Transportation Research Part E 72 (2014) 192–209

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Proactive vehicle routing with inferred demand to solve the bikesharing rebalancing problem

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ARTICLE INFO

Article history:
Received 13 February 2014
Received in revised form 30 September 2014
Accepted 9 October 2014

Keywords:
Bikesharing
Dynamic rebalancing problem
Proactive vehicle routing
Gradient boosting
Simulation

ABSTRACT

Bikesharing suffers from the effects of fluctuating demand that leads to system inefficiencies. We propose a framework to solve the dynamic bikesharing repositioning problem based on four core models: a demand forecasting model, a station inventory model, a redistribution needs model, and a vehicle-routing model. The approach is proactive instead of reactive, as bike repositioning occurs before inefficiencies are observed. The framework is tested using data from the Hubway Bikesharing system. Simulation results indicate that system performance improvements of 7% are achieved reducing the number of empty and full events by 57% and 76%, respectively, during PM peaks.

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1. Introduction

Bikesharing is a sustainable and environmentally friendly transportation mode that offers bikes "on-demand" to improve daily urban mobility. A typical current bikesharing system operates as follows: a member can pick up a bike from any of the stations available in the system and must return it before a predefined time period to any other station that has empty docks available. Stations have a fixed capacity and a time limit is imposed to ensure high bike usage and bike rotation.

Bikesharing systems compete with other forms of public transportation in urban environments. In the United States, as of 2012 there were 15 IT-based bikesharing programs (Shaheen et al., 2012) and major US cities, such as New York, San Francisco, Chicago, Forth Worth or Columbus launched their own bikesharing programs during 2013. Similar trends are observed around the world (Meddin and DeMaio, 2007; Shaheen et al., 2012).

Although bikesharing systems potentially offer a viable alternative for enhancing urban mobility, they suffer from the effects of fluctuating spatial and temporal demand that inherently lead to severe system inefficiencies; e.g. having empty or full stations for long periods of time. These inefficiencies are embedded in the fabric of bikesharing because one-way trips are allowed and the operator has little control over the behavior of the users. As a result, some stations are empty and some others are full, impeding potential users to either pick up or drop off bikes at their desired stations, degrading the level of service, system performance and causing disappointment that may result in loss of users. To resolve these inefficiencies, bikesharing operators are compelled to reposition bikes dynamically to avoid the system from collapsing (Fricker et al., 2012). It has also been demonstrated that knowledge of future demands can aid in these repositioning tasks, reducing relocation costs and increasing the system performance (Barth and Todd, 1999).

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http://dx.doi.org/10.1016/j.tre.2014.10.005
1366-5545/Published by Elsevier Ltd.

The research presented in this paper outlines a comprehensive framework to solve the dynamic bikesharing rebalancing problem—finding the optimal routes and inventory levels to keep the bikesharing system balanced while it is in operation (Caggiani and Ottomanelli, 2012; Contardo et al., 2012; Rainer-Harbach et al., 2013; Raviv et al., 2013; Schuijbroek et al., 2013). The framework is based on four core models: (1) a demand forecasting model at the station level, (2) a station inventory model, (3) a redistribution needs model, and (4) a vehicle routing model.

The dynamic bikesharing rebalancing problem can be seen as a One-Commodity Pickup-and-Delivery Vehicle Routing Problem (1-PDTSP) (Hernandez-Perez and Salazar-Gonzalez, 2004) with the added complexity that the inventory at the stations is flexible (Schuijbroek et al., 2013). We see the methodology presented in the paper as an heuristic to solve such a problem that on its core uses anticipated future demands to decouple the inventory and the routing problem, reducing the complexity, making it scalable, proactive instead of reactive and allowing for real time decision-making. Vehicle routes are built dynamically based on current and expected events in a proactive manner, as inefficiencies are resolved before they actually occur, increasing customer satisfaction. As routes are being built periodically, operator interaction is permitted, overriding current routing decisions.

The routing problem maximizes the utility gained by removing inefficiencies from the system, it is selective (not all stations are visited), keeps track of the vehicle inventory, can handle a non-homogenous fleet and allows for pick ups or drop offs at buffering stations—stations that are in a balanced state but some bikes can be removed or added without causing future inefficiencies—solving the issue of having an empty or full vehicle that is not able to respond to existing inefficiencies.

The proposed predictive model has the potential to help determine more efficient user-based relocation policies by means of incentives or dynamic pricing policies. It is also self-adaptive, as it is regularly retrained as new system data are being acquired. Further enhancements to the predictive module can be made if bikesharing system users data were available—for example, offering discounts to users that express the need of a bike at a given station using a mobile application. Doing so can improve the predictive model and lead to better routing decisions.

Although the models developed in this paper pertain specifically to the dynamic rebalancing problem in bikesharing, the general framework has application in dynamic logistics resource operations and management in various other demand–supply operational scenarios; e.g., directly in the balancing of electric vehicles in the ZEV-NET shared-use station car system (City of Irvine, 2014), or with some modification to the problem of distribution of emergency medical personnel (by type of specialty) in such disasters as earthquakes and hurricanes. Furthermore, models developed on the framework could also be implemented to efficiently distribute vehicles in a hypothetical one-way carsharing system using a fleet of autonomous vehicles.

The framework has been tested under various simulation scenarios with variable time steps using data from The Hubway Bikesharing system in Boston (Hubway, 2011). The simulation results show that level of service can be improved compared to the "do nothing" scenario, especially in reducing the observed number of full and empty events. Managerial decisions are also simulated, testing for the impact of the number and the capacity of the vehicles used for rebalancing operations.

The structure of the paper is as follows. Section 2 reviews current literature on solving the bikesharing rebalancing problem. Section 3 describes the framework, methodology behind each model and data used. Section 4 outlines the simulation procedure. Section 5 reports the results under different simulation scenarios, and conclusions are drawn in Section 6.

2. Related work

Bikesharing-related literature has been growing as more and more systems are being implemented. Relative to issues addressed in this paper, there are two main areas of interest: forecasting future demands in shared ride systems, and approaches to formulate and solve the dynamic bikesharing rebalancing problem.

Concerning forecasting future demands a variety of techniques have been explored. Initial insights can be found in the carsharing literature, which has a longer history of investigation. Barth and Todd (1999) show under a simulation framework that for a one-way carsharing system the knowledge of future demands significantly impacts performance measures. Four different predictive techniques are tested on real data from the Honda Intelligent Community Vehicle System (ICVS) in Kek et al. (2005): Neural Networks (NN), regression, selective moving average and Holt's model. The results indicate that NN has the best performance. Based on this research, Cheu et al. (2006) ran tests on an expanded dataset of ICVS comparing NNs and Support Vector Machines (SVM). Their results also show that NNs lead to better performance and it is argued that they can better capture nonlinearities in the system. These results motivated the later implementation of a decision support system to optimize operator-based relocation operations in carsharing systems (Kek et al., 2009), which is modeled as a variation of a pick-up and delivery problem.

In the bikesharing literature, Froehlich et al. (2009) and Kaltenbrunner et al. (2010) use data from the *Bicing*, the bikesharing system in Barcelona (Spain). Froehlich et al. (2009) test four different predictive techniques: last value, historic mean, historic trend and a Bayesian Network (BN). The best results are obtained with the BN, with an average error of 8%, averaged over all days and prediction windows used (10, 20, 30, 60, 90 and 120 min). As expected, prediction errors increase with the prediction window. Kaltenbrunner et al. (2010) implement an Auto-Regressive Moving Average (ARMA) model with an FIR low-pass filter to predict station states. Mean absolute errors in a 60-min prediction window of 1.39 bikes with a maximum error of 6 bikes are reported.

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