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Discrete Optimization

An exact algorithm for the static rebalancing problem arising in bicycle sharing systems

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ABSTRACT

Bicycle sharing systems can significantly reduce traffic, pollution, and the need for parking spaces in city centers. One of the keys to success for a bicycle sharing system is the efficiency of rebalancing operations, where the number of bicycles in each station has to be restored to its target value by a truck through pickup and delivery operations. *The Static Bicycle Rebalancing Problem* aims to determine a minimum cost sequence of stations to be visited by a single vehicle as well as the amount of bicycles to be collected or delivered at each station. Multiple visits to a station are allowed, as well as using stations as temporary storage. This paper presents an exact algorithm for the problem and results of computational tests on benchmark instances from the literature. The computational experiments show that instances with up to 60 stations can be solved to optimality within 2 hours of computing time.

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1. Introduction

Urban transportation is a critical issue in large cities due to the dramatic increase and agglomeration of citizens and services in city centers. Congestion is a frequent and major issue and the associated decision problems are highly complex. Since the Buchanan report (Buchanan, 1963), civil engineers proposed many effective techniques to mitigate the effects of urbanization on traffic. Shared mobility systems offer one of the most promising solutions and have the potential to reduce congestion in urban areas. In particular, bicycle sharing systems proved to be an effective solution to solve the "last mile" problem (Liu, Jia, & Cheng, 2012).

De Maio (2009) surveys the development of bicycle sharing systems starting from the 1960s, when Witte Fiesten (white bicycles) were first introduced in Amsterdam. Although this first generation of shared bicycles did not prove to be successful, the second generation of bicycles introduced in Denmark in the early 1990s was more effective, due to stronger and dedicated bicycles and coin-based payment systems. The third generation was first introduced in 1996 at the University of Portsmouth in the UK, where students could rent a bicycle using a smart card. This generation of bicycles proved to be a success, drastically reducing the number of thefts and damaged bicycles. It quickly became clear that IT tools capable of tracking bicycles, storing information about their usage and data about the users were necessary to improve the quality of service and decrease the rate of stolen/damaged bicycles. De Maio (2009) reports about 120 bicycle sharing systems running as of 2009, some of which consist of tens of thousands of bicycles. Impressive results in terms of increased bicycle usage, reduced CO_2 gas emissions, and consequent public health improvements are also reported. The efficiency of bicycle sharing systems largely depends on the effectiveness of operational strategies implemented by the network operators.

One of the key requirements identified by De Maio (2009) for the fourth generation of bicycle sharing systems is a good redistribution system. Despite initiatives aimed at promoting users to redistribute bicycles, the most common technique implemented to relocate bicycles from areas of high supply/low demand to areas of low supply/high demand is using trucks. The use of large trucks can be expensive and have a heavy CO_2 footprint, therefore many cities migrate to electric vehicles or start using vehicle routing optimization software to decrease the transportation costs and fuel consumption.

In this paper, we study the *Static Bicycle Rebalancing Problem* (SBRP), introduced by Benchimol, Benchimol, Chappert, De La Taille, Laroche, Meunier, and Robinet (2011). The SBRP aims to find a minimum cost route for a vehicle that starts and ends its service at a *depot*, and restores the inventory level at every bicycle station to its target value by picking up and delivering bicycles as necessary. The vehicle may visit any station more than once, and may use stations as temporary storage for bicycles (i.e., preemption). The term *static*

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refers to the assumption that the number of bicycles at each station is known in advance and does not change during the pickup and delivery operations, as opposed to *dynamic* problems in which the number of bicycles may change during the operations due to users renting and returning bicycles. The SBRP is of interest for many bicycle sharing systems that rebalance the stations during the night. Although the SBRP has been studied by Chemla, Meunier, and Wolfler Calvo (2013), the authors succeeded in providing a strong lower bound and an effective heuristic solution method, but not an exact algorithm. In this study, we propose an exact algorithm for the SBRP and present extensive computational results on benchmark instances from the literature.

The remainder of this paper is organized as follows. In Section 2, we provide a survey of the literature on bicycle rebalancing problems arising in bicycle sharing systems. In Section 3, we present the mathematical problem definition of the SBRP. In Section 4, elements of the exact algorithm for the SBRP are stated. In Section 5, we present a simple heuristic for generating upper bounds. In Section 6, we provide the results of our computational experiments. Finally, we give our concluding remarks in Section 7.

2. Literature survey

There is an increasing interest in optimization problems arising in bicycle sharing systems. Among the problems studied are the integration of bicycle sharing systems with other transportation systems (Chow & Sayarshad, 2014), the problem of reserving parking spaces in one-way vehicle sharing systems (Kaspi, Raviv, & Tzur, 2014), the dynamics of bicycles usage during the day (Agatz, Erera, Savelsbergh, & Wang, 2011), and the effects of fuel price variations on the bicycles usage (Smith & Kauermann, 2011). Recently, bicycle rebalancing problems have received a significant amount of interest from the research community. Given the high degree of complexity, metaheuristics have been proposed to tackle larger instances and problems with multiple vehicles. We refer the interested reader to the heuristic papers by Rainer-Harbach, Papazek, Raidl, Hu, and Kloimüllner (2014), Papazek, Raidl, Rainer-Harbach, and Hu (2013), Gaspero, Rendl, and Urli (2013), and Schuijbroek, Hampshire, and van Hoeve (2013). In what follows, we will focus on the studies about exact methods for bicycle rebalancing problems.

Nair and Miller-Hooks (2011) study the dynamic problem of rebalancing a shared mobility system by using stochastic programming, where the demand at each station is modeled using a set of scenarios. Their modeling approach uses chance constraints, which guarantee that a given percentage of scenarios will be satisfied by the redistribution plans. The objective is to minimize the redistribution costs. However, this model does not return any operational routing decisions. Contardo, Morency, and Rousseau (2012) solve the dynamic rebalancing problem that aims to minimize the overall unmet demand, using a flow formulation defined on a space–time network. The formulation is solved by means of a Benders decomposition embedded in a column generation framework. We refer the interested reader to Chemla, Meunier, Pradeau, Wolfler Calvo, and Yahiaoui (2013) for further reading on dynamic problems.

Raviv, Tzur, and Forma (2013) study the multi vehicles static rebalancing problem, in which the objective is to simultaneously minimize the routing cost and the customer dissatisfaction. The latter is modeled using a piecewise linear convex function of the number of bicycles at stations. The customer dissatisfaction function for a station attains its maximum when the station is full (the customers would not be able to return their bicycles) or empty (the customers would not be able to rent a bicycle). It is assumed that stations are visited at most once, service times are taken into account and the overall trip duration of each vehicle is bounded. The authors present two mathematical formulations, dominance rules, and valid inequalities. Their formulations are tested on artificial instances with up to 60 stations and one or two vehicles. The authors also introduce instances inspired by the Capital Bikeshare in Washington DC with up to 104 stations. Both formulations struggle to solve instances with two vehicles with respect to a single vehicle. Moreover, the authors point out that the constraint of a single visit is restrictive and may considerably limit the quality of the solutions achieved.

Chemla, Meunier, and Wolfler Calvo (2013) propose a mathematical formulation for the SBRP defined over a *time-expanded graph*, in which each station is replicated as many times as an upper bound on the number of visits possible to the station. The formulation uses four index variables and becomes intractable for medium-sized instances of SBRP. Therefore, the authors introduce two relaxations, the first of which uses two sets of two-index variables corresponding to the number of times each arc is traversed and the number of bicycles being carried on each arc, respectively. The second relaxation uses only variables representing the number of times an arc is traversed. The two relaxations are proven equivalent, but the linear relaxation of the second provides higher quality lower bounds, due to stronger capacity constraints. A Tabu Search algorithm is also developed and a set of benchmark instances is generated, with up to 100 stations to be visited. The authors report that the current number of stations visited in Paris by a vehicle with capacity $Q = 20$ bicycles is typically 50, with each station having capacity 30 bicycles. The gaps between the best upper bound solutions and lower bounds is roughly 2% for realistic-sized instances and up to 5% for instances with up to 100 stations.

Erdoğan, Laporte, and Wolfler Calvo (2014) extend the single vehicle static rebalancing problem by assuming that the number of bicycles at a station after the repositioning should lie within a given interval rather than a specific target number, and a station can be visited at most once. The authors solve the problem exactly using two methods, a Benders decomposition based branch-and-cut algorithm and a traditional branch-and-cut algorithm. Drawing upon the similarity of the problem with the *One Commodity Pickup and Delivery Traveling Salesman Problem* (1-PDTSP), they adapt valid inequalities studied in depth by Hernández-Pérez and Salazar-González (2004, 2007). Instances with up to 50 stations have been solved to optimality, and the Benders decomposition based branch-and-cut is observed to outperform the traditional branch-and-cut algorithm.

Dell'Amico, Hadjicostantinou, Iori, and Novellani (2014) solve the multi vehicle static problem where the overall transportation cost is minimized and each station has to be visited exactly once. Four alternative mixed integer linear mathematical formulations are compared and inequalities are used to strengthen the formulations.

3. Problem definition

We now provide a mathematical definition of the SBRP. We are given a complete directed graph $G = (V, A)$. The vertex set $V = \{0, 1, \ldots, n\}$ consists of the depot (vertex 0, arrival and departure node for the vehicle) and the bicycle stations $V\backslash\{0\}$. The number of bicycles at a station $i \in \{1, \ldots, n\}$ is initially p_i, the target number of bicycles is q_i, and the capacity of station i is C_i. Note that the capacity is necessary because preemption is allowed. Therefore, stations that are initially *balanced* (i.e., $p_i = q_i$) could also be visited with the purpose of temporarily parking or collecting bicycles. Each arc (i, j) has an associated travel cost c_{ij}, which may represent the fuel consumption, the travel time, or the CO_2 emission. The vehicle can carry at most Q bicycles at a time. The objective is to minimize the overall solution cost, ensuring that the vehicle departs and arrives at the depot and the target number of bicycles is allocated to each station at the end of the tour.

The SBRP has been proven to be $\mathcal{NP}$-hard by Benchimol et al. (2011), as well as its special cases for complete graphs and bipartite graphs with unit costs. The authors also propose a 9.5-approximation algorithm for the general case, a 2-approximation algorithm for the special case with a complete graph and unit costs, as well as lower

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