Title: Charging Infrastructure Planning in Urban Networks Considering Detour and Queuing Delay

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Keywords: Charging station, Charger, Urban Network, Detour, Queue, Optimization

1. Introduction

Global warming, crude oil price fluctuations, and concerns over traffic emissions have all led the car industry toward electric vehicles (EV) (*1*, *2*). EVs are known to reduce on-road emissions and if accompanied by renewable sources of energy, they can mitigate air pollution significantly. Limited range, insufficient supporting infrastructure, and long charging times have hindered the acceptance of the EVs in the market (*1*, *3*). Providing supporting charging infrastructure may mitigate the challenges associated with EVs and increase their market share (*4*). Recent studies have investigated the location of charging infrastructure, through variety of approaches. One approach uses households' travel data and an agent-based model, to minimize the number of trips not being fulfilled by electric miles (*2*). Taxi trajectories have also been used to locate the charging stations in urban areas. Studies suggest the locations with the longest dwell time and as the candidate points for building charging stations (*5*). In an extension to this study, an optimization model is proposed to find the optimum locations maximizing the vehicle-miles-traveled (*6*). As the GPS data for private EVs might not be available, some studies have used the origin-destination demand to model the vehicles' behavior (*7*). Although the urban trips can usually be fulfilled with a full battery, not every EV start with a fully charged battery. Therefore, the state of charge data at the start of the trip should be acquired. Some studies have used simulations to estimate this data and predict the charging behavior of EVs (*8*). This study contributes to the literature in the following aspects: 1) Formulating the problem considering initial state of charge variations, range anxiety, path feasibility, detour delay, and queuing delay 2) Incorporating a decomposition technique to linearize the problem formulation 3) Presenting a framework that estimates different initial state of charges for EVs.

2. Methodology

This study aims to find the optimum location of charging infrastructure in urban areas. For this purpose, the required data is collected including market share of electric vehicles, land use, land acquisition cost, utility provision cost, dynamic origin-destination demand tables, and road network information. Then, a mesoscopic simulation framework is used to capture travel patterns in urban areas (DYNASMART-P). The vehicle trajectories, including start/end time, origin/destination, and traveled distance for each vehicle, as well as time-dependent zone-to-zone travel times and distances are the output of the traffic simulation. These data are used as inputs to the developed optimization model in this study to locate charging stations and specify the number of required chargers at each station. The initial state of charge (I-SOC) is one of the main factors affecting the charging needs of EV users in the urban areas. Thus, an I-SOC simulator is developed to realistically estimate a state of charge for each trip based on the land use at trip origin and destination and trip purpose. EVs that require charging to fulfill their trip, are used as inputs to the optimization model to find the best configuration of charging infrastructure that provides feasibility for all EV trips considering users' delays. The framework designed in this study is presented in Figure 1.

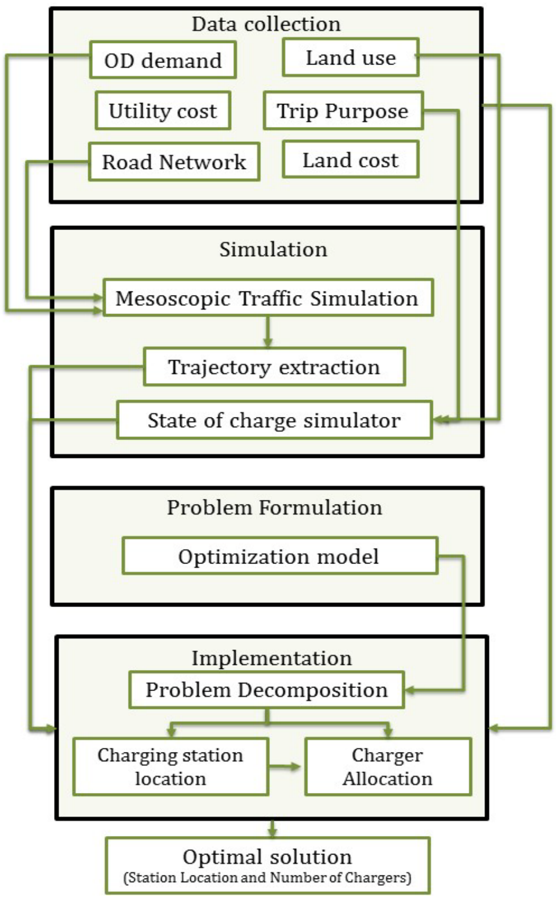


Figure 1 General research framework

The objective function of this study consists of two main terms. The first term calculates the total infrastructure investment cost including the total cost of charging stations and chargers (i.e. modules cost, electricity provision cost, and land cost). The next term provides the monetary value of the total delay experienced in the network, which includes the charging delay, queuing delay, and detour time. The main constraints of this model include tracking the state of charge, flow conservation, detour time, and queuing constraints.

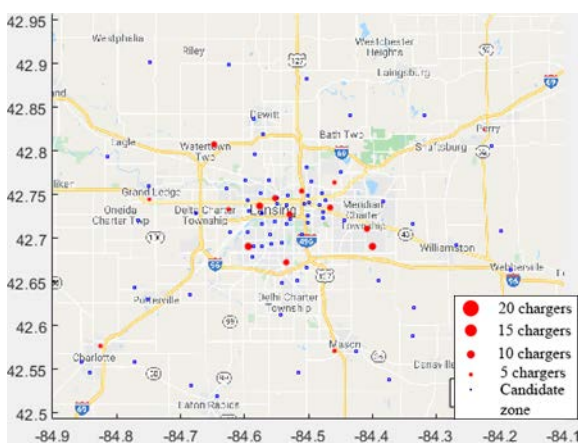
The optimization model is a mixed-integer problem with non-linear constraints. Due to the computational complexity, the commercial solvers cannot provide solutions efficiently for these types of problems, especially for large-scale networks. In this study, using a decomposition technique, the problem is divided into two sub-problems. The first sub-problem finds the optimum location of charging stations in the network minimizing the cost of charging stations and the travel detour for users. The objective function of this sub-problem along with its constraints form a mixed-integer program with linear constraints. A commercial solver, CPLEX, is used to solve this problem. In addition, for large scale applications a meta-heuristic algorithm based on the simulated annealing approach is implemented. The second sub-problem finds the number of required chargers at each of the selected charging stations, minimizing the cost of chargers and the queue experienced by EV users. Both overflow and random arrival queues are considered in this modeling framework. The objective function of this sub-problem along with its constraints form a mixed-integer problem with nonlinear constraints. This sub-problem, with a convex objective function, is solved analytically using the Golden-section search technique, which is designed to find the extreme value of a function in a pre-defined interval as its domain.

3. Results

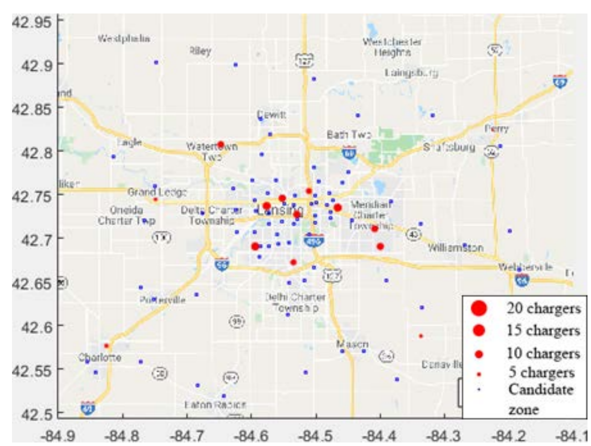
The Greater Lansing area and its vicinity are used as the case study. Sensitivity analysis has been performed on the battery and charger type. The optimum configuration of charging infrastructure for four scenarios are provided in Table 1, with the inputs to the model presented in the first four rows and summarized outputs in the next six rows. The output data includes the number of charging stations, the total number of chargers at each charging stations, total charging delay, station cost, charger cost, and total investment cost. Figures 2 (a-d) show the charging infrastructure configuration for the tested scenarios for the Lansing area. The red dots in these figures represent charging stations, and the size of each dot shows the number of chargers at each station. The blue dots show candidate locations that have not been selected to be equipped with charging stations.

Table 1 Scenario results for the city of the Lansing area: charging stations, chargers, required investment, and charge time

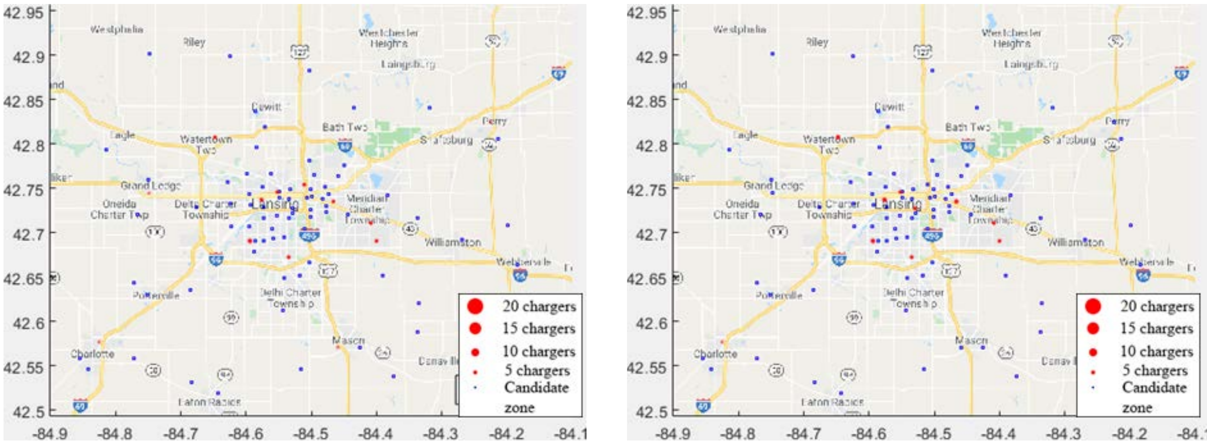
Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of candidate zones	92	92	92	92
EV trips	28,574	28,574	28,574	28,574
Number of selected stations	16	14	13	10
Total number of chargers in all stations	85	89	36	33
Station cost (Million dollar)	2.52	2.21	2.47	1.88
Charger cost (Million dollar)	3.39	3.56	2.96	2.73
Total infrastructure cost (Million dollar)	5.91	5.78	5.43	4.62
Average charging and queuing delay (min)	10.80	14.74	3.83	5.26



(a)



(b)



(c) (d)

Figure 2- Charging station and charger configuration for the Greater Lansing area and its vicinity for a)70 kWh battery-50 kW charger b) 100 kWh battery-50 kW charger c) 70 kWh battery-150 kW charger d) 100 kWh battery-150 kW charger

4. Conclusion

This study proposes a framework to find the optimal configuration of charging stations for urban areas. This paper presents the approach and results for the Lansing area and Detroit regional network as the case study. The main findings of this study are:

- Developing a modeling framework that can estimate the required infrastructure investment for a given market share of EVs. The framework identifies optimal locations for charging stations and the required number of chargers at each location.
- 150 kW chargers even though more expensive per piece, reduce the total charging and waiting time of EVs, compared to 50 kW chargers. Thus, implementing a network of 150 kW chargers is less costly than a network of 50 kW chargers.
- Battery size does not affect the location and number of chargers required to support urban trips significantly, unlike the intercity networks that are studied by the same authors in recent publications.
- Building a network of 150 kW chargers can support the trips, even if the vehicles can only accept up to 50 kW of power. However, this would add up the users' delay significantly.

5. Acknowledgment

This work was supported by the Department of Energy and Energy Services under Award Number EE008653.

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