A bilevel optimisation model for the selection of parking and charging facilities for EV-based ride-hailing services

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1 Introduction

Mobility as a Service (MaaS) and Park & Ride (P&R) initiatives are switfly gaining popularity around the world as remedial measures to reduce traffic congestion. These schemes have introduced major shifts in the interaction between travellers, transport infrastructure, and public transport schemes. Several initiatives that promote the use of MaaS schemes to reduce private usage already exist [Hesketh et al., 2017; Hellmann, 2014]. Their introduction has also coincided with the increasing uptake of Electric Vehicles (EVs). While EVs are more environmentally friendly [Uherek et al., 2010; Van Mierlo et al., 2006], they suffer from decreased range (80 to 300 miles [Transport for London, 2019a]) capabilities compared to conventional vehicles. Although current research efforts are primarily focused on new battery technologies to increase their range [Kouchachvili et al., 2018], they are still potentially many years away from widespread adoption. Charging speeds have been improving recently, but the number of rapid chargers available for use is limited. The average time needed to charge a typical EV according to the three most common charging levels (slow, fast, and rapid) are listed in Table 1.

Although new charging facilities are being installed continuously, the growth in the number of EVs is currently surpassing the growth in the number of charging points [Environment Committee, 2018]. The issue intensifies if we take into consideration the charging demand by Transport Network Companies (TNC) fleet. Most ride-sharing fleet operators have plans to transition their fleets towards EVs in the near future, with many already operating a mix of conventional, hybrid and electric vehicles. The average distance travelled in a ride-sharing vehicle is around 1,000 miles per week [Takahashi, 2018], meaning that it needs recharging every 1-2 days. Adding up the time due to queue delays in charging points [Jung et al., 2014] the problem worsens. Therefore, to maintain the current level of convenience provided by MaaS, the supporting charging infrastructure needs to be sufficient to meet the demand.

Across London there are around 2,000 charging points [Mayor of London, 2018] and 150 rapid charging points [Transport for London, 2019a]. In comparison, the number of EVs in the city is 12,000 [Environment Committee, 2018]. Considering that there are already more than 80,000 private hire vehicle licences [Transport for London, 2019b] and that TNCs aim to transition to fully EVs in the near future (e.g. Uber [Uber UK, 2018]), it is clear that the

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Charging level	Charging rate	Time to fully charge
Slow	3 kW	8 hours
Fast	7-22 kW	3-4 hours
Rapid	43-50 kW	30 minutes (80% charge)

Table 1: The rate and time to charge for various charging levels [Griffiths, 2019]

number of charging points must significantly increase. Given this shortage, the search for an empty charging location is likely to reduce the efficiency of an EV-based ride-sharing platform, and contribute to an increase in the number of overall empty vehicle-miles travelled, a commonly used metric of fleet efficiency and a proxy for contribution to congestion.

London City Council supports the establishment of rapid charging points to be used by taxis only [Transport for London, 2019a], with some TNCs already investing in installing their own charging points [Lekach, 2018]. Despite this, a number of spatial and temporal parameters need to be taken into account before installing new charging points. Firstly, the charging demand across every zone, which varies throughout the day, needs to be met. Secondly, due to the limited budgets for the charging infrastructure, the number of charging points to be installed is bounded. In addition to the installation and maintenance costs, which depend on the type of the charger, the cost of renting the parking spaces must also be considered.

On-street restrictions set by the council have to be taken into consideration. On-street parking permits sold to TNCs for an extended period of time are limited as otherwise there is not sufficient availability of spaces for residents and pay and display machines, negatively affecting the public image of the local authority [Barter, 2017].

Many studies have focused on variations of the facility location problem. Xiong et al. [2018] proposed a bilevel optimisation model for the placement of EV charging points. The objective of the upper-level of the problem, set by the government, aims to minimise the social cost. In the lower-level, a congestion game is formulated between the EV drivers, each of whom aims to minimise his personal cost which is equal to the travel time to reach the station and the waiting time in the station queue to recharge. Asamer et al. [2016] solved an optimisation problem optimally to find the regions for the placement of charging stations used by taxi companies. The objective of the problem was to maximally satisfy the charging demand of the taxis under a predefined budget. The charging demand was predicted based on the customer origin-destination trip data. In a similar setting but solely for taxis, Gopalakrishnan et al. [2016] predicted the charging demand using supervised learning on road traffic data and points of interest to the passengers (e.g. restaurants, shopping centres, etc.). Next, the authors implemented a heuristic to solve a budgeted optimisation problem to determine the exact locations of the charging stations that ensured all points of interest were covered. Jung et al. [2014] proposed a stochastic bilevel optimisation formulation for the placement of stations with the upper-level objective of minimising the empty miles travelled and the queue delays at charging stations. From a different perspective with regard to the impact that large-scale EV charging can have on the power grid, Luo et al. [2017] presented a game theoretic model and proposed a mechanism for the placement of charging stations in a number of stages. At each stage, the charging demand of the customers is predicted using a nested logit model and then the strategic interactions of the service providers for the placement of stations are analysed using a Bayesian game. The authors considered three charging providers, each being responsible for the installation of charging points of a specific type of charging level (slow, fast, rapid). One limitation of these models is the lack of consideration given to the placement of TNC charging facilities with council restrictions on on-street parking and charging permits (over extended periods of time).

To address this omission, we propose a bilevel optimisation model for the Charging Facility

Placement (CFP) problem similar to [Xiong et al., 2018] but from the viewpoint of TNC operators only. We assume that TNC drivers can relocate to any zone to charge the vehicle's battery. Although there may be some cases where the empty miles travelled will be substantial, there are various reasons why a TNC driver will prefer to travel such a distance for charging. It could be due to the reduced cost per hour compared to other charging points (due to low demand in the area), the charging point is rapid and enables the EV to fully recharge in less than an hour, or even that the driver uses a charging point in a zone with high customer demand [Garg and Ranu, 2018]. However, to feasibly solve the CFP problem, the number of charging points in the adjacent zones are able to satisfy the demand.

The upper-level objective of CFP is the minimisation of the total cost to install the charging infrastructure and the time cost (converted into monetary units) induced when the TNC vehicle does not serve a customer (idling time). The lower-level is a congestion game played by the TNC drivers, each of whom aims to minimise his idle time which can either be the travelling time to the charging point, the cruising time to find an available charging point, the waiting time in a queue to charge the vehicle's battery, or all together. The council restrictions on the maximum number of spaces available on-street for dedicated long-term charging points for TNCs are incorporated as constraints in the upper-level of CFP for every zone considered in the problem. Contrary to previous work, the TNCs require a minimum number of rapid charge points to be placed in each zone.

2 Model description

The objective of a TNC operator is to place off-street (parking facilities) or on-street (kerbside) charging points that satisfy demand for the minimum total cost. The cost function in the objective is the sum of the installation and maintenance costs and the cost of TNC driver idle time. The integer variables s_i, f_i and r_i indicate the number of slow, fast, and rapid chargers that should be installed in facility i and the cost of each of these chargers is c_i^s, c_i^f, c_i^r respectively.

We assume that the candidate parking facilities where charging points can be placed are given in the input of the problem and that the TNCs take into account the restrictions set by the local authorities. Specifically, there is a limited number of on-street spaces where charging points can be placed and used exclusively by TNCs for long periods of time.

The study is focused on the Greater London area and is divided into a fixed number of zones. In order to satisfy the charging demand for a given zone, it is assumed that a sufficient number of charging points are installed in not only the zone, but also in adjacent zones. We use the adjacency matrix A to indicate the neighbouring zones, e.g. $A_{zj} = 1$ if zone j is adjacent to zone z. We assume that a zone is adjacent to itself.

Although the charging demand varies with time, the input parameter of zone demand, denoted by d_z, takes the value of the maximum predicted demand on each zone. Each candidate facility at location i is associated with a capacity CAP_i denoting the number of available spaces to install charging points and a binary parameter α_i which denotes the type of the facility, i.e. $\alpha_i = 1$ if i is located on-street and $\alpha_i = 0$ if it is located off-street. A binary matrix B is used to indicate whether a facility belongs to a zone or not (e.g. $B_{iz} = 1$ if facility i belongs to zone z and $B_{iz} = 0$ otherwise). Since TNCs need to charge their fleet as quickly as possible, we assume that they demand a minimum number of rapid chargers to be installed, denoted by R.

We define the idling time t_v, to be the total time that vehicle v serves no customer. That is equal to total time from the vehicle's latest drop-off location to the preferred charging point and the time from the charging point to its next pick-up location, the cruising time spent to find an available charging point or one with low waiting time, the waiting time in the (possible) queue to recharge and the charging time.

The charging point located at position i is selected by driver v with probability p_{vi}. The expected idling time of vehicle v to recharge at charging point i is denoted as T_{vi}. The bilevel programming formulation of the CFP problem is presented below:

$$\min \sum_{i \in F} c_i^s s_i + c_i^f f_i + c_i^r r_i + \lambda \sum_{v \in V} t_v \tag{1}$$

$$\text{s.t} \sum_{j \in Z} A_{zj} \sum_{i \in F} B_{ij} y_i \geq \gamma d_z, \qquad \forall z \in Z \tag{2}$$

$$y_i = s_i + f_i + r_i, \qquad \forall i \in F \tag{3}$$

$$\sum_{i \in F} r_i \geq R \tag{4}$$

$$\sum_{i \in F} \alpha_i B_{iz} y_i \leq N_z, \qquad \forall z \in Z \tag{5}$$

$$y_i \leq CAP_i, \qquad \forall i \in F \tag{6}$$

$$y_i, s_i, f_i, r_i \in \mathbb{N}, \qquad \forall i \in F \tag{7}$$

$$t_v \in \arg\min \sum_{i \in F} p_{vi} T_{vi}, \qquad \forall v \in V \tag{8}$$

$$\text{s.t} \sum_{i \in F} p_{vi} = 1, \qquad \forall v \in V \tag{9}$$

$$0 \leq p_{vi} \leq 1, \qquad \forall v \in V, i \in F \tag{10}$$

where F, Z denote the sets of the candidate facilities and the set of zones, respectively. The objective (1) minimises the total cost of slow, fast, and rapid charging points as well as the total time cost when the vehicle remains idle. λ is a factor to convert the time into a monetary cost. Constraints (2) ensure that the number of charging points installed per zone satisfies at least a proportion of the maximum demand in the zone and surrounding zones, where γ denotes the proportion of charging demand to be satisfied. Constraints (3) indicate that the total number of charging points y_i at location i is equal to the sum of the slow s_i, fast f_i and rapid r_i charging points. Constraint (4) ensures that the minimum number of rapid charging points required by the TNC operator is met. The limit on the number of spaces to place on-street charging points per zone is given in constraints (5). Constraints (6) ensure that the spaces needed to install charging points per facility cannot exceed its capacity. Constraints (7) indicate that the variables y_i, s_i, f_i, r_i must have integer values. The lower-level objective minimises the idle time cost of each vehicle v denoted by its cost function T_{vi}. Equations (9) and constraints (10) ensure that the probability rules are satisfied.

3 Expected results

We predict the charging demand for each zone in the Greater London area using a supervised learning method with real road traffic flows, and points of interest data obtained from a publicly-available source in a similar way to [Gopalakrishnan et al., 2016]. First, the single objective optimisation problem is solved optimally using a greedy algorithm. The single objective is derived from objective (1) by omitting the time cost of the vehicles and constraints (2) - (7). Next, we solve the bilevel problem by relaxing the integrality constraints and rounding the values in such a way that the feasibility of the resulting solution is preserved. We further propose heuristics such as simulated annealing and genetic algorithms. We then compare the value of the equilibrium of the underlying lower-level game to the optimal solution by computing the price of anarchy [Koutsoupias and Papadimitriou, 2009]. Finally, agent-based mesoscopic simulations are performed to investigate the sensitivity of various model parameters.

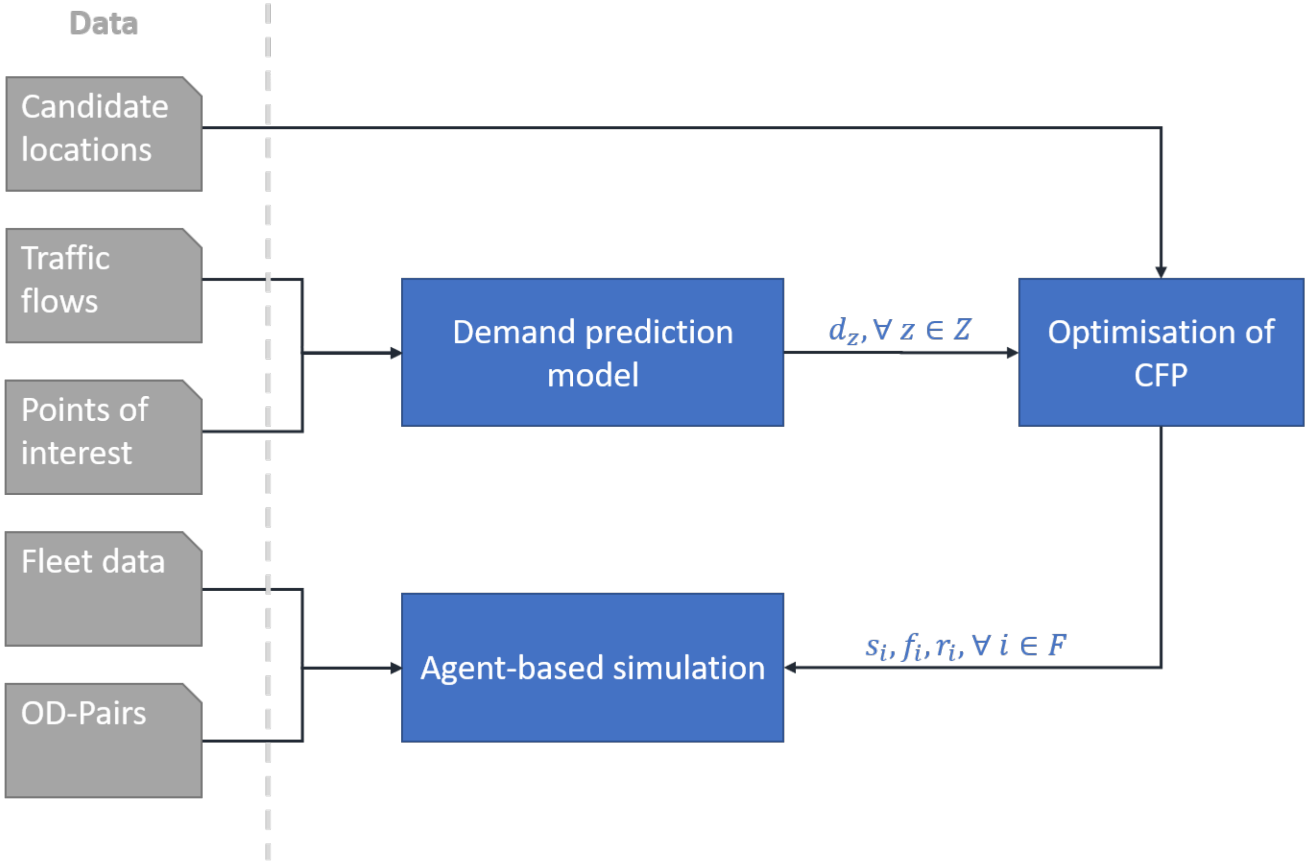

Figure 1: Flowchart of the algorithm for the model described in this study

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