Bike Sharing: A Review on the Literature

Gonçalves, Filipe (filipeg@ua.pt) (http://orcid.org/0009-0003-9663-463X)
DETI - Departamento de Eletrónica, Telecomunicações e Informática
IEETA - Instituto de Engenharia Electrónica e Informática de Aveiro
Universidade de Aveiro, Portugal

***Abstract*—This paper provides an overview on the literature on bike sharing systems, using the Scopus database for scientific publications. This review will examine previous works, such as other reviews, synthesis and analysis on their problems and successes, with various examples from around the world. All the analysed papers underwent a methodological search, which resulted in over 1300 included papers and 500 screened publications. Several themes will be discussed that have emerged based on the literature. First, the evolution of bike sharing systems from its inception in 1965, categorized in five generations. Second, the modal shift from using a private transportation to a shared bike, constituting a major benefit for more sustainable cities. Finally, the problem of reallocating bikes into stations or areas, divided into two different categories: the bike rebalancing problem, the demand prediction of bikes.**

***Index Terms*—review, analysis, Scopus, advanced search of publications, bike sharing, dockless bike sharing, first/last mile, modal shift, reallocation, bike rebalancing problem, demand prediction, machine learning, deep learning, data, infrastructure, database**

I. Introduction

Bike sharing, or the shared use of a bicycle fleet, is a new sustainable transportation alternative that emerged as a result of growing concerns about global motorisation and climate change. Some of the benefits on the development and use of a bike sharing system (BSS) include enhanced mobility, lower implementation cost compared to other modes of transportation, reduced traffic congestion, fuel consumption and greenhouse gas emissions, improved public health and increased environmental awareness [1]. As an example, more than 8300 tonnes of fuel were saved by the use of BSSs in Shanghai, China, which consequently reduced the gas emissions and improved air quality in the city [2].

Standard BSSs allow users to rent a bike from a docking station and return it to another, however, not all BSSs require physical stations. Dockless BSSs provide rapid and flexible mobility, as bikes can be found and parked anywhere. These short-term bikes might feature technologies such as a built-in global positioning system (GPS) that allow operators to track their movements and position, either in a station or during a trip, to prevent theft [3] [4].

BSSs have grown exponentially, since their origin in 1965, in Amsterdam, Netherlands. Their primary travel purposes include work-related activities, leisure across different age groups and residential consumption [5].

The existing bike sharing literature can be mainly divided into two domains: the analysis, review and synthesis of different BSSs and their characteristics, problems and implications; and the analysis, development and comparison of different rebalancing models for the bike repositioning problem [2].

This paper provides an overview on BSSs, mainly the methodology for the systematic search for papers, examples on their successes and failures, the reallocation problem and its solutions, and recommendations for future work.

II. Search and Screening Methodology

This section presents the methodology used in the search for relevant scientific publications. Briefly, the comprehensive search was conducted in the Scopus database, followed by a systematic screening process and an in-depth analysis of the selected literature.

A. Complete Search

The first step in any selection process is to identify the best criteria. Any variation of these arguments can lead to disparate outcomes, from the many methods of identifying a BSS to the type of document to screen or the time frame for the review. The terms ”bikesharing”, ”bike sharing”, and ”bike-sharing” were defined as key expressions to appear in the title, keywords or abstract. Additionally, the papers must be published and written in English, and they must be published before 2025. The full script for the complete search is as follows: `TITLE-ABS-KEY ("bike-sharing" OR "bikesharing" OR "bike sharing") AND LANGUAGE (english) AND PUBYEAR < 2025`.

This search produced more than 2,700 documents with distribution presented in Figure 1, of which 60% were articles and 30% were conference papers.

B. Advanced Search

An advanced search was carried out, using the same key expressions and time frame, but restricting the source of documents to only journals, with the query: `TITLE-ABS-KEY ("bike-sharing" OR "bikesharing" OR "bike sharing") AND SRCTYPE (j) AND LANGUAGE (english) AND PUBYEAR < 2025`.

This search resulted in nearly 1,800 documents, that were then manually screened based on the title and abstract and divided into two different relational tables, one for the included papers aggregated using a theme system, which yielded a total of 1,316 papers, and another for the excluded papers based on a exclusion condition system.

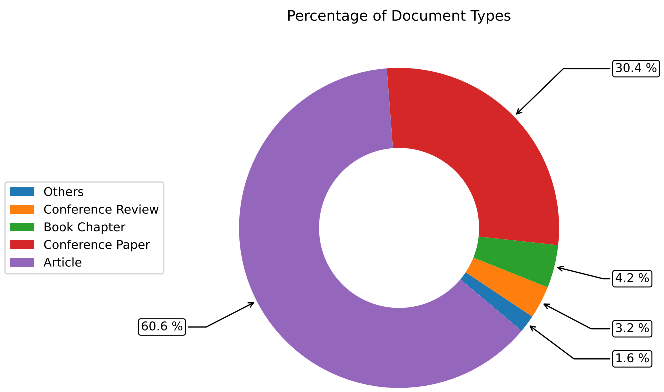

Fig. 1. Types of the documents

Figure 2 depicts the number of total and included documents published in each year. With the number of published papers rising at an almost exponential rate each year, BSSs are expanding like never before. It is evident that there is much to learn about this topic: from a handful of papers prior to 2011 to nearly achieving 300 papers in 2021, with the number of publications remaining above 250 every year after, and even though BSSs were widely used before the start of the decade, more than 90% of all documents were published after 2016.

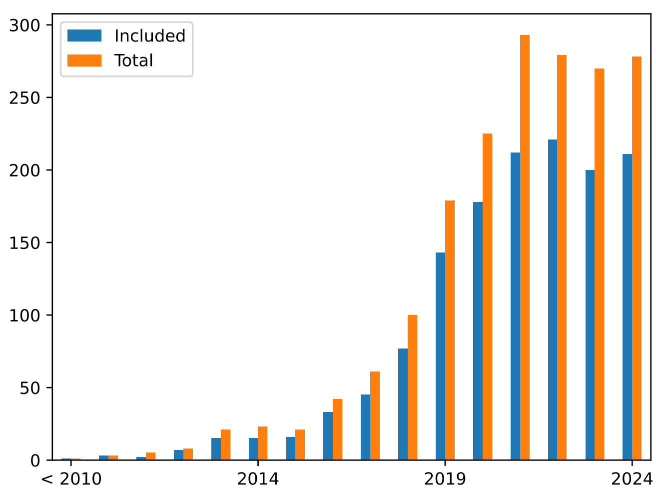

Fig. 2. Number of Total and Included Papers per Year

Across all 1,316 papers, the inclusion selection was implemented using a theme system, in which one paper is outlined by the most relevant theme for easier filtering, listed as follows:

- Case Study: Any general study on bike sharing - the economy, the impacts, the problems, how to promote a BSS, comparative analysis of different types of BSSs, studies on BSSs, and so on;
- Rebalancing: Any study on the bike rebalancing problem, demand prediction models, algorithms for the location of the stations, travel pattern recognition for route recommendations and spatio-temporal models for BSSs;
- Examples: Any study on a specific city (studies on countries could be classified based on the impacts, problems, etc.), which could be of the failure or success of a given BSS;
- First/Last Mile: Any study on the correlation between a BSS and any transportation method (metro, bus, taxi, etc.), where the user's journey begins or ends on a BSS;
- Sustainability: Any research on the green impact of BSSs.

Similarly, the exclusion criteria for the excluded papers is listed below:

- Mobility: Any study on mobility as a service like taxi demand or vehicle travel time, and mobility sharing like car or scooter sharing;
- Not Focused on Bike Sharing: Any study that uses bike sharing as an example or as a dataset to a problem outside the scope of BSSs;
- Error: Any erratum study.

Figure 3 shows the percentage of included and excluded papers based on the different themes, in green, and exclusion conditions, in red, providing an analysis of how in-depth the papers are becoming. The majority of the included papers analyse either different case studies or the rebalancing problem, and consequently the discussion and evolution in these areas is far more developed compared to studies on sustainability, which represent 4% of the total number of documents. Moreover, almost 23% of all papers were excluded from the screening process as most of them are studies on mobility as a service, shared mobility or studies that reference BSSs as an example or use data from BSSs to solve their problems. Nonetheless, more than three quarters of all the documents were selected for the next process, meaning that the majority of the literature can be included in any type of analysis of BSSs.

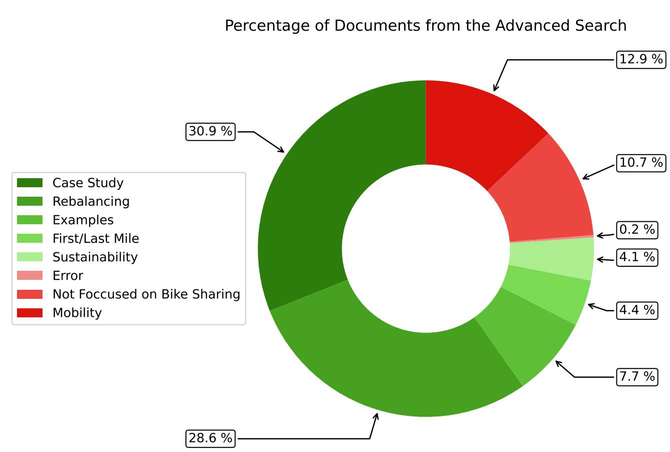

Fig. 3. Themes and Conditions for the 1316 Documents

C. Paper Screening

1,316 papers resulted from the advanced search. While there is a variety of useful information about BSSs, it is hard to do an in-depth analysis of each one. However, filtering papers by number of citations, publication year, or even both has certain problems: Filtering by number of citations means that recent papers that have yet to receive as many citations will be ignored; Filtering by year implies that the number of citations is meaningless, which is false; Filtering by year and number of citations means that if we only get the best papers each year, papers from later years will be excluded. The solution is to use both the publication year and the number of citations to calculate the *impact* (1) of the papers.

$$impact = \frac{number\_of\_citations}{number\_of\_years\_since\_publication} \quad (1)$$

The *impact* will look into the mean number of citations per year published, which solves the limitations of filtering based on only the number of citations or the number of published years and ensures that we get the best papers possible.

This process reduced the number of included papers to approximately 500, with almost 340 of these papers discussing and analysing the rebalancing problem.

D. Methodology

To differentiate between included and excluded publications, a variety of tools were developed to automate the process. The manual selection's script iterates through all of the papers, enumerating their information and waiting for an "enter", from the user, to include the paper or any other letter to exclude it. Following that, the user would either select the theme for the included paper or the exclusion criteria for the excluded paper. It also saved an offset of the included and excluded papers, allowing the user to exit the program while saving its most recent changes. The screening process was accomplished using another script to go over all the included documents and the user would decide which publications were chosen for the literature review, based on the impact and theme of the papers.

III. Literature Review

The review addresses the evolution of BSSs worldwide, their problems, potential solutions and their implications, as well as a variety of examples of their successes and failures.

Previous studies summarized and classified BSSs into four generations [1]:

- **First Generation**: White bikes (free bike systems) introduced in Amsterdam in the 1965-1994;
- **Second Generation**: Coin-deposit systems, starting with Bycyklen in Copenhagen in the 1995-1997;
- **Third Generation**: IT-based systems, the first of which appeared in Rennes, France, in the 1998-2009;
- **Fourth Generation**: Focusing on demand-responsive, multi-modal systems, in the 2009-2015.

The first generation relied significantly on the use of free bicycles that were often randomly parked throughout the city. This resulted in the failure of Cambridge's Green Bike Scheme, with nearly 300 stolen bicycles [6] and the failure of the Amsterdam's White Bikes, which had some of their fleet thrown into channels [7].

The second generation is best known for its docking system, which allowed bikes to be parked and locked in stations. Bicycles were then unlocked with a coin deposit of roughly 3$, which was refunded upon return. The first of this generation is the Bycyklen in Copenhagen, which still continued to operate in 2012 with over 2,000 bicycles and 110 stations [1]. In this system, users could have their bicycles for indefinite time, as their only loss was the coin deposited in the docking station, continuing the cases of theft and vandalism [8].

The third generation gained popularity by incorporating innovative technologies for bicycle tracking, parking and pickup. It introduced bicycles with locks, paid memberships and an anti theft program that required users to show their ID to ride the vehicles. In 2007, Paris launched its biggest bike sharing system to date, named Vélib with over 20,000 bicycles [4].

The fourth generation would eventually include electric bicycles, more efficient and flexible stations, a simpler user interface, and some form of a redistribution system. The Montreal's BIXI program marks the start of this generation, with over 5,000 bicycles and 400 stations, featuring solar-powered mobile stations, as well as GPS integration into the bikes, which reduces theft and vandalism compared to previous systems and allows for easier bike redistribution [1].

While the concept, design and technologies of global BSSs have been evolving since well before the century started, it is not until 2007 that we can visually see the results of these improvements, shown in Figure 4 until the second quarter of 2012.

Comparing with the Figure 1, we can see the delay of almost 10 years, between the start of the popularity in BSSs and the surge of its literature.

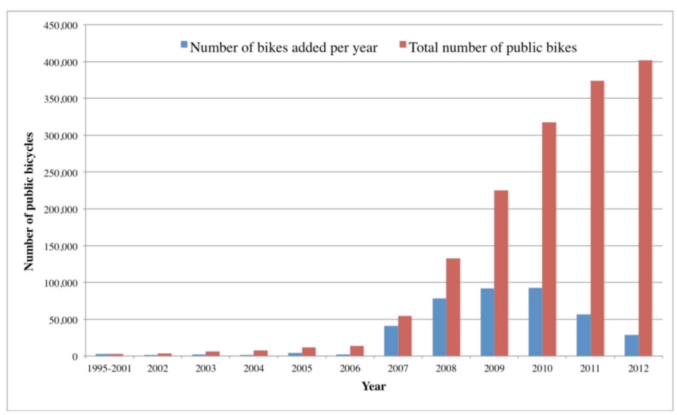

Fig. 4. Global growth in bike share programs. [4]

In 2005, China entered the world of BSSs with the Beijing program. From then and until 2012 China had twelve cities with formal public BSSs, totalling over 180,500 bikes [9]. In 2011, Wuhan and Hangzhou had world's largest systems with 70,000 and 65,000 bicycles, respectively [10]. The sudden implementation of many BSSs is rooted in the decline in bicycle utilisation since the 1990s [11]. The economic growth, longer trip distances and deteriorating cycling environments were the major factors behind said decline, as China was called "Kingdom of Bicycles" for its reliance on bicycle usage [11].

There are many more examples of BSSs being studied around the world, whether it is to just analyse its implications [12] [13], impacts [14], desires [15], demand [16] and even ridership influencing factors [17], analyse user's behaviour and adoption [11] [18], create machine learning models [19], compare different bike sharing approaches, or to just analyse and study a new case study [20] [21] [22] [23] [24].

Nonetheless, the increased demand and thirst for evolution and improvements in BSSs led to the development of new technologies and different approaches to the problem. The fifth generation started from the introduction of a new technology [8]: the dockless station [25]. This innovation makes it easier for any user to complete or begin a trip, since the bicycles can be parked anywhere and the users can access them instantly without the responsibility of returning them to a specific dock [26]. A reallocation team is then required to organize all the bikes into different parking areas.

The implementation of dockless BSSs increased cycling in urban areas, with significant reduction in car usage and carbon emissions [27]. In 2016, both Mobike and Ofo's dockless BSSs were introduced in China's first tier cities, Beijing, Shanghai, Guangzhou and Shenzhen, and in just one year their popularity skyrocketed. The previous four cities quickly grew to 200 cities, with over 23 million bikes and 221 million users [28].

Additionally, depending on the transport mode substituted by the use of BSSs, defined as modal shift [8], dockless or standard programs could be of great benefit. Kun Gao et al. [29] indicates that depending on the mode of transportation substituted, the modal shift can be beneficial or not. Replacing a private car, resulting in fewer car trips, reduces energy consumption and exhaust emissions during the trip; Replacing transit trips will not be of benefit, as schedules won't change; Replacing walking may even impose negative impacts on dockless BSSs.

Nonetheless, utilizing these systems to commute between two modes of public transport is very common: In Beijing a significant percentage of shared bikes were found active near bus stops and metro stations [26]; A study on how car congestion near subway stations can affect bike utilization [30] concluded in favour of the transportation mode substitution; From a survey made on car drivers [31], travel distance didn't matter, and users were willing to substitute their mode of transport.

However, when compared with standard systems, dockless bike sharing programs have significantly more theft, misuse and vandalism-related problems [32]. Bikes can be parked anywhere, occupying urban space, impacting traffic [28] and limiting access to facilities, pedestrian and cycling lanes and bus stops [29]. The primary challenge, however, is a direct consequence of these problems: The reallocation of the bicycles, which emit more greenhouse gases the more disperse are the bikes [28]. In standard BSSs, the rebalancing problem is also a big issue as some stations can be under supplied and have high demand, leading to the failure of China's standard and Singapore's dockless BSSs in 2019 [33].

Whether it is simply reallocating existing or new bikes into stations or, in dockless BSSs, repositioning the randomly parked bikes into specific areas, this process requires not only manpower, but also some kind of system to manage which bikes are repositioned to which stations, if any. The literature divided the solution in two categories:

- **Bike Repositioning Problem** (BRP): Calculation of the optimal truck routes and the loading and unloading of bikes at each station [34];
- **Demand Prediction** (DP): The prediction of the number of bikes left in a station at a certain point in time.

There are multiple studies that try to create efficient truck routes to minimize the greenhouse gas emissions [34] or user dissatisfaction [35] while minimizing travelling time and/or distance between stations. Others try to incentivize the users to rebalance themselves, with lower expected cost to end a trip in a station with less bikes or higher demand [36] [37]. The problem also lies in the number of bikes loaded and unloaded at each station [34], which is dependent on the route the truck will take.

Many of these studies focus on achieving a solution based on mathematical algorithms, with ordinary differential equations [38] and/or decision processes [39] [40] [41], or mathematical optimizations [42] [43] [44] [45] [46]; Applying some kind of heuristic [47] [48] [49]; Basing the solution around the stations, using their location [50] [34] and/or grouping them into clusters [47] [46]; and many more.

In comparison, the demand prediction problem is more straightforward but equally complex. Fixing it is crucial for effective bike repositioning, as stations can't be left empty while others are full [51].

Lei Lin et al. [51] divided the prediction models in the literature in three groups:

- **City-level**: Focused on predicting the total bike usage for an entire city;
- **Cluster-level**: Focused on grouping stations into clusters;
- **Station-level**: Focused on predicting demand for each station.

The first group, while it simplifies the issue, doesn't contribute in solving the rebalancing problem. Furthermore, it doesn't utilize most of the data extracted from a bike sharing system, like trip duration, origin and destination [51]. Romain Giot et al. [52], made predictions for the next day using Capital Bike Sharing system's data, using algorithms like Ridge Regression, Adaboost Regression, Support Vector Regression, Random Forecast Tree and Gradient Boosting Regression Tree.

The second group creates clusters of stations based on geographical locations and/or temporal demand patterns, assuming stations can be correlated and that the total demand of these stations can be predicted as a cluster [51]: Stations near a residential area might behave similarly between them, as well as stations near shopping centres or stations near public transport stops. Some examples of cluster-level predictions are: Community Detection Algorithm and Agglomerative Hierarchical Clustering [53], and K-Means Clustering and Latent Dirichlet Allocation [54].

The third group is much more challenging to implement [51]. Some studies implement linear regression models to predict monthly [55] or hourly [56] rentals, while others go further with neural networks [51] [57] or other machine and deep learning models.

However, these groups were devised with only station-based systems in mind. Travel patterns and trip frequency provide valuable insights in understanding the demand of these systems, but nothing can be said about the demand on dockless BSSs [58]. Without a station to forecast the number of bikes at a certain time, it becomes difficult to predict the demand in a singular place.

The demand prediction is mostly done by modelling the problem using a machine or deep learning algorithm. Table I depicts the ten most used artificial intelligence models, either to solve the problem or as baseline to compare to original models and the most used evaluation metrics to score the models, for the 50 most impactful papers in demand prediction.

TABLE I
DEMAND PREDICTION MODELS BY NUMBER OF PAPERS

Acronym	Full Name	# Papers	Evaluation Metrics
LSTM	Long Short-Term Memory	11	RMSE, MAE, MAPE, MSE, PCC, SMAPE
ARIMA	Autoregressive Integrated Moving Average	11	RMSE, MAE, MAPE, R^2, RMSER, MAER, RMSLE, ER
HA	Historical Average	9	RMSE, MAE, MAPE, R^2, PCC, RMSLE, ER
RF	Random Forest Algorithm	9	RMSE, MAE, R^2, CV, MAE, RMSE, RMSLE
LR	Linear Regression	9	RMSE, MAE, R^2, CV, RMSER, MAER
XGBoost	Extreme Gradient Boosting	6	RMSE, MAE, MAPE, PCC
KNN	K-Nearest Neighbours	5	RMSE, MAE, MAPE, R^2
SVM	Support Vector Machine	5	RMSE, MAE, MAPE, R^2, CV
ANN	Artificial Neural Network	4	RMSE, MAE, MAPE, MAE, RMSE, RMSLE
RNN	Recurrent Neural Network	4	RMSE, MAE, MAPE, R^2, PCC, SMAPE, MSE

Since the solution is to predict the number of bikes at a certain point in time, a time-series forecasting model is necessary. When modelling this type of data in BSSs, the ANN [58] is one of the most common algorithms used, however it doesn't account for temporal dependencies in the model structure. By recurrently connecting hidden layers at different timestamps, RNN [58] [59] [60] [57] could overcome the limitation, but it is still not fit for the time-series data with long time lags [58]. To solve the problem, the LSTM is used in several studies, with neural networks to fit the data of station-free sharing bikes [58], with an irregular convolutional layer to predict bike demand among similar urban areas [61], with a convolutional neural network for feature extraction on input data combined with the support sequence prediction of LSTM [62], and with spatial and temporal usage patterns to predict the short-run demand for station based systems [63]. It was also used as baseline comparator [51] [57] [64] [65] [60] [59].

Just like LSTM, ARIMA is commonly used for forecasting time-series, applied widely in traffic prediction [66]. Its performance can be significantly influenced by model tuning, and several variants can also generate better results [64], like ARMA which is commonly used for understanding and predicting future values in a time series [67] [68] [69], and the Seasonal ARIMA (SARIMA) and ARIMAX [70]. It is also used as baseline comparator in many studies [61] [59].

In regards to HA, it uses the historical average demand for prediction. Predicting the travel demand for a specific day at a specific time will result in the average from all past values in that specific day and time in the training dataset [64]. This model usually appears as only a comparator to other models [57] [65] [58], as both HA and its variant MA (Moving Average) are naive but competitive models [71].

Furthermore, RF can be used to overcome the problem of a model containing large amounts of predictors, which becomes more complex and overfits the data. The RF algorithm creates an ensemble of decision trees and randomly selects a subset of features to grow each tree [72]. It was applied as baseline comparator [73] or as the solution model using seasonal change data [74].

Another model used is the SVM [58], that was developed to seek the finest hyper-plane classification of data, which is transformed into a high-dimensional feature space where it can be linearly segregated through kernel functions to differentiate two groups that are not linearly separable [75]. It's used as baseline comparator [75], but an important branch has been applied widely in traffic flow prediction, SVR [65], or as baseline comparator as well [59] [74].

In comparison, LR is the simplest method, taking one or more X features in the input and outputting the number of bikes predicted [75]. Many regressions have been used as comparator models like the Gradient Boost Regression Tree [67], Vector Auto-Regression [57], Classification and Regression Trees [74], Geographically weighted regression [76], as well as the LR [70].

Others like XGBoost [58] [51] [64] [57], based on an implementation of gradient boosted decision trees, and KNN [67] [76] [74], predicts based on it-s K closes neighbours, are mostly used as baseline comparators.

More models have been considered, including, convolutional and recurrent networks (Graph Convolutional Network [51], Dynamic Transition Convolutional Neural Network and

Diffusion Convolutional Recurrent Neural Network [57]); LASSO (Least Absolute Shrinkage and Selection Operator) [51] and HP (Hierarchical prediction) [67]. Most of these models, which are implemented just a handful of times, are largely used to compare to other models.

These studies use various metrics to evaluate model performance, including error metrics such as Error Rate (ER), Mean Absolute Error (MAE) and its rate (MAER), Mean Absolute Percent Error (MAPE) and Symmetrical MAPE (SMAPE). Other error metrics include Mean Squared Error (MSE), Root MSE (RMSE) and its rate (RMSER) as well as Root Mean Squared Logarithmic Error (RMSLE). Association metrics, such as Pearson's Correlation Coefficient (PCC) and Coefficient of Determination (R^2), as well as variation metrics (Coefficient of Variation, CV) are also used to assess model performance.

MSE and RMSE are mostly applied when large errors must be penalized, as they are highly sensitive to outliers, however RSME is widely used in measuring the error of regression models [57]. They are calculated using the following equations, $MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2$ and $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$:

MAE and MAPE are used when all the errors are treated equally. They are calculated using the following equations, $MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|$ and $MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{x_i - y_i}{x_i}| \times 100$:

MAE is similar to ER, however MAE is used for regression tasks, while ER is mostly used for classifications tasks where correctness matters. The R^2 is useful for model comparison and variance explanation, it helps understand how good the model fitted the data, as a R^2 value of 1 means a perfect model.

The MAE is the average absolute error, which can better reflect the actual situation of the predicted value error. The RMSE is the arithmetic RMSE, which is more sensitive to outliers owing to the degree of change in the evaluation data. [77]

Only looking at the evaluation metrics when comparing two different models, however, is not recommended. Some studies predict the number of bikes after 10, 15, 20 or 30 minutes [58] while others only predict after one hour [56], or one month [55], or even in a specific time period [51]. The features used while modelling the solution will most likely be different from one model to another, some might use weather data in their predictions [78], while others use the stations location [51]. The data used to train and test the model is usually different from study to study, being impossible to conclude from two different datasets which model is better.

Choosing from the many existing models is one of the biggest problems in the demand prediction problem, as each use case has different problems at hand, using different data and features, and creating a model, training and testing is completely subjective.

Nonetheless, BSSs incorporate more than just bikes, stations, truck routes and demand prediction models. The development of these programs demand an enormous amount of effort, dedication and work. Dashboards filled with relevant information, like the number of bicycles in use, parked and in maintenance, the number of stations in the system and their occupancy and the number of users in the system and their trip record, are required for the operator's backstage work. Since some bikes come with an in-built tracking device, it is critical to have a map that indicates the position and state of the bicycles. Additionally, with ever growing technology and new "intelligent" bikes with stronger hardware and better firmware, bikes may also communicate with the system. Consequently, to receive the messages of the bike, process them and send a response back, a service oriented architecture is needed. Finally, a way to save all the information gathered from the use of the system can be implemented using a relational database, as all the information can be inserted into a relational model. The users can then rent a bike from the many kiosks or using a built mobile application, which allows them to view the available bikes, stations, their trip history. They can also rent a bike, see the progress in real time of their trip and understand when a trip is finished. If the system is not free, then a service that manages all the payments of the users is also required.

In conclusion, it is far more important to understand all the different elements that go into creating a successful bike sharing program, from the benefits and problems it will cause, the solutions developed, to the architecture and services needed, than the outcome of the system, as many bike sharing failures could be avoided with better planning and strategies.

CONCLUSION

Using the Scopus database for scientific publications, an advanced search was conducted that resulted in 500 papers used in the evaluation of BSSs. Five generations of BSSs have been identified, each with greater technologies and solutions to the previous problems, and many benefits. New insights for BSSs were provided, as many bikes were observed parked near train stations and bus stops, indicating a modal shift away from using private cars or taxis. High demand stations in standard systems and randomly parked bikes in dockless programs, are some of the main problems of these systems. Many studies have been conducted, either to find the most efficient truck routes or to develop and compare the best possible predictive models for the number of available bikes in a station at a certain period of time. Additionally, the infrastructure, including the database, services and dashboards and mobile application are important components not mentioned in the literature.

Although this study provides a systematic review of BSSs, it is not possible to conduct a comprehensive analysis on all the included literature. Not referenced and analysed papers may cover important information not mentioned in this review. In the future it would be beneficial to analyse more information such as the impact of Covid-19 in the bike sharing programs, more examples of different BSSs on their failures and successes, or the algorithms on user recommendation routes. Bike sharing is an ever growing business, even for the years to come, and it is necessary to understand what makes a bike sharing system fail and succeed.

REFERENCES

[1] Susan A. Shaheen, Stacey Guzman, and Hua Zhang. Bikesharing in europe, the americas, and asia: Past, present, and future. *Transportation Research Record*, 2143(1):159–167, 2010.

[2] Yongping Zhang and Zhifu Mi. Environmental benefits of bike sharing: A big data-based analysis. *Applied Energy*, 220:296–301, 2018.

[3] Mingyang Du and Lin Cheng. Better understanding the characteristics and influential factors of different travel patterns in free-floating bike sharing: Evidence from nanjing, china. *Sustainability*, 10(4), 2018.

[4] Simon Washington Elliot Fishman and Narelle Haworth. Bike share: A synthesis of the literature. *Transport Reviews*, 33(2):148–165, 2013.

[5] Mingzhuang Hua, Xuewu Chen, Jingxu Chen, Long Cheng, and Da Lei. How does dockless bike sharing serve users in nanjing, china? user surveys vs. trip records. *Research in Transportation Business Management*, 43:100701, 2022.

[6] P Midgley. Shared smart bicycle schemes in european cities. *Global Transport Knowledge Partnership (gTKP).(http://www. uncrd. or. jp/env/4th-regional-estforum/Presentations/28_PS4_gTKP. pdf, accessed March 12, 2012)*, 2009.

[7] Ezgi Eren and Volkan Emre Uz. A review on bike-sharing: The factors affecting bike-sharing demand. *Sustainable Cities and Society*, 54:101882, 2020.

[8] Xinwei Ma, Yufei Yuan, Niels Van Oort, and Serge Hoogendoorn. Bike-sharing systems' impact on modal shift: A case study in delft, the netherlands. *Journal of Cleaner Production*, 259:120846, 2020.

[9] Susan A. Shaheen Hua Zhang and Xingpeng Chen. Bicycle evolution in china: From the 1900s to the present. *International Journal of Sustainable Transportation*, 8(5):317–335, 2014.

[10] China News. Wuhan free rental bikes up to 70,000 intelligent rent but also the system starts, 2011. Retrieved August 9, 2012.

[11] Susan A. Shaheen, Hua Zhang, Elliot Martin, and Stacey Guzman. China's hangzhou public bicycle: Understanding early adoption and behavioral response to bikesharing. *Transportation Research Record*, 2247(1):33–41, 2011.

[12] Ran An, Renee Zahnow, Dorina Pojani, and Jonathan Corcoran. Weather and cycling in new york: The case of citibike. *Journal of Transport Geography*, 77:97–112, 2019.

[13] Or Caspi and Robert B. Noland. Bikesharing in philadelphia: Do lower-income areas generate trips? *Travel Behaviour and Society*, 16:143–152, 2019.

[14] Adrian Hernandez, Meredith Raymer, and Ying Chen. Where did bike-share boom? analyzing impact of infrastructure lockdowns on bike-sharing in chicago. *Transportation Research Interdisciplinary Perspectives*, 23:101015, 2024.

[15] Hongtai Yang, Yibei Zhang, Lizhi Zhong, Xiaojia Zhang, and Ziwen Ling. Exploring spatial variation of bike sharing trip production and attraction: A study based on chicago's divvy system. *Applied Geography*, 115:102130, 2020.

[16] Joseph Chibwe, Shahram Heydari, Ahmadreza Faghih Imani, and Aneta Scurtu. An exploratory analysis of the trend in the demand for the london bike-sharing system: From london olympics to covid-19 pandemic. *Sustainable Cities and Society*, 69:102871, 2021.

[17] Yi He, Ziqi Song, Zhaocai Liu, and N. N. Sze. Factors influencing electric bike share ridership: Analysis of park city, utah. *Transportation Research Record*, 2673(5):12–22, 2019.

[18] Alexandros Nikitas, Pontus Wallgren, and Oskar Rexfelt. The paradox of public acceptance of bike sharing in gothenburg. *Proceedings of the Institution of Civil Engineers - Engineering Sustainability*, 169(3):101–113, 2016.

[19] Santhanakrishnan Narayanan, Nikita Makarov, Evripidis Magkos, Josep Maria Salanova Grau, Georgia Aifadopoulou, and Constantinos Antoniou. Can bike-sharing reduce car use in alexandroupolis? an exploration through the comparison of discrete choice and machine learning models. *Smart Cities*, 6(3):1239–1253, 2023.

[20] Tiago Fontes, Miguel Arantes, Paulo V. Figueiredo, and Paulo Novais. A cluster-based approach using smartphone data for bike-sharing docking stations identification: Lisbon case study. *Smart Cities*, 5(1):251–275, 2022.

[21] Francesco Bruzzone, Mariangela Scorrano, and Silvio Nocera. The combination of e-bike-sharing and demand-responsive transport systems in rural areas: A case study of velenje. *Research in Transportation Business Management*, 40:100570, 2021. Active Travel and Mobility Management.

[22] Frédéric Dobruszkes and Michał Dziecielski. Does docked bike-sharing usage complement or overlap public transport? the case of brussels, belgium. *Transportation Planning and Technology*, 47(6):834–851, 2024.

[23] Barbara Laa and Günter Emberger. Bike sharing: Regulatory options for conflicting interests – case study vienna. *Transport Policy*, 98:148–157, 2020.

[24] Siti Norida Wahab, Rohana Sham, Amir 'AatieffAmir Hussin, Shakerin Ismail, and Salini Devi Rajendran. Urban transportation: A case study on bike-sharing usage in klang valley. *International Journal of Supply Chain Management*, 7(5):470 – 476, 2018. Cited by: 14.

[25] Hongyun Si, Jian gang Shi, Guangdong Wu, Jindao Chen, and Xianbo Zhao. Mapping the bike sharing research published from 2010 to 2018: A scientometric review. *Journal of Cleaner Production*, 213:415–427, 2019.

[26] Dea van Lierop Zheyan Chen and Dick Ettema. Dockless bike-sharing systems: what are the implications? *Transport Reviews*, 40(3):333–353, 2020.

[27] Juelin Yin, Lixian Qian, and Junjie Shen. From value co-creation to value co-destruction? the case of dockless bike sharing in china. *Transportation Research Part D: Transport and Environment*, 71:169–185, 2019. The roles of users in low-carbon transport innovations: Electrified, automated, and shared mobility.

[28] Mingzhuang Hua, Xuewu Chen, Shujie Zheng, Long Cheng, and Jingxu Chen. Estimating the parking demand of free-floating bike sharing: A journey-data-based study of nanjing, china. *Journal of Cleaner Production*, 244:118764, 2020.

[29] Kun Gao, Aoyong Li, Yang Liu, Jorge Gil, and Yiming Bie. Unraveling the mode substitution of dockless bike-sharing systems and its determinants: A trip level data-driven interpretation. *Sustainable Cities and Society*, 98:104820, 2023.

[30] Yichun Fan and Siqi Zheng. Dockless bike sharing alleviates road congestion by complementing subway travel: Evidence from beijing. *Cities*, 107:102895, 2020.

[31] Xinwei Ma, Ruiming Cao, and Jianbiao Wang. Effects of psychological factors on modal shift from car to dockless bike sharing: A case study of nanjing, china. *International Journal of Environmental Research and Public Health*, 16(18), 2019.

[32] Efthimios Bakogiannis, Maria Siti, Stefanos Tsigdinos, Avgi Vassi, and Alexandros Nikitas. Monitoring the first dockless bike sharing system in greece: Understanding user perceptions, usage patterns and adoption barriers. *Research in Transportation Business Management*, 33:100432, 2019.

[33] Jie Song, Liye Zhang, Zheng Qin, and Muhamad Azfar Ramli. Where are public bikes? the decline of dockless bike-sharing supply in singapore and its resulting impact on ridership activities. *Transportation Research Part A: Policy and Practice*, 146:72–90, 2021.

[34] C.S. Shui and W.Y. Szeto. Dynamic green bike repositioning problem – a hybrid rolling horizon artificial bee colony algorithm approach. *Transportation Research Part D: Transport and Environment*, 60:119–136, 2018. Special Issue on Traffic Modeling for Low-Emission Transport.

[35] Luca Di Gaspero, Andrea Rendl, and Tommaso Urli. Constraint-based approaches for balancing bike sharing systems. In Christian Schulte, editor, *Principles and Practice of Constraint Programming*, pages 758–773, Berlin, Heidelberg, 2013. Springer Berlin Heidelberg.

[36] Christine Fricker and Nicolas Gast. Incentives and redistribution in homogeneous bike-sharing systems with stations of finite capacity. *EURO Journal on Transportation and Logistics*, 5(3):261–291, August 2016.

[37] Ariel Waserhole and Vincent Jost. Vehicle sharing system pricing regulation: Transit optimization of intractable queuing network. *HAL Id: hal-00751744*, pages 1–20, 2012.

[38] Christine Fricker and Nicolas Gast. Incentives and redistribution in homogeneous bike-sharing systems with stations of finite capacity. *EURO Journal on Transportation and Logistics*, 5(3):261–291, 2016.

[39] Benjamin Legros. 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, 2019.

[40] Supriyo Ghosh, Pradeep Varakantham, Yossiri Adulyasak, and Patrick Jaillet. Dynamic repositioning to reduce lost demand in bike sharing systems. *Journal of Artificial Intelligence Research*, 58:387–430, February 2017.

[41] Leonardo Caggiani, Rosalia Camporeale, Michele Ottomanelli, and Wai Yuen Szeto. A modeling framework for the dynamic management of free-floating bike-sharing systems. *Transportation Research Part C: Emerging Technologies*, 87:159–182, 2018.

[42] Aritra Pal and Yu Zhang. Free-floating bike sharing: Solving real-life large-scale static rebalancing problems. *Transportation Research Part C: Emerging Technologies*, 80:92–116, 2017.

[43] Tal Raviv, Michal Tzur, and Iris A. Forma. Static repositioning in a bike-sharing system: models and solution approaches. *EURO Journal on Transportation and Logistics*, 2(3):187–229, 2013.

[44] Mauro Dell'Amico, Eleni Hadjicostantinou, Manuel Iori, and Stefano Novellani. The bike sharing rebalancing problem: Mathematical formulations and benchmark instances. *Omega*, 45:7–19, 2014.

[45] Dong Zhang, Chuhang Yu, Jitamitra Desai, H.Y.K. Lau, and Sandeep Srivathsan. A time-space network flow approach to dynamic repositioning in bicycle sharing systems. *Transportation Research Part B: Methodological*, 103:188–207, 2017. Green Urban Transportation.

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

[47] Iris A. Forma, Tal Raviv, and Michal Tzur. A 3-step math heuristic for the static repositioning problem in bike-sharing systems. *Transportation Research Part B: Methodological*, 71:230–247, 2015.

[48] Fábio Cruz, Anand Subramanian, Bruno P. Bruck, and Manuel Iori. A heuristic algorithm for a single vehicle static bike sharing rebalancing problem. *Computers Operations Research*, 79:19–33, 2017.

[49] Sin C. Ho and W.Y. Szeto. Solving a static repositioning problem in bike-sharing systems using iterated tabu search. *Transportation Research Part E: Logistics and Transportation Review*, 69:180–198, 2014.

[50] Chenyi Fu, Ning Zhu, Shoufeng Ma, and Ronghui Liu. A two-stage robust approach to integrated station location and rebalancing vehicle service design in bike-sharing systems. *European Journal of Operational Research*, 298(3):915–938, 2022.

[51] Lei Lin, Zhengbing He, and Srinivas Peeta. Predicting station-level hourly demand in a large-scale bike-sharing network: A graph convolutional neural network approach. *Transportation Research Part C: Emerging Technologies*, 97:258–276, 2018.

[52] Romain Giot and Raphaël Cherrier. Predicting bikeshare system usage up to one day ahead. In *2014 IEEE Symposium on Computational Intelligence in Vehicles and Transportation Systems (CIVTS)*, pages 22–29, 2014.

[53] Xiaolu Zhou. Understanding spatiotemporal patterns of biking behavior by analyzing massive bike sharing data in chicago. *PLOS ONE*, 10(10):1–20, 10 2015.

[54] Jie Bao, Chengcheng Xu, Pan Liu, and Wei Wang. Exploring bikesharing travel patterns and trip purposes using smart card data and online point of interests. *Networks and Spatial Economics*, 17(4):1231 – 1253, 2017. Cited by: 127.

[55] R. Rixey. Station-level forecasting of bikesharing ridership. *Transportation Research Record*, (2387):46 – 55, 2013. Cited by: 230.

[56] Ahmadreza Faghih-Imani, Naveen Eluru, Ahmed M. El-Geneidy, Michael Rabbat, and Usama Haq. How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (bixi) in montreal. *Journal of Transport Geography*, 41:306–314, 2014.

[57] Bowen Du, Xiao Hu, Leilei Sun, Junming Liu, Yanan Qiao, and Weifeng Lv. Traffic demand prediction based on dynamic transition convolutional neural network. *IEEE Transactions on Intelligent Transportation Systems*, 22(2):1237–1247, 2021.

[58] Chengcheng Xu, Junyi Ji, and Pan Liu. The station-free sharing bike demand forecasting with a deep learning approach and large-scale datasets. *Transportation Research Part C: Emerging Technologies*, 95:47–60, 2018.

[59] Shih-Hsiung Lee and Hsuan-Chih Ku. A dual attention-based recurrent neural network for short-term bike sharing usage demand prediction. *IEEE Transactions on Intelligent Transportation Systems*, 24(4):4621–4630, 2023.

[60] Guangnian Xiao, Ruinan Wang, Chunqin Zhang, and Anning Ni. Demand prediction for a public bike sharing program based on spatio-temporal graph convolutional networks. *Multimedia Tools and Applications*, 80(15):22907–22925, March 2020.

[61] Xinyu Li, Yang Xu, Xiaohu Zhang, Wenzhong Shi, Yang Yue, and Qingquan Li. Improving short-term bike sharing demand forecast through an irregular convolutional neural network. *Transportation Research Part C: Emerging Technologies*, 147:103984, 2023.

[62] Aliasghar Mehdizadeh Dastjerdi and Catherine Morency. Bike-sharing demand prediction at community level under covid-19 using deep learning. *Sensors*, 22(3), 2022.

[63] Xinwei Ma, Yurui Yin, Yuchuan Jin, Mingjia He, and Minqing Zhu. Short-term prediction of bike-sharing demand using multi-source data: A spatial-temporal graph attentional lstm approach. *Applied Sciences*, 12(3), 2022.

[64] Yuanxuan Yang, Alison Heppenstall, Andy Turner, and Alexis Comber. Using graph structural information about flows to enhance short-term demand prediction in bike-sharing systems. *Computers, Environment and Urban Systems*, 83:101521, 2020.

[65] Wenjie Zi, Wei Xiong, Hao Chen, and Luo Chen. Tagcn: Station-level demand prediction for bike-sharing system via a temporal attention graph convolution network. *Information Sciences*, 561:274–285, 2021.

[66] Mascha Van Der Voort, Mark Dougherty, and Susan Watson. Combining kohonen maps with arima time series models to forecast traffic flow. *Transportation Research Part C: Emerging Technologies*, 4(5):307 – 318, 1996. Cited by: 719; All Open Access, Green Open Access.

[67] Wenzhen Jia, Yanyan Tan, Li Liu, Jing Li, Huaxiang Zhang, and Kai Zhao. Hierarchical prediction based on two-level gaussian mixture model clustering for bike-sharing system. *Knowledge-Based Systems*, 178:84–97, 2019.

[68] Ahmadreza Faghih-Imani, Robert Hampshire, Lavanya Marla, and Naveen Eluru. An empirical analysis of bike sharing usage and rebalancing: Evidence from barcelona and seville. *Transportation Research Part A: Policy and Practice*, 97:177–191, 2017.

[69] Andreas Kaltenbrunner, Rodrigo Meza, Jens Grivolla, Joan Codina, and Rafael Banchs. Urban cycles and mobility patterns: Exploring and predicting trends in a bicycle-based public transport system. *Pervasive and Mobile Computing*, 6(4):455–466, 2010.

[70] Yexin Li and Yu Zheng. Citywide bike usage prediction in a bike-sharing system. *IEEE Transactions on Knowledge and Data Engineering*, 32(6):1079–1091, 2020.

[71] Weiwei Jiang. Bike sharing usage prediction with deep learning: a survey. *Neural Computing and Applications*, 34(18):15369–15385, June 2022.

[72] Huthaifa I. Ashqar, Mohammed Elhenawy, and Hesham A. Rakha. Modeling bike counts in a bike-sharing system considering the effect of weather conditions. *Case Studies on Transport Policy*, 7(2):261–268, 2019.

[73] Ying Lv, Danyue Zhi, Huijun Sun, and Geqi Qi. Mobility pattern recognition based prediction for the subway station related bike-sharing trips. *Transportation Research Part C: Emerging Technologies*, 133:103404, 2021.

[74] Sathishkumar V. E. and Yongyun Cho. Season wise bike sharing demand analysis using random forest algorithm. *Computational Intelligence*, 40(1):e12287, 2024.

[75] Sathishkumar V E, Jangwoo Park, and Yongyun Cho. Using data mining techniques for bike sharing demand prediction in metropolitan city. *Computer Communications*, 153:353–366, 2020.

[76] Xudong Wang, Zhanhong Cheng, Martin Trépanier, and Lijun Sun. Modeling bike-sharing demand using a regression model with spatially varying coefficients. *Journal of Transport Geography*, 93:103059, 2021.

[77] Tiantian Xu, Guangjie Han, Xingyue Qi, Jiaxin Du, Chuan Lin, and Lei Shu. A hybrid machine learning model for demand prediction of edge-computing-based bike-sharing system using internet of things. *IEEE Internet of Things Journal*, 7(8):7345–7356, 2020.

[78] Sathishkumar V E and Yongyun Cho. A rule-based model for seoul bike sharing demand prediction using weather data. *European Journal of Remote Sensing*, 53(sup1):166 – 183, 2020. Cited by: 57; All Open Access, Gold Open Access.