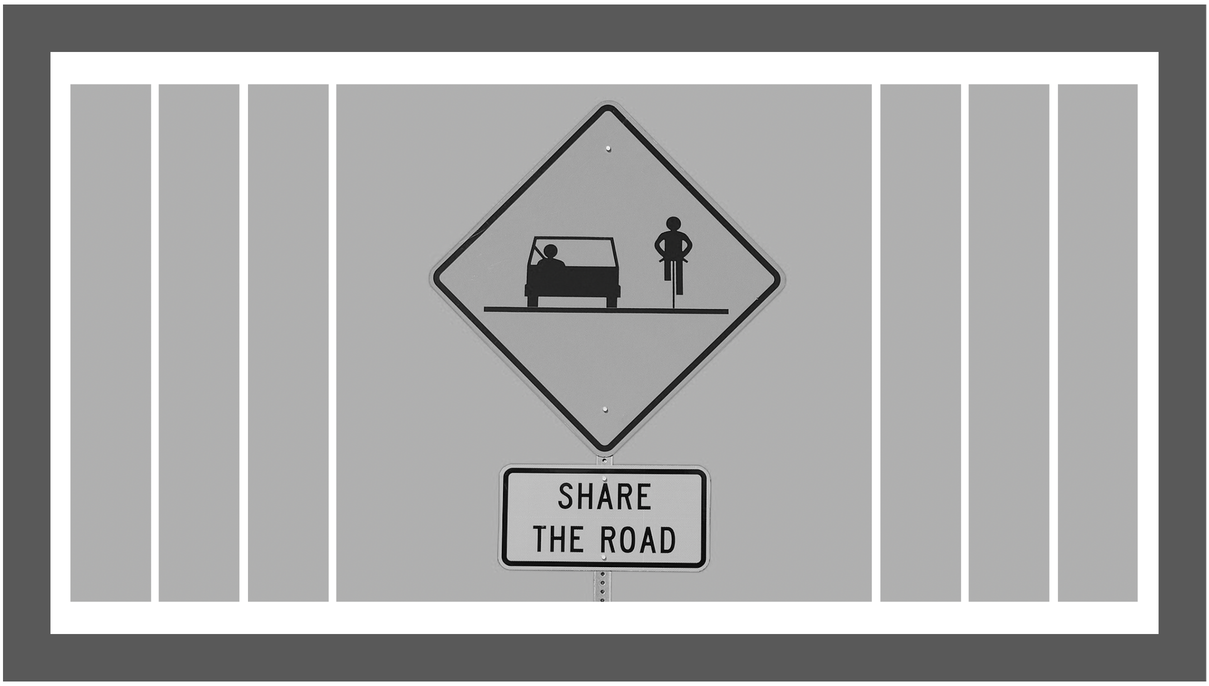

Vehicle Sharing Systems: Does demand forecasting yield a better service?

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May 2020

STRC | 20th Swiss Transport Research Conference
Monte Verità / Ascona, May 13 – 15, 2020

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May 2020

Abstract

Although the idea of vehicle sharing systems (VSSs) emerges back in 1940s, sustaining such a system became simpler with the improvements in technology in the past decade. In addition to that, people have become more concerned about environmental effects and try to find solutions on reducing emission and energy consumption. On the other hand, VSSs require effort to make them profitable. In this paper, we focus on the two of the operational level challenges, which are the demand forecasting and routing for the rebalancing operations, in a one-way station-based bike sharing system (BSS). Since the data collection is exhaustive and costly, we would like to find the answer to whether it is worth to collect data and develop demand prediction models. In order to do that, we create a simulation of a city BSS in operation during the day. Then, using a mathematical model from the literature, we assess the rebalancing costs under two scenarios: one where we assume the perfect demand forecast, and the other where the future demand is unknown. By this way, we determine the trade-off between the lost demand and the rebalancing cost under the mentioned scenarios, and assess the benefit of forecasting the demand. Lastly, we present a case study on the Swiss BSS named PubliBike.

Keywords

Vehicle sharing systems; Demand forecasting; Rebalancing operations; The value of demand forecasting

1 Introduction

A vehicle sharing system (VSS) offers users to rent vehicles for a short period of time. The users are identified by an RFID card or through a mobile application. The price of the trip is generally determined according to trip duration and length. This type of shared mobility is becoming more and more popular due to both financial and environmental effects. On the other hand, they face many challenges, such as inventory management of vehicles and parking spots, imbalance of vehicles, pricing strategies, and demand forecasting. If these are not addressed properly, the system experiences a significant loss of customers and therefore revenue.

The idea of sharing vehicles came up in the late 1940s with cars. The first known car sharing system (CSS), Selbstfahrergemeinschaft, was initiated in Zurich, Switzerland, in 1948 (Shaheen *et al.,* 1998). On the other hand, the first bike sharing system (BSS) was introduced in 1965 by the organization Provo. This system was not profit oriented. The bikes were left unlocked and therefore the system was abused (Shaheen *et al.,* 2010).

Following the technological and operational improvements, profit-based companies saw the opportunity in these systems and started investing money. Midgley (2011) analyzes the five different BSS generations that caused change in the operation.

A VSS has several kinds of configurations: (i) the type of trips offered: return trip or one-way, (ii) the imbalance management strategy: user-based, static staff-based, or dynamic staff-based, (iii) the pricing strategy: fixed or dynamic, (iv) the parking organization: station-based or free-floating.

The user is supposed to drop the vehicle off to the pick-up station after the usage in a return trip configuration. On the other hand, one-way trips allow the user to park anywhere designed in the city. One-way trips are much more flexible from the user perspective, however, it brings the problem of imbalance. The vehicles tend to accumulate in the stations or areas which are mainly trip destinations, which often causes a lack of vehicles in the frequent trip origins.

To overcome imbalance, rebalancing operations are introduced, which relocate the vehicles from stations with high availability and low demand to the stations with high demand and low availability to satisfy user demand at a higher level. In the user-based strategy, the users are offered incentives to make trips that improves the balance of the system, when necessary. The staff-based rebalancing operations might take place at a different time of the day in different VSSs. Static rebalancing is done when the system is closed, generally during the night, every day. Dynamic rebalancing, on the other hand, is flexible and executed throughout the day.

The dynamic pricing strategy is closely related to the user-based rebalancing operations. In this configuration, the user gets different pricing due to her trip characteristics, such as origin, destination, time of the day, and trip duration. In fixed pricing, all users and trips are considered and priced the same according to their trip duration and/or length. The origin and destination stations as well as the time of the day are not relevant.

The station-based systems require that the vehicles are parked at some designated parking areas for the VSS in particular. For the free-floating configuration, the pick-up and drop-off locations might be any parking spot in the city. This configuration is more flexible from the user point of view yet it introduces complexity to the operator concerning the imbalance.

The literature focuses almost exclusively on the routing aspect of rebalancing operations in VSSs. Moreover, contrarily to a classical public transport service, the operations of the system are influenced a lot by the demand patterns. Although these are indeed important parts of the problem, we did not find any work which studies the importance of demand forecasting. In other words, the upper bound on the cost of demand forecasting, such as collecting data and processing, is not discussed in the literature. To fill this gap, this work puts the first and simplistic attempt to investigate how demand forecasting models affect the operations in the context of BSSs. This will be achieved by identifying the value of demand modeling by exploiting the extensive research on rebalancing operations and demand forecasting in VSSs.

The value of demand forecasting can represent the upper budget limit to spend on demand forecasting. The aim is to guide the decision maker (i.e. operator). The operator can analyze the trade-off between the cases where forecasting is done and not done. It is also important to know how much it brings so that the budget can be adjusted for these operations. We also want to analyze whether forecasting the demand and acting accordingly causes any damage due to unplanned activities.

The rest of the paper is organized as follows: Section 2 presents the literature review on rebalancing operations and demand forecasting in VSSs. Afterwards, we talk about the methodological framework and the details of the simulation and optimization modules in Section 3. The experimental results done on a Swiss BSS PubliBike are discussed in Section 4. Finally, in Section 5, we conclude the paper and suggest possible future research directions.

2 State of the art

In this section we briefly discuss the literature on rebalancing opeations (Section 2.1) and demand forecasting (Section 2.2). We focus our review on the station-based BSSs. The reader may refer to Laporte *et al.* (2018) for a more thorough literature survey in VSSs.

2.1 Literature on rebalancing operations

The most of the research is based on static operator-based rebalancing operations. One of them is addressed by Raviv *et al.* (2013) under the setting of station-based BSSs where the stations are capacitated. They propose two mixed integer linear programming (MILP) formulations based on one-commodity pickup and delivery traveling salesman problem (1-PDTSP) to find the routing for rebalancing operations. The objective function is minimizing the operating costs. In addition to that, it takes the user satisfaction into account as well as the loading and unloading times. To overcome the computational complexity, the authors propose a two-phase solution method.

In Dell'Amico *et al.* (2014), the authors present four MILP formulations to solve the same problem. These models are strengthened by introducing valid inequalities. Furthermore, because of the exponential number of constraints, tailor-made branch and cut algorithms are developed.

Schuijbroek *et al.* (2017) present two solution approaches: one using a mixed integer programming (MIP) and one using a constraint programming (CP). They also integrate the required inventory level estimation via a Markov chain structure. It should be noted that this paper presents the first CP approach to the static rebalancing problem. In order to reduce the computational complexity the authors cluster the stations.

Liu *et al.* (2016) also use clustering to reduce the size of the network. The station level bike demand prediction is done using the historical data and weather report, including the temperature, humidity, wind speed, and visibility. Then, route optimization is conducted within each cluster.

In Pfrommer *et al.* (2014), the authors aim to combine the dynamic rebalancing operations with dynamic pricing (i.e. user-based rebalancing) in a station-based BSS. A predictive model is used to see the future demand. For the routing algorithm, they use a time-expanded network (as in Boyacı *et al.* (2017)) and develop a mixed integer quadratic program (MIQP).

We see in the literature that optimization models are proposed to solve the imbalance related problems in BSSs. Simulation, heuristics and metaheuristics are also utilized especially when the optimization models are too time consuming.

2.2 Literature on demand forecasting

As well as analyzing the system and optimizing parameters, the data collection is also an important part to manage VSSs. As an example, Campbell *et al.* (2016) conduct a stated preference survey in Beijing, China, for a station-based BSS, in which users can take conventional or electric bikes. Then, a multinomial logit model is developed to model mode-choice. The study by Kutela and Teng (2019) is conducted in 25 different university campuses which result in 177 stations in total. They use Negative Binomial (NB) and Mixed Effect Negative Binomial (MENB) to identify the important characteristics on the demand. Although the methodology is not new to the literature, the collected data from 25 different systems provide valuable insights.

One of the research questions related to demand forecasting is to identify the important factors of the corresponding VSS. In works Ashqar *et al.* (2019) and Scott and Ciuro (2019), the authors consider a station-based BSS. In Ashqar *et al.* (2019), the authors aim to understand the bike count's behavior by including the weather conditions. Two models are developed based on Poisson Regression Model (PRM) and Negative Binomial Regression Model (NBRM). In Scott and Ciuro (2019), the authors use the data related to weather conditions, temporal variables, station attributes, and socio-economic characteristics of the users to analyze the number of pick-up and drop-offs. Since traditional linear regression assume independence between the observations, they use the random intercept multilevel modeling to identify the factors affecting the ridership.

Indeed, the regression models are not the only methodology used to forecast the demand. For example, in Raviv *et al.* (2013) and Schuijbroek *et al.* (2017), the authors include a Markov chain structure to estimate the number of vehicles per station in the steady state. On the other hand, the authors in Faghih-Imani *et al.* (2017) start by creating a data set which identifies the user arrivals and departures per station, as well as rebalancing operations. Authors test assumptions about the factors that influence customer arrivals and departures and rebalancing refill and removal. They apply a methodology for analyzing such systems using behavioral models, in particular, autoregressive moving average (ARMA) models. Finally, they present the first empirical analysis of system rebalancing by the operator focused on understanding the factors creating such imbalances, using an approach consisting of a binary logit model, for identifying stations that need rebalancing, and a linear regression model for the amount of rebalancing. This analysis can help in creating plans for rebalancing well in advance, as well as in creating incentive mechanisms for customers to rebalance bikes.

We see that various methods are used to forecast the demand in VSSs in the literature. This forecast is used to aid other operations of VSS such as rebalancing operations and pricing. However, we did not see any work studying the added value of constructing such a model. In this paper, we aim to address this gap in the literature.

3 Methodology

We propose a methodological framework to analyze the effect of demand forecasting. This framework consists of two main modules: (i) simulation and (ii) optimization. The daily trip demand is simulated with a discrete event simulator and the routing of rebalancing operations is determined using an optimization model. This work deals with a one-way station-based BSS where static rebalancing and fixed pricing are adopted.

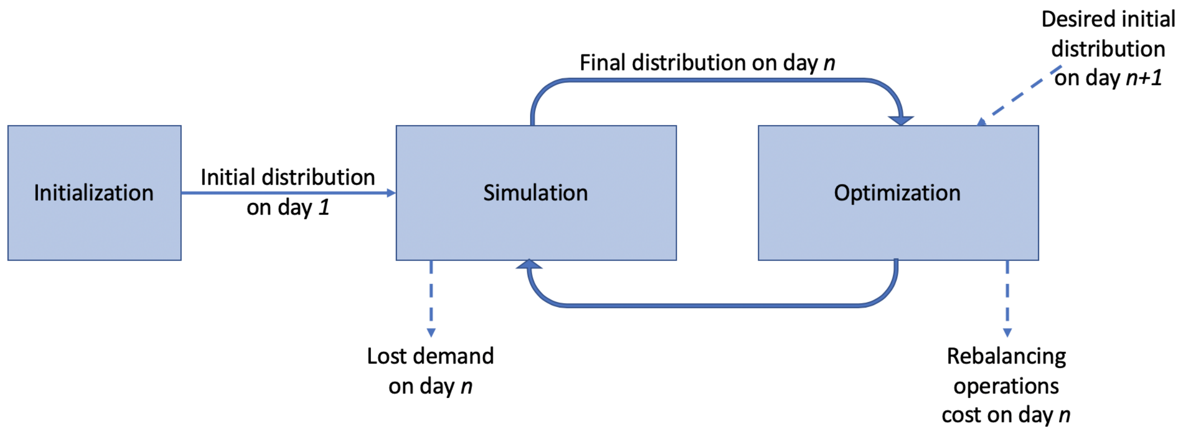
We start by giving the general idea of the framework and how it is used to determine the value of demand forecasting (Section 3.1). Then, we discuss the details of simulation (Section 3.2) and optimization (Section 3.3) modules.

3.1 The framework

The dynamics of our approach is illustrated in Fig. 1. After initializing the parameters, the simulator simulates the daily trips and determines the final distribution of the bikes. Then, the difference between the number of bikes at each station at the end of the day and the number of bikes desired at the beginning of the next day (demand of a station) is calculated. The result is given as an input to the optimization module. The optimization module solves the rebalancing problem and determines the routing for the rebalancing vehicles (i.e. trucks). At this stage of the research we assume that the rebalancing operations take place as planned and the desired initial distribution for the following day is achieved. Afterwards, the simulation of the following day is triggered.

We consider two extreme cases of VSS operations: (i) known demand, and (ii) unknown demand. The first assumes the perfect future demand knowledge and the second assumes no knowledge on demand. In known demand case, we distribute the bikes among stations according to future demand knowledge. In order to use the perfect demand knowledge, we adapt the initial

Figure 1: The framework for VSS simulation and rebalancing optimization



distribution of bikes among stations. The number of bike defficiencies throughout the day is calculated. Then, the maximum defficiency is assigned as the initial number of bikes at the beginning of the day. In unknown demand case, we uniformly distribute the bikes everyday among the stations.

By comparing these two extreme cases, we aim to assess the maximum budget that should be allocated for demand forecasting, i.e. data collection and development of demand forecasting models. The necessity of rebalancing operations can also be examined. We also analyze the effect of spatial (e.g. city characteristics) and temporal (e.g. rush hours) differences on this upper bound.

3.2 Simulation

The state variable of the system is time, denoted as t, and the time horizon is T. The time is not discretized but drawn for each event according to the Poisson distribution. Within $[0, T]$, O-D pair requests arrive to the system. After T, the events in the system are served and no more O-D pair requests are generated. We denote the number of stations by N. C_i, for $i = 1..N$, represents the capacity of station i. The distance from station i to station j with mode k is denoted as c_{ij}^k, where $i = 1..N$, $j = 1..N$, and $k = \{$'walking', 'bicycle', 'car'$\}$.

The time horizon is divided into P number of time windows, each denoted TW_p, where $p = 1..P$. This differentiation makes the simulator flexible at the temporal level to test different behaviors during the day, such as rush hours and specific event times. Therefore, the O-D pair request

Table 1: Event types

Event	Triggered Event	Queue
`Sim Start`	`REQUEST`, `Sim End`	-
`REQUEST`	`REQUEST` (if $t < T$), `PICKUP` (if there is an available station within 20 min walk)	$ns = ns + 1$ -
`PICKUP`	`DROPOFF` (if there are available vehicles)	$nu = nu + 1$
`DROPOFF`	`DROPOFF` (if no parking available), `COMPLETED`	- $nu = nu - 1$
`COMPLETED`		$ns = ns - 1$
`Sim End`		-

rates are also specific to these time windows. λ_p provides the information on the rate of requests for time window p, where $p = 1..P$.

The number of people in the system (ns) and the number of people using a vehicle (nu) at that time are recorded as indicators. These indicators allow us to extract the number of lost demand. The number of lost demand is equal to the number of users who opt-out because of unavailability of bikes or parking spots.

The simulation module consists of four event types: (i) `REQUEST`, (ii) `PICKUP`, (iii) `DROPOFF`, and (iv) `COMPLETED`. The triggered events are added to the event list and this list is kept in chronological order. Table 1 summarizes the event types, the triggered event(s) by each event and the change in event queue status.

The `REQUEST` event is generated at the beginning of the simulation for each O-D pair request. These `REQUEST` events form the initial event list in chronological order. By this way, the simulator keeps track of the time. As soon as a `REQUEST` event is observed in the event list ns is increased by 1 and a `PICKUP` event is generated if there is a station with a positive number of vehicles within walking distance. If there are no vehicles at the stations within walking distance, the user opts-out (lost demand), and the ns is decreased by 1.

When a `PICKUP` event appears in the event list, a `DROPOFF` event, which consists of the desired drop-off station information, is generated if there is at least one vehicle at that station and nu is increased by 1. Otherwise, the user opts-out (lost demand) and leaves the system. In this case, we decrease ns by 1.

The `DROPOFF` event triggers either another `DROPOFF` event or a `COMPLETED` event. The user chooses a drop-off station according to his/her destination location. However, in some cases, the user might not be able to find an available parking spot there. Then, another `DROPOFF` event is triggered and the user tries the next closest available station. If there is at least one vehicle available at the corresponding drop-off station, then a `COMPLETED` event is generated and nu is decreased by 1. The `COMPLETED` event is removed from the queue as soon as the user reaches the destination point which also makes him/her leave the system, i.e. ns is decreased by 1.

3.3 Optimization

There are several optimization programs in the literature related to rebalancing operations in VSSs. This experimentation considers the MILP formulation for a BSS from Dell'Amico *et al.* (2014). They consider a station-based configuration and adopt static rebalancing. This formulation is selected due to the availability of the simulator, thus the full information on demand for O-D pair requests. Among four different models, we use F1, which is presented below.

The notation for the number of stations is the same as in the simulation module. The set of stations is defined as $V = \{0..N\}$ where $\{0\}$ is the depot. m is the number of relocation vehicles available and Q stands for each relocation vehicle's capacity. θ_j represents the load of a vehicle after it leaves node j, where $j \in V$. The cost of traveling between station i and j is denoted by c_{ij} and it corresponds to the length of the shortest path between i and j. The cost from the depot to and from any station is assumed to be zero. Lastly, the model takes the demand at each station, q_i for all $i \in V$. This is an input provided by the simulation (see Fig. 1). Given these, F1 finds the routing plan for the relocation vehicles

where

$$x_{ij} = \begin{cases} 1, & \text{if arc } (i, j) \text{ is used by a relocation vehicle} \\ 0, & \text{otherwise} \end{cases} \qquad \forall i, j \in V. \tag{1}$$

$$(F1)\ \min \quad \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij} \tag{2}$$

$$\text{s.to} \quad \sum_{i\in V} x_{ij} = 1 \qquad \forall j \in V \setminus \{0\} \tag{3}$$

$$\sum_{i\in V} x_{ji} = 1 \qquad \forall j \in V \setminus \{0\} \tag{4}$$

$$\sum_{j\in V} x_{0j} \leq m \tag{5}$$

$$\sum_{j\in V\setminus\{0\}} x_{0j} - \sum_{j\in V\setminus\{0\}} x_{j0} = 0 \tag{6}$$

$$\sum_{i\in S}\sum_{j\in S} x_{ij} \leq |S| - 1 \qquad \forall S \subseteq V \setminus \{0\}, S \neq \emptyset \tag{7}$$

$$\theta_j \geq \max\{0, q_j\} \qquad \forall j \in V \tag{8}$$

$$\theta_j \leq \min\{Q, Q + q_j\} \qquad \forall j \in V \tag{9}$$

$$\theta_j - \theta_i + M(1 - x_{ij}) \geq q_j \qquad \forall i \in V, j \in V \setminus \{0\} \tag{10}$$

$$\theta_i - \theta_j + M(1 - x_{ij}) \geq q_j \qquad \forall i \in V \setminus \{0\}, j \in V \tag{11}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i, j \in V \tag{12}$$

The objective function (Eq. (2)) minimizes the cost. Eqs. (3) and (4) make sure that every node except the depot is served exactly once. Following two sets of constraints, Eqs. (5) and (6), assure that no more than m vehicles are used and all used vehicles return to the depot at the end of their route. The constraint set (Eq. (7)) is a typical cutset constraint which is used for subtour elimination. Eqs. (8) and (9) defines the upper bound on the load of a vehicle. The flow conservation is achieved by Eqs. (10) and (11). Last constraint set (Eq. (12)) imposes binary restrictions on decision variables x_{ij}'s.

Given the exponential number of constraints, the model becomes intractable for large instances. The classical subtour elimination constraints that are used in F1 corresponds to Dantzig-Fulkerson-Johnson (DFJ) formulation (Dantzig *et al.,* 1954). This formulation introduces 2^{N+1} number of constraints. In Miller *et al.* (1960), the authors introduce a new formulation, i.e. Miller-Tucker-Zemlin (MTZ), using additional decision variables and decrease the number of constraints to $(N + 1)^2$. In order to overcome the computational burden, this work provides an extension to F1 by utilizing the MTZ constraints (Eqs. (18) and (19)). For this purpose, a new decision variable, u_i $\forall i \in V \setminus \{0\}$, is introduced.

Furthermore, we use the valid inequalities proposed by Dell'Amico *et al.* (2014). Since there is no feasible solution consecutively going through three nodes which have a total supply/demand larger than the capacity, these solutions can be exluded. For this purpose, they define the set

$$S(i, j) = \{h \in V \setminus \{0\}, h \neq i, h \neq j : |q_i + q_j + q_h| > Q\}$$

and introduce Eqs. (24) and (25).

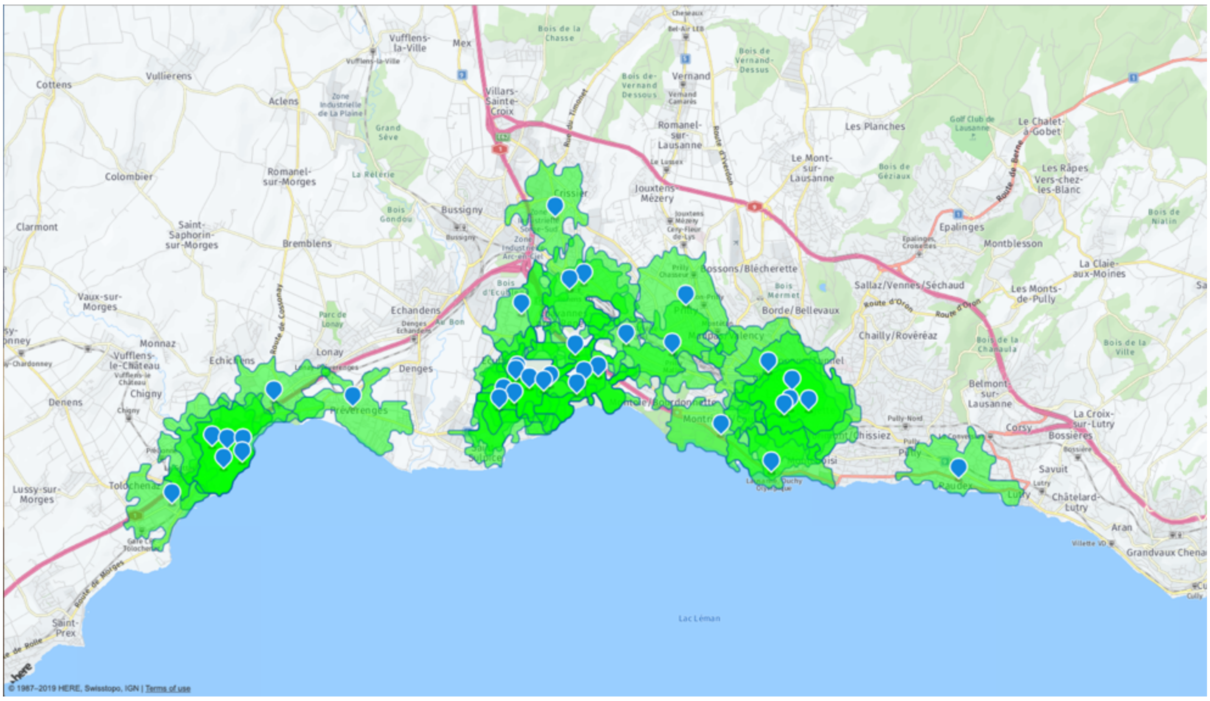
Finally, we present the final version of the optimization model in $(F1_M)$.

$$
\begin{aligned}
(F1_M)\ \min \quad & \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} & & (13)\\
\text{s.to} \quad & \sum_{i \in V} x_{ij} = 1 & \forall j \in V \setminus \{0\} \quad & (14)\\
& \sum_{i \in V} x_{ji} = 1 & \forall j \in V \setminus \{0\} \quad & (15)\\
& \sum_{j \in V} x_{0j} \leq m & & (16)\\
& \sum_{j \in V \setminus \{0\}} x_{0j} - \sum_{j \in V \setminus \{0\}} x_{j0} = 0 & & (17)\\
& u_i - u_j + N * x_{ij} \leq n - 1 & \forall i, j \in V \setminus \{0\} \quad & (18)\\
& 1 \leq u_i \leq N & \forall i \in V \quad & (19)\\
& \theta_j \geq \max\{0, q_j\} & \forall j \in V \quad & (20)\\
& \theta_j \leq \min\{Q, Q + q_j\} & \forall j \in V \quad & (21)\\
& \theta_j - \theta_i + M(1 - x_{ij}) \geq q_j & \forall i \in V, j \in V \setminus \{0\} \quad & (22)\\
& \theta_i - \theta_j + M(1 - x_{ij}) \geq q_j & \forall i \in V \setminus \{0\}, j \in V \quad & (23)\\
& x_{ij} + \sum_{h \in S(i,j)} x_{jh} \leq 1 & \forall i, j \in V \setminus \{0\}, h \in S(i, j) \quad & (24)\\
& \sum_{h \in S(i,j)} x_{hi} + x_{ij} \leq 1 & \forall i, j \in V \setminus \{0\}, h \in S(i, j) \quad & (25)\\
& x_{ii} = 0 & \forall i \in V \quad & (26)\\
& x_{ij} \in \{0, 1\} & \forall i, j \in V \quad & (27)
\end{aligned}
$$

4 Computational experiments

The simulation is implemented on a computer with 8 GB RAM and 2.3 GHz Intel Core i5 processor in *python* and *python* API for CPLEX 12.10 is used to solve the optimization model. The constructed environment includes the station information from Lausanne-Morges district of

Figure 2: PubliBike stations (Lausanne-Morges district)



PubliBike BSS from Switzerland, which has a one-way station-based configuration. We assume that static rebalancing is done at the end of every day.

The considered system has 35 stations (Fig. 2) and 175 bikes. The capacity of a relocating vehicle, Q, is set to 40 bikes and the number of such vehicles, m, is set to 2. Since the stations of PubliBike do not have lockers, it is possible to leave the bike regardless of the number of bikes existing in that station. Therefore, the capacity of each station is set to infinity.

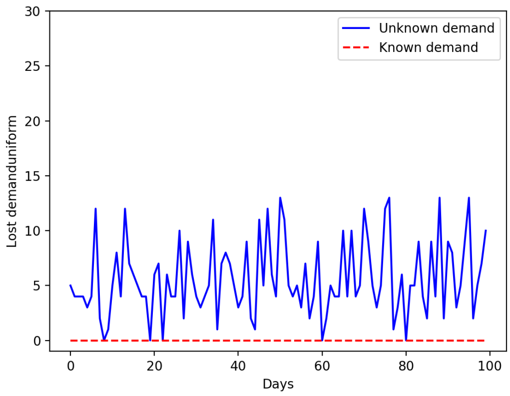
For uniform scenario, we set λ_p, for all $p = 1..P$, is equal to 20 requests per hour.

For the scenarios which take temporal differences into account, we set different λ_p values for each time window p. Specifically, we create 5 time windows: 00:00-05:59, 06:00-08:59, 09:00-15:59, 16:00-19:59, and 20:00-23:59. We set $\lambda = \{2, 40, 20, 40, 12\}$. These time windows are designed to represent the rush hours and steady hours. Furthermore, the expected total number of O-D pair requests in a day is kept the same as in the uniform scenarios.

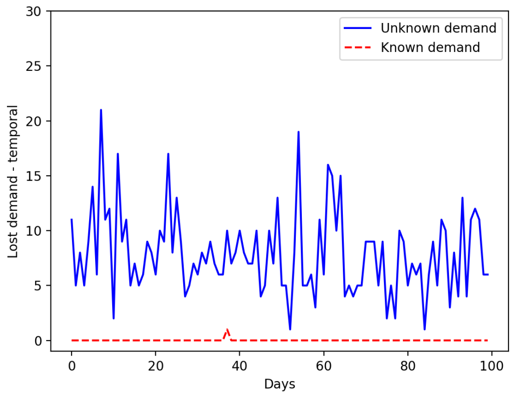
For the scenarios which take spatial differences, i.e., difference in altitude, into account, we again set λ_p, for all $p = 1..P$, is equal to 20 requests per hour. On the other hand, less demand is generated for the uphill trips compared to downhill ones. Knowing the altitude of each station, i.e., alt_i, $\forall i \in V$, the trips are deleted from the scenario with probability $(alt_{DO} - alt_{PU}/2)$, where

Figure 3: Lost demand throughout the days

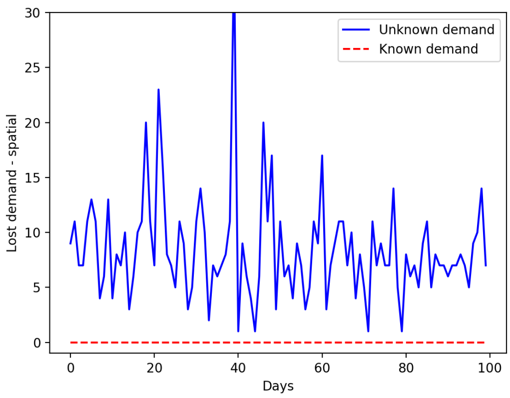
(a) Uniform



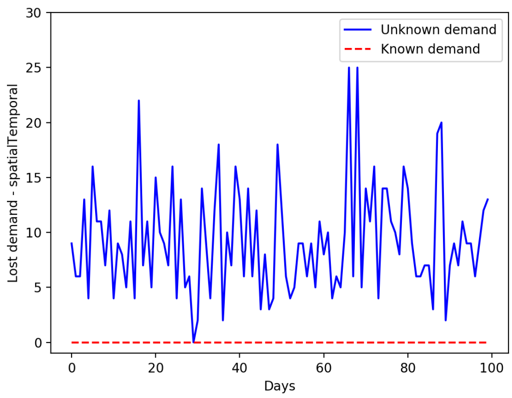
(b) Temporal



(c) Spatial



(d) Both spatial and temporal



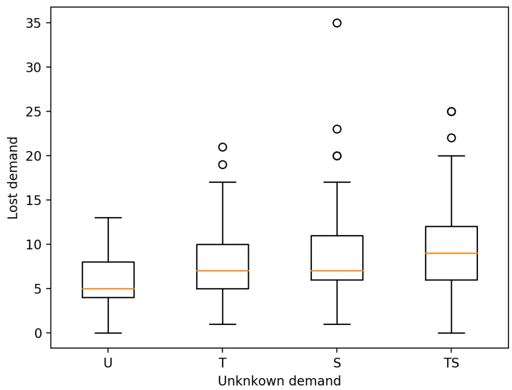
DO corresponds to drop-off station and *PU* to pick-up station. For Lausanne-Morges case study, spatial differences are important since the city has considerably high altitude difference.

The last set of scenarios, which take both the spatial and temporal differences into account, use the properties of both the spatial and temporal differences at the same time.

Each scenario is generated and used for both known and unknown demand cases to compare the lost demand and rebalancing operations cost. The objective function is built with the cost value being the distance traveled by the truck(s) carrying the bikes. Since we are interested in the evaluation of the added value of demand forecasting, the number of lost demand and the total number of O-D pair requests are presented along with the rebalancing costs. Lost demand corresponds to the number of users who opt-out because of unavailability of bikes.

The computational time burden results from the mathematical model. However, with 35 stations

Figure 5: Lost demand over 100 days (Unknown demand case)



it is still solvable in reasonable time with the modifications on the formulation of Dell'Amico *et al.* (2014).

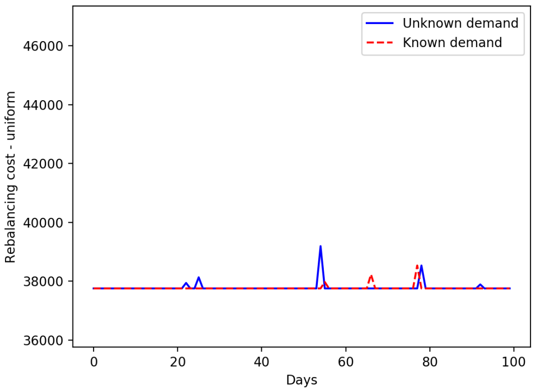
We first investigate the effect of knowing the O-D trip requests on lost demand (Fig. 3). We plot both the unknown and known demand cases on the same plot to identify the difference. For all four scenarios, we see that the lost demand for the known case is zero (with one exception on day 38 for the temporal scenario). Therefore, we see an obvious difference between the two cases by means of lost demand.

We also compare the effect of each scenario on the lost demand. For uniform scenario, the average lost demand per day corresponds to 5.64, whilst this value is 7.91, 8.44, and 9.3 for temporal, spatial, and spatial temporal scenarios, respectively. We also identify these different effects of scenarios on the lost demand in Fig. 5. We see that the lost demand tends to increase in nonuniform scenarios.

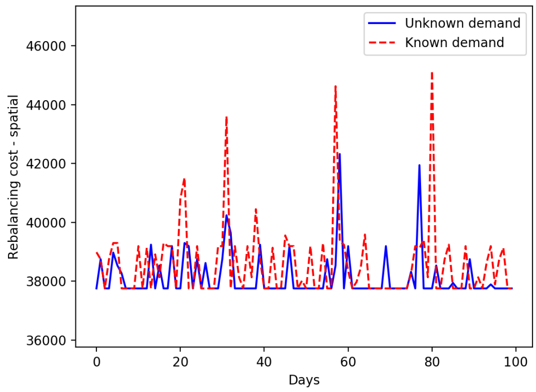
Finally, we analyze whether the rebalancing cost is affected by the demand knowledge or scenario type. Figure 6 shows the rebalancing cost over 100 days. We see that the difference is negligible for uniform and temporal scenarios. On the other hand, we see the cost varies for spatial, and spatial and temporal scenarios. This can be explained by the fact that accummulation in specific stations cause deviation from the optimal routes. Furthermore, we see that the known demand case causes higher rebalancing cost. In these cases, the reduced lost demand is compensated by the additional rebalancing cost. Depending on the monetary value of the lost demand, the decision maker can assess the necessity of rebalancing operations by comparing the lost demand and the rebalancing cost.

Figure 6: Rebalancing cost throughout the days

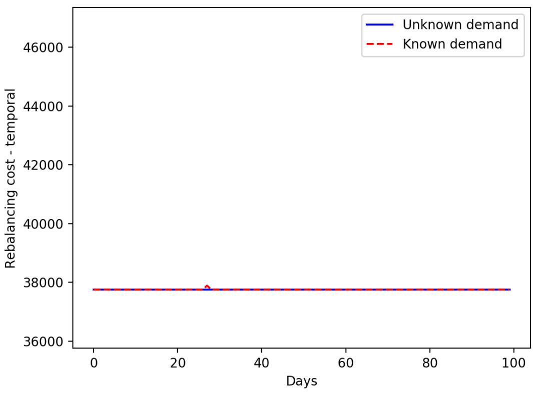
(a) Uniform



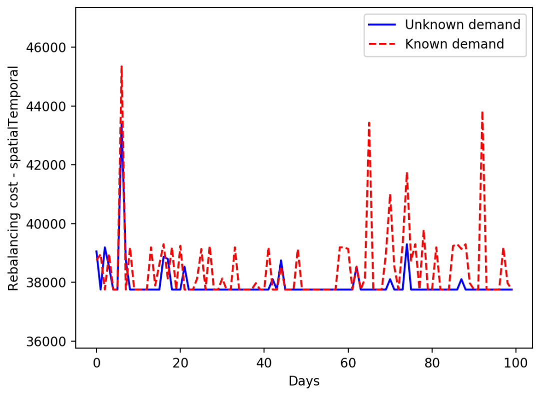
(b) Spatial



(c) Temporal



(d) Both spatial and temporal



5 Conclusion and future work

Like in many fields of research, the demand forecasting process is one of the several challenges in the context of VSSs. Although there are many studies worked on demand forecasting, none set an upper bound on the cost of such operations. Therefore, this work presents an attempt to determine the value of demand forecasting. Optimization and simulation modules are developed to include two aspects of the operations: supply and demand. By this way, we are able to investigate the trade off between the cost of rebalancing operations and lost demand in the case of known and unknown demand cases.

We perform computational experiments on a BSS, PubliBike, in Lausanne-Morges district of Switzerland. We see a significant improvement in the number of lost demand with the demand knowledge. No clear relation between the lost demand and rebalancing costs is found yet, but we will further investigate this by increasing the number of experiment repetitions. Furthermore, it is worth to note that these results solely rely on the simulation parameters. Different scenarios might lead to different results.

The future work includes the development of another simulation module which mimics the rebalancing operations. By this way, we will be able to see whether the results of the optimization module can be applied in real life perfectly. Moreover, the demand distribution is an important element in this framework. Following work also aims to analyze different scenarios and real data. At this stage of the research, only the results for BSSs is presented whereas the simulator is easily adaptable to CSSs. The future work also includes the extension of the BSS simulator and adapting it to a CSS as well as different configurations such as dynamic rebalancing and free-floating.

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