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Towards effective rebalancing of bike-sharing systems with regular and electric bikes

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Abstract : The emerging demand for electric bicycles in recent years has prompted several bike-sharing systems (BSS) around the world to adapt their service to a new wave of commuters. Many of these systems have incorporated electric bikes into their network while still maintaining the use of regular mechanical bicycles. However, the presence of two types of bikes in a BSS network may impact how rebalancing operations should be conducted in the system. Regular and electric bikes may exhibit distinct demand patterns throughout the day, which can hinder efficient planning of such operations. In this paper, we propose a new model that provides rebalancing recommendations based on the demand prediction for each type of bike. Additionally, we simulate the performance of our model under different scenarios, considering commuters' varying inclination to substitute their preferred bike with one of a different type. In one simulated scenario, our model successfully reduced lost demand by approximately 40% compared to the current rebalancing strategy employed by the real-world BSS studied. Moreover, it decreased the number of rebalancing operations conducted by approximately 12%, resulting in benefits not only in terms of cost reduction but also in reducing greenhouse gas emissions.

Keywords: Bike-sharing, rebalancing, e-bikes, inventory management

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1 Introduction

In the last years, we have seen bike-sharing systems (BSS) gaining the spotlight in the transportation scene due to their numerous advantages such as the absence of greenhouse gases emission, the promotion of a healthy lifestyle, as well as easy and facilitated access. The history of this mobility service dates back to the 60s and has continuously evolved over time (Si et al., 2019). The fourth BSS generation, which we are currently experiencing, is marked by the inclusion of solar-powered docking stations, real-time system data, mobile apps, flexible parking, and electric bikes, also known as e-bikes (Julio and Monzon, 2022).

In comparison with regular bikes, e-bikes are faster, easier to ride, especially on hilly paths, and overall they cause less fatigue (Ji et al., 2014). To make BSSs more attractive to a group of commuters who are mainly interested in these advantages, BSSs around the world have introduced e-bikes into their networks – e.g. BIXI (Montréal), Citi Bike (New York). Nonetheless, regular bikes still please loyal commuters who search for health benefits or for a cheaper transportation mode. In (Zhu, 2021), it is shown that the introduction of e-bikes in BSSs, alongside regular bikes, contributed significantly to the augmentation of BSSs revenues. However, a network with two types of bikes indeed introduces new challenges at every step of the service's logistics.

This challenge is especially hard for dock-based BSSs where the docks at the stations must be shared by both types of bikes. As such, too many bikes of a given type may lead to lost demand of the second type, and vice-versa, given that the number of docks is limited at each station. Hence, at the moment of rebalancing the inventory of a station, it is important to dynamically determine the number of ideal available bikes of each type in the stations of the system to guarantee its effective service.

Figure 1 presents the hourly average number of bikes rented on BIXI-Montreal in July 2022, where we can observe that the demand for regular and electric bike trips bounces over the day. Figure 2 highlights the considerable variation in e-bike demand per station at BIXI. While we can identify areas with high demand, it is notable that high-demand stations can be found adjacent to low-demand stations. This shows that understanding bike demand at station level is a complex task – even more in the presence of a heterogeneous bike offer. Additionally, the demand for bikes has undergone a significant transformation in recent years, driven by the shifts in working habits brought about by the COVID-19 pandemic (Hossain et al., 2023; Shaik and Ahmed, 2022).

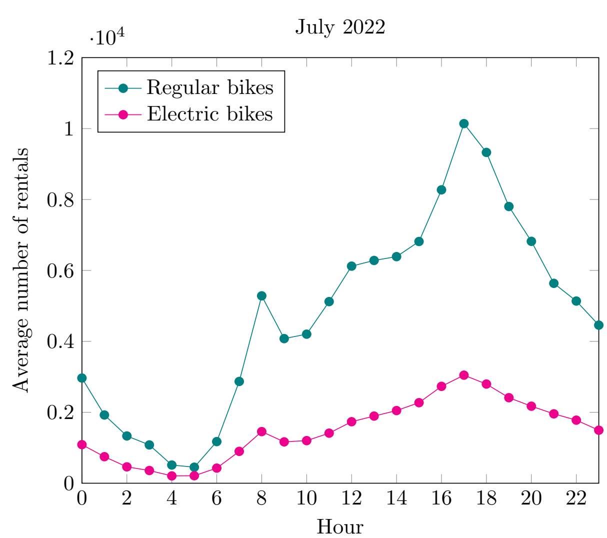

Figure 1: Hourly average number of rentals on BIXI-Montreal BSS in July 2022

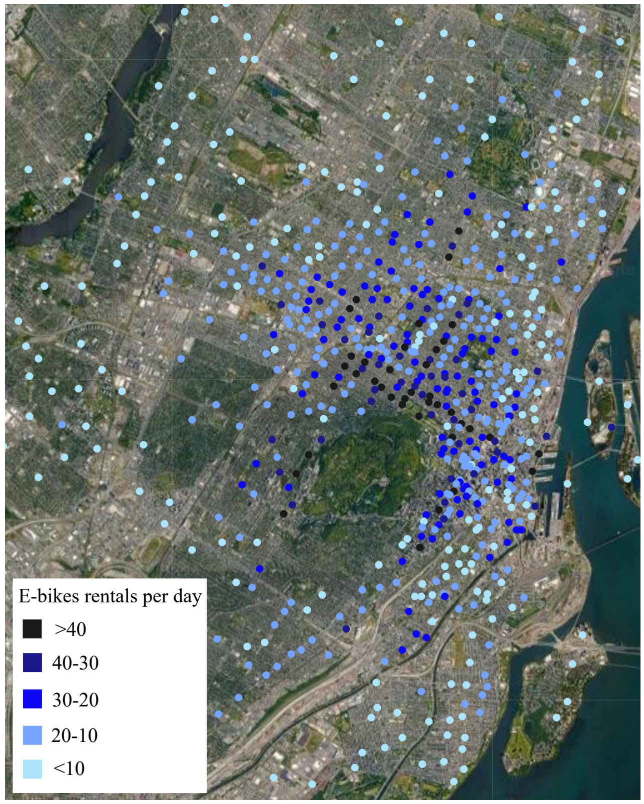

Figure 2: Average number of rented e-bikes per day at BIXI in July 2022

Besides, reallocating bikes through rebalancing operations can be quite expensive since it involves fuel costs, truck maintenance, driver's salary, etc. The trucks used for rebalancing are also responsible for CO_2 emissions and other polluting gases, which contradicts the BSS's commitment to sustainability. Therefore, it is important to optimize the effectiveness of rebalancing operations, updating the inventories of stations that yield minimal lost demand in the system. Nonetheless, leaving to the operator alone the task of understanding both demands and their correlations, while assuring that the rebalancing operations respect the BSS's limited resources, may lead to suboptimal rebalancing decisions.

The primary objective of our paper is to underscore the significance of incorporating demand predictions for both regular and electric bikes when making dynamic rebalancing decisions within a station-based bike-sharing system (BSS). In light of this, we propose a model that identifies imbalanced stations and determines the target inventory for each bike type. Essentially, our model provides recommendations for when and how many bikes of each type should be added or removed during the rebalancing process. By considering the expected demand for each bike type within a specific time period and accounting for station capacity, our model aims to optimize the rebalancing performance.

To evaluate our model effectiveness, we collected data from BIXI-Montreal[1] and conducted simulations to compare the inventory response between our proposed rebalancing strategy and the one currently employed by BIXI. Furthermore, our simulations explore various policies regarding the option of replacing one type of bike with another for a trip.

The paper is organized as follows. Section 2 reviews relevant literature on our research topic. Section 3 describes the proposed model to compute inventory intervals and target inventory for both

[1] www.bixi.com

regular and electric bikes. Section 4 presents the data, the tuning process, the inventory simulator, and the results of our experiments. Finally, our final remarks are given in Section 5.

2 Related works

One key performance indicator to assess a BSS is its *service level*, which is computed as the ratio between the number of satisfied trips and the total number of demanded trips (Schuijbroek et al., 2017). It indicates whether a BSS is able to meet the commuters' demand, which is paramount for customer satisfaction.

The strategies to improve the service level in BSSs can be grouped into two main categories: network planning and operational rebalancing. The first consists of designing an ideal network configuration by optimizing the number of stations, docks and bikes, the location of the stations, initial inventories, etc., to reduce the total lost demand in the system (Raviv and Kolka, 2013; Schuijbroek et al., 2017; Datner et al., 2019). The second represents an intervention, that can be performed either by the BSS operator or by the commuters, to redistribute the network's assets, e.g. bikes or batteries, among the stations (Bulhões et al., 2018; Lowalekar et al., 2017; Possani and Castillo, 2021; Forma et al., 2015; Tan et al., 2021).

Table 1: Summary of strategies to improve the service level in EBSS

Strategy	Research article	Network	Parking	Methodology
Operational rebalancing	(Fukushige et al., 2022)	Modal	Free-floating	User-based approach for rebalancing
	(Tan et al., 2021)	Modal	Parking locations	Optimization of routes for battery exchange
	(Zhou et al., 2022)	Modal	Free-floating	Optimization of routes for battery exchange
Network planning	(Zhu, 2021)	Bimodal	Station-based	Optimization of bikes and e-bikes fleet
	(Chen et al., 2020)	Modal	Station-based	Optimization of bikes fleet and number of docks
	(Zhou et al., 2020)	Modal	Parking locations	Optimization of parking locations
	(Martinez et al., 2012)	Bimodal	Station-based	Optimization of stations locations
	(Soriguera et al., 2020)	Modal	Station-based	Optimization of e-bikes fleet, number of stations, number of docks, and rebalancing rate

Many studies in the literature have proposed strategies to improve the service level in BSSs. However, works that consider systems with shared e-bikes, hereafter denoted EBSSs, have just recently emerged. Table 1 summarizes the main works in the literature whose goal is to improve the service level in EBSSs. They are classified according to the strategy to improve the service level (operational rebalancing or network planning), the BSS network composition (modal or bimodal), the parking configuration (capacitated station-based, uncapacitated parking locations or free-floating), and their methodology.

The works of (Fukushige et al., 2022; Tan et al., 2021; Zhou et al., 2022) propose operational rebalancing strategies since they both deal with the reallocation of resources in the system. In (Fukushige et al., 2022) the authors study a user-based approach to better understand in which scenarios BSS commuters are stimulated to return bikes to a desired location under financial incentives. In (Tan et al., 2021; Zhou et al., 2022), both works present models that propose traveling routes for exchanging discharged batteries for charged batteries among e-bikes in the system. Battery recharging is directly related to the performance of the service provided since e-bikes with discharged batteries remain unused in the system. In our model, we assume that the battery recharging is performed during the rebalancing process itself. This is not a strong assumption in reality. At Bixi-Montreal, almost 20% of the stations are powered, allowing battery recharging on site. The remaining references address network planning strategies, i.e., they approach the problem of fleet dimensioning ((Zhu, 2021; Chen et al., 2020; Soriguera et al., 2020)), dock dimensioning (Chen et al., 2020; Soriguera et al., 2020)), locating the stations ((Zhou et al., 2020; Martinez et al., 2012)) and rebalancing rate, i.e., reallocated bikes per hour ((Soriguera et al., 2020)).

Our proposed model proposes to optimize the service level of a bimodal and station-based EBSS using target inventory values and inventory intervals to assist in the rebalancing process. The target inventory value represents the ideal number of bikes for a station and it is often used to establish how many bikes that station should have in a given time period in order to maximize its service level (Huang et al., 2020; Datner et al., 2019; Liu et al., 2016; Raviv and Kolka, 2013). The inventory interval consists of an acceptable range in which the inventory can fluctuate while still meeting the expected demand. They are usually used to select which stations from the network need to be rebalanced (Hulot et al., 2018; Schuijbroek et al., 2017; Haider et al., 2018).

3 Proposed model

In this Section, we present the model developed to automatically generate target inventory values and inventory intervals for bimodal BSS based on demand prediction.

3.1 Target inventory values

Addressing the challenge of generating target values for two different demands that share station docks requires careful consideration to ensure that both demands are met without exceeding the station's capacity. So, to ensure the feasibility of the rebalancing recommendations provided by our target inventory values, our model divides the number of docks for each demand based on their respective service levels. Additionally, it establishes the optimal initial inventory within the allocated number of reserved docks for each demand.

Our model starts by training a machine-learning model to predict hourly rentals and returns at station-level for both types of bikes. In this work, we used the GBT-based predictive model introduced in (Hulot et al., 2018) which considers historical data as well as exogenous features such as weather conditions or holidays.

After forecasting the demand at each station of the BSS, we calculate their respective service levels. In our study, considering the availability of two types of bikes, we chose to compute the proportion of satisfied trips independently for each bike type. This approach allows us to assess the service level for each type of bike individually, taking into account their specific demand patterns and availability.

To calculate the service level of a station, we model its inventory as a queue with a single server. The capacity of this queue is set to match the number of available docks at that particular station. Similar to other works that address the random rentals and returns of commuters in a BSS, such as (Raviv et al., 2013; Schuijbroek et al., 2017; Hulot et al., 2018; Ghosh et al., 2017; Shu et al., 2013; Kabra et al., 2020; George and Xia, 2011), we assumed that the trips follow a Poisson distribution, so that the times between rentals and returns follow exponential distributions.

For a station s with an initial inventory of f and a specific number of docks, denoted as $C^{\mathcal{R}}$, allocated for regular bikes out of the total capacity of C_s docks, the expected service level for regular bikes during the time period $[0, T]$ can be computed as follows:

$$SL_s^{\mathcal{R}}(f, T, C^{\mathcal{R}}) = \frac{\int_0^T \mu_s^{\mathcal{R}}(t)(1 - p_s^{\mathcal{R}}(f, 0, t)) + \lambda_s^{\mathcal{R}}(t)(1 - p_s^{\mathcal{R}}(f, C^{\mathcal{R}}, t))dt}{\int_0^T \mu_s^{\mathcal{R}}(t) + \lambda_s^{\mathcal{R}}(t)dt}, \tag{1}$$

where $p_s^{\mathcal{R}}(f, N, t)$ is the probability that the station s stores N regular bikes at hour t, knowing that its initial inventory is equal to f at time 0; $\mu_s^{\mathcal{R}}(t)$ and $\lambda_s^{\mathcal{R}}(t)$ represent the predicted rental and return for regular bikes at hour t and station s. Here, the superscript $\mathcal{R}$ refers to values that are specific to regular bikes. Likewise, the service levels for e-bikes are computed as in Equation (1) by replacing $\mu_s^{\mathcal{R}}(t)$, $\lambda_s^{\mathcal{R}}(t)$, $p_s^{\mathcal{R}}(f, N, t)$ and $C^{\mathcal{R}}$ by $\mu_s^{\mathcal{E}}(t)$, $\lambda_s^{\mathcal{E}}(t)$, $p_s^{\mathcal{E}}(f, N, t)$ and $C^{\mathcal{E}}$, respectively, where the superscript $\mathcal{E}$ refers to values regarding e-bikes only.

Indeed, Equation (1) depends on the number of docks $C^{\mathcal{R}}$ allocated to regular bikes at the analyzed time period. This allocation may vary to optimize the performance of the system based on the anticipated trip demand. In our model, the number of docks allotted for regular and electric bikes at station s for time period $[0,T]$, denoted $C_s^{\mathcal{R}}(T)$ and $C_s^{\mathcal{E}}(T)$, respectively, are determined as:

$$C_s^{\mathcal{R}}(T) = \underset{\overline{C}\in\{0,\dots,C_s\}}{\arg\max} \left\{\Lambda_s^{\mathcal{R}}(T,\overline{C}) + \Lambda_s^{\mathcal{E}}(T,\overline{C}-C_s)\right\}, \tag{2}$$

and

$$C_s^{\mathcal{E}}(T) = C_s - C_s^{\mathcal{R}}(T), \tag{3}$$

where function $\Lambda_s^{\mathcal{R}}(T,x)$ (resp. $\Lambda_s^{\mathcal{E}}(T,x)$) is chosen as the maximum or the average value of $SL_s^{\mathcal{R}}(f,T,x)$ (resp. $SL_s^{\mathcal{E}}(f,T,x)$) for $f \in \{0,\dots,x\}$. The choice of the function as max or avg. influences the service level we want to optimize (the best or the average-case, respectively).

Once the number of docks reserved for regular bikes and e-bikes are determined, our model proceeds to compute the target inventory values for regular and e-bikes for time period $[0,T]$ as:

$$\mathcal{T}_s^{\mathcal{R}}(T) = \underset{f\in\{0,\dots,C_s^{\mathcal{R}}(T)\}}{\arg\max} \{SL_s^{\mathcal{R}}(f,T,C_s^{\mathcal{R}}(T))\}, \tag{4}$$

and

$$\mathcal{T}_s^{\mathcal{E}}(T) = \underset{f\in\{0,\dots,C_s^{\mathcal{E}}(T)\}}{\arg\max} \{SL_s^{\mathcal{E}}(f,T,C_s^{\mathcal{R}}(T))\}. \tag{5}$$

The computed target values respect the capacity of the station and the number of docks reserved for each type of bike. This ensures that the recommended rebalancing actions based on the target inventory values are practical and feasible to implement.

3.2 Inventory intervals

Considering only the total rentals or returns without distinguishing between different types of demand can obscure the identification of lost demand for a specific type of bike. Similarly, creating inventory intervals tailored to each demand while assuming that the total number of docks is always available can lead to undesirable situations. For instance, a station may become completely full without triggering any alerts because neither demand (for regular or e-bikes) has exceeded its upper or lower bounds. Therefore, it is crucial to take into account the station capacity when setting inventory intervals to ensure optimal inventory management and prevent potential issues.

To calculate the inventory intervals, we begin by computing the maximum and minimum service levels for each demand for time period $[0,T]$, which are given by

$$\underline{SL}_s^{\mathcal{R}}(T) = \min_{f\in\{0,\dots,C^{\mathcal{R}}\}} SL_s^{\mathcal{R}}(f,T,C_s^{\mathcal{R}}(T)), \tag{6}$$

and

$$\overline{SL}_s^{\mathcal{R}}(T) = \max_{f\in\{0,\dots,C^{\mathcal{R}}\}} SL_s^{\mathcal{R}}(f,T,C_s^{\mathcal{R}}(T)) \tag{7}$$

for regular bikes. These values can be analogously obtained for e-bikes, by replacing the superscript $\mathcal{R}$ by $\mathcal{E}$.

Then, accepted service levels at station s for time period $[0,T]$ are calculated for each type of bike as:

$$\Omega_s^{\mathcal{R}}(T) = \underline{SL}_s^{\mathcal{R}}(T) + \beta^{\mathcal{R}}(\overline{SL}_s^{\mathcal{R}}(T) - \underline{SL}_s^{\mathcal{R}}(T)), \tag{8}$$

and

$$\Omega_s^{\mathcal{E}}(T) = \underline{SL}_s^{\mathcal{E}}(T) + \beta^{\mathcal{E}}(\overline{SL}_s^{\mathcal{E}}(T) - \underline{SL}_s^{\mathcal{E}}(T)), \tag{9}$$

The model incorporates two hyperparameters, $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$, which are specific to each type of bike. These hyperparameters provide flexibility for the operator to fine-tune the computed inventory intervals for a station based on the behaviour patterns of its user base. By separately adjusting the values of $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$, the operator can also customize the inventory intervals to be more or less stringent for each demand type throughout the day.

Finally, the inventory intervals for regular bikes and e-bikes at station s for time period $[0, T]$ are computed as:

$$\mathcal{I}_s^{\mathcal{R}}(T) = \{f \in \{0, ..., C_s^{\mathcal{R}}(T)\} | SL_s^{\mathcal{R}}(f, T, C_s^{\mathcal{R}}(T)) \geq \Omega_s^{\mathcal{R}}(T)\} \tag{10}$$

and

$$labeleq8\mathcal{I}_s^{\mathcal{E}}(T) = \{f \in \{0, ..., C_s^{\mathcal{E}}(T)\} | SL_s^{\mathcal{E}}(f, T, C_s^{\mathcal{E}}(T)) \geq \Omega_s^{\mathcal{E}}(T)\} \tag{11}$$

4 Computational experiments

In this section, we assess our model in comparison with the approach used by BIXI in 2022. First, we will present the data used in our experiments. Then, we briefly explain our simulations to emulate the inventories based on the rebalancing strategy applied. Next, we discuss the process for selecting the best hyperparameters, $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$, for our model. At last, we present the results collected from our experiments.

4.1 Data

In light of the fact that BIXI added a considerable amount of e-bikes to its network in 2022, we opted to collect only the data from the aforementioned year. Thus, the data used in our experiments contain hourly information from April to September 2022, being grouped into three categories: temporal, weather, and trip data. The first category includes time features, such as hour, day, day of the week, month, and holidays. The second category contains data describing the weather, such as temperature, humidity, rain, and wind speed. Both temporal and weather data were collected from the official website of the Government of Canada[2] (except for the holiday feature which was manually noted). The trip data is composed of the number of rentals and returns at each station and it was provided by BIXI[3]. In addition to the data mentioned before, BIXI also provided the inventory intervals used in 2022 and network information that includes the capacity of the 745 stations and the proportion of regular bikes ($\approx 75\%$) and electric bikes ($\approx 25\%$) in their network.

The collected data was divided between train, validation, and test datasets. We chose to do a chronological division of the datasets to resemble a real case, in which the training dataset has no merged data with the test dataset. So, the training dataset is composed of data from April 2022 to July 2022, the validation dataset contains data from August 2022, and the test dataset has data from September 2022.

4.2 Experiment

Our proposed model, denoted hereafter shared-$\mathcal{RE}$, is compared against a baseline approach, namely B0, that corresponds to the strategy applied by BIXI operators in 2022. The inventory intervals and target inventory values used to assist the rebalancing operations at BIXI were manually determined by their operators. These decisions were based on historical trip data at each station, without differentiation between regular bikes and e-bikes.

4.2.1 Simulation of B0

Simulation B0 begins by initializing the inventories of regular and electric bikes at the stations with their respective target inventory values. However, it is worth noting that BIXI employs a unique target

[2] https://climate.weather.gc.ca/
[3] https://bixi.com

inventory value for each station during specific time periods. To decouple this single target inventory value between regular bikes and e-bikes, a straightforward approach is to distribute it based on the proportion of each bike type rented at the station during the observed period. This distribution can be determined by analyzing the training dataset, which ensures that the distribution of bikes aligns with the observed rental patterns.[4]

Then, at each simulated hour, the inventory of each station is updated with the historical rentals and returns from BIXI data. At this point, the simulated inventory can detect cases of lost demand due to either missing bikes or docks.

After updating the inventory, the simulation verifies which stations triggered a rebalancing alert, that is, which stations surpass the bounds of their inventory interval. The simulation also keeps track of the lost demand, i.e., how many bikes were missing during the rentals and how many bikes could not be returned due to full stations by assuming that all rentals and returns happen simultaneously at every simulated hour. Thus, we stress the network to capture its possible failures.

The simulation of B0 rebalances the inventories of all the stations that raise an alert. The amount of rebalanced stations per hour while simulating B0 is then used as the maximal number of stations that can be rebalanced when simulating our model shared-$\mathcal{RE}$.

Figure 3 illustrates the simulation of the bike inventory of a station using B0. In the illustration, the station raised an alert due to the shortage of bikes, i.e. its inventory (3) is below the inventory lower bound (4). After rebalancing, the inventory of regular and e-bikes at the station is updated according to the target inventory value and the station's historical demand observed in the training data.

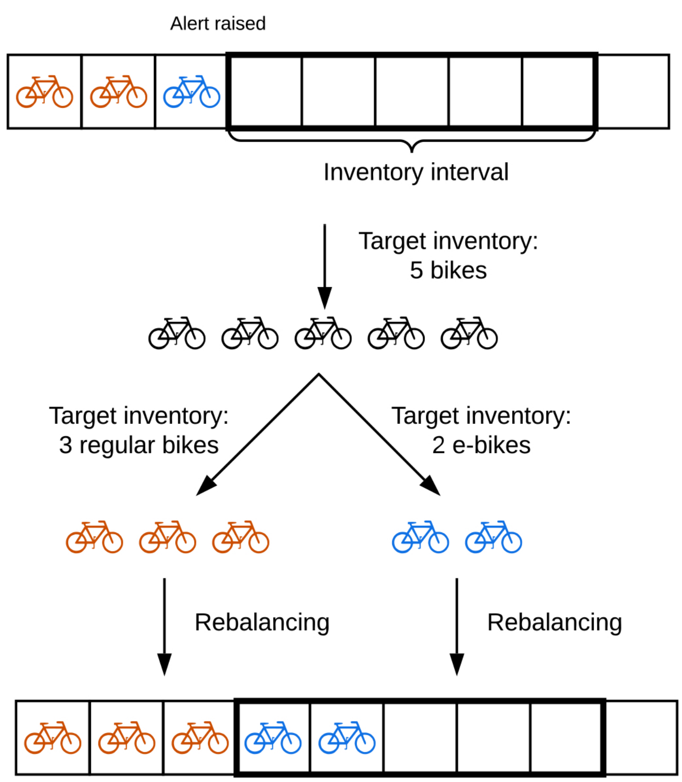

Figure 3: Simulation of the inventory and rebalancing process in the model B0. Orange bikes represent regular bikes whereas blue bikes represent e-bikes

[4]The target value of regular bikes is possibly rounded-up, while that of e-bikes is possibly rounded-down.

4.2.2 Simulation of our model

shared-$\mathcal{RE}$ provides inventory intervals and target inventory values for each type of bike used in the EBSS. Therefore, alerts are individually raised for each type of bike demand, and stations are rebalanced according to the associated target inventory values.

Similar to the simulation of B0, the simulation of shared-$\mathcal{RE}$ emulates the inventory based on rentals, returns, and rebalancing operations conducted hourly. However, in this scenario, the target inventory and inventory intervals are customized for each demand. This allows the rebalancing alerts to identify and address inventory deficiencies or excesses specific to each demand, and calculate target inventory values accordingly.

Since the inventory intervals generated by shared-$\mathcal{RE}$ are associated with each type of demand, it is expected that a greater number of alerts will be raised, potentially resulting in increased rebalancing activities. To address this concern, our model restricts the hourly rebalancing operations based on the recorded rebalancing operations of B0. Consequently, if the number of alerts raised by shared-$\mathcal{RE}$ within an hour exceeds the number of rebalancing operations performed in that same hour in the B0 simulation, we select stations at random for rebalancing among those that raised alerts.

During the simulation of our model, the rebalancing process is conducted to replenish the inventory of a station, taking into account the target values for regular and electric bikes. These target values are separately computed based on the demand for each type of bike, as explained in Section 3.2. This approach enables the rebalancing process to be triggered by the demand of a specific bike type. In Figure 4, for example, only the inventory of e-bikes drops below the lower bound of its inventory interval. Subsequently, the rebalancing process focuses on restoring both the regular and e-bike inventories to their respective target values. This reflects a more realistic operational scenario, as an employee is already dispatched to the station for replenishment. In the given example, two e-bikes and one regular bike are added to the station during the rebalancing process.[5]

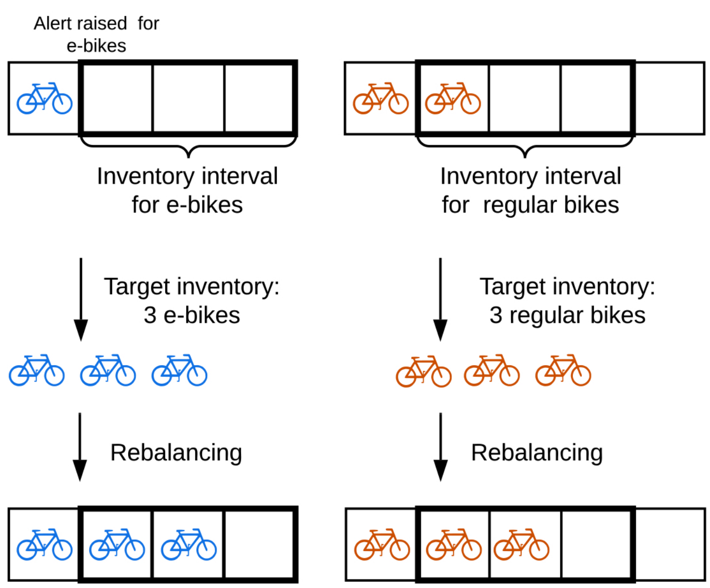

Figure 4: Simulation of the inventory and rebalancing process in our model. Orange bikes represent regular bikes whereas blue bikes represent e-bikes

[5]The code for both simulations, as well as the proposed model, can be accessed in the repository located at `https://github.com/datascientistbss/Paper_Journal.git.`

4.3 Analysis of commuters preferences

Based on the commuters' preferences, four different scenarios are emulated regarding bike substitutions:

- None: in this scenario, users never replace their desired bike with another type.
- All bikes: in this scenario, users are flexible in their preferences and will always accept any available bike, regardless of their initial choice.
- Reg. bike → E-bikes: only users who seek regular bikes accept an e-bike if the first is unavailable.
- E-bike → Reg. bikes: only users who seek for an e-bike accept a regular bike if the first is unavailable.

By simulating these different scenarios, we can analyze the impact of bike substitution preferences on the overall bike availability and system performance. This provides insights into the feasibility and desirability of allowing bike substitutions in a bike-sharing system and helps optimize the allocation and utilization of bikes based on customer preferences.

4.4 Tuning

The values of $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$ were tuned through simulations with the validation set with the objective of minimizing the lost demand – recall that the number of rebalancing operations are limited by B0. Table 2 presents the optimized hyperparameter values, where shared-$\mathcal{RE}_{max}$ and shared-$\mathcal{RE}_{avg}$ refer to the use of $\Lambda_s(\cdot)$ as the maximum or the average service level obtained for different values of the initial inventory (see Section 3.1–Eq.2).

The relatively low values of $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$ chosen for each simulation lead to wider inventory intervals. This outcome is not surprising considering that shared-$\mathcal{RE}$ randomly selects stations for rebalancing due to limited rebalancing capacity. In this context, wider inventory intervals serve as a stringent filter, allowing alerts to be raised only for highly unbalanced stations. Conversely, narrow inventory intervals result in a larger number of stations raising alerts, reducing the probability of selecting the most unbalanced stations for rebalancing. Hence, the advantage of wider inventory intervals becomes evident in this scenario, as they enhance the effectiveness of the rebalancing process by focusing on the most unbalanced stations.

The analysis of Table 2 reveals a discernible pattern in the values of the hyperparameters $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$ based on the bike substitution policy implemented. When there are no bike substitutions or restrictions on bike types, the values of both hyperparameters are fairly similar. However, in scenarios where regular bikes can be substituted with e-bikes, the inventory intervals display greater stringency towards e-bikes, leading to lower values of $\beta^{\mathcal{R}}$ and higher values of $\beta^{\mathcal{E}}$. Conversely, in the scenario where only electric bikes can be replaced by regular bikes, the hyperparameter results exhibit the opposite trend. This demonstrates the model's ability to prioritize each demand independently, as wells as its capacity to adapt to the users preferences.

As can be observed from Table 2, there is a pattern in the hyperparameters $\beta^{\mathcal{R}}$ and $\beta^{\mathcal{E}}$ according to the bike substitution policy applied. In the scenario in which there are no bike substitutions or any type of bike can be replaced by the other bike, the values of both hyperparameters are fairly similar. However, in the scenario in which regular bikes can be replaced by electric bikes, the inventory intervals tend to be more exigent with e-bikes than regular bikes meaning lower values of $\beta^{\mathcal{R}}$ and higher values of $\beta^{\mathcal{E}}$. In the fourth scenario, in which only electric bikes can be replaced by regular bikes, the opposite results are observed for the hyperparameters. Therefore, our model is able to prioritize each demand independently and it easily adapts to the BSS's different trip patterns.

4.5 Results

Our results compile the number of rebalancing operations and lost demand computed from the simulations of the baseline and our proposed models. The inventory intervals and the target values for B0

Table 2: Optimized hyperparameters values used in the tests

Bike substitution	Model	$(\beta_B^{\mathcal{R}},\beta_B^{\mathcal{E}})$
None	shared-$\mathcal{RE}_{max}$	(0.2,0.2)
	shared-$\mathcal{RE}_{avg}$	(0.2,0.3)
All bikes	shared-$\mathcal{RE}_{max}$	(0.2,0.4)
	shared-$\mathcal{RE}_{avg}$	(0.3,0.3)
Reg. bikes → E-bikes	shared-$\mathcal{RE}_{max}$	(0.2,0.4)
	shared-$\mathcal{RE}_{avg}$	(0.2,0.4)
E-bikes → Reg. bikes	shared-$\mathcal{RE}_{max}$	(0.3,0.1)
	shared-$\mathcal{RE}_{avg}$	(0.3,0.1)

were provided by BIXI for the following time periods in a day: from 6 am to 9 am, from 9 am to 11 am, from 11 am to 4 pm, from 4 pm to 7 pm, and from 10 pm to 6 am. These same time periods were used by shared-$\mathcal{RE}$ to compute inventory intervals and target values.

Table 3 presents the results regarding the number of rebalancing operations per hour and the percentage of lost demand over the total served demand, for both regular and electric bikes, from the simulations of models B0, and shared-$\mathcal{RE}$ and its different settings of bike substitution. The results from shared-$\mathcal{RE}_{max}$ and shared-$\mathcal{RE}_{avg}$ are averaged over 10 iterations due to the random aspect of its rebalancing procedure.

Table 3: Results regarding the simulated models: the average number of rebalancing operations per hour and the lost demand (in % with respect to the total served demand)

Simulated model	Bike substitution	Lost demand (regular bikes) %	Lost demand (e-bikes) %	Rebalancing operations
B0	None	1.94	2.45	49.19
shared-$\mathcal{RE}_{max}$		2.35	0.89	46.74
shared-$\mathcal{RE}_{avg}$		2.41	0.86	47.08
B0	All bikes	1.34	0.95	52.79
shared-$\mathcal{RE}_{max}$		1.09	0.58	45.13
shared-$\mathcal{RE}_{avg}$		1.07	0.56	45.19
B0	Reg. bikes → E-bikes	1.32	2.54	51.79
shared-$\mathcal{RE}_{max}$		1.09	0.87	45.25
shared-$\mathcal{RE}_{avg}$		1.06	0.84	45.32
B0	E-bikes → Reg. bikes	1.96	0.93	50.02
shared-$\mathcal{RE}_{max}$		2.31	0.59	46.80
shared-$\mathcal{RE}_{avg}$		2.39	0.57	47.10

In summary, the results show that:

- The performance of both shared-$\mathcal{RE}_{max}$ and shared-$\mathcal{RE}_{avg}$ indicates a minimal difference in terms of lost demand and rebalancing operations when implementing the dock division at a station based on either the best or average service level provided.
- Our model demonstrates superior performance compared to BIXI in three different scenarios involving user preferences, except for that where commuters seeking e-bikes are willing to rent regular bikes instead – – which is the most unlikely scenario in fact. Additionally, the inventory intervals and target inventory generated by our model consistently reduce the amount of lost demand for e-bikes compared to BIXI's rebalancing strategy. This indicates that our models, shared-$\mathcal{RE}_{max}$ and shared-$\mathcal{RE}_{avg}$, effectively identify and adapt to the increasing demand for e-bikes better than theB0.
- When comparing the various configurations of user preferences, the results align with our expectations across all models. The scenario where no bike substitution is allowed generates the highest lost demand, while the scenario where any substitution is accepted yields the lowest

demand loss. The remaining scenarios fall somewhere in between these extremes. Notably, the scenario where only regular bikes can be replaced by electric bikes results in less lost demand than the reverse scenario. This can be attributed to the considerably higher demand for regular bikes observed in our simulation data, which can be partially attributed to the fact that 2/3 of BIXI's bikes are regular ones. Consequently, the majority of lost demand cases computed in our simulations involve regular bikes.

- By introducing the option to replace regular bikes with electric bikes, the occurrences of lost demand can be significantly reduced. This is due to the potential to fulfill the demand for regular bikes with available electric bikes, thereby mitigating lost opportunities for riders.
- Across all simulated scenarios, the models shared-$\mathcal{RE}_{max}$ and shared-$\mathcal{RE}_{avg}$ consistently required significantly fewer rebalancing operations compared to theB0 strategy. This reduction in rebalancing operations directly contributes to a lower environmental impact of the Electric Bike Sharing System (EBSS), particularly in terms of carbon emissions. This aligns with the growing emphasis on environmentally friendly practices in transportation systems.

5 Conclusion

Rebalancing bike-sharing systems is a multifaceted task that encompasses numerous factors such as demand variability, time sensitivity, and user preferences. To address this challenge, we propose a model capable of providing targeted rebalancing recommendations for station-based Electric Bike Sharing Systems (EBSS) with a bimodal network comprising both regular and e-bikes. Our model leverages predicted demand for the upcoming hours to tailor recommendations specific to each type of bike demand. By doing so, the model aims to assist operators in the intricate decision-making process of rebalancing BSSs, with the goal of maximizing user satisfaction while simultaneously minimizing operating costs and mitigating environmental impact.

Our model, called shared-$\mathcal{RE}$, offers an automated division of docks per station based on predicted demand while allowing for customization according to the operator's requirements for each demand. One significant advantage is that our model independently adjusts the inventory intervals for each bike type. This flexibility is crucial as it accommodates the varying preferences of BSS users. The reported results of our study demonstrate that our proposed model outperforms the real-world use case under examination in terms of its ability to adapt to diverse trip patterns and commuters' preferences. In the two scenarios with the greatest difference in performance compared to B0, shared-$\mathcal{RE}_{max}$ and shared-$\mathcal{RE}_{avg}$ managed to reduce between 25% to 40% the cases of lost demand. Additionally, our model successfully reduced between 4% to 15% the number of rebalancing operations in all scenarios, which can have a substantial impact on the long-term expenses of a BSS.

The results demonstrate the importance of comprehending commuters' preferences and their willingness to substitute their initial bike choice when designing a rebalancing strategy. This understanding enables operators to make informed decisions regarding the supply of each bike type, ensuring the provision of a high-quality service. Additionally, our results show that actively encouraging commuters to consider alternative bikes when their desired option is unavailable can have a significant impact on reducing the lost demand. This effect was particularly pronounced when the initially preferred bike type exhibits higher demand compared to the other. By promoting bike substitution, operators can effectively mitigate the occurrence of lost demand, leading to improved service reliability and user satisfaction.

It is important to acknowledge that due to the use of actual trip data in our experiments, we have not considered information about trips that were not undertaken due to bikes or docks unavailability (i.e., unobserved demand). In future research, we plan to address this limitation by conducting experiments using synthetic data. This will enable us to explore a wider range of scenarios and accurately quantify demand losses, allowing for a more comprehensive evaluation of the rebalancing recommendations.

Finally, the rebalancing recommendations provided by our model can be seamlessly integrated into optimization routing models. This integration would allow for the optimization of the entire rebalancing process in a unified manner, maximizing the effectiveness and efficiency of the system as a whole. This direction holds promise for future research and offers potential for further improvements in the field of bike-sharing system management.

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