A Holistic Decision Making Framework for a Vehicle Sharing System

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Abstract. The vehicle sharing systems (VSSs) are becoming more and more popular due to both financial and environmental effects. On the other hand, they face many challenges, such as inventory management of the vehicles and parking spots, imbalance of the vehicles, pricing strategies, and demand forecasting. If these are not addressed properly, the system experiences a significant loss of customers and therefore revenue. Although efficient methods to solve these problems are well-studied in the literature, there does not exist any work in the literature which considers a VSS as a whole, and identifies and analyzes all of its components and their relations, to the best of our knowledge. Therefore, this work provides a new framework for a VSS management from a wider perspective by addressing the components and their relations with the inclusion of a time dimension. The proposed framework is aimed to apply for any kind of VSS. After addressing as many problems as possible related to a VSS, we will focus on the application of the framework to the light electric vehicle (LEV) sharing system.

Keywords: Vehicle sharing systems · Decision making framework · Strategic planning · Tactical planning · Operational planning

1 Introduction

The idea of vehicle sharing systems (VSSs) bases back 1940s [9,18]. However, due to the lack of identification of the customers, the constructed systems were not as practical as nowadays. With technological improvements, the VSSs are now able to identify the customers through a mobile phone application, a magnetic card, etc. Therefore, the notion of vehicle-sharing has become more and more popular during the last 20 years. The car-sharing systems (CSSs) are available in over 600, where the bicycle-sharing systems (BSSs) in more than 700 cities in several countries [16,17]. For CSSs, for instance, as of February 2018 car2go, which is the largest CSS company in the world, announced that their system serves to 3 million registered members, of which more than a half being in Europe, on its own. They also claim that they experience 30% growth in car2go membership year-over-year [3].

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The increasing usage of VSSs brought many challenging questions. The VSS companies try to maximize the profits by analyzing their costs and revenues. The number of vehicles to be used in the system, the rebalancing structure to be deployed, the demand estimation for a vehicle or for a parking spot and pricing schema of the trips can be counted among the most common problems investigated in the literature. However, to the best of our knowledge, the literature lacks a holistic analysis of the system. In other words, there is no work providing the components of this system in a nutshell and identifying inter- and intra-relations of these components. Therefore, this work aims to fill this gap in the literature and provide a general framework for the VSSs.

While identifying the components of the system, it is also important to think about the time horizon and the corresponding decisions such as strategic, tactical, and operational. The two literature surveys from Laporte et al. [10,11] talk about these decision levels and provide a summary of existing works and place them under these levels, but do not discuss the relations within or between these decision levels or the problems discussed. Our work does not only construct the framework itself but also defines the relations within decision levels and the problems.

Moreover, the future work aims to apply this proposed framework for the newly introduced light electric vehicles (LEVs). As the existing studies are focused on BSSs and CSSs, the existing methodologies became inapplicable for the LEVs. The rebalancing methods, for instance, are not convenient for the LEVs since a LEV is not as small as a bicycle, making it unsuitable for rebalancing with a truck, and has only one seat, preventing the transport of staff, which is common in car rebalancing operations. Also, demand forecasting becomes a challenging task since LEVs are allowed to be parked on any designated spot in the city. LEVs also serve for a higher portion of the population since they do not require a driving license. Moreover, as the vehicle is electric there should exist a fleet of workers who replace the batteries. It is also good to note that although the future work consists of an application on LEVs, the framework is aimed to apply not only to conventional vehicles but also other vehicle types which might be introduced in the future.

The paper is organized as follows: The second chapter presents a brief literature review on VSSs and their components. In the third chapter the proposed framework is presented. The last chapter includes the conclusions and future work.

2 Literature Review

There exists numerous studies in the literature about VSSs. In this section, we talk about the studies that are related to our context. The reader may find other literature surveys in [10,11].

One of the most studied problems in VSSs is the imbalance of the vehicles observed in the system. People using the system may not find a spot to park their vehicles in the destination, or they may not find a vehicle in the origin.

There have been a considerable set of recent studies on bike rebalancing. In BSSs the rebalancing is usually performed using trucks or similar vehicles [7,12,14], which relocate the bikes from station with high availability and low demand to the stations with high demand and low availability. Therefore, the bike rebalancing problem consists of two major parts: estimation of the required inventory level of stations or city zones, and the routing of relocating vehicles. The relocating vehicles routing is most often formulated as an optimization problem based on either capacitated traveling salesman problem (TSP) [14] or vehicle routing problem (VRP) [7,12].

Resolving this issue in CSSs involves staff members to redistribute the vehicles between stations. This, however, yields the subsequent problem of relocating the staff itself between two stations and two car balancing operations. In most of the reviewed literature, these two problems are tackled jointly, by defining optimization problems whose solutions determine simultaneously the rebalancing of both vehicles and staff [5,13]. The strength of [13] and [5] is that they are both evaluated on real case studies in Toronto, Canada, and Nice, France, respectively. However, neither of the approaches [5,13] include the forecasting of the demand and relocation of vehicles according to it where in [8] it is emphasized that the relation between these is important. In [5], authors account for the demand uncertainty, but in the case of high demand, the vehicle requests are denied, which implies loss of demand. As the loss of demand comes with many drawbacks such as bringing the company into disrepute, the constructed framework should be able to predict the demand and rebalance vehicles in advance in order to reduce the demand loss as much as it is allowed by the available data. With respect to the used methodology, in [13] the problem definition is based on the multi TSP, while in [5] the authors have tailored a specific Mixed Integer Linear Programming (MILP) for this purpose.

The demand estimation problem can be addressed by machine learning algorithms used for forecasting [12], by simulating the demand with a Poisson process [7], or even by calculating the worst-case demand, as the solution of optimization problem, and optimizing the rebalancing strategy according to it [7]. Combining these two components of the system, demand forecasting and rebalancing, the problem can be formulated as a two player game [7] or only sequentially forecasting the demand and rebalancing the vehicles afterwards [12]. In the case of two player game, one player is creating a high demand, while the other is rebalancing the vehicles to reduce the demand loss as much as possible.

On the other hand, the demand and rebalancing problems can also be manipulated by different pricing schemas. For instance, decreasing the price of the trip from a low demand area to a high one triggers users to utilize that option. By this way, the system does not only encourage customers to use the system but also rebalances itself. However, in some cases it may end up with demand loss because of the high pricing for the trips from high demand areas to low ones. Therefore, this trade-off should be analyzed in detail. In practice, the companies tend to use a fixed value for a starting price and a variable amount which increases with the time and/or the distance covered. In theory, there exist different approaches for dynamic pricing. The authors in [8] tackled the vehicle imbalance problem by defining a pricing schema which motivates the users to do trips which lower the imbalance and brings the system closer to the equilibrium state. Their work showed that using only pricing strategy, i.e. without any relocation, can improve the balance of the system, but will serve less demand. The authors in [6] assign dynamic prices independently of their origin whereas in [20] the price is set as soon as the itinerary of the customer is revealed and fixed till the end of the trip. The approach in [20] is further extended with another approach using a fluid approximation [19]. In [15], the authors applied their methodology on a case study on a BSS in London, and it is shown that the level of service was improved with the introduction of dynamic pricing schema for the weekends. However, during the weekdays, because of the rush hours, they could not come up with a pricing schema that will improve the performance of the system. Therefore, the literature still lacks research in terms of pricing in VSSs.

One of the most recent surveys conducted by Laporte et al. [11] puts emphasis on different decision levels of the VSSs as well as the problems faced. They come up with a two dimensional classification where one is the type of the problem and the other is the decision level. Their results show that there still exists lack of research in some specific areas such as pricing incentives and routing problems at strategical level or locating stations in tactical and operational levels. For instance, they claim that determining the optimal inventory level at each station within a theoretical framework has not received much attention although it is closely related to the rebalancing problem.

Putting all these together, there do not exist any studies which take all the components of the system into account to the best of our knowledge. Moreover, they do not consider the time dimension within the system. We think that a proper optimization framework for VSSs should provide a decision support in each of the levels, i.e. strategic, tactical, and operational. Furthermore, according to [11], the existing studies on the VSSs do not consider vehicles other than cars or bicycles. However, with the recent introduction of new type of vehicles [1], the proposed methodologies became inapplicable. Therefore, it is important to construct a framework for any kind of VSS which is another aim of this work. The next section provides the details on the proposed framework.

3 Proposed Framework

Before going into the details of the framework, we would like to give the idea behind. As in every decision model, we first gather data, then we construct models to be able to represent the data, and finally, take actions according to the outputs of these models for the future. These notions form each decision problem and represent one dimension of the proposed framework. Since we want to solve decision problem on both supply and demand side, these form the second framework dimension. Finally, in order to introduce the time dimension to our framework, we analyze supply and demand decision problems on all planning levels, i.e. strategic, tactical, and operational. The proposed framework has been illustrated in Fig. 1. By this way, we are able to place each problem component in one of the 18 boxes. We represent the interaction between the components with white, the dependence with blue, and intra-level interactions with a dashed line. Next, we review the main problems observed in a VSS and place those in boxes of Fig. 1.

The inventory management of the vehicles and parking spots include works on (1) optimizing the fleet size of the vehicles that will serve to the customers [4], (2) deciding the optimal location and the size of the parking facilities in order to prevent both overstocking and understocking of the vehicles [4], (3) optimizing the routing of the fleet of workers who are responsible for the maintenance of the vehicles and their fuel/battery level depending on the type of the vehicle [5]. The first corresponds to tactical level decisions and can be changed in mid-term. The second, on the other hand, is generally decided at the beginning of the system installment in the case of station-based systems, which places under strategic level. Daily or hourly decisions are made to overcome the third problem, which makes it to be placed under operational level decisions. For instance, for electric vehicles, the battery is also an issue for the developer. There are several approaches for keeping the battery level sufficient for each user. Some examples are: (1) the users are required to charge the batteries in certain locations if it is under a certain threshold, (2) the company replaces the batteries of the vehicles by monitoring their levels and (3) the company hires staff to drive the vehicles to the charging stations. The first one is not user-friendly as it needs time and makes the user responsible from an act where the second and the third put responsibility on the company. These decisions are made on a daily basis.

Because of the dynamics in the city, these systems also experience imbalance during the day. The vehicle rebalancing can be dynamic, where the relocation is performed during the system operation, or static, where the relocation is done when the system is closed (e.g. over night) [11]. To minimize the cost of such an implementation, this problem is layered into several subproblems in the literature: (1) optimizing the staff allocation and relocation who are responsible for the rebalancing, (2) routing of vehicles performing rebalancing in the case of BSSs, (3) routing of the relocated vehicles in the case of CSSs [5,13]. The decisions regarding the type of rebalancing strategy can be made in both strategic and tactical level: the former level decisions correspond to the type of vehicles used and the latter the time of the operation. After, the daily decisions regarding that strategy should be addressed under operational level decisions. Also, the decision maker should decide the level of service to be provided in the strategic level.

From pricing point of view, there exist many applications in the industry. Some companies work with a fixed price to reserve the vehicle and it increases with the distance and/or time the customer travels with the vehicle. Some others also try to encourage people so that they return the vehicles to the place where they actually picked up to serve balancing issues [2]. On the other hand, there also exist studies in the literature where they assume that dynamic pricing is possible [9]. With such an approach the company aims to manipulate the market so that the system will need less rebalancing while the revenue is not sacrificed. The pricing component can be placed under both tactical and operational level decisions. The tactical level decisions can be thought as the pricing strategy, i.e. dynamic or fixed, to be applied and the offers that will be presented to the customers, and the short-term decisions can be made through deciding the actual price. Furthermore, the determination of budget for advertisement and market placement can be listed in the strategic level decisions that will relate pricing in lower decision levels.

Last but not least, one of the main problems faced in VSSs is forecasting the demand. First of all, with different type of vehicles the people are expected to behave differently. For instance, LEVs are available for a higher portion of the population since they do not require a driving license as in a car or no effort to ride it as in a bicycle. Second of all, the type of the stations, which can be fixed and free-floating [11], also affects the forecasting procedure. The type of the stations should be decided at strategic level. After, the historical demand data helps the decision maker to design the network accordingly, i.e. placing the stations and deciding their capacities for the fixed station case, allocating parking spots throughout the city for the free-floating case. Note that the capacities are determined with the help of the forecasting done on mode- and destination-choice. In the second level, the mid-term demand forecasting model should be constructed to be able to come up with the pricing strategy. The short-term decisions regarding this problem correspond to forecasting the demand for the vehicles and the parking spots -which can be considered as forecasting the supply- per station or zone.

The type of the data used for the models also varies with the decision level. At supply side the geographical characteristics of the city cannot be changed and therefore is an input at strategical level. However, the seasonality or the important events taking place in the city may affect mid-term decisions. Within the operational level, we deploy current state of the system as the input at supply side. The demand side of the information relies on the historical demand and the aggregation is mostly related to the level of decision.

Figure 1 provides the overall picture discussed above and the relationship between the components of the aforementioned problems with time dimension. The vertical relations are represented with one-way white arrows since the data is an input to the constructed models and the models with the input data help the decision maker to decide on the action. The horizontal interaction at the *Models* level is two-way and represented with a white arrow because these models interact with each other, where in *Data* level it is a two-way blue relation since these information depend each other. The interactions between the decision levels are from the *Actions* component of the upper level to the *Models* of the lower level. These interactions represent the fact that the chosen actions on the upper planning level determine to a great extend the used models and their outputs in the lower planning level. For instance, the pricing strategy to be applied affects the approach taken in both tactical and operational levels. Therefore, this relation is represented with dashed one-way arrows.

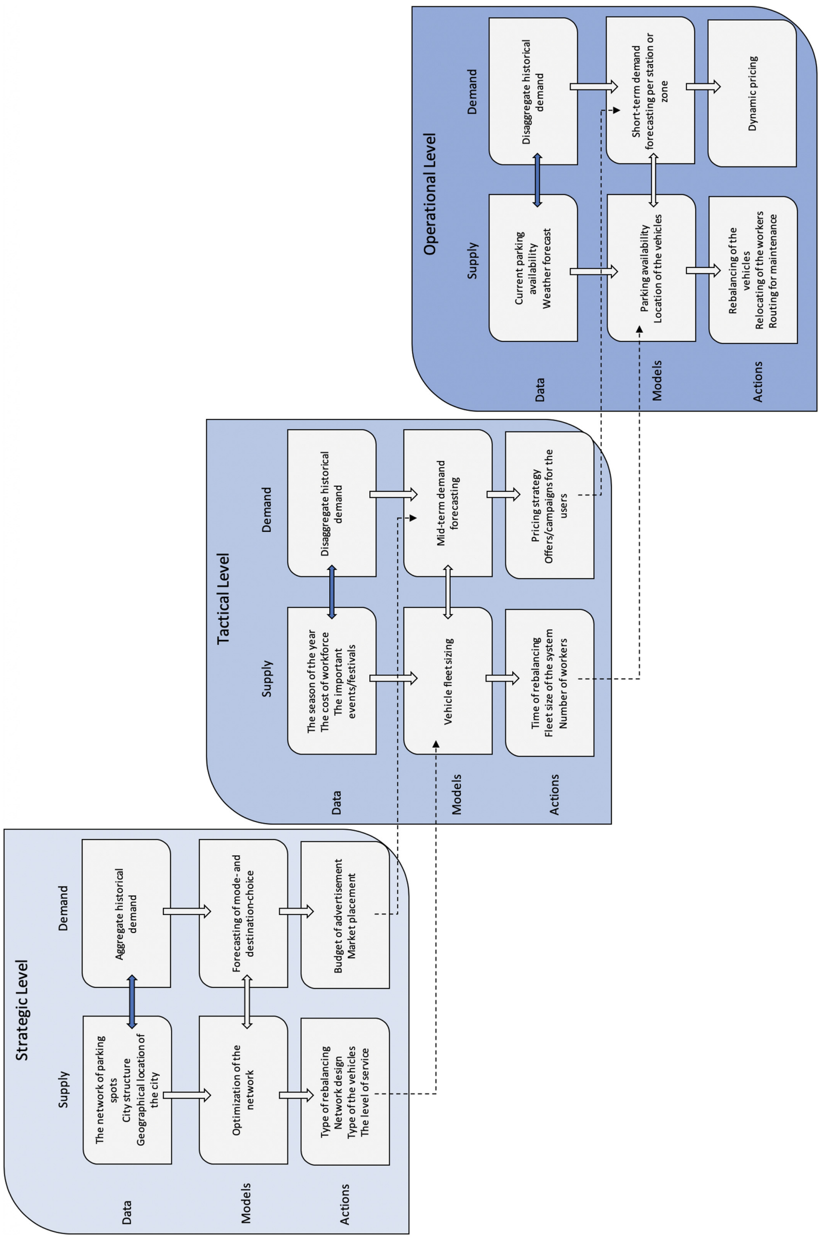

Fig. 1. Vehicle sharing system framework (Color figure online)

4 Conclusion and Future Work

Through the review of available literature, we have identified a lack of a unified approach of modeling all VSS aspects, with respect to different planning horizons, and a holistic solution approach to the related problems. Consequently, the goal of our work is to create a framework for VSS management that will encompass all decision-making tasks of the system and provide the best possible solution to the problems related to them. In order to achieve this, we have to simultaneously take into account all aspects of the system, i.e., to consider the impact the solutions of different problems have on each other. The contribution of this paper is to provide a wider perspective on the design and operations of shared mobility systems. While the literature has focused mainly on specific problems such as the routing aspect, many other methodological challenges are associated with such systems. The proposed framework provides a methodological map that may not be comprehensive, but attempts to cover the most important challenges of these mobility systems.

Our further goal is the apply the framework to a system of shared LEVs, and design framework components tailored to the unique characteristics of such vehicles. To the best of our knowledge, the specific problems arising in the LEV sharing systems have not yet been addressed in the literature, and this paper represents the first consideration of such system. We have also seen that the literature lacks of disaggregate demand forecasting in the operational level. Therefore, we are going to focus firstly on the demand modeling and forecasting. We will try to avoid unrealistic assumptions to represent the real-world system better. Moreover, the dynamic pricing module is also of interest of future work.

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