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Review

Electric Vehicles Charging Infrastructure Demand and Deployment: Challenges and Solutions

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Abstract: Present trends indicate that electrical vehicles (EVs) are favourable technology for road network transportation. The lack of easily accessible charging stations will be a negative growth driver for EV adoption. Consequently, the charging station placement and scheduling of charging activity have gained momentum among researchers all over the world. Different planning and scheduling models have been proposed in the literature. Each model is unique and has both advantages and disadvantages. Moreover, the performance of the models also varies and is location specific. A model suitable for a developing country may not be appropriate for a developed country and vice versa. This paper provides a classification and overview of charging station placement and charging activity scheduling as well as the global scenario of charging infrastructure planning. Further, this work provides the challenges and solutions to the EV charging infrastructure demand and deployment. The recommendations and future scope of EV charging infrastructure are also highlighted in this paper.

Keywords: electric vehicle; charging station; charging planning model; charging scheduling

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1. Introduction

The emerging global concerns related to environmental degradation and global warming have boosted the market penetration of electric vehicles (EVs) as an eco-friendly option. The rapid growth in the usage of EVs demands the expansion of ecological charging frames, as the EVs have a limited driving range depending on various conditions [1]. The unplanned placement of EV charging stations raises various technical and economic issues in the distribution network. The various technical issues are injection of harmonic, poor power quality, large voltage variations [2–6], stability [7], degradation of reliability [8], etc. Planning and energy management in charging stations are complex issues where a lot of effort is given by researchers and policymakers. Compressive reviews on electric vehicle charging are presented in [9,10].

In recent years, charging technologies have also advanced with the introduction of new innovations such as flash charging by Asea Brown Boveri (ABB) [11], and the charging butler robot concept by Volkswagen [12]. In [13], a bi-level stochastic encoding model has been proposed for congestion management in charging stations under power demand uncertainty. A dynamic planning scheme for energy management in the charging stations under uncertainty was proposed in [14]. In [15], a game theory-based approach has been proposed for determining pricing strategy in a photovoltaic (PV) assisted charging station considering the minimization of battery degradation cost as well as charging cost and maximization of operational revenue. An energy management strategy was proposed for EVs in a smart microgrid environment in [16], and similarly in [17] a smart charging strategy using metaheuristics is proposed.

The EV drivers' convenience and road network topology should also be considered in the placement of charging stations. In [18], a mix-integer linear programming (MILP) model was proposed to plan the charging infrastructure considering inter-city traffic. In [19], fleet sizing and charging optimization were performed for electric buses. In [20], an optimization model dependent on the real-world driving data of EVs was proposed. Several researchers have proposed a vehicle to grid (V2G) enabled electric vehicle charging station (EVCS) in the distribution network considering power system loading capability [21,22]. It is observed from the existing literature that transport engineers are concerned with the EVCS citation problem considering only economic factors and EV driver's convenience [23–26]. The charging of EVs with renewable energy resources is discussed in [27,28].

On the other hand, power system engineers give more stress to voltage stability, reliability, power losses [29], and other factors related to distribution networks while dealing with the EVCS citation problem [29–33]. There are many papers that depict diverse perspectives on the EVCS citation problem [22,34–37]. Lately, researchers have started considering both transport and distribution systems while modelling the complexity of EVCS locations [36–38]. Moreover, the superiority of the charging station placement models considering transport and distribution system is elaborated in [22]. The work not only presents an overview of the existing planning models but also provides critical insight into all the models. The key features, mathematical formulations, advantages, and disadvantages of those planning models are also presented. Moreover, an overview of the global scenario of EVCS is offered thereby reporting the standards, policies, regulations, and existing business model.

In [22,34], the charging station placement methodologies, and the impact of charging station placement on the electric grid are reviewed comprehensively. In [35] the recent trend in optimization techniques for getting optimal charging station locations is reviewed. In [36,37] the policies, methodologies, and challenges of EV charging station placement in China are studied. Various works in the area of EV charging strategies, control, EVS in the market, and microgrids are presented in Table 1. Compared to the existing review works on EV charging station placement, the contributions of the present work are as follows:

- A classification of the planning models for charging station placement is provided.
- An overview of the planning models is provided thereby elaborating the mathematical formulations and simulation results.
- A comparison of the planning model is provided illuminating the key features, advantages, and disadvantages of each model.
- Area-wise suitability of the planning models is suggested.
- An overview of the operation and scheduling of charging activity in the charging station is presented.
- An overview of the global scenario of charging infrastructure planning is presented thereby reporting the standards, policies, regulations, and existing business model.

Table 1. Summary of various EV charging, scheduling, and control strategies.

S. No.	Consideration	References	Remarks
1	Decentralized charging control, and scheduling	[38–66]	Many works reported both scheduling and charging.
2	EVs in the electricity market	[67–76]	Both the energy market and ancillary services are discussed.
3	EVs in smart grids and microgrids	[66,77–86]	Role of EVs in smart grid and microgrids are presented.
4	Intelligent system applications in solving EV problems.	[87–96]	Agent-based, data-driven-based, and other nature-based techniques are used.
5	Performance evaluation charging algorithms	[96–100]	Various studies are carried out.

The manuscript has been organized as follows. Section 2 presents a general perspective of charging station placement. Section 3 presents a brief classification of the planning models. Sections 4 and 5 present static and dynamic planning models, respectively. Section 6 presents the comparison of planning models and elaborates on the complexities of the charging schedule. Section 7 presents some recommendations and finally, the future research direction in charging infrastructure planning followed by concluding remarks.

2. General Perspective of Charging Station Placement

EVCS citation is a distinctive scheduling problem seeking an optimal allocation and sizing of charging stations as cost-effective factors, operating parameters of distribution network, and EV driver's convenience. The characteristics of a good charging station placement model are as follows:

- The model must take into account both transport and distribution network parameters
- The model must have the ability to consider economic factors associated with the establishment of charging stations
- The model must consider EV drivers' convenience
- The model must consider the security of the distribution network
- The model should be able to produce the output planning results with less computational costs

A systematic overview of the charging station placement is shown in Figure 1. The first step of the charging station placement problem is the selection of the test network where charging stations are to be placed. Then the input parameters required for computing the optimal locations and number of charging stations are set. Consequently, the objective functions and constraints are defined and finally optimization is performed. The general mathematical formulation of the charging station placement problem is as follows [22]:

$$Min(\mathrm{J}) = f(\mathrm{l}, \mu_{fast}, \mu_{slow}) \quad (1)$$

where, J is the objective function l, μ_{fast}, and μ_{slow} are the decision variable matrices.

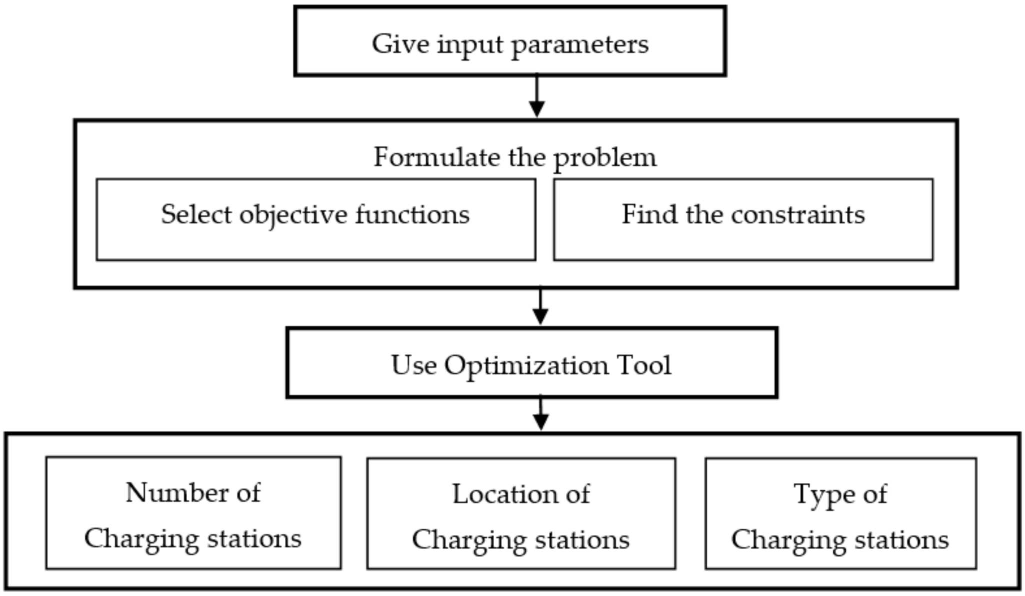

Figure 1. Steps of charging station placement solution.

The list of objective functions is shown in Table 1. The distribution network objective functions describing the smooth operation of the power grid include the parameters such as voltage stability, reliability, power loss, etc. Transport network objective functions include EV flow, distance, accessibility index, etc. Apart from transport and distribution network objective functions, there are economic objective functions including different types of cost as shown in Table 2.

$$\mu_{fast}{}^{min} \leq \mu_{fast} \leq \mu_{fast}{}^{max} \text{ and } \mu_{fast}{}^{min} \leq \mu_{slow} \leq \mu_{fast}{}^{max} \tag{2}$$

$$g_j(l, \mu_{fast}, \mu_{slow}) \tag{3}$$

$$h_k(l, \mu_{fast}, \mu_{slow}) \tag{4}$$

Table 2. Various objective functions of placement problem [101].

Economic Objectives	Transport Network Objectives	Distribution System Objectives
Installation cost	Flow of EVs	Power loss
Operation cost	Travelling distance	Net benefit
Maintenance cost	Accessibility of CS	Total harmonic distortion
Reinforcement cost	Time required for charging	Voltage stability
Equipment cost	Waiting time	Reliability

The list of constraints is given in Table 3.

Table 3. Various constraints of placement problem [102].

Equality Constraints	Inequality Constraints
Charging demand balance	Limit on number of charging stations
Real and reactive power balance	Current limit and voltage limits
	Budget limit

The first constraint takes into account the average delay probability for obtaining the charging service while the second constraint takes the average service coverage into consideration.

3. Classification of Planning Models

The placement problem of charging stations (CS) provides the optimal location of charging stations (CSs). The objective functions, associated constraints, EV drivers' behaviour and load modelling are different for each planning model. Figure 2 shows the classifications of various planning models for EV charging station placement. Detailed descriptions of all the classifications of the charging station placement problem shown in Figure 2 are presented in the subsequent sections.

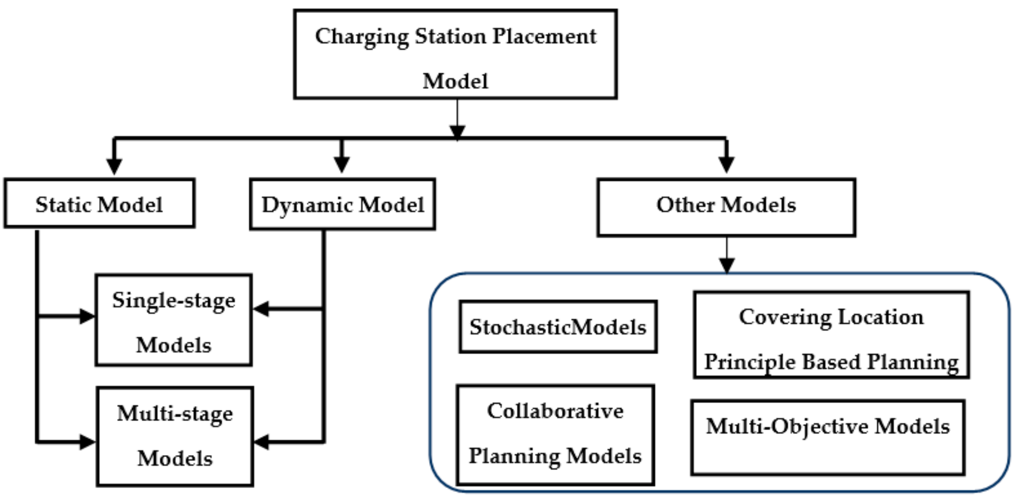

Figure 2. CS placement problem classification.

3.1. Static Planning Models

As the name indicates, the static models formulate the charging station placement problem as static. The time variability of load demand is not considered in the static planning models. Static models generally formulate the problem considering the worst-case peak loading condition. The reason behind this is that if the model can sustain peak load conditions, then it can sustain any other loading conditions. Further, depending upon the stages involved in the planning model, the static models are classified into single-stage and multi-stage static models.

3.1.1. Stage Static Planning Model I (SS I)

This planning model is suggested by Wang et al. in 2013 [39] and is treated as one of the pioneering works in the CS placement considering transport and distribution networks. This work modelled the CS placement problem in a multi-objective framework taking into account the EV driver's convenience and the reduction of voltage deviation and power losses due to placement of the EV charger load. The objective functions considered in the planning model were maximization of EV flow, minimization of power losses, and voltage deviations. Theoretically, EV flow is defined as the number of EVs traversing in the edges connecting two nodes of the transport network [40]. The introduction of a new EV charging load causes changes in the power flow of the distribution system resulting in a change in current and voltage of the nodes. Consequently, the power losses of the distribution network increase. For computational simplicity, the power loss was expressed as a function of the active and reactive power demand of charging stations. Voltage deviation was expressed as the ratio of the difference between voltage after charging station placement and base case voltage to base case voltage. The following objectives, with the constraints, are normally used.

- Maximization of EV flow (F_1) ensuring the convenience of the EV drivers subject to the following:
    1. Capacity limit of EV charging stations,
    2. EV charging stations to be built in accordance with the investment
    3. A single CS of a specific capacity can be developed at a particular location.
- Minimization of power loss (F_2) subject to the equality constraints: power flow balance constraint at the charging station, and real and reactive power flow balance of the distribution network. The inequality constraints are the nodal voltage limits and branch power flow limits. The availability of charging power of the stations must be more than charging demand.
- Minimization of voltage deviation(F_3) subject to the same equality and inequality constraints used for power loss minimization.

The planning model was tested on a 25-node road network and an IEEE 33-bus distribution network. The 25-node road network, which is not a practical network, is a test system. Hence, the traffic flows along the routes were generated artificially by the centre of gravity method [40]. The authors solved the CS placement problem for different combinations of objective functions and constraints as given by:

- Case 1—Objective function F_2 and F_3
- Case 2—Objective function F_1
- Case 3—Objective function F_1, F_2, F_3

The simulation results showed that the third case where all the three objective functions and all the constraints were considered yielded better results. In Case 1, the power loss and voltage deviation were less compared to Cases 2 and 3 However, in Case 1 charging stations were placed at nodes 12, 13, 14, and 16. Placement of the charging stations in such close proximity would result in inconvenience for the EV drivers. Case 2 takes into account only EV flow and neglects distribution network parameters. Consequently, the power losses and voltage deviation were quite high (0.2575 MW and 3.251%) in Case 2.

Simulation results established that Case 3 was a better planning scheme than Case 2 and Case 1 where a trade-off was achieved between the safety of the power system and EV drivers' convenience.

3.1.2. Stage Static Planning Model II (SS I)

This planning model is suggested by Islam et al. in 2015 [41]. The planning model was concerned with only siting of CSs. The sizing of CSs was performed by deterministic formulae. In addition, the model considers only the placement of rapid fast charging stations while formulating the CS placement problem. The model considered establishment or build-up cost, traveling energy loss, and substation energy loss costs as objective functions. Establishment cost includes the cost of land, distribution transformers, chargers, and underground distribution cables. Traveling energy loss cost includes the additional cost incurred because of traveling the distance between charging point demand and CSs. Substation energy loss includes the increased power losses due to the placement of CSs.

The objective functions along with the different constraints considered in this planning model are presented below:

- Minimization of built-up cost or establishment cost (O1) including the fixed cost, land cost which depends on the number of chargers at a station, charger cost, underground cable cost, transformer cost, and operation cost.
- Minimization of traveling energy cost (O2) which is equal to the route distance, cost of electricity, and electricity consumed.
- Minimization of power loss due to the placement of the charging station (O2).

3.1.3. Single-Stage Static Planning Model III (SS III)

This planning model was put forward by Zhang et al. in 2016 [42]. An integrated planning framework is proposed for different types of charging facilities like public charging stations (PCSs) in parking lots, home charging stations (HCSs), and roadside fast-charging stations (FCSs). Cost of charging equipment, operation, and maintenance cost, electricity cost, and the cost of traveling the distance between charging demand points and CSs, the time required for charging, waiting time at the charging station are all considered as objective functions in this planning model. The cost for home charging, public charging, and fast charging are modelled separately in the objective function. Moreover, a novel method for forecasting the spatial and temporal distribution of PEV charging demands was included in the model. The travel time cost takes into account the EV driver's convenience.

The planning model was validated on a practical system of Longgang District in Shenzhen, China. The aforesaid district covers an area of 196 km^2. The average PEV population of that district was predicted to be 16,000 in 2020. The planning model was validated for different cases as shown in Table 4. From the results, it was observed that the number of *FCSs* in all of the six cases was the same. It was obvious that deploying fewer but larger *FCSs* needs fewer charging spots and fewer fixed investments. The results indicated that the saving in the investment costs by deploying larger *FCSs* were more than the corresponding increase in time and extra electricity costs. The sensitivity analysis was performed by varying PEV population and departure SOC. Simulation results showed that for low PEV penetration level, the number of *FCS* did not increase with the time costs. Additionally, it is seen that for a departure SOC of 100% the planning results were more conservative. For realistic and practical planning, the departure SOC must be based on real-PEV charging survey data.

Table 4. Various constraints of placement problem.

Case	Service Ability (SA) of HCS (%)	Service Ability (SA) of HCS and PCS (%)	Consideration of Weather Condition
1	50	50	No
2	30	50	Yes
3	50	50	Yes
4	80	50	Yes
5	50	0	Yes
6	50	100	Yes

3.1.4. Single Stage Static Planning Model V (SS V)

This planning model was put forward by Zhang et al. in 2018 [45]. In this formulation, the CS placement problem is formulated as an MILP model. A capacitated-flow refueling local model (CFRLM) was also integrated with this model for capturing EV charging demands. The objective functions considered in this model were minimization of charging station investment cost, power distribution network expansion cost, and the penalty for unsatisfied charging demands. A detailed explanation of the expansion of the road network that is a key feature of CFRLM can be found in refs. [40,46]. The equality constraint used is the difference between outflow and inflow which equals the virtual supply and demand arising at the nodes. The inequality constraints are the charging stations capacity, the maximum limit of charging spots in the charging stations, safe limits of branch currents, and bus voltages. This planning model was validated on a coupled 25-bus transport network and a 14-bus distribution network. The charging station planning was conducted for different peak hour EV traffic flow. The planning results obtained are summarized in Table 5. It is seen that as EV flow increased, the model allocated a greater number of charging stations and charging spots in the charging stations to meet the charging demand. However, when the EV flow was 1500/h. the percentage of unsatisfied charging demand was 0.28%.

Table 5. Summary of the planning results of SS V.

EV Flow (/h)	No of Stations	No of Spots	Total Cost (M$)	Unsatisfied Demand (%)
1000	19	938	57.25	0
1500	21	1382	97.20	0.28

3.1.5. Single Stage Static Planning Model VI (SS VI)

This model, which was proposed by Deb et al. [47], formulates the CSs placement problem in multi-objective framework including total cost, voltage stability reliability power loss (VRP) index and accessibility index. The first objective function is the minimization of installation cost (both slow and fast charging) and operation cost (price of electricity). The second objective is to minimize the VRP. It was assumed in the planning model that the building, labour, land, charger, and electricity costs were same at all the nodes. Hence, the installation and operating cost were independent of the location of CSs. The VRP index [3] is a function of location and number of CSs. The distance matrix is defined as the distance between the charging point demand and CSs whereas the reduced distance matrix provides the distance between its nearest CS and charging point demand.

3.1.6. Multi-Stage Static Planning Model I (MS I)

This planning model was proposed by Luo et al. in 2016 [48]. In this planning model, the placement strategy of the charging stations was provided for incremental growth in EV penetration rates for three service providers that dominate the EV charging industry. An optimal placement policy at the start of each stage was found for all the service providers. The optimization was aimed at maximization of the profit of the service providers subject to service delay and service coverage constraints. The impact of EV charging load on the power grid was considered in the planning modelling by imposing a penalty for causing disturbance to the grid. At each stage, an optimal placement policy was computed for all the service providers by solving the optimization problem, which maximizes the profit of the charging service providers. Profit is the difference between the revenue earned by providing charging service to the EV drivers and the penalty imposed for causing disturbance to the grid. The optimization is performed in agreement with two quality service constraints. The first constraint considers the average delay probability for obtaining the charging service and the second constraint takes the average service coverage into consideration. Monte Carlo simulation (MCS) is used for the computation of parameters.

This planning model was validated for four stages by varying the penetration rates of EVs.in San Pedro District of Los Angeles, USA The planning results obtained are given in Table 6. It is observed that at each stage, more stations were introduced to the network with the increasing penetration rate of EVs while the coverage of the charging stations also increased. Level 1 charging is applied from a 120 V domestic outlet and 4–5 miles of range per hour can be provided through it, while in Level 2 charging EVs are charged at the rate of 12–60 miles per hour. Level 3 charging is the DC fast charging that is used in most civic CSs.

Table 6. Summary of the planning results of MS I.

Penetration Rate (%)	No of Level 1 Stations	No of Level 2 Stations	No of Level 3 Stations	Delay Probability	Coverage
0.32	13	9	4	0.5	4.1
0.64	20	15	8	0.55	5.95
0.96	26	20	13	0.55	8.6
1.28	31	25	18	0.48	11.4

3.1.7. Multi-Stage Static Planning Model II (MS II)

In 2018, a two-stage planning model was proposed by Deb et al. [49]. A fuzzy inference considered for candidate locations of CSs is first obtained considering distance, grid stability, and road traffic. Bayesian network is used to model the randomness in road traffic. Then, the CS placement problem is formulated as the objective function having cost, VRP index, accessibility index, and waiting time. In Stage I, Mamdani fuzzy inference (MFI) [50] is used to find the locations. of CSs. It is a normal practice to place the CSs at the common nodes of distribution and road network. Due to the congestion of the network, the voltage stability cannot be ignored. The distance from the closest distribution node to the road network node are considered along with traffic intensity, and grid stability for CS placement. The fuzzy nature of these factors motivated the use of MFI which is utilized for the placement of CSs as shown in Figure 3.

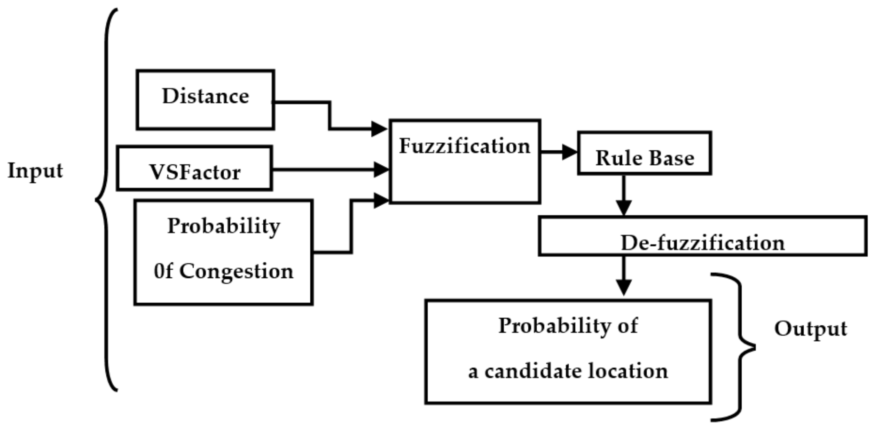

Figure 3. Mamdani fuzzy inference for placement of CSs [102].

In Stage 2, the optimal locations of CSs are obtained from the set of candidate locations, the number of charging points (fast/slow), and fast/slow CSs. The objective functions include cost, VRP index, distance from charging demand points to the CSs, and waiting time. The first three objective functions of this planning model are same as that of SS VI.

3.2. Dynamic Planning

One of the major challenges of a power system is the time variability of load both at the aggregate level and the local level. The dynamic planning (DP) models take into account the time variability of loads of the power system network while modelling the charging station placement problem. Further, depending upon the stages involved in the planning model, the dynamic models are subdivided into single-stage dynamic models and multi-stage dynamic models. The dynamic planning models present in the existing literature are elaborated in the subsequent sub-sections.

3.2.1. Single Stage Dynamic Planning Model I (SD I)

This planning model is suggested by Xiang et al. in 2016 [51]. The variability of load demand was taken into account in this model by aggregating the scenarios formed by generating different load templates. The aggregated load profile at the *i*th bus is as follows:

$$P_{Li,t,m} = \sum_{k=1}^{K} P_{Bi}\sigma_{k,t,m}N_{k,i} \tag{5}$$

where $P_{Li,t,m}$ is the aggregated load demand at the *i*th bus in time t; P_{Bi} is the base value of load profile and is the profile coefficient of the *k*th type of load in time t for scenario m.

The minimization of overall cost associated with the establishment of CSs and the cost associated with loss in the charging station is carried out. Various technical constraints are also used in this planning model A queuing model is used to determine the capacity of the CSs after traffic assignment. The planning model was validated on the coupled IEEE 33-bus distribution network and Sioux Falls Road network for eight load scenarios. The optimization problem yielded twelve planning schemes. For the best planning scheme, the optimized value of cost was USD 5.6126×10^6.

3.2.2. Single Stage Dynamic Planning Model II (SD II)

This planning model was put forward by Rajabi et al. in the year 2017 [52]. The model considered zonal EV population and inter-district EV tours. The variation of grid load during different times of the year was also considered in this model. The objective function is the minimization of station development cost, grid operator cost, and EV user's cost. The grid loss cost depends on the additional power loss incurred due to EV charging. The power loss was computed by solving AC load flow equations for all the load scenarios and time. The constraints considered are the apparent power limit, line loading limit, and bus voltage limit of the distribution system. The planning model was validated on the practical network of Northwest Tehran, Iran for four different cases as below:

- Case 1: Summer electric load
- Case 2: No inter-district EV circulation, constant electric load, and uniform EV charging during off-peak hours
- Case 3: No inter-district EV circulation, constant electric load, and uniform EV charging during peak hours
- Case 4: Preference-based alternate time of charging

Simulation results confirmed the importance of correct load scenario modelling, EV circulation, and EV user preference-based charging for determining the optimal allocation strategy for the charging stations. Case 4 was beneficial for EV drivers as they incurred less cost due to preference-based charging. Case 2 was beneficial for grid operators because of charging during the off-peak hours.

3.2.3. Multi-Stage Dynamic Planning Model I (MD I)

This planning model was proposed by Zhang et al. in the year 2018 [53]. The model has the capacity of considering the heterogeneous EV driving range and charging demand. This model is an extension of the planning model SS V with the following new features:

- Two-stage planning model where the first stage involves finding the required number of charging spots in the station-based charging demand.
- Consideration of variable loading of the power grid.

The model was validated on a coupled 25-node highway transport network and 14-node distribution network. Simulation results showed that consideration of the heterogeneous driving range of EVs could provide more practical and economic results.

3.3. Other Planning Models

Apart from the planning models described in previous sections, a few planning models exist which do not directly fall under static or dynamic models. These planning models are reported in this section. Only an overview of the models is provided. Detailed mathematic formulations of the models can be found from the respective references.

3.3.1. Multi-Objective Collaborative Planning Model (MC)

This planning model was proposed by Yao et al. in 2014 [54]. The model is a collaborative planning model for integrated power systems and charging stations. The model is the first collaborative planning model in the paradigm of the charging station placement problem. All the earlier models are two-step sequential planning models addressing the deployment of charging stations and the expansion of radial distribution networks separately. Additionally, this model solved the charging station placement problem for two types of charging facilities named charging posts and fast-charging stations. The planning model assumed that charging posts served as the primary source of charging EVs, and fast-charging stations were used for satisfying the urgent charging needs of EVs. This collaborative planning model formulated the CS placement problem in a multi-objective framework with minimization of investment cost, energy losses, and simultaneously maximizing EV flow.

3.3.2. Covering Location Principle Based Planning Model (CLP)

This planning model was suggested by Leeprechanon et al. in 2016 [55]. The formulation aimed at maximization of the ability to charge stations to satisfy the EV charging demand. For proper justification of the covering flow model, the EV demand node was assumed to be a fixed location where most EV drivers reside. The purpose of this model was to serve demand fully within the full and partial coverage distance. This model also considers constraints related to distribution networks like voltage limit, current limit, and power flow balance equation.

3.3.3. Stochastic Collaborative Planning Model (SC)

This planning model was put forward by Wang et al. in 2016 [56]. The salient features of this model are stochastic modelling of EV charging time and duration. It was considered that the starting charging time and duration of EVs in the charging stations follow a subnormal and lognormal distribution, respectively. The model aimed to minimize the investment and operation costs, simultaneously maximizing the captured EV flow. Consideration of uncertainty related to EV charging start time and duration make this model more realistic.

4. Comparison of Planning Models

Figure 4 shows the different categories of the models (in percentage) available in the literature. From Figure 4, it can be seen that the majority of CS planning models are static models. For comparison, Table 7 presents the mapping between objective functions and the planning models whereas Table 8 shows the mapping between constraints and the planning model. Each planning model is unique and has both advantages and disadvantages. Therefore, it is difficult to say which model is the best. However, the performance of the models is also very much location specific. Thus, evaluation of the models in a generic way is avoided. An important factor that affects the charging infrastructure planning is the type of location. The structure of road and power distribution network differs from city to city. Hence, the model suitable for a city with high traffic intensity may not be suitable for a city with low traffic intensity. Similarly, the model suitable for a city with strong and robust grid structure may not be suitable for a city with weak grid structure.

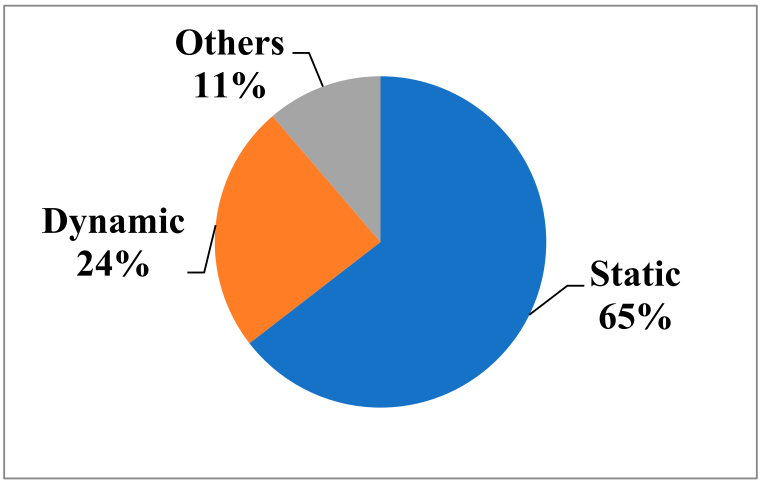

Figure 4. Percentage distribution of different models.

Table 7. Mapping between objective functions and planning model.

Objectives	SS-I	SS-II	SS-III	SS-IV	SS-V	SS-VI	MS-I	MS-II	SD-I	SD-II	MD-I	MC	CLP	SC
Voltage Deviation	√											√		
Power loss	√	√										√		
EV flow	√													√
VRP Index						√		√						
Accessibility index						√		√					√	
Profit							√					√		
Waiting time								√						
Investment cost		√	√	√	√	√		√	√	√	√			√
Operation cost			√	√	√	√		√	√	√	√	√		√
Maintenance cost			√									√		
Equipment cost				√		√		√		√		√		
Land cost				√		√		√				√		
Reinforcement cost		√			√						√	√		
Travel time cost			√	√						√				
Energy/Power loss cost								√		√				
Penalty for AENS				√								√		
Waiting time cost		√												
Penalty for unsatisfied charging demand					√						√			
Penalty for violating operating parameters of power grid				√		√								

Table 8. Mapping between constraints and planning model.

Constrains	SS-I	SS-II	SS-III	SS-IV	SS-V	SS-VI	MS-I	MS-II	SD-I	SD-II	MD-I	MC	CLP	SC
CS capacity limit	√											√		
Voltage limit	√	√		√	√	√		√	√	√	√	√	√	√
Line flow limit	√			√	√	√		√	√		√	√	√	√
Charging demand balance	√													
Number of CS limit		√		√	√	√		√	√		√	√	√	√
Number of charger limit		√			√			√	√		√			
Charging capacity		√												
Apparent power										√		√	√	√
Loading capacity limit				√		√		√	√	√				
Service availability														
Service ability					√						√			
Service constraints							√							
Power flow balance	√							√				√	√	
Power flow balance equations of distribution system	√					√			√					

Charging infrastructure planners are always concerned with the question of which planning model is suitable for them. Another question that concerns the charging station planners is whether the existing model can be adapted to meet their needs or if there is the necessity of developing new models. The suitability of the planning models solely depends on the area in which charging station placement needs to be carried out. The topology of the road network and power grid, the traffic conditions prevalent in the area, and the economic conditions of the area must all be considered while selecting a planning model. The area-wise suitability of the planning models is proposed in Table 9. It is suggested that adapting the existing planning models to meet the needs of the planners is less troublesome and time-consuming than developing new models. Further, Table 10 elaborates the findings of some case studies on charger placement. The ratios of EV to charging point as proposed by various countries are given in Table 11.

Table 9. Area wise suitability of Planning Models.

Planning Model	Area	Planning Model	Area
SS I	Urban areas of developed and wealthy nations where budget is not a constraint	MS II	Urban area with route specific public EVs where there is random traffic leading to congestion
SS II	Areas of developing nations	SD I	Areas of developing nations
SS III	Area where home charging is prevalent	SD II	Area with inter-district EV flow
SS IV	Urban area for route specific public EVs	MD I	Highways
SS V	Highways	MC	Area with rapid growing EV population
SS VI	Urban area with route specific public EVs where there is random traffic leading to congestion	CLP	Residential small area
MS I	Urban area where there is competition among the charging service providers	SC	Area with random road traffic

Table 10. Summary of case studies on charging station placement [103].

Regions	Data Source	Considerations
USA-Boston	Cell phone location data	Parking, driver discomfort, cost
USA-Chicago and South Bend	Census data, public map data	Energy consumption, cost, parking
USA-California	Past charger utilization and travel surveys,	Cost and regional traffic
EU-Liege, Belgium	GIS data of city and province	Commute patterns, business locations, transit,
EU-Bolzano and South Tyrol, Italy	GIS data of city and province	Parking, transit, power supply
Singapore	City and national traffic and GIS data	Traffic impacts, vehicle range
Beijing, China	Taxi fleet data	Parking, traffic impacts, power supply

Table 11. EV to charge point ratio proposed by several organizations [36].

Organizations	Regions	Ratio
European Council	European Union	10
NDRC	China	8 (pilot cities) + 15 (other cities)
IEA EV Initiative	Worldwide	8
EPRI	USA	7–14
NREL	USA	24
CEC/NREL	California	27

5. Charging Scheduling Problem

EVs have emerged as a clean and environment-friendly alternative to internal combustion engine (ICE) driven vehicles. The charging load of EVs is quite high and uncoordinated charging of the EVs may lead to severe problems such as voltage fluctuations, harmonics, as well as degradation of reliability of the system [57–61].

Hence, the charge scheduling problem of EVs is an important problem that has attracted researchers globally. The input of the charge scheduling problem is an EV set along with different grid, user, as well as aggregator side parameters. The output is the schedule (start and end time) of the charging activity. It closely resembles an optimization problem concerned with optimizing electric grid and/or aggregator-side parameters subject to the different constraints. The objective function, constraints, and parameters vary widely, giving rise to different formulations of the problem. The charge scheduling models available in the literature can be classified as in Figure 5.

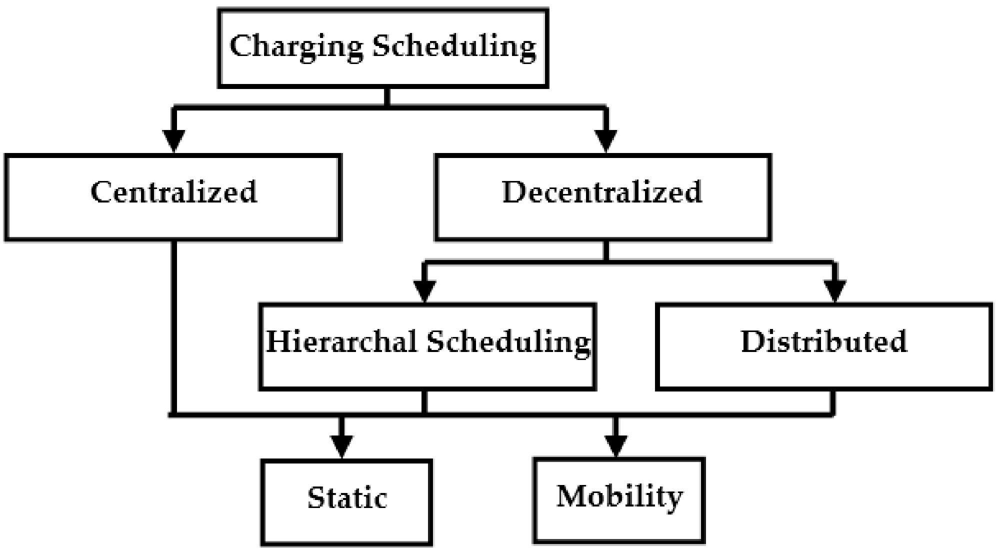

Figure 5. Classification of charge scheduling problem [103].

5.1. Centralized Scheduling Model

As the name indicates, in centralized scheduling model, the optimization of EV charge scheduling is performed centrally at the aggregator level after collecting information about power requirement of the EVs. The EVs can communicate electrical parameters like maximum battery capacity, SOC, and charge rate to the aggregator. Each aggregator makes a contract with the independent system operator (ISO) based on the requirement of aggregated power. On receiving the contracts from different aggregators, an energy management system at the ISO decides the appropriate power share for each aggregator within their contracted boundary considering the other loads, the power generation capacity from different generators, and the grid constraints. Then, each aggregator executes an optimization routine to schedule the EV charging in such a way that the EVs anticipated energy requirements are met.

5.2. Decentralized Scheduling Model

In decentralized charging control, each EV has some computing capability and the decision to charge is jointly taken by each EV in coordination with the aggregator. Each EV communicates their net energy requirements to the aggregator and uses part of this information collected at the aggregator to decide on an optimal schedule. Scalability is one of the advantages of using decentralized control, where penetration of a large number of EVs is allowed in the scheduling process. However, absence of a complete set of information at any EV makes the charge scheduling suboptimal.

5.3. Static Scheduling Model

Static charging is charging in which the mobility of the EVs is ignored [54]. The EVs are treated as stationary loads with no temporal properties related to the mobility of the EVs. This model keeps the problem formulation simple. Some authors consider it to investigate the impact of other parameters on the grid. However, this class of model lacks realistic flavour.

5.4. Mobility Aware Scheduling Model

The mobility-aware scheduling model can consider different mobility and uncertainty aspects associated with EVs such as arrival/departure times of an EV to/from a CS, trip history of EVs, and unplanned departure of EVs, thereby adding realistic flavour to the problem [61]. The spatiotemporal behavioural trait of the EVs can be modelled by this class. In this class of modelling, the request of charging can be known based on expected arrival times at CS and their effects on grid load may be studied [61–66]. Figures 6 and 7 represents the number of installed public EV charging stations in different counties of Estonia. The majority of stations are in the capital, i.e., Tallinn followed by Tartu and Pärnu.

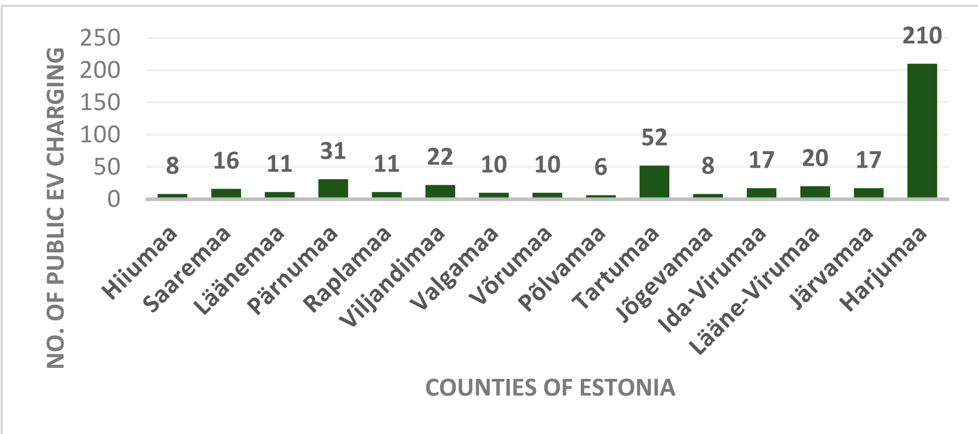

Figure 6. Public charging stations in different counties of Estonia [103].

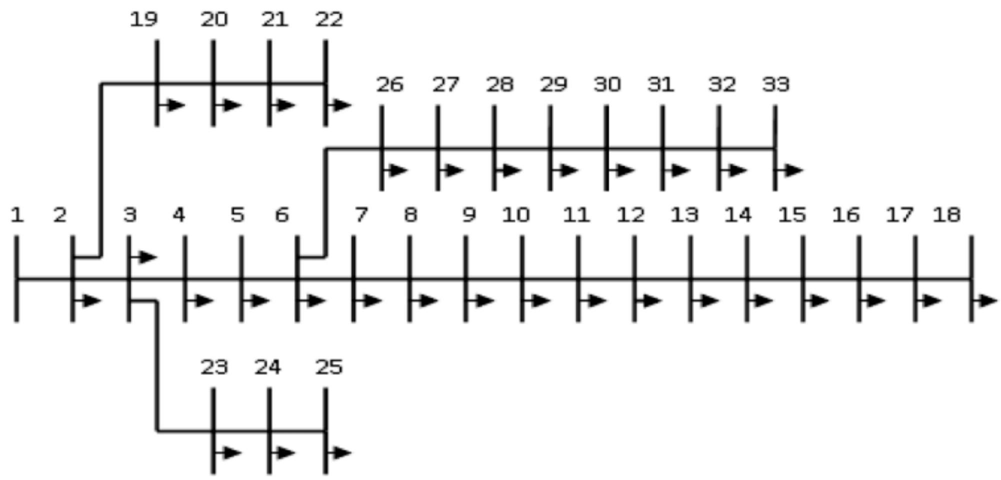

Figure 7. IEEE 33-bus radial distribution system.

6. Recommendations and Future Research Direction in Charging Infrastructure Planning

The key recommendations that must be considered for charging infrastructure planning are as follows:

- Specific charging requirements must be targeted. Construction of charging infrastructure (CI) is costly, and the availability of CI is a complex problem. Therefore, it is desirable for a government program to focus on one form of CI having a clear and well-defined need. This will also help to encourage and promote geographic coverage.
- Competition among charging service providers will help in facilitating the growth of the early infrastructure and will also aid in recognizing the effective business models
- Regulators should assist in developing, through government programs, an effective private-sector leadership for competition and innovation.
- Clear and easily accessible information including the subsidies and accepting that application on various programs helps all the stakeholders.

Charging infrastructure planning is an emerging area of research that has witnessed a lot of research effort in recent years. The future scope of research in this area is identified as listed below.

6.1. Planning of Vehicle to Grid (V2G) Enabled Charging

EVs can provide the power to electric grid by the V2G scheme which enables EVs to support the electric grid in high cost or/and power outages. V2G also enables EVs to improve the power quality and grid stability in the presence of a high renewable power generation. Thus, the planning of V2G enabled CSs is a promising research area. There is the necessity of analysing the techno-economic feasibility of the V2G scheme; formulating efficient planning models for V2G enabled charging stations with net benefit as one of the objective functions.

6.2. Feasibility Analysis and Location-Based Planning of Hybrid CS in Presence of Renewable Energy Resources

EVs are a clean mode of transportation without any local emissions. However, the power required to run the EVs using non-renewable energy sources is not emission-free. The increased penetration of EVs in the system will cause an increase in the net power demand to charge them. The electric grid may not be capable to meet the peak load demand. Renewable energy sources can be utilized to satisfy the peak load demand. In this context, the feasibility analysis of hybrid CSs is a new area of research.

6.3. Smart Charging Strategy for EVs

Improper planning of CSs; uncoordinated charging may threaten the smooth operating of the power system. However, smart charging facilitates EVs to act as generation or demand assets for grid operators. Smart charging permits a certain level of control over the charging process. The main forms of such charging include V1G, V2G, and V2H/B. In V1G or controlled charging, EVs act as demand response resources by throttling their charging rate [97]. The V1G or controlled charging scheme is a one-way interaction between EVs and the grid that manages the EV charging remotely thereby assisting in load management. In V2G, EVs provide power back to the grid and thereby assist in load management. In V2B/H, EVs act as supplement power suppliers to the home. Smart charging helps in congestion management, reliability improvement, frequency regulation, as well as voltage profile improvement of the distribution network. There is a necessity to explore smart charging strategies such as the impact of smart charging (V2G and V1G) on congestion management, reliability improvement, frequency regulation, demand response, and voltage profile improvement of distribution networks. A technical, as well as an economic analysis, should be carried out. A feasibility analysis of whether a V2H/B system can provide benefits during sustained outage conditions is required.

6.4. Smart Pricing Strategy for Charging

The problem of voltage deviation, average energy not served, and harmonics can be solved to a certain extent by adopting a smart pricing strategy in the charging stations. If most of the charging activities take place during off-peak hours, then the excessive load demand because of the EV load can be controlled. Hence, a dynamic pricing strategy is more beneficial than compared uniform pricing strategy. However, delaying the charging process may cause inconvenience to the EV drivers. Thus, devising efficient pricing strategies in the charging stations is also a new promising area of research in the coming years.

6.5. EV Battery Burnout Problem

The advent of EVs is a game-changer towards decarbonization of the transport sector and shift to sustainable energy. However, the fire issues related to the EV battery promotes apprehension and concern. EVs must meet stringent safety requirements as well as achieve the driving range, reliability, and cost targets expected by consumers. Thus, the EV battery burnout problem is an emerging area of research. The probable causes of burnout will be analysed and further recommendations will be given to avoid the EV battery burnout problem.

6.6. Charging Requirement for Emergency EV Fleet

Globally, there is a target of a 100 percent paradigm shift from ICE-driven vehicles to EVs. Hence, it is expected that emergency vehicle fleets such as ambulances and fire engines will also be electrified in the near future. However, it is observed that globally there are no well-defined rules and regulations for addressing the charging requirements of the emergency fleets. The emergency fleets must be given priority in the charging stations and there should be separate charging spots in the charging station designated especially for the emergency fleets. There should also be at least one charging station allocated at a safe distance from hospital or fire brigade complexes for charging the emergency fleets. Further, street charging can also be an attractive option for these emergency fleets.

7. Conclusions

Large scale penetration of EVs requires deployment of a charging infrastructure which can be easily accessible. Starting with the general perspective of charging station placement, comprehensive planning models are discussed in this paper. Charging station placement and scheduling of charging activity are classified and described in detail. Each planning model has key features and limitations, both the static and dynamic models. Since each planning model has unique characteristics, it is very difficult to establish the supremacy of one model over the other. Improvements of the existing planning models and recommendations for charger placement are also proposed in this work. Further, the recommendations of charging station placement along with key challenges are presented comprehensively in this work. This paper will be useful to EV CS planners, engineers, and industry professionals from the planning stage to the optimal deployment of a sustainable charging infrastructure in the field.

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