An optimization 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, determining pricing strategies, and demand forecasting. If these are not addressed properly, the system experiences a significant loss of customers and therefore revenue. This work provides a 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 be applicable for any kind of VSS. After identifying as many problems as possible related to a VSS, the future work will focus on the application of the framework to a light electric vehicle (LEV) sharing system.

Keywords

Transportation; Vehicle sharing systems; Forecasting; Decision making framework

1 Introduction

The idea of vehicle sharing systems (VSSs) dates back to 1940s (Wikipedia contributors, 2019b, Jorge *et al.,* 2015). However, due to the lack of technical means to identify 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 1000 cities, whereas the bicycle-sharing systems (BSSs) in more than 700 cities in several countries (Wikipedia contributors, 2019a,b). For CSSs, for instance, the estimated number of registered members was 1.7 million as of December 2012 (Wikipedia contributors, 2019b), and 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 (car2go, 2019).

Before going into the details of challenges for the design and operations of a VSS, let us introduce some concepts. In terms of the trips there exist two types: one-way and return trips. In return trips, one has to bring the vehicle back to the station where it was picked up. For one-way trips, the vehicle can be dropped anywhere allowed by the system. This brings us to the second concept: where to pick-up and drop-off the vehicles. The two kinds of station configurations are station-based and free-floating. In the former configuration, the parking places for the vehicles are fixed and the user is obliged to take the car to the stations whereas the latter does not have any specific parking areas, that is, the vehicles can be parked on any designated spot in the city. The latter gives more freedom to the user since the parking spots are more spread in the city. For pricing, there are many combinations, but we can list all under two main ones: static and dynamic pricing. Static pricing sets a price level regardless of the vehicle pick-up and drop-off place and time whereas in dynamic pricing the price may depend on those.

The increasing usage of VSSs brought many challenging questions to the operators of the system, i.e. decision makers. The VSS companies try to maximize the profits by analyzing their costs and revenues. The number of vehicles to be used in the system, keeping the balance of available number of vehicles and parking spots in the system (deployment of a rebalancing structure), 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.

This work aims to come up with a holistic analysis of the system by providing the components of this system in a nutshell and identifying inter- and intra-relations of these components. 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. Our work does not only construct the framework itself but also defines the relations between decision levels and the problems.

Moreover, the future work aims to apply this proposed framework for the newly introduced light electric vehicles (LEVs) (ENUU, 2019). 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 way of refueling the vehicles, which can be e.g. replacing the batteries or recharging the batteries while the vehicle is at the station. 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: Section 2 presents a brief literature review on VSSs and their components. In Section 3 the proposed framework is presented. Section 4 discusses the research questions in a VSS context and Section 5 includes the conclusions and future work.

2 Literature Review

There exist numerous studies in the literature about VSSs. In this section, we talk about the studies that are relatively recent. The reader may find other literature surveys in Laporte *et al.* (2015, 2018).

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 (Ghosh *et al.*, 2016, Liu *et al.*, 2016, Pal and Zhang, 2017), 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) (Pal and Zhang, 2017) or vehicle routing problem (VRP) (Ghosh *et al.,* 2016, Liu *et al.,* 2016).

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 (Nourinejad *et al.,* 2015, Boyacı *et al.,* 2017). The strength of Nourinejad *et al.* (2015) and Boyacı *et al.* (2017) is that they are both evaluated on real case studies in Toronto, Canada, and Nice, France, respectively. However, neither of the approaches include the forecasting of the demand and relocation of vehicles according to it whereas in Jorge and Correia (2013) it is emphasized that the relation between these is important. In Boyacı *et al.* (2017), 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 Nourinejad *et al.* (2015) the problem definition is based on the multi TSP, while in Boyacı *et al.* (2017) the authors have tailored a specific MILP for this purpose.

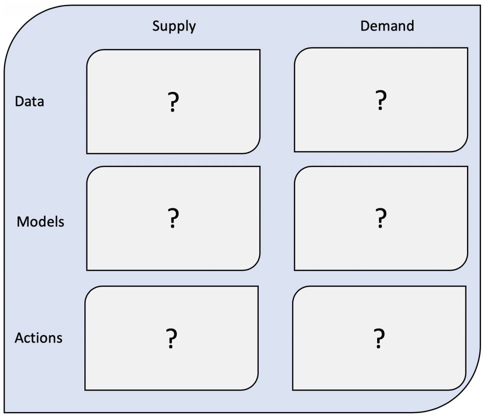
The demand estimation problem is addressed by machine learning algorithms used for forecasting (Liu *et al.,* 2016), by simulating the demand with a Poisson process (Ghosh *et al.,* 2016), or even by calculating the worst-case demand, as the solution of optimization problem, and optimizing the rebalancing strategy according to it (Ghosh *et al.,* 2016). Combining these two components of the system, demand forecasting and rebalancing, the problem is formulated as a two player game (Ghosh *et al.,* 2016) or only sequentially forecasting the demand and rebalancing the vehicles afterwards (Liu *et al.,* 2016). 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 schemes. 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 exists different approaches for dynamic pricing. The authors in Jorge and Correia (2013) tackled the vehicle imbalance problem by defining a pricing scheme which incentives 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 Chemla *et al.* (2013) assign dynamic prices independently of their origin whereas in Waserhole (2013) 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 Waserhole (2013) is further extended with another approach using a fluid approximation (Waserhole and Jost, 2013). In Pfrommer *et al.* (2014), the authors proposed a model predictive control to set pricing incentives and 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. Laporte *et al.* (2018) 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 strategic 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. Therefore, in this work, we take this idea further and define the relations between the components of the system. Our motivation comes from the fact that all the components of the system are connected both within and between decision levels.

In this paper, we extend and generalize the framework proposed by Laporte et al, by introducing three decision levels, as well as a time dimension. In order to assess the generic character of our framework, we comment it on a recently proposed VSS using vehicles that have features common to both bikes and cars. Furthermore, according to Laporte *et al.* (2018), 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 (e.g. ENUU (2019)), the proposed methodologies became inapplicable. Moreover, in the future the companies will tend to offer VSSs that combines all types of vehicles in order to reach as many customers as possible. 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.

Figure 1: A decision level



3 Proposed framework

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. One layer of the framework is presented in Fig. 1.

To introduce the time dimension to our framework, we analyze supply and demand decision problems at all planning levels, i.e. strategic, tactical, and operational. These levels correspond to long-term (more than a year), mid-term (4-6 months), and short-term decisions (daily/hourly), respectively. In other words, we construct such decision tools for each level which extends our framework as in Fig. 2. By this way, we are able to place each problem 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. The relations can be one-way or both-ways. One-way interaction means that the results of one component affects the other component. This also can be considered as one component feeding the other. A two-way interaction between the components show that they interact with each other. The dependence relation, on the other hand, is both ways and a change in one of them triggers an opposite effect in the other. Last but not least, the intra-level interactions are identical in the meaning to interaction relations but they exist only between the decision levels.

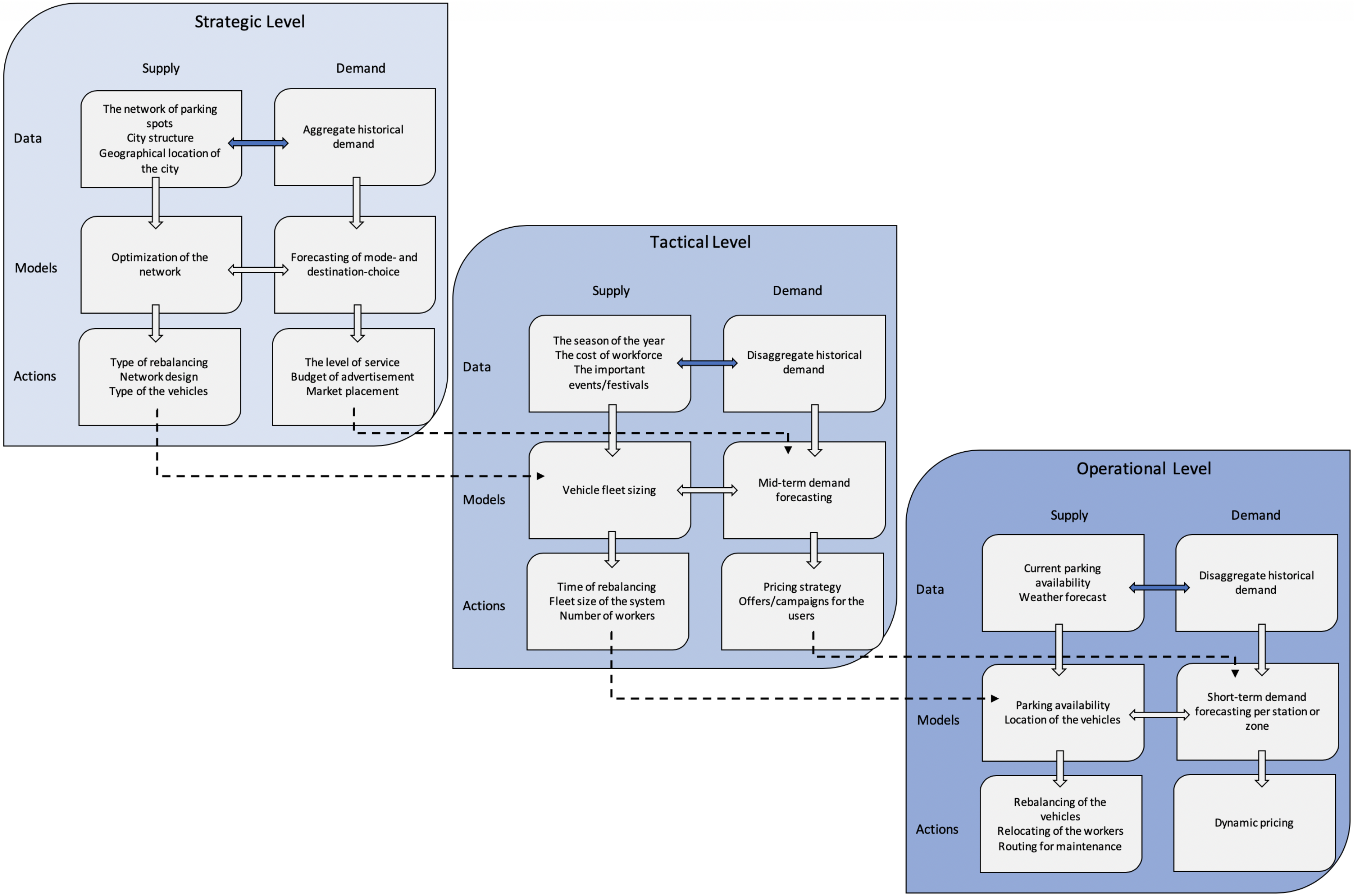
In the following subsections, we review the main problems observed in a VSS. To do that, we introduce notions regarding the problems, and place those in boxes of Fig. 1 in three decision levels. The first subsection discusses the supply and the second the demand part in detail. After all, we link all and come up with the final framework (Fig. 2).

3.1 Supply

When we talk about inventory, we refer to the number of parking spots and vehicles available, and the fuel of the vehicle. 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 (Boyacı *et al.,* 2015), (2) deciding the optimal location and the size of the parking facilities in order to prevent both overstocking and understocking of the vehicles (Boyacı *et al.,* 2015), (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 (Boyacı *et al.,* 2017). The first corresponds to tactical level decisions and can be changed in mid-term. The company may increase or decrease the number of vehicles in the system once they monitor such a need. The reason that the *fleet size of the system* cannot be placed under operational level is that it is not practical to change this for just a short period of time. This action could be taken after solving the model *vehicle fleet sizing*. The second task of deciding the optimal location, 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. However, one may also consider this as the parking spots available throughout the city in the case of free-floating systems. The decision maker then should decide on how much availability to offer in which part of the network. Therefore, this problem can be also referred by the problem of *network design*. So, using the *optimization of the network* model, one may come up with the *network design* of the system. Daily or hourly decisions are made to overcome the third problem, *routing for maintenance*, which makes it to be placed under operational level decisions. For instance, for electric vehicles, keeping the battery level sufficient for each user is also an issue for the decision maker. There are several approaches to overcome this issue. 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 hires staff to replace 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 whilst the second and the third put responsibility on the company. The decision maker may introduce some pricing incentives, which we will discuss later, to get rid of the disadvantages of the first. These decisions are made in 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) (Laporte *et al.,* 2018). To minimize the cost of such an implementation, this problem is layered

Figure 2: Vehicle sharing system framework



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 (Boyacı *et al.,* 2017*,* Nourinejad *et al.,* 2015). 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. *Type of rebalancing* strongly relates to the type of the vehicles used in the system. For instance, it is not efficient to use big trucks to rebalance a CSS since it is not possible to carry dozens of cars on a truck. On the other hand, for a BSS, it is generally not practical and desirable to rebalance bikes using human power since it is exhaustive. Also, a worker cannot relocate another worker (which might rebalance another vehicle later on) while rebalancing the bike. One needs to know about the demand in the next time step so that the rebalancing operations to be made can be decided. That is why we need to determine the *time of rebalancing* operations in order to be able to forecast accordingly. In the case of static rebalancing, the forecast should be daily and the vehicles should be placed to the best possible places in the system while the system is closed. For dynamic rebalancing, on the other hand, the forecasting can be done at any time step. The decision maker should determine the best for the system of interest. After, the daily decisions regarding the decided strategies should be addressed under operational level decisions. These can be the *routing of the rebalancing operations* and *relocating of the workers*. To come up with these solutions one needs to model the *parking availability* and the *location of the vehicles*.

The problems discussed so far were mainly based on the decisions on the supply side. We should also illustrate the type of the data needed to build the corresponding models and to take actions. The data that can be placed under strategic level should be unalterable anytime or at least for short- or mid-term. For instance, the *geographical location of the city* and *city structure* cannot change anytime. Also, the majority of *the network of the parking spots* would stay the same in long-term. To have drastic changes there must occur extraordinary events (e.g. earthquake), that is why we place them under the strategic level. As we change our time horizon from long-term to mid-term, our concerns move to seasonal or specific changes. *The season of the year* is, for example, is an important aspect since it affects the forecasting. Also *the important events/festivals* taking place in the city changes everyday decisions and should be taken into consideration to increase the level-of-service, i.e. to decrease the lost demand. Moreover, *the cost of workforce* is an input which can change time to time and therefore affects mid-term decisions. There exists data types that may change the dynamics of the system instantly, such as *current parking availability* and *weather forecast*. A user tends not to use a BSS on a rainy day or an extremely hot day. Similarly, if a parking spot is not available to the user at the destination point, then s/he tends not to use the system. In order to understand the effects of such things we need the *current parking availability* as an input to the demand model at operational level.

3.2 Demand

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 (Mobility, 2019). This approach is not applicable in a free-floating system. On the other hand, there also exist studies in the literature where they assume that dynamic pricing is possible (Jorge *et al.*, 2015). With such an approach the company aims to manipulate the market so that the system will need less rebalancing executed by the company while the revenue is not sacrificed. However, although the revenue is not sacrificed, this does not necessarily mean that the level-of service stays the same. Also, with different levels of pricing throughout the day may result confusion from the user perspective and user may leave the system, i.e. opt-out. Therefore, with the introduction of dynamic pricing other concerns such as lost demand and level-of-service should also be analyzed and the objective needs to be set accordingly. Following the discussion, we see that 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/campaigns that will be presented to the customers*. Although it is easy to announce any offers to the customers or change the pricing strategy even in a day, the nature of these decisions requires at least a mid-term analysis to be made. The short-term decisions can be made through deciding the actual price. Furthermore, *the level of service*, 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 (Laporte *et al.,* 2018), also affects the forecasting procedure. The type of the stations should be decided at strategic level within the *network design*. 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 *forecasting on mode- and destination-choice*. The results of this model will help the decision maker to take actions on *the level of service*, *budget of advertisement*, and *market placement*. In the tactical level, the *mid-term demand forecasting* model should be constructed to be able to come up with the pricing strategy. This model requires a disaggregate historical demand data so that the data can be manipulated and aggregated at any level to come up with the strategies. The short-term decisions regarding this problem correspond to forecasting the demand of the vehicles and the parking spots -which can be considered as forecasting the supply- per station or zone, i.e. *short-term demand forecasting per station and zone*. This obviously utilizes disaggregate demand data and monitors and analyzes the system in detail.

The type of the demand data used for the models also varies with the decision level. The demand side of the information relies on the historical demand and the aggregation is mostly related to the level of decision. As the horizon gets shorter the disaggregation increases since we want to be responsive to the changes in the system.

3.3 Integration of the components

This subsection integrates all the components together and discusses the relations between them. Here, we discuss everything at high-level. One may refer to the previous subsections for further details.

Fig. 2 provides the overall picture discussed above and the relationship between the components of system 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. For instance, the pricing strategy to be applied affects the approach taken in both tactical and operational levels. The horizontal interaction at the *Models* level is two-way and represented with a white arrow since these models interact with each other because of the dependent data they are using. At the *Data* level it is a two-way blue relation since these information depend each other. For example, when a vehicle demand occurs on a spot, i.e. picked-up, then it will create one more supply of a parking spot. 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. Therefore, this relation is represented with dashed one-way arrows.

4 Open research questions

Looking to the literature that we have reviewed, we have noticed that the disaggregate demand modelling has not gained much attention. The existing works mainly focus on the routing problems for vehicle rebalancing and staff relocating. Therefore, we would like to focus more on the demand module of the framework and analyze its dynamics. Today's systems/products are more customer-oriented and specialized, which means that they are put in the center of the system. Thus, our motivation stems from this idea and encourages us to identify the demand structure of the system at all decision levels. Please note that we refer to both vehicle and parking spot demand with the notion *demand* unless specified.

We understand from the proposed framework that VSSs cannot be investigated from only one point of view. Because of the close relation of the demand component with pricing and parking availability, we think that all of them should be examined simultaneously instead of putting assumptions on the components that are less of interest.

With technological improvements, the systems tend to provide new features to the customers. The user can be informed about an updated price through a mobile application which gives the decision maker flexibility to change the prices dynamically. To serve rebalancing, for instance, the price of the trip can be decreased such that a user drives the car to the high demand low supply area. In order to preserve the balance in the system, the customers may be directed to other cars rather than their first choice with again some pricing incentives.

One other problem faced in such systems is parking the vehicles, especially in CSSs. The decision maker may introduce trip types where the customers book a parking spot at the destination in advance. The decision maker can either utilize that parking spot until that time or fully block it from reservation until it arrives.

However, these ideas raise another question: is the disaggregate demand really worth modelling? To investigate this, we want to compare a system with no prior information on future demand and with perfect information of it. The gains and losses between these two extreme configurations should be significantly on behalf of perfect information case so that it would be meaningful to construct a model. In order to examine this, one needs to know all the parameters of the system. The cost of the workforce, the value of time, the distribution of demand, and parking fees could be listed among those parameters.

We will do this comparison by simulating the system with the given specifications. By this way, it will also be compatible to any kind of system in which one wants to analyze whether it is important or not to model the demand. The so-called simulation will include three main components: demand, pricing, and parking availability. This will enable us to change any parameter and investigate the effects of them.

Upto now, we were discussing about CSSs and BSSs mostly. But the reason behind the fact that we want to build a framework which is applicable to all VSSs is that different kind of vehicles in a VSS are showing up recently. An interesting example to the new type of vehicles in a VSS is launched in 2018 in Biel, Switzerland by company ENUU (ENUU, 2019). This newly introduced LEV takes advantages both from a car and a bicycle as discussed before. We aim to analyze the system requirements for this LEV sharing system and provide an application of the framework that we have constructed.

From the decision maker point of view there exists another question to be answered: the objective that the company wants to achieve. We have discussed on some outcomes of the system, i.e. the revenue, the level of service, the demand that is satisfied/lost. With the help of this framework, all of these components can be monitored and analyzed. The problem can be solved with a multi-objective approach or only one of the objectives can be chosen which represents the mission of the company. One should note that these objectives are not necessarily produce similar results. The work of Jorge and Correia (2013) is a very good example to such application. Therefore, there still exists research gap in defining the objective of the system.

5 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 and 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.

Moreover, studies taking place in automobile industry are mostly oriented at autonomous vehicles recently. This brings new queries about VSSs. In an autonomous case, a VSS will basically be a taxicab community without any drivers. The users will be able to get on and off anywhere they like and the autonomous car continues to the origin of the next customer if there is any. From the user's perspective, the fact that they will not spend any time to park the vehicle makes the VSS experience even better. However, the company has to think about the other effects, such as traffic congestion within the city. Therefore, although the vehicles are smart enough to be able to drive without a driver, they still need to be routed so that the negative effects of the system are minimized.

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 for our future work.

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