An Integrated Optimization-Simulation Framework for Vehicle and Personnel Relocations of Electric Car-Sharing Systems

Burak Boyacı[1], Konstantinos Zografos[1], Nikolas Geroliminis[2]

[1] Department of Management Science; Lancaster University, United Kingdom
{b.boyaci, k.zografos}@lancaster.ac.uk
[2] Urban Transport Systems Lab (LUTS), Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland
nikolas.geroliminis@epfl.ch

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1 Introduction

Car-sharing is a new concept which enables users to rent cars for short period of times. Car-sharing systems can be classified as *one-way* or *round-trip* according to restrictions imposed for pick-up and drop-off locations. In more restricted round-trip systems, users have to return vehicles where they have picked them up, whereas one-way systems allow users to return vehicles to different drop-off stations. In addition, one-way systems have two types. If the car-sharing system operates with designated parking locations it is characterized as *non-floating*. If the users are allowed to drop-off vehicles with defined borders then the system is called *free-floating*. Previous related work in studying operational issues of car-sharing systems include [1], [2] and [3].

In this research we are dealing with operational decisions of *one-way non-floating electric* car sharing systems with *reservations* and *dynamic relocations*, i.e. relocation can be done anytime during the operations. Our previous work in this area is addressing issues related to strategic [4] and operational problem [5], and simulation of relocation operations [6]. In this paper we are introducing the following new modelling concepts: (i) station clustering and (ii) integration of optimization with simulation for the operational problem.

2 Modelling Framework

The proposed framework consists of the following three modules: (i) data preprocessing, (ii) optimization, and (iii) simulation. The data preprocessing module prepares the data inputs for the subsequent optimization and simulation modules and addresses issues related to the conversion of round-trip journeys into one-way demand and creation of clusters of stations for determining at the optimization module relocation flows between stations belonging to different or the same cluster.

The optimization module involves three mathematical models: (i) station clustering, (ii) operations optimization and (iii) personnel flow. The output of the optimization module is used by the simulation module in order to test the feasibility of the optimization outcome in terms of vehicle recharging requirements. After the first iteration of the optimization process, if the results of the simulation are feasible then the optimization process is stopped. If the simulation results are not feasible, the vehicles that require further charging are restricted to stay in the station and the optimization model is solved again considering the new constraints. The structure of the proposed model and their interrelationship are illustrated in Fig. 1.

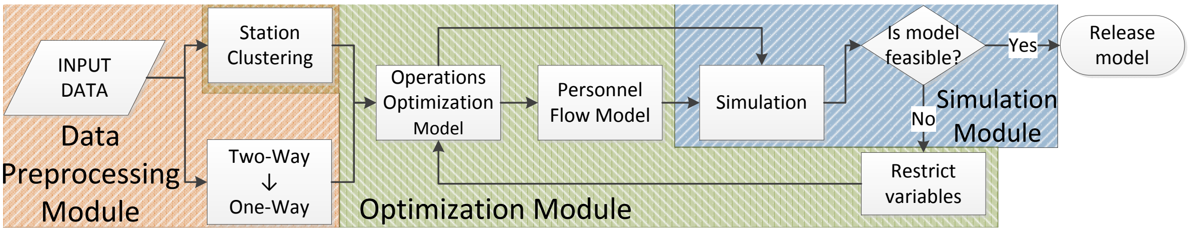

Figure 1: Flow chart for the solution framework.

2.1 Optimization Module

The optimization model has the following three objectives. (i) minimize unserved demand, (ii) minimize relocation personnel, and (iii) maximize the time vehicles stay in the station in order to be charged. A weighting method is used to solve the resulting multiobjective problem.

The physical framework of the model is composed of nodes and arcs with location (stations) and time (time intervals) dimensions. Each rental is regarded as a flow between different station-time interval pairs. There is a binary variable associated with each rental which indicates if the rental is accepted or not. The complete network is duplicated for all vehicles and different personnel shifts, e.g. a rental is a flow on the vehicles' network, a relocation is a flow in both vehicles' and related personnel's shift and a relocation without vehicle is a flow in related personnel's shift. There are also capacity restrictions for each node. Net vehicle flow at any time interval, i.e. the difference between total vehicle flow entering to and exiting from the node until given time interval, should be a non-negative value less than or equal to the capacity of the station.

The system under consideration operates with electric vehicles with limited range (120km) and need to be charged in order to keep them operating (4min of charging for every 1km travelled). In order to be sure that every vehicle has enough power to operate we add "soft" constraints to the optimization model. The use of soft constraints "induce" vehicles to stay at their destination stations to be charged after their rentals for some time.

As stated above, we deal with a system with *dynamic relocations* in which relocations are handled throughout the day as long as there is relocation personnel available. This assumption inflates the number of variables to the order of millions. If T and S stands for time interval and station sets respectively, this model have $2|T||S|^2$ relocation related variables. In order to tackle the problem, we model relocations over clusters. When there is a relocation between two stations, it is assumed that relocations are done in three artificial states: (i) from origin node to origin node's cluster, (ii) from origin node's cluster to destination node's cluster and (iii) from destination node's cluster to destination node. This change decreases number of variables more than 90% and mathematical model's solution times to acceptable limits ($\sim$ 60s). If P is the set of clusters, the new model has $2|T|\left(|P|^2 + 2|P||S|\right)$ relocation related variables. A relocation flow between is shown in Fig. 2.

The solution of the flows optimization model consists of the accepted rental requests and personnel flows with/without vehicle on the network. It creates aggregate flows which have to be disaggregated

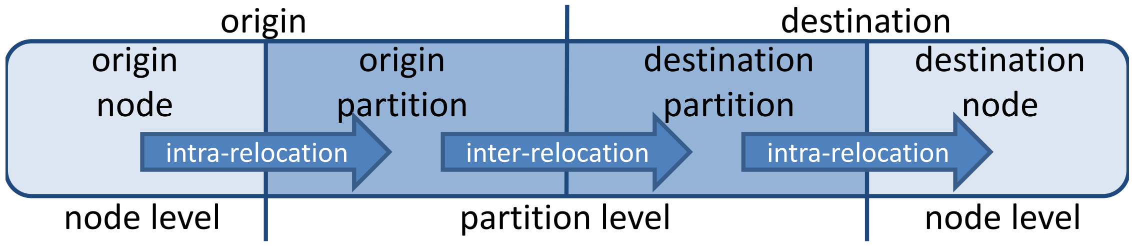

Figure 2: Relocation flow between stations

to correspond to specific relocation personnel. For this reason, we run another model which creates relocation personnel assignments from flows based on their feasible combinations. This model is run separately for each shift. These rosters are fed to the simulator with the other needed parameters, e.g. accepted demand, personnel per shift, to check the feasibility of the result in terms of recharging requirements.

2.2 Simulation Module

We developed a discrete event simulator to simulate the system operations. The flow diagram for the events shown in Fig. 3. Rentals and relocations are fed to the simulator (see Read Rentals and Read Relocations events), which simulates the system with these parameters. If there is any infeasibility in charging levels of any vehicles, the binary variables that keeps track of the charging operations of related vehicles are forced to have value 1. In other words, if there is a vehicle to be rented with a charging level below threshold, we force this vehicle to stay longer at the station that was previously rented in order to be properly charged. Then we run the optimization module with the additional constraints and we repeat the process until we have feasible solutions for the charging of the vehicles.

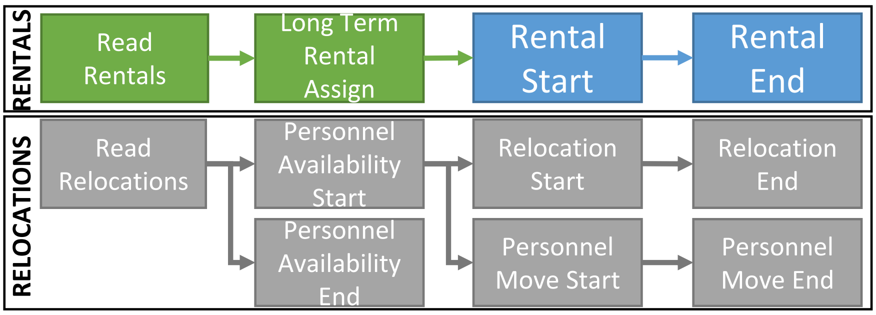

Figure 3: Simplified structure of events and their links to one another in the simulator.

3 Preliminary Results and Conclusions

We have used the parameters of a real electric car-sharing system operating in France. In this system, there are 66 stations with 3 parking spots one of which has a vehicle at the beginning of the day. There are three 6-hour working shifts which cover all 16 (6am-10pm) operating hours of the system. Table 1 provides the comparison of the rental requests for the systems with/without relocation for different demand levels (200, 300 and 400 rentals/day). For each parameter set (with/without relocation and demand level), 10 independent request sets are created and solved with the same parameters.

		with relocation			without relocation		
	demand	200	300	400	200	300	400
average	# personnel per shift	4.0	7.7	12.5	0.0	0.0	0.0
	# lost demand	0.0	0.2	14.6	75.8	120.6	179.1
	unserved demand (%)	0.0	0.1	3.7	37.9	40.2	44.8

Table 1: Comparing systems with and without relocation

Computational results show that, system rejects small portion (3.7%) of requests when demand is 400 requests/day with relocation operations. When there is no relocations at all, this value is incomparably large (44.8%). Even for 200 requests/day, the system without relocation can only serve 62.1% of the whole requests. When relocation is considered the system serves all of them with 12 personnel-shifts (i.e. 4 personnel on average, 72 personnel-hours) in total. We can also observe from the results that, the system with relocation can cope with 300 requests/day but further investments are needed to serve 400 requests/day.

We have proposed and solved an operational model of one-way car-sharing system. We developed a framework with a simulator and three MILP models to handle the operational decisions in these systems. Experimental results showed that, the developed framework is quite efficient and can be used even during the operations. We also observed that depending on the demand scenario need for relocation personnel can be quite high. To have a system that can operate more economically, demand should be controlled with different pricing strategies. That is the reason, our future research direction includes different pricing strategies that will consider both the users and the operator benefit at the same time.

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