A review of bicycle-sharing service planning problems

C.S. Shui [a] and W.Y. Szeto*[b, c]

[a] Department of Transportation and Logistics, The National Chiao Tung University, Hsinchu, Taiwan ROC

[b] Department of Civil Engineering, The University of Hong Kong, Hong Kong

[c] The University of Hong Kong Shenzhen Institute of Research and Innovation, Shenzhen, PR China

* Email: ceszeto@hku.hk

Abstract

This paper reviews and systematically classifies the existing literature of bicycle-sharing service planning problems (BSPPs) at strategic, tactical, and operational decision levels with the reference to the novel bicycle sharing service planning process introduced herein. The current research gaps are identified and discussed. The future research directions of the three decision level problems are proposed according to four main categories, namely new diversity, realism, integrality, and technology. This review also points out important future research directions for multi-level BSPPs and the integration of bicycle sharing systems with existing multi-modal transportation systems.

Keywords: bicycle sharing service planning problem; bicycle relocation; bikeway network design; bicycle station design; relocation service planning; demand management

1. Bicycle-sharing service planning process

Bicycle sharing systems (BSSs) have been rapidly developed and adopted worldwide since the end of the 2000s. The survey from Meddin & DeMaio (2020) has shown that there are around 2,110 bicycle sharing programs and approximately 17,792,000 bicycles in service worldwide. These shared bicycles can be used for the first or last-mile trips to connect travelers with public transport systems from their origins/destinations or substitute the trips initially served by other modes. With the continuous expansion of BSSs, more and more design, operation, and management issues of the bicycle sharing service are generated. Therefore, in the past decade, the number of publications addressing different bicycle-sharing service planning problems (BSPPs) has grown drastically.

劇烈地

BSPPs are related to overall bicycle sharing service planning, which is a highly complex and challenging problem, as it involves several stages of interrelated managerial decisions and the reaction of the cyclists to these decisions has to be taken into account in each stage. The planning process usually possesses three targets: to obtain a network layout with bicycle stations and bikeways; to assign adequate shared bicycles to the stations via repositioning vehicles and incentives offered to the users, and to ensure that the final planning cost does not exceed the budget available. According to these targets, this planning process can be divided into eight steps: (1) bikeway network design, (2) bicycle station design, (3) fleet sizing design, (4) static bicycle relocation, (5) static demand management, (6) inventory level management, (7) dynamic bicycle relocation, and (8) dynamic demand management. It is noted that sometimes some of the steps can be skipped in the planning process as they can be covered by other steps or are not required in some bicycle-sharing services. For example, for bicycle rebalancing, a bike-sharing system (BSS) can only rely on static bicycle relocation but adopts neither dynamic bicycle relocation nor dynamic demand management; and a free-floating BSS does not require a bicycle station design. Ideally, these steps should be undergone simultaneously to capture interactions and feedbacks among steps, and thus achieve global planning. However, due to the complexity of the planning problem in each step, an overall planning approach seems intractable 棘手的 in practice and the overall planning problem is commonly broken down into sub-problems that are tackled one by one.

We notice that there are various terms to describe each of these steps in the literature. For instance, static bicycle relocation can be named “static rebalancing” (e.g., Chemla et al., 2013a; Kadri et al., 2016), “bicycle sharing system balancing” (e.g., Di Gaspero et al., 2013a), “static repositioning” (e.g., Raviv et al., 2013; Ho & Szeto, 2014), or “bicycle sharing rebalancing” (e.g., Dell’Amico et al., 2016). Therefore, in this review, we adopt unified terminologies for the planning problems involved in the planning process to facilitate the discussions in the remainder of this paper.

Table 1 briefly describes these eight steps in the planning process. We classify them according to their planning decision-making levels. The *strategic* level involves *long-term* decisions related to bicycle sharing service infrastructures (including bikeways and bicycle stations) in an existing or a non-existence network and sometimes total bicycle inventories; the *tactical* level focuses on *medium-term* decisions that help to maintain the performance of a bicycle-sharing service commonly by the efficient use of existing resources, and the *operational* level involves *short-term* decisions taken from time to time to respond to the daily operation of a BSS in general. The term ‘bicycle-sharing service planning problem’ (BSPP) is then defined as a general designation of problems in all eight steps of the bicycle sharing service planning process (including problems with multiple levels of decisions). Note that it is possible to have BSPPs that involve more than one level of decision (e.g., Chow & Sayarshad, 2014). We classify them as multi-level BSPPs.

Despite a rapid expansion in the body of literature of BSPPs in the recent decade, only two papers reviewed the operations research issues of BSSs (Laporte et al., 2015, 2018). Their original and updated works classified the planning problems of shared mobility systems into five categories: station location, fleet dimensioning, station inventory, rebalancing incentives, and vehicle repositioning. For each category, the authors highlighted the mathematical models, solution methods, and results of the studied problems in the existing literature. They mainly consider sharing service planning problems about car and bicycle sharing systems made up of stations in which users can take or return a vehicle including a public bicycle. Nevertheless, their reviews do not cover the following:

1. They do not cover a few recent yet critical BSPPs, such as pricing scheme design problems, bikeway network design problems, and multi-level BSPPs.
2. They do not discuss the new BSPPs that relate to new technology or strategies, including new bicycle types, new cycling infrastructures, and new relocation strategies, but these innovations raise important

questions on bicycle-sharing service planning, such as how to design the network with multiple types of bicycle infrastructures and what should the best operational strategy be for BSSs with multiple bicycle types.

3. They do not consider BSPPs incorporating cycling as one of the transport modes or one part of a combined mode in a multi-modal transport network, while the synergy 協同作用 of cycling and public transit is shown to be significant (Rixey, 2013).

Providing that the abovementioned BSPPs are important problems in bicycle-sharing service planning that have not been classified yet, it is necessary to develop a new classification framework that can capture these problems. This paper presents a new view of the literature by providing a holistic 整體的 view of BSPPs and a novel classification. This paper introduces a bicycle-sharing service planning process, in which each step in the process presents an individual sub-problem in bicycle-sharing service planning and we classify the sub-problems and their combinations according to the level of decision making (i.e., strategic, tactical, operational, and mixed levels). The current BSPPs are then classified into one of these sub-problems. As the main focus of this paper is on the planning issues of bicycle-sharing service, those papers which do not involve bicycle-sharing service planning decisions, such as cycling safety and cyclists' choice behavior, are not covered in the remaining part of our paper unless they are considered together with bicycle-sharing service planning. Meanwhile, this paper addresses two ongoing topics, bicycles in a multi-modal transportation system and technological advancements of bicycles, and discusses the linkages between each of these two topics and BSPPs. Afterward, future research directions are proposed from four perspectives, namely new diversity, realism, integrality, and technology. New diversity corresponds to the unexplored yet important BSPPs. Realism is related to the studies that consider the realistic features of BSPPs such as uncertainty, dynamicity, or users' responses to a plan, in which dynamicity underlines the necessity to consider time-dependent parameters to describe the real-time network changes. Integrality discusses the *integration* of bicycle-sharing service planning with existing road and public transport service planning. Technology refers to the adoption of new technologies for cycling.

The contributions of this paper lie in the following:

1. Introduction of a novel planning process for bicycle-sharing services and a systematic classification of BSPPs;
2. Identification of research gaps in BSPPs; and
3. Provision of future research directions of BSPPs initiated by the emerging technologies and infrastructure of bicycles and the interactions of cycling and other transport modes.

The remainder of the paper is organized as follows. Section 2 reviews the current developments for BSPPs. Section 3 presents the future research directions of BSPPs. Section 4 gives a summary of this paper.

Table 1 Bicycle-sharing service planning process

Decision-	**Planning activity**	**Major independent inputs**	**Outputs/Decisions**

making level			
Strategic	Bikeway network design	Network topology (including vehicular roads and sometimes existing bikeways and bike stations) Bike origin-destination (OD) demand data Bikeway characteristics Budget	New bikeway layout (and sometimes bikeway type)
	Bicycle station design	Network topology OD demand data/station demand Station characteristics	Station locations Station sizes
	Fleet sizing design	OD demand data/station demand Station locations/characteristics Budget	Initial station inventory levels Total bicycle fleet size
Tactical	Static bicycle relocation	Bicycle station network Relocation fleet (The capacity and number of vehicles in the relocation fleet) The initial state of each bicycle station	Vehicle routes Pickup and drop-off quantities of all stations
	Static demand management	Bicycle station network Nominal OD demand data/arrival and departure rates	Demand regulation strategies (e.g., incentive details such as locations, prices; and parking space reservation)
Operational	Inventory level management	Bicycle station network Users' departure and arrival rates/time-dependent OD demand realizations The probability that a bicycle is returned to a station in an unusable condition (when broken bikes are considered)	Target inventory levels/the target range of inventory levels, and/or the number of broken bikes at all stations
	Dynamic bicycle relocation	Repositioning fleet information (Repositioning vehicles available, vehicle capacities, and operating costs) Bicycle station network Initial bicycle level and capacity at each station Target bicycle and bicycle rack levels at each station in each period Time-dependent bicycle rent and return data Time-dependent travel speed	The repositioning routes of all vehicles Loading and unloading activities at every visited station (for bike repositioning) Bicycle flow per each pickup and drop-off station pair in each time interval (for relocation service)
	Dynamic demand management	Bicycle station network Time-dependent OD demand data/arrival and	Demand management strategy in *each time interval* within a day

	departure rates	(e.g., incentive details such as time, locations, prices, and parking space reservations)

2. Current bicycle-sharing service planning problems

We summarize existing studies in Tables 2–5 using the classification based on the decision-making level and planning activity in Table 1. The “problem” column defines the planning problem. The “objective functions” and “major constraints” columns highlight the considered objective functions/performance measures and the major constraints in each study, respectively. It is noted that the symbol “/” between the objective functions denotes that these objective functions are used in different single objective optimization models, while the symbol “;” denotes that the objective functions are included in a single Pareto optimization model. The “applications” column shows the real-life applications of the proposed model(s). For the applications, “Ex:” means that the examples are retrieved from the cities where the BSS is implemented; “AI” represents the artificial instances that can be the small instances for the illustrative purpose or the randomly generated instances; “BM” represents the benchmark instances or standard network instances; “TH” means that the study is purely theoretical and no numerical study is provided. Finally, the “specialties” column highlights, if any, the unique features possessed by a study. The studies in these tables are sorted by problem type, then year, and finally alphabetical order.

In this section, a brief review of each class of BSPP is provided. In particular, the first three sub-sections focus on the strategic, tactical, and operational BSPPs whereas the fourth sub-section discusses the BSPPs with multi-level (ML) decisions. The fifth section is introduced to review the role of cycling in a multi-modal transportation system and recapitulate the BSPPs that have modeled in a multi-modal system framework.

2.1. Strategic bicycle-sharing service planning problems (S-BSPPs)

An S-BSPP is aimed at determining the bicycle-sharing service network layout, being formed by bikeways and/or bicycle stations, given the network topology and characteristics, bike OD demand, and a set of objectives and constraints. The existing S-BSPPs can be sub-divided into four problem types according to the involved bicycle infrastructure: bikeway design problems, bicycle station design problems, fleet sizing design problems, and bikeway and bicycle station design problems. Table 2 summarizes the existing S-BSPP studies based on problem type, objectives, major constraints, applications, and model specialties. It can be seen that most of the studies focus on only designing one type of infrastructural component, and the body of work on bicycle station design is larger than that of bikeway design. Moreover, most S-BSPP studies assume that the OD demand is deterministic and fixed and thus does not respond to the changes in bicycle-sharing services.

2.1.1. Bikeway network design problems

A bikeway network design problem can be classified into three types according to the types of bikeways: bike path, bike lane, and bike route (Lin & Yu, 2013). A bike path is an exclusive bikeway segregated from motorized traffic and pedestrians; a bike route is a portion of a roadway marked by roadside signs or colored pavement for cyclists while use by motorized vehicles is permitted, and a bike lane is a portion of a road marked off by painted lines for cyclists, and is sometimes shared with pedestrians. Various bikeway types have different levels of cycling risks and comfort, construction and maintenance costs, and road widths. Bike path network design problems focus on determining the locations of bike paths (and sometimes with intersections) subject to the level of service requirements of these paths (e.g., Smith, 2011; Duthie & Unnikrishnan, 2014). Bike route network design problems focus on determining the locations and widths of bike routes, while these problems have not been studied in the literature. Bike lane network design problems focus on determining the locations of bike lanes to increase the modal share of cycling (e.g., Sohn, 2011; Mesbah et al., 2012). Although providing more bike lanes can improve the level of service and thus the modal share of cycling, there are adverse impacts to vehicular traffic, which can be an increase in travel time (e.g., Sohn, 2011; Mesbah et al., 2012), a decrease in the available driving space (road capacity), and a reduction in the number of on-road parking spaces (e.g., Lin & Yu, 2013). However, none of their papers discuss the actual impacts of *different* bikeway types (which have different roadway capacity reductions) on the vehicle flow pattern. Moreover, the cyclists' safety due to the difference in bikeway types is seldom considered, although the level of safety varies among different bikeway types (Geller, 2006) and can influence the cyclists' route choice (e.g., Klobucar & Fricker, 2007) and the usage volume on bikeways.

In the above studies, most of their models focus on new bikeway network design for segregated or shared bikeways but not on the improvement of existing bikeway networks. In fact, after launching a bicycle-sharing program or providing new cycling infrastructures, there is often an increase in cycling demand in the bikeway network, which leads to an increase in the usage of existing cycling infrastructures. To improve the level of service, the network should be expanded. Some more work can be done for (1) bikeway network expansion or (2) multi-phase bikeway network design given that the bikeway network can be expanded sequentially. Moreover, new kinds of bikeway infrastructures have been introduced in recent years, including cycling superhighways (e.g., in London and Copenhagen), park connectors, and inter-district cycling routes (e.g., in Singapore), to give cyclists safer and smoother rides and connect different aggregate bikeway networks (or bike paths) into a unified large network. The design of these new bikeway facilities can be a future research direction. Furthermore, most existing bikeway network design models assume very simple cyclists' route choice behavior. For example, there is only one type of cyclist who selects the lowest travel time route or the shortest path to cycle (e.g., Duthie & Unnikrishnan, 2014; Mesbah et al., 2012). This assumption ignores the existence of different types of cyclists who have various preferences in route choices (e.g., Geller, 2006) as well as multiple attributes (which can be deterministic or perceptual) that affect route choice (e.g., Ehrgott et al., 2012). More realistic route choice behavior models should be developed and captured in bikeway network design models.

2.1.2. Bicycle station network design problems

A bicycle station network design problem is aimed at mainly determining the locations and capacities of bicycle stations, and sometimes bicycle inventory levels at each station (e.g., Garcia-Gutierrez et al., 2014; Çelebi et al., 2018). Almost all bicycle station network design models include bicycle station location decisions because the resultant locations determine the demand coverage of a bicycle-sharing service, which is one key design attribute. Aiming at designing an economically viable bicycle station network, the operator's profit (or net revenue) and investment cost are commonly captured in the design constraints (e.g., Frade & Ribeiro, 2015). The bicycle station location can also be determined under the influence of the co-existing transportation systems as one of the design decisions (e.g., Garcia-Gutierrez et al., 2014). Besides mathematical models, some studies adopt the geographic information system (GIS) to obtain a bicycle station network design (e.g., García-Palomares et al., 2012; Wang et al., 2016). The GIS can be used for evaluating the quality of bicycle infrastructures and analyze potential demand distributions (e.g., Rybarczyk & Wu, 2010; Larsen et al., 2013), obtaining the spatial distribution of the potential demand and the total number of trips based on the given street network, buildings, transport zones, and stations in the designated region (e.g., García-Palomares et al., 2012), or identifying hot spots with insufficient bikes or bike racks (e.g., Wang et al., 2016). In other words, GIS can help to identify the potential candidate locations for a bicycle station, which can be subsequently used for location selection. Compared with the usage of only mathematical models, the inclusion of GIS implies a heavier burden of data collection and processing and higher complexity of the design model.

In these studies, their models are usually applicable for BSSs with manpower one-seat bicycles and fixed bicycle docks at stations. However, technological advancements revolutionize BSSs by introducing new bicycle types (e.g., electric bicycles, cargo bicycles, two-seat bicycles, and free-floating bicycles) and mobile bicycle docks. Each new type of bicycle has its corresponding requirement for bicycle parking. For instance, electric bicycles (e-bikes) require battery charging or swapping facilities at bicycle docks whereas free-floating bicycles do not need bicycle docks and can be parked freely. These new bicycle types can induce new research problems such as the determination of locations and quantities of charging docks for e-bikes, the determination of the locations of the parking zones for free-floating bikes, or the design of a hybrid BSS with both station-based and free-floating bikes (as suggested by Albiński et al., 2018). In addition, as these new types of bicycles can be provided together with manpower one-seat bicycles, more researches are needed to tackle the bicycle station network design problem with multiple bicycle types. Regarding mobile bicycle docks, they have been set up in some countries (e.g., Singapore and Armenia) for improving bicycle utilization by periodically redistributing not only shared bicycles but also bicycle docks (Shu et al., 2013) or acting as mobile recharging docks for e-bikes. They can also be a solution to expand station capacities *temporarily* to handle sparse booming one-way bike trips due to periodic events.

2.1.3. Fleet sizing design problems

A fleet sizing design problem is to determine the initial number of bicycles needed to be deployed in the whole BSS and the initial number of bicycles at each station. While the daily allocation of bicycles is an operational decision that affects the utilization rate of a BSS (Shu et al., 2013), the initial bicycle fleet size should be a strategic decision as the investment costs of bicycles are not negligible. Fleet sizing design is usually coupled with station capacity design as the provisions of bicycles and bicycle docks at each station are closely related. Up to the authors' knowledge, Fricker & Gast (2016) published the only paper that focuses on the fleet sizing design problem but they only provided a theoretic framework instead of solving a real case problem. Nevertheless, the importance of this problem is not negligible after the raise of free-floating bicycles that do not require bicycle docks. When bicycle parking is not constrained by the docks, the operator should consider how many bicycles should be deployed to capture cycling demand and ensure the system's viability, which is a problem highlighted by Shu et al. (2013).

2.1.4. Mixed (bikeway and bicycle station) design problems

The mixed design problem is to determine the locations of bicycle stations and bikeways simultaneously, in which the design decisions are those used for bikeway and bicycle station designs. It is noted that two studies (Lin & Yang, 2011; Lin et al., 2013) assumed that all OD pairs are connected by bike paths and thus connectivity between stations does not become a critical issue. However, this assumption does not hold in some cities and future studies should relax this assumption. Moreover, the research gaps mentioned in Sections 2.1.1 and 2.1.2 are applied to this class of problem, including mixed design problems with multiple bike types, multiple bikeway types, and multiple demand classes.

2.2. Tactical bicycle-sharing service planning problems (T-BSPPs)

The tactical problems aim to optimize the utilization of the resources and the infrastructures of BSSs. In a BSS, bicycles, and sometimes bicycle racks, become the major resources that need optimization. By investigating BSSs worldwide, the tactical issues were identified in some studies (e.g., Pucher et al., 2011; Fishman et al., 2013), but the solutions proposed to handle them were only descriptive. The two main tactical problems in bicycle-sharing service planning are nighttime bicycle relocation service planning (or known as static bike repositioning) and static demand management problems. The static bike repositioning problem aims to regulate the inventory level of each station of the whole system at nighttime through vehicle-based bicycle relocations whereas the static demand management problem aims at increasing cycling demand and attracting or enforcing the users to relocate bicycles. These two types of planning problems are classified as tactical but not operational because they involve intermediate-term planning decisions that are insensible to the real-time changes in a BSS. Table 3 summarizes the T-BSPP studies according to the same considerations as in Table 2. Two observations can be made. First, almost all T-BSPPs are static bicycle relocation service planning problems (SBRPs) while only one paper is related to the static demand management problem. Second, none of the existing T-BSPPs have simultaneously considered both the SBRP and the static demand management problem. The combined effect of implementing more than one tactic has yet to be examined. This implies that the combined problem has large rooms for further studies.

2.2.1. Static bicycle relocation service planning problems

Static bike relocation aims to deploy a fleet of vehicles to redistribute shared bicycles during nighttime (where customer demand is negligible). The corresponding SBRP (or commonly known as the static bike repositioning problem) is to determine vehicle routes (station visiting sequences) and the loading and unloading quantities (number of bicycles to be picked up/dropped off) at each visited station. The SBRP is a popular problem both in practice and in the research field as it is easy to model and the impact of repositioning is more significant during nighttime than daytime (Laporte et al., 2015) given that there is less traffic during nighttime and it is more efficient (Institute for Transportation & Development Policy, 2013). It is noted that the current literature always focuses on the deterministic versions of bike repositioning problems (BRPs) while robust counterparts have not been considered yet. It is also noted there is only one paper on stochastic demand (see Dell'Amico et al., 2018).

Why stochastic BRP?

The current SBRPs focus on mainly the minimization of operating time and total user demand dissatisfaction in a BSS. The operating time is expressed as the total vehicle travel time, and sometimes with total loading and unloading times. The total user demand dissatisfaction can be in the form of unmet demand (e.g., Szeto et al., 2016), the penalty cost (e.g., Raviv et al., 2013; Ho & Szeto, 2014; Tang & Dai, 2018), or the deviation from the target inventory level (e.g., Rainer-Harbach et al., 2015; Di Gaspero et al., 2016). Whereas the operating time is the key concern of private operators, the total user demand dissatisfaction is a societal benefit measure and should be included in the objective by the government as the operator. When more than one measure is included in the objective function, the weighted sum approach is commonly adopted (e.g., Raviv et al., 2013; Ho & Szeto, 2017). Alternatively, all measures are translated into costs before adding them up (e.g., Li et al., 2016). However, environmental and other societal benefit measures, such as greenhouse gas emissions and fuel consumption, have seldom been considered in existing BRPs.

An SBRP includes a list of service and operational requirements to be achieved. Service requirements state the required station conditions at the end of a repositioning operation, including meeting a predefined interval (e.g., Erdoğan et al., 2014) and removing all broken bikes (e.g., Wang & Szeto, 2018), which are commonly found in BSSs (Institute for Transportation & Development Policy, 2013). Operational requirements are concerned with resource limitations and possible loading and unloading strategies within the operation. Resource limitations include the number of vehicles available, the maximum service time, or the operational period. Possible loading and unloading strategies include the number of visits per station per vehicle, depot supply/demand, monotonicity, temporary storage, and split delivery. The readers can refer to the study of Shui (2017) for the details of these operational requirements.

The SBRP with free-floating bicycles have been considered in recent studies (e.g., Pal & Zhang, 2017; Liu et al., 2018). This class of problems is more challenging compared with the station-based counterpart because free-floating bicycles can be returned anywhere, including at locations that are easily accessed (e.g., in popular bicycle parking areas) and hardly accessed (Liu et al., 2018). As only a few recent studies on this class of problems are found, more works can be done in the future, particularly from the perspective of the operator. For example, the operator can determine the fleet mix of repositioning trucks for collecting easily and hardly accessed bicycles. Aiming at reducing the number of hardly accessed bicycles, the operator can set the parking (or penalty) zones in the free-floating BSS that allow (or disallow) the return of free-floating bicycles.

The role of labor in bicycle relocation has been ignored in existing studies. For example, instead of deploying vehicles for collecting hardly accessed bicycles, another practical solution for bicycle relocation is to use manpower for the collection. The overall relocation plan becomes a simultaneous vehicle and labor routing problem. The labor can be assigned not only for broken bicycles' collection (e.g., Wang & Szeto (2018) and Alvarez-Valdes et al. (2016)) but also for on-site bicycle repairing and maintenance. The rostering and job assignment of the labor, which can be coupled with the maintenance frequency, can be an important future research direction.

2.2.2. Static demand management problems

Static demand management (SDM) problems are concerned with medium-term planning decisions about *directing* cycling demand to effectively utilize the existing resources and voluntarily get involved in system regulation. It can be achieved by providing incentives or implementing regulations that are deterministic and usually stationary to affect users' decisions. Though it shares a similar aim with the real-time demand management problem (which are discussed in Section 2.3.2), it can be distinguished from the latter because its decisions have a longer implementation period, seldom change over time, and do not involve look-ahead issues.

Two SDM examples can be found in the literature. The first one is the parking space reservation studied by Kaspi et al. (2016b). Parking space reservation requires an operator to determine whether a cyclist can make a trip with a bicycle rack reserved before starting to cycle. Kaspi et al. (2016b) formulated an optimization problem to calculate the lower bound of expected total excess time (defined as the difference between the actual journey time and the lowest travel time between an OD pair) to assess the potential improvement that may be achieved by *any* passive regulation, and devised a tighter bound of expected total excess time for parking space reservations. The operator has complete discretions to allow/deny the reservation of a bicycle rack at the destination of a customer when he/she attempts to rent a bike. This part of their study can be regarded as a tactical problem because it aims at the effective use of resources over a predetermined planning horizon. The second one is to adopt different rental prices per origin and destination station pair (e.g., Haider et al., 2018).

The operator needs to determine the optimal price per each traversing link to minimize the total number of surplus and deficit stations. The authors showed that the cost of offering incentives is much smaller than the cost reduction from vehicle-based repositioning.

Despite sparse literature, SDM covers a large number of unaddressed yet practically significant problems in BSS operations. First, while pricing has a significant impact on demand (due to pricing elasticity) and system utilization, several planning problems related to pricing, such as the fare structure design and location (or station-based) pricing, have not been addressed. Moreover, different pricing mechanisms of the membership scheme (one of the major sources of revenue in a BSS (Shaheen et al., 2014)) can be explored and compared. Second, very little literature has considered the combined cycling and public transit mode together with some tactical decisions such as pricing (e.g., Friedrich & Noekel, 2017; Kumar et al., 2016), which is a good research direction. Third, in addition to the top-down design problems, the bottom-up approach that takes the perspective of BSS users and considers their actions has been rarely studied. Using the bottom-up approach, Raimbault (2015) investigated the effects of two user-targeted strategical parameters, namely the quantity of information obtained by the users from a BSS and their propensity 傾向 to walk after dropping off shared bicycles, on increasing the system level of service, which can be represented by the reductions in the proportion of adverse effects and the total quantity of detours. For future research, the effects of more user-targeted strategical parameters (e.g., waiting time at a fixed place (either for a parking space or a bike) and access time to a bicycle pickup station) towards the users' behaviors can be studied. The combination of the bottom-up and the top-down approaches to designing incentive strategies can also be explored. Lastly, no studies have addressed the users' behaviors about their failures to return the bikes at the suggested stations after they accept the incentives, while these failures could influence the actual pattern of station inventory levels. This can be another future research direction.

2.3. Operational bicycle-sharing service planning problems (O-BSPPs)

The O-BSPP targets at optimizing the system performance via real-time bicycle inventory level regulation, bicycle relocation, or real-time user incentives, given the time-dependent OD demand, the vehicle fleet characteristics (for bicycle relocation), and the planning objectives and constraints. The existing O-BSPP can be sub-divided into three sub-problems: inventory level management, dynamic bicycle relocation, and dynamic incentives. Compared with T-BSPPs, these three sub-problems involve short-term decisions. Table 4 summarizes the O-BSPP studies in a way similar to Tables 2 and 3. It is noted that only Schuijbroek et al. (2017) considered two types of operational decisions (inventory management and dynamic bike relocation problems) whereas other studies considered only one type. Moreover, there is no study of dynamic signal control for bikes at intersections.

2.3.1. Inventory level management problems

Inventory level management problems focus on the determination of the target inventory level of usable bikes, the target range of the inventory level of usable bikes, and/or the existing number of unusable bikes at each station *during the relocation operation*. Two studies (Raviv & Kolka, 2013; Schuijbroek et al., 2017) modeled the problem in a *single* station context in which the station's target inventory level is determined independently and the interactions of inventory levels among stations are not considered. The former aims for user dissatisfaction minimization whereas the latter targets at meeting the lower bounds of the fractions of satisfied bicycle pickup demand and the fractions of satisfied bicycle return demand.

The problem can also be extended to consider multiple stations or the presence of unusable bicycles. Regarding multiple stations, very often, the interactions of inventory levels among stations are not negligible during inventory management especially when the spillover of demand in a station creates additional demand at nearby stations (Rudloff & Lackner, 2014). Datner et al. (2019) formulated the inventory level management problem with station interactions, in which the cyclists are allowed to roam between stations to rent and return their bicycles, and showed that the optimal inventory levels obtained by their proposed method can save 7% - 9% of excess time compared with the solution without considering the spillover effect. On the other hand, the presence of unusable bicycles also creates challenges in inventory management as they have negative effects on user dissatisfaction. Kaspi et al. (2017) modeled a single station inventory management problem that captures unusable bicycles and revealed that the presence of unusable bicycles (despite their quantity) has a significant disturbance on user dissatisfaction. Their study revealed the negative impacts of unusable bicycles as a reduction in station capacity and a deterrent to service quality. To eliminate these adverse impacts, in addition to static bike relocation at nighttime (e.g., Wang & Szeto, 2018), another solution is to remove these unusable bicycles by dynamic bicycle relocation operation (discussed in Section 2.3.2). Furthermore, if the lifetime of a usable bicycle can be tracked, another potential problem is to determine the maintenance schedule for bicycles according to the estimated time for a bicycle to become unusable.

2.3.2. Dynamic bike relocation problems

Dynamic bicycle relocation, similar to static bicycle relocation, aims to redistribute shared bicycles by a fleet of vehicles. Compared with the static counterpart, dynamic bicycle relocation is implemented throughout the daytime and takes the real-time usage of the system into account, so the routing and loading/unloading decisions are time-dependent. Unlike incentive-based relocation (mentioned in Section 2.3.3), it can efficiently solve the large-scale bicycle imbalance during the daytime (Reiss & Bogenberger, 2017).

Table 4 shows that the existing dynamic bicycle relocation studies can be further divided into two classes. The first class is the dynamic relocation service (DRS) planning problem that determines the relocation services within the planning horizon (which include the pickup and drop-off station pairs and the quantities of relocated bicycles in different time intervals). The second class is the dynamic bicycle repositioning problem (DBRP) that determines vehicle routing and loading and unloading decisions at each visited station in different periods.

Very often, the DRS planning problem includes costs and the deviations from the target inventory level in the objective functions and/or planning constraints. There is a wide range of costs in the literature (e.g., the relocation, operational, holding, and handling costs of bicycles (Sayarshad et al., 2012; Lu, 2016)). Costs can be combined with revenues as profits in an objective function (e.g., Sayarshad et al., 2012; Yan et al., 2018) or placed in budget constraints (e.g., Neumann-Saavedra et al., 2016). The deviations from the target inventory level captured in an objective function can be bicycle deficits only (e.g., Shu et al., 2013) or both bicycle rack deficits and bicycle deficits (e.g., Maggioni et al., 2019) at all stations. Similarly, the deviations can be captured in a planning constraint (e.g., Vogel et al., 2014). The DRS planning problem sometimes considered demand uncertainty, which can be formulated as a robust optimization model (e.g., Lu, 2016) or a stochastic optimization model (e.g., Yan et al., 2018; Maggioni et al., 2019). These studies revealed the value and significance of handling demand uncertainty by showing a plan that has a better service level compared with that obtained from the deterministic model (despite having a higher cost). Yet, other uncertainties in the relocation service (e.g., travel time, the presence of broken bicycles and bicycle racks, and the repairing time for a bicycle) that may hinder the service have not been addressed in the literature.

Similar to SBRPs, most DBRPs possess unmet demand minimization as the sole objective or one of the objectives (while the unmet demand can be expressed in various forms) while other forms of measures (mostly related to costs) are included in the objective function. However, DBRPs are more complicated than the static counterparts as the routing and loading decisions need to consider time-dependent demand, which is required to be accurately forecasted. In general, a dynamic bicycle repositioning operation can be decomposed into three stages: users' demand forecasting, loading and unloading quantity determination, and vehicle routing (e.g., Regue & Recker, 2014; Zhang et al., 2017). To tackle the complexity of the three-stage problem, different sequential, partially integrated, or fully integrated solution methodologies have been proposed in the literature. Sequential methodologies divided the DBRP into three stages and then model and solve each stage sequentially (e.g., Regue & Recker, 2014), in which the solutions obtained in earlier stages can be the inputs to subsequent stages. The partially integrated ones make simplifications on some of the stages to reduce problem complexity and the remaining stages are combined and solved together. The fully integrated ones consider the design decisions of all three stages within one solution method (e.g., Zhang et al., 2017). In the literature, most of the DBRPs can be formulated into a partially integrated model and the methodologies for users' demand forecasting are often omitted in those studies (e.g., Contardo et al., 2012; Shui & Szeto, 2018).

The problem complexity of DBRPs is higher than that of DRS planning problems because of the adopted time discretization approaches. All DRS planning problems are formulated as time-space network flow models with larger periods (e.g., about an hour). DBRPs can also be formulated as time-space network flow models (e.g., Contardo et al., 2012; Zhang et al., 2017) or broken down into less complicated sub-problems using the rolling horizon approach (e.g., Brinkmann et al., 2016; Shui & Szeto, 2018). However, the whole operational period is discretized into more small periods to allow the operator to respond to the changes in demand quicker to obtain better performance (Ghosh et al., 2017). In the literature, the granularity of the time discretization for the time-space network is about 5 minutes (e.g., Zhang et al., 2017). For the studies that adopt time-space networks, the simplest yet least practical method is to assume that a repositioning vehicle travels between a pair of stations and finishes the repositioning service within one interval, while a more realistic approach is to allow the vehicle to travel between stations with multiple intervals. For the latter approach, the vehicle may wait at a station until the start of the next period or stay at a station for multiple smaller periods. For the studies that do not use time-space networks, there are different methods of handling deviations between discretized and actual service times of a route, including setting an assumption that a vehicle travels between stations and finishes the loading operations within a time interval (e.g., Caggiani & Ottomanelli, 2012; 2013), setting a restriction that only one trip is allowed per period despite the remaining time (e.g., Regue & Recker, 2014), or having a flexible length for each time interval (e.g., Shui & Szeto, 2018; Kloimüllner et al., 2014). Even though there is a list of methods to handle the time discretization issue in DBRPs, there are rooms for discovering other approaches to formulate DBRPs and comparing the performance of the existing approaches.

While dynamic bicycle relocation is significant in improving the level of service of the system, repositioning vehicles create a burden on the environment due to vehicle emissions (Shui & Szeto, 2018). This requires using more environmentally friendly relocation strategies despite adopting green planning objectives, such as the use of electric/hybrid vehicles, unused public transport capacities for relocation, or relocation through crowdsourcing, which should be explored in future studies. On the other hand, new bicycle types, heterogeneous vehicle fleets, and demand uncertainty induce more complicated DBRPs that deserve attention in the future.

2.3.3. Dynamic demand management problems

Dynamic demand management aims to motivate shared-bike users for better resource utilization. It can be achieved by providing incentives and implementing regulations to encourage or require these users to pick up bicycles at stations with excess bicycle supply and/or to return bikes to stations with a low inventory level at a particular time point. Compared with SDM in Section 2.2.2, dynamic demand management involves *short-term*, *real-time*, and *demand-responsive* decisions that need to consider the *current* and projected states of the system. The literature has mainly investigated three strategies, namely dynamic pricing incentives (user-based relocation), best-of-two regulation, and parking space reservation.

Dynamic pricing incentives are the most common incentives studied in the literature to respond to the rapid changes in station inventory levels during the operation. While the planning objectives can be service level maximization or total travel cost minimization, the prices can be set at the return station location for each time interval (e.g., Chemla et al., 2013b) with the consideration of both the current state of a BSS and the destination of each cycling trip (e.g., Pfrommer et al., 2014; Singla et al., 2015). Offering incentives can improve the service rates of a BSS (Ruch et al., 2014), and is cheaper and can maintain the number of ‘no parking’ events (i.e., the number of users unable to find bicycle docks) at a lower level than the provision of vehicle-based relocation in large BSSs (Chemla et al., 2013b). Meanwhile, some dynamic pricing incentives are proposed to motivate cyclists to have *extra* trips for proactively executing repositioning tasks. The design objective becomes maximizing the difference between the benefits (e.g., profit from reduced lost demand and a reduced number of out-of-stock events) and the payouts (e.g., lost demand due to moving bikes and the total cost for the points awarded to bike angels) of the corresponding studied strategy (e.g., Ghosh & Varakantham (2017) and Chung et al. (2018)).

The best-of-two regulation allows a user to choose two stations for parking and the system forces him/her to go to the least congested one (Fricker & Gast, 2016). The authors proposed two models (i.e., regulation exclusive and regulation inclusive models), which are aimed at determining the optimal bicycle fleet size such that the proportion of problematic stations (i.e., stations which are either full or empty) is minimized. The results showed that the proportion of problematic stations is much lower when the best-of-two regulation is implemented and the two choices are randomly picked. Nevertheless, the studied problems are highly restricted by the model assumptions and thus the models become less applicable to real network scenarios.

For parking space reservation, as the discretions are made in real-time, it is regarded as an operational but not a tactical problem. The two studies by Kaspi et al. (2014; 2016b) compared the performance of complete parking reservation, partial parking reservation, and no-reservation policies and showed that complete parking reservations can achieve the lowest total excess time while all partial parking reservation policies can save more excess time better than no-reservation policy.

To the best of our knowledge, though these strategies have been proved effective, none of the above strategies have been implemented in practice. Moreover, with the increasing popularity of mobile devices, other dynamic incentives (such as scoring/reward schemes, monetary rewards for members) can be examined in the future. Furthermore, mobility-as-a-service can also integrate with dynamic incentives to encourage user-relocation. The effectiveness should be analyzed in the future. In addition, the unaddressed problems stated in Section 2.2.2 should also be investigated in the dynamic context.

2.4. Multi-level bicycle-sharing service planning problems (ML-BSPPs)

Multi-level BSPPs refers to the problems that involve at least two levels of planning decisions (e.g., strategic decisions with tactical decisions, tactical decisions with operational decisions, and strategic decisions with operational decisions). Note that currently there are no three-level planning problems in the literature. Compared Table 5 with Tables 2-4, it is observed that the body of literature of ML-BSPPs is much smaller than that of the above single-level BSPPs and the existing combination is combining strategic and operational decisions (e.g., Martinez et al., 2012; Chow & Sayarshad, 2014; Yan et al., 2017). The operational decisions can be the number of relocated bicycles in each period in relocation service planning. The strategic decisions can be bicycle station locations (e.g., Yan et al., 2017), the numbers of bicycles and bicycle docks (e.g., Chow & Sayarshad, 2014), and the combination of these two (e.g., Martinez et al., 2012). As multi-level BSPPs are a very recent topic and the literature only covers strategic and operational decisions, there are rooms to combine other planning decisions at different levels to have new planning problems. For instance, the tactical pricing or other user incentives' decisions can be considered together with strategic station location decisions, inventory management decisions, or dynamic vehicle-based repositioning decisions. Tactical pricing or vehicle-based repositioning can be combined with dynamic user-based relocation. The strategic station location, bicycle depot location, and repairing center location designs can also integrate with the operational repositioning strategy planning to facilitate broken bike collection.

The advantages of the integrated modeling approach for BSPPs (i.e., considering the multiple level planning decisions of BSPPs) are not clearly revealed in the existing studies. Yan et al. (2017) explained that both strategic and operational planning problems are crucial and interrelated in a successful BSS and thus require an integrated view to plan for both of them simultaneously. Nevertheless, these reasons are weak because no numerical examples have been established to demonstrate that to what extent integrated planning can yield better results than sequential planning. Therefore, further studies are required to quantify the benefit of the integrated approach.

2.5. Bicycle-sharing service planning problems in a multi-modal system

The above sections classify the BSPPs according to the involved decisions. In most reviewed problems, bicycle-sharing service planning is studied in an isolated context in which the planning does not consider other transportation systems. Despite the existence of a large number of empirical studies on the role of cycling in a multi-modal transportation system, very few studies involve bicycle-sharing service planning or joint planning of both bike-sharing and public transport service planning in a multi-modal transportation system. The exceptions only address bicycle-sharing service planning with the consideration of the adverse effects on the roadway network (e.g., Sohn, 2011; Mesbah et al., 2012), but not on other transport networks. This contradicts the role of cycling in a multi-modal transportation system as a solution to the first-mile/last-mile problem. In fact, the synergy of cycling and public transport is recognized (Rixey, 2013), which can be due to modal integration (Fishman et al., 2013).

Modal integration focuses on the seamless connection between cycling and public transit and expands the catchment area of public transit (Shelat et al., 2018) to encourage travelers to adopt both modes for their trips. Krizek & Stonebraker (2011) recognized four common types of modal integration strategies, including bicycle-on-transit (bringing shared bicycles on a train/bus), bicycle-to-transit (using an owner's bicycle to cycle to and park at the access transit station), two-bicycle (using an owner's bicycle to cycle to and park at the access transit station and another owner's bicycle to leave from the egress transit station), and shared-bicycle (using shared bicycles located close to transit stations, origins, and destinations). Among these four types of integration, the bike-on-transit and the shared-bicycle strategies can directly correlate with bicycle-sharing service planning because they (can) involve shared bicycles. However, no existing BSPPs have been focused on these directions. The bicycle-on-transit strategy can increase the in-vehicle congestion of a congested transit system and hence the maximum number of bikes allowed onboard should be planned in such a system. Moreover, bikes take up more space than passengers. The fare for cyclists with bikes onboard should, therefore, be higher in congested transit systems. With the bicycle-on-transit strategy, unused shared bicycles can be transported by transit vehicles and thus fewer repositioning vehicles are required to be deployed. New operational tactics should be developed (e.g., timetabling repositioning operations to fit the schedule of public transit) and compared with existing practice to examine their efficiency. The shared bicycle strategy requires bicycle availability at both access and egress locations, which can induce strategic (e.g., station location and initial inventory design), tactical (e.g., static relocation and pricing strategies), and operational problems (e.g., inventory management problems). Moreover, given that the parking spaces close to transit stations can be limited, implementing pricing strategies for regulating the bicycle parking activities around transit stations can be a viable solution (Molin & Maat, 2015). Yet, this pricing problem has not been formulated as a T-BSPP for theoretical analysis. Furthermore, to promote bike-and-ride, optimal discounts should be given, which has not been examined.

While modal integration implies that cycling can be complementary to public transit, cycling can substitute public transit, meaning that a transit trip can be replaced with a cycling trip. This type of modal substitution implies competition between cycling and public transit in a multi-modal transport network. Empirical studies show that cycling can substitute public transit, especially the bus mode, with the introduction of BSSs (e.g., Shaheen et al., 2013; Fishman et al., 2014; Campbell & Brakewood, 2017). To the best of our knowledge, only Li et al. (2015) demonstrated the substitution of public transit by cycling in examining the rental price decision of a bicycle-sharing service in a multi-modal network with four modes (i.e., auto, bus, combined bus and bicycle, and bicycle). However, the combined mode can only be used in a bus-first-bicycle-second manner and their model is only a multimodal equilibrium model that is used for the sensitivity analysis of design decisions. A multi-modal transport network design model that captures cycling as a competing mode has not been found in the literature yet. A future direction can be developing this design model. Furthermore, with the introduction of other new shared light vehicles (e.g., e-scooters and e-motorcycles), the competition between bicycles and these modes is another future possible trend. This opens rooms for studying new planning problems that consider this competition in a multi-modal network.

3. Future research directions

This section outlines the gaps for future research directions for each of the problem categories stated in Section 2 and discusses the upcoming challenges and opportunities of the research of BSPPs.

3.1. Strategic bicycle-sharing service planning problems (S-BSPPs)

3.1.1. New diversity

1. *Expansion of existing bikeway networks*

   As mentioned in Section 2.1.1, most bikeway network design models focus on designing new bikeway networks for segregated or shared bikeways but not on the improvement of existing bikeway networks. In fact, after launching a bicycle-sharing program or providing new cycling infrastructures, there is often an increase in cycling demand in the bikeway network, which leads to an increase in the usage of existing cycling infrastructures, and therefore requires the expansion of the bikeway network to increase the level of service. This expansion can be constructing new bikeways, while the responses of the different types of cyclists to the new network changes and the critical attributes to route and station choice should be captured in the design.
2. *Time-dependent or multi-phase bikeway network design*

   This is a natural extension of the network expansion problem, which has also been adopted for street capacity expansion (e.g., O'Brien & Szeto, 2007) and transport network improvement (e.g., Szeto & Lo, 2008). Subject to the budgetary constraint and the practical considerations, very few bikeway networks would have a large number of bikeways at the initial stage. Instead, a bikeway network is generally expanded over the given planning horizon phase by phase to capture the demand and land-use changes. The design problem is, therefore, to determine the sequence of construction of new bikeways to optimize the design objectives within the planning horizon.
3. *New cycling infrastructure designs*

   As highlighted in Section 2.1.1, new types of cycling infrastructures (e.g., cycling superhighways, park connectors, and inter-district cycling routes) have been recently introduced worldwide to improve the safety and connectivity of the bikeway network. The alignments of these new infrastructures should deserve a specific treatment. The design problems should also consider the cyclists' route choice behaviors when these new infrastructures are added into existing bikeway networks because the usage of the new and existing infrastructures are expected to be different.
4. *Optimal multi-type bikeway network layout considering the trade-off between cyclists' safety and impacts to road traffic conditions*

   Following the discussion in Section 2.1.1, in addition to construction costs, maintenance costs, and road widths, the cycling risks of different types of bikeways (e.g., on-street and separated bicycle facilities) are different while cyclists have a hierarchy of preferences among all bike facilities, favoring separate paths and/or lanes over cycling in roadways with motorized traffic (Buehler & Dill, 2016). On one hand, the use of bikeways can increase if the cyclists' perception of safety is improved (Kang & Fricker, 2013). On the other hand, safer bikeways are often costlier and occupy more roadway space, which adversely affects drivers by decreasing available driving space for traffic and on-road parking spaces. In other words, the more the bikeways, the higher the travel time of vehicle users. Though the existing studies in planning an urban bikeway network always include the adverse impacts to the vehicular traffic (which can be in terms of the reduction in road width, road capacity, or on-road parking space) (e.g., Lin & Yu, 2013; Mesbah et al., 2012; Sohn, 2011), none of these studies have examined about the actual impacts of *different* bikeway types (which have different roadway capacity reductions) on the vehicle flow pattern. Moreover, the cyclists' safety due to the difference in bikeway types is seldom considered although the level of safety varies among different bikeway types (Geller, 2006) and affects the usage volume on bikeways. This leaves a research question: how should the planner consider the trade-off between cyclists' safety and the impacts on vehicle traffic conditions when determining the optimal bikeway network layout with multiple bikeway types? To address this question, cyclists' safety and the impacts to the road traffic conditions can either explicitly be modeled in the constraints in the bikeway design problem or implicitly captured in an overall service level measurement.

5. *Station design with multiple bicycle types*

   Section 2.1.2 shortlists various new types of bicycles that serve for different trip purposes. Two-seat bikes (tandems) let two cyclists of different abilities cycle together without anyone being left behind. Cargo bicycles provide enough capacities in the front part of the bicycles for transporting heavier goods safely. E-bicycles become the most competitive new bicycle type as they provide higher speed with less human effort compared with manpower bicycles. They remove some barriers (e.g., terrain) of cycling via manpower bicycles and increase cyclists' mobility (Langford et al., 2013). They increase bicycle usage and generate fewer emissions than cars (Fyhri & Fearnley, 2015; Cherry et al., 2009; Fishman & Cherry, 2016). However, regarding the setup cost, a pedal shared e-bicycle is more expensive than a same-quality non-electric bicycle (Ji et al., 2014). Battery charging banks may also be required for the continuous operation of a BSS as e-bicycles require charging from time to time, implying another setup cost. The hybridization of e-bicycles with pedal bicycles in BSSs will also soon become an inevitable trend worldwide to capture the benefits from both e-bicycles and pedal bicycles. Regarding these new bicycle types, a possible novel S-BSPP is to determine the number of bicycle docks for each bicycle type at each station, given that these new bicycle types may require different types of bicycle docks (that have different setup costs and occupied spaces).

6. *New economic measures*

   The predominant economic components introduced in the reviewed models are mainly the setup costs (e.g., the investment costs for bikeways, bicycle stations, and bicycles), while some additional economic components include the revenue of BSSs with pricing schemes and the government subsidy (Frade & Ribeiro, 2015). These economic components may be sufficient for bike-sharing operators but are far from sufficient for the local governments (which aim to develop bicycle-sharing services) to evaluate the economic viability of their bicycle-sharing services as these components ignore the indirect costs (e.g., health cost and pollution cost) related to bicycle-sharing services. In fact, a long list of cycling and bike-sharing benefits has been identified in the recent literature and these benefits can be classified according to the three major beneficiaries, namely the individuals, the bike-sharing operators, and the society. The individuals' benefits include cost savings, convenience, safety, improved health, and the saved journey time of travelers by bicycle instead of car (see the studies of Krizec, 2007; Jensen et al., 2010; Woodcock et al., 2014; Ricci, 2015; Bullock et al., 2017). Operators' benefits are the operating revenues from advertising sales, gifts' sales, grants, sponsorships, membership fees, and usage fees, while these profits can be impacted by station locations, membership retention, discounts, and new revenue sources (Shaheen et al., 2014). Societal benefits include business sales, public health benefits, time savings, productivity benefits, improved public transport efficiency, livability, pollution reduction, and the wider economic benefits (WEBs) such as enhanced labor force participation and productivity gains (see the studies of Krizec, 2007; Bullock et al., 2017). Most of them (e.g., improved transport efficiency, health benefits, benefits to the local community, and time savings) can be included in S-BSPPs to assess their current and potential economic benefits. Aiming at developing an economically viable and sustainable mode in the long run, other sources of revenues (e.g., advertisement) and expenditures (e.g., depreciation cost) from different stakeholders can be included in S-BSPPs in future studies.

7. *A complete framework for evaluating the economic viability of bicycle-sharing services*

   It is another extension related to the new economic measures. The existing S-BSPPs are modeled under an implicit assumption that a new bicycle-sharing service must benefit society. However, none of the studies can answer the following questions: When can this service provide economic benefits to the investor? How much is the total benefit? Is the bicycle-sharing service an economically viable and sustainable option in the long run? To address these questions, a complete economic viability evaluation framework for bicycle-sharing services should be proposed in the future.

3.1.2. Realism

1. *Capturing multiple attributes for cyclists' route choice*

   Section 2.1.1 reveals that most bikeway network design models ignore that cyclists' route choice is influenced by multiple attributes (which can be deterministic or perceptual). Developing utility functions or formulating multi-objective problems to capture selected attributes are potential ways to incorporate these attributes into the route choice behavior model of bikeway network design models. Examples include the utility functions of cyclist routes derived from GPS data (e.g., Menghini et al., 2010; Hood et al., 2011; Broach et al., 2012) and the bi-objective bicycle route choice model that optimizes travel time and route suitability (e.g., Ehrgott et al., 2012). They have not yet been captured in bikeway network design models and should be considered in future studies.

2. *Adoption of different user equilibrium models*

   Following the discussion about route choice models in Section 2.1.1, the existing bikeway network design models formulate the cyclists' route choice problem as a shortest path problem (e.g., Sohn, 2011) or a deterministic user equilibrium (UE) problem (e.g., Mesbah et al., 2012). However, other equilibrium concepts, such as stochastic UE (SUE) and bounded rationality UE (BRUE) (e.g., Mahmassani & Chang, 1987), can be applied to bikeway network design problems in the future to capture the more realistic behavior of users. SUE assumes that a traveler chooses the path with the minimum *perceived* path utility. BRUE assumes that a traveler considers routes to be equally attractive when the travel costs of these routes are within an 'indifference band' of the shortest path cost.

3. *Capturing multiple classes of cyclists*

   Section 2.1.1 highlights that all existing bikeway network design studies assume that the cyclists are homogeneous and have identical route choice behavior. This strong assumption cannot coincide with the findings that different types of cyclists have their corresponding perceptions of the physical environment (e.g., Geller, 2006; Dill & McNeil, 2013). Although the deviations in perceptions may create differences in route choice behavior (e.g., inexperienced cyclists only cycle on bike paths), multiple types of cyclists have not been considered in the existing studies. Therefore, capturing these types of cyclists in bikeway network design problems should be a good and important research direction.

4. *Modeling demand uncertainty and elasticity*

   Section 2.1 points out that deterministic and fixed demand has been generally adopted in existing strategic bike-sharing service planning models. To demonstrate the robustness of the design, stochastic or robust demand scenarios should be considered in future studies. Furthermore, given that cycling infrastructure is a key motivator for cycling demand, the demand elasticity with respect to the provision of cycling infrastructures (e.g., the density of bikeways and bicycle station capacity) should be taken into account in future studies.

3.1.3. Integrality

1. *Strategic bikeway design with vehicle flow reassignment*

   Following the discussion in Section 2.1.1, the width proportion of a bikeway to a roadway is the main issue in combined bikeway and roadway design. The width proportion determines roadway capacity reduction and the level of cycling risk. Specifically, a narrow bikeway results in a high cycling risk while a narrow roadway results in low road capacity and thus high vehicle travel time. However, none of the existing studies have considered the width proportion in their design. Sohn (2011) and Mesbah et al. (2012) fixed the degree of roadway capacity reduction to determine the optimal bikeway layout in an existing roadway network, while Lin & Yu (2013) ignored the reassignment of vehicle flows due to the introduction of bikeways and introduced three levels of roadway capacity reduction based on three bikeway types. A new design problem is to determine the optimal bikeway layout with the simultaneous consideration of multiple levels of roadway capacity reduction and the reassignment of vehicle flows.

2. *Simultaneous station location design for cycling and public transit under bike-transit integration*

   As stated in Section 2.5, the synergy of public transit and cycling has been recognized; cycling usage is strongly correlated with public transit (Rixey, 2013). However, no methodology has been proposed to optimize the benefits from this synergy such as to maximize the transit demand coverage. The model proposed by Chow & Sayarshad (2014) only determined the capacity and inventory level at each bike station assuming that no transit network design was taken place simultaneously. Therefore, some further extensions for optimizing the benefits from this synergy can be made by combining the design of bicycle station locations with the station locations of the bus or other public transport modes. Different from the rail mode in which the change in alignment is impossible, the station locations of other public transit modes (e.g., bus) in the existing network can be reset at a low cost. For new areas, transit stations can be designed with bike stations together to improve the connectivity between public transit and cycling. By relying on cycling to solve the first/last mile problem in both existing and new areas, transit stations can be more dispersed and the catchment area of the transit service can be larger if bicycle stations are designed to be proximate to these transit stations.

3. *Design of capacity of bike stations with the consideration of existing transit stations*
   To optimize the benefits from the synergy of public transit and cycling, another potential strategic design problem is to consider existing transit stations (for bike-transit travel) and determine the allocation of parking spaces at each bike station proximate to every existing transit station, such that the travelers can access to public transit stations by public bike in the most convenient way.

3.1.4. Technology

1. *Strategic location design for mobile bicycle stations*
   Section 2.1.2 highlights the importance of mobile docks as a solution for locations with low daily cycling demand but a high utilization rate due to periodic events (e.g., train arrivals, sports events, and concerts) to replace setting up large bicycle stations that *permanently* occupy a lot of space. Mobile docks are often in the form of carts or vans, so returned bicycles at these docks can be easily relocated to other locations. A mobile dock can form a mobile bicycle station while a mobile bicycle station can be formed by more than one mobile dock. Compared with setting up fixed bike stations, setting up mobile bicycle stations may be a costly option, but mobile bicycle stations can improve bicycle utilization in a BSS (by periodically redistributing mobile bicycle stations in addition to shared bicycles) and reduce the risk of installing bike stations at wrong locations (as mobile bicycle stations could be easily relocated) (Shu et al., 2013). Furthermore, these mobile bicycle stations enable the operator to design fixed bicycle stations with smaller station capacity as mobile bicycle stations can provide additional capacity at locations of fixed bike stations when necessary. A lot more research on the strategic design problem with mobile bicycle stations can be done, including the strategic location design problem of mobile bicycle stations.
2. *Parking area location design for free-floating bicycles*
   As a new bike type listed in Section 2.1.2, free-floating (or station-less) bicycles utilize GPS to track their locations and thus enable users to park these bicycles at locations closer to their destinations without the restriction of bicycle station locations freely. Bicycle docks and stations are replaced with the smart lock placed at the rear wheel of each shared bicycle that can be unlocked by scanning its QR code and getting locked again manually. The setup cost for a free-floating BSS is lower than that for a station-based counterpart as the operator only needs to define the locations for placing free-floating bicycles without installing bicycle stations' facilities. Nevertheless, designing the locations of permitted

parking areas for these bikes is still necessary as this can facilitate the repositioning operation of a BSS with free-floating bikes and address the issue of illegal/improper parking. Therefore, one possible research direction is to design the locations of permitted parking areas for these bikes.

3. *Determination of the area for the free-floating system and the proportion of free-floating bikes in a hybrid BSS*

   Section 2.1.22 mentions a recent research problem about establishing a hybrid BSS with free-floating and station-based bicycles as suggested by Albiński et al. (2018). A related research problem is to determine the area for the free-floating system in a BSS with both free-floating and station-based bicycles and also the proportions (and fleet sizes) of free-floating and station-based bicycles to meet bike-sharing demand but limit the bike search and redistribution costs. Compared with shared bikes that must be returned to stations in a station-based BSS, freely-parked free-floating bicycles result in a more scattered bicycle distribution. Sometimes free-floating bicycles are returned in undesignated areas (e.g., under the water, on a tree, and piled up on streets). More time for bike assistants is thus required to handle these bicycles and put them at locations that are easy to access (e.g., next to traffic lights or bus stations) and hence the bike search cost is higher. Moreover, the more the free-floating bicycles, the higher the bike search and redistribution costs. The proposed research problem considers the issues of high bike search and redistribution cost and is worth exploring.

4. *Determination of the location of bicycle stations with (mobile) charging facilities for e-bikes and the number of mobile charging docks*

   As indicated in Section 2.1.2, charging facilities are necessary infrastructures for BSSs with e-bikes. However, it is impossible to set up charging facilities at all bicycle stations due to a high construction cost. Therefore, it is important to design the locations of bicycle stations with and without charging ports and determine the number of mobile charging docks in a BSS with e-bikes (if available) to minimize the setup cost while a reliable energy level of e-bikes is guaranteed. This important problem has not been studied yet and is, therefore, a good future research direction.

3.2. Tactical bicycle-sharing service planning problems (T-BSPPs)

3.2.1. New diversity

1. *Location pricing design*

   Location pricing (mentioned in Section 2.2.2) has been addressed by the literature slightly (e.g., Haider et al., 2018). It has a lot of research potential. The idea of location pricing is to offer monetary incentives for BSS users to shift their origins and destinations. It can be either deterring or rewarding depending on the initial cost per trip. Compared with a dynamic pricing scheme that motivates BSS users for instant bicycle distribution, a static pricing scheme with regular revisions is easier to implement and the cyclists' behavior can be altered in a prolonged way. The most common example of the static pricing scheme includes setting discounts (extra fees) for parking bicycles at stations with a low (high) usage rate. Another example is the station pairing discount, in which the operator offers discounts for BSS users traveling between some designated OD pairs (in particular time intervals). This can simultaneously motivate BSS users to pick up bicycles at under-utilized stations and return bicycles to high demand or empty stations to achieve the operation goal of bicycle relocation by BSS users.

2. *Membership schemes of a BSS*
Following the discussion in Section 2.2.2, the membership scheme with its subscription fees, as one of the important sources of the revenue of a BSS (Shaheen et al., 2014), has not been studied with the aim to maximize the subscription rate. The design problem is not limited to the determination of membership fees but also the membership duration and status. The membership duration states the subscription period and the status defines the privileges that can be enjoyed by a particular class of members. These privileges can be, for instance, a priority bicycle booking/parking reservation, a prolonged discount rate, or a right to borrow two bicycles simultaneously, etc. Future studies can focus on determining the membership scheme that maximizes the subscription rate and analyzing the revenues and subscription rates brought from offering different membership strategies.
3. *Fare structure design*
Following the discussion of fare structure design in Section 2.2.2, one major source of the revenue of a BSS is the usage fare (Institute for Transportation & Development Policy, 2013). In practice, the most common fare structure is based on a stepwise function that has a low or even no rental price for the first half an hour and increases stepwise for longer rental periods. However, no studies have investigated the optimal fare structure that can maximize revenue. The optimal fare structure should cover the optimal flat rate, the optimal time-varying rate, and the optimal length of the corresponding rental period. Moreover, a BSS with multiple bicycle types should separately have a fare structure for each bicycle type to maximize the revenue. More analysis should be carried out on fare structure design.
4. *Multiple tactical strategies*
As mentioned in Section 2.2, the combined effect of implementing multiple tactics should be investigated. Current tactical problems usually consider a single tactic. It is unclear whether the benefit of each tactic is simply additive or multiplicative. If there is a diminishing return, it may not be a good idea to implement all tactics.
5. *Maintenance and repairs of bicycles and stations*
Broken bicycles often appear in a BSS, as highlighted in Section 2.2.1 Determining the optimal maintenance strategy is thus important as maintenance contributes to the operational cost of a BSS. Existing maintenance strategies include on-site repairs, off-site repairs, and the direct replacement of broken bicycles, in which each of them incurs different labor, time, and investment costs. Depending on the conditions of broken bicycles, simple maintenance strategies may not be better than mixed maintenance strategies if a BSS has bicycles with different damaging levels. Furthermore, the collection of broken bikes for the case of off-site repairs can be formulated as the service level requirements in the vehicle-based repositioning problem such as imposing time windows for collecting broken bicycles and setting penalty costs for late removals of broken bicycles. Another maintenance issue is to determine a

maintenance schedule for the bicycles and stations of a BSS to keep the level of service. These three directions have not been studied yet and are worth exploring.

6. *Labor roster and job assignment*
   To support the maintenance and repair operations, the operator needs to determine the roster and allocate the jobs to all labors in which the crews for the operator can be heterogeneous in terms of working efficiency. This can be an important research direction in the future.
7. *User-targeted strategies' evaluations from a bottom-up approach*
   Section 2.2.2 mentions that the bottom-up approach takes the perspective of BSS users instead of the operators and has been used for evaluating the effects of user-targeted strategies (provision of sufficient information to BSS users and provision of more bike stations to reduce their walking distance to destination) on increasing the system level of service (see Raimbault, 2015). This approach is expected to be useful in accurately evaluating other user-targeted strategies (e.g., waiting time at a fixed place (either for a parking space or a bike) and access time to a bicycle pickup station) as the users' reactions to the strategies are included. Therefore, this approach should be further studied.

3.2.2. Realism

1. *Modeling demand uncertainty and elasticity*
   Following the discussion in Section 2.2.2, demand uncertainty can be associated with the destination choice behavior of the cyclists who accept the financial incentives. When they do not return shared bicycles at the expected return stations but instead at other stations, the expected bicycle arrival rates of all these stations and thus the numbers of bicycles and bicycle racks at these stations are simultaneously affected. We should consider this behavior when modeling T-BSPPs in future studies. Moreover, as stated in the same section, the price elasticity of demand can be considered in future studies given that no existing studies have addressed how BSS users respond to financial incentives.
2. *Combining top-down and bottom-up approaches to designing incentive strategies*
   The combination of the two approaches, suggested in Section 2.2.2, aims to incorporate the benefits of the bottom-up approach into the top-down incentive design problem. The bottom-up approach can improve the centralized decision-making process (in which the operator assumes cooperative users' decisions) commonly adopted in the top-down approach to catering for the realistic decentralized decision making of BSS users. However, considering the decentralized decision making in designing incentive strategies increases problem complexity and the resultant problems often need to be represented as bi-level optimization models. The benefits of the combined approach should, therefore, be quantified in the future to justify the necessity and importance of this approach.
3. *Simultaneous determination of optimal maintenance, repositioning, and maintenance crew deployment strategies*
   Following the discussion of the fifth direction in Section 3.2.1, maintenance is necessary for any BSS. It covers the preventive and repair activities of the bicycle stations and bicycles and is a large line item

under operational costs (Institute for Transportation & Development Policy, 2013). The maintenance and repair work of shared bicycles can be done at repairing centers or on-site depending on the severity of the deterioration whereas the bicycle racks can only be repaired on-site. For both cases, the site concerned must be visited by maintenance crews and the maintenance strategy should, therefore, be considered together with the bicycle repositioning strategy to increase operational effectiveness. To determine an optimal integrated maintenance and repositioning plan, the proportions of shared bicycles facing major and minor repairs within the system should be firstly estimated and followed by the cost comparisons between different maintenance options (e.g., on-site repairs, off-site repairs, and bicycle replacements). In addition, the personnel allocation should be considered given that the maintenance options have a direct impact on crew deployment. Therefore, it is important to simultaneously determine optimal maintenance, repositioning, and crew deployment strategies, which should be studied in the future.

3.2.3. Integrality

1. *Optimal discounts for the bike-and-ride mode*

   Following the discussion in Section 2.5, the combined mode of public transit and cycling is found in practice (Cervero et al., 2013) but the actual competitiveness of this mode is unclear. To boost the market share of this combined mode, offering monetary discounts to cyclists that adopt transit to complete their journeys is a direct approach, while smart cards can be a possible medium to validate the eligibility for claiming the discount. Future studies should focus on proposing the optimal discount mechanism for the bike-and-ride travelers (including the price and the period for offering discounts).
2. *Optimal fare and quantity of bicycles on transit*

   As stated in Section 2.5, one way of integrating public transport and cycling is to allow bicycles to be brought into transit compartments. When bicycles on transit are allowed, a potential tactical problem for the transit operator is to determine the maximum number and the price of onboard bicycles to increase the utilization of transit compartments while maintaining the service level of passengers.
3. *Parking pricing at bike stations near transit stations*

   As pointed out in Section 2.5, given that the parking spaces close to transit stations can be limited, implementing pricing strategies for regulating the bicycle parking activities around transit stations can be a viable solution (Molin & Maat, 2015). Yet, this pricing problem has not been formulated as a T-BSPP for theoretical analysis. This T-BSPP deserves further investigations.

3.2.4. Technology

1. *Fare structure, incentive setting, and relocation services in a BSS with both e-bikes and manpower bicycles*

   When new bicycle types are introduced in BSSs, new relocation and pricing strategies are required in addition to new station design as stated in the fifth direction of Section 3.1.1. As one of the new bicycle types, e-bikes have shown their competitiveness with manpower bicycles due to their longer travel distance, higher speed, and lower effort requirement. Though the high setup and maintenance costs deter the wide adoption of e-bikes, there is a high potential to develop a BSS with both manpower and e-bikes to cater to the need of different classes of bike users and cover the setup and maintenance costs. Determining the financial incentives, the fare structure, and the relocation services for both e-bikes and manpower bicycles in a mixed fleet BSS thus becomes an important issue, which should be studied in the future.

repair, charging

3.3. Operational bicycle-sharing service planning problems (O-BSPPs)

3.3.1. New diversity

1. *Green bicycle relocation operations*
   Following the discussion in Section 2.3.2, general bicycle repositioning heavily relies on fossil-fueled vehicles, which creates threats to the environmental creditability of BSSs as the operation generates a lot of greenhouse gases (Wiersma, 2010). It is, therefore, necessary to consider environmental measures in BRPs to alleviate the negative effects brought by the repositioning operations (e.g., a high fuel consumption rate, a large number of air pollutants). Though till now only Shui & Szeto (2018) and Wang & Szeto (2018) have considered an environmental objective (i.e., minimizing CO_2 emissions) in their vehicle-based repositioning studies, it is expected that more studies will focus on this issue to alleviate the adverse environmental impacts. Moreover, green bicycle repositioning can be exercised through the use of *electric* trucks. However, the use of electric trucks in bicycle repositioning has not yet been studied in the literature. This usage deserves consideration in future research.
2. *Dynamic signal control for bikes*
   Very few studies have considered bikeway intersections (e.g., Duthie & Unnikrishnan, 2014) and the intersections of bikeways and other roadways (e.g., vehicular roadway and walkway) in measuring bikeway safety (e.g., Lin et al., 2013) whereas none of them have considered the signal design for bicycles at intersections (see Section 2.3). In fact, bicycles can either share the signals with vehicles/pedestrians or possess their own set of signals at intersections in real-time. There is a large room to develop methodologies for dynamic signal control for bikes in the future.
3. *Dynamic user-targeted strategies' evaluations from a bottom-up approach*
   As an extension to the research direction of user-targeted strategies' evaluation in Section 3.2.1, this direction considers the dynamic user-targeted strategies (e.g., online bicycle/bicycle-parking reservations and time-dependent pricing), which have not been explored but are important.

3.3.2. Realism

1. *Capturing multiple types of bicycles and relocation vehicles*
   Following the discussion in Section 2.3.2, current dynamic bicycle relocation problems consider the multi-vehicle case but not multiple types of bicycles or repositioning vehicles. For DBRPs with multiple bicycle types, subject to the operational constraints, they involve more tedious loading and unloading strategies as surplus bicycles of a particular type may not solve a shortfall in another bicycle type. Even if the problem can be disaggregated into separate problems with a single bicycle type (i.e., no interactions between bicycle types), the whole problem complexity is still higher than that of the DBRP with a single type. On the other hand, DBRPs with multiple types of vehicles are considered to be practical extensions of the homogeneous fleet because the simultaneous plan of the fleet mix and the repositioning strategy can minimize the fuel consumption cost of the repositioning operation while improving the utilization of vehicle capacity. These two considerations should be captured in future DBRP studies.
2. *Capturing demand uncertainty in dynamic user-based relocation*
   Following the discussion in Section 3.2.2, BSS users can regret *at any time* before the end of their bicycle returns. This implies that future dynamic user-based relocation models should capture a probability of their regrets (i.e., failures to accomplish their required trips). At the same time, the models should consider the probability of other alternative outcomes (e.g., returning to other stations instead of the specified station) given that shared bicycles must be returned to any station in the system.
3. *Capturing supply uncertainty in DBRPs*
   Following the discussion in Section 2.3.2, existing DBRP studies lack the consideration of supply uncertainties related to the numbers of broken bicycles and bicycle docks, the travel time of repositioning vehicles (especially in daytime repositioning), and the repairing time for a bicycle. Given that these uncertainties can deteriorate the service level of a BSS, they should be captured by future studies.
4. *Capturing new operating cost attributes*
   Although a wide range of costs is considered in the DBRP literature (see Section 2.3.2), the operating cost considered is usually equivalent to the operating time cost (e.g., Zhang et al., 2017). Nevertheless, other attributes such as labor wages and vehicle fuel costs should be considered in future studies as they are not negligible expenditures in bicycle repositioning operations.
5. *Modeling demand uncertainty in DBRPs*
   Following the discussion in Section 2.3.2, demand uncertainty in DBRPs is mainly related to the cycling demand in each time interval, which can greatly influence the inventory decision in each period. It is therefore important to capture demand uncertainty. This uncertainty can be modeled by stochastic and robust optimization approaches. Currently, very limited studies for DBRPs have considered these approaches. A lot more work can be done on modeling demand uncertainty in DBRPs in the future.

3.3.3. Integrality

1. *Synchronization of repositioning operations with transit schedules*
   Using underutilized public transport can be a tool for daytime bike relocation (see Section 2.3.2). Compared with conventional repositioning vehicles, public transit can transport more bicycles for a longer distance. In particular, some transit modes (e.g., rail and light rail) can transport bicycles with more stable travel time. In other words, public transit can be a feasible, reliable and maybe cheaper option to replace repositioning vehicles for the distant repositioning of bicycles. Future works can focus on the synchronization of repositioning operations with transit schedules to handle both long- and short-distance repositioning.
2. *Synchronization of optimal inventory levels in different periods with transit schedules and relocation services*
   This one is a natural extension of the last research direction. To handle large shared bicycle (and bicycle parks) demands in peak hours without creating huge unmet demand, a potential planning problem for future studies is to plan for the inventory levels of the shared bicycles and bicycle docks and also the relocation service during different periods that can synchronize with transit schedules.
3. *Integration of dynamic incentives with the operation of Mobility-as-a-service (MaaS)*
   Following the discussion in Section 2.3.3, the raise of MaaS offers a wide range of integrated modes aiming at minimizing total travel cost. This wide range of options makes the destination of the first-mile and the origin of the last-mile more flexible. The operator can integrate the user-based relocation with MaaS by lowering the real-time prices of the cycling trips starting from (ending at) some pickup (drop-off) points that have insufficient bicycle docks (bicycles) to direct users to those points. This integration can be an important future study.

3.3.4. Technology

1. *Dynamic reward/penalty parking zone location planning for free-floating bicycles and dynamic reward/penalty setting for user-relocation*
   In addition to the strategic parking zone location design for free-floating bicycles mentioned in Section 3.1.4, the operator should determine the tolerable distance from these locations such that these bicycles do not require relocation/repositioning. As the real-time locations of all free-floating bicycles are known with the help of GPS and the demand for shared bikes varies over time of day, the operator can determine the dynamic locations of reward zones (which can provide rewards for the users who park these bicycles at the recommended locations) and penalty zones (which impose penalties for illegal parking) and the *real-time* reward/penalty imposed in each zone to reduce the cost of dynamic vehicle-based repositioning. This unstudied planning problem can be an interesting future research topic.
2. *Reservation duration planning and penalties for missing reservations*
   The parking reservation scheme of Kaspi et al. (2014, 2016b) (mentioned in Section 2.3.3) can be implemented in both station-based and free-floating BSSs with the help of mobile apps. The mobile apps can allow BSS users reserving shared bicycles (and racks) in advance and the smart locks

associated with the bicycles (and racks) can only be unlocked by the users who reserve them. The practical issues such as the duration for each reservation and the penalty for missing each reservation can be planning problems for future studies.

3. *Zoning design, bicycle assistant routing, and dynamic vehicle-based repositioning that considers easily accessed locations for free-floating bicycles*
   Current studies mainly focus on repositioning and inventory level management issues in station-based BSSs where their bicycle stations have fixed locations and capacities. However, for free-floating BSSs, which do not have tangible bicycle stations, the predictions of bicycle arrivals and returns are usually performed at the zonal level and thus highly dependent on the way of zoning. Moreover, as aforementioned in Section 3.1.4, compared with station-based bicycles, free-floating bicycles result in a more scattered bicycle distribution and more time for bike assistants is required to handle free-floating bicycles. It is therefore important to plan for the routes of bicycle assistants to collect free-floating bicycles in order to minimize the total time for collection. It is also important to determine the dynamic vehicle-based repositioning strategy for transporting free-floating bicycles from undesignated areas or hardly accessed locations to easily accessed locations to ensure that all free-floating bikes can be used all the times. Future research can be performed on the bicycle assistant routing problem for bicycle collection and the dynamic vehicle-based repositioning problem in addition to the zoning problem.
4. *Daytime maintenance issues for e-bikes*
   Other than the repositioning issue for e-bikes mentioned in Section 3.2.4, there are daytime maintenance issues. To guarantee a satisfactory service level of a BSS with e-bikes, the operators should monitor the remaining battery levels of the e-bikes in the daytime and determine the best strategies to ensure sufficient e-bikes under satisfactory conditions. A lot of work can be done to address these maintenance issues (for example, battery swap, bicycle replacement, and repositioning e-bikes to charging stations).

3.4. Multi-level bicycle-sharing service planning problems (ML-BSPPs)

3.4.1. Integrated strategic and tactical problems

1. *Combined station location and pricing design*
   Following the discussion in Section 2.4, the integration of station location design and price setting can be a possible extension, in which the price-setting can deploy existing pricing schemes, such as location pricing. Moreover, for systems with multiple bicycle types, a promising future direction is to study the station location design and the pricing issue for several bicycle types, given that each bicycle type has different pricing and station capacity requirements. As cyclists' demand is jointly influenced by station locations and pricing schemes, the behavioral models in these combined design models should be able to estimate both the start and end station location choices of users and their reactions to price changes.

3.4.2. Integrated tactical and operational problems

1. *Mixed dynamic user-based and static vehicle-based repositioning strategy*
   Current planning problems usually consider a single incentive or way of relocation. In reality, it is common that a bike-sharing operator implements hybrid relocation strategies. An example is a combined strategy of dynamic user-based relocation and static vehicle-based repositioning (mentioned in Section 2.4), which can decrease the operational cost of vehicle-based bike repositioning and hence the total operational cost. However, there are few methodologies to help bike-sharing operators to determine an optimal mixed operational/tactical strategy for bike repositioning. It is worthwhile to propose more methodologies for them in future studies.
2. *A complete membership payment and incentive scheme*
   Following the discussion in Section 2.4, scoring/reward schemes have been implemented in some operating BSSs such as Vélib' and Citibike to provide scores for the cyclists who relocate shared bicycles from bicycle surplus stations to bicycle deficit stations manually. While the real-time score setting is an operational decision, these scores can be used to pay for the weekly and monthly membership fees of the system, while other privileges can be offered to the cyclists. The methods for designing the scoring and reward schemes deserve more investigations because the users' behaviors in different BSSs may have large deviations.

3.4.3. Integrated strategic and operational problems

1. *Integrated bicycle facility location design and dynamic bike repositioning strategy planning*
   Following the discussion in Section 2.4, a possible combination of the strategic and operational problems for future studies is to determine the minimal system setup and operating costs of a BSS. Given that the BSS operator needs to set up bicycle facilities (e.g., bicycle stations, depots, and repairing centers), provide bicycles, and plan for a feasible dynamic repositioning strategy at the initial stage, the operator may want to determine the locations of bicycle facilities and thus undergo station clustering for bike repositioning to compute the fleet size and the best routes of repositioning vehicles. The operator may also need to determine the optimal number of depots and repairing centers, which affect the strategies of system maintenance (broken bike collection) and inventory level management. These decision decisions can be captured in the combined problem.
2. *Determination of the charging infrastructure, method, and schedule of e-bikes and the dynamic relocation strategy*
   This one is an extension of the research direction about e-bike maintenance in Section 3.3.4 by introducing the strategic decision about the charging infrastructure. The infrastructure required depends on the charging method selected. The common charging methods include slow charging, quick charging, and battery swapping. Compared with slow charging, quick charging can have a lower charging time but a higher setup cost, and thus cannot be provided in all stations; battery swapping requires manpower

and hence induces higher manpower cost than quick/slow charging. All charging methods require the operator to make a charging schedule and reposition bikes to battery charging/swapping facilities as these facilities are always limited, which in turn is due to a limited budget. Determining the charging method, the corresponding infrastructure, the charging schedule, and the dynamic repositioning strategy of e-bikes should be an important issue for the success of e-bike implementation and be studied in the future.

quantity + location + type of charging facility

reposition + charging/swapping (multi-type)

fare structure of renting e-bike

3.4.4. Three-level integration

offer monetary incentives for the bike user to relocate e-bike to charging station

Integration between e-bike & transit

1. *Combination of station location, pricing, and inventory level setting*

   As stated in Section 2.4, no three-level integration problem has been studied in the existing literature. In fact, three-level integration is approaching the complete bicycle-sharing service planning process while some of the planning problems are not considered. One unexplored problem is to determine bicycle station location setting (strategic), static price setting (tactical), and inventory level setting (operational) of a BSS to maximize the profit with a satisfactory level of service. Nevertheless, given that the planning decisions of all three levels are interrelated and hierarchical, the problem complexity becomes very high and thus more sophisticated solution methods are also required.

3.5. Bicycle-sharing service planning problems in a multi-modal transport system

Sections 3.1.3, 3.2.3, and 3.3.3 provide future directions on the modal integration of cycling with other modes (e.g., automobile and public transit) that involve intermodal connections. This section reviews the possible future directions about modal substitution.

1. *Incorporating cycling into multi-modal network design with the consideration of modal substitution*

   Following the discussion in Section 2.5, one possible extension of BSPPs is to study new problems that integrate cycling into multi-modal network design and consider the competition between cycling and other modes. In fact, the literature for BSPPs in multi-modal transport systems is very limited, while a single-mode BSPP can be extended to a multi-modal transport network design problem. The BSPP can be formulated in a given multi-modal transport network with the existence of competition. The resultant modal substitution effect can be reflected in several ways: (1) the modal split with other modes (e.g., Friedrich & Noekel, 2017), (2) the vehicle flow reassignment after the introduction of bike routes in existing roadways (e.g., Mesbah et al., 2012), and (3) the combined effects of (1) and (2) (e.g., Li et al., 2015). The main design objective can be set to increase the modal share of bicycles in the multi-modal transport network.

2. *Modeling the BSPP over a multi-modal network with bikes and multiple competing light vehicles*

   This review focuses on BSPPs with the consideration of cycling and classical modes. However, it is noted that other forms of micro-mobility modes have been developed in recent years (e.g., e-scooters and e-motorcycles) as stated in Section 2.5 while these forms have been operated independently. Providing that these modes are targeted at the same group of cycling customers, future studies should model the competition, and evaluate and propose the operation tactics (e.g., implementing pricing, increasing station density, and introducing e-bikes) in a multi-modal transport network with bikes and these competing light vehicles.

4. Conclusions

This review classifies the current bicycle-sharing service planning problems (BSPPs) based on a novel eight-step bicycle-sharing service planning process framework in which the planning problems can be categorized into strategic, tactical, and operational decision levels. Major research gaps in BSPPs are pinpointed and four groups of future research directions are presented. First, the existing literature seldom considers emerging technologies or infrastructures in bicycle-sharing service planning, such as e-bikes, cycling superhighways, and free-floating bicycles. This paper discusses the potential research topics of embedding these innovations to create a system with multiple bicycle types and multiple types of infrastructures. Second, this paper extensively discusses the potential service planning problems that incorporate cycling and other transport modes into a multi-modal transport network. In these problems, shared bicycles can either be part of a combined mode or replace other transport modes depending on their interactions with the transport modes included in the network. Subject to the relationships between cycling and other transport modes, future studies can be related to the multi-modal, intermodal, and co-modal planning. Third, this paper presents a list of potential multi-level BSPPs. It is expected that future research can have more explorations of integrated planning and compare the performance between integrated and sequential planning. Fourth, this paper introduces new diversities of BSPPs and more realistic BSPPs. To conclude, despite a lot of BSPP studies have been performed, there are still plenty of research directions about BSPPs. It is expected that the body of research about BSPPs will continue to grow as BSSs will still play an important role in the future.

Acknowledgments

This research was supported by a grant from the National Natural Science Foundation of China (No. 71771194), a grant from Ministry of Science and Technology (No. MOST108-2218-E-009-062), and the General Research Fund of the Research Grants Council (RGC) of Hong Kong (No. 17200119). We are grateful to the three reviewers for their constructive comments.

References

Albiński, S., Fontaine, P., & Minner, S. (2018). Performance analysis of a hybrid bike sharing system: A service level-based approach under censored demand observations. *Transportation Research Part E: Logistics and Transportation Review*, *116*, 59-69.

Alvarez-Valdes, R., Belenguer, J. M., Benavent, E., Bermudez, J. D., Muñoz, F., Vercher, E., & Verdejo, F. (2016). Optimizing the level of service quality of a bike-sharing system. *Omega*, *62*, 163-175.

Angeloudis, P., Hu, J., & Bell, M. G. H. (2014). A strategic repositioning algorithm for bicycle-sharing schemes. *Transportmetrica A: Transport Science*, *10*(8), 759-774.

Arabzad, S. M., Shirouyehzad, H., Bashiri, M., Tavakkoli-Moghaddam, R., & Najafi, E. (2018). Rebalancing static bike-sharing systems: A two-period two-commodity multi-depot mathematical model. *Transport*, *33*(3), 718-726.

Benchimol, M., Benchimol, P., Chappert, B., De La Taille, A., Laroche, F., Meunier, F., & Robinet, L. (2011). Balancing the stations of a self service "bike hire" system. *RAIRO-Operations Research*, *45*(1), 37-61.

Brinkmann, J., Ulmer, M. W., & Mattfeld, D. C. (2015). Short-term strategies for stochastic inventory routing in bike sharing systems. *Transportation Research Procedia*, *10*, 364-373.

Brinkmann, J., Ulmer, M. W., & Mattfeld, D. C. (2016). Inventory routing for bike sharing systems. *Transportation Research Procedia*, *19*, 316-327.

Brinkmann, J., Ulmer, M. W., & Mattfeld, D. C. (2019). Dynamic lookahead policies for stochastic-dynamic inventory routing in bike sharing systems. *Computers and Operations Research*, *106*, 260-279.

Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, *46*(10), 1730-1740.

Buehler, R., & Dill, J. (2016). Bikeway networks: A review of effects on cycling. *Transport Reviews*, *36*(1), 9-27.

Bulhões, T., Subramanian, A., Erdoğan, G., & Laporte, G. (2018). The static bike relocation problem with multiple vehicles and visits. *European Journal of Operational Research*, *264*(2), 508-523.

Bullock, C., Brereton, F., & Bailey, S. (2017). The economic contribution of public bike-share to the sustainability and efficient functioning of cities. *Sustainable Cities and Society*, *28*, 76-87.

Caggiani, L., & Ottomanelli, M. (2012). A modular soft computing based method for vehicles repositioning in bike-sharing systems. *Procedia-Social and Behavioral Sciences*, *54*, 675-684.

Caggiani, L., & Ottomanelli, M. (2013). A dynamic simulation based model for optimal fleet repositioning in bike-sharing systems. *Procedia-Social and Behavioral Sciences*, *87*, 203-210.

Caggiani, L., Camporeale, R., Ottomanelli, M., & Szeto, W. Y. (2018). A modeling framework for the dynamic management of free-floating bike-sharing systems. *Transportation Research Part C: Emerging Technologies*, *87*, 159-182.

Caggiani, L., Camporeale, R., Marinelli, M., & Ottomanelli, M. (2019). User satisfaction based model for resource allocation in bike-sharing systems. *Transport Policy*, *80*, 117-126.

Campbell, K. B., & Brakewood, C. (2017). Sharing riders: How bikesharing impacts bus ridership in New York City. *Transportation Research Part A: Policy and Practice*, *100*, 264-282.

Çelebi, D., Yörüsün, A., & Işık, H. (2018). Bicycle sharing system design with capacity allocations. *Transportation Research Part B: Methodological*, *114*, 86-98.

Cervero, R., Caldwell, B., and Cuellar, J. (2013). Bike-and-ride: Build it and they will come. *Journal of Public Transportation*, *16*(4), 83-105.

Chemla, D., Meunier, F., & Calvo, R. W. (2013a). Bike sharing systems: Solving the static rebalancing problem. *Discrete Optimization*, *10*(2), 120-146.

Chemla, D., Meunier, F., Pradeau, T., Calvo, R. W., & Yahiaoui, H. (2013b). Self-service bike sharing systems: Simulation, repositioning, pricing. Retrieved from https://hal-univ-paris13.archives-ouvertes.fr/file/index/docid/824078/filename/RealTime-BikeSharing_final.pdf [access on 27 March 2018].

Cherry, C. R., Weinert, J. X., & Xinmiao, Y. (2009). Comparative environmental impacts of electric bikes in China. *Transportation Research Part D: Transport and Environment*, *14*(5), 281-290.

Chiariotti, F., Pielli, C., Zanella, A., & Zorzi, M. (2018). A dynamic approach to rebalancing bike-sharing systems. *Sensors*, *18*, 512.

Chow, J. Y. J., & Sayarshad, H. R. (2014). Symbiotic network design strategies in the presence of coexisting transportation networks. *Transportation Research Part B: Methodological*, *62*, 13-34.

Chung, H., Freund, D., & Shmoys, D. B. (2018). Bike Angels: An analysis of Citi Bike's incentive program. In *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies*, *5*, ACM.

Conrow, L., Murray, A. T., & Fischer, H. A. (2018). An optimization approach for equitable bicycle share station siting. *Journal of Transport Geography*, *69*, 163-170.

Contardo, C., Morency, C., & Rousseau, L. M. (2012). Balancing a dynamic public bike-sharing system (*Vol. 4*). CIRRELT.

Cruz, F., Subramanian, A., Bruck, B. P., & Iori, M. (2017). A heuristic algorithm for a single vehicle static bike sharing rebalancing problem. *Computers and Operations Research*, *79*, 19-33.

Datner, S., Raviv, T., Tzur, M., & Chemla, D. (2019). Setting inventory levels in a bike sharing network. *Transportation Science, 53*(1), 62–76.

Dell'Amico, M., Hadjicostantinou, E., Iori, M., & Novellani, S. (2014). The bike sharing rebalancing problem: Mathematical formulations and benchmark instances. *Omega*, *45*, 7-19.

Dell'Amico, M., Iori, M., Novellani, S., & Stützle, T. (2016). A destroy and repair algorithm for the bike sharing rebalancing problem. *Computers and Operations Research*, *71*, 149-162.

Dell'Amico, M., Iori, M., Novellani, S., & Subramanian, A. (2018). The bike sharing rebalancing problem with stochastic demands. *Transportation Research Part B: Methodological*, *118*, 362-380.

Di Gaspero, L., Rendl, A., & Urli, T. (2013a). A hybrid ACO+CP for balancing bicycle sharing systems. In *Hybrid Metaheuristics* (pp. 198-212). Springer Berlin Heidelberg.

Di Gaspero, L., Rendl, A., & Urli, T. (2013b). Constraint-based approaches for balancing bike sharing systems. In *Principles and Practice of Constraint Programming* (pp. 758-773). Springer Berlin Heidelberg.

Di Gaspero, L., Rendl, A., & Urli, T. (2016). Balancing bike sharing systems with constraint programming. *Constraints*, *21*(2), 318-348.

Dill, J., & McNeil, N. (2013). Four types of cyclists? Examination of typology for better understanding of bicycling behavior and potential. *Transportation Research Record: Journal of the Transportation Research Board*, *2387*, 129-138.

Duthie, J., & Unnikrishnan, A. (2014). Optimization framework for bicycle sharing service design. *Journal of*

Transportation Engineering, *140*(7), 04014028.

Ehrgott, M., Wang, J. Y., Raith, A., & Houtte, C. V. (2012). A bi-objective cyclist route choice model. *Transportation Research Part A: Policy and Practice*, *46*(4), 652-663.

Erdoğan, G., Laporte, G., and Calvo, R. W. (2014). The static bicycle relocation problem with demand intervals. *European Journal of Operational Research*, *238*(2), 451-457.

Erdoğan, G., Battarra, M., & Calvo, R. W. (2015). An exact algorithm for the static rebalancing problem arising in bicycle sharing systems. *European Journal of Operational Research*, *245*(3), 667-679.

Espegren, H. M., Kristianslund, J., Andersson, H., & Fagerholt, K. (2016). The static bicycle repositioning problem-Literature survey and new formulation. In *International Conference on Computational Logistics* (pp. 337-351). Springer International Publishing.

Fishman, E., Washington, S., & Haworth, N. (2013). Bike share: A synthesis of the literature. *Transport Reviews*, *33*(2), 148-165.

Fishman, E., Washington, S., & Haworth, N. (2014). Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transportation Research Part D: Transport and Environment*, *31*, 13-20.

Fishman, E., & Cherry, C. (2016). E-bikes in the mainstream: Reviewing a decade of research. *Transport Reviews*, *36*(1), 72-91.

Forma, I. A., Raviv, T., & Tzur, M. (2015). A 3-step math heuristic for the static repositioning problem in bike-sharing systems. *Transportation Research Part B: Methodological*, *71*, 230-247.

Frade, I., & Ribeiro, A. (2015). Bike-sharing stations: A maximal covering location approach. *Transportation Research Part A: Policy and Practice*, *82*, 216-227.

Fricker, C., & Gast, N. (2016). Incentives and redistribution in homogeneous bike-sharing systems with stations of finite capacity. *EURO Journal on Transportation and Logistics*, *5*(3), 261-291.

Friedrich, M., & Noekel, K. (2017). Modeling intermodal networks with public transport and vehicle sharing systems. *EURO Journal on Transportation and Logistics*, *6*(3), 271-288.

Fyhri, A., & Fearnley, N. (2015). Effects of e-bikes on bicycle use and mode share. *Transportation Research Part D: Transport and Environment*, *36*, 45-52.

Garcia-Gutierrez, J., Romero-Torres, J., & Gaytan-Iniestra, J. (2014). Dimensioning of a bike sharing system (BSS): A study case in Nezahualcoyotl, Mexico. *Procedia-Social and Behavioral Sciences*, *162*, 253-262.

García-Palomares, J. C., Gutiérrez, J., & Latorre, M. (2012). Optimizing the location of stations in bike-sharing programs: A GIS approach. *Applied Geography*, *35*(1), 235-246.

Geller, R. (2006). *Four Types of Cyclists*. Portland Bureau of Transportation, Portland, OR. Retrieved from https://www.portlandoregon.gov/transportation/article/264746 [access on 27 March 2018].

Ghosh, S., & Varakantham, P. (2017). Incentivizing the use of bike trailers for dynamic repositioning in bike sharing systems, In *Proceedings of the Twenty-Seventh International Conference on Automated Planning and Scheduling* (*ICAPS 2017*) (pp. 373-381), AAAI.

Ghosh, S., Varakantham, P., Adulyasak, Y., & Jaillet, P. (2017). Dynamic repositioning to reduce lost demand in bike sharing systems. *Journal of Artificial Intelligence Research*, *58*, 387-430.

Haider, Z., Nikolaev, A., Kang, J. E., & Kwon, C. (2018). Inventory rebalancing through pricing in public bike sharing systems. *European Journal of Operational Research*, *270*(1), 103-117.

Ho, S. C., & Szeto, W. Y. (2014). Solving a static repositioning problem in bike-sharing systems using iterated tabu search. *Transportation Research Part E: Logistics and Transportation Review*, *69*, 180-198.

Ho, S. C., & Szeto, W. Y. (2017). A hybrid large neighborhood search for the static multi-vehicle bike-repositioning problem. *Transportation Research Part B: Methodological*, *95*, 340-363.

Hood, J., Sall, E., & Charlton, B. (2011). A GPS-based bicycle route choice model for San Francisco, California. *Transportation Letters*, *3*(1), 63-75.

Institute for Transportation & Development Policy (2013). *The Bike-Share Planning Guide*. Institute for Transportation & Development Policy.

Jensen, P., Rouquier, J. B., Ovtracht, N., & Robardet, C. (2010). Characterizing the speed and paths of shared bicycle use in Lyon. *Transportation Research Part D: Transport and Environment*, *15*(8), 522-524.

Ji, S., Cherry, C. R., Han, L. D., & Jordan, D. A. (2014). Electric bike sharing: Simulation of user demand and system availability. *Journal of Cleaner Production*, *85*, 250-257.

Kadri, A. A., Kacem, I., & Labadi, K. (2016). A branch-and-bound algorithm for solving the static rebalancing problem in bicycle-sharing systems. *Computers and Industrial Engineering*, *95*, 41-52.

Kadri, A. A., Kacem, I., & Labadi, K. (2019). Lower and upper bounds for scheduling multiple balancing vehicles in bicycle-sharing systems. *Soft Computing*, *23*(14), 5945-5966.

Kang, L., & Fricker, J. D. (2013). Bicyclist commuters' choice of on-street versus off-street route segments. *Transportation*, *40*(5), 887-902.

Kaspi, M., Raviv, T., & Tzur, M. (2014). Parking reservation policies in one-way vehicle sharing systems. *Transportation Research Part B: Methodological*, *62*, 35-50.

Kaspi, M., Raviv, T., & Tzur, M. (2016a). Detection of unusable bicycles in bike-sharing systems. *Omega*, *65*, 10-16.

Kaspi, M., Raviv, T., Tzur, M., & Galili, H. (2016b). Regulating vehicle sharing systems through parking reservation policies: Analysis and performance bounds. *European Journal of Operational Research*, *251*(3), 969-987.

Kaspi, M., Raviv, T., & Tzur, M. (2017). Bike-sharing systems: User dissatisfaction in the presence of unusable bicycles. *IISE Transactions*, *49*(2), 144-158.

Klobucar, M. S., & Fricker, J. D. (2007). Network evaluation tool to improve real and perceived bicycle safety. *Transportation Research Record: Journal of the Transportation Research Board*, *2031*, 25-33.

Kloimüllner, C., Papazek, P., Hu, B., Raidl, G. R. (2014). Balancing bicycle sharing systems: An approach for the dynamic case. In *Evolutionary Computation in Combinatorial Optimization* (pp. 73-84), Springer, Berlin Heidelberg.

Kloimüllner, C., & Raidl, G. R. (2017). Full-load route planning for balancing bike sharing systems by logic-based Benders decomposition. *Networks*, *69*, 270-289.

Krizec, K. J. (2007). Estimating the economic benefits of bicycling and bicycle facilities: An interpretive review and proposed methods. In *Essays on Transport Economics* (pp. 219-248). Physica-Verlag HD.

Krizek, K., & Stonebraker, E. (2011). Assessing options to enhance bicycle and transit integration. *Transportation Research Record: Journal of the Transportation Research Board*, *2217*, 162-167.

Kumar, A. A., Kang, J. E., Kwon, C., & Nikolaev, A. (2016). Inferring origin-destination pairs and utility-based travel preferences of shared mobility system users in a multi-modal environment. *Transportation Research Part B: Methodological*, *91*, 270-291.

Langford, B., Cherry, C., Yoon, T., Worley, S., & Smith, D. (2013). North America's first E-Bikeshare: A year of experience. *Transportation Research Record: Journal of the Transportation Research Board*, *2387*, 120-128.

Larsen, J., Patterson, Z., & El-Geneidy, A. (2013). Build it. But where? The use of geographic information systems in identifying locations for new cycling infrastructure. *International Journal of Sustainable Transportation*, *7*(4), 299-317.

Laporte, G., Meunier, F., & Calvo, R. W. (2015). Shared mobility systems. *4OR*, *13*(4), 341-360.

Laporte, G., Meunier, F., & Calvo, R. W. (2018). Shared mobility systems: An updated survey. *Annals of Operations Research*, *271*(1), 105-126.

Leclaire, P., & Couffin, F. (2018). Method for static rebalancing of a bike sharing system. *IFAC-PapersOnLine*, *51*(11), 1561-1566.

Legros, B. (2019). Dynamic repositioning strategy in a bike-sharing system; how to prioritize and how to rebalance a bike station. *European Journal of Operational Research*, *272*(2), 740-753.

Li, Y., Szeto, W. Y., Long, J., & Shui, C. S. (2016). A multiple type bike repositioning problem. *Transportation Research Part B: Methodological*, *90*, 263-278.

Li, Z. C., Yao, M. Z., Lam, W. H. K., Sumalee, A., & Choi, K. (2015). Modeling the effects of public bicycle schemes in a congested multi-modal road network. *International Journal of Sustainable Transportation*, *9*(4), 282-297.

Lin, J. H., & Chou, T. C. (2012). A geo-aware and VRP-based public bicycle redistribution system. *International Journal of Vehicular Technology*. Article ID 963427, 14 pages.

Lin, J. R., & Yang, T. H. (2011). Strategic design of public bicycle sharing systems with service level constraints. *Transportation Research Part E: Logistics and Transportation Review*, *47*(2), 284-294.

Lin, J. R., Yang, T. H., & Chang, Y. C. (2013). A hub location inventory model for bicycle sharing system design: Formulation and solution. *Computers and Industrial Engineering*, *65*(1), 77-86.

Lin, J. J., & Yu, C. J. (2013). A bikeway network design model for urban areas. *Transportation*, *40*(1), 1-24.

Liu, Y., Szeto, W. Y., & Ho, S. C. (2018). A static free-floating bike repositioning problem with multiple heterogeneous vehicles, multiple depots, and multiple visits. *Transportation Research Part C: Emerging Technologies*, *92*, 208-242.

Lu, C. C. (2016). Robust multi-period fleet allocation models for bike-sharing systems. *Networks and Spatial Economics*, *16*(1), 61-82.

Maggioni, F., Cagnolari, M., Bertazzi, L., & Wallace, S. W. (2019). Stochastic optimization models for a bike-sharing problem with transshipment. *European Journal of Operational Research*, *276*(1), 272-283.

Mahmassani, H. S., & Chang, G. L. (1987). On boundedly rational user equilibrium in transportation systems. *Transportation Science*, *21*(2), 89-99.

Martinez, L. M., Caetano, L., Eiró, T., & Cruz, F. (2012). An optimisation algorithm to establish the location of stations of a mixed fleet biking system: An application to the city of Lisbon. *Procedia-Social and Behavioral Sciences*, *54*, 513-524.

Meddin, R., & DeMaio, P. (2020). The bike-sharing world map. Retrieved from http://www.bikesharingworld.com/ [access on 16 March 2020].

Menghini, G., Carrasco, N., Schüssler, N., & Axhausen, K. W. (2010). Route choice of cyclists in Zurich. *Transportation Research Part A: Policy and Practice*, *44*(9), 754-765.

Mesbah, M., Thompson, R., & Moridpour, S. (2012). Bilevel optimization approach to design of network of bike lanes. *Transportation Research Record: Journal of the Transportation Research Board*, *2284*, 21-28.

Molin, E., & Maat, K. (2015). Bicycle parking demand at railway stations: Capturing price-walking trade offs. *Research in Transportation Economics*, *53*, 3-12.

Nair, R., Miller-Hooks, E., Hampshire, R. C., & Bušić, A. (2013). Large-scale vehicle sharing systems: Analysis of Vélib'. *International Journal of Sustainable Transportation*, *7*(1), 85-106.

Neumann-Saavedra, B. A., Vogel, P., & Mattfeld, D. C. (2015). Anticipatory service network design of bike sharing systems. *Transportation Research Procedia*, *10*, 355-363.

Neumann-Saavedra, B. A., Crainic, T. G., Gendron, B., Mattfeld, D. C., & Römer, M. (2016). Service network design of bike sharing systems with resource constraints. In *International Conference on Computational Logistics* (pp. 352-366). Springer International Publishing.

O'Brien, L., & Szeto, W. Y. (2007). The discrete network design problem over time. *HKIE Transactions*, *14*(4), 47-55.

Pal, A., & Zhang, Y. (2017). Free-floating bike sharing: Solving real-life large-scale static rebalancing problems. *Transportation Research Part C: Emerging Technologies*, *80*, 92-116.

Papazek, P., Raidl, G. R., Rainer-Harbach, M., & Hu, B. (2013). A PILOT/VND/GRASP hybrid for the static balancing of public bicycle sharing systems. In *International Conference on Computer Aided Systems Theory* (pp. 372-379), Springer Berlin Heidelberg.

Papazek, P., Kloimüllner, C., Hu, B., & Raidl, G. R. (2014). Balancing bicycle sharing systems: An analysis of path relinking and recombination within a GRASP hybrid. In *Parallel Problem Solving from Nature – PPSN XIII* (pp. 792-801). Springer International Publishing.

Park, C., & Sohn, S. Y. (2017). An optimization approach for the placement of bicycle-sharing stations to reduce short car trips: An application to the city of Seoul. *Transportation Research Part A: Policy and Practice*, *105*, 154-166.

Pfrommer, J., Warrington, J., Schildbach, G., & Morari, M. (2014). Dynamic vehicle redistribution and online price incentives in shared mobility systems. *IEEE Transactions on Intelligent Transportation Systems*, *15*(4), 1567-1578.

Pucher, J., Buehler, R., & Seinen, M. (2011). Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies. *Transportation Research Part A: Policy and Practice*, *45*(6), 451-

475.

Raidl, G.R., Hu, B., Rainer-Harbach, M., & Papazek, P. (2013). Balancing bicycle sharing systems: Improving a VNS by efficiently determining optimal loading operations. In *Hybrid Metaheuristics* (pp. 130-143). Springer Berlin Heidelberg.

Raimbault, J. (2015). User-based solutions for increasing level of service in bike-sharing transportation systems. In *Complex Systems Design & Management* (pp. 31-44). Springer, Cham.

Rainer-Harbach, M., Papazek, P., Hu, B. and Raidl, G. R. (2013). Balancing bicycle sharing systems: A variable neighborhood search approach. In *European Conference on Evolutionary Computation in Combinatorial Optimization* (pp. 121-132), Springer Berlin Heidelberg.

Rainer-Harbach, M., Papazek, P., Raidl, G. R., Hu, B., & Kloimüllner, C. (2015). PILOT, GRASP, and VNS approaches for the static balancing of bicycle sharing systems. *Journal of Global Optimization*, *63*(3), 597-629.

Raviv, T., & Kolka, O. (2013). Optimal inventory management of a bike-sharing station. *IIE Transactions*, *45*(10), 1077-1093.

Raviv, T., Tzur, M., & Forma, I. A. (2013). Static repositioning in a bike-sharing system: Models and solution approaches. *EURO Journal on Transportation and Logistics*, *2*(3), 187-229.

Reiss, S., & Bogenberger, K. (2017). A relocation strategy for Munich's bike sharing system: Combining an operator-based and a user-based scheme. *Transportation Research Procedia*, *22*, 105-114.

Regue, R., & Recker, W. (2014). Proactive vehicle routing with inferred demand to solve the bikesharing rebalancing problem. *Transportation Research Part E: Logistics and Transportation Review*, *72*, 192-209.

Ricci, M. (2015). Bike sharing: A review of evidence on impacts and processes of implementation and operation. *Research in Transportation Business and Management*, *15*, 28-38.

Rixey, R. (2013). Station-level forecasting of bikesharing ridership: Station network effects in three US systems. *Transportation Research Record: Journal of the Transportation Research Board*, *2387*, 46-55.

Romero, J. P., Ibeas, A., Moura, J. L., Benavente, J., & Alonso, B. (2012). A simulation-optimization approach to design efficient systems of bike-sharing. *Procedia-Social and Behavioral Sciences*, *54*, 646-655.

Ruch, C., Warrington, J., & Morari, M. (2014). Rule-based price control for bike sharing systems. In: *Proceedings of 2014 European Control Conference (ECC)*, 708-713.

Rudloff, C., & Lackner, B. (2014). Modeling demand for bikesharing systems: Neighboring stations as source for demand and reason for structural breaks. *Transportation Research Record: Journal of the Transportation Research Board*, *2430*, 1-11.

Rybarczyk, G., & Wu, C. (2010). Bicycle facility planning using GIS and multi-criteria decision analysis. *Applied Geography*, *30*(2), 282-293.

Sayarshad, H., Tavassoli, S., & Zhao, F. (2012). A multi-periodic optimization formulation for bike planning and bike utilization. *Applied Mathematical Modelling*, *36*, 4944-4951.

Schuijbroek, J., Hampshire, R. C., & Van Hoeve, W. J. (2017). Inventory rebalancing and vehicle routing in bike sharing systems. *European Journal of Operational Research*, *257*(3), 992-1004.

Shaheen, S. A., Martin, E. W., & Cohen, A. P. (2013). Public bikesharing and modal shift behavior: A comparative study of early bikesharing systems in North America. *International Journal of Transport*, *1*(1), 35-53.

Shaheen, S. A., Martin, E. W., Cohen, A. P., Chan, N. D., & Pogodzinsk, M. (2014). Public bikesharing in North America during a period of rapid expansion: Understanding business models, industry trends and user impacts, *MTI Report 12-29*, Mineta Transportation Institute Publications.

Shelat, S., Huisman, R., & van Oort, N. (2018). Analysing the trip and user characteristics of the combined bicycle and transit mode. *Research in Transportation Economics*, *69*, 68-76.

Shu, J., Chou, M. C., Liu, Q., Teo, C. P., & Wang, I. L. (2013). Models for effective deployment and redistribution of bicycles within public bicycle-sharing systems. *Operations Research*, *61*(6), 1346-1359.

Shui, C. S. (2017). *Development of a multi-type bike repositioning model with exact loading and unloading strategies*. Ph.D. Thesis, The University of Hong Kong.

Shui, C. S., & Szeto, W. Y. (2018). Dynamic green bike repositioning problem–A hybrid rolling horizon artificial bee colony algorithm approach. *Transportation Research Part D: Transport and Environment*, *60*, 119-136.

Singla, A., Santoni, M., Bartók, G., Mukerji, P., Meenen, M., & Krause, A. (2015). Incentivizing users for balancing bike sharing systems. In *Proceedings of Twenty-Ninth AAAI Conference of Artificial Intelligence*, 723-729.

Smith, H. (2011). *A Mathematical Optimization Model for a Bicycle sharing service Design Considering Bicycle Level of Service.* Doctoral dissertation, University of Maryland, College Park.

Sohn, K. (2011). Multi-objective optimization of a road diet network design. *Transportation Research Part A: Policy and Practice*, *45*(6), 499-511.

Szeto, W. Y., Liu, Y., & Ho, S. C. (2016). Chemical reaction optimization for solving a static bike repositioning problem. *Transportation Research Part D: Transport and Environment*, *47*, 104-135.

Szeto, W. Y., & Lo, H. K. (2008). Time-dependent transport network improvement and tolling strategies. *Transportation Research Part A: Policy and Practice*, *42*(2), 376-391.

Szeto, W. Y., & Shui, C. S. (2018). Exact loading and unloading strategies for the static multi-vehicle bike repositioning problem. *Transportation Research Part B: Methodological*, *109*, 176-211.

Tang, Y., & Dai, B. R. (2018). A partial demand fulfilling capacity constrained clustering algorithm to static bike rebalancing problem. In *Industrial Conference on Data Mining* (pp. 240-253). Springer, Cham.

Vogel, P., Neumann-Saavedra, B. A., & Mattfeld, D. C. (2014). A hybrid metaheuristic to solve the resource allocation problem in bike sharing systems. In *Hybrid Metaheuristics* (pp. 16-29). Springer International Publishing.

Vogel, P. (2016). *Service Network Design of Bike Sharing Systems: Analysis and Optimization*. Springer International Publishing.

Wang, J., Tsai, C.-H., & Lin, P.-C. (2016). Applying spatial-temporal analysis and retail location theory to public bikes site selection in Taipei. *Transportation Research Part A: Policy and Practice*, *94*, pp. 45-61.

Wang, Y., & Szeto, W. Y. (2018). Static green repositioning in bike sharing systems with broken bikes. *Transportation Research Part D: Transport and Environment*, *65*, 438-457.

Wiersma, B. (2010). Bicycle sharing system: Role, effects and application to Plymouth. Master Thesis, University of Groningen. Retrieved from https://www.rug.nl/research/portal/files/14446525/EES-2010-102M_BoukeWiersma.pdf. [access on 27 March 2018].

Woodcock, J., Tainio, M., Cheshire, J., O'Brien, O., & Goodman, A. (2014). Health effects of the London bicycle sharing system: Health impact modelling study. *BMJ*, *348*, g425.

Yan, S., Lin, J. R., Chen, Y. C., & Xie, F. R. (2017). Rental bike location and allocation under stochastic demands. *Computers and Industrial Engineering*, *107*, 1-11.

Yan, S., Lu, C. C., & Wang, M. H. (2018). Stochastic fleet deployment models for public bicycle rental systems. *International Journal of Sustainable Transportation*, *12*(1), 39-52.

Zhang, D., Yu, C., Desai, J., Lau, H. Y. K., & Srivathsan, S. (2017). A time-space network flow approach to dynamic repositioning in bicycle sharing systems. *Transportation Research Part B: Methodological*, *103*, 188-207.

Appendix: Tables 2-5

Table 2 A summary of the studies of strategic BSPPs

First author	Year	Problem	Objective functions	Major constraints	Applications	Specialties
Sohn	2011	Bikeway	Average time taken for motorists to travel a unit distance; automobile share	Budget	BM	Variable mode share
Smith	2011	Bikeway	Weighted sum of the travel distance of bicycle trips and the score for the level of service of bikeways	Budget, level of service for bike paths	Ex: Baltimore	Bicycle level of service
Mesbah	2012	Bikeway	Weighted sum of total travel distance on bikeways and total travel time by car	Budget	AI	Bicycle congestion
Lin	2013	Bikeway	Cyclist risk; cyclists' comfort; service coverage; adverse impacts of the bikeway network on traffic	Budget	Ex: Taipei	Multiple bikeway types
Duthie	2014	Bikeway	Total cost of improving roadway segments and intersections to a desired suitable level for biking	Maximal path length	Ex: Austin	Length constraint
Romero	2012	Bicycle station	Number of bicycle users	Station capacity	Ex: Santander	Combined modal split-assignment model, micro-simulation

Garcia-Gutierrez	2014	Bicycle station	Sum of the costs of private traffic users, public transportation users, and bike users, and the operating costs of the public transportation system and the BSS	Operational and physical constraints of the transport modes	Ex: Nezahualcoyotl	Bi-level, modal split
Frade	2015	Bicycle station	Demand coverage	Budget, station capacity, and bike availability	Ex: Coimbra	Multi-period supplementary budget[1]
Park	2017	Bicycle station	Total travel cost between demand sources and their closest bicycle stations/maximal demand coverage by facilities	--	Ex: Seoul	--
Çelebi	2018	Bicycle station	Total unsatisfied demand	At least one station per demand location; station capacity	Ex: Istanbul	Explicit allocation of demand locations to stations
Conrow	2018	Bicycle station	Total bicycle sharing service coverage; potential user demand coverage	--	Ex: Phoenix	--
Caggiani	2019	Bicycle station	Weighted sum of the number of lost users, zero-vehicle time, and full-port time	Budget, station capacity	AI	Spatiotemporal clustering of

[1] It is the budget given by the provider of the system to cover losses resulting from the shortfall between its operating costs and revenue from the subscription fees

			(duration of the station to be full)			demand
Lin	2011	Mixed	Sum of travel costs, the setup costs for stations and bike lanes, the penalty costs for uncovered demand, bicycle stock costs, and safety stock costs	--	AI	Stock and safety stock costs
Lin	2013	Mixed	Sum of travel costs, the setup costs for stations, the penalty costs for uncovered demand, and bike inventory costs.	Minimum bike inventory per station	AI	--

Table 3 A summary of the studies of tactical BSPPs

First author	Year	Problem	Objective functions	Major constraints	Applications	Specialties
Benchimol	2011	SBRP	Total travel cost	Perfect balance	TH	--
Lin	2012	SBRP	Total transportation time or distance	Service time	Ex: Kaohsiung, Washington DC	Actual path optimization
Chemla	2013a	SBRP	Total travel cost	Perfect balance, multiple visits	BM	Buffer station
Di Gaspero	2013a	SBRP	(b)	Service time, monotonicity	Ex: Vienna	--
Di Gaspero	2013b	SBRP	(a)	Service time, monotonicity	Ex: Vienna	Step model
Papazek	2013	SBRP	(b)	(c)	Ex: Vienna	--
Raidl	2013	SBRP	(b)	(c)	Ex: Vienna	Optimal loading instruction
Rainer-Harbach	2013	SBRP	(b)	(c)	Ex: Vienna	Algorithm comparisons
Raviv	2013	SBRP	Weighted sum of total travel time and the total penalties for bike or bike rack shortages	Service time, at most a single visit	Ex: Paris, Washington DC	Time-, arc-, and sequence-indexed models
Angeloudis	2014	SBRP	(d)	Dual-bounded service time, at least one visit	Ex: London	Separate and iterative routing-loading decisions

Dell'Amico	2014	SBRP	Total travel cost	Generalized subtour elimination, exactly one visit	Ex: 22 cities worldwide	Four mathematical models
Erdoğan	2014	SBRP	Total travel and (bicycle) handling cost	Demand interval requirement	BM	Demand intervals
Ho	2014	SBRP	Total penalty cost	Multiple depot visits, non-empty vehicle return to depots, service time	BM, Ex: Paris	--
Papazek	2014	SBRP	(b)	Multiple visits, service time	Ex: Vienna	--
Erdoğan	2015	SBRP	Total travel cost	Perfect balance, multiple visits	BM, Ex: 17 cities worldwide	Separation algorithm, buffer stations
Forma	2015	SBRP	Weighted sum of total travel time and the penalty cost for bike or bike rack shortages	Service time, at most a single visit	Ex: Paris	3-step math heuristic
Rainer-Harbach	2015	SBRP	(b)	(c)	Ex: Vienna	Algorithm comparisons
Alvarez-Valdes	2016	SBRP	Weighted sum of total service time and the coefficient of variations of the duration of the routes	Complete removal of broken bikes, perfect balance	Ex: Palma	Broken bikes

Dell'Amico	2016	SBRP	Total travel cost	Generalized subtour elimination, exactly one visit	Ex: 32 cities worldwide	New solution method
Di Gaspero	2016	SBRP	(b)	(c)	Ex: Vienna, New York City; BM from 7 countries	Step model and routing model
Espegren	2016	SBRP	Weigthed sum of the deviation between the final and target inventory levels and total service time (i.e., driving, parking, and handling times)	Service time, at most one visit	Ex: Oslo	Heterogeneous bicycle fleet
Kadri	2016	SBRP	Sum of the product of the absolute deviation of the station inventory level from the acceptable level and the station imbalance time	Exactly one visit	AI	No loading strategies
Li	2016	SBRP	Sum of vehicle travel cost, the total imbalance penalties for all bike types, and the total substitution and occupancy penalties	Service time, substitution, occupancy	AI; BM	Multiple bike types
Szeto	2016	SBRP	Weighted sum of total unsatisfied bike demand and the	Service time	Ex: Vienna	New solution method

			total operational time of all vehicles			
Cruz	2017	SBRP	Route cost	Perfect balance	BM	Algorithm comparisons, buffer stations
Ho	2017	SBRP	Weighted sum of the total travel time and the total penalties for bike and bike rack shortages	Service time, at most a single visit	BM	Algorithm comparisons
Kloimüllner	2017	SBRP	Total number of station visits	Full vehicle load, service time	Ex: Vienna	Comparisons between full load and partial load
Pal	2017	SBRP	Makespan of the rebalancing fleet (Maximum rebalancing time)	Perfect balance, multiple visits	BM; Ex: Tampa, Chicago	Decomposed network
Arabzad	2018	SBRP	Sum of total travel cost and repositioning truck implementation cost	Single visit, multiple depots, heterogeneous repositioning fleet, perfect balance, distance	Ex: Bari	Two bike types, multiple periods
Bulhões	2018	SBRP	Total travel time	Service time, multiple visits	Ex: 23 cities worldwide	--
Dell'Amico	2018	SBRP	Travel cost plus the total penalty	Visit all stations once	Ex: Reggio	Stochastic

			cost for an insufficient or excess number of bikes of each station		Emilia, Washington DC, Arlington County, Chicago	demand
Leclaire	2018	SBRP	Sum of the total unmet demands of bike and bike docks	Service time	AI	Unified Modelling Language class diagram
Liu	2018	SBRP	Weighted sum of total unmet bike demand, the inconvenience of getting a bike, and vehicles' total operational time	Heterogeneous repositioning fleet, multiple visits, multiple depots	Ex: Vienna	Heterogeneous repositioning fleet
Szeto	2018	SBRP	Weighted sum of the positive deviation from the tolerance of total demand dissatisfaction and the service time	Exactly one visit	BM	Exact loading and unloading strategies
Tang	2018	SBRP	Weighted sum of the total travel time and the total penalties for bike and bike rack shortages	Service time, at most a single visit	Ex: Paris	Algorithm comparison
Wang	2018	SBRP	Total CO_2 emissions of all vehicles	Perfect balance, multiple visits, complete removal of broken bikes	AI; Ex: Vienna	Broken bikes, emission objective

Kadri	2019	SBRP	Sum of the product of the absolute deviation of the station inventory level from the acceptable level and the station imbalance time	Single visit	AI	Algorithm comparison
Haider	2018	Incentives	Total number of unbalanced stations	--	Ex: Washington DC	Walking cost
Kaspi	2016b	Parking reservation	Sum of the total excess time of all selected itineraries and total waiting times (i.e., expected total excess time of all system users)	--	Ex: Washington DC, Alexandria, Arlington County, Montgomery County, Tel Aviv	Partial parking reservation

Note: (a) – weighted sum of total absolute deviation from the target number of bicycles and the total time required by all vehicles; (b) – weighted sum of the total absolute deviation from the target number of bicycles, the total number of loading/unloading quantities, and the overall time required by all vehicles; (c) – multiple visits, monotonicity, service time; (d) – this study solves the problem in two stages iteratively: the first stage objective function is the total travel time of all routes (including fixed service time at each station), while the second stage objective function is the total time of bikes spent in transit.

Table 4 A summary of the studies of operational BSPPs

First author	Year	Problem	Objective functions	Major constraints	Applications	Specialties
Raviv	2013	Inventory	User demand dissatisfaction	--	Ex: Tel Aviv	Single station
Kaspi	2016a	Inventory	Number of unusable bikes/lockers		Ex: Washington D.C.	Unusable bikes
Kaspi	2017	Inventory	Extended user dissatisfaction	--	Ex: Washington D.C.	Single station, both usable and unusable bikes
Datner	2019	Inventory	Total travel time of all users	--	Ex: Washington DC, Boston, Chicago	Decentralized decision making, demand spillover to nearby stations
Sayarshad	2012	DRS	Total benefit to the company	--	Ex: Tehran	--
Nair	2013	DRS	Total redistribution cost	Probabilistic level of service	Ex: Paris	Joint chance constraint
Shu	2013	DRS	Total expected rented bicycle flows minus the total relocation cost of empty bicycles	Proportionality	Ex: Singapore	
Vogel	2014	DRS	Sum of relocation costs and the costs for violating service levels in terms of insufficient	Safety buffer	Ex: Vienna	--

			bikes and bike racks			
Lu	2016	DRS	Sum of bike supply cost, holding cost, redistribution cost, and the penalty cost for losing customers	Fleet size	Ex: New Taipei City	Robustness
Neumann-Saavedra	2016	DRS	Service level	Budget, fleet size, fill level	Ex: San Francisco	Resource constraint
Vogel	2016	DRS	Sum of relocation costs and the costs for violating service levels in terms of insufficient bikes and bike racks	Safety buffer	AI; Ex: Vienna	--
Yan	2018	DRS	Expected cost/expected number of customers served	--	Ex: New Taipei City	Stochastic model
Maggioni	2019	DRS	Sum of the procurement cost for the assigned bikes, the expected cost for shortages and overflows, and the expected transshipment cost for repositioning bikes	--	Ex: Bergamo	Stochastic model
Caggiani	2012	DBRP	Total relocation and lost user costs	--	AI	Variable gap time
Contardo	2012	DBRP	Total shortage and excess of	At most one visit per	AI	--

			bicycles	period		
Caggiani	2013	DBRP	Total relocation and lost user cost	--	AI	Constant gap time
Chemla	2013b	DBRP	Mean number of users finding a bike per unit of time/probability of the first *m* users finding a bike	No roaming, infinite vehicle, and station capacities	AI	--
Kloimüllner	2014	DBRP	Weighted sum of the unfulfilled demands of both bikes and slots, absolute deviation from the target fill level, the total number of loading and unloading quantities, and total driving time	Service time	Ex: Vienna	Event-based notations
Pfrommer	2014	DBRP	Ratio of added utility per invested time	--	Ex: London	--
Regue	2014	DBRP	Weighted sum of utilities gained by visiting stations with large inefficiencies and stations with neighbor stations that are expected to have large inefficiencies in the future, and	--	Ex: Boston	Four-step design model, new performance measure; buffer station

			the normalized travel time for visiting buffering stations			
Brinkmann	2015	DBRP	Expected number of due date violations	Service time, multiple visits	Ex: Vienna	Markov decision process
Neumann-Saavedra	2015	DBRP	Sum of transportation cost and the recourse costs for penalizing service and allocation violations	Service tour constraint	Ex: Vienna	Concept of service tour
Brinkmann	2016	DBRP	Square of deviation between fill level and the target interval	Service time	Ex: Vienna	Fill intervals
Ghosh	2017	DBRP	Overall system profit	--	Ex: Washington DC, Boston	Comparison with static and online repositioning
Zhang	2017	DBRP	Sum of vehicle travel cost and total expected user dissatisfaction	At most one visit	Ex: Washington DC, Paris	Benchmark comparisons
Caggiani	2018	DBRP	Sum of the travel times of the vehicles, the travel times of the vehicle to cover the maximum width of the clusters, and the total loading and unloading times	--	AI	

Chiariotti	2018	DBRP	Weighted sum of the difference between the minimum survival times among all the stations after and before the repositioning operation and the operational cost of the vehicles	--	Ex: New York City	Survival time objective
Shui	2018	DBRP	Weighted sum of total unmet bike demand and the total fuel and CO_2 emission cost of the operating vehicle	Service time, multiple visits	Ex: Vienna	Emission objective
Brinkmann	2019	DBRP	Expected total unsatisfied demands of bikes and bike racks	--	Ex: Minneapolis	Dynamic lookahead
Legros	2019	DBRP	Long-run overall rate of the arrivals of unsatisfied users who cannot find available bikes and empty docks.	Infinite vehicle capacity	AI	Explicit optimal inventory level
Schuijbroek	2017	Inventory and DBRP	Makespan of the rebalancing fleet (Maximum tour length/cost)	Service level requirement	Ex: Boston, Washington DC	Cluster routing
Chemla	2013b	Incentives	Total travel cost of all users	--	AI	Dynamic pricing with multiple fixed

						intervals
Pfrommer	2014	Incentives	Weighted sum of the squared deviation from the optimal state and the squared cost caused by incentive payout	Payout bounds	Ex: London	Dynamic pricing with multiple fixed intervals
Singla	2015	Incentives	Service level	Budget	Ex: Boston	Posted-price model
Ghosh	2017	Incentives	Weighted difference in the reduced lost demand using bike trailers minus the increase in lost demand due to moving bikes using the trailers	Budget	Ex: Boston	--
Chung	2018	Incentives	Total reduction in out-of-stock events minus the total cost for the points awarded to bike angels	-	Ex. New York City	--
Fricker	2016	Best-of-two regulation	Proportion of problematic stations	Homogeneous fleet and station	AI	Best-of-two strategy
Kaspi	2014	Parking reservation	Total excess time spent by all users due to shortages of bikes and bike racks	Capacity	Ex: Tel Aviv	Complete parking reservation
Kaspi	2016b	Parking	Sum of the total excess time of	--	Ex: Washington DC,	Partial parking

	reservation	all selected itineraries and total waiting times	Alexandria, Arlington County, Montgomery County, Tel Aviv	reservation

Table 5 A summary of the studies of ML-BSPPs

First author	Year	Problem	Objective functions	Major constraints	Applications	Specialties
Martinez	2012	Station location and dynamic bike relocation	Net revenue	Depot capacity, fleet size	Ex: Lisbon	Three fare schemes, two bike types
Chow	2014	Station location and dynamic bike relocation	(Transit) Sum of travel costs and early/late arrival costs; (Bicycle) Sum of travel costs, relocation costs, and daily bike deployment costs	Budget, station capacity	AI; Ex: Toronto	Co-existing transportation networks
Yan	2017	Station location and dynamic bike relocation	Sum of the investment costs of the bike fleet, the fixed costs of bike rental stations, the expected operating costs, the expected costs of a shortage of bikes, and the expected costs of an excess of bikes; total demand coverage	--	Ex: New Taipei City	Stochastic model