The added-value of demand forecasting in bike sharing systems: A general framework and selected case studies

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1 INTRODUCTION

Transportation is becoming more and more essential in the developing world. According to Pachauri *et al.* (2014), it is observed that transportation is responsible for 14% of the greenhouse gas emissions in 2014. When the end-use sectors are also considered, it accounts for the second-largest shares of U.S. greenhouse gas emissions by 28.7% in 2019 (EPA, 2021). With the increasing environmental concerns, the idea of shared mobility, such as ride-hailing, ride-sharing, and vehicle sharing, has emerged in recent years.

Our previous work examines the components of vehicle sharing systems (VSSs) and the challenges faced in terms of decision level, actors, and layers (Ataç *et al.*, 2021c). The reader can kindly refer to this work for the terminology in VSSs. Although the operational level challenges demand forecasting and rebalancing operations optimization are widely studied, we observe that there is a lack of investigating the relationship between them and the value of demand forecasting. Here, we regard this value through a quantification of the improvement of rebalancing operations in presence of demand forecast. Therefore, we explore the value of demand forecasting in bike-sharing systems (BSSs) in this work. This work considers a one-way station-based BSS where rebalancing operations are conducted when the system is low in operation, i.e., static rebalancing. An early version of this work (Ataç *et al.*, 2021a) presents an optimization-simulation framework for BSSs and shows results on synthetic data. In this work, we incorporate a clustering module to solve larger instances and present results on selected real-life case studies.

2 METHODOLOGY

Several methods are used in the literature to forecast trip demand and bike count behavior in BSSs. These include regression (Ashqar *et al.*, 2019), Markov chain (Schuijbroek *et al.*, 2017), and behavioral models (Faghih-Imani *et al.*, 2017). In addition to the historical trip records, methods also use historical weather, socio-economic characteristics of the users, air quality, etc.

The more information is available for forecasting, the more precise the models are. However, collecting and analyzing such information is not always trivial. Therefore, knowing the value of demand forecasting is essential. It allows the decision maker know the upper limit for the budget allowance of demand forecasting operations.

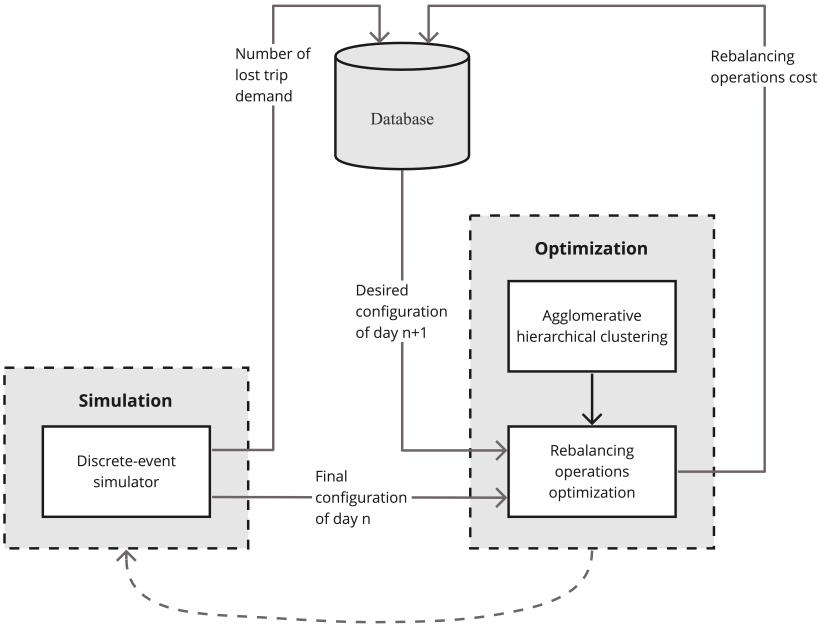

Figure 1 – *The framework for VSS simulation and rebalancing optimization*

Figure 1 illustrates our framework that involves two main modules, namely simulation and optimization. The optimization module further splits into two parts, i.e., clustering and rebalancing. The input parameters are passed to the simulation module and a full day is simulated. Then, the final configuration of the simulated day, the desired initial configuration for the following day, and precomputed clustering information are given to the optimization module that calculates the best routing for the rebalancing trucks. The number of lost trip demand and the cost of rebalancing operations are recorded as performance measures and stored in the database. The dashed arrow represents the iterative process of the framework.

We consider two extreme cases: the first, unknown demand case, assumes that the trip demand information is not available to the operator. Therefore, the vehicles are rebalanced to the same initial configuration every day. The second, known demand case, assumes perfect knowledge about the future demand. In other words, the operator knows where and when a trip demand will occur. The initial configuration of the next day is determined according to this information. This helps us to assess the maximum budget allocation to forecast the trip demand.

2.1 Simulation

A discrete event simulator that simulates the trip demand of one full day of one-way station-based BSS with capacitated stations is built for this framework (kindly see the details in Ataç *et al.* (2021a)). The number, location, and capacity of stations, time of the trip request, location of origin and destination, and distance between stations are passed to the simulator. Then, the final bike configuration is obtained from the simulator, that is passed to the optimization module.

2.2 Clustering and rebalancing operations optimization

Generally, rebalancing operations can be modeled as mixed integer linear programming (Dell'Amico *et al.*, 2014). Although the rebalancing operations optimization can be optimally solved for small size instances, the complexity of the models exponentially increases with the problem size. To overcome that, station clustering is one of the approaches to split the problem into sub problems (Lahoorpoor *et al.*, 2019). In Ataç *et al.* (2021b), we test different clustering approaches that can be applied for rebalancing operations optimization. As a result, we use the agglomerative hierarchical clustering according to station locations in this work.

We utilize and modify the rebalancing operations optimization model, named F1, from Dell'Amico *et al.* (2014). Furthermore, the model is solved only for the subset of stations that have non zero demand (Ataç *et al.*, 2021b). The final configuration, that is received from the simulator, and the desired initial configuration are used to calculate the demand of a station. Along with this information, the number of stations, distance between stations, number and capacity of the trucks are utilized in the rebalancing operations optimization.

3 NUMERICAL EXPERIMENTS

3.1 Data sets

This work applies the introduced framework to four case studies: nextbike Sarajevo, nextbike Berlin, Divvy Chicago, and Citi Bike New York. These case studies operate with 21, 298, 681, and 1361 stations, respectively. The data for the first two are obtained from their system in real time and then preprocessed to obtain O-D trip information. The data for the last two are publicly available. The O-D trip request time and location and destination location information are taken from the real data, and simulated using the developed simulator to see whether this trip is feasible, given the initial configuration of the system.

3.2 Results

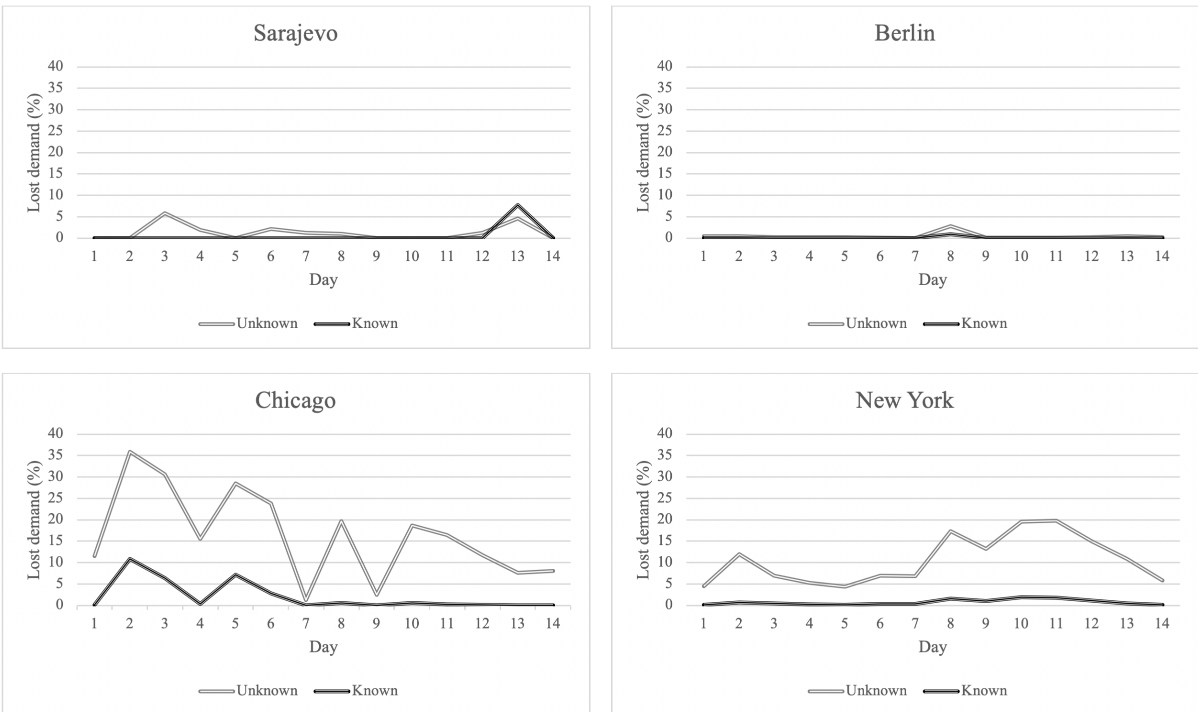

Figure 2 – *Unknown vs known case*

In Figure 2, we present results for 14 consecutive days. The horizontal axis shows the days where the vertical axis shows the ratio of lost and total trip demand. As expected, unknown demand case produces more lost demand than the known case. On the other hand, it is worth to note that the perfect demand knowledge does not guarantee satisfying all the trip demand. This can be due to the station capacity, the number of bikes available, etc. Thanks to the extended framework, we observe that the benefit of demand forecasting in larger instances, i.e., Chicago and New York, is clearer and more significant than in smaller ones, i.e., Sarajevo and Berlin. This indicates that smaller systems do not necessarily require precise demand forecasting.

Having analyzed the information passed from the optimization module to the database, we also notice that the rebalancing operations cost,that is obtained by solving the rebalancing operations optimization model, does not significantly change from one case to the other. This shows that the use of demand forecasting does not affect the rebalancing cost as the routes tend to be similar to each other.

4 CONCLUSION AND FUTURE WORK

The proposed framework is able to assess the need of precise demand forecasting in different BSSs. It also assists the decision maker by informing them on the upper limit of the budget for demand forecasting. This way, the decision maker is informed about the trade-off.

The numerical experiments presented so far show results for the two extreme cases. The key finding is that the demand forecasting might not significantly decrease demand loss nor improve rebalancing operations in smaller BSSs. Therefore, the operators of such systems should assess the potential benefits of demand forecasting before investing into creation of the needed models. As it is not possible to know the true demand in advance (unless the system is reservation based), one future research direction may include looking into different levels of knowledge in trip demand by deteriorating this information. Furthermore, this framework can form a base to test different values of input parameters to see their effects on the system and to support the decision maker in both tactical and operational level decisions. Finally, another future research direction might be looking into the effect of clustering on results.

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