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Inventory rebalancing through pricing in public bike sharing systems

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ABSTRACT

This paper presents a new conceptual approach to improve the operational performance of public bike sharing systems using pricing schemes. Its methodological developments are accompanied by experimental analyses with bike demand data from Capital Bikeshare program of Washington, DC (USA). An optimized price vector determines the incentive levels that can persuade system customers to take bikes from, or park them at, neighboring stations so as to strategically minimize the number of imbalanced stations. This strategy intentionally makes some imbalanced stations even more imbalanced, creating hub stations. This reduces the need for trucks and dedicated staff to carry out inventory repositioning. For smaller networks, a bi-level optimization model with a single level reformulation is introduced to minimize the number of imbalanced stations optimally. The results are compared with a heuristic approach that adjusts route prices by segregating the stations into different categories based on their current inventory profile, projected future demand, and maximum and minimum inventory values calculated to fulfill certain desired service level requirements. We use a routing model for repositioning trucks to show that the proposed optimization model and the latter heuristic approach, called the iterative price adjustment scheme (IPAS), reduce the overall operating cost while partially or fully obviating the need for a manual repositioning operation.

1. Introduction

Increasingly, Public Bike Sharing Systems (BSS) are being adopted by many major cities throughout the world. Bikes are being touted as a way to achieve sustainable mobility in an urban setting while also helping to alleviate the last mile problem in urban transportation (Shaheen, Guzman, & Zhang, 2010). As of February 19, 2018, bike sharing systems are operating in 1560 cities worldwide and another 402 such systems are in planning or under construction with a growing interest in more and more cities (Meddin & DeMaio, 2018). One of the major problems faced by these systems is the operational issue of repositioning of bikes between different stations. Demand variability causes certain stations to become too full or too empty to effectively service new customers. This not only affects the desired service level but also incurs spurious operational costs. According to a report by New York City Department of City Planning (2009) based on different case studies, the total capital cost for a bike sharing system varies from \$3000/bike to \$4400/bike in different cities. When averaged across programs, the yearly operating cost for a bike share program is around \$1600/bike.

The operating cost consists of system operations, administration, marketing and utility costs associated with hardwired stations. System operation forms the largest share of these costs and includes functions such as: maintenance of all equipment, rebalancing of bikes, customer service operations, and IT support (The Pennsylvania Environmental Council, 2013). Clearly, the repositioning of bikes from stations too full to stations too empty is a huge operational overhead. In fact, for Vélib system in Paris, the average cost of a single repositioning for a single bike is \$3 (DeMaio, 2009). A system-wide snapshot of Capital Bikeshare at 9:30 a.m. on May 15, 2014 shows that 88 out of 202 stations are *imbalanced* considering 90% service level (see Section 3.1).

The contribution of this work lies in the development of methods – both exact and heuristic – and algorithms that bike sharing system managers can use to reduce the number of imbalanced stations by rebalancing their inventory through price incentives/disincentives. To do so, we will intentionally make some imbalanced stations more imbalanced, making them function as *hubs*. If only a few highly imbalanced stations exist in the system, bike redistribution can be handled with a few regular short time truck trips. With the reduced number of imbalanced stations, the truck redistribution operation becomes simpler and efficient resulting in

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operating cost reduction. This observation is key to our idea of designing dynamic pricing policies. We seek to ensure that surplus bikes are gathered predominantly at 'surplus accumulation' stations (hubs for bikes), and similarly, the deficiency of bikes mainly occurs at 'lack accumulation' stations (hubs for docks).

We understand that the practical implementation of the pricing policy can be challenging and must be discussed. Nowadays, many modern bike sharing stations are equipped with a computer terminal with a touch screen. When a bike user tries to checkout a bike, the user will be asked to choose his or her destination. Based on the current state of the system, the user will be provided with alternate journey choices with information about the price to be charged for each choice at the time of return. A mobile webpage or an application can also be used to provide on the go information about the prices even before the bike user approaches a bike station.

We assume that bike users exhibit a homogeneous sensitivity to the price and always seek to maximize their utility. Such indirect control by the system operator in the bi-level programming context is also very common in the Stackelberg game (or leader–follower game) setting for economics and policy studies (Bard, 1991). We also did not consider the demand elasticity of price. We assumed that travel demand is fixed and users choose the lowest priced alternative to make the journey.

To determine the price incentives, we formulate a bi-level optimization model in Section 3 and provide a single-level reformulation that may be useful for small networks. In Section 4, we propose a heuristic algorithm, called the Iterative Price Adjustment Scheme (IPAS), and compare its performance with the single-level optimization model (P) solved by a commercial solver. We conclude that we can successfully reduce the number of imbalanced stations, by giving travelers multiple journey choices and changing the cost of those journeys through pricing. We also demonstrate that the cost of the same degree of manual rebalancing outweighs the price incentives offered.

The performance of IPAS is demonstrated by computational experiments in Section 5. Using the data from Capital Bikeshare in Washington, D.C., we show how our approaches manage to successfully minimize the number of imbalanced stations. The efficacy of our heuristic approaches vis-à-vis execution time, while bringing satisfactory improvement to the overall objective of minimizing the number of imbalanced stations is also shown. In Section 5.3.2, we use a routing model to show how the smaller number of imbalanced stations achieved as a result of a pricing scheme translates into a simpler and more efficient static repositioning operation using trucks.

2. Literature review

Bike sharing systems have recently garnered an increased interest from the research community due to their growing importance in sustainable urban transport systems. DeMaio (2009) and Shaheen et al. (2010) separately discuss the history, impacts, models of provision and the future of public BSS. They identify improved redistribution of bikes as a key challenge facing BSS. Schuijbroek, Hampshire, and Van Hoeve (2017) have an excellent and comprehensive description of BSS literature. They divide up the BSS literature into four major streams including strategic design, demand analysis, service level analysis, and rebalancing operations. We, thus, refer readers to Schuijbroek et al. (2017) for general literature review, and limit this section to reviewing relevant literature on bike sharing systems, in particular, rebalancing operations.

Rebalancing operations are a big part of operating costs of a bike sharing system (The Pennsylvania Environmental Council, 2013). Generally, bike sharing systems employ two methods to redistribute the bikes: truck-based manual redistribution and pricing-based rebalancing.

Most bike sharing systems have a fleet of trucks that move around and pick and drop bikes. Vélib has 20 trucks (Benchimol et al., 2011) operating 24 hours to carry out manual rebalancing. Trucks and crew required to operate these have huge associated costs. Paul DeMaio of MetroBike, LLC, mentions a conversation with Luud Schimmelpennick, a pioneer of bike sharing concept, in DeMaio (2009). He reports that according to Schimmelpennick the cost for distribution of a single bike for JCDecaux is $3 and that any scheme that offers incentives to customers would increase the redistribution efficiency at a fraction of the current cost. Since some kind of manual balancing is always required, most of rebalancing literature is focused on optimal truck routing.

Several papers have recently studied truck-based manual bike redistribution. Benchimol et al. (2011) introduces several approximation algorithms for static rebalancing of bikes at the end of the day. Raviv, Tzur, and Forma (2013) introduced several formulations for static rebalancing problem with the objective of minimizing the expected user dissatisfaction. Chemla, Meunier, and Calvo (2013) present an exact model for the static rebalancing problem and two relaxations that they then solve using a branch-and-cut algorithm in conjunction with tabu search. Dell'Amico, Hadjicostantinou, Iori, and Novellani (2014) also propose several MILP formulations for bike rebalancing problem and then propose a branch-and-cut algorithm to solve these models. They apply their approach on 65 benchmark instances to compare the performance of their MILP formulations. Contardo, Morency, and Rousseau (2012) introduce a dynamic public bike sharing balancing problem (DPBSBP) to rebalance a BSS during daytime which constitutes peak hours. They solve the DPBSBP problem using Dantzig–Wolfe decomposition and Benders decomposition to derive lower bounds and fast feasible solutions. Caggiani and Ottomanelli (2012) construct a modular Decision Support System (DSS) for dynamic bike redistribution. Shu, Chou, Liu, Teo, and Wang (2013) discuss under-utilization of bike sharing systems in Chinese cities and propose a deterministic model to optimally deploy bikes and docking capacity at different stations. They also evaluate the value of redistribution and its impact on the number of trips supported by the system.

There is a recent trend in BBS literature to introduce a scheme of incentives to get users to move bikes away from the crowded stations and into the less occupied stations. Vélib operates a V+ scheme to induce users to avoid certain stations and prefer others. Users get 15 minutes of added travel time if they place the bikes at one of the hundred uphill stations (Fricker & Gast, 2016). The incentives can be in the form of extra added time, as is the case with Vélib, or some cash discounts. The literature on user incentive schemes is not as plentiful as that on rebalancing through trucks (Fricker & Gast, 2016). Fricker and Gast (2016) present a two-choice model in which each user is provided with two station choices at the time of a rental and is given an incentive to choose the station with the lower load as a destination. They show that even if a fraction of the users make the intended choice, the number of imbalanced stations comes down dramatically.

Waserhole, Jost et al. (2012) solve an optimization model for setting the trip prices through a Markov Decision Process framework based on Continuous-Time Markov Chain. They present a Fluid Approximation approach and build a mathematical programming model for the fluid approximation of the Stochastic VSS Pricing Problem with continuous prices. A simulation model is also implemented to check the performance of fluid approximation heuristic. Pfrommer, Warrington, Schildbach, and Morari (2014) introduced a tailored algorithm for dynamic route planning for multiple trucks for redistribution of bikes and then devised a system of price incentives computed based on Model