OPTIMAL DEPLOYMENT OF FAST CHARGING STATIONS

Sina Bahrami, University of Toronto
Motahareh Shafiee Fard, Sharif University of Technology
Matthew J. Roorda, University of Toronto
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Introduction

The transportation sector is a major greenhouse gas producer. Policies are needed to promote the use of Electric Vehicles (EVs) (Chapman, 2007; Samaras and Meisterling, 2008; IEA, 2012; Nie et al., 2016) due to their energy effectiveness and reduced emissions. However, the lack of EV fast charging infrastructure prevents widespread usage of EVs due to their limited driving range (Eberle and von Helmolt, 2010). On the other hand, the high construction cost associated with such charging stations makes building them financially non-beneficial without sufficient recharging demand. This is a “chicken and egg” problem (Lim and Kuby, 2010), and motivates governments to provide subsidies for constructing fast charging stations. For instance, the province of British Columbia in Canada has the plan to build 570 charging stations for electric vehicles across the province (GLOBE Foundation, 2012).

The location of charging stations has an influence on EV users’ route choice decisions, which in turn may have an impact on transportation network performance. We explain this effect using the network in Fig. 1 which is a modified version of the network presented in Braess’ paradox. Travel demand between OD pair (1, 4) is equal to 6, and half of the users are willing to use EVs, if there are fast charging stations. Table 1 presents the link properties. The driving range of EVs and traditional vehicles (combustion engine vehicles) are assumed equal to 10 and 20, respectively. Also, it is assumed that vehicles leave their origins with full fuel tank and battery. This assumption is reasonable since EVs can charge their batteries at their origins or destinations with Level 1 chargers, which can be installed easily at residential locations, where EVs dwell for long times. The ubiquitous gas stations also provide the ability to leave origin with full fuel tank. Table 2 and 3 present the flows and travel times of links and paths under four different scenarios, respectively. In the first scenario, there are not any fast charging stations, and users consequently do not use EVs. In this case, all paths have similar travel time (92) and total system travel time is equal to 552. In the second scenario, a fast charging station is installed at node 2, and paths 1 (1→ 4) and 3 (1→3→ 5) have become feasible for EVs. It can be seen that link and path flows under this condition are similar to the first scenario and total system travel time is 552. In the third scenario, the fast charging station is installed at node 3 instead of node 2. In this case, only path 2 (links 2→5) is feasible for EVs. In this case, total system travel time decreases to 527.1. In the fourth scenario, we assume that there are fast chargers at both node 2 and 3. It can be seen that although building two charging station is more expensive, it increases the total system travel time to 552 again. Also, it is worth to mention that scenarios two to four provide similar network coverage.

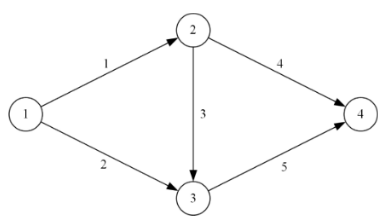

Figure 1- Transportation network.

Table 1- Link properties.

Link	travel time function	length
1	$10x_1$	6
2	$50 + x_2$	6
3	$10 + x_3$	5
4	$50 + x_4$	5
5	$10x_5$	5

Table 2-Link flows and travel times under equilibrium condition.

Link	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	flow	travel time	flow	travel time	flow	travel time	flow	travel time
1	4	40.0	4	40.0	3	30.0	4	40.0
2	2	52.0	2	52.0	3	53.0	2	52.0
3	2	12.0	2	12.0	1.08	11.1	2	12.0
4	2	52.0	2	52.0	1.92	51.9	2	52.0
5	4	40.0	4	40.0	4.08	40.8	4	40.0

Table 3- Path flows and travel times.

Path	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	flow	travel time	flow	travel time	flow	travel time	flow	travel time
1	2	92.0	2	92.0	1.92	81.9	2	92.0
2	2	92.0	2	92.0	3	93.8	2	92.0
3	2	92.0	2	92.0	1.08	81.9	2	92.0

The abovementioned example highlights the impact of blind deployment of charging stations in a network. Hence, it is critical to assist decision makers in the deployment of fast charging stations in metropolitan areas. It is worth to mention that the problem of deploying charging stations in urban areas is eliminated due to battery technology improvements in recent years. Currently, most EVs have a driving range of 100 km to 160 km (U.S. Department of Energy, 2014) that is longer than most of urban trips' distances, and EV users can charge their vehicles overnight in their homes with slow chargers. However, these driving ranges are not enough for completing intercity trips, and drivers also do not tend to dwell for long times to charge their batteries with slow chargers in the middle of their routes (Community Energy Association, 2013). An optimal set of locations not only can increase EVs widespread usage by extending network coverage, but also can improve network performance. This performance improvement could decrease traffic congestion in the network and reduce the need for further investment by governments for constructing more roads or designing tolling systems.

The reminder of paper is as follow. Section 2 presents the existing literature. The mathematical model is presented in section 3. It follows with the numerical example and sensitivity analysis in section 4. Finally, section 5 concludes the paper.

Literature review

The existing literature can be categorized into two major types: trip characteristics, and flow dependent. Trip characteristics models are dedicated to slow charging stations, and assume that EVs recharge their batteries in locations where they dwell for long times (Frade et al., 2011; Chen et al., 2013; Xi et al., 2013). They generally use regression models to find EVs' tours and their dwell times in different locations. Their objective is to find the critical locations, which are common among more users and provide the maximum network coverage. These models neglect the traffic network and link flows. However, for fast refueling facilities like battery swap stations, it is more realistic to consider that EVs visit them in the middle of their routes between origins and destinations whenever it is needed. This assumption leads to the development of flow dependent models. Kuby and Lim (2005) develop the first flow refueling location model considering the limited driving range of alternative fuel vehicles. They assume that there is only one shortest path between an OD pair, and all vehicles traverse through that path. Hence, they try to locate a given number of refueling stations in locations that maximize the covered demand. Wang (2007), and Wang and Lin (2009) try to find the minimum number of such locations, which cover the whole transportation network. Kim and Kuby (2012) extend the flow refueling location model by considering that EVs may deviate from their shortest paths to visit a charging station. Although the existing literature considers the possibility of deviating from shortest paths for recharging, they neglect the effect of deviating flows on links travel times and shortest paths. Chen et al. (2013) investigate the effect of charging station locations on route choice and network performance under the equilibrium condition. They use total network travel time as the network performance criterion and show how it changes when the locations of charging stations are changed in a network. However, they leave finding the problem of finding optimal locations for future research. In this study, we make the first attempt to model this problem. Hence, we model a nonlinear complementarity problem to optimize the location of fast charging stations. The objective is to maximize network coverage while minimizing the total network travel time.

Mathematical Model

In this section, a complementarity model is presented for finding the optimal location of fast charging stations. Consider the following notation:

$G(V,A)$	Transportation graph
V	Set of vertices
A	Set of links
K_{rs}	Set of paths between OD pair (r,s)
q^{rs}	Total demand between OD pair (r,s)
f_k^{rs}	Traffic flow of path $k \in K_{rs}$
$\boldsymbol{f}$	Vector of all path flows
T_k^{rs}	Travel time on path $k \in K_{rs}$
x_a	Traffic flow on link a
$t_a(x_a)$	Travel time on link a
$\delta_{a,k}^{rs}$	Path-link Incidence array
u_{rs}	Shortest travel time between OD pair (r,s) (including charging time)
$\boldsymbol{u}$	Vector of u_{rs}
y_j	Binary variable equal to 1 if a charging station is established in node j and 0 otherwise
N_n	Set of candidate locations for charging stations
n	maximum number of charging stations

Subscript c and e specify use of the parameter for combustion engine vehicles and EVs respectively.

$$Min \sum_{a \in A} x_a t_a(x_a) \tag{1}$$

Subject to:

$$(T_{k_c}^{rs}(\boldsymbol{f}) - u_c^{rs}) f_{k_c}^{rs} = 0 \qquad \forall\, k_c \in K_c^{rs}, rs \in W \tag{2}$$

$(T_{k_e}^{rs}(\boldsymbol{f}) - u_e^{rs})f_{k_e}^{rs} = 0 \quad \forall\, k_e \in K_e^{rs}, rs \in W \quad (3)$

$T_{k_c}^{rs}(\boldsymbol{f}) - u_c^{rs} \geq 0 \quad \forall\, k_c \in K_c^{rs}, rs \in W \quad (4)$

$T_{k_e}^{rs}(\boldsymbol{f}) - u_e^{rs} \geq 0 \quad \forall\, k_e \in K_e^{rs}, rs \in W \quad (5)$

$\sum_{k_c \in K_c^{rs}} f_{k_c}^{rs} = q_c^{rs} \quad \forall\, rs \in W \quad (6)$

$\sum_{k_e \in K_e^{rs}} f_{k_e}^{rs} = q_e^{rs} \quad \forall\, rs \in W \quad (7)$

$f_{k_c}^{rs} \geq 0 \quad \forall\, k_c \in K_c^{rs}, rs \in W \quad (8)$

$f_{k_e}^{rs} \geq 0 \quad \forall\, k_e \in K_e^{rs}, rs \in W, m \in M \quad (9)$

$\sum_{j \in N^n} y_j \leq n \quad (10)$

$y_j = \{0,1\} \quad \forall j \in N^n \quad (11)$

in which

$T_{k_c}^{rs}(\boldsymbol{f}) = \sum_{a \in A} \delta_{a,k_c}^{rs} t_a(x_a) \quad \forall\, k_c \in K_c^{rs}, rs \in W \quad (12)$

$T_{k_e}^{rs}(\boldsymbol{f}) = \sum_{a \in A} \delta_{a,k_e}^{rs} t_a(x_a) + T_{k_e}^{c}(\boldsymbol{y}) \quad \forall\, k_e \in K_e^{rs}, rs \in W \quad (13)$

$x_a = x_{ac} + x_{ae} \quad (14)$

$x_{ac} = \sum_{rs \in W} \sum_{k_c \in K_c^{rs}} \delta_{a,k_c}^{rs} f_{k_c}^{rs} \quad \forall\, a \in A \quad (15)$

$x_{ae} = \sum_{rs \in W} \sum_{k_e \in K_e^{rs}} \delta_{a,k_e}^{rs} f_{k_e}^{rs} \quad \forall\, a \in A \quad (16)$

The objective function (Equation 1) minimizes the total network travel time. Equations (2) and (4) state that travel times of utilized paths between OD pair (r, s) by combustion engine vehicles are equal to u_c^{rs}, and it is equal or less than travel times of unutilized paths. Equations (3) and (5) state similar conditions for EVs. Equations (6) and (7) ensure that the path flows are equal to travel demand between an OD pair. Equations (8) and (9) state the non-negativity of path flows for combustion engine vehicles and EVs, respectively. Equation (10) ensures that the number of deployed charging stations is less than the maximum number of charging stations. The value of n can be recognized by the total available budget. Equation (11) is the integrality condition of the binary decision variable. Equations (12) and (13) compute the travel time of each path. The second term of equation (13) is the EVs battery recharging time when visiting charging stations in the middle of their routes. Equations (14) to (16) compute the flow of each link. The EVs driving range and possibility of its extension by visiting charging stations in the middle of route is implied in set of paths (K_e^{rs}). We use the model presented by Bahrami et al. (2017) to generate such paths.

Numerical experiment

The well-known Sioux Falls network is used to find the optimal location of charging stations. This network has been used in many publications to compare the results. The topology of the Sioux Falls network is illustrated in figure 2. Link properties and demands are taken from He et al. (2014). The volume-delay function used for the network follows the BPR equation, which is

$$t_a(x_a) = t_a^0(1 + 0.15(\frac{x_a}{c_a})^4)$$

where t_a^0 is the free-flow travel time and c_a is the capacity (measured in vehicles per hour) of link a. The average link length is 6 km in this network, hence, driving range of EVs is assumed to be 16km to be consistent. We assume that the budget limit allows building a maximum of 4 charging stations. Figure 3 presents the network coverage for different combination of charging locations. It can be seen that 67% of OD can use EVs even without installing any charging stations. As the number of installed charging station increases, the range of network coverage also increases. For instance, the network coverage varies between 67.2% and 77.8% with one charging station, while it differs between 70.6% and 100% with four charging stations. It also can be seen that even one optimal charging station can provide more network coverage than four non-optimal ones. Figure 4 presents the number that the presence of a node in a combination provides full network coverage. Node 5 has the highest repetition (155 times), while node 1 has the lowest (5 times). Finally, we solve the model presented in previous section with $n = 4$, and do sensitivity analysis on how the total network travel time changes when the EVs' market share increases. There are 10626 different combinations of 4 charging location in this network. The model only considers 335 combinations, which provide full network coverage. Figure 5 depicts total network travel time variation for some of these combinations.

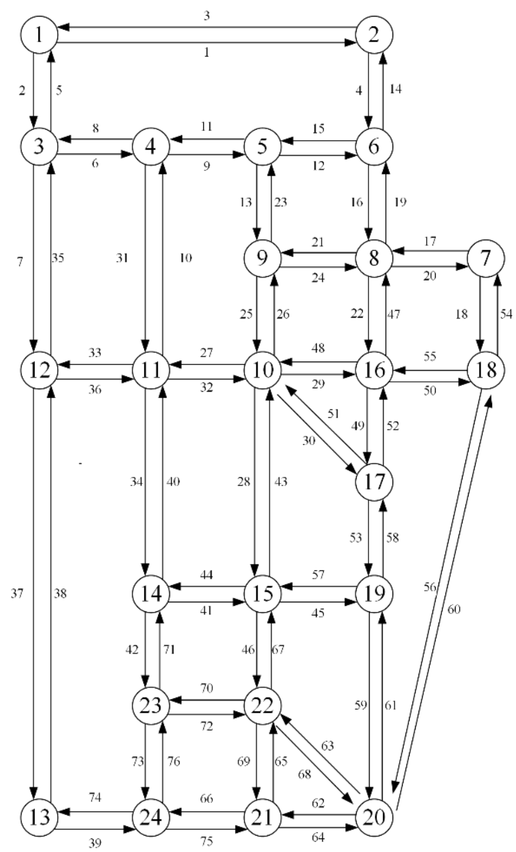

Figure 2- Sioux Falls network.

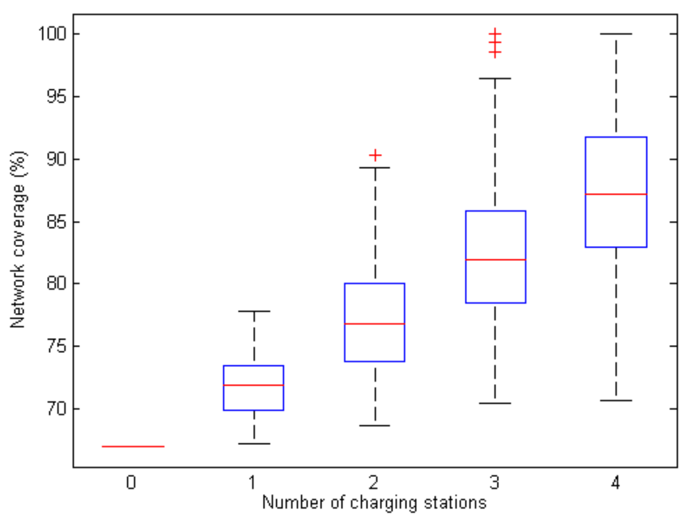

Figure 3- Network coverage for different combinations of charging locations.

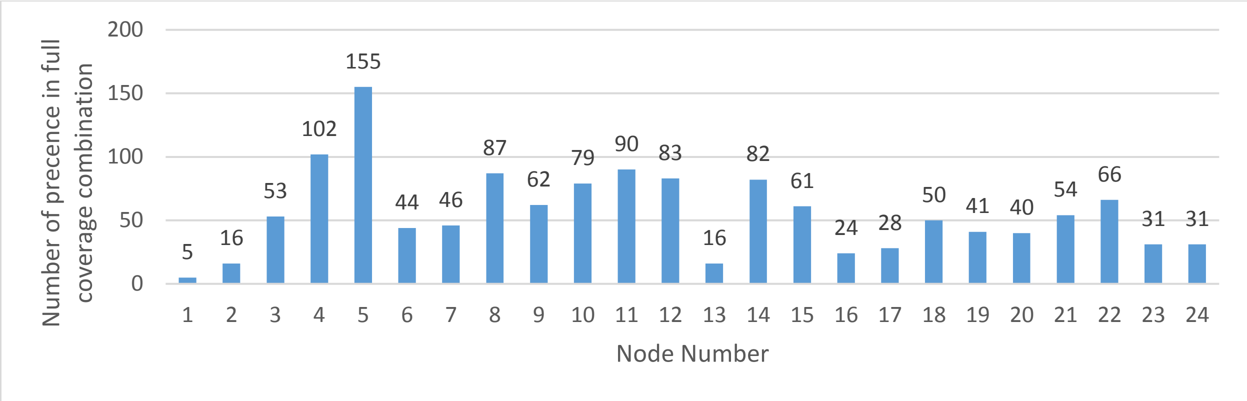

Figure 4- Presence of a node in a full network combination.

It can be seen in figure 5 that although the total network travel times are very close for different combinations when the EVs' market share is low, it varies significantly when the market share increases. This graph also highlights the importance of considering both traffic flow condition and network coverage in selecting the optimal location of charging stations. The both combination of building charging stations in nodes (7, 12, 19, 21) and (5, 10, 11, 22) provides the full network coverage. However, the latter combination decreases the total network travel time by 97% in comparison with the earlier combination.

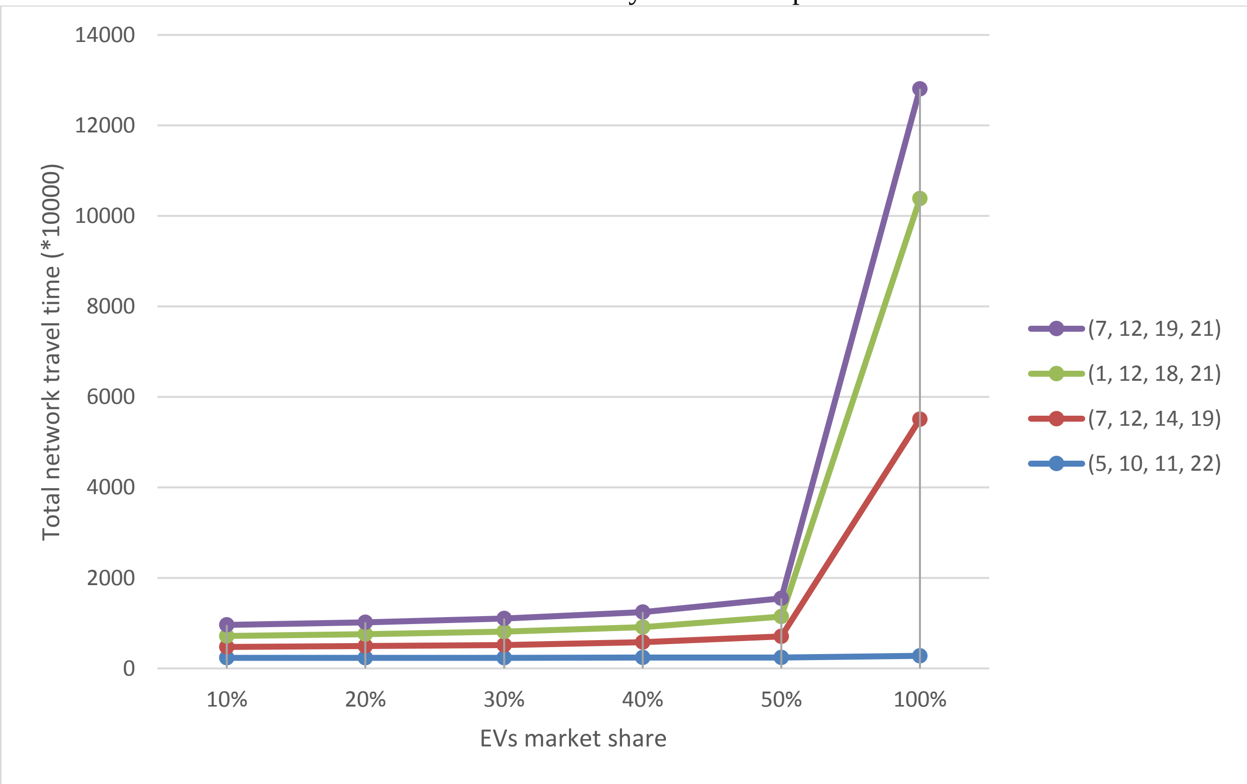

Figure 5- Total network travel time variation.

Conclusion

The EV market share has increased due to growing concern over environmental issues, financial incentives, and battery technology developments. Currently, EVs have sufficient driving range for intra-city trips where drivers can charge their vehicles at home or at the location of their activities. For inter-city travel, however, the trip distances are much longer and vehicles need to charge en-route to increase their driving range. Charging en-route is different from home-charging. Whereas in home-charging people can leave their vehicles plugged-in and come back later, en-route charging requires that drivers wait until the charging process is complete. Hence, it is critical to have fast chargers that cut down the charging time considerably and increase the charging coverage in order to promote EV penetration in the market. However, the high cost associated with constructing fast charging stations limits the number of charging stations that can be deployed and necessitates choosing their locations optimally.

In this study, we solve a nonlinear complementarity problem to optimize the location of fast charging stations to maximize network coverage and minimize total network travel time. Results show that optimizing the location of charging stations can reduce the total travel time by up to 21% whereas unregulated expansion of the charging infrastructure can actually increase the total network travel time.

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