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## Article

# Vehicle sharing systems: A review and a holistic management framework

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## Vehicle sharing systems: A review and a holistic management framework

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### ABSTRACT

Although different vehicle sharing systems (VSSs) use different vehicle types, the management challenges and optimization problems to be solved are similar or even the same. This observation led us to create a generalized and holistic VSS management framework, which aims to be applicable to the system using any vehicle type. The framework components, their mutual relationships, and framework tasks have been identified through a thorough and systematic literature review. Furthermore, the literature is positioned in the line with the framework. Finally, the framework and systematic literature review allowed us to identify gaps in the literature, and interesting research avenues.

### 1. Introduction

A vehicle sharing system (VSS) offers users to rent vehicles for a short period of time. The price of the trip is generally determined according to its duration and length. The majority of existing applications of this service include car sharing systems (CSSs), electric CSSs (eCSSs), and bike sharing systems (BSSs). Some recent applications also include autonomous connected electric vehicle (ACEV)-based CSSs and electric light vehicles, i.e., personal intelligent city accessible vehicle (PICAV) sharing systems, moped sharing systems (MSSs), kick scooter sharing systems (SSSs), and light electric vehicle sharing systems (LEVSSs). This type of shared mobility is 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 vehicles and parking spots, imbalance of vehicles, pricing strategies, and demand forecasting. If these are not addressed properly, the system may experience a significant loss of users and therefore revenue.

The idea of sharing vehicles arose in the late 1940s with cars. The first known CSS, Selbstfahrgemeinschaft, was initiated in Zurich, Switzerland, in 1948 (Shaheen et al., 1998). The idea came up again in the early 1970s. Some examples were Procotip, which was initiated in France, in 1971, and Witkar, initiated in 1973, in Amsterdam. However, these particular applications did not last long and disappeared.

As for CSSs, Amsterdam also pioneered the BSSs. The first BSS was introduced in 1965 by the organization Provo. The organization distributed 50 bikes throughout the inner city and left them for free use. These bikes were identified with their white color and they were left

unlocked. Despite the environmental objectives of the organization, the system was abused and the thefts and damages could not be prevented (Shaheen et al., 2010). With the technological and operational improvements, now it is easier to identify users and secure bikes. Midgley (2011) analyzes these improvements in five different generations that caused change in the operation of BSSs. Although these first initiations were mostly based on the economic and environmental reasons, profit-based companies saw the opportunity in these systems and invested money.

The first sharing system that uses a vehicle different from cars and bikes started with mopeds. The company Scoot launched an MSS at the beginning of 2012 in San Francisco with 10 vehicles and expanded to 50 through the end of the year (Lawler, 2012). In 2017, the first sharing system using electric kick scooters was launched in Santa Monica, California. The company Bird announced that 10 million rides were done in the first year of application (Bird, 2018). In 2018, a start-up named ENUU launched a new type of VSS that uses light electric vehicles in Switzerland. Later, another company named Getaround deployed similar vehicles in Rotterdam (Getaround, 2019).

VSSs are not only profitable from the operator perspective but also for the users since it is less costly than owning the vehicle. For instance, the costs of parking, fuel, insurance, and maintenance are all included in the price of the usage. It also allows to use the system occasionally rather than on a daily basis. According to Bates and Leibling (2012), a study concerning the UK shows that an average car is in use only 3–4% of the time. It is parked the rest of the time, i.e., 96–97%. Another study conducted by Shoup (2011) also points out that this proportion is 95%. These

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findings further encourage users to share a vehicle for both environmental and convenience perspectives.

A VSS has several kinds of configurations. These can be characterized by

- the type of trips offered: return trip or one-way,
- the imbalance management strategy: user-based, static staff-based, or dynamic staff-based,
- the pricing strategy: fixed or dynamic,
- the parking organization: station-based or free-floating.

In return-trip configuration, the user is requested to return the vehicle to the pick-up location. It is not imposed in a one-way system, which is therefore more flexible for the users.

One-way systems suffer from imbalance, since vehicles tend to accumulate in some popular destinations. Consequently, it generates shortage of vehicles in other locations. The operator must therefore rebalance the fleet. It can be done by providing incentives to users, i.e., user-based rebalancing, in order to reduce the imbalance. It can also be done by the staff, who can either drive each vehicle to a desired location or use trucks to move vehicles around. We refer to these trucks as rebalancing trucks and to shared vehicles as vehicles throughout this paper. Staff-based rebalancing can be further divided into two categories: static and dynamic. Static rebalancing is done when the system is closed, generally during the night, every day. Dynamic rebalancing, on the other hand, is flexible and executed throughout the day. We see two applications of dynamic rebalancing operations, i.e., offline and online. In the former, the demand knowledge is assumed to be known in advance and the rebalancing operations that will take place throughout the day is calculated once at the beginning of the day. It is not updated during the day even though more information might become available. On the other hand, online rebalancing is reactive to the updates during the day. The routing decisions can change.

The pricing incentives are proposed to the users, to promote user-based rebalancing. These incentives are usually implemented using a dynamic pricing strategy. A pricing strategy is called dynamic when the price of the trip does not only depend on the characteristics of the trip (origin, destination, trip length and duration), but also on the context (time of day, status of the fleet, congestion level, etc.). If the price is based only on the trip characteristic, it is called static.

Finally, a system is station-based if the vehicles must be picked up and dropped off in some designated parking areas for the VSS in particular. If it is not the case, i.e., if a vehicle can be dropped off at any public parking place, it is called free-floating. The free-floating configuration is more flexible from the user point of view yet it introduces complexity to the operator.

This paper analyzes the previous works that either deal with a particular problem isolated from the other ones, or represent reviews of such papers. In the light of this extensive review, we propose a general framework characterizing the operations of a VSS. The proposed framework is built from the decision maker's point of view and aimed to be applicable for any kind of VSS. In other words, we approach all problems in a holistic manner by identifying their mutual dependencies and relations. The literature review is then positioned according to the proposed framework to be able to identify the research gaps and future research directions in the field. In addition to that, we perform a thorough analysis of the future work suggested by the reviewed papers. For each proposed further research path, we strive to identify other works which address it. By that, additional open research questions are identified.

The structure of the paper is as follows: In the light of the literature review, the proposed framework is introduced in Section 2. Then, Section 3 presents an extensive literature review under framework structure and Section 4 discusses the future work analysis, identified research gaps and research directions. In Section 5, we conclude the paper.

## 2. Proposed framework

This section illustrates the proposed framework that is designed to be applicable to a VSS with any type of vehicle. The challenges faced in VSSs can be classified by their decision levels. Another relevant classification deals with the type of actor that is under analysis: the suppliers (that is, the operators who supply service) or the users (that is, the people who generate demand). Finally, the solution methods to analyze challenges involve the following three layers, i.e., data, models, and actions, which are identified as the third dimension of the framework. Therefore, we take them as further criteria for classification. As a result, we introduce three different dimensions for our framework. The main terminology used and the framework are presented in Section 2.1. Following Sections 2.2, 2.3, and 2.4 give the details about the decision levels of the framework.

### 2.1. Terminology and the framework

The framework consists of three dimensions: decision levels, actors, and layers. The components refer to the challenges faced, data obtained, models developed and actions taken in general. The modules are either a combination of one decision level, one actor, and one layer (either models or actions), or one decision level and data layer. The components are placed in modules. There are 15 modules in this framework, illustrated in Fig. 1.

The first dimension deals with the horizon of the decision levels: strategic, tactical, and operational. The strategic level corresponds to the long-term planning horizon typically equal to more than a year. The scope of the system is defined at this level. The tactical level refers to the mid-term planning horizon. The decisions made here are subject to change within 4–6 months. This level can be considered as an intermediate level which connects the strategic and operational levels. The operational level monitors the current status of the system and defines the physical actions to be taken in the short term (a day, or a couple of hours).

The second dimension, actors, deals with the type of actors that are under consideration. The operators, on the supply side, organize the system and try to generate profit. The users, on the demand side, want to perform their trip in the best possible conditions in terms of travel time, cost, convenience, arrival time, etc.

The third and last dimension, layers, deals with the specific methodological aspects, and has three levels: data, models, and actions. Data provide information about the system and its context. The models quantify the objectives and constraints of the system. They are necessary to handle quantities for which no data is available, in particular about the future (forecasting). Finally, the quantities provided by the data and the models are used to perform specific actions.

We define two types of relations between the modules: intra-level interactions represented with white arrows and inter-level interactions represented with dashed arrows. The intra-level interaction represents the information flow between the modules within the same decision level. The inter-level interaction passes the outputs of a higher decision level to the lower one's models layer as inputs.

We discuss the various parts of the framework in the following sections.

### 2.2. Strategic level

The data used at this level is typically aggregate, and usually static. It includes for example, the geographical location and characteristics of the city, the network of the parking spots, the economic status of the area and the distribution of welfare. An important piece of data is the aggregate historical travel demand typically in the form of origin-destination matrices, organized by mode, and time of day.

**Demand** Demand models at the strategic level involve mode and destination choice models. They are used to take business decisions

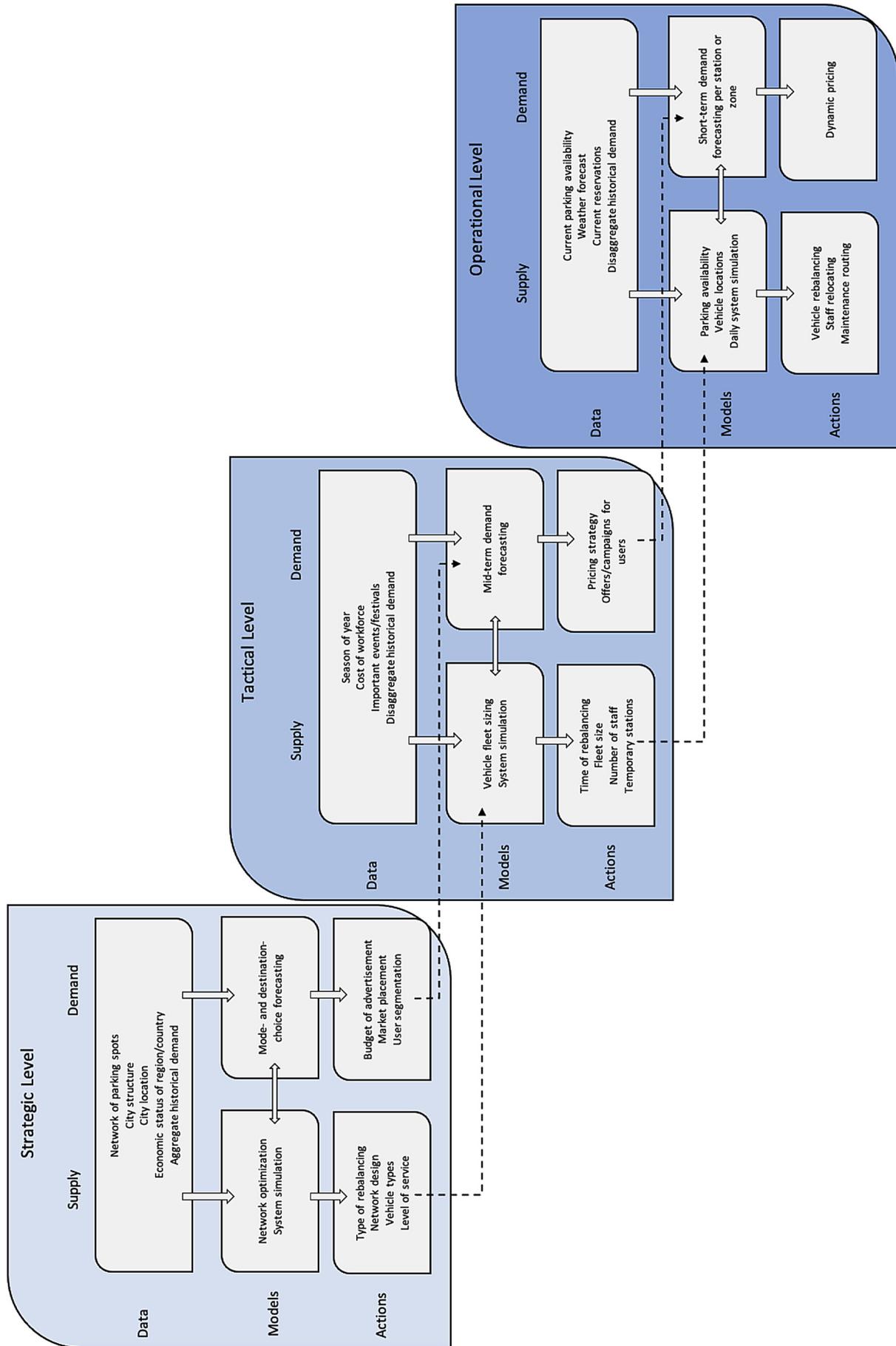


Fig. 1. Vehicle sharing system framework.

related to (i) user segmentation, that is the identification of the segments of the population that are likely to adopt the system, (ii) the advertisement investment, and (iii) the market placement.

**Supply** Supply models at the strategic level involve mainly a network design optimization model, possibly combined with a simulation of the demand/supply interactions. They support the decisions related to the network topology, the type of vehicles used, the type for rebalancing strategy, and the level of service offered.

As part of the network design, deciding the optimal location and the size of the parking facilities is an important decision to be made to prevent both overstocking and understocking of the vehicles. These decisions are done at the beginning of the system installment in the case of station-based configurations. The situation does not change for the free-floating configuration since each parking spot can be considered as a station with only one vehicle capacity. In this layer, the simulation component helps the operator to evaluate the system and take actions accordingly.

The type of rebalancing refers to the strategy used in the rebalancing operations and strongly relates to the type of 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 staff member cannot relocate another one. Moreover, the user-based strategies can be used to improve the balance in the system or a combination of staff-based and user-based approaches might be applied.

Lastly, the level of service that the operator wants to provide to the users should be decided at this level. If the operator wants to place importance on the users, then the strategy might be increasing the number of vehicles and/or parking spots in the city. On the other hand, if the operator is more capital oriented, the investment on the physical components of the system (vehicles, parking spot, etc.) is more crucial than the level of service, which makes it a secondary objective for the operator.

### 2.3. Tactical level

The data used at this level corresponds to mid-term time horizon and seasonal characteristics. It includes the seasonal weather forecast, precipitation, important events/festivals, and cost of the workforce. Contrarily to the strategic level, this level incorporates the disaggregate historical demand data. The disaggregate data helps the operator to develop a model that forecasts the demand in mid-term and take action for the mid-term time horizon. One should note that this disaggregate demand data can be aggregated at any level to come up with the actions. Aggregations can be performed according to any criteria such as the selected time period, origins, and destinations.

**Demand** The inputs regarding the budget and the target audience passed from the strategic level are used as attributes for the mid-term demand forecasting. They are used to take actions related to (i) pricing strategy (fixed or dynamic) and (ii) the offers/campaigns for the users. In the case of fixed pricing, the values for pricing is also determined at this level.

**Supply** Supply models at the tactical level involve a vehicle fleet sizing model, possibly combined with a simulation of the demand/supply interactions. They support the decisions related to the fleet size of the system, the number of staff, the time of rebalancing strategy (static or dynamic), and possible temporary stations.

The operator monitors the system and adjusts the fleet size. The fleet sizing is determined at this decision level since it is not practical to change this for just a short period of time. The operator should be able to monitor and analyze such a need in a reasonable amount of time. In order to evaluate the current and/or possible future applications of strategies, such as rebalancing, reservations, and pricing, we also include a component that simulates the system.

In the static rebalancing case, the operator should decide at what time of the day the rebalancing will be done whilst in dynamic case the operator

also needs to decide the frequency of the rebalancing operations as well as doing it online or offline. Accordingly, the number of staff should be determined to be able to rebalance the system. Lastly, locating temporary stations for possible important events/festivals is also done here.

### 2.4. Operational level

The data used at this level is disaggregate, and usually dynamic. It includes for example, daily weather forecast, the current parking availability, and current reservations (if applicable). The disaggregate historical travel demand data is detailed in location, time, and mode.

**Demand** Demand models at the operational level involve short-term demand forecasting per station/zone. It is used to decide the actual pricing in the case of dynamic pricing.

**Supply** Supply models at the operational level involve the models for parking availability and the location of the vehicles in the next time window. They support routing decisions related to the rebalancing operations and maintenance. Routing for rebalancing operations can be examined under two cases: routing for rebalancing trucks and staff relocation. Simulation component at this level helps the operator to analyze changes in the routing strategies by using the short-term data.

## 3. Literature review

In this section, we review the literature on the VSSs from a decision making point of view. We start with some review papers providing a general idea about the main aspects discussed so far. Then, we organize our review according to the different horizons related to the planning and management of a VSS. Section 3.1 covers the strategic level, corresponding to the long-term decisions (typically more than a year). Section 3.2 deals with the tactical level, corresponding to the mid-term decisions (typically, between a month and a year). Finally, Section 3.3 covers the operational level, corresponding to the short-term decisions (typically, between a couple of hours and a day). As in any classification task, the boundaries between classes may be fuzzy. For certain papers, we identify that they span more than one decision level. Such papers are presented in multiple sections, where in each of them, the aspects of the corresponding level are discussed.

We first discuss five review papers. [Jorge and Correia \(2013\)](#) provide a thorough review about CSSs, with special emphasis on demand estimation. In particular, they observe that linear regression is the most popular technique for demand estimation, as opposed to choice models. They also point out the fact that the simulation models developed for one-way systems are too context specific and cannot be generalized. The articles that they have considered did not include any free-floating system. Moreover, they claim that the inclusion of the other modes of transportation, such as public transportation and private car, is also necessary for the realistic scenarios.

[Laporte et al. \(2018\)](#) propose a general literature review on sharing systems. They also include the BSSs, and different configurations of the sharing systems in the review, i.e., free-floating and station-based, and static and dynamic rebalancing. They classify the former studies by problem type and decision level and stress the fact that some combinatorial questions, such as optimal inventory level within a theoretical framework, remain to be answered. They also state that the dynamic and stochastic characteristics of these systems bring complexity which has not been addressed in the literature. Although they include both car and bike sharing systems in the review, most of the work is on the BSSs. Therefore, the latest studies for CSSs are not comprehensively discussed.

This gap has been partially addressed by the review paper of [Illgen and Höck \(2019\)](#). They focus on the rebalancing problem in one-way CSSs. They organize the paper by classifying the works in terms of the methodology used to solve the rebalancing problem. They take the idea of [Laporte et al. \(2018\)](#) about the decision levels, and improve it by mapping the problem types to the decision levels. However, they do not map the works themselves to the decision levels. As in [Jorge and Correia](#)

(2013), Illgen and Höck (2019) also suggest that the stochasticity in VSSs should be examined further.

In Nath and Rambha (2019), the authors focus on the BSSs of any configuration. As in Laporte et al. (2018), the review is done by classifying the former works under problem type and decision level. However, this study considers only the strategic and operational decision levels. The most recent studies are discussed and suggestions for future work are provided. These include the consideration of the effects of elastic demand for the rebalancing operations and identifying the interactions between the supply and demand rather than regarding them as two independent actors.

Another recent work by He et al. (2019) considers the problem types

and identify the corresponding decision level for each problem type. However, as in Nath and Rambha (2019), they do not consider the tactical level decisions. The focus is on the free-floating systems that use electric vehicles in particular, which form the latest trends in VSSs. They point out the fact that the literature still lacks some concepts for the electric vehicle usage in VSSs, such as the placement of charging stations, integration of real-time data, and the charging schedules. Finally, they reckon that with more detailed operational data, different aspects of the origin-destination (O-D) demand pattern can be observed and can lead to conclusions on the impacts on the ridership.

We provide first an overview to the configurations used in the works in Table 1. The works are ordered in alphabetical order and the vehicle

**Table 1**  
Summary of the configurations.

Author	Year	Vehicle type	Objective function				Trips		Parking		Rebalancing operation				Pricing	
			RC	LOS	Other	N/A	RT	OW	SB	FF	N	S	D	UB	F	D
Aguilera-García et al.	2020	MSS				✓		✓		✓		✓				✓
Ashqar et al.	2019	BSS				✓		✓		✓		✓				✓
Balac et al.	2019	CSS			✓			✓		✓				✓		✓
Barth and Todd	1999	eCSS	✓	✓				✓		✓			✓	✓		✓
Boyacı and Zografos	2019	eCSS	✓					✓		✓				✓		✓
Boyacı et al.	2015	eCSS	✓					✓		✓				✓		✓
Boyacı et al.	2017	eCSS	✓	✓				✓		✓				✓		✓
Bruglieri et al.	2019	eCSS	✓					✓		✓				✓		✓
Caggiani et al.	2019	BSS				✓		✓		✓		✓				✓
Caggiani et al.	2020	BSS			✓			✓		✓		✓				✓
Campbell et al.	2016	BSS				✓		✓		✓		✓				✓
Çelebi et al.	2018	BSS		✓				✓		✓		✓				✓
Cepolina and Farina	2012	PICAV	✓					✓		✓					✓	✓
Chemla et al.	2013	BSS	✓					✓		✓				✓		✓
Chiariotti et al.	2018	BSS	✓					✓		✓				✓		✓
Ciari et al.	2013	CSS				✓	✓			✓		✓				✓
Clemente et al.	2017	CSS	✓					✓		✓					✓	✓
Degele et al.	2018	MSS				✓		✓			✓	✓				✓
Dell'Amico et al.	2014	BSS	✓					✓		✓			✓			✓
Deng and Cardin	2018	VSS	✓	✓				✓		✓				✓		✓
Faghih-Imani et al.	2017	BSS				✓		✓		✓				✓		✓
Febbraro et al.	2012	CSS	✓					✓		✓					✓	✓
George and Xia	2011	VSS	✓					✓		✓		✓				✓
Ghosh et al.	2017	BSS	✓	✓				✓		✓				✓		✓
Ghosh et al.	2016	BSS		✓				✓		✓				✓		✓
Hansen and Pantuso	2018	CSS	✓					✓		✓		✓				✓
Huang et al.	2020	eCSS	✓	✓				✓		✓				✓		✓
Illgen and Höck	2018	CSS				✓		✓		✓		✓				✓
Jin et al.	2020	eCSS				✓		✓		✓		✓				✓
Jorge et al.	2014	CSS	✓					✓		✓				✓		✓
Jorge et al.	2015	CSS	✓					✓		✓						✓
Kaspi et al.	2014	BSS		✓				✓		✓		✓				✓
Kaspi et al.	2016	BSS		✓				✓		✓		✓				✓
Kek et al.	2006	CSS	✓	✓				✓		✓				✓		✓
Kek et al.	2009	CSS	✓	✓				✓		✓				✓		✓
Kumar and Bierlaire	2012	eCSS		✓				✓		✓		✓				✓
Kutela and Teng	2019	BSS				✓		✓		✓		✓				✓

(continued on next page)

Table 1 (continued)

Author	Year	Vehicle type	Objective function				Trips		Parking		Rebalancing operation				Pricing	
			RC	LOS	Other	N/A	RT	OW	SB	FF	N	S	D	UB	F	D
Li et al.	2018	CSS				✓		✓		✓		✓				✓
Lin et al.	2018	BSS				✓		✓	✓		✓					✓
Liu et al.	2016	BSS	✓					✓	✓			✓				✓
Masoud et al.	2019	SSS	✓					✓		✓	✓					✓
Miao et al.	2019	ACEV-CSS	✓	✓				✓	✓	✓			✓			✓
Morton	2020	BSS				✓		✓	✓		✓					✓
Nair and Miller-Hooks	2011	VSS	✓	✓				✓	✓			✓				✓
Nourinejad and Roorda	2014	CSS	✓					✓	✓				✓			✓
Nourinejad et al.	2015	CSS	✓					✓	✓				✓			✓
Pal and Zhang	2017	BSS	✓					✓		✓		✓				✓
Pfrommer et al.	2014	BSS	✓					✓	✓				✓	✓		✓
Raviv et al.	2013	BSS	✓					✓	✓			✓				✓
Repoux et al.	2019	CSS		✓				✓	✓				✓			✓
Rossi et al.	2016	CSS	✓	✓				✓		✓			✓			✓
Schuijbroek et al.	2017	BSS			✓			✓	✓			✓				✓
Scott and Ciuro	2019	BSS				✓		✓	✓		✓					✓
Shu et al.	2013	BSS	✓	✓				✓	✓			✓	✓			✓
Soriguera and Jiménez	2020	BSS	✓					✓	✓				✓			✓
Warrington and Ruchti	2019	VSS	✓	✓				✓	✓	✓			✓			✓
Waserhole and Jost	2012	VSS	✓					✓	✓					✓		✓
Weikl and Bogenberger	2015	CSS	✓					✓		✓			✓			✓
Wu et al.	2019a	CSS				✓		✓		✓	✓					✓
Wu et al.	2019b	BSS	✓	✓				✓		✓				✓		✓
Yuan et al.	2019	BSS	✓					✓	✓				✓			✓
Zhang et al.	2019	eCSS	✓					✓	✓		✓		✓			✓
Zhao et al.	2018	CSS	✓					✓	✓			✓				✓

type used and the objective of the system is included under the columns *Vehicle type* and *Objective function*, respectively. The objectives considered in each study are characterized as (i) cost-related (RC) such as maximizing revenue/profit and minimizing the cost, (ii) maximizing the level of service (LOS), (iii) other objective types (Other), and (iv) not applicable (N/A), which denotes that the study does not define an optimization problem, nor an objective function. As mentioned in Section 1, we characterize the types of VSSs by (i) the type of trips, (ii) the parking organization, (iii) the type of rebalancing operations, and (iv) the pricing strategy. These are placed in columns of Table 1 in the same order. The *Trips* column is further divided into return-trip (RT) and one-way (OW). The *Parking*, i.e., parking organization, has two sub categories: station-based (SB) and free-floating (FF). Under the *Rebalancing operations* column we have four classes: not mentioned or not applied (N), static (S), dynamic (D), and user-based (UB). Lastly, the *Pricing* is categorized as either fixed (F) or dynamic (D). This table is provided to the reader to give her an idea about the reviewed works distribution among different configurations as another insight into the state of the art literature.

Among the papers we review, we were able to include at least one work for each type of VSS. Moreover, in some papers the work is concerned with VSSs in general, which means that they are compatible with both BSSs and CSSs. We see that works on one-way systems are more popular than the return-trip systems. The number of papers which study station-based configuration is much higher than the free-floating configuration in the study that we reviewed. We observe that the user-based rebalancing operations are fewer compared to the other

strategies. This also implies the fact that dynamic pricing is not studied as much as fixed pricing.

We further organize the reviewed articles according to the proposed framework (Section 1), and present this organization in Table 2.

The first and the second columns give the author names and the year the study is published, respectively. The next six columns represent the two dimensions of the framework, i.e., decision levels and actors. If a paper belongs to a combination of decision level and actor, the information regarding the third dimension, i.e., layers, is provided at the intersection with the corresponding study. Here “M” represents the models module and “A” represents the actions module. Papers which contain “M” develop a model, and papers which contain “A” discuss the actions considering a case study. We have seen from the literature that the data can be collected through surveys, obtained from private companies or open source repositories, and created synthetically. Since all analyzed approaches use the data obtained via one of those aspects, the data module is not illustrated in Table 2.

The last row of the table shows the total number of studies reviewed and their distribution among the two dimensions of the framework.

### 3.1. Strategic level

The strategic level corresponds to long-term decisions, with a horizon longer than a year, say. The most salient issues discussed in the literature are related to (i) data, (ii) business model, and (iii) system design.

Two types of data are crucial for the design and operations of a VSS:

**Table 2**  
Summary of the presented works.

Author	Year	Strategic level		Tactical level		Operation level	
		Supply	Demand	Supply	Demand	Supply	Demand
Aguilera-García et al.	2020	-	MA	-	-	-	-
Ashqar et al.	2019	-	-	-	-	-	M
Balac et al.	2019	-	-	MA	MA	-	-
Barth and Todd	1999	MA	-	-	-	-	-
Boyacı and Zografos	2019	-	-	-	-	MA	-
Boyacı et al.	2015	MA	-	MA	-	-	-
Boyacı et al.	2017	-	-	-	-	MA	A
Bruglieri et al.	2019	-	-	-	-	MA	-
Caggiani et al.	2019	MA	-	-	-	-	-
Caggiani et al.	2020	MA	-	-	-	-	-
Campbell et al.	2016	-	M	-	-	-	-
Çelebi et al.	2018	MA	-	-	-	-	-
Cepolina and Farina	2012	-	-	MA	-	-	-
Chemla et al.	2013	-	-	-	-	MA	A
Chiariotti et al.	2018	-	-	MA	-	-	-
Ciari et al.	2013	-	M	-	-	-	-
Clemente et al.	2017	-	-	MA	-	-	-
Degele et al.	2018	-	A	-	-	-	-
Dell'Amico et al.	2014	-	-	-	-	MA	-
Deng and Cardin	2018	MA	-	-	-	-	-
Faghih-Imani et al.	2017	-	-	-	-	MA	MA
Febbraro et al.	2012	-	-	-	-	-	MA
George and Xia	2011	-	-	MA	-	-	-
Ghosh et al.	2017	-	-	A	-	MA	-
Ghosh et al.	2016	-	-	-	-	MA	-
Hansen and Pantuso	2018	-	-	MA	-	-	-
Huang et al.	2020	MA	-	MA	-	MA	-
Illgen and Höck	2018	MA	-	-	-	-	-
Jin et al.	2020	-	M	-	-	-	-
Jorge et al.	2014	-	-	-	-	M	-
Jorge et al.	2015	-	-	-	-	-	MA
Kaspi et al.	2014	-	-	MA	-	-	-
Kaspi et al.	2016	-	-	MA	-	-	-
Kek et al.	2006	-	-	-	-	MA	-
Kek et al.	2009	-	-	-	-	MA	-
Kumar and Bierlaire	2012	-	-	A	-	-	-
Kutela and Teng	2019	-	-	-	M	-	-
Li et al.	2018	-	-	A	MA	-	-
Lin et al.	2018	-	-	-	-	-	MA
Liu et al.	2016	-	-	-	-	MA	-
Masoud et al.	2019	-	-	-	-	MA	-
Miao et al.	2019	MA	-	-	-	-	-
Morton	2020	-	MA	-	-	-	-
Nair and Miller-Hooks	2011	-	-	-	-	MA	-
Nourinejad and Roorda	2014	-	-	MA	-	-	-
Nourinejad et al.	2015	-	-	-	-	MA	-
Pal and Zhang	2017	-	-	-	-	MA	-

(continued on next page)

Table 2 (continued)

Author	Year	Strategic level		Tactical level		Operation level	
		Supply	Demand	Supply	Demand	Supply	Demand
Pfrommer et al.	2014	-	-	-	-	MA	MA
Raviv et al.	2013	-	-	-	-	MA	-
Repoux et al.	2019	A	-	MA	-	-	-
Rossi et al.	2016	-	-	-	-	MA	-
Schuijbroek et al.	2017	-	-	-	-	MA	M
Scott and Ciuro	2019	-	-	-	M	-	-
Shu et al.	2013	-	-	MA	-	MA	-
Soriguera and Jiménez	2020	MA	-	MA	-	-	-
Warrington and Ruchti	2019	-	-	-	-	MA	-
Waserhole and Jost	2012	-	-	-	-	MA	-
Weikl and Bogenberger	2015	-	-	-	-	MA	-
Wu et al.	2019a	-	MA	-	-	-	-
Wu et al.	2019b	-	-	-	-	-	MA
Yuan et al.	2019	MA	-	MA	-	MA	-
Zhang et al.	2019	-	-	-	-	MA	-
Zhao et al.	2018	-	-	-	-	MA	-
<b>Total number of works = 63</b>		<b>12</b>	<b>7</b>	<b>18</b>	<b>4</b>	<b>28</b>	<b>10</b>

- demand data, such as VSS trip history, socio-economic and demographic information, mobility and travel-related variables, personal attitudes and preferences, and perceptions of VSS, and
- data describing the VSS and geographical location the VSS is operating at, such as VSS configuration, city terrain characteristics and elevation, parking locations, and weather conditions.

Demand data is recorded during the previous VSS operations, e.g. trip history, or collected using stated preferences surveys (Campbell et al., 2016; Aguilera-García et al., 2020; Wu et al., 2019a; Çelebi et al., 2018; Jin et al., 2020), where the respondents make decisions in the context of hypothetical situations. Additionally, demand data can be extracted from mobile phone trajectory of the users (Miao et al., 2019).

### 3.1.1. Demand

Using the demand data, we can build different types of demand forecasting models. Firstly, the mode-choice models can be constructed. Such models estimate whether the users will accept and use the offered VSS service, in the presence of the other transportation systems (Aguilera-García et al., 2020; Wu et al., 2019a; Jin et al., 2020). Also, users may have a choice between different types of shared vehicles (Campbell et al., 2016; Illgen and Höck, 2018), such as between conventional and electric bikes, or between different VSS configurations (Wu et al., 2019a). The methodologies for building such models include logit models (Campbell et al., 2016; Aguilera-García et al., 2020; Wu et al., 2019a; Jin et al., 2020), risky-choice behavior models (Wu et al., 2019a), or simulation (Illgen and Höck, 2018).

Demand data, together with location characteristics and weather data, may also be used to model and forecast the average usage of a VSS, for a certain period, such as hourly or daily. Here, the forecast may be at the station level (Kutela and Teng, 2019; Ciari et al., 2013), or at the zone level, which is usually done in case of free-floating VSSs. The forecast is performed by using binomial models (Kutela and Teng, 2019), micro-simulation (Ciari et al., 2013), or queuing theory (Çelebi et al., 2018). Furthermore, the environmental conditions such as air quality can also be considered to examine the variation in demand for cycling (Morton, 2020).

Long term decisions are also related to the business model for the VSS. The literature deals with issues such as market placement, user

segmentation, and budget allocation, in the ways respectively presented in the following paragraphs.

By simulating a VSS and analyzing the ratio of total number of vehicles to the product of the total number of trips per day and the number of stations, we can select vehicle types that are the best fit for an observed market (Illgen and Höck, 2018). This approach is also suitable for determining the appropriate time for the transition from conventional CSS to electric CSS. In Illgen and Höck (2018), the authors concluded that this transition should be rather gradual than immediate.

Regarding the market research, Degele et al. (2018) also put effort on the analysis of user segmentation in an MSS. The authors apply hierarchical clustering and identify four different user segments, i.e., geographic, demographic, psychographic, and behavioral. In order to assess the impact of each segment for business development, the authors provide a growth-share matrix and determine which segments contribute to the total revenue most. These results show the segments to target through advertisement and marketing. Morton (2020) analyzes two different types of users in BSSs. He shows that regular and casual users tend to differently react to changes in weather and air quality measures.

Budget allocation can be performed through network design. I.e., while determining the optimal number of docks and bikes to allocate to each station that will minimize the lost demand, the budget limit can be regarded as a constraint (Caggiani et al., 2019).

### 3.1.2. Supply

The last set of issues at the strategic level relates to the network design. This includes works on station location and size, vehicle allocation, fleet composition, and type of rebalancing. All these decisions may be made to favor and focus on either the operator performance or user satisfaction. In the former case, system operations are evaluated with operator-oriented performance indicators, such as operations costs, number of vehicle relocations (NoR), or average state of battery charge or fuel tank (Deng and Cardin, 2018; Barth and Todd, 1999; Soriguera and Jiménez, 2020). In the latter case, the performance indicators are user-oriented and may include lost demand, zero-vehicle-time (ZVT), full-port-time (FPT), average and total user waiting times, number of users waiting, NoR, or waiting time vs. NoR analysis (Caggiani et al., 2019; Barth and Todd, 1999; Çelebi et al., 2018). The user-oriented performance indicators, or a subset of them, are often jointly denoted

as the level of service (LOS). In Caggiani et al., 2020, the authors also consider the equality among population groups while maintaining accessibility and coverage.

The station location and sizing, and vehicle allocation problems are modeled as mixed integer linear problems (MILP, Boyacı et al., 2015) or mixed integer non-linear problems (MINLP, Çelebi et al., 2018; Soriguera and Jiménez, 2020). Before solving them, the problem instance size can be reduced by spatio-temporal clustering, in particular when modeling a dense VSS (Caggiani et al., 2019). Afterwards, the problem may be solved with genetic algorithms (Caggiani et al., 2019, 2020), dynamic programming (Çelebi et al., 2018), Lagrangian relaxation, particle swarm optimization, or simulation (Deng and Cardin, 2018). Here, the goals are to minimize the system operation costs (Deng and Cardin, 2018; Soriguera and Jiménez, 2020), maximize operator revenue (Boyacı et al., 2015), achieve a certain LOS (Caggiani et al., 2019), minimize the unequal VSS accessibility of different population groups (Caggiani et al., 2020), or combine the two goals into a multi-objective problem (Boyacı et al., 2015).

With the favorable locations and sizes of stations, and vehicles distribution, the operator consequently reduces the rebalancing activities as well. Several works, such as Soriguera and Jiménez (2020) and Boyacı et al. (2015), evaluate these network design decisions through the performance of rebalancing operations. In an extreme case, if the number of rebalancing trucks is not enough to keep the LOS at a desired level, rebalancing operations may not be conducted at all (Deng and Cardin, 2018).

Some studies also account for the subsidies paid by the public or governmental agencies (Boyacı et al., 2015), and show that the increase of subsidy cause more vehicles in the system. Therefore, the system becomes less dependent on rebalancing operations.

Another task at the strategic decision level is to determine the type of rebalancing. Such analysis can be performed through a discrete-event simulation which account for the stochasticity of demand (Barth and Todd, 1999). The simulator identifies the vehicle availability, distribution, and energy management. The system operations are then evaluated by monitoring different operator- and user-oriented performance measures (Barth and Todd, 1999).

Determining whether a VSS should be configured as station-based or free-floating can be considered a generalization of the station location and sizing problem, where in the latter configuration, each parking spot is considered as a station of unit capacity. In Soriguera and Jiménez (2020), the authors see that free-floating configurations are able to provide a better LOS. In the same work, they also claim that when the e-bikes are used in a station-based configuration, the charging process does not put much restriction on the system. Therefore, station-based systems can be converted from traditional bikes to e-bikes. They claim that the good part of implementing e-bikes is to attract the user, increase demand, and decrease imbalance. These are possible since users also do uphill trips and longer distances. The city structure and the distance traveled are less relevant.

Apart from the conventional CSSs, efforts are done in the context of autonomous and electric vehicles. One such example is the work of Miao et al. (2019), who model an ACEV-based CSS and its optimal planning. A two-stage multi-objective optimization model is proposed. The first stage optimizes the total served trip distance and minimizes the total cost whilst the charging infrastructure allocation is considered in the second stage. The proposed model is solved by a non dominated sorting genetic algorithm-II (NSGA-II). The authors find that the charging infrastructure speed has an influence on the performance of the system. As the charging gets faster, the satisfied trip demands and total daily served trip distance improve. They also state that the combined system of ACEVs and conventional cars demonstrate great improvements. This result is aligned with the Illgen and Höck (2018) in the sense that the adoption of electric vehicles in VSSs should not necessarily be immediate.

Yuan et al. (2019) and Huang et al. (2020) approach the planning of a VSS and an eCSS, respectively, from the broadest perspective we

encountered in the literature. Yuan et al. (2019) determine the number, location and the capacity of stations, fleet size, depot location, rebalancing and maintenance plans simultaneously in a station-based BSS. To achieve this, they develop a MILP to combine all these decisions while considering the stochastic demand and LOS. The latter is defined with the coverage range of each station and the availability rate of bikes at each station. The objective function consists of two main components, i.e., the capital cost and the expected operating cost. The constraints are categorized as either bike station or operational constraints. The bike station constraints include the subjective distance constraints, location selection constraints and docking unit constraints. The subjective distance concept mimics the human perception of the actual distance. The subjective distance represents the trip distance greater than the Euclidean and less than the real (Manhattan) distance, and is modeled as the Euclidean distance multiplied by a factor  $\alpha$ . The operational constraints, on the other hand, deal with the rebalancing constraints and depot constraints. One thing to point out is that the rebalancing constraints are not actual rebalancing operations but the balance/flow conservation of the system. The results on a BSS in Changping, Beijing show that the availability factor, which represents the proximity to a station, is an important factor. This also implies the need to change the station distribution from unevenly to almost evenly. This result can be considered similar to the one in Çelebi et al. (2018). They both imply that the stations should not be placed at the exact spot of the highest demand, but rather around it. In the case studies of Yuan et al. (2019) and Çelebi et al. (2018), such station location resulted in an increase of covered area and convenience of the VSS service.

The strategic level decisions of Huang et al. (2020) consist of station capacity. A MINLP is developed that maximizes total profit of the operator and considers fleet and station sizing, demand satisfaction, and required rebalancing operations. They propose a customized solution algorithm to avoid computational difficulties. They determine lower and upper bounds for the strategic and tactical level decisions and then solve the operational level problems. As a last step, the solution is improved using the golden section and shadow price algorithms.

### 3.1.3. Conclusion

We see that, at the strategic level, the authors approach the problems both from the operator's and user's points of view. In other words, the problem objectives maximize the profitability of the system or user satisfaction. However, it is more common that the user satisfaction is incorporated in the performance measures, which are modeled as constraints. The solution methodologies include optimization models, simulation tools, and various exact and heuristic algorithms.

## 3.2. Tactical level

The bridge between the strategic and operational levels is defined by the tactical level. This section covers works from the literature coping with the mid-term decisions. There are three major aspects discussed in the literature: (i) demand modeling and pricing, (ii) fleet sizing, and (iii) system evaluation.

### 3.2.1. Demand

Demand modeling includes number of daily trips forecasting, the reaction of the users when pricing incentives are proposed, and what happens when a new type of mode is introduced into an already existing system.

The influencing factors on the number of daily trips can be determined using linear regression, user equilibrium models (Li et al., 2018), or random intercept multilevel models (Scott and Ciuro, 2019). The results of Li et al. (2018) show that the fleet size, distribution and rental-parking price significantly influence the usage of a free-floating CSS. Furthermore, Scott and Ciuro (2019) observe that weather conditions, daylight, and employment are among the influencing factors.

Logit models can then be used to forecast the number of daily trip

demand (Kutela and Teng, 2019). Moreover, the developed models can be compared using the number of daily trips forecast as a performance measure (Kutela and Teng, 2019). This way, the operator understands the demand structure in the mid-term time horizon, and decides on the pricing strategy and the type of campaigns.

The user behavior can be represented by a Markovian model (Kaspi et al., 2014; George and Xia, 2011; Chiariotti et al., 2018) or by a user behavior model (Kaspi et al., 2016).

The prices vary with the trip characteristics such as drop-off location (Hansen and Pantuso, 2018) or different price schemes are determined to decide pricing strategy (Clemente et al., 2017; Balac et al., 2019; Li et al., 2018). These strategies determine an incentive or deterring price component. The outcomes from the utilized strategies are compared to analyze the user behavior.

The solution approaches to determine pricing strategies consist of both optimization and simulation. In the case of optimization, the objective function can be set to maximizing the system revenue (Hansen and Pantuso, 2018) or maximizing the LOS (Clemente et al., 2017). The main decisions can be the number of vehicles necessary in each parking area (Clemente et al., 2017), the price of the service, and the utility obtained by the user (Hansen and Pantuso, 2018). Hansen and Pantuso (2018) define this utility as a sum of a deterministic function of price and the attributes of the transportation service, and the error term. The simulation is used to mimic the system operation to be able to evaluate the performance measures such as the LOS (Clemente et al., 2017) or the profit (Balac et al., 2019). The considered events in the simulation usually include arrival of a user, departure of a user, pick-up, drop-off, and maintenance activities. Finally, Clemente et al. (2017) merge these two approaches in a single framework.

In Hansen and Pantuso (2018), the importance of the relation between the market power and the pricing strategy is emphasized. They point out the fact that the market power of the VSS should be high enough to charge a drop-off fee. It is also noted that including elements such as the purpose of the trip, weather conditions and carry-on items in the utility specification might affect the results.

Balac et al. (2019) contribute to the literature by considering the competition between operators for the first time. Their framework simulates a free-floating CSS. The computational experiments reveal that when competition is introduced to the system with different price levels, the whole system is more profitable. The majority of the market share is owned by the low-price provider resulting in higher profit. On the other hand, due to high cost of rebalancing staff, depreciation, fuel, maintenance and tire costs, the rebalancing operations are shown to be unprofitable under competition.

### 3.2.2. Supply

On the supply side, the most investigated challenge is the fleet sizing, as mentioned in Li et al. (2018). For this purpose, the works either optimize the fleet size (George and Xia, 2011; Boyacı et al., 2015; Yuan et al., 2019; Cepolina and Farina, 2012; Huang et al., 2020; Shu et al., 2013) or analyze the effect of it on the system (Ghosh et al., 2017; Soriguera and Jiménez, 2020). One of the interesting properties of this problem is that it is usually combined with problems from different decision levels, such as network design (Boyacı et al., 2015; Yuan et al., 2019; Soriguera and Jiménez, 2020; Huang et al., 2020) and vehicle rebalancing (Ghosh et al., 2017; Yuan et al., 2019; Huang et al., 2020; Shu et al., 2013).

George and Xia (2011) incorporate the LOS as a constraint in their model. The results show that as the target LOS gets higher, the required fleet size increases exponentially and the profit decreases. Shu et al. (2013) determine the number of bicycles by examining an equilibrium state of the BSS network. They state that the number of bikes at each station stabilizes after a number of time periods. Soriguera and Jiménez (2020) analyze the effect of fleet sizing in a BSS. They show that the optimal fleet size is mostly related to the cost of one bike where the objective is to minimize the sum of operator and user costs.

Although we are concerned about mid-term time horizon at this decision level, some works propose computationally efficient approaches too. For example, George and Xia (2011) use an approximation method based on Schweitzer-Bard Mean Value Analysis. In Cepolina and Farina (2012), simulated annealing is used to come up with the optimal fleet size and its distribution among the parking lots. Huang et al. (2020) determine lower and upper bounds for the fleet size. Then, the operational level problem is solved and the fleet size is updated using golden search and shadow price algorithms. This loop iterates until there is a small difference in profit between two iterations.

Beside fleet sizing, supply decisions may include the modification of the configuration of the system, which was planned at the strategic level. Indeed, although it is very important to analyze and optimally locate the stations at the beginning of a VSS construction, other needs might arise. These include altering the configuration of the network, such as locating additional stations, merging station locations, and discarding stations. Change in demand patterns, vehicle types, pricing might affect spatial trip demand. One of such cases studied in the literature considers a return-trip CSS where electric vehicles are deployed (Kumar and Bierlaire, 2012). The authors work on an existing CSS, AutoBleue, in Nice, France and locate additional stations. First, an analysis on the system is done. Regression is used to analyze and determine the influencing factors of the system in urban areas. Then, an optimization model is developed to determine the station locations while taking the attractiveness of the locations into account. This model is solved via an iterative heuristic because of computational limitations. The methodology is observed to provide better performance in stations. Moreover, the placement of stations at low demand regions is justified with the fact that it helps the brand awareness and connectivity.

Additional supply side decisions include the evaluation of the rebalancing strategy and policies, such as parking and trip reservations. The analysis of these aspects may lead to a modification in the system configuration.

One of the basic strategy evaluations is analyzing the following three scenarios on a VSS: (i) no rebalancing, (ii) static rebalancing, and (iii) dynamic rebalancing. In particular, Chiariotti et al. (2018) perform such analysis on a station-based BSS. In a more detailed evaluation, different kinds of rebalancing operations can be compared. For example, Repoux et al. (2019) analyze the effects of dynamic rebalancing strategies in one-way CSSs with complete journey reservations. They propose a new "proactive rebalancing strategy". The evaluated dynamic rebalancing strategies are as follows: (i) One vehicle one spot inventory policy, which prioritizes stations based on available number of vehicles and spots. This helps the strategy to deal with inventory management and rebalancing duration at the same time, and (ii) Markovian estimation policy in which the state is given using the available cars, reserved cars for one-way trip, reserved cars for return-trip, and reserved spots. Shu et al. (2013) evaluate the static and periodic rebalancing operations. The periodic rebalancing is considered as static rebalancing repeated a few times per day.

The perfect demand information is assumed to be known in Repoux et al. (2019) whilst it is modeled as birth and death processes in Chiariotti et al. (2018). Both works aim to maximize the LOS. In Chiariotti et al. (2018), the objective function considers: (i) the difference between the station becomes full or empty among all the stations before and after rebalancing operations, (ii) the fixed cost for each vehicle in fleet, and (iii) the variable cost that depends on the distance traveled by the rebalancing trucks. The nodes which have the smallest survival times are selected using an algorithm which includes the routing problem.

The results from Chiariotti et al. (2018) show that the dynamic rebalancing outperforms the others. They find that in addition to historical data, the current trends and the weather information is important to gather more information on the demand patterns. Although they make simplifications, the improvement compared to the current system is considerably high. Therefore, this encourages future work with relaxed assumptions. Repoux et al. (2019) show that the improvements obtained with complex rebalancing strategies are quite limited compared to the

approximated upper bound. Fleet size, station capacity, and rental rules are found to be important components of a VSS. All in all, the authors conclude that a better informed CSS provides a higher LOS.

The evaluation of parking reservation policies is also studied in the literature. To evaluate these policies, Kaspi et al. (2014) use simulations in a one-way VSS. They compare performance of two strategies: (i) No Reservation (NR) and (ii) Complete Parking Reservation (CPR), in which the user must first reserve the parking space at the destination station before taking the vehicle. The following work from Kaspi et al. (2016) formulates an MILP. It determines the lower bound on the excess time, i.e., the difference between the actual and the shortest possible trip time, under NR. Using the lower bound, the authors evaluate several partial parking reservation policies as well as NR policy. These policies are: (i) Trip based partial reservation policy, in which reservation is required if the trip time is shorter than a pre-determined threshold, (ii) Station based partial reservation policy, in which reservation is required if the difference between the pick-up and drop-offs at the desired station is higher than a pre-determined value, i.e., difference threshold, and (iii) Time limited partial reservation policy, in which reservations are required for each user, but it is valid for a limited time.

Nourinejad and Roorda (2014) develop a benchmark mixed integer problem (MIP) to analyze vehicle reservation policies. The model is based on a multiple traveling salesman problem (TSP). In this work, users are required to reserve the vehicle more than a pre-specified time in advance. The proposed framework for the dynamic model combines both simulation and optimization. The objective is to minimize the fleet size, rebalancing operations, and parking costs for the given system configuration and simulated demand. They use total revenue, total cost of rebalancing, fleet utilization, and system reliability to assess the performance of the dynamic model.

The results point out the importance of future trip demand knowledge (Kaspi et al., 2014; Nourinejad and Roorda, 2014). In the case of partial reservation policies, the more information gathered from the user, the better the system performs (Kaspi et al., 2016). Furthermore, under different demand scenarios, Nourinejad and Roorda (2014) observe that when the demand is higher, solving the model yields higher fleet size and rebalancing time. They also experiment the impact of reservation time. They observe that as the reservation time values increase the fleet size decreases and the rebalancing time increases. They also report a threshold value for the reservation time after which the fleet size stays almost the same since the system can be rebalanced within this reservation time. This finding supports the fact that even short term demand knowledge improves the system operation.

### 3.2.3. Conclusion

At the tactical level, a strong emphasis is put on the analysis of the usage of the system, and the number of daily trips. Decisions made at the strategic level must also be reconsidered in the light of a more precise knowledge of the demand. Finally, it appears that several tactical decisions are supported by policy evaluation methods. An important exception is the fleet sizing decisions, usually based on optimization models.

## 3.3. Operational level

The last element of the framework consists of the operational level decisions. These decisions are concerned with the short-term time horizon. Therefore, the works that cope with daily/hourly operations and decisions are reviewed. Four main aspects are discussed in the literature with respect to this level: (i) demand forecasting, (ii) dynamic pricing, (iii) truck and staff routing for rebalancing and maintenance, and (iv) system evaluation.

### 3.3.1. Demand

The demand forecasting models are designed to come up with the hourly demand per station/zone (Faghih-Imani et al., 2017; Lin et al., 2018) or the expected number of vehicles at stations/zones (Ashqar et al.,

2019). The main concern appears to be the correlation structures. To resolve this issue, Faghih-Imani et al. (2017) use autoregressive moving average (ARMA) models. This model is created for each sub-city district, which makes it appropriate for usage in free-floating and station-based systems. Lin et al. (2018) use a novel Graph Convolutional Neural Network with Data-driven Graph Filter (GCNN-DDGF) model. The novelty of GCNN-DDGF is that it is capable of capturing hidden heterogeneous pairwise correlations between stations, which improves the prediction accuracy. Furthermore, Ashqar et al. (2019) apply Random Forest which protects against the impact of colinearity between predictors and can handle non-linear variables and categorical interactions.

User behavior can be mimicked in real operations by rule-based models. Although Kaspi et al. (2016) develop such a model to tackle the tactical question of introducing parking reservation, the model nature allows it to be used in presenting the demand at the operational level. In cases when there is no available data for building trained forecasting models, such models can be used as their replacement.

Logit models can be utilized to understand the factors creating imbalance and a linear regression model may help to determine the amount of rebalancing operations. The first such empirical analysis on operator-based rebalancing is conducted by Faghih-Imani et al. (2017). They claim that their analysis can help in creating plans for rebalancing well in advance, as well as in creating incentive mechanisms for users to rebalance bikes. The identified factors are then utilized in the models. Therefore, it is important to justify the feature selection by a systematic approach. We see that the work of Lin et al. (2018) lacks this justification and this can be counted as the major shortcoming of their approach. Furthermore, several often used features are missing, such as weather, day, season, or special events. These were included in both Faghih-Imani et al. (2017) and Ashqar et al. (2019) and were found to be relevant. Furthermore, Ashqar et al. (2019) use the developed models to see which stations are significantly different from the others. This also helps the operator to see which stations cause the imbalance.

In the case of multiple regression models, the best can be selected by Bayesian Information Criterion. For example, Ashqar et al. (2019) compare two models that are developed based on Poisson regression model (PRM) and negative binomial (NB) regression model. They find that NB outperforms PRM.

The user-based rebalancing strategies can be used in order to reduce the need for rebalancing operations. This kind of strategy can be used independently (Waserhole and Jost, 2012; Febbraro et al., 2012; Wu et al., 2019b) or can be supported with operator-based rebalancing operations (Pfrommer et al., 2014; Chemla et al., 2013).

The works use optimization models (Chemla et al., 2013), discrete-event simulation (Febbraro et al., 2012; Wu et al., 2019b), Markovian formulation (Waserhole and Jost, 2012), and model-based receding horizon optimization principles (Pfrommer et al., 2014) to determine the price levels. Febbraro et al. (2012) propose a methodology which includes two phases. In the first phase, the optimal location to drop-off the vehicle is determined, and in the second phase, the amount of incentive which will be given to the user is derived. The rebalancing problem to minimize the rejection ratio of reservations is solved using a non-linear integer problem to complete the first phase. However, a solution methodology for the second phase is not discussed in this study and left as a future work. Waserhole and Jost (2012) suggest a fluid approximation to overcome the computational complexity. They replace the stochastic demand by a continuous deterministic flow. The model becomes the limit of a scaled Markovian model, in which the fleet, the station capacities and demand are scaled by a common factor.

Logit models can be utilized to understand the behavior of the users with respect to incentives (Febbraro et al., 2012) or spatial and temporal flexibility (Boyacı and Zografos, 2019). Febbraro et al. (2012) provide two choices to the users, i.e., "accept" and "not accept". Their model includes two attributes, one being the distance between the "wished for" and "proposed" parking zones and the other being the applied discount. They state that it is difficult to estimate the coefficients because of the

lack of data. In continuation of the work of [Boyacı et al. \(2017\)](#), [Boyacı and Zografos \(2019\)](#) utilize a framework to analyze the effect of users' spatial and/or temporal flexibility regarding vehicle pick-ups and drop-offs and reservation processing type on the performance. The proposed framework consists of three modules: preprocessing, optimization, and simulation. These modules model the one-way eCSS operations realistically in terms of the vehicle rebalancing and staff relocation, and battery charging requirements. The results show that the spatial flexibility has a more significant effect than the temporal flexibility.

The computational experiments are conducted to understand the effect of dynamic pricing on LOS. [Chemla et al. \(2013\)](#) show that dynamic pricing improves the system LOS, which is defined as the percentage of users who were able to find a bike at their origin and were able to park their bikes at their destination. Short term decisions seem to be more efficient than the long term ones. Furthermore, the pricing method seems to be promising especially when the size of the problem increases. In [Pfrommer et al. \(2014\)](#), the level of service is defined as the ratio of difference between the number of potential users and no-service events, and the number of potential users. The results show that it is possible to keep the LOS considerably high on weekends only with the pricing incentives and without the use of rebalancing workers. [Febbraro et al. \(2012\)](#) report a threshold value for the fleet size and observe in their case that when this threshold is exceeded, the percentage of reservation rejections decreases drastically.

The stochasticity in demand and price elasticity are essential factors to consider since this configuration is dynamic. [Chemla et al. \(2013\)](#) and [Waserhole and Jost \(2012\)](#) acknowledge that these dimensions are important and they lack in their methodology. However, they also propose them as future work. The frequency of price updates should also be adjusted accordingly. [Chemla et al. \(2013\)](#) update the prices every 15 min, whilst [Waserhole and Jost \(2012\)](#) every 5 min. The users should not be discouraged due to too frequent updates but also the nature of the dynamic pricing should be kept. In other words, the trade-off should be analyzed to determine the frequency of updates.

### 3.3.2. Supply

As discussed in [Faghih-Imani et al. \(2017\)](#) and [Ashqar et al. \(2019\)](#), the output of demand forecasting is an essential input for decisions whether to conduct rebalancing operations and how to apply them. We first present the works that are concerned with static rebalancing. Such operations are less complex compared to dynamic rebalancing since the routing schedule is not changed during system operation.

We see that static rebalancing is mostly studied in the context of station-based BSSs and the optimization models are adopted to solve the routing problem ([Raviv et al., 2013](#); [Schuijbroek et al., 2017](#); [Dell'Amico et al., 2014](#); [Liu et al., 2016](#)). The system configuration affects the characteristics of the developed optimization model. MILP models are the most commonly used approach to find the optimal routing ([Raviv et al., 2013](#); [Dell'Amico et al., 2014](#)). Although [Pal and Zhang \(2017\)](#) tackle with free-floating BSSs and [Bruglieri et al. \(2019\)](#) station-based eCSSs, the solution approach is not different. Furthermore, [Shu et al. \(2013\)](#) do not only rebalance bikes, but also propose an approach which includes mobile docks and can be used to determine the number of docks to install in each station on a daily level, by using the available historical demand data. [Liu et al. \(2016\)](#) develop a MINLP model that integrates the station level bike demand prediction using the historical trip and weather data. [Schuijbroek et al. \(2017\)](#) also integrate the required inventory level estimation by a Markov chain structure. They develop an MIP for the routing decisions as well as a constraint programming (CP) approach. It should be noted that this paper presents the first CP approach to solve the static rebalancing problem.

The computational burden has always been an issue for the routing problems. Valid inequalities and dominance rules are thus proposed for some of optimization models ([Raviv et al., 2013](#); [Dell'Amico et al., 2014](#)). [Pal and Zhang \(2017\)](#) believe that column generation can speed up the solution time. Some works use clustering to reduce the size of the

network and solve the routing problem for each cluster ([Schuijbroek et al., 2017](#); [Liu et al., 2016](#)).

To overcome computational complexity we also see applications of heuristics ([Raviv et al., 2013](#); [Schuijbroek et al., 2017](#); [Pal and Zhang, 2017](#)), metaheuristics ([Bruglieri et al., 2019](#)), and branch and cut algorithms ([Dell'Amico et al., 2014](#)). [Raviv et al. \(2013\)](#) provide algorithmic enhancements via a two-phase solution method and arc deletion. The results are robust to the traffic volume of the system, in other words, to the change in demand. [Schuijbroek et al. \(2017\)](#) propose a heuristic that outperforms the pure MIP and CP solutions, especially for instances with a larger vehicle fleet and a lower number of stations per vehicle. [Pal and Zhang \(2017\)](#) develop a heuristic which is a hybrid of Nested Large Neighborhood Search (NLNS) and Variable Neighborhood Descent (VND). They also consider changing the fleet size during the rebalancing operations, in order to allow maintenance at the depot. [Bruglieri et al. \(2019\)](#) propose a metaheuristic algorithm based on the Adaptive Large Neighborhood Search (ALNS). The authors take into account the particularities of electric vehicles (EVs), such as battery levels and charging requirements. They state that the proposed ALNS-based heuristic reveals to be the most effective and efficient methodology to solve the EV rebalancing problem.

Unlike [Pal and Zhang \(2017\)](#), the maintenance can also be done at the spot. In the case of free-floating SSSs, the operator should be able to access to the e-scooters that have insufficient or empty batteries. This is another dimension of the problem compared to station-based conventional VSSs. [Masoud et al. \(2019\)](#) develop an MILP for e-scooter chargers allocation (ESCA) problem in order to assign the chargers to the scooters. Its objective is to minimize the charging operation cost, which is influenced by two components: (i) the distance between the charger and the e-scooter and (ii) penalties for additional chargers added to the system. Since the model is NP-hard, the authors propose two algorithms to solve the large-scale instances. The first is based on a many-to-one matching algorithm, named adapted college admission (ACA) algorithm, whilst the second applies black hole optimizer (BHO), which is a metaheuristic. The results show that ACA produces better results compared to BHO for large-size instances, which vary from 150 to 564 stations.

The optimization models are the most studied solution approach for dynamic rebalancing operations, too. The objective function is usually designated as cost minimization ([Nourinejad et al., 2015](#)), maximizing profit ([Weikl and Bogenberger, 2015](#); [Ghosh et al., 2017](#)), or minimizing the lost demand ([Ghosh et al., 2016](#)).

Since the time dimension is also present in dynamic rebalancing, it is more demanding in terms of computational time compared to static rebalancing. The authors are able to propose linear optimization models; however, they turn out to be computationally intractable. The size of network is usually reduced by station clustering ([Boyacı et al., 2017](#); [Weikl and Bogenberger, 2015](#); [Ghosh et al., 2017](#); [Chemla et al., 2013](#)). Whereas [Boyacı et al. \(2017\)](#) rebalance the vehicles within clusters, [Weikl and Bogenberger \(2015\)](#) also consider inter-cluster rebalancing when necessary. [Chemla et al. \(2013\)](#) provide the dynamic rebalancing strategy for one rebalancing truck. When one truck is not sufficient for the rebalancing operations, the area is divided into clusters and the same procedure is applied within the clusters.

Decomposition methods and decoupling the problem into sub problems are other approaches to overcome the intractability issue ([Ghosh et al., 2017](#); [Nourinejad et al., 2015](#); [Weikl and Bogenberger, 2015](#); [Rossi et al., 2016](#)). [Ghosh et al. \(2017\)](#) use Lagrangian dual decomposition (LDD) and separate the routing and rebalancing problems. They also group the stations to decrease the number of stations. [Nourinejad et al. \(2015\)](#) also divide the main problem into two sub problems and use a heuristic based on a decomposition method. In [Weikl and Bogenberger \(2015\)](#), the optimization algorithm is responsible for determining the quantities of required inter-cluster rebalancing operations. Subsequently, two rule-based methods determine inter- and intra-cluster rebalancing operations, at the level of individual vehicles, and service trips. [Huang et al. \(2020\)](#) use the lower and upper bounds of strategic and tactical

level decisions, i.e., station capacity and fleet size, to determine the rebalancing operations by means of an LP.

Stochastic programming can also be used to decouple the problem. [Warrington and Ruchti \(2019\)](#) propose a two-stage stochastic programming approach. The first stage contains the decisions of planned rebalancing truck journey, and loading and unloading at a node. The second stage takes the first stage decisions and a demand realization as inputs. Then, the completed shared vehicle journeys that minimize the rebalancing cost are obtained. The uncertainty in the future demand can be considered by a scenario generation approach, too ([Ghosh et al., 2016](#)). Maintenance trips and battery recharging/refueling requirements of the vehicles can also be conducted at the same time with rebalancing operations ([Weikl and Bogenberger, 2015](#)).

In [Ghosh et al. \(2016\)](#), the problem is treated as an iterative game between the operator and the adversary. The latter determines the worst case demand scenario. Then, the operator finds the optimal routing to rebalance the vehicles and tries to minimize the worst case lost demand over all scenarios, which is provided by the adversary. An MILP is developed for each player. These two MILPs are solved consecutively until the system converges.

Simulations can be utilized in order to identify whether a solution is feasible in terms of any operational requirements, such as vehicle charging and maintenance. In [Boyacı et al. \(2017\)](#), simulation and optimization are used to come up with a realistic solution. If the solution provided by the optimization module is found to be infeasible by the simulation, then additional constraints are imposed and the optimization model is solved again.

The computational experiments provide useful insights. [Nourinejad et al. \(2015\)](#) analyze the effect of marginal vehicle cost and demand. They test four different scenarios in terms of vehicle cost and three in terms of demand. For each of the scenarios, an optimization problem is solved to obtain vehicle rebalancing and staff relocation times and fleet size. They see that the vehicle rebalancing and staff relocation times increase with the vehicle cost. Moreover, they see that the demand affects the fleet size more than the staff size. [Boyacı et al. \(2017\)](#) show that the demand forecasting and initial distribution of vehicles among the stations are generally important aspects. [Ghosh et al. \(2016\)](#) observe that the lost demand is reduced by at least 18% on average and 10% in the worst case demand scenario. Both [Ghosh et al. \(2016\)](#) and [Ghosh et al. \(2017\)](#) are able to claim the robustness of their approaches with respect to the changes in the number of vehicles and the unit cost for routing. [Shu et al. \(2013\)](#) state that as the fleet size increases, imbalances are observed not necessarily in the city center but also in different congested areas of the network such as interchange stations.

A study which combines dynamic pricing and dynamic online rebalancing operations, in a station-based BSS, is fulfilled by [Pfrommer et al. \(2014\)](#). A Monte-Carlo simulation is used to estimate the daily demand. A dynamic truck routing algorithm and dynamic price incentives for users are compared in terms of LOS. For the routing algorithm, they use a time-expanded network (as in [Boyacı et al., 2017](#)) and develop a mixed integer quadratic problem (MIQP). To determine the pricing incentives, Model Predictive Control (MPC), which is a quadratic program, is utilized. The results imply that the LOS improves with the incentives and weekends are more likely to show improvement compared to weekdays.

The autonomous vehicles, unlike the conventional and electric vehicles, are able to rebalance themselves without any exogenous help. Regarding this, an interesting problem definition is introduced by [Rossi et al. \(2016\)](#). The contribution of this work is to include congestion in the modeling, too. In order to solve the routing problem of such a system within a capacitated transportation network, they introduce a linear optimization model, namely congestion-free routing and rebalancing problem (CRRP). Trip requests are assumed to be known, as in a system with reservations only. On the other hand, CRRP does not necessarily give integral solutions and rounding techniques are not applicable. Therefore, an integral CRRP is developed to obtain integral results on the flows. Although it is NP-hard, the authors exploit its structural properties

and decouple the problem into routing and rebalancing. The results show that on symmetric road networks, it is always possible to route vehicles for rebalancing in a coordinated way that does not increase traffic congestion. The authors suggest considering the stochasticity in demand and travel time as future work.

Instead of rebalancing operations, the balance of the system can be maintained by vehicle assignment and relays, which denotes sequentially taking two vehicles to complete longer trips. [Zhang et al. \(2019\)](#) work on such a strategy and use a space-time-battery network flow model for an eCSS. This model is an extension of the conventional space-time network flow model where each node represents a specific pair of location and time. In this model, battery information is also included in nodes. Each vehicle is modeled as a commodity and the battery is modeled as a resource of the commodity. The demand is assumed to be known and the problem solution assigns trip requests to the available vehicles. An unassigned request is rejected. The solution is obtained by a heuristic algorithm guided by linear programming (LP) relaxations. Through extensive numerical experiments, authors demonstrate that the proposed solution approach could consistently obtain satisfactory solutions in an efficient way. With optimized EV assignment and relays, the eCSS may achieve a higher vehicle utilization rate compared to a non-electric CSS. Numerical results also reveal that optimized EV assignment is essential to circumventing battery constraints when most trips are short. When the proportion of long trips is significant, relays can play an important role to improve the eCSS's performance.

Although fleet distribution is a decision mainly addressed at the tactical level, its short-term adjustment may lead to the improvement of the system performance, either from the operator's or user's perspective. Therefore, altering the fleet distribution is investigated at this decision level, too. Furthermore, already deployed policies are revisited and new policies are compared to the existing ones. The differentiation between the decision levels are done according to the simulated time interval and the data used.

[Kek et al. \(2006\)](#) develop a time-stepping simulation model to evaluate rebalancing strategies. Then, this work is further improved by [Kek et al. \(2009\)](#) by introducing an additional optimizer and a trend filter. The former denotes an MILP which is based on a time-space network and minimizes the cost of rebalancing operations. The latter represents a heuristic algorithm and takes the output of the optimizer, which includes the number of staff, staff and vehicle movement, and station status. Then, it proposes realistic values for these parameters. This work contributes to literature with the usage of these heuristics within the trend filter. [Nair and Miller-Hooks \(2011\)](#) develop a chance constrained model with desired reliability  $p$  (CCM- $p$ ). Their aim is to use the optimal fleet distribution that minimizes the lost demand to compare different rebalancing strategies. The model accounts for demand uncertainty by satisfying  $p$ -proportion of all demand scenarios in the planning horizon. The solution to the model is taken care of by  $p$ -efficient points (PEP) enumeration and a cone-generation method is studied. [Jorge et al. \(2014\)](#) inspire from [Kek et al. \(2009\)](#) and [Nair and Miller-Hooks \(2011\)](#) and integrate a new mathematical model into a simulation. The former optimizes the rebalancing operations while maximizing the profitability. The latter evaluates different rebalancing strategies.

We see that the performance indicators are usually ZVT, FPT, and NoR, with the goal to be kept at minimum. [Kek et al. \(2006\)](#) and [Kek et al. \(2009\)](#) observe that the proposed methodology increases the operational efficiency and therefore increase in profit is expected. They also see that the ZVT and FPT are influenced by the vehicle to trip-station ratio. The higher the ratio the more utilized and spread among the stations the vehicles are. In [Nair and Miller-Hooks \(2011\)](#), the performance indicators are determined as the true reliability of the model, rebalancing cost, and the robustness.

In [Nair and Miller-Hooks \(2011\)](#) additionally, nine different rebalancing strategies are tested and it is found that the strategies which account for demand stochasticity provide more reliability than the static strategies. [Jorge et al. \(2014\)](#) compare, from the VSS profit point of view,

eight rebalancing strategies, based on the fixed rules, with the optimal rebalancing solutions obtained by solving a mathematical model. In all cases, the future demand is assumed to be known. The results show that the simulated rebalancing strategies produce substantially less profit than the optimal rebalancing solutions, showing that it is difficult to design effective real-time strategies based on fixed rules. Nevertheless, they report that improvements in profit are achieved, even with the fixed-rule rebalancing strategies, which the authors regard as realistic in practical operations of VSSs. The optimal solutions provided by the mathematical model are regarded as the upper bounds on the profit gains that can be achieved. Shu et al. (2013) examine the effect of static and periodic rebalancing. In the latter, rebalancing is performed several times per day, rather than all the time as in dynamic rebalancing. They observe that periodic rebalancing is required only a small number of times per day, and that there is a break even point from which the frequent periodic rebalancing does not add much value.

To evaluate different pricing strategies, optimization models can be used. As an extension of Jorge et al. (2014), Jorge et al. (2015) propose an MINLP formulation that maximizes the total daily profit to solve trip pricing problem for one-way car sharing systems (TPPOCS). The price elasticity is taken into account via additional decision variables. The prices per pair of zones and period of the day, are obtained via clustering the stations in terms of their vehicle needs or ability to provide vehicles. Although the problem size is reduced by clustering, the methodology is still computationally expensive. Therefore, they come up with a meta-heuristic algorithm based on iterated local search.

An interesting conclusion regarding the operational level is deduced by Yuan et al. (2019). The holistic approach that they follow in their work help them to compare the value of three decision levels. They point out that in the case study conducted with Changping BSS in Beijing, over a 10 year horizon, the rebalancing costs were the 5.7% of the total cost whereas the capital cost was 79% and the maintenance cost was 15.3%. This stresses the fact that operational activities do not play as much role as the strategic and tactical decisions.

### 3.3.3. Conclusion

We observe that the literature focuses on rebalancing operations at the operational level decisions. Both simulation and optimization methods are used to propose solutions for these operations. Since we talk about short-term decisions, the computational complexity is another burden at this level. As considering continuous time frames increases the computational complexity, the authors tend to discretize the time and use time-expanded networks.

## 4. The research gaps and findings

In order to identify the gaps in the literature, we use Table 2, which summarizes the placement of the reviewed works in our framework. The first observation is that there is significantly more focus on supply aspects rather than demand aspects in the literature. In particular, demand forecasting, budget allocation, market placement, and the pricing strategies are promising research avenues.

We also observe that the short-term decisions (operational level) attract more attention than longer term decisions (tactical and strategic levels). Many pieces of research focus on the improvement of rebalancing operations at the operational level, trying to reduce the computational time as well as offering new approaches and solution strategies to the problem. Furthermore, through the literature review, we have not found any works dealing with very short term decisions, such as real-time decisions. However, we consider this reasonable due to the nature of the observed system, frequency of demand changes, and possible frequency of VSS service.

Among 63 reviewed papers, only 8 of them provide an inter-decision level analysis. Boyacı et al. (2015), Repoux et al. (2019), and Soriguera and Jiménez (2020) combine strategic and tactical level decisions whilst Ghosh et al. (2017) and Shu et al. (2013) combine tactical and

operational level decisions. Yuan et al. (2019) and Huang et al. (2020) study a more holistic approach and combine all decision levels at the supply side. This reveals the lack of research related to integration of the different decision levels. We believe that the integration provides a more holistic approach and a better understanding of the overall system.

Regarding the field of the studies in the literature, we see that the main focus is directed to CSSs and BSSs. This is expected since the new types of VSSs have emerged only during the last decade. On the other hand, the new type of VSSs are observable in most of the cities, such as SSSs and MSSs. The strategic level studies are done on MSSs by Degele et al. (2018) and Aguilera-García et al. (2020). A study by Masoud et al. (2019) studies the operational level decisions on SSSs. Therefore, these new types of VSSs should be studied systematically in order to improve both the user experience and the operator's profit.

Although there are a few studies which discuss the environmental aspects of the VSSs, Morton (2020) introduces air quality measures for the first time. Another pioneer work, which is conducted by Caggiani et al. (2020), discusses the equity measures which depict the discrimination between different population groups.

As one of the research gaps, we have identified a lack of research on the topic of destination-choice prediction at all decision levels. The same conclusion has been reached in Balac et al. (2019). At the strategic and tactical level, the destination-choice prediction could be used for determining the locations and sizes of permanent and temporary stations, respectively. Finally, at the operational level, destination-choice should be predicted for the purpose of determining the need for free parking places, which would further contribute to improving rebalancing operations and determining pricing incentives.

Also, we see only one study regarding competition in VSSs (Balac et al., 2019). Given that some cities deploy more than one operator of VSSs, this is a relevant topic to focus on.

Furthermore, we include an additional type of classification which points out the future work directions suggested by the authors of reviewed papers in Table 3. This table consists of four columns. First two correspond to the reviewed work. The third column, *Suggested future work directions*, presents the recommendations for future studies. Here, we do not list future work directions that imply only a minor or unspecified improvement of the current work. The fourth column is devoted to the works which have addressed the suggested research gap. A dash is used to denote that none such work has been identified.

By constructing Table 3, we have tried to determine additional un-addressed research paths. The majority of research paths can be sorted into the following three groups. Some of these paths are related to further introduction of stochasticity, such as introducing the last minute reservations and cancellations in the system management. Other group of paths suggest further development of demand models such as rich demand models that incorporate jointly environment, system, and user properties. This way the authors aim at representing a more realistic system. Finally, a group of paths suggest introducing new configurations of VSSs such as a hybrid free-floating and station-based VSS, and return-trip and one-way trips.

All uncovered research paths, identified by our analysis, may be found in Table 3. Therefrom, we conclude that the research paths are manifold and fairly the same number of open questions exists on supply and demand sides of VSSs.

We limit Table 3 to only works that propose a research paths with conceptual advancements. Additionally, many works which face computational complexity suggest using heuristic or meta-heuristic algorithms (such as Nair and Miller-Hooks, 2011, Chemla et al., 2013, and Dell'Amico et al., 2014), or column generation and adding valid inequalities (such as Pal and Zhang, 2017) as solution methodologies in the future work.

## 5. Conclusion

In this paper, we have presented the holistic framework for

**Table 3**  
Suggested future work directions.

Author	Year	Suggested future work directions	Addressed by
Aguilera-García et al.	2020	Considering heterogeneity in individuals' preferences	Li et al. (2018), Jin et al. (2020), Aguilera-García et al. (2020)
		Quantifying the impacts of a wider adoption of MSSs	–
Ashqar et al.	2019	Investigating variables such as bikes coming from other stations and relative locations of each station	–
Balac et al.	2019	A real-life case study which involves competition of sharing systems	–
		Developing a destination-choice model	–
		Considering last-minute reservations	–
Boyacı and Zografos	2019	Improving clustering by adding a feedback loop between the rebalancing optimization and station clustering models	–
		Integrating behavioral models to operational decisions	–
Boyacı et al.	2015	Incorporating a simulation model to better represent rebalancing operations	Boyacı et al. (2017)
		Modeling the operational level with battery requirement constraints	Boyacı et al. (2017)
Boyacı et al.	2017	Extending the models to the systems with no reservations	–
		Combining rebalancing operations and dynamic pricing	Boyacı and Zografos (2019), Chemla et al. (2013), Pfrommer et al. (2014)
Caggiani et al.	2019	Performing a temporal clustering of stations with respect to the days of the week	Lin et al. (2018) <sup>a</sup>
Caggiani et al.	2020	Developing an equality-based bi-level programming where the second level is a demand model	–
		Considering vertical equity indices	–
Campbell et al.	2016	Analyzing the effect of weather and air quality in relation to objective measures	Morton (2020)
		Integrating cost structures and rebalancing operations	–
Çelebi et al.	2018	Developing a demand model that takes weather, LOS, availability, and user behavior into account	–
		Considering multiple rebalancing trucks and their capacity	–
Chiariotti et al.	2018	Clustering stations to reduce the rebalancing problem size	Schuijbroek et al. (2017)
		Modeling user satisfaction	–
Ciari et al.	2013	Incorporating a reservation system	Kaspi et al. (2016), Huang et al. (2020), Repoux et al. (2019)
Clemente et al.	2017	Dynamic determination of incentives during the trip	Pfrommer et al. (2014), Waserhole and Jost (2012)
		Refining the user segments using further information and expanding to a multi-factor classification	–
Degele et al.	2018	Considering the spatial distribution of the rentals	Ataç et al. (2020)
		Considering flexibility in system design to respond to the changing demand	Cardin et al. (2017)
Febbraro et al.	2012	Introducing electric vehicles into the simulation-based optimization model for vehicle rebalancing	Boyacı et al. (2017), Boyacı and Zografos (2019)
George and Xia	2011	Utilizing queueing network model to derive efficient rebalancing strategies	–
		Optimizing the capacity of stations	Huang et al. (2020), Yuan et al. (2019), Caggiani et al. (2020)
Ghosh et al.	2017	Extending with a robust optimization technique to account for demand realizations	–
Ghosh et al.	2016	Considering multi-step planning to better account for the future demand stochasticity	–
		Applying a decomposition technique to solve the rebalancing operations	Ghosh et al. (2017)
Huang et al.	2020	Optimizing the number of charging piles per station	–
		Considering the stochastic demand in mode-choice forecasting	Aguilera-García et al. (2020), Jin et al. (2020)
		Finding an appropriate pricing strategy that balances demand and vehicle supply	–
Illgen and Höck	2018	Investigating battery degeneration over time and time-dependent electricity costs in eCSSs	–
		Introducing dynamic pricing models into simulation of eCSSs	–
		Assessing the life-cycle of an eCSS	–
Jin et al.	2020	Short-term/real-time demand estimation	–
		Inducing trip demand shift from private vehicles to VSSs using incentives	–
Jorge et al.	2014	Including stochastic trip variability and the travel time	Yuan et al. (2019), Ataç et al. (2020)

(continued on next page)

Table 3 (continued)

Author	Year	Suggested future work directions	Addressed by
Jorge et al.	2015	Studying different principles to determine the demand zones, i.e., station clusters	Caggiani et al. (2019), Schuijbroek et al. (2017), Boyacı et al. (2017)
		Investigating the efficiency of dynamic pricing in terms of imbalance	Pfrommer et al. (2014)
		Analyzing the influence of price on the demand variation	–
Kaspi et al.	2014	Considering the misuse of the system by the users	Kaspi et al. (2016)
		Predicting the near future of the system using the information received via reservations	–
Kaspi et al.	2016	Developing a measure, which combines several objectives for itinerary evaluation	–
		Examining the effects of parking reservation policies on the profit	–
Kumar and Bierlaire	2012	Introducing one-way trips in a VSS, while retaining the return trips	–
Kutela and Teng	2019	Exploring the effect of station vicinity to the ridership to determine station locations	Boyacı et al. (2015)
		Exploring network density influence on the ridership	–
Li et al.	2018	Modeling users' choice behavior and incorporating socio-economic characteristics	Aguilera-García et al. (2020), Jin et al. (2020)
		Linking the activity-based model to operational level supply policies	–
		Considering competition among multiple sharing systems	Balac et al. (2019)
Lin et al.	2018	Including weather and social events in the demand model	Morton (2020), Kutela and Teng (2019)
		Incorporating this model in dynamic rebalancing operations	–
Masoud et al.	2019	Considering the inaccuracy of the vehicle positions	–
		Using fuzzy logic to address the uncertainty	–
Miao et al.	2019	Considering non-overlapping and equal size zones, such as hexagon cells	Weikl and Bogenberger (2015)
		Incorporating and clustering the charging infrastructure	–
Morton	2020	Examining different categories of cyclists (e.g. by sex or age)	Kutela and Teng (2019)
Nair and Miller-Hooks	2011	Incorporating staff relocation operations to rebalancing operations	Boyacı and Zografos (2019), Zhao et al. (2018), Boyacı et al. (2017), Nourinejad et al. (2015)
Nourinejad and Roorda	2014	Assigning each user to a station to reduce rebalancing costs	–
Nourinejad et al.	2015	Incorporating stochastic demand into the vehicle rebalancing and staff relocating problem	Nourinejad and Roorda (2014), Ataç et al. (2020) <sup>b</sup>
		Including user waiting time as a cost component	–
		Considering the parking availability	Repoux et al. (2019), Kaspi et al. (2014)
Pal and Zhang	2017	Extending the proposed valid inequalities	–
		Column generation approach to overcome computational complexity	–
		Studying partial rebalancing operations, which will not serve all expected demand	Boyacı et al. (2015)
Pfrommer et al.	2014	Relaxing deterministic user arrival assumption	Yuan et al. (2019), Ataç et al. (2020)
		Relaxing linearized user reaction to incentives assumption	–
Raviv et al.	2013	Including several depots in the system	–
		Improving the demand model using data mining models	Ashqar et al. (2019), Lin et al. (2018), Faghih-Imani et al. (2017)
		Designing robust methods, with respect to unplanned events for rebalancing operations	–
Repoux et al.	2019	Considering both dynamic rebalancing and dynamic pricing	Pfrommer et al. (2014), Chemla et al. (2013)
Rossi et al.	2016	Incorporating stochastic demand and travel information for rebalancing operations	Nourinejad and Roorda (2014) <sup>c</sup> , Ataç et al. (2020) <sup>c</sup>
		Exploring the integration with public transit	–
Scott and Ciuro	2019	Exploring the influence of the geographical location and context on the ridership	Faghih-Imani et al. (2017)
Shu et al.	2013	Exploring incentive schemes	–
		Including demand endogenously to be dependent on the given incentives	–
Soriguera and Jiménez	2020	Considering mixed system type, i.e. free-floating with a small number of stations	–

(continued on next page)

Table 3 (continued)

Author	Year	Suggested future work directions	Addressed by
Warrington and Ruchti	2019	Considering FFBS	Pal and Zhang (2017), Wu et al. (2019b)
Weikl and Bogenberger	2015	Creating a task assignment model for rebalancing staff to increase the number of service trips in the given time window	–
		Estimating rebalancing model sensitivity to the variation in zoning of the service area	–
Wu et al.	2019a	Investigating the optimality of different market-making mechanisms from different perspectives	–
		Analyzing the difference between myopic and strategic behavior of users	–
Wu et al.	2019b	Consideration of non-stationary Poisson process for demand modeling	–
		Introducing environmental performance measures for system evaluation	Miao et al. (2019)
Yuan et al.	2019	Considering preventative and repair activities for station maintenance	–
Zhang et al.	2019	Introducing stochastic demand into the EV allocation model	–
		Jointly solving the staff scheduling problem	Zhao et al. (2018), Boyacı et al. (2017), Nourinejad et al. (2015)
Zhao et al.	2018	Incorporating a detailed charging process into rebalancing operations	Soriguera and Jiménez (2020)
		Considering the stochasticity of travel time and battery charging	–
		Introducing uncertainty in the demand, in the form of last minute trip cancellation	–

<sup>a</sup> The analysis on the days is done.

<sup>b</sup> Stochastic demand is incorporated only in vehicle rebalancing problem.

<sup>c</sup> Only stochastic demand is covered.

management and operations optimization of VSSs. The optimization problems which appear in these systems repeat themselves, i.e., with a rather small variations the same management approaches can be used in different VSSs. Therefore, with the framework, we aim to address all possible VSS configurations and vehicle types. In the light of the framework, a thorough literature review on VSS management and optimization has been presented. Simultaneously, the conclusions drawn from the review have contributed to produce the framework architecture, components, and required tasks.

From the literature review, we have also concluded that a vast number of methodologies for solving most planning problems in VSSs exist. Nevertheless, by mapping the existing works to the framework, we have also identified unanswered research questions, such as the lack of literature dealing with users' destination-choice analysis or competing VSSs. Also, certain vehicle types, such as moped and e-scooters, are not thoroughly studied although they are very popular in practice.

The open research questions have been discovered additionally by a thorough analysis of the further research paths proposed by the reviewed papers. Here, we have tried to match each of the suggested research paths with other papers which tackle it. The analysis is presented in Section 4 and Table 3, and reveals many uncovered research paths. Therefrom, the further research of VSS management and optimization seems justified.

In our future work, we intend to further extend the framework through analysis of other VSSs or other types of such systems which are yet to be introduced in the practice. Although we find the proposed framework to be the most comprehensive work of such kind on the topic of VSSs, we must allow possibility that not all management and optimization tasks have been covered by it.

Additionally, we believe that the general framework is not unique to the VSSs. Although it is designed for the VSSs, the framework could be applicable for other transportation or logistic settings. Therefore, the application of the framework to the other systems will be considered in our future research agenda.

Also, driven by the presented framework, we have identified the first concrete research question we intend to tackle. Although there are many works on the demand forecasting models, none of them tries to determine

the exact value of such models and justify the investment in building them. Therefore, our next research step will be to quantify the improvement of system operations when demand forecasting models are applied.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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