Dynamic Vehicle Allocation and Charging Policies for Shared Autonomous Electric Vehicles

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Abstract

Vehicle sharing systems, which are considered to be a sustainable solution for urban transportation, can nowadays be found in many cities (He et al. [2017]). In New York City, for example, there are three types of vehicle sharing services. The first, also the most popular, is ride-sharing, where a platform coordinates the rides shared by drivers with customers who need a ride. As shown in Figure 1(a), the drivers pick up the customers at their origins and drop off them at their destinations. Since the drivers instead of the platform (e.g., Uber) own the vehicles, the drivers may reject the match proposed by the platform, which may increase the overall driving distances (Wang et al. [2017]). Free-floating vehicle sharing is another vehicle sharing service (e.g., car2go). Customers choosing this service have to first search a vehicle in their proximity, go to it, and then drive to their destinations. This is shown in Figure 1(b). The vehicle can be left at any parking space at the destination. However, the company offering this service needs to hire a crew to reposition and to refuel the vehicles for maintaining daily operations (Perlman [2014]). Station-based vehicle sharing is a service where vehicles must be picked up and left at designated refueling or recharging stations (shown in Figure 1(c)). Since the platform owns all vehicles, customers must drive vehicles themselves in both free-floating and station-based vehicle sharing systems. To attract more customers to use these two types of services, more vehicles need to be deployed and more stations to be built in the service region, which lowers the utilization of the vehicles.

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Autonomous electric vehicle (AEV) sharing systems can reduce the disadvantages of the three vehicle sharing services (Daimler 2017, Jing 2017). From the customer perspective, it is similar to ride-sharing. The only difference between ride-sharing and AEV sharing is that the latter does not need drivers (illustrated in Figure 1(d)). From the platform perspective, the platform (or another company) owns the vehicles, which are autonomous and electric. In an AEV sharing system all processes, especially matching vehicles with customers and charging vehicles, need to be controlled by the platform. Moreover, customer patience times may vary with travel distances. In practice, long-distance customers can endure a longer waiting time than customer who wish to travel a short distance. If the waiting times of customers exceed their maximal patience time, they will leave the system and choose for other transport options. Loosing a long-distance customer implies revenue loss. Therefore, operating an AEV sharing system introduces a new challenge: how should the platform allocate vehicles to customers and when to charge them?

There are some differences with manned vehicle sharing systems. In ride-sharing, there is no need to consider refueling or recharging because the platform does not own the vehicles (Bai et al. 2018). For free-floating and station-based vehicle sharing services, refueling or recharging is executed manually, and also outside the control of the platform. Therefore, in literature on these systems, activities related to charging are usually simplified as exogenous parameters rather than endogenous decisions (He et al. 2017; Bai et al. 2018). In the studies on vehicle routing and recharging, charging times and paths
to charging stations are captured as decision variables in deterministic models (Schiffer and Walther, 2017; Sweda et al., 2017). However, these models are not applicable in the vehicle sharing case where travel demands are stochastic. These stochastic systems can be modeled using a semi-open queueing network (SOQN). Such models can capture dynamic stochastic demand served by a fixed number of circulating resources and have been widely used to model internal transport in container terminals or warehouses (e.g. Zou et al., 2018). In this study, we first adopt a SOQN model for the AEV sharing system to obtain key performance measures (e.g., customer waiting times and loss rates) under given customer-to-vehicle allocation and charging decisions. Then, we introduce a Markov decision process (MDP), where optimal vehicle allocation and charging decisions can be taken dynamically, using the SOQN as a building block.

Figure 2: An example of the dynamics of the AEV sharing service

Figure 2 gives an example of how vehicles are allocated to customers and when they are charged. Customers require different battery capacities, depending on the distance they plan to travel. To capture this difference, customers are aggregated into two classes, with different arrival rates, according to travel distance (i.e., short- and long-distance customers). The idle vehicles in the pool have different discrete remaining charge levels. Vehicles allocated to customers consume battery capacity for 1) the pickup process – from the vehicle’s dwell point to the customer’s origin, 2) the delivery process – from the customer’s origin to his or her destination, and 3) visiting a charging station – from the customer’s destination to a nearby charging station. In Figure 2, one battery charge unit
is required to pick up a customer from any class and one battery charge unit is required to visit a charging station. Due to the battery constraint, a vehicle with 3 remaining charge units can only serve short-distance customers and the vehicles with 4 or 5 charge units can serve customers from both classes. With technologies such as autonomous driving, GPS, and battery sensors, vehicles with a sufficient battery level can be allocated to serve any fitting customer, and the charging time can be controlled. For example, in Figure 2 the vehicles are charged partially to 4 charge units instead of fully charged to 5 units. Partial charging is much faster than full charging, and it may allow vehicles to become active in transport sooner, thereby reducing the waiting time of customers. We model the dynamics of the AEV sharing system in an SOQN model, which is shown in Figure 3(a).

Customers of each customer class need to be synchronized with a fitting vehicle, allocated to the customer. This is modeled as a synchronization station with a queue for customers and a queue for vehicles. To estimate the performance measures of the system, we aggregate the original SOQN into a compact one by replacing the nodes [3-8] (shown in Figure 3(a)) into a load-dependent (LD) node [0] (shown in Figure 3(b)). According to Norton's theorem [Bolch et al., 2006] this node is equivalent to the closed network [3-8] assuming this network has a product form. The service rate of node [0] depends on the number of vehicles in this node. Therefore, once the number idle vehicles waiting...
in the two synchronization stations is known, we can obtain the load-dependent service rate of node [0]. This allows us to use a two-dimensional tuple to represent the system state. By assuming that all service nodes are exponential, the system can be described by a Markov chain when vehicle allocation and charging probabilities are known. Then, system performance measures, such as customer waiting times, customer lost rates, and charging station utilization can be obtained. The charging and allocation probabilities are later used as decisions to be taken in the MDP model.

Simulation results show that the analytically estimated performance measures obtained by solving the Markov chain are accurate. Since the analytical model can be solved relatively fast (for small instances), this allows use it as a building block in the MDP to determine vehicle allocation and charging decisions dynamically. The vehicle allocation decision is modeled by the probability to dynamically allocate vehicles that can serve both customer classes (i.e. with a high remaining battery capacity), to only short-distance customers. The decision variable capturing vehicle charging is the probability that a vehicle visiting the charging station, charges only partially. For tractability, the action space is discrete. The states are the same as those defined in the Markov Chain. The MDP minimizes the system cost, which includes customer waiting time, customer loss due to overly long waiting, and empty driving to visit charging stations. By analyzing properties of the MDP and solving it optimally for small instances, we find that optimal vehicle allocation and charging decisions depend on the system state. An interesting finding is that it is beneficial to reserve some idle vehicles with high remaining battery levels for future short-distance customers even if there are long-distance customers waiting. Based on these findings, we propose a state-dependent policy where the decisions are made according to the information on the number of waiting customers and the maximal customer patience times. Finally, we test the performance of the state-dependent policy for small instances, as well as a large case study based on the operating data of the taxi service in New York City. Numerical results show that the state-dependent policy is near-optimal in small instances and it outperforms other candidate policies in both small and large instances.

We can draw the following conclusions. First, dynamic vehicle charging and customer allocation can effectively work to reduce system cost. Second, information about the number of waiting customers and maximal customer patience times can be used to dy-
namically allocate vehicles to customers. Third, reserving some idle high battery level vehicles to wait for future short-distance customers can be beneficial even if long-distance customers are waiting for pick-up.

References


