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Summary

In the last decade, bike sharing systems have emerged in cities to propose a sustainable and convenient way to realize last mile trips. They can be with (station-based bike sharing systems, SBBSSs) or without stations (free-floating bike sharing systems, FFBSSs). With a FFBSS, users can find the closest bike available in the city thanks to an app on their phone, rent it, realize their trip, and lock the bike anywhere in the city. The FFBSS offers more flexibility to users than the SBBSS but brings some specific challenges, such as the disorderly parking, the congestion of sidewalks, the large number of bike locations, and the complex redistribution operations. The scientific literature has addressed those challenges and the FFBSS operations. We review it by tackling three main subjects. The first one focuses on discretizing the bike locations by dividing the geographical area where a FFBSS is active into zones. This operation is necessary because the number of bike locations is higher with a FFBSS than a SBBSS. The second subject consists in forecasting the rental demand in each zone, helping to satisfy user demand and to improve the utilization rate of the system. The last topic focuses on redistribution models, to maintain a desired quantity of bikes at each zone by moving bikes from one place to another. We conclude by highlighting the research directions in the field of FFBSS operations identified in the literature.

Keywords : free floating, dockless, bike sharing, operations

JEL Classification: R40, R41

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Operations for free-floating bike sharing systems: a literature review

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Abstract

In the last decade, bike sharing systems have emerged in cities to propose a sustainable and convenient way to realize last mile trips. They can be with (station-based bike sharing systems, SBBSSs) or without stations (free-floating bike sharing systems, FFBSSs). With a FFBSS, users can find the closest bike available in the city thanks to an app on their phone, rent it, realize their trip, and lock the bike anywhere in the city. The FFBSS offers more flexibility to users than the SBBSS but brings some specific challenges, such as the disorderly parking, the congestion of sidewalks, the large number of bike locations, and the complex redistribution operations. The scientific literature has addressed those challenges and the FFBSS operations. We review it by tackling three main subjects. The first one focuses on discretizing the bike locations by dividing the geographical area where a FFBSS is active into zones. This operation is necessary because the number of bike locations is higher with a FFBSS than a SBBSS. The second subject consists in forecasting the rental demand in each zone, helping to satisfy user demand and to improve the utilization rate of the system. The last topic focuses on redistribution models, to maintain a desired quantity of bikes at each zone by moving bikes from one place to another. We conclude by highlighting the research directions in the field of FFBSS operations identified in the literature.

Key words— free floating, dockless, bike sharing, operations

1 Introduction

The concept of sharing economy has emerged recently within different sectors. It consists in sharing products or services with other users instead of individually owning them (Möhlmann, 2015). With the availability of digital platforms, the number of applications of the sharing economy has increased in the sectors of tourism, rental of real estate, transportation, etc. with companies such as Airbnb, Uber, etc. (Gao & Li, 2020; Richardson, 2015). In this context, as well as with the increase of sustainability concerns, shared micro-mobility has notably emerged, with for instance the rental of bikes, scooters, and other low-speed modes (McKenzie, 2020; Shaheen & Cohen, 2019).

Among the micro-mobility systems, bike sharing systems (BSSs) offer a convenient way to realize last-mile trips. At first, the station-based bike sharing system (SBBSS) appeared, with several stations spread within the city where users can pick up and drop off bikes. Recently, the free-floating bike sharing system (FFBSS), without stations, has been developed thanks to the built-in GPS placed on bikes offering to track it in real-time (Pal & Zhang, 2017). With a FFBSS, users can find the closest bike available in the city thanks to an app on their phone. Then, they walk up to the bike and rent it. After realizing their trip, they can lock the bike anywhere within the system boundaries in the city.

FFBSS offer more flexibility to users as they may drop off the rented bikes where they want and reduce the start-up costs for the operator (Caggiani, Camporeale, Ottomanelli, & Szeto, 2018; Chen, Wang, Sun, Waygood, & Yang, 2020a). But it may lead to disorderly parking, the need for frequent redistribution of bikes to other locations, or the congestion of sidewalks (Cui, Kuby, Salon, & Thigpen, 2018; Wang, Yang, Wang, Douglas, & Su, 2021; Zhang, Lin, & Mi, 2019c). To deal with those challenges, operations such as demand forecasting and redistribution of the bicycle fleet are key to FFBSSs. They have been discussed in the literature but, to the best of our knowledge, no literature review exists to discuss, compare and synthesize the scientific knowledge about FFBSS operations. However, being an emerging topic, the number of papers about FFBSSs increases rapidly. Therefore, this paper presents a survey on FFBSS operations. Moreover, we identify the research directions that could be addressed in future research about FFBSS operations.

We selected scientific papers among those containing — i.e. in their title, abstract, and keywords — the following words: free floating or dockless; and sharing or share; and bike or bicycle. Among those papers, we identify three main subjects. They are the focus of this literature review on FFBSS operations.

The first subject relates to the division into zones of the geographical area where a FFBSS is active. A challenge induced by the free-floating aspect of those systems is the number of potential bike locations that is much higher than for a SBBSS (Liu, Szeto, & Ho, 2018; Liu & Tian, 2021; Mo, Liu, & Chan, 2021; Pal & Zhang, 2017). A way to deal with this complexity consists in discretizing the bike locations into zones. To do so, some authors use a fixed grid size (Ai et al., 2019; Caggiani et al., 2018; Zhang et al., 2019c), while others apply clustering techniques (Caggiani et al., 2018; Hua, Chen, Zheng, Cheng, & Chen, 2020b; Liu & Tian, 2021).

The second subject focuses on forecasting the rental demand in each zone, in terms of the number of bikes required at different moments of the day (Hua et al., 2020a). The demand forecasting is necessary to organize the redistribution activities afterward and thus helps satisfy user demand, improving the utilization rate of the system, and reducing the management costs (Ai et al., 2019; Caggiani, Ottomanelli, Camporeale, & Binetti, 2017; Guidon, Becker, & Axhausen, 2019).

The third main topic relates to redistribution activities. Redistribution consists in maintaining the desired quantity of bikes in each zone by moving bikes from one place to another (Benchimol et al., 2011; Chemla, Meunier, & Wolfler Calvo, 2013; Pal & Zhang, 2017). Redistribution is necessary because the bike distribution may turn out to be unbalanced in time and space, and congestion of city sidewalks may happen due to the possibility for users to park their bikes in unrestrained locations (Gao, Ji, Yan, Fan, & Guo, 2020; Jin & Tong, 2020; Pan, Cai, Fang, Tang, & Huang, 2019; Zhai, Liu, Du, & Wu, 2019).

Our paper is structured as follows. Section 2 presents the context in which FFBSSs evolve, the main advantages and challenges encountered with those systems. Sections 3, 4, and 5 present a literature review of the three main subjects discussed above: the division of the geographical area into zones, the FFBSS demand forecasting, and the redistribution. Then in Section 6, we summarize studies about other operational problems of FFBSSs: geofence parking, the initial implementation of a FFBSS, and the management of malfunctioning bikes. Then, Section 7 presents the research gaps highlighted in the literature, offering future research directions in the field of FFBSS operations. We conclude the paper in Section 8.

2 Context

Before reviewing in detail the three main operational problems of FFBSSs, we discuss a few topics to contextualize FFBSSs. Section 2.1 introduces the BSS. In Section 2.2, the FFBSS and its specifications are presented.

2.1 Bike Sharing System

In this section, we summarize the history and evolution of BSSs, and then discuss their benefits.

2.1.1 History and evolution of the BSS

The first BSS was introduced in Amsterdam in 1965, called "de Witte Fietsen". This name comes from the fact that bikes were painted in white and left free for public use in the city. Unfortunately, as this system had no locks, the white bikes were often stolen or vandalized (DeMaio, 2009; Shaheen, Guzman, & Zhang, 2010).

In the 1990s, the second generation of BSSs appeared, notably in Denmark, and used coin-deposit stations to avoid thefts. Users had to take a bike at a station and leave a small deposit in exchange. However, with no time limit for bike usage and the anonymity of the users, thefts kept occurring (DeMaio, 2009; Shaheen et al., 2010).

To solve theft issues, the third generation of BSSs relied on user identification through IT systems — i.e. characterized by smartcards to rent a bike, transaction kiosks at stations, and payment systems — offering greater control over bike usage (DeMaio, 2009; Shaheen et al., 2010). These BSSs were initially implemented in an English university in 1996 and then further developed in France (DeMaio, 2009). From that point, BSSs have progressively gained worldwide popularity. In 2008, third generation BSSs were present in Brazil, Chile, China, New Zealand, South Korea, Taiwan, and the U.S (DeMaio, 2009).

The fourth generation of BSSs is mainly characterized by the introduction of the free-floating BSS (FFBSS) (Chen, Lierop, & Ettema, 2020b; Shaheen et al., 2010). Several technological advancements allowed the introduction of FFBSSs. The first feature is that bikes are equipped with GPS offering the possibility to track them in real-time (Pal & Zhang, 2017; Parkes, Marsden, Shaheen, & Cohen, 2013). Secondly, the internet and communication technologies, smartphone applications in particular, allow users to easily check the availability of bikes (Gu, Kim, & Currie, 2019). For most FFBSSs, the phone application also allows to lock and unlock a bike and pay for the trip (Si, Shi, Wu, Chen, & Zhao, 2019). Electric bikes can also be associated with the fourth generation of BSSs (Gu et al., 2019; Shaheen et al., 2010).

BSSs became more and more popular in the last decade. The number of BSSs operating worldwide grew from 363 in 2010 to 1236 in 2016 and, in the same period, the bicycle fleets increased from 139,000 to 2,294,600 bikes (Gu et al., 2019; Meddin et al., 2021). In 2017, the number of BSSs increased to 1767 BSSs, due mainly to the expansion of FFBSSs in China (Meddin et al., 2021). China is by far the country with the most BSSs in the world, with 673 BSSs in 2021 (Meddin et al., 2021) — 221 million users and 16 million bikes in 2017 (Chen et al., 2020b; Gao & Li, 2020; Li, Wang, Zhang, Yun, & Yuan, 2018a). It is followed by the U.S. (174 BSSs), Germany (107 BSSs), Italy (104 BSSs), and France (70 BSSs) (Meddin et al., 2021). BSSs are thus prominently present in Europe (41%), China (35%) and North America (11%) (Meddin et al., 2021).

2.1.2 Benefits of the BSS

BSSs offer several benefits, firstly for their users. Using a BSS exempts users from owning a bike. Therefore, they don't have the drawbacks associated with bike ownership, such as cost and responsibility (Chen et al., 2020b; Gu et al., 2019; Pal & Zhang, 2017). Moreover, using a BSS instead of another transportation mode involves physical activity, which is good for the health (Chen et al., 2020b; DeMaio, 2009; Fishman, Washington, & Haworth, 2014; Si et al., 2019). Another benefit of BSSs is the fact that they can be used as a first mile / last mile connection to other public transport (DeMaio, 2009; Pal & Zhang, 2017; Parkes et al., 2013; Shaheen et al., 2010).

Furthermore, BSSs have a broad positive impact on users of other transportation modes and on society in general. BSSs benefit car users by reducing traffic congestion (Hirsch et al., 2019; Lazarus, Pourquier, Feng, Hammel, & Shaheen, 2020; Shaheen et al., 2010). It is also beneficial for the environment because BSSs are an emission-free way to commute, therefore it helps reduce pollution (Parkes et al., 2013; Shaheen et al., 2010).

2.2 Free-floating Bike Sharing System

In this section, we discuss FFBSSs specifically, by comparing them to SBBSSs and detailing their advantages and challenges.

2.2.1 Comparisons with the SBBSS

In the literature, several differences between SBBSSs and FFBSSs are identified. The first element relates to the duration and distance of the trips realized with both systems. Researchers disagree about whether trips are longer, in duration and distance, with SBBSSs (as argued by Ma et al. (2020)) or with FFBSSs (Lazarus et al., 2020; Li, Zhang, Du, & Yang, 2019). McKenzie (2018), argues that FFBSSs trips are probably shorter because users don't have to search for a bike station at the end of their trip. However, Ji, Ma, He, Jin, and Yuan (2020b) claim that both types of systems result in similar riding duration and distance. Lazarus et al. (2020) and Ma et al. (2020) compare the usage rate of a FFBSS and a SBBSS in a city and find that, indeed, the FFBSS has a greater usage rate with more trips realized in a day than the SBBSS.

Another distinction between FFBSSs and SBBSSs is the purpose of the trips realized with each system. According to Chen, Chen, Chen, and Cheng (2021b), Lazarus et al. (2020), Li et al. (2019), and McKenzie (2018), SBBSSs are more widely used by commuters while FFBSSs are rather used for leisure and non-commute activities. It implies that the demand is more variable for FFBSSs (Li et al., 2019). Some studies (Li et al., 2019; Ma et al., 2020) also distinguish the type of users for each system. They identify that elderly persons are more likely to use a SBBSS while young people and student groups are more likely to use a FFBSS.

The place and the population density where trips are realized are also of interest. Chen et al. (2021b) explain that both FFBSS and SBBSS usages are positively correlated with the population density and presence of restaurants. On the contrary, Ma et al. (2020) argue that the density of points of interest is positively correlated with FFBSS usage while it is the opposite for a SBBSS.

Another characteristic that differs between FFBSSs and SBBSSs is that FFBSSs are often managed by a private company while SBBSSs are more likely public-private partnerships or operating through advertising models (DeMaio, 2009; Hirsch et al., 2019). On the other hand, FFBSSs use almost exclusively "for-profit" models (Gu et al., 2019; Hirsch et al., 2019).

2.2.2 Benefits of the FFBSS

FFBSSs are not constrained by station limitations of SBBSSs that induce fixed locations, limited station capacity, and the need for the operator to place and build stations. This leads to various benefits for FFBSSs, besides those of BSSs in general (see Section 2.1.2).

The first benefit is system flexibility for users, as they may drop off the rented bikes where they want (Caggiani et al., 2018; Chen et al., 2020a; Gu et al., 2019; Soriguera & Jiménez-Meroño, 2020). In fact, compared to SBBSSs, flexibility and the fact that there is no need to ride to a station are the main reasons for FFBSS implementation. They can lock the bikes at their final destination, saving them time (Chen et al., 2020b; Kou & Cai, 2021; Pal & Zhang, 2017).

Another issue encountered with SBBSSs that does not occur with FFBSSs is the limited station capacity. With a SBBSS, a user who finishes his/her trip may identify on his/her Smartphone a station with vacant posts, ride to it, and then realize that the station is actually full because another user came in the meantime (Chen et al., 2020b; Pal & Zhang, 2017). It leads to a waste of time for the users. On the contrary, with FFBSSs, users may drop off their bikes without worrying about finding a vacant spot.

For operators, FFBSSs present advantages as well. As they do not have to build bike stations, the start-up investment is reduced (Caggiani et al., 2018; Pal & Zhang, 2017). Moreover, FFBSSs overcome the fact that the number of stations is often restricted by space limitations in a city (Chen et al., 2020b).

2.2.3 Challenges generated by the FFBSS

Besides the benefits that FFBSSs offer, the absence of stations generate several challenges that are summarized in the following.

Irregular parking. Leaving bikes on sidewalks leads to irregular parking behaviors, inducing a violation of pedestrian rights, obstruction of metro stations, and congestion of cycle paths (Gao & Li, 2020; Gu et al., 2019; Hirsch et al., 2019). To counter this problem, some studies suggest that local authorities should introduce regulations for better management and development of FFBSSs (Laa & Emberger, 2020; Rahim Taleqani, Vogiatzis, & Hough, 2020; Sun, Li, & Zuo, 2019; Xu, Bian, Rong, Wang, & Yin, 2019). Another solution to irregular parking behaviors consists in implementing geofence parking where users have to replace the rented bikes (Cheng, Guo, Chen, & Qin, 2019; Liu & Tian, 2021; Zhang et al., 2019c; Zhao & Ong, 2021), as detailed in Section 6.1.

Malfunctioning bikes. As bikes are spread throughout the city and not at bike stations, checking the condition of bikes is more difficult for FFBSS operators. Therefore, some bikes are damaged and abandoned, requiring maintenance, which is a loss for operators as well as for users (Chen et al., 2020a; Chen et al., 2020b; Usama, Shen, & Zahoor, 2019; Yin, Qian, & Shen, 2019). This issue and possible solutions are discussed in more detail in Section 6.3.

Vandalism. Given that bikes are left everywhere throughout the city, FFBSSs are more exposed to thefts and vandalism (Gao & Li, 2020; Gu et al., 2019; Laa & Emberger, 2020; Lan, Ma, Zhu, Mangalagiu, & Thornton, 2017).

Dispersion of bikes. Redistribution operations are more challenging with FFBSSs because bikes are not in restricted stations. Therefore, the average imbalance is increased for FFBSSs compared to SBBSSs (Caggiani et al., 2018; Kou & Cai, 2021; Liu & Tian, 2021; Soriguera & Jiménez-Meroño, 2020).

3 Dividing the geographical area

FFBSSs having no predefined stations, the number of exact bike locations is much greater, and potentially infinite, which brings a complexity that FFBSSs have to deal with (Liu & Tian, 2021; Mo et al., 2021; Pal & Zhang, 2017). Several studies aim at dividing into multiple zones the geographical area where a FFBSS is active. Some of these studies use a fixed division of the space, such as a fixed grid size or a fixed number of zones (see Section 3.1), while others apply clustering techniques (see Section 3.2).

3.1 Fixed division

To divide the geographical area where a FFBSS is active into zones, a first option consists in fixing a common size for these zones or fixing a number of zones. Table 1 lists the publications applying these methods as well as the zone size and the city studied.

A key question when the zone size is fixed is to decide this size. As seen in Table 1, this size varies from 500m squares to 4km squares but most studies choose a size between 150m and 1km. Fixing a specific zone size may induce some difficulties. The first one is to choose a size that represents reality. Users who want to rent a bike should be able to find one within reasonable walking distance. So, the radius of a zone may represent the distance that users are willing to walk to find a bike available. Walkable distances are said to be on average 400-500m (Liu & Tian, 2021). So, a higher size should be avoided. However, considering a small zone size increases the computational complexity. Moreover, too small cells may conduct to excessive variability while too large cells reduce traffic flows (Song, Zhang, Qin, & Ramli, 2021). Thus, it is necessary to find a good balance (Jin & Tong, 2020).

Various ways to fix this size exist, related to the length of the trips, or the range of the app. For example, Song et al. (2021) choose to divide the area into 300m squares because 80% of the trips realized are greater than 300m. Meanwhile, Yang, Ding, Qu, and Ran (2019) decide to apply a size of 1km squares because users may only see bikes within a radius of 1km around them on the app.

Another problem related to the zone size with FFBSSs, and known for other transportation problems, is the modifiable areal unit problem (MAUP) (Horner & Murray, 2002; Song et al., 2021). It means that the scale of the aggregation of spatial points leads to fluctuations in the outcomes (Liu & Tian, 2021; Manley, Flowerdew, & Steel, 2006; Song et al., 2021).

Instead of choosing a specific zone size, other studies fix the number of zones. Bao, Yu, and Wu (2019) divide the city of Shanghai (China) into a 5x5 grid, i.e. 25 zones. Reiss and Bogenberger (2015, 2016) consider the determination of zones as a facility location problem. They fix the number of zones to 40 and the zone size is proportional to the demand observed in the past.

Another solution for the MAUP is to rather apply clustering techniques to create zones, as discussed in the next section.

3.2 Clustering techniques

Clustering techniques can also be used to divide the geographical area of a FFBSS into zones. The purpose of clustering algorithms is to group a set of points into several clusters. Elements within a cluster are supposed to reach a high correlation while elements among distinct clusters

Table 1: Publications related to the division of the FFBSS area into zones with predetermined criteria.

Article	**Journal/Conference**	**City**	**Zone side size or number**
Reiss and Bogenberger (2015)	*IEEE International Conference on Intelligent Transportation Systems 2015*	Munich (Germany)	40 zones
Reiss and Bogenberger (2016)	*Transportation Research Procedia*	Munich (Germany)	40 zones
Caggiani, Camporeale, Ottomanelli, and Szeto (2018)	*Transportation Research Part C*	Unknown, $9km^2$	500m
Xu, Ji, and Liu (2018)	*Transportation Research Part C*	Nanjing (China)	118 zones of $1km^2$ on average
Ai et al. (2019)	*Neural Computing and Applications*	Chengdu (China)	4km
Bao, Yu, and Wu (2019)	*IET Intelligent Transport Systems*	Shangai (China)	25 zones
Cheng, Guo, Chen, and Qin (2019)	*IEEE Access*	Beijing (China)	200m
Yang, Ding, Qu, and Ran (2019)	*Sustainability*	Nanjing (China)	1km
Zhang, Lin, and Mi (2019c)	*Journal of Cleaner Production*	Shangai (China)	50m
Wang, Li, Gu, and Xie (2020)	*IET Intelligent Transport Systems*	Beijing (China)	150m
Song, Zhang, Qin, and Ramli (2021)	*Computers, Environment and Urban Systems*	Singapore	300m

should have a low correlation (Caggiani et al., 2017; Zhang & Meng, 2019). In the case of a FFBSS, the points to cluster correspond to bike locations, each cluster represents a zone, and the correlation is computed through the euclidean distance between the points (Zhao & Ong, 2021). Various clustering techniques are applied to a FFBSS such as K-means, density-based, spatio-temporal, and combinations of several clustering algorithms. We describe those techniques and the existing applications to FFBSSs in the following. Table 2 lists the studies using clustering techniques to create zones for a FFBSS.

3.2.1 K-means

One of the most well-known clustering techniques is the K-means algorithm. For this algorithm, the number of clusters, K, has to be determined in advance. Initially, K random cluster centroids are created. Then, each element, corresponding to a bike location in the case of a FFBSS, is associated with the nearest cluster centroid. After that, the new centroid is computed for each cluster. In the next iteration, the algorithm associates each element to the nearest centroid and then computes the new centroids again. This process is iterated until the clusters remain unchanged (Hua et al., 2020b).

For the case of FFBSSs, Hua et al. (2020b) compare the K-means algorithm with other clustering techniques: density-based clustering (see Section 3.2.2) and spatio-temporal clustering (see Section 3.2.3). According to their numerical experiments, the K-means algorithm offers the best results regarding FFBSS demand forecasting. In a later study, Hua et al. (2020a) create zones by using only the K-means algorithm. They fix the number of clusters to 4000 to reach an acceptable walking distance for users.

The K-means algorithm may also be combined with other clustering techniques. Caggiani et al. (2018) use the K-means algorithm in a spatio-temporal clustering method (see Section 3.2.3). Zhao and Ong (2021) combine the K-means with a density-based clustering algorithm to create zones. Finally, Liu and Tian (2021) use the K-means algorithm at a macro-level followed by a complex network at a medium-level and then a density-based clustering algorithm at a micro-level.

3.2.2 Density-based

With density-based clustering algorithms, zones are constituted based on the density of bikes, i.e. a high concentration of bikes at one place form a zone (Xie et al., 2020). The most common of those algorithms is the Density-Based Spatial Clustering of Applications with Noise (DBSCAN), where two parameters are required: ϵ — corresponding to the maximum distance — and $minPts$ — the minimum number of points (Gu et al., 2020; Hua et al., 2020b; Zhao & Ong, 2021). The algorithm works as follows. To start with, one point, corresponding to a bike location, is selected such that the number of neighboring points within the distance ϵ from the point selected is at

Table 2: Publications related to the division of the FFBSS area into zones with clustering techniques.

			Method						
				Density-based					
Article	**Journal/Conference**	**City**	**K-means**	**DBSCAN**	**Density Peaks**	**DADC**	**Spatio-temporal**	**Hierarchical**	**Complex network**
Caggiani, Ottomanelli, Camporeale, and Binetti (2017)	*Advances in Intelligent Systems and Computing*	London (UK)	✓				✓	✓	
Gu et al. (2020)	*IEEE Transactions on Knowledge and Data Engineering*	Shanghai (China)		✓					
Hua, Chen, Zheng, Cheng, and Chen (2020b)	*Journal of Cleaner Production*	Nanjing (China)	✓	✓			✓		
Hua et al. (2020a)	*IET Intelligent Transport Systems*	Nanjing (China)	✓						
Xie et al. (2020)	*Concurrency and Computation: Practice and Experience*	Beijing (China)			✓				
Chen, Li, Li, Yu, and Zeng (2021a)	*ACM Transactions on Intelligent Systems and Technology*	Haidan, Fengtai, Dongcheng and Xicheng Districts (China)		✓	✓	✓			
Liu and Tian (2021)	*Journal of Cleaner Production*	Nanjing (China)	✓	✓					✓
Zhao and Ong (2021)	*Transportation Research Part A*	Xiamen (China)	✓	✓					

least *minPts*. All of those points form a cluster. Then, the operation is repeated with a new starting point till no more new starting point is identified. Finally, points that are not included in any cluster are considered as outliers and form the noise set (Gu et al., 2020; Hua et al., 2020b; Zhao & Ong, 2021).

Gu et al. (2020) use the DBSCAN algorithm to create zones for the FFBSS Mobike in Shanghai (China). After the clustering part, they construct a flow matrix representing the trips between each zone. Based on that, they predict future bike flows. Hua et al. (2020b) compare DBSCAN with different clustering techniques but, as explained in Section 3.2.1, they show that K-means offers better results in terms of rental forecasting. Liu and Tian (2021) and Zhao and Ong (2021) create a hybrid clustering method including DBSCAN and argue that their model is more effective regarding the future predictions.

Besides DBSCAN, other density-based clustering algorithms are used in the creation of zones for FFBSSs. Xie et al. (2020) apply the Density Peaks Clustering algorithm which aims to identify high-density regions separated by low-density regions. Chen, Li, Li, Yu, and Zeng (2021a) use a Domain Adaptive Density Clustering (DADC) algorithm and compare it with the Density Peaks Clustering and DBSCAN algorithms. They show that the Domain Adaptive Density Clustering algorithm is more accurate than the two others based on a clustering accuracy indicator, the Area Under ROC Curve (Chen et al., 2021a).

3.2.3 Spatio-temporal

The last main clustering technique used for FFBSSs is spatio-temporal clustering. This technique requires two main steps (Caggiani et al., 2017; Hua et al., 2020b). The first one consists in aggregating the data temporally to identify temporal trends. Then, for each temporal cluster, data is aggregated spatially to create spatio-temporal clusters. For each step, i.e. temporal and spatial, a clustering technique, such as those presented above, is applied.

Spatio-temporal clustering algorithms are interesting for FFBSSs because, compared to other clustering techniques, they include the temporal aspect and bike usage may vary depending on the moment of the day (Hua et al., 2020b).

Caggiani et al. (2017) apply a hierarchical clustering method to create the temporal clusters and then, a K-means clustering algorithm to aggregate them spatially. Hua et al. (2020b) compare the spatio-temporal clustering technique to the K-means and DBSCAN algorithms.

4 FFBSS demand forecasting

After dividing the geographical area into zones, the next step for operating a FFBSS is forecasting the demand in each zone. Thanks to demand forecasting, operators can better adapt the redistribution of bikes to the zones to satisfy the demand (Ai et al., 2019; Caggiani et al., 2017; Guidon et al., 2019). The anticipation of bike distribution may improve the utilization rate and reduce the management costs (Ai et al., 2019; Caggiani et al., 2017; Guidon et al., 2019). According to Hua et al. (2020a), the FFBSS demand forecasting is divided into two parts: usage forecasting, which consists in predicting the departures and arrivals in each zone, and bike distribution forecasting, which aims to predict the number of bikes available in each zone.

Before presenting the FFBSS demand forecasting models in Section 4.3, we first discuss in Section 4.1 the spatio-temporal analyses proposed in the literature that are a useful preliminary step to comprehend the demand, and briefly mention in Section 4.2 the type of data that is commonly used in FFBSS forecasting models.

4.1 Spatio-temporal analysis

To facilitate the FFBSS demand forecasting, a spatio-temporal analysis may be realized, to highlight patterns of bike usage. FFBSS spatio-temporal analyses typically identify morning and evening peaks in bike usage. The exact time duration of those peaks may vary from one study to another, but they agree that the morning peak starts at 7:00 while the evening peak starts at 17:00 (Ai et al., 2019; Bao et al., 2019; Hua et al., 2020a; Xu, Ji, & Liu, 2018). A midday peak may also be identified but it is weaker (Ai et al., 2019; Hua et al., 2020a; Xu et al., 2018). Those peaks are identified during the weekdays when main trips are realized to commute (Bao et al., 2019), while no peaks appear during the weekends when the trip purpose is mainly for leisure (Bao et al., 2019; Song et al., 2021).

Some of the spatio-temporal analyses compute the average riding distance, time, or speed. The average riding distance and time found to be respectively between 2200m and 2400m and between 12 and 20 minutes (Ai et al., 2019; Bao et al., 2019; Hua et al., 2020a). Reiss and Bogenberger (2015) address the idle time of bikes — i.e. the time between the rental and the prior return — in their spatio-temporal analysis and, in a subsequent paper (Reiss & Bogenberger, 2016), they use this parameter in their forecasting model. They find that idle times are lower in the inner area of Munich (Germany) than in the outer parts of the city, where they can be longer than 10 days. The main areas for FFBSS usage, hotspots, are subway stations, bus stops, district business, commercial centers, university and college campuses (Gu et al., 2020; Hua et al., 2020b; Song et al., 2021; Yang et al., 2019).

Besides the spatio-temporal factors, other factors of bike usage, such as weather conditions and air quality, are studied. Reiss and Bogenberger (2015) show that, in Munich, more trips are accomplished during the summer months. Unsurprisingly, rainfalls have a significant impact on bike usage (Bao et al., 2019; Hua et al., 2020b; Reiss & Bogenberger, 2015; Xiao, Wang, Zhang, & Ni, 2020). Xiao et al. (2020) add that temperature has also an influence. Finally, air quality seems to impact bike usage as well (Xiao et al., 2020; Xu et al., 2018).

4.2 Type of data

Most forecasting models use data about past bike trips of one or several FFBSSs in a specific city, except Caggiani et al. (2017) who use data from a SBBSS. Most often, the information available about past bike trips is the following: bike number, pick-up location, pick-up time, return location, and return time (Ai et al., 2019; Reiss & Bogenberger, 2015; Zhang et al., 2019c).

In addition to information about past bike trips, other data may be used. Bao et al. (2019) and Xu et al. (2018) include exogenous variables, such as the weather and air quality parameters. Gu et al. (2020) and Guidon et al. (2019) use weather information. Hua et al. (2020b) also include the result of a survey of FFBSS users in Nanjing to know the usage proportion of a specific FFBSS — i.e. Mobike — among FFBSSs active in the city.

Table 3 mentions the type of data used by each study about FFBSS demand forecasting as well as the city where the FFBSS is.

4.3 Forecasting models

After discussing spatio-temporal analyses that help forecasting, and the type of data used, in this section we come to present the models applied in the literature to forecast the FFBSS demand. Table 3 lists all the studies and their characteristics.

4.3.1 Neural networks

Neural networks are a well-known forecasting technique, notably for transportation applications and more specifically for FFBSSs (Caggiani et al., 2017; Xu et al., 2018). As explained previously, one specificity of FFBSSs is the higher number of bike locations compared to SBBSSs, inducing larger data sets (Chen et al., 2021a). This can be handled by neural networks as they recognize complex and non-linear patterns (Caggiani et al., 2017). The following

Table 3: Publications related to FFBSS demand forecasting.

Article	Journal/Conference	Data from	City	Method
Reiss and Bogenberger (2015)	*IEEE International Conference on Intelligent Transportation Systems 2015*	Call a Bike (FFBSS)	Munich (Germany)	Offline demand module
Reiss and Bogenberger (2016)	*Transportation Research Procedia*	Call a Bike (FFBSS)	Munich (Germany)	Model considering demand, origin/ destination, idle time
Caggiani, Ottomanelli, Camporeale, and Binetti (2017)	*Advances in Intelligent Systems and Computing*	Barclay's Cycle Hire (SBBSS)	London (UK)	NARNN
Xu, Ji, and Liu (2018)	*Transportation Research Part C*	Undisclosed FFBSS + Weather data	Nanjing (China)	LSTM
Ai et al. (2019)	*Neural Computing and Applications*	Mobike and Ofo (FFBSSs)	Chengdu (China)	LSTM and conv-LSTM
Bao, Yu, and Wu (2019)	*IET Intelligent Transport Systems*	Mobike (FFBSS) + Weather data	Shangai (China)	Combination of LSTM and conv-LSTM
Guidon, Becker, and Axhausen (2019)	*IEEE International Conference on Intelligent Transportation Systems 2019*	Smide (FFBSS) + Weather data	Zurich (Switzerland)	Random survival forest
Gu et al. (2020)	*IEEE Transactions on Knowledge and Data Engineering*	Mobike (FFBSS) + Weather data	Shanghai (China)	Interpretable bike flow prediction
Hua, Chen, Zheng, Cheng, and Chen (2020b)	*Journal of Cleaner Production*	Mobike (FFBSS) + Survey	Nanjing (China)	Formula considering the number of bikes rented in a zone
Hua et al. (2020a)	*IET Intelligent Transport Systems*	Mobike (FFBSS)	Nanjing (China)	Random forest
Xie et al. (2020)	*Concurrency and Computation: Practice and Experience*	14 FFBSSs	Beijing (China)	Adapted model of LSTM, with an autoencoder
Chen, Li, Li, Yu, and Zeng (2021a)	*ACM Transactions on Intelligent Systems and Technology*	Undisclosed FFBSS	Haidan, Fengtai, Dongcheng and Xicheng Districts (China)	GGNN

paragraphs present the various types of neural networks considered in the FFBSS literature.

NARNN. Caggiani et al. (2018), Caggiani et al. (2017) apply Non-linear Autoregressive Neural Network (NARNN) to forecast the FFBSS demand. Their model aims at predicting time series by training the neural network on a series of past values. The training process consists in minimizing performance evaluation functions — i.e. Mean Squared Error or denoising autoencoder.

LSTM. The long short-term memory (LSTM) neural network is a prediction system composed of an input layer, one or several hidden layers, and an output layer. These multiple layers help to better capture complex relationships between the inputs and the outputs (Ai et al., 2019; Xu et al., 2018). This is particularly useful to fit time-series data as it reveals not only short-term dependencies but also long-term dependencies by using memory cells in the hidden layers (Ai et al., 2019; Xu et al., 2018). Xu et al. (2018) apply this technique to forecast the FFBSS demand and compare it with seven other predictive approaches, i.e. one-step forecast, harmonic analysis, autoregressive integrated moving average, extreme gradient boosting, support vector machine, artificial neural network, and recurrent neural network. They show that the

LSTM neural network offers better results than the other forecasting methods in terms of predictive performance, measured by the Mean Absolute Percentage Error. Xie et al. (2020) also use a LSTM neural network to forecast the FFBSS demand, and adapt the model with an autoencoder to enhance user privacy.

conv-LSTM. Besides the temporal aspect, the bike distribution also presents a spatial dimension, which tends to be neglected by LSTM neural networks (Ai et al., 2019; Bao et al., 2019). As a consequence, the convolutional long short-term memory (conv-LSTM) neural network has been developed to integrate spatial dependencies. Ai et al. (2019) compare the performance of LSTM and conv-LSTM neural networks on FFBSS demand forecasting using accuracy metrics — i.e. Root Mean Square Error and Mean Absolute Error — and show that the conv-LSTM neural network outperforms the LSTM one. Bao et al. (2019) combine both LSTM and conv-LSTM into a deep learning framework. They then show that it leads to the best performance compared to other classical models, i.e. convolutional neural network, LSTM, artificial neural network, gradient boosted regression trees, auto-regressive integrated moving average.

GGNN. Chen et al. (2021a) use a Gated Graph Neural Network (GGNN) not only to forecast the FFBSS demand but also to determine the zone locations. In other words, the model aims to predict where and how many bikes will be required in the future to satisfy the FFBSS demand. They show that GGNN leads to the highest prediction accuracy, compared to other models — i.e. graph neural network, graph convolutional network, LSTM — in terms of two metrics — i.e. Area Under the Curve and Root Mean Squared Error.

4.3.2 Random Forest

A random forest is a prediction system composed of many regression trees, often used for regression and classification problems (Guidon et al., 2019; Oshiro, Perez, & Baranauskas, 2012). When random forest models are applied to forecast the FFBSS demand, their main benefit is that they can deal fast and efficiently with large data sets (Hua et al., 2020a; Oshiro et al., 2012).

Guidon et al. (2019) build an extension of the classical random forest, called a random survival forest model, to forecast the FFBSS demand. However, they find that the model presents a low predictive capability. Hua et al. (2020a) get more promising results. They compare their random forest model to five other models — i.e. harmonic analysis, one-step forecast, vector auto-regressive, LSTM, decision tree —, using accuracy metrics — i.e. Root Mean Squared Error and Mean Absolute Error. They find that random forest most often gets the best results, except in some scenarios where LSTM and vector auto-regressive models present advantages.

4.3.3 Alternative models

Besides neural networks and random forests, other forecasting models have been proposed in the literature. Reiss and Bogenberger were the first to develop a forecasting model for FFBSSs (Reiss & Bogenberger, 2015, 2016). They forecast the demand in a specific time slot and zone based on past data using three factors: a demand factor, considering the rentals and stock; an origin/destination factor, considering the rented and returned bikes; and an idle time factor, considering the time bikes are unused. Then, they use their prediction model as a basis to suggest a redistribution of the fleet. Hua et al. (2020b) consider as parameters the proportion of Mobike bikes among FFBSSs active in Nanjing, the maximum number of Mobike bikes in the zone, the capacity of the zone, and a safety factor. Gu et al. (2020) build a model called *Interpretable Bike Flow Prediction*. They construct matrices containing the bike flow between each zone during a specific period of time in the past. Based on that, the model finds a set of base matrices and a coefficient to best fit the original data and then, predicts the future bike flow.

5 Redistribution

Accurate predictions offered by demand forecasting models help operators to better manage the redistribution of bicycles among zones (Caggiani et al., 2018; Liu et al., 2018). Redistribution consists in maintaining a desired quantity of bikes at each zone by moving bikes from one place to another to better fulfill the demand and satisfy users while improving the utilization rate and the reliability of the system (Chemla et al., 2013; Du, Cheng, Li, & Tang, 2020; Liu et al., 2018; Pan et al., 2019).

Two types of redistribution are identified, operator-based and user-based, presented respectively in Section 5.1 and Section 5.2.

5.1 Operator-based redistribution

Operator-based redistribution is more common. The operator uses one or several vehicles to transport bikes from one zone to another (Caggiani et al., 2018; Pal & Zhang, 2017; Pan et al., 2019). The redistribution is said to be static if performed during the night when the use of the system is negligible (Caggiani et al., 2018; Pal & Zhang, 2017). In contrast, the redistribution is dynamic if realized during the day, when the system is in use (Caggiani et al., 2018; Du et al., 2020; Pal & Zhang, 2017).

Operator-based redistribution can be analyzed as a Pickup and Delivery Problem (Caggiani et al., 2018; Zhang, Meng, & Wang, 2019a) or a Vehicle Routing Problem (Pal & Zhang, 2017; Zhang et al., 2019a), consisting in determining the optimal truck routes (Ji, Jin, Ma, & Zhang, 2020a).

Table 4 lists the studies related to operator-based redistribution, showing if the model is static or dynamic, how it is solved, and what is the objective function. In the

Table 4: Publications related to operator-based redistribution.

Article	Journal/ Conference	Dynamic	Objective function: Min cost	Min makespan	Max revenue	Max user satisfaction	Method
Reiss and Bogenberger (2015)	*IEEE International Conference on Intelligent Transportation Systems 2015*		✓				Online optimization module
Pal and Zhang (2017)	*Transportation Research Part C*			✓			Nested large neighborhood search and Variable neighborhood descent
Caggiani, Camporeale, Ottomanelli, and Szeto (2018)	*Transportation Research Part C*	✓	✓			✓	Redistribution matrix and paths
Liu, Szeto, and Ho (2018)	*Transportation Research Part C*			✓		✓	Chemical reaction optimization (CRO)
Liu and Xu (2019)	*International Conference on Service-Oriented Computing 2018 Workshops*				✓		Genetic algorithm
Zhai, Liu, Du, and Wu (2019)	*ISPRS International Journal of Geo-Information*		✓				Linear programming
Du, Cheng, Li, and Tang (2020)	*Transportation Research Part E*			✓			Greedy-genetic heuristic
Fan, Ma, and Li (2020)	*Processes*	✓	✓				MVA (small instances); FES (large instances)
Jin and Tong (2020)	*ISPRS International Journal of Geo-Information*		✓				Exact model & Region decomposition heuristic
Teng, Zhang, Li, and Liang (2020)	*IEEE Access*				✓		Two-stage heuristic
Mo, Liu, and Chan (2021)	*Algorithms*				✓		Rebalance strategy optimization

following, we use the latter to structure our more detailed description of the studies.

Cost distance. Cost, or distance, minimization is an important objective for operator-based redistribution. Reiss and Bogenberger (2015) develop an Online Optimization Module that identifies the optimal route for the operator's vehicle while satisfying the demand. To do so, they divide the geographical area into 40 zones (see Section 3.1), forecast the number of bikes necessary in each zone at each time period (see Section 4.3), and finally, compute the optimal redistribution. Zhai et al. (2019) propose a linear programming model to organize the redistribution activities. Jin and Tong (2020) propose an exact optimization model which can be applied when the number of zones is small — i.e. when zone size is at least 800m in their case study. For a larger number of zones, they use a region decomposition heuristic.

Those three studies propose static redistribution models. On the opposite, Fan, Ma, and Li (2020) devise a dynamic redistribution model with costs minimization. In their study, two models are suggested. The first one is only for small FFBSSs and applies a mean value analysis (MVA) algorithm. The second one may be used for

FFBSSs of larger size and applies a flow equivalent server (FES) algorithm.

Make-span. The make-span — i.e. the duration of the redistribution activities — may also be minimized. Pal and Zhang (2017) argue that, with more than one vehicle, minimizing the make-span is preferable to distance minimization as it avoids having one vehicle being used significantly longer than another. They first propose an exact model, which shows to be intractable for realistic FFBSS instances. So, they then develop a heuristic method combining a Nested Large Neighborhood Search and a Variable Neighborhood Descent. Du et al. (2020) propose a greedy-genetic heuristic to minimize the make-span of the redistribution. They not only redistribute the bicycle fleet but also suggest collecting malfunctioning bikes simultaneously. The results show a reduction in the duration of the redistribution activities by 11% to 28.5% compared to separate activities (redistribution and collection of malfunctioning bikes).

Revenue. Some studies focus on maximizing the overall revenue of the operator, effectively combining cost minimization and income maximization. Liu and Xu (2019) apply a genetic algorithm to maximize the revenue. They consider two types of bike locations: the easily accessed ones and the hardly accessed ones. They attribute a rental demand of 0 at hardly accessed bike locations for users. So, the redistribution process tends to replace the bikes from those hardly accessed locations to easily accessed ones while satisfying the predicted rental demand. They test their method on a numerical study of 25 bike locations — i.e. 5 easily accessed locations and 20 hardly accessed ones.

In a similar manner, Mo et al. (2021) consider a Markovian queueing network where bike locations have a demand assigned and their model aims at redistributing bikes from low-demand bike locations to high-demand bike locations by maximizing the revenue.

Teng, Zhang, Li, and Liang (2020) develop a two-stage heuristic that first predicts the number of bikes to supply in each zone considering the problem as a stochastic mixed-integer programming model. Then, it determines the redistribution routes by maximizing the revenue.

User satisfaction. Other studies also consider user satisfaction in the objective function. According to Caggiani et al. (2018), increasing user satisfaction leads to higher long-term revenue for the operator. The impact of user satisfaction on revenues may be direct, with greater utilization of the system, or indirect, due to positive communication from users.

Caggiani et al. (2018) thus maximize user satisfaction besides minimizing costs. To do so, they apply a two-step strategy: first determining a redistribution matrix minimizing the times during which zones have an insufficient number of bikes; then, taking this matrix as a constraint and finding the redistribution routes that minimize costs. Besides minimizing the makespan, Liu et al. (2018) aim at improving user satisfaction by minimizing the inconvenience level of finding a bike and the total unmet demand. For this, they apply an enhanced version of chemical reaction optimization (CRO) to strengthen the transfers from hardly accessed locations to easily accessed ones to make it easier for users of getting bikes.

5.2 User-based redistribution

User-based redistribution consists in increasing users' involvement in the redistribution activities by changing their pick-up or drop-off locations (Caggiani et al., 2018; Pan et al., 2019; Zhang et al., 2019a). It can be realized mainly by offering them incentives or introducing penalties to incite them to replace bikes where the demand is high or to rent bikes where the demand is low (Ji et al., 2020a; Pan et al., 2019).

User-based redistribution tackles different disadvantages of operator-based redistribution. Firstly, redistribution costs are significantly reduced for the operator (Ji et al., 2020a; Wu, Liu, & Shi, 2019). Moreover, while operator-based redistribution makes it difficult to adjust the bike distribution in real time as it is often realized during the night, user-based redistribution is more flexible (Wu et al., 2019). Therefore, applying a user-based redistribution is an economical, ecological and flexible way to redistribute the bicycle fleet while reducing the costs for the operator (Heitz, Blume, Scherrer, Stöckle, & Bachmann, 2019; Ji et al., 2020a; Pan et al., 2019).

In Section 5.2.1, different strategies for user-based redistribution are presented. Then, Section 5.2.2 highlights the models to optimize user-based redistribution.

5.2.1 Strategies for user-based redistribution

This section presents the various strategies that can be applied to motivate users to participate in redistribution activities.

Incentives. Incentives can be offered to users to motivate them picking a bike in oversupplied zones or to park the rented bike in undersupplied zones (Ji et al., 2020a; Pan et al., 2019; Zhai et al., 2019). According to Reiss and Bogenberger (2017), 15% of users are willing to adapt their route if incited to do so.

Monetary incentives are the most commonly mentioned in the literature. It can be a fixed reward if a bike is dropped off at a specific zone or it can be proportional to the demand and the number of bikes in a zone (Heitz et al., 2019; Ji et al., 2020a). The higher the incentive, the longer the detour that users are willing to travel (Gao et al., 2020). According to Reiss and Bogenberger (2017), the monetary incentive is often between a 10% and a 80% fare discount. Zhang et al. (2019a) go further by suggesting offering a free ride on top of a monetary reward to users who cycle from oversupplied zones to undersupplied

Table 5: Publications related to user-based redistribution.

Article	Journal/Conference	Method
Reiss and Bogenberger (2017)	*Transportation Research Procedia*	Monetary incentives for a user-based redistribution of 15% of the bicycle fleet, operator-based for the rest
Heitz, Blume, Scherrer, Stöckle, and Bachmann (2019)	*Smart Service Systems, Operations Management, and Analytics*	Simulation and empirical study
Pan, Cai, Fang, Tang, and Huang (2019)	*Proceedings of the AAAI Conference on Artificial Intelligence*	Deep reinforcement learning
Wu, Liu, and Shi (2019)	*Sustainability*	Ranking and selection approach
Zhang, Meng, and Wang (2019a)	*Transportation Research Part B*	Dynamic traffic assignment model and pricing strategies
Ji, Jin, Ma, and Zhang (2020a)	*IEEE Access*	Utility function maximization

zones. It may also be seen as a way to attract new users to the system. Instead of offering monetary rewards, the operator may also provide free minutes to users for their future trips (Heitz et al., 2019).

Penalties. Another way to convince users to participate in the redistribution activities is to give them penalties that discourage them to park their bikes at some places (Zhai et al., 2019; Zhang et al., 2019c). Gao et al. (2020) show in their study that incentives are more effective than penalties, especially when the additional walking is longer than 10 minutes.

Warning messages. Su, Wang, Yang, and Wang (2020) suggest sending warning messages to users via the application of the FFBSS to reduce their disorderly parking behavior. They argue that, even if less effective than incentives, it is a budget-neutral measure for the operator.

5.2.2 User-based redistribution models

In this section, we present models developed in the literature to optimize the user-based redistribution in a FFBSS. They are summarized in Table 5.

To implement a user-based redistribution, Heitz et al. (2019) develop a two stages methodology. In the first step, a simulation model analyzes the effect of incentives on system usage. Then, they conduct an empirical social research study to understand the needs, value perception, and user motivations.

Pan et al. (2019) develop a deep reinforcement learning algorithm, called hierarchical reinforcement pricing, that captures both temporal and spatial dependencies. The algorithm can suggest to a user an alternate bike with a certain price incentive, aiming to maximize the number of satisfied users under a budget constraint. Wu et al. (2019) develop a ranking and selection (R&S) model to determine the optimal incentive plan for user-based redistribution. The objective is to maximize the profit under a service level constraint, i.e. with a sufficient ratio of satisfied demand over the demand forecast.

Zhang et al. (2019a) compare three pricing strategies for a user-based redistribution: negatives pricing, i.e. users get paid for their trip; free pricing; positive pricing, i.e. users only get a discount. To do so, they implement a dynamic traffic assignment model, which identifies the profit maximizing strategy. They conclude that free pricing and negative pricing are the most profitable strategies and that negative pricing attracts new users to the system. Ji et al. (2020a) also create a model aiming at determining the incentives for user-based redistribution, intending to maximize users' utility. The utility function depends on the additional distance for replacing a bike, the value of the monetary incentive, the walking and cycling speeds, and the value of users' time.

Finally, some studies propose to apply user-based redistribution as a complement to operator-based redistribution. According to Zhai et al. (2019), a user-based redistribution can be used as an auxiliary means to reduce the redistribution costs for the operator. In the same spirit, Jin and Tong (2020) approve this statement and recommend applying an operator-based redistribution between zones of big size (i.e. at least 800m) and implementing user-based redistribution strategies for finer scales (i.e. 100m and 200m). Reiss and Bogenberger (2017) propose an approach in two stages. In the first stage, if less than 15% of the bicycle fleet has to be redistributed, user-based redistribution is judged sufficient. Otherwise, the second stage consists in implementing an operator-based redistribution for zones with high imbalances, by determining a route minimizing the costs for the operator, and a user-based redistribution for other zones, by offering incentives to users.

6 Other FFBSS operations

In this section, we address briefly other FFBSS operations, besides the three main ones described before. First, the operationalization of geofence parking is presented in Section 6.1. Then in Section 6.2, we present studies addressing the initial implementation of a FFBSS. Finally, Section 6.3 addresses the problem of malfunctioning bikes.

6.1 Geofence parking

With geofence parking, the app forbids to park the bike elsewhere by detecting the bike location by GPS. It has been introduced in some cities in China to solve the problem of parking disorder (Chen et al., 2020a; Sun et al., 2019; Yin et al., 2019). Geofence parking, which strictly defines virtual stations, should be distinguished from the division of the geographical area into zones, as seen in Section 3, which aggregates the data about bike locations. With geofence parking, an important part of the area where the FFBSS is active is not included in any virtual station. For some FFBSSs, users must park their bikes in a virtual station (Sun et al., 2019). Other FFBSSs offer price incentives to encourage users to park their bikes in a virtual station (Zhang et al., 2019c). When introducing geofence parking, as the low installation cost allows to open a sufficient number of geofence parking locations, FFBSSs still keep important advantages compared to SBBSSs, such as convenience, flexibility, and accessibility (Zhang et al., 2019c).

Several papers focus on elaborating methods to implement geofence parking for FFBSSs. Rahim Taleqani et al. (2020) develop an integer programming formulation and a heuristic algorithm to locate geofence sites. Cheng et al. (2019) propose a two-step process that first identifies the hotspots and then selects the virtual stations in the top-ranking hotspots. Zhang et al. (2019c) introduce a methodological framework to locate virtual stations and decide their capacities. A hybrid clustering algorithm is constructed by Zhao and Ong (2021) to identify potential parking facilities. Sun et al. (2019) apply a MILP and a clustering algorithm to determine virtual stations.

6.2 Initial implementation of a FFBSS

While most operational problems studied are related to already implemented FFBSSs, some papers investigate the various decisions that need to be made to implement a FFBSS in a city: the size of the bicycle fleet, the coverage area, the bike locations, and the redistribution strategic decisions — i.e. the number of redistribution vehicles, the staff, the intensity of redistribution operations (Caggiani et al., 2018; Soriguera & Jiménez-Meroño, 2020; Wang, Li, Gu, & Xie, 2020; Zhang & Meng, 2019).

Li et al. (2018a) study the initial implementation of a FFBSS in a city to maximize the number of bike trips while minimizing the number of bikes deployed. They address this problem as a large-scale nonlinear integer programming model and solve it using a branch and bound approach. Soriguera and Jiménez-Meroño (2020) consider the problem of implementing a FFBSS to minimize agency costs and user costs. Wang et al. (2020) develop a mix-integer nonlinear program that aims at minimizing the total walking distance of users when implementing a new FFBSS in a city. Zhang and Meng (2019) consider the successive introduction of two FFBSSs in a city, the market leader first and the market follower second. In a later study, Zhang, Meng, Wang, and Du (2021) focus on two potential scenarios for implementing a FFBSS. The first one consists in attracting a maximum number of users and the second one aims at minimizing the resources required to cover the largest service area.

6.3 Malfunctioning bikes

A recurring issue for FFBSSs is the handling of malfunctioning bikes, leading to a large number of unusable bikes (Fan et al., 2020; Si, Su, Wu, Liu, & Zhao, 2020). It occurs due to wear and tear but, also due to the imperfect management by operators and the lack of care by users (Du et al., 2020). It induces several issues such as impaired service quality, safety problems, a waste of resources for the operator, and inconvenience to the public environment (Fan, Li, Wu, & Zhang, 2019; Li, Zhang, Sun, & Liu, 2018b; Wang & Szeto, 2018).

To address this issue, some studies introduce the collection of malfunctioning bikes in their redistribution models. Du et al. (2020) integrate the collection in their redistribution model that aims at minimizing the makespan (see Section 5.1). Teng et al. (2020) consider a two-stage heuristic that takes three main decisions: the number of usable bikes to redistribute in each zone, the number of unusable bikes to be recovered in each zone, and the route of the vehicles to execute those activities. Usama et al. (2019) also incorporate the management of malfunctioning bikes in their redistribution model with a small number of zones. The model by Fan et al. (2019) focuses on the maintenance of malfunctioning bikes. More precisely, it manages the unusable bikes by moving them from the system to the maintenance shop; and then, bringing the repaired bikes back in the system.

7 Research directions

This section highlights the future research directions identified within the literature about FFBSS operations. When dividing the geographical area into zones arbitrarily, fixing the zone size to a spatial unit may lead to the modifiable areal unit problem (see Section 3.1). Therefore, Song et al. (2021) suggest further investigating this issue for FFBSSs, in particular by further developing clustering techniques to divide the area.

As discussed in Section 4.1, spatio-temporal analyses have demonstrated that factors other than past bike trip data are valuable to forecast FFBSS demand. Such factors are for example weather conditions, air quality, or the location of hotspot places. However, only a few studies use these additional parameters in their FFBSS demand forecasting models while several authors suggest considering them (Ai et al., 2019; Gu et al., 2020; Guidon et al., 2019; Hua et al., 2020a; Yang et al., 2019; Zhang, Lin, & Liu, 2019b). Other models could also be applied to forecast the FFBSS demand, such as transformer neural networks models (Liu et al., 2021).

Regarding the redistribution operations, detailed in Section 5, three main research directions may be identified. The first one is related to dynamic redistribution. In Table 4, we see that only two papers focus on dynamic redistribution while the others consider static redistribution. However, several authors argue that models should be developed to better respond to the dynamic nature of FFBSSs (Caggiani et al., 2018; Du et al., 2020; Ji et al., 2020a; Liu & Xu, 2019; Usama et al., 2019).

The second research direction related to redistribution operations is the exploration of alternative model objectives. Caggiani et al. (2018) suggest further analysis on how to balance multiple objectives, such as cost minimization and user satisfaction maximization. Given that FFBSSs offer a green transportation mode, Wu et al. (2019) indicate that an environmental performance measure could be considered, which is not yet the case in studies about FFBSS redistribution (see Table 4).

The complexity of redistribution models, due to a large number of bike locations, is the third avenue of future research. Liu et al. (2018) advice to apply clustering techniques to reduce the number of nodes (see Section 3.2). Du et al. (2020) and Wu et al. (2019) suggest further investigating the relaxation of redistribution models to improve their efficiency.

A research direction identified for all FFBSS operations relates to the data used and the extension of the models. Several authors recognize that it would be interesting to apply their studies to larger data sets (Liu & Tian, 2021; Song et al., 2021; Wang et al., 2020). Cheng et al. (2019), Yang et al. (2019), Zhang et al. (2019b), and Zhao and Ong (2021) advise exploring the transferability of the methods developed to other cities by testing it on other data sets. In the same vein, according to Hua et al. (2020b), Rahim Taleqani et al. (2020), and Zhang et al. (2019c), future studies could focus on considering not only data from one particular FFBSS but also data from several FFBSSs in a city to have a better view of FFBSS usage. Besides the test and comparison of different data sets, various authors acknowledge the need for further comparisons between methods and for benchmarking (Bao et al., 2019; Caggiani et al., 2018; Xie et al., 2020).

Note that in this work, we do not address the determination of the price of bike trips as it is not considered as strictly an operational problem. However, it could be interesting to explore the integrated management of price with FFBSS operations (Zhang & Meng, 2019).

8 Conclusion

FFBSSs have grown in popularity in the last 5 years as a sustainable in-city transportation option. This paper offers researchers and operators a summary of the now rather extensive number of studies related to FFBSS operations. Moreover, it suggests future research directions.

The first operational problem addressed in this paper relates to the division into zones of the geographical area where a FFBSS is active. Two main methods are used to realize the division: applying a fixed grid size or using clustering techniques — K-means, density-based, spatio-temporal. The main research direction identified in that field is the modifiable areal unit problem that should be further studied.

Secondly, we summarize the studies concerning FFBSS demand forecasting. Several models of neural networks — LSTM, conv-LSTM, hybrid framework, NARNN, GGNN — are applied in the literature, as well as random forest and other models. Related to FFBSS demand forecasting, future research could focus on integrating factors such as weather conditions, air quality, and the location of hotspot places as those factors are identified as impacting FFBSS usage.

Following that, we address studies about the redistribution of the bicycle fleet. When the redistribution is operator-based, an optimization model is often proposed, mainly including routing decisions, with various possible objectives and solution methods. For user-based redistribution, different strategies may be applied such as incentives, penalties, and warning messages. The main research directions related to FFBSS redistribution is about the implementation of dynamic models and the calibration of multiple objectives within the optimization.

Finally, we briefly address other FFBSS operations. Among them, geofence parking offers a low-cost solution to reduce parking disorder while maintaining flexibility, but it requires locating geofence sites. The initial implementation of a FFBSS is then discussed, involving decisions such as coverage area, number and locations of bikes. The last operational problem introduced relates to the collection of malfunctioning bikes.

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