage with minimum number of charging stations.
   (b) According to the model the route must be covered with at least one charging station.
   (c) Range anxiety coverage is also taken into account.
   (d) Congested routes are avoided to bypass complexity in the problem.
2. Drawbacks
   (a) No infrastructure planning is taken into account
   (b) Consideration of probabilistic random walks instead of random walks may not give optimal solution every time.
   (c) The proposal has not pointed to the waiting queue length.
   (d) All EV are assumed to have same rate of charging but in reality, each vehicle can have different charging rates.

Von et al. proposal [50] is based on reinforcement learning. The objective of the model is to choose a charging station placement plan which maximizes the benefit consisting of influential radius and coverage area but minimizes the cost function comprising of travel time, waiting time, and charging time. The advantages and drawbacks of the proposed model are jotted down.

I. Advantages
   a) The penalty/ reward function in reinforcement learning is used to determine the optimal placement of charging stations.
   b) Charging points from one CS to another are relocated based on required demand.
   c) The model considers a greedy approach for maximum coverage and minimum costs.
   d) Home charging coverage is taken into account while computing the benefit function.
   e) Budget consisting of infrastructure cost and charger cost are taken into consideration.

II. Drawbacks
   (a) Use of Haversine formula takes air distance not road distance.
   (b) Each CS is considered to have an equal distribution of coverage. Only charging points are relocated based on demand.
   (c) The model has considered the energy required to charge each vehicle is the same but in practice it will not be same
   (d) No queue length considered.

6 Conclusion and future scope

The adoption of EVs is still in its infancy. The dimensions of the distribution network, as well as the investor's mindset owing to investment and profit, may be impacted by the position of the electric vehicle charging station. The charging stations must need to serve EVs to provide smooth traffic flow and wide availability. Furthermore, the position of charging station has impact over decision of the EV user's to charge the vehicle. Several factors have direct impacts on the selection of proper location of charging stations. The recent developments in the paradigm for placement and proper planning of charging infrastructure are presented in the current review article. It has reviewed in details about the techniques used, tools applied for the simulation, the location of the testing area from which data is collected, and moreover the advantages and drawbacks of the techniques. It is being noticed that there is no general acceptable model available in this research domain. The advantages and drawbacks pointed in this review article will help the researchers to propose a general acceptable model in future for optimal placement of charging station for electric vehicle.

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