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Solving the station-based one-way carsharing network planning problem with relocations and non-linear demand

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A R T I C L E I N F O

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A B S T R A C T

One-way station-based carsharing systems allow users to return a rented car to any designated station, which could be different from the origin station. Existing research has been mainly focused on the vehicle relocation problem to deal with the travel demand fluctuation over time and demand imbalance in space. However, the strategic planning of the stations' location and their capacity for one-way carsharing systems has not been well studied yet, especially when considering vehicle relocations simultaneously. This paper presents a Mixed-integer Non-linear Programming (MINLP) model to solve the carsharing station location and capacity problem with vehicle relocations. This entails considering several important components which are for the first time integrated in the same model. Firstly, relocation operations and corresponding relocation costs are taken into consideration to address the imbalance between trip requests and vehicle availability. Secondly, the flexible travel demand at various time steps is taken as the input to the model avoiding deterministic requests. Thirdly, a logit model is constructed to represent the non-linear demand rate by using the ratio of carsharing utility and private car utility. To solve the MINLP model, a customized gradient algorithm is proposed. The application to the SIP network in Suzhou, China, demonstrates that the algorithm can solve a real world large scale problem in reasonable time. The results identify the pricing and parking space rental costs as the key factors influencing the profitability of carsharing operators. Also, the carsharing station location and fleet size impact the vehicle relocation and carsharing patronage.

1. Introduction

Traffic congestion and its main consequences on productive time loss and air pollution are regarded as the main issues resulting from the urbanization process due to the quick growth of private cars usage (Beckmann, 2013). Moreover the increasing car ownership imposes great pressure on parking in urban areas. Therefore, reducing the use of private cars is essential in order to tackle traffic congestion, thus reducing air pollution, time lost, and save land resources. Carsharing is a transport demand management measure that was first adopted informally in the 1940s, when groups of citizens needed to save travel costs due to a rise in gasoline prices. A representative example was the system called "Sefage" in Zurich, Switzerland, in 1948 (Correia and Antunes, 2012; Shaheen and Cohen, 2012), a non-governmental club consisting of citizens who were willing to share vehicles in their neighborhoods. This earliest vehicle sharing was only used by a small number of people but the concept had been created. Nevertheless it was only in the 1980s that carsharing started to become more popular in Europe and in the USA (Shaheen et al., 1999). By October 2014, there were 33 countries operating carsharing systems encompassing around 4,800,000 members and over 104,000 vehicles in more than 1531

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cities (Shaheen and Cohen, 2014). In recent years, carsharing is becoming even more attractive and pervasive around the world due to its low price and flexible car-return policies. Carsharing is expected to significantly increase its market penetration in the next ten years (Zhou et al., 2017). Herbawi et al. (2016) pointed out that carsharing, if used for a greater part of the mobility needs of travelers, can be a bridging mode between private cars and public transportation.

Carsharing systems can be divided into two categories: round-trip and one-way, based on the operation mode (Jorge et al., 2015a, Shaheen et al., 2015; Boyacı et al., 2017). The older more traditional companies provide round-trip carsharing services, in which the vehicle should be returned to the original rental station. One-way carsharing allows users to return the vehicle to any designated station and the price is usually determined based on a combination of trip duration and trip distance (such as GoGet) or simply based on the trip duration (such as EVCARD). Therefore, one-way carsharing can attract more trip motives other than just the occasional shopping or leisure trip as is usually the case for round-trip systems (such as ZipCar). Due to the daily fluctuations of urban travelling demand, one-way carsharing systems cannot serve all potential demand increase (resulting from its added flexibility) because many vehicles may be needed in one station whilst another may be packed with vehicles that are not needed at that moment. However given the very significant improvement in service convenience, one-way carsharing is witnessing a soaring popularity in Europe and the USA with many companies expanding their services (e.g., Car2go, DriveNow, GoGet and Hertz 24/7). At this stage, carsharing operators seem to be focusing mainly on growing, either expanding geographic coverage in cities where they are operating or by offering the system in more cities around the world. Yet companies are still facing great challenges in the planning and operation of their systems.

The asymmetric demand between pairs of stations, leading to an obvious solution of vehicle relocation along a day, is common practice in carsharing systems (Jorge et al., 2014) but also bike sharing (Li et al., 2016b). The vehicle relocation problem would actually be easier and cheaper to do if it would be possible to move the cars easily in a truck. Vehicle routing has been extensively studied to rebalance bicycles among stations in public bicycle sharing systems, therefore the same algorithms could be potentially used for cars as well (Ho and Szeto, 2017). However, relocating a bundle of vehicles together by heavy trucks may not even be possible to do in a city center. The main reason is that loading and unloading vehicles needs large operational space and time. Instead, staff-based relocations are more frequently utilized in carsharing operations. To maximize the benefit of such relocations operators are faced with the need to weigh the relocation costs and the potential trips that clients may be able to do with those vehicles (Nair and Miller-Hooks, 2011).

There are three relocation mechanisms based on the available information, namely, a static method to maintain a minimum threshold of available cars at each station; a predictive method based on historical demand; and an exact based on perfect knowledge on future demand (Barth and Todd, 1999). Optimization methods were usually adopted for predictive relocation (Bruglieri et al., 2014). Kek et al. (2009) studied the relocation personal assignment problem by establishing a Mixed Integer Linear Programming (MILP). Furthermore, with the same Singapore case-study from Kek et al. (2009), Nair and Miller-Hooks (2011) proposed a Divide-and-conquer algorithm to manage fleet redistribution considering asymmetric and variable demand. Weikl and Bogenberger (2015) divided a study region into macroscopic zones, and developed a MILP model for inter zone relocation and a rule-based method for microscopic intra zone relocation. On the other hand, a simulation-based method was also used for testing a rolling-horizon relocation mechanism with perfect demand information by Barth and Todd (1999). They developed a simulation model for a community car club in Southern California to analyze the performance of the system. Boyacı et al. (2017) developed an integrated framework using Mixed-integer Non-linear Programming (MINLP) optimization and simulation to make operational decisions related to vehicle relocations and staff allocation. In addition to the above mentioned operator-based strategies, user-based strategies, where various incentives are presented to encourage users to carry out vehicle relocation (Jorge et al., 2015b), have been proposed. Febbraro et al. (2012) used discrete event simulation to test a user-based carsharing relocation model by offering a fare discount. From the research mentioned above, it is possible to conclude that vehicle relocation is a complex problem to solve. To combine it with other operational decisions presents an even greater challenge.

One of those challenges in carsharing systems modeling lies in the demand sensitivity to the level of service that is being offered to the clients which is a function of the number of stations, walking distance, price, car availability, etc. For example, demand loss is inevitable when there are not enough cars at a station. To circumvent such problem, some studies have assumed a potential abundant demand for this type of service which would be significantly larger than vehicle supply. It is considered that clients would choose carsharing for sure if this was available to them. Nourinejad and Roorda (2014) introduced a dynamic model to maximize the total profit by servicing part of the total carsharing demand rather than all demand. Jorge et al. (2015b) considered elastic demand where carsharing requests were assumed to be linearly decreasing with regard to price. They developed a MINLP based on elastic pricing to obtain a higher balance between demand and supply at each station. The optimal dynamic pricing was obtained when no relocations were needed. However, other factors that affect the utility of carsharing services are ignored the current literature, which presents an important research gap that we want to tackle in the present study.

The last challenge arises from the strategic decision of where to locate and how many parking places to provide in the network of carsharing stations (Jian et al., 2016). A few studies have investigated the joint optimization of station capacity and fleet size for a given network of stations (Cepolina and Farina, 2012; Fassi et al., 2012; Hu and Liu, 2016). Cepolina and Farina (2012) drew upon the convenience of microscopic simulation to design the fleet dimension of personal intelligent vehicles in pedestrian commercial streets. Hu and Liu (2016) developed a mixed queuing network model to address the reservation policy and road congestion effect in one-way carsharing systems. Fassi et al. (2012) presented a discrete event simulation method to evaluate the carsharing network's growth strategies to meet the future demand. Some studies looked into the carsharing depot location problem. For example, Correia and Antunes (2012) proposed three MILP models to optimize the depot location, station capacity as well as the vehicle fleet size under what they called a controlled, full and conditional service scheme of selecting customers. A classical Lisbon case with 75