Electric Vehicles Equilibrium Model that Considers Queue Delay and Mixed Traffic

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Abstract

This study develops an equilibrium model for electric vehicles (EVs) that considers both queue delays in charging stations and flow dependent travel times. This is a user equilibrium model that accounts for travel, charging and queuing time in the path choice modelling of EVs and the complementary traffic. Waiting and service times in charging stations are represented by an m/m/k queuing system. The model considers multiple vehicle and driver classes, expressing different battery capacity, initial charge state and range anxiety level. Feasible paths are found for multiple classes given their limited travel range. A numerical application exemplifies the limitations of EVs assignment and their impact on flow distribution.

Keywords: Electric vehicle, Network equilibrium, EV charging, Queue delay

1. Introduction

The growing concern of climate change has been drawing wide attention to the reduction of greenhouse gases (GHG) emissions. The transportation sector is a major contributor to GHG emissions, evaluated by roughly 30% in the United States, Canada and Europe [(US EPA, 2016), (Environment and Climate Change Canada, 2017), (European Environment Agency, 2018)]. EVs are one of a cartel of environmental solutions, suggesting a way to curtail the emissions produced by road transportation, significantly reduce inter-city air pollution, and decrease our dependency on limited fossil energy sources. EVs have zero tank-to-wheel emissions, and depending on the electric energy source, can have substantially lower well-to-wheel emissions than those of internal combustion engine vehicles (ICEVs).

A major obstacle to mass adoption is the limited travel range of EVs, together with a limited availability of charging stations. This is a chicken-and-egg problem as the limited penetration of EVs decrease the value of installing charging stations infrastructure, and the limited availability of charging stations limits EVs demand. The willingness of customers to purchase EVs is widely dependent on their effective allocation, and the degree of discomfort required for battery charging.

In recent years, many studies have focused on the optimal allocation of charging stations. The structure of an infrastructure allocation problem is bi-level, as the relationship between different decision makers is hierarchical. The siting of new charging stations (leader's decisions) should respond to the anticipated EVs demand and vehicle distribution in the network (follower's decisions), while the demand and path choice depend on the available infrastructure. Nevertheless, most models handle the problem in a single level where the EV assignment is embedded within the charging station allocation model. This is performed by simply assigning the given demand to a few paths connecting an origin-destination (O-D) pair, if the travel range is feasible for EV. Most models consider only the shortest path between each O-D pair. This approach has several drawbacks, as it restricts the assignment by ignoring other feasible paths. In addition, the demand is only assigned when satisfactory infrastructure is allocated along the considered shortest path. In practice, a driver may be willing to conduct a small detour in order to charge her vehicle. Moreover, it does not reflect the independent nature of user's path choice that depends on network flow, charging stations occupancy and personal preferences.

The traffic assignment problem (TAP) is one of the classic problems in transportation modelling, as it features finding an estimated flow distribution for a given network topology and fixed demand matrix. The main property of EVs special case is the limited range of vehicles and the charging occurrences, requiring path alternation and the consideration of charging time.

Few studies have considered EVs assignment as an independent problem (e.g., Jung et al. (2014), He et al. (2014), Li et al., 2016, He et al (2018)). These models have several common limitations. First, most developed equilibrium models considered only EVs demand in the network. As the main share of the demand is still ICEVs, considering only the EVs when evaluating flow dependent travel times is unrealistic. Second, charging times are commonly not considered, or evaluated solely by the amount of energy charged.

The first to model waiting times at charging stations by a queue delay function were Jung et al. (2014), that developed a dynamic bi-level model for the allocation of new servers in electric taxi stations. This prominent study considered flow-dependent charging times in a lower-level simulation model. Travel times were not flow-dependent, and the model simulates only taxis traffic. An m/m/k queueing system denotes a service with k servers where arrival rate and service rate are both assumed to be Poisson processes. The formulation of the average queue length and waiting time in such a system can be reviewed in Adan and Resing (2002). This modelling was used by Jung et al. (2014) to describe charging stations queue in their simulation model of taxis operation. In the suggested model, this approach is adopted and incorporated in a user equilibrium modelling. The flow dependent queue delays and link travel times, together with the energy-dependent charging times, comprise the total travel time considered in the path choice process. To the best of our knowledge, this study is the first to consider queueing system, and mixed traffic together in a user equilibrium model.

Unlike ICEVs refueling, the EVs recharging significantly extends the travel time. The attractiveness of candidate locations was not considered in previous models. As the charging time is considerable, nearby services are likely to affect station attractiveness.

The objective of this study is to develop a realistic and efficient model for mixed EVs and ICEVs assignment, considering flow-dependent travel time, charging time and queue delay. The model accommodates different classes of drivers and vehicles, expressing several categories of battery capacities and range anxieties. In addition, it considers variations in the time value associated with waiting in different stations. This feature is essential to properly evaluate the utilization of existing and candidate charging stations.

2. Methodology

Due to the limited length of this paper we omit the formulation of the problem. Note, that the problem can be simply formulated by two complementary parts: a resource-constrained shortest path (RCSP) and a user equilibrium. The first finds shortest paths for different travel and charging times, subject to range limitations, and the last evaluates flow distribution considering flow dependent travel, charging and waiting times, while utilizing a given path set.

Considering the complexity of the problem, we applied a heuristic approach that enables to efficiently handle large-scale networks. The suggested model includes two main modules: path set generation and a user equilibrium. The first part generates a large set of candidate paths for each demand category of each O-D pair, and the second part evaluates the distribution of vehicles between the attractive paths. The general scheme of the model is presented in Figure 1.

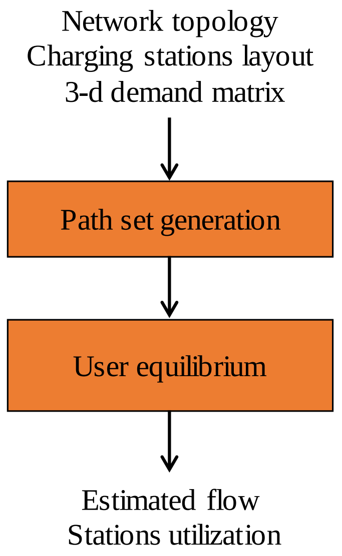

Figure 1. General model scheme

The generation of paths in a preliminary step obviates their generation during the iterative equilibrium procedure. The RCSP is known to be NP-Complete (Desrosiers et al., 1984) and therefore, this property has a very significant contribution to the efficiency of the model.

2.1 Path set generation

The generation of a large candidate path set is a stand-alone module, preliminary to the iterative equilibrium model. A path set is formed for each demand category of each O-D pair.

In the first step, a path set with no range constraints is generated for each O-D pair. This path set is used for the main share of the demand (i.e., ICEVs) and possibly, for some of the EVs demand categories, in case their range limit enables it. For each O-D pair the following procedure is applied:

Considering free flow travel times, the shortest path is found. This path is always the first in the O-D path set. Then, Gaussian noise is added to the links' travel time and the shortest path is found again. This path is then checked for validity; two conditions are checked: (1) the path is new to the list, and (2) the total travel time does not exceed some pre-determined detour time, compared to the shortest path (30% longer in this paper). If both conditions are met the path is added to the list. The randomization of travel times and path finding is repeated iteratively until the path set is full (at least 15 paths for each demand category in this paper) or until no new path is found during a pre-determined number of successive iterations (20 in this paper).

Next, the path set of the most restricting demand category (i.e., the one with that minimal travel range) is checked; in case it is not full, the following heuristic is applied:

Considering the O-D location and travel range, the list of candidates charging stations is narrowed down according to geographically relevancy. As illustrated in Figure 2, charging stations located within a polygon that lines the relevant geographical area, are candidate for in-route charging. For each candidate charging station, the model finds the shortest path from the origin to the station, and from the station to the destination. If each of the path segments meets the range constraint, it is added to a temporary list. In case the O-D pair is remote, multiple polygons can enable multiple re-charging stops. In this case path segments are found also between charging stations located in different polygons. Range feasibility is checked after each path segment generation, to avoid redundant path generation.

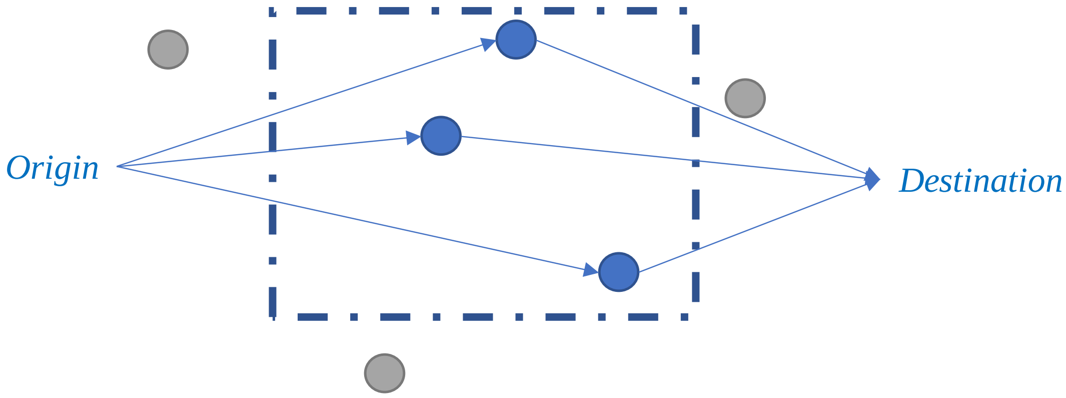

Figure 2. Candidates in-route charging stations

The temporary list is then sorted with respect to the paths total travel time. The shortest path, and paths that does not exceed some pre-determined detour time (30% longer in this paper), are saved to the path set.

2.2 User equilibrium

After a large set of candidate routes is generated, a user equilibrium algorithm is applied to evaluate the distribution of vehicles in the network. We apply the classic Frank-Wolfe algorithm, a non-linear optimization method, well-known for its efficiency in solving the TAP.

Initially, the demand is loaded fully to the shortest path, in an All or-nothing procedure. Each demand category of each O-D pair is assigned to its shortest feasible path. Next, flow-dependent travel and charging times are computed. Using the updated times, an auxiliary solution is found, by loading the full demand to the updated shortest paths. The algorithm then minimizes the user generalized cost on a hyper-plane defined between the initial and the auxiliary solutions, to find a new solution. This procedure is repeated until the difference between two subsequent solutions is small enough. This difference is evaluated by the root mean square error (RMSE) between link flows.

3. Results

The suggested model is exemplified on the benchmark test network of Sioux-Falls (LeBlanc et al., 1975). We chose this network due to its wide use in charging station allocation and EVs assignment models. Network topology and charging stations layout in the base run, are presented in Figure 3. The charging stations locations were arbitrary selected, consistent with He et al. (2014).

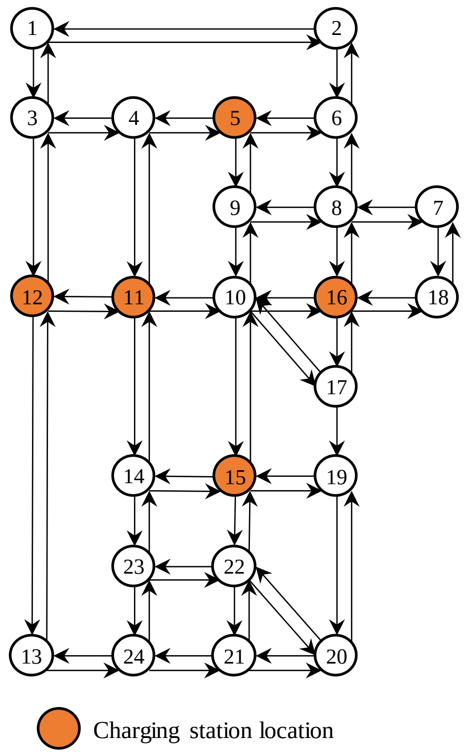

Figure 3. Sioux-Falls network and charging stations layout

The parameters of the base run are given as follows: link distances are assumed to be 1.5 times the link free-flow travel times. Battery capacity, consumption rate and the comfortable range were set to 24 kWh, 0.29 kWh/mi and 0 mi respectively (all values are consistent with He et al. (2014)). As the model is intended for in-route charging stations, we assumed all the installed stations comprise level 3 type fast chargers. For the base run, we assumed 20% of the demand is EVs, where the rest is ICEVs. The initial battery state was arbitrarily set as 0.2, 0.5 and 0.8, for 25%, 50% and 25% of the EVs, to represent different demand categories. The chargers' number in each station was arbitrarily set to [1, 2, 1, 4, 2] for the stations located in nodes [5,11 ,12 ,15,16] respectively.

The convergence of the model is smooth and fast, as shown in Figure 4. Setting the required RMSE between two adjacent solutions (i.e., the stopping criterion) to 10^{-6}, the algorithm converged after roughly 30 iterations. Running times for the test network ranged from 40 to 60 seconds on a personal computer with Intel ® Core ™ i5-8250U 1.8GHz CPU and 8GB RAM. Comparably, He et al. (2014) reported a running time of 30 minutes for the same network on a similar computer. The reduction in running times in the suggested model can be attributed mainly to the generation of paths in a preceding process and not within the iterative one.

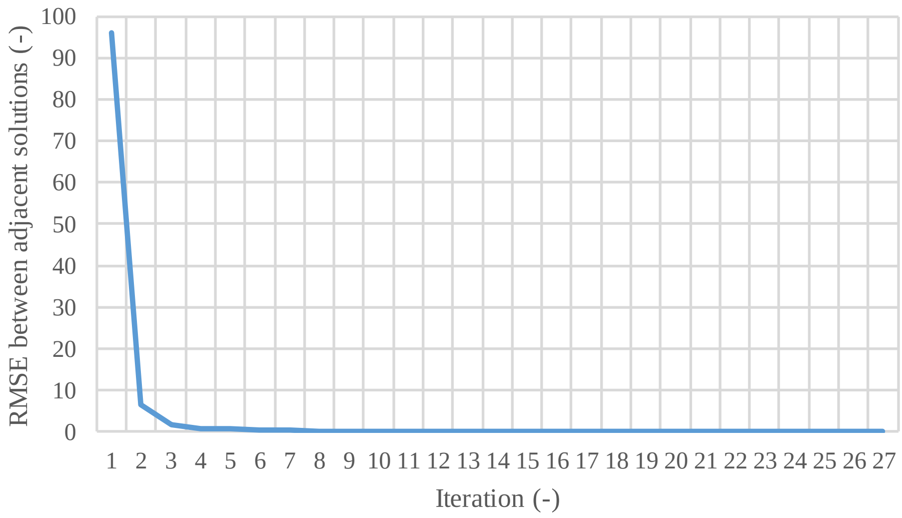

Figure 4. Equilibrium model convergence

For the base run parameters, the EVs demand was assigned fully, as feasible paths were found for all demand categories of all the O-D pairs. This result is compatible with He et al. (2014). Stations located in the center of the network (11,12,16) were used more than others (5,15), comfortably functioning as a halfway stop.

The system time is defined as the total generalized cost, i.e., travel and charging times spent in the network. System time in the solution was found to be $9.95 \cdot 10^6$ min, where charging time share was roughly 1%. Although charging time is a fraction of the system time, EVs found to have a significant impact on vehicle distribution.

Figure 5 presents the system time for different EV share values. The system time is higher for higher EVs share, showing a monotonic dependency, with a nearly parabolic trend. The two components comprising the system time, i.e., the total travel and charging times show the exact same trend. It should be noted, that this effect is likely to be moderated for a broader charging station layout.

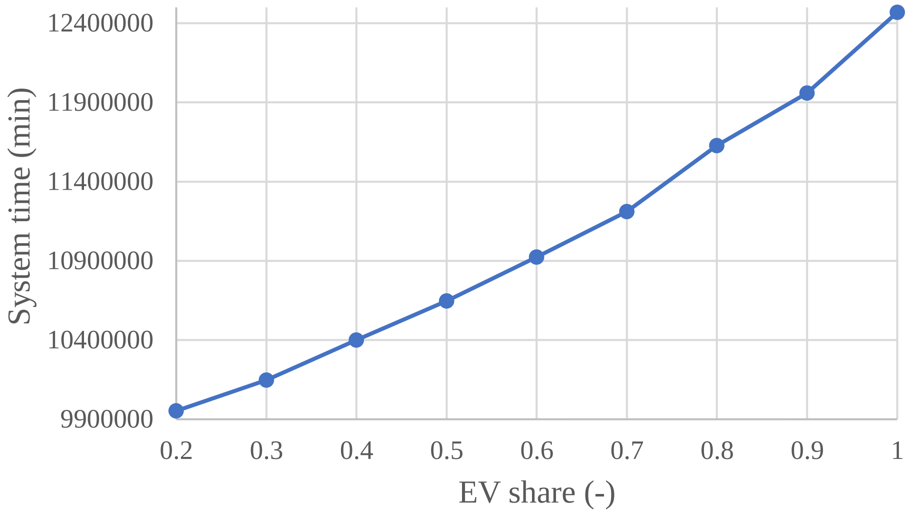

Figure 5. System time as a function of EV share

The sensitivity of charging time to the layout of charging stations is presented in Figure 6, showing the total charging time for different station allocation scenarios. In each scenario, 5 charging stations were allocated. Locations were selected using a uniform distribution probability for all nodes in the test network. Number of chargers at each station was kept the same as in the base run. Feasible paths were found for almost all O-D pairs in all scenarios. The amount of charged energy was almost identical in all scenarios, conversely, queueing times showed high variation. Some of the scenarios offered an efficient coverage of the network, distributing the EVs and reducing queueing time, while others caused bottlenecks in central and/or isolated stations.

Figure 7 presents the percentage of unsatisfied demand, as a function of range anxiety. The demand is assigned fully only for an unrealistic range anxiety value of 0. As the comfortable range increase, the percentage of vehicles that cannot complete their journey is higher. The gradual accent of the unsatisfied demand ratio is related to the demand categories, representing groups of vehicles with different initial charging state. Range anxiety value showed a noteworthy impact on the ability of the network to serve the demand. A minor decrease in range anxiety can lead to a major growth in demand satisfaction potential.

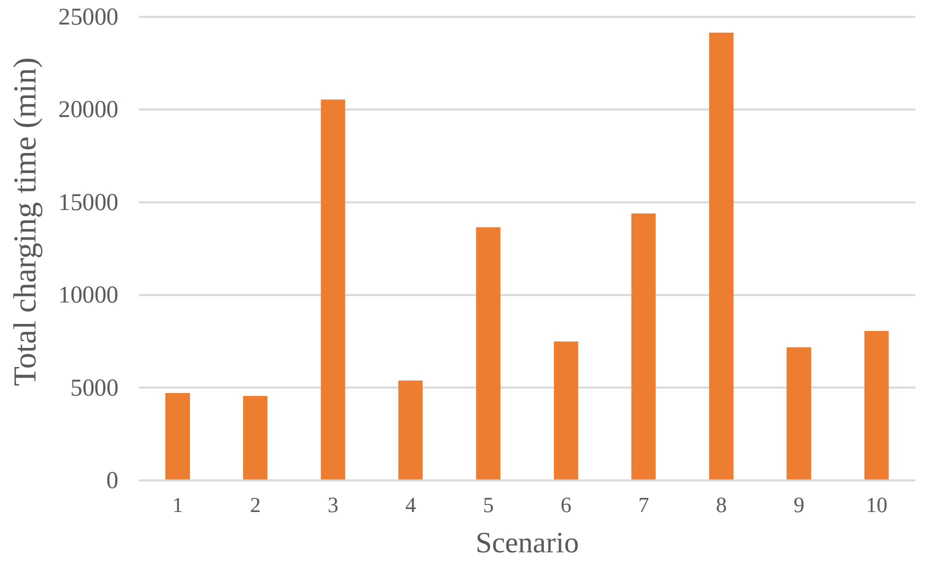

Figure 6. Total charging times for different station allocation scenarios

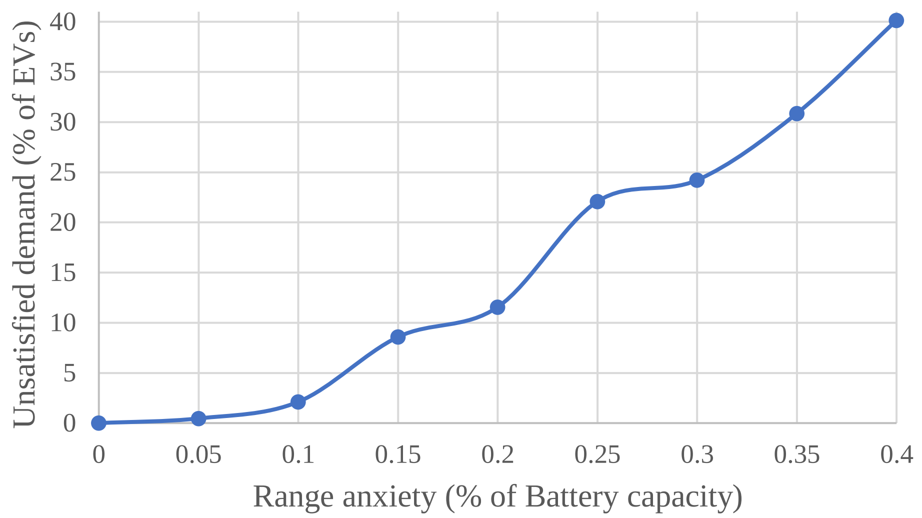

Figure 7. Unsatisfied demand proportion as a function of range anxiety

4. Conclusions

This study develops a user equilibrium model for mixed EVs and ICEVs, considering queue delay times at charging stations. The model accommodates multiple driver and vehicle classes by considering different demand categories, representing different range anxiety values, battery capacities and initial battery charge states.

While ICEVs path choice is assumed to be driven solely by travel times, EVs path choice is driven also by range limitation and charging times. The results indicate that EVs greatly affect the flow distribution in the network. Even though charging time consists of only a small part of the system time, a higher share of EVs increase system time substantially. The relatively narrow path set of EVs limit their path selection and their ability to alternate path in response to congestion. A broader installation of charging infrastructure can moderate this effect.

The suggested model provides an evaluation tool to assess candidate charging stations complete layouts and specific locations. The evaluation can be based on station(s) utilization, system time, flow patterns, and demand satisfaction. The proportion of unsatisfied demand can be used as a feedback to revise the estimated EVs demand, that is used as an input for the suggested model.

The model is currently applied and tested for a large-scale transportation network. Future work includes the integration of the developed model in a bi-level optimization model for the allocation of charging stations.

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