Chapter

Fast-Charging Infrastructure Planning Model for Urban Electric Vehicles

Tran Van Hung

Abstract

Electric vehicles have become a trend as a replacement to gasoline-powered vehicles and will be a sustainable substitution to conventional vehicles. As the number of electric vehicles in cities increases, the charging demand has surged. The optimal location of the charging station plays an important role in the electric vehicle transit system. This chapter discusses the planning of electric vehicle charging infrastructure for urban. The purpose of this work develops an electric vehicle fast-charging facility planning model by considering battery degradation and vehicle heterogeneity in driving range, and considering various influencing factors such as traffic conditions, user charging costs, daily travel, charging behavior, and distribution network constraints. This work identifies optimal fast-charging stations to minimize the total cost of the transit system for deploying fast-charging networks. Besides, this chapter also analyzes some optimization modeling approach for the fast charging location planning, and point out future research directions.

Keywords: Fast-charging station, charging network, charging station planning, electric vehicles, EVs traffic flow

1. Introduction

Global environmental and energy problems are becoming more and more serious, and one of the main causes is fossil fuel-consuming transportation. Electric vehicles have obvious advantages in energy saving and emission reduction (such as reducing gas emissions, air pollution especially PM2.5 fine dust and noise, reducing dependence on fossil fuels, promoting industrial development and using renewable energy), so they are growing rapidly. Electric vehicles are the most promising solution for a green and clean environment when the world is more dependent on renewable energy sources. At the same time, they have also become an alternative to gasoline-powered vehicles and are promoted by policymakers worldwide as a solution to combat environmental problems and stimulate the economy. Electric vehicles are considered an extremely effective and urgent solution in the electrification of the transportation sector, and it will be an indispensable means of transportation in the future. Electric vehicles have been proven as a tool to reduce the negative effects of petroleum extraction, importation, refining and combustion. However, electric vehicles face many disadvantages compared to conventional gasoline and diesel-powered vehicles, including high initial investment costs, limited driving range and especially a scarcity of available stations for recharging them. The popularity of electric vehicles in the future, more or less depends on the development of the infrastructure to serve this type of vehicle. Demand for electric vehicles is expected to increase over the next few years, it is still constrained by many factors especially battery cost and availability of charging station infrastructure. Investors are willing to invest in charging station infrastructure if and only if there is a sufficiently large number of electric vehicles in the network.

To attract consumers to purchase and use electric vehicles, charging station infrastructure must be deployed in convenient locations that are coordinated with each other. A power battery is one of the most important components of electric vehicles and the fundamental challenge for electric vehicles is to ensure a suitable energy storage device capable of supporting high range, fast charging and efficient driving. With an increasing number of electric vehicles on the road, the implementation of an efficient and well-planned charging infrastructure is highly desirable. In order to gradually replace traditional means of transport and put electric vehicles into use on a large scales, the construction of electric vehicle charging facilities has received strong support from governments around the world and has been focused on by scientists. As the number of electric vehicles in the city increases, the optimal location of the charging station plays an important role in ensuring the efficient operation of electric vehicles. To solve this problem, there are many design parameters related to charging stations available in the electric vehicle network that need to be considered. These parameters need to be involved to determine the optimal electric vehicle fast-charging station infrastructure. These parameters typically include: location, level, size and capacity of charging stations.

There are typically two different types of charging station configurations for electric vehicles: inter-city charging stations and intra-city charging stations. With inter-city charging stations required for electric vehicles to travel long distances, the electric vehicle will charge during the electric vehicle's journey. In contrast, for intra-city or urban charging stations with short distance travels, the electric vehicle's charging can be done when the electric vehicle finishes its journey. Different charging station locating approaches should be applied to the different charging demands.

2. Literature review

Battery electric vehicles have enjoyed fast-growing adoption in recent year, however a number of factors are restricting the development of electric vehicles [1]. One of the typical limitations is that electric vehicles take a long time to charge. DC fast charging requires around half an hour to fill up to 80% of the battery capacity, whereas AC slow charging may take 6–8 h to fully recharge the battery [2]. In addition, electric vehicle charging piles are considered to be inconvenient and insuffïcient in number at present [3]. Fang He et al. [4] have proposed how to optimally locate public charging stations for electric vehicles on the road network, considering drivers' spontaneous adjustments and interactions of travel and recharging decisions. This paper adopts a tour-based approach to analyze the complete tour of the driver that may consist of several trips in a pre-determined order, and assume that their drivers simultaneously decide tour paths and recharging plans to minimize the travel and recharging times while ensuring not running out of charge before completing their tours.

The location model based on flow demand was first proposed by Hodgson, who developed a Flow-Capture Location Model (FCLM) based on the maximum coverage. On this basis, Kuby considered the driving range of the vehicle and proposed the Flow-Refueling Location Model (FRLM) [5, 6], Capacitated Fow Refueling Location Model (CFRLM) that considers capacity constraints [7] and Deviation-Fow Refueling Location Model (DFRLM) [8]. Patrick Jochem et al. [9] were extended the flow-refueling location model (FRLM) to the German autobahn, this model extension comprehends mainly the inclusion of the access distance for traffic participants to their closest network node. Traditionally, the FRLM has been formulated using a two-stage approach: the first stage generates combinations of locations capable of serving the round trip on each route, and then a mixed-integer programming is used to locate p facilities to maximize the flow refueled given the feasible combinations created in the first stage. Ismail Capar et al. [10] presented a Mixed-Binary-Integer Programming (MBIP) formula, which is an improvement of FRLM. The FRLM and flexible reformulation FRLM (FRFRLM) is used by Cheng Wang et al. [11] to solve the large-scale transportation network problem within a reasonable time.

Travel demand is the indispensable component to generate the travel routes of EVs, which provide the basic geographic information to locate charging stations. Several studies conducted the planning of EV charging stations with assumed traffic flow and network [12–14]. Jianmin Jia et al. [15] presents the approach to locate charging stations utilizing the reconstructed EVs trajectory derived from the Cellular Signaling Data, investigated the large-scale CSD and illustrated the method to generate the 24-hour travel demand for each EV. With the development of information technology, researchers started to explore the trajectory data in the locating problems of charging station on the basis of the floating vehicles, such as taxis, with Global Positioning System (GPS) devices [16]. The travel demand model can provide quick estimation of EV trips, while the trajectory data, such as the taxi GPS data, would better represent the real-world travel patterns of EVs. For locating fast-charging stations, in [17] Csaba Csiszár was presented an arc-based location optimisation method realized by using a geographic information system and greedy algorithm.

3. Charging station model description and method

From the point of view of modern city planning, the location of EVs charging stations must meet the requirements of the city transportation network layout. While from the perspective of power system planning, the location of EVs charging stations should be in accordance with the current situation in short-term as well as long-term planning of the distribution system involved. EVs charging stations must be close to load centers and respect constraints on load balance, power quality, and power supply reliability of urban. From the perspective of EVs' owners, the sites of EV charging stations should be in locations which are convenient for EV's owners and near the charging demands. Furthermore, other factors, such as the location adaptability and land price, should also be considered. Thus, the initial candidate sites of EV charging stations can be determined with the aforementioned factors properly considered.

3.1 Illustrative example and electric vehicle data collection

We first use a simple illustrative example to highlight the importance of considering the trip sequence in describing the travel and charging behaviors in a common use case of electric vehicles. In **Figure 1**, assuming network nodes (1), (2), (3), (4) and (5) are candidate locations for charging station placement. Node 1 was set as origin and node (5) was set as destination. The distance of each link are also shown

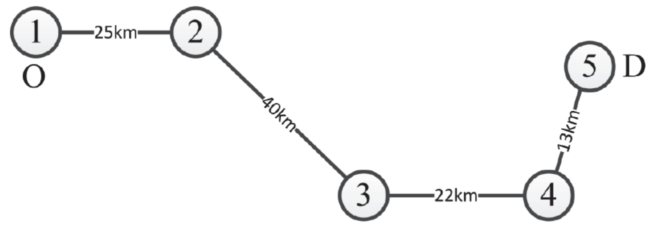

Figure 1.
An example network with a single O-D.

in the Figure. A full journey would be (1,2), (2,3), (3,4), (4,5) to reach the destination, and then back (5.4), (4, 3), (3,2), (2,1) to return to the original position. We first assume that the vehicle battery range R ¡40 km when the tour starts, there is no chance for vehicles to complete the trip between the O-D pair because vehicles cannot complete the trip (2,3). When R = 40, the charging station can choose one of two alternatives with (1,2,3,4) or (1,2,3,5). Under both solutions, electric vehicles will be charged at nodes (1), (2) and (3). If at (4) is placed a charging station, vehicles charged at (4) can reach the destination and return to (4). Next, after being fully charged at (4), the vehicle can return to the origin by charging again at (3) and (2). Similarly, we can see that when R = 50, it does not need to place the charging station at (1) anymore because a fully charged vehicale at (2) (while returning from the destination) can reach the origin and have enough electric capacity to travel to (2) when a new trip is next start. When R = 200 km, a single charging station at any node is sufficient to charge the entire journey because even after a full charge at (1), the vehicles will have enough battery capacity to reach (5) and go back to (1).

Through the above simple example, we see that the range of battery electric vehicle plays a decisive role in the distribution of charging stations on the traffic network in the city. First, if there is no charging station built at the origin then there should be at least one charging station was built within the R/2 distance to the origin node. Second, if there is a charging station was built at a location, the next charging station should be within the range R. Finally, if the vehicle range is greater than or equal to two times the path length, a single charging station at any node can provide electrical power whole journey. Thus, if there is a charging station at the origin node, the model will start the round trip with a fully charged state (State of Charge - SoC = 100%). If there is no charging station at the origin node, vehicles will start with the remaining battery SoC observed at the end of the previous trip. With the assumption of constant energy consumption and roundtrips it is secured that each trip will at least start with SoC of 50%.

The problem of placing charging stations for electric vehicles involves finding the optimal location of charging stations in the transport network so that the operating parameters of the vehicle network are least affected. Real-world vehicle travel patterns, especially for electric vehicles, provide abundant information to investigate charging demand. Nevertheless, it is impractical to adopt the travel information from all private vehicles. Therefore, GPS location data and vehicle's trace collection was considered to provide the travel information.

Besides the commute trips, the other purpose trips were also considered in this model. The purpose of activity locations was determined by the time of day. For instance, the "home" location is defined as the place with the most visits between 8 pm and 8 am for each day during the observation period, while the "work" location is defined as the place with the most visits on weekdays between 8 am and 8 pm during the observation period. The rest of the locations are regarded as the "other", such as shopping and recreation. With the activity location and purpose inferred from the vehicle's traces, the 24-hour travel demand for the electric vehicle is able to generate based on the time sequence of each activity.

3.2 Charging station model descriptions

We focus on the urban electric vehicle fast charging infrastructure planning model and investigate the positioning aspects of fast charging stations in the dense residential areas road network. It supports city trips, where charging infrastructure and BEVs both play an important role in optimizing electric vehicle charging station locations. Consider a metropolitan road network where all vehicles in the network are assumed to be battery electric vehicles. This assumption is not necessarily restrictive as the model proposed below can be easily extended to accommodate both electric and regular vehicles. Let G(N,A) be a transportation network of the electric vehicles system, where N is the set of nodes (i.e., origins, destination, junctions) and A is the set of directed links (arcs). While all nodes in N are eligible candidate sites for stations, the set of O-D nodes can be a subset of N. Thus, an unpopulated road junction can be included as a candidate site but need not be included as an O-D node. Next, given a set of O-D pairs (Q) with a nonnegative traffic flow (fq), the set of nodes visited while traveling on path q (Nq), and vehicle range (R), the FRLM is defined as the problem of locating p facilities on the network G(N,A) to maximize the total traffic flow refueled. Traffic flow between an O-D pair q is considered as refueled only when vehicles leaving the origin can reach the destination and return back to the origin without running out of fuel. Before presenting the problem definition, we discuss related assumptions and present additional notation, subsequently. It is assumed that the traffic and path between the O-D pairs are known in advance. Traffic assigned a unique path is usually the shortest path determined by the Disktra algorithm [18]. From a problem formulation perspective, the proposed model can easily be extended to multiple avenues; therefore, this assumption is not restrictive. Although in some cases flow information may not be available, it can be obtained from the traffic demand matrix or through O-D estimation methods. Therefore, it is also reasonable to assume that the traffic volume is known in advance.

This work applied and extended the flow-refueling location model (FRLM) developed by Capar et al. (2013) [19, 20] as a basis. The formulation of the problem is as follows.

$$Max\left[\sum_{q\in Q} f_q y_q\right] \tag{1}$$

Subject to:

$$\sum_{i\in K^q{}_{j,k}} z_i \geq y_q \forall q\in Q, a_{\,j,k}\in A_q \tag{2}$$

$$\sum_{i\in N} z_i = p \tag{3}$$

$$z_i, y_q \in \{0,1\} \forall q\in Q, i\in N \tag{4}$$

Where,

f_q: Traffic volumes on the shortest path between O-D pair q.

$a_{\,j,k}$: A directional arc starting from node j and ending at the node k.

A_q: Set of directional arcs on path q, sorted from origin to destination and back to origin.

$K^q{}_{j,k}$: Set of candidate nodes, which can refuel the directional arc $a_{\,j,k}$ in A_q.

M: Set of O-D nodes where $M\in N$.

N: Set of nodes which constitute the network, $N = \{1, 2, \dots, n\}$.
p: The number of stations to be located.
q: Index of O-D pairs.
Q: Set of O-D pairs.
y_q and z_i are decision variables. =1 if the flow on path q is recharged (and feasible), and equal 0 if not; z_i =1 if a service station is built at node i, and z_i =0 if not.
$i; j; k$: Indexes for potential facilities at nodes.
The set of candidate sites accessible from the mth candidate site on a path q can be calculated from [10]:

$$K^q_{j,k} = \begin{cases} \left[N_q | d^q_{j,r} \le R, r > j\right] & \forall q \in Q, j = 1, 2, \dots, M_q, k = 1 \\ \left[N_q | d^q_{j,r} < R, r > j\right] & \forall q \in Q, j = 2, \dots, M_q, k = 0 \\ \left[N_q | d^q_{j,r} \le R/2, r > j\right] & \forall q \in Q, j = 1, k = 0 \end{cases} \quad (5)$$

Where,
$K^q_{j,k}$: is the set of candidate sites accessible from the mth candidate site on a path q.
N_q: is the set of candidate sites on a path q, now sorted in sequential order from origin to destination.
M_q: the number of candidate sites on path q beyond the origin but not within half the range R of the destination of path q, that is, in the distance interval $(0, D_q - R/2)$ on path q; if $(D_q - R/2 \le 0)$ then M_q =0, with D_q is the length of the shortest path of an O-D pair q.
R: the range of electric vehicle.

The battery range of an EV trip represents the maximum length an EV can travel without charging, which is imposed by the battery technology. Here, "charging" is used to broadly represent battery recharge, battery exchange, or any other option to obtain a fully charged battery for the EV to continue its travel. To develop a widely applicable fast-charging station location optimisation method that considers the several relevant variables of the electromobility systems, which are as follows: trafic flow volume, the usual range of battery electric vehicle, general user demand, and especially taking into account the effect of traffic congestion; however, trafic flow volume, range of electric vehicle, and the number of EVs are the most critical parameters. The outlined method first computes static ranking variables based on statistics and spatial relations (getting and summing close attribute values). Then the selection of those candidate sites that fit the scenario goals was performed by GIS scripting.

In fast-charging infrastructure location optimization method, the set of candidate sites $K^q_{j,k}$ (Eq. (5)) was combined with the vehicle traffic data from the EV trajectory was grouped into charging demand clusters through clustering analysis to determine the optimal locations for charging stations.

3.3 Traffic congestion coefficient

The energy consumption of an electric vehicle depends not only on the distance it travels, but also on the density of vehicle traffic on the road. Traffic congestion at different times of the day plays an important part in the energy consumption of an electric vehicle. We use a traffic congestion coefficient [21] to analyze the interlink between traffic and energy consumption. This coefficient is calculated as the ratio of actual energy consumed by an electric vehicle to cover a certain distance during particular hour of the day, to the energy consumed by it during the same period to cover the same distance on an empty road under ideal conditions. The coefficient varies between 0 to 1, with 1 reflecting an empty road condition and 0 being standstill traffic. This traffic congestion coefficient might vary from place to place. This coefficient takes into consideration the energy loss due to frequent breaking and accelerating and extra energy consumed during vehicle ignition. All other minor inefficiencies are included in this coefficient.

$$\tau = \frac{d_{act}}{d_{idc}} \tag{6}$$

Where,
τ: Traffic congestion coefficient.
d_{act}: Actual distance travellled by an electric vehicle.
d_{idc}: Distance travellled by an electric vehicle under ideal condition.

Before scheduling the next trip for EV, its state of charge has to be assessed to evaluate whether the remaining battery level is sufficient enough to take the next trip or to travel to the nearest charging station. A general equation for the distance that an EV can travel during a certain hour of the day can be derived as [22]:

$$D = \sum_{i}^{i+1} (I_{SoC_i} - SoC_{\min}) \times R \times \tau_i \tag{7}$$

Where,
D: Distance traveled over the operating period per day, (km).
I_{SoC_i}: Initial State of Charge of the Battery at the start of an hour, (%).
$SoC_{\min}$: Minimum State of Charge of the battery, (%).
R: Range of an electric vehicle under ideal conditions, with low traffic and no obstacles, in a single charge, (km).
τ: Traffic Congestion Coefficient.

4. Application: a case study

The geographical information of the transport system was extracted from OpenStreetMap [23]. The survey area is in Cau Giay district, Hanoi city (Vietnam). It is comprised of 166 nodes (geographical points) and approximately 500 sections of roads (straight lines connecting two nodes) with lengths ranging from a few meters up to 10 km. Office/work hours are based on the Vietnam legislation are from 8 am to 17 pm. This information is used to create the vehicles' plans.

This network has 363 arcs and 166 junctions (vertices), each of which serves as a candidate site. The OD flow of electric vehicles and the distance between the OD points in Cau Giay district during a working day are provided. There are 166 candidate sites and 5000 O-D pairs were tested in a working day. Note that because the model ensures that the return trip is rechargable, by extension so are the round trips starting at either end. For illustration purposes, **Figure 2** shows, the transportation system indicating roads, as bold lines. In the transportation network shown in **Figure 2**, there are 166 candidate sites for the fast-charging station. These were locations where fast-charging stations can be deployed, highlighted in green, and numbered from 1 to 166. However, not all of them have been selected for

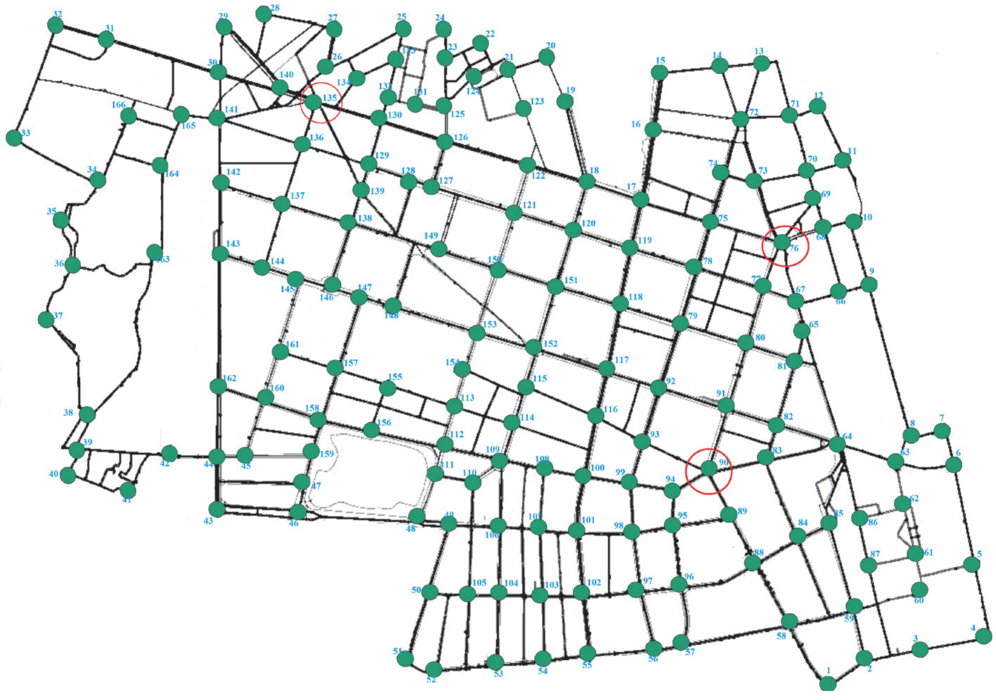

Figure 2.
Transportation network in Cau Giay District, Hanoi, Vietnam.

fast-charging station deployment. The selection depends on the vehicles traffic flow through the candidate sites' locations. Therefore, the vehicle traffic flows through nodes were evaluated, the node with high traffic will be prioritized for selection to deploy the fast-charging station. The three candidate nodes circled in red in **Figure 2** (nodes 76, 90, and 135) are nodes with high media flow as assessed through simulation. These nodes are located on arterial traffic routes which vehicles from outside enter the center and vice versa. The traffic flow profiles for nodes 76, 90, and 135 of intense vehicle movement, surveyed during the average 1-day period, was shown in **Figure 5**.

Before the traffic flow simulation, the routes of each vehicle must be defined, i.e. the shortest path between the points in their plans (Dijkstra's algorithm [18]). After each traffic flow simulation, vehicles facing traffic jams have their routes recalculated. The travel time of each vehicle depends on the length of the section of road belonging to its route and the actual velocity. All vehicles perform their routes concurrently. This process is repeated for a pre-defined number of iterations to reduce the travel times individually [24].

It can be noted from **Figure 3** that most of the trips are shorter than 35 km. Generally, the travel modes of trips consist of walking, riding a bicycle, using public transit, and using a private car. The walk and bicycle travel modes have short trip lengths mainly under 10 km. Therefore, the daily trips whose length is over 20 km are assumed to be EV trips in this survey, and these trips were used to generate basic travel demand.

The hourly travel demand was imported into SUMO (Simulation of Urban Mobility) [25] for vehicle traffic flow analysis to generate the trajectory of the EVs. Since the EVs may have multiple trips in a day, the time sequenced trajectories between different activity locations for one EV were merged to reconstruct the complete daily trip. **Figure 4** illustrates an EV trajectory example, trajectory 1 illustrates the route from home to work, while trajectory 2 illustrates a different route since the EV traveled to other purpose activity place during the trip from work to home. Both trajectory 1 and trajectory 2 make up the complete daily trip for one EV.

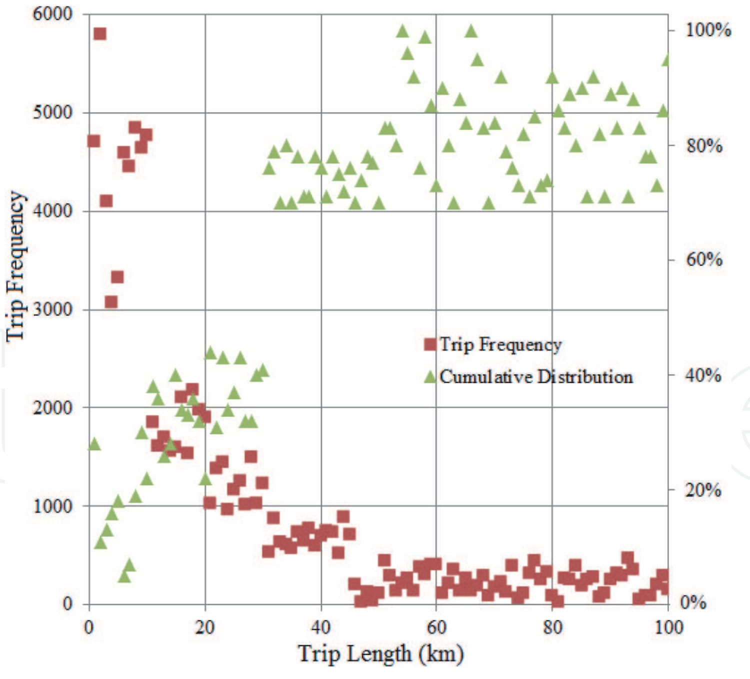

Figure 3.
Distribution of trip frequencies by cumulative trip length.

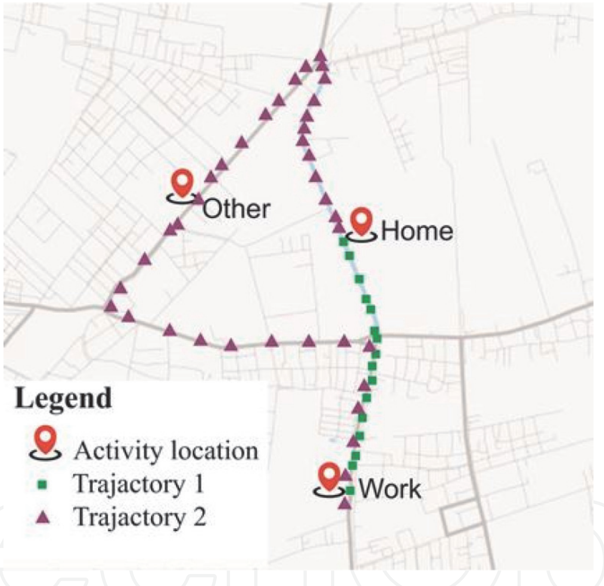

Figure 4.
An example of EV trajectory with other purpose trip.

In traffic flow analysis, we applied to the 166 nodes in the traffic network, one O-D flow contains the information about how many vehicles are driving from O to D and back in a day, a week or a certain period of time. The set of locations of nodes with high traffic is determined through simulation data analysis which are preferred locations in the fast-charging station selection.

Table 1 shows an exemplary O-D pair from node (76) to node (90). The distance from node (76) to node (90) is 32 km. The path of this O-D flow shown in the table starts at node (76) and continues all the way crossing nodes (77), (80), and (91) until it reaches node (90) and come back. Traffic flow through all nodes are evaluated. The high traffic flow sections of roads are considered to be potential fast charging stations locations. The traffic flow profiles of nodes locations (76), (90) and (135) are plotted on **Figure 5**. Each profile is unique, consequence of vehicles

From node (O)	To node (D)	Flow volumne (trips/day)	Distance (km)	Shortest path (via nodes)	Distances between nodes (76–77/77–80/80–91/91–90)
76	90	124	32	76–77–80–91–90–91–80–77-76	7/8/8/9

Table 1.
Table entries for the O-D pair 76–90.

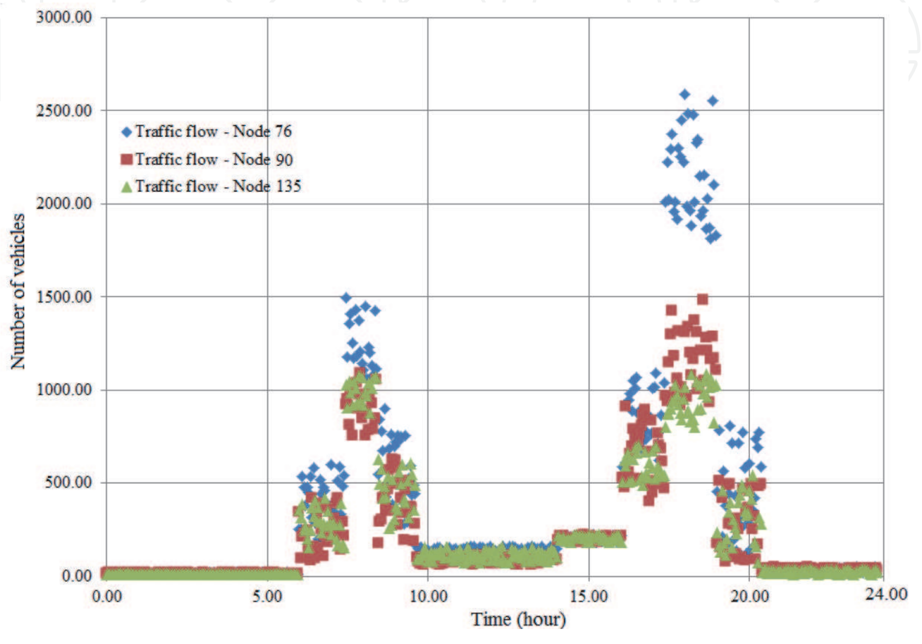

Figure 5.
Traffic flow profiles for three roads of intense vehicle movement.

flowing towards city centre in the morning and the other way around after work. High and thin peaks indicate possible traffic jams.

Characteristics of electric vehicles used in this survey are shown in **Table 2**. Fast-charging stations are assumed to be immediately available to EVs that arrive for charging, i.e. EVs do not wait to charge.

The travel times of EVs can be translated into cost. Thus, initially, fast-charging stations locations are selected using the most used routes of regular vehicles based on traffic flows. So, the selected fast-charging stations locations might be suitable for some EVs, it will not necessarily be aligned with the routes of all EVs. Several EVs go to charge in this fast charging stations causing traffic jams, leads to larger travel times within the region. This highlights the importance of evaluating the selected locations. Besides, traffic congestion is quite a serious problem in developing cities, especially with mixed traffic characteristics like in Hanoi. Traffic congestion affects the distance traveled by EVs, and this must be taken into account when planning electric vehicle charging stations. **Figure 6** shows the variations in the traffic congestion coefficient over the day, calculated using the Eq. (6). Survey time is from 7 am to 10 pm.

From all candidate sites, the top 18 busiest sections of roads are considered to be potential fast-charging station locations (red circle in **Figure 7**). Most of these fast-charging station locations are outside the city centre, on the northern and western areas due to the population distribution. With the fast-charging station locations identified, the traffic flow analysis is performed for each of the fast-charging station cases: from one to 18 fast-charging station locations.

Variable	Value
Battery Capacity	280 Ah
Technology	Lithium-ion
Battery on-board power	15.4 kWh
Driving Range	140 Km
Charging point power demand	50 kW
SoC_{crit}	40%

Table 2.
Characteristics (average) of EVs [26].

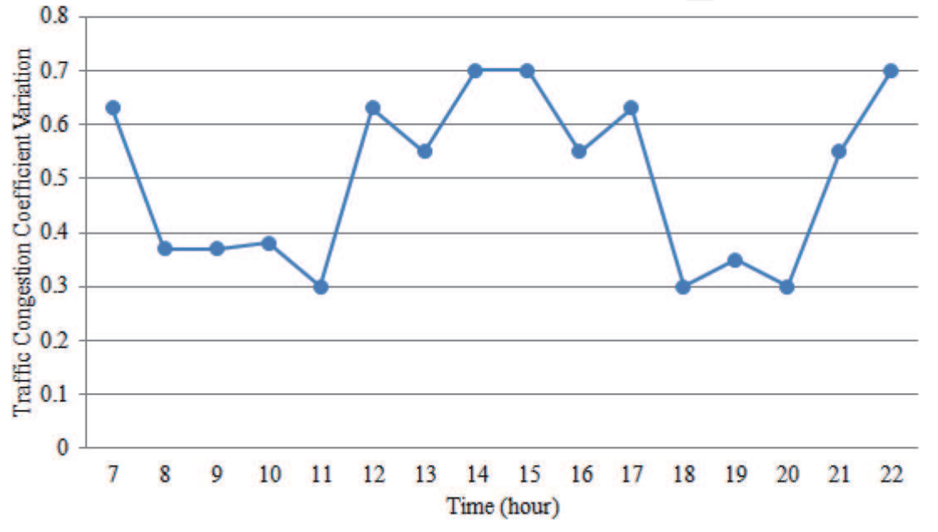

Figure 6.
Traffic congestion coefficient variation.

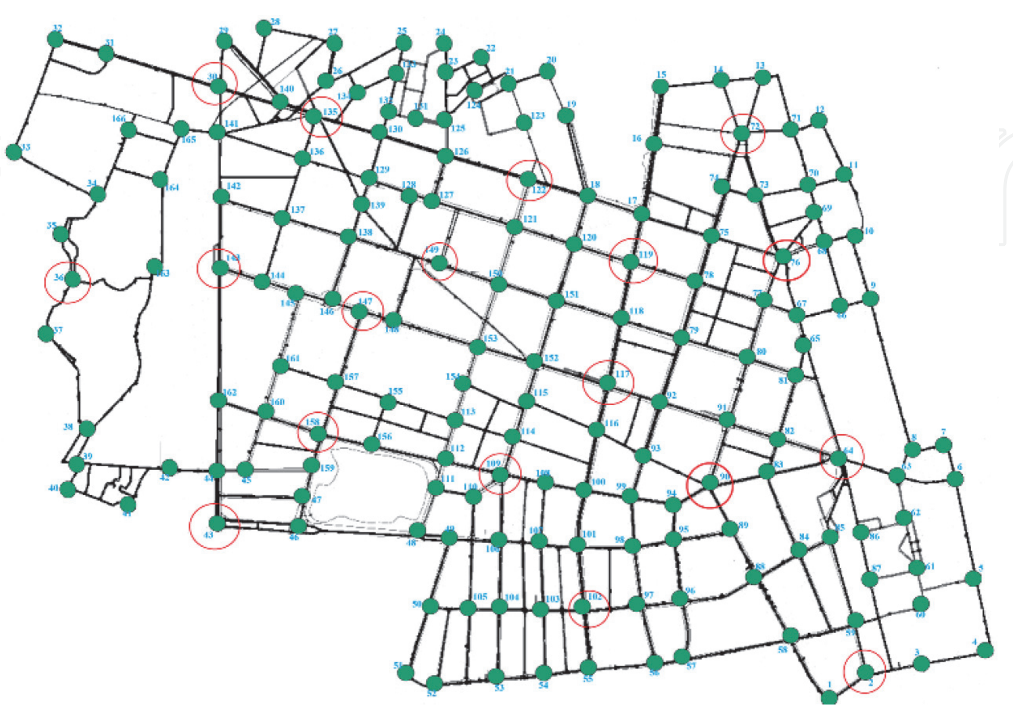

Figure 7.
Potential fast-charging station locations with high traffic flow of EVs.

5. Conclusions

The daily increase in the number of EVs brings in a big challenge for the planning of charging stations. In order to deal with the placement issues of EV charging stations, this chapter presents an optimized model for locating fast-charging stations using the EV trajectories reconstructed from simulation. In this model, battery degradation, the range of electric vehicle, traffic congestion conditions and especially vehicles traffic flow have considered to determine the optimal locations for the fast-charging station network. This is a quick and efficient way to solve the location problem of fast-charging stations. However, this approach is based on the assumption that the EVs will take the route derived from the simulation, which can be veriï¬ed. under the connected vehicle environment in the future. It can also be further improved if more research can be carried out to investigate the deployment of the local institutional and spatial settings.

Author details

Tran Van Hung
University of Transport and Communications, Hanoi, Vietnam

*Address all correspondence to: hungtv_ktdt@utc.edu.vn

References

[1] Chung, S.H.; Kwon, C. Multi-period planning for electric car charging station ocations: A case of Korean Expressways. Eur. J. Oper. Res. 2015, 242, 677–687.

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

[3] Explore The Difference between Fast Charging and Slow Charging Based on the Principle of Lithium Batteries. Available online: http://www.juda.cn/news/22476.html

[4] Fang He, Yafeng Yin, Jing Zhou. Deploying public charging stations for electric vehicles on urban road networks. Transportation Research Part C 60 (2015) 227–240.

[5] Kuby, M.; Lim, S. Location of Alternative-Fuel Stations Using the Flow-Refueling Location Model and Dispersion of candidate Sites on Arcs. Netw. Spat. Econ. 2007, 7, 129–152.

[6] Upchurch, C.; Kuby, M.; Lim, S. A Model for Location of Capacitated Alternative-Fuel Stations. Geogr. Anal. 2009, 41, 85–106.

[7] Kim, J.G.; Kuby, M. The deviation-flow refueling location model for optimizing a network of refueling stations. Int. J. Hydrogen Energy 2012, 37, 5406–5420.

[8] Kim, J.G.; Kuby, M. A network transformation heuristic approach for the deviation flow refueling location model. Comput. Oper. Res. 2013, 40, 1122–1131.

[9] Patrick Jochem et al. Optimizing the allocation of fast charging infrastructure along the German autobahn. Springer-Verlag Berlin Heidelberg 2015, J Bus Econ (2016) 86:513–535. DOI 10.1007/s11573-015-0781-5

[10] Ismail Capar, Michael J. Kuby: An Efficient Formulation of the Flow Refueling Location Model for Alternative Fuel Stations. DOI: 10.1080/0740817X.2011.635175

[11] Cheng Wang et al. Electric Vehicle Charging Facility Planning Based on Flow Demand—A Case Study. https://doi.org/10.3390/su13094952. 2021

[12] Kou, L.F.; Liu, Z.F.; Zhou, H. Modeling algorithm of charging station planning for regional electric vehicle. Mod. Electr. Power 2010, 27, 44–48.

[13] Ge, S.Y.; Liang, F.E.; Hong, L.; Long, W.A. The planning of electric vehicle charging stations in the urban area.In Proceedings of the Electric Mechanical Engineering and Information Technology (EMEIT) Conference, Yichang, China, 16–18 September 2011.

[14] Wu, C.Y.; Li, C.B.; Du, L.; Cao, Y.J. A method for electric Charging infrastructure planning. Autom. Electr. Power Syst. 2010, 34, 36–39.

[15] Jianmin Jia, Chenhui Liu and Tao Wan. Planning of the Charging Station for Electric Vehicles Utilizing Cellular Signaling Data. Sustainability 2019, 11, 643; doi:10.3390/su11030643

[16] Zhang, H.; Shi, B.; Zhuge, C.; Wang, W. Detecting Taxi Travel Patterns using GPS Trajectory Data: A Case Study of Beijing. KSCE J. Civ. Eng. 2019, 1–9.

[17] Csaba Csiszár et al. Location optimisation method for fast-charging stations along national roads. https://doi.org/10.1016/j.jtrangeo.2020.102833

[18] Dijkstra, E.W.: 'A note in two problems in connexion with graphs', Numer. Math., 1959, 1, (1), pp. 269–271

[19] Capar, I., Kuby, M., Leon, V.J., Tsai, Y.-J., 2013. An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. Eur. J. Operat. Res.227 (1), 142–151. https://doi.org/10.1016/j.ejor.2012.11.033.

[20] Treiber, M., Kesting, A.: 'Traffic flow dynamics: data, models and simulation' (Springer, Berlin, 2013)

[21] Ameya Ulhas Ghodke et al. Intra-city EV charging optimization based on vehicle usage pattern and traffic congestion analysis. 2nd International Conference on Large Scale Grid Integration of Renewable Energy, India, July 2019.

[22] Ameya Ulhas Ghodke et al. Intra-city EV charging optimization based on vehicle usage pattern and traffic congestion analysis. 2nd International Conference on Large-Scale Grid Integration of Renewable Energy, 2019.

[23] 'Map data copyrighted by OpenStreetMap contributors'. Available at https://www.openstreetmap.org, accessed 26 November 2019

[24] Treiber, M., Kesting, A.: â'Traffic flow dynamics: data, models and simulation' (Springer, Berlin, 2013)

[25] D. Krajzewicz, "Traffic simulation with SUMO–simulation of urban mobility," in Fundamentals of traffic simulation, Springer, 2010, pp. 269–293.

[26] Recargo Inc.: 'Compare Electric Cars and Plug-in Hybrids by Features, Price, Range'. Available at http://www.plugincars.com/cars, accessed 26 November 2019