Proceedings of the Eighth International Symposium on Combinatorial Search (SoCS-2015)

Dynamic Redeployment to Counter Congestion or Starvation in Vehicle Sharing Systems

Supriyo Ghosh, Pradeep Varakantham, Yossiri Adulyasak†, Patrick Jaillet‡
School of Information Systems, Singapore Management University, Singapore 178902
†Singapore-MIT Alliance for Research and Technology (SMART), Massachusetts Institute of Technology
‡Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology
supriyog.2013@phdis.smu.edu.sg, pradeepv@smu.edu.sg, yossiri@smart.mit.edu, jaillet@mit.edu

Abstract

Vehicle sharing (ex: bike sharing, car sharing) systems, an attractive alternative of private transportation, are widely adopted in major cities around the world. In vehicle-sharing systems, base stations (ex: docking stations for bikes) are strategically placed throughout a city and each of the base stations contain a pre-determined number of vehicles at the beginning of each day. Due to the stochastic and individualistic movement of customers, there is typically either congestion (more than required) or starvation (fewer than required) of vehicles at certain base stations,which causes a significant loss in demand. We propose to dynamically redeploy idle vehicles using carriers so as to minimize lost demand or alternatively maximize revenue for the vehicle sharing company. To that end, we contribute an optimization formulation to jointly address the redeployment (of vehicles) and routing (of carriers) problems and provide two approaches that rely on decomposability and abstraction of problem domains to reduce the computation time significantly.

1 Introduction

Shared Transportation Systems (STS) offer attractive alternatives to deal with serious concerns of private transportation such as increased carbon emissions, traffic congestion and usage of non-renewable resources. Popular examples of STS are bike sharing (ex: Capital Bikeshare in Washington DC, Hubway in Boston, Bixi in Montreal, Velib in Paris, Wuhan and Hangzhou Public Bicycle in Hangzhou) and car sharing (ex: Car2go in Seattle, Zipcar in USA) systems, which are installed in many major cities around the world. Bike sharing systems are widely adopted with 747 active systems, a fleet of over 772,000 bicycles and 235 systems in planning or under construction. A bike-sharing system (BSS) typically has a few hundred base stations scattered throughout a city. At the beginning of the day, each station is stocked with a pre-determined number of bikes. Users with a membership card can pickup and return bikes from any designated station, each of which has a finite number of docks. At the end of the work day, carrier vehicles (ex: trucks) are used to move bikes around so as to return to some pre-determined configuration at the beginning of the day.

Due to the individual movement of customers according to their needs, there is often congestion (more than required) or starvation (fewer than required) of bikes on aggregate at certain base stations. This (particularly starvation) can result in a significant loss of customer demand. Such loss in demand can have two undesirable outcomes: (a) loss in revenue; (b) increase in carbon emissions, as people can resort to fuel burning modes of transport. So, there is a practical need to minimize the lost demand and our approach is to dynamically redeploy bikes with the help of carriers (typically medium to large sized trucks) during the day. However, because carriers incur a cost in performing redeployment, we have to consider the trade-off between minimizing lost demand (alternatively maximizing revenue) and cost of using carriers for redeployment. Henceforth, we refer to this problem as the Dynamic Redeployment and Routing Problem (**DRRP**).

DRRP is an NP-Hard problem and therefore, we focus on principled approximations. Specifically, our key contributions are as follows (1) A mixed integer and linear optimization formulation to maximize profit for the bike sharing company by trading off between: (a) computing the optimal re-deployment strategy (i.e., how many vehicles have to be picked or dropped from each base station and when) for bikes; **and** (b) computing the optimal routing policy (i.e., what is the order of base stations according to which redeployment happens) for the carriers. (2) A Lagrangian dual decomposition method to exploit the weak dependency between the component which computes re-deployment strategy for bikes and the component which computes routing policy for carriers. (3) An abstraction mechanism that groups nearby base stations to reduce the size of the decision problem and consequently, improve scalability.

2 Solution Approach

We employ a data driven approach to solve DRRP. That is to say, we compute redeployment and routing strategies for a given training data set of demand values and evaluate the performance of the computed redeployment and routing strategies on a testing data set. Note that we only have the information about successful bike trips, thus we employ a standard method adopted in (Shu et al. 2013) to predict the actual demand, where the demand is represented using a *Poisson distribution* with mean computed from historical data. Specifically, we develop a Mixed Integer Linear Problem (MILP) formulation for solving DRRP with expected demand values, that are obtained from the training data set.

Given the customer demand of bikes between different stations, the goal is to maximize profit or alternatively minimize loss of the bike sharing company by redeploying bikes using carrier vehicles (to satisfy customer demand). However, because carriers incure a significant cost in redeployment, we represent the trade-off between lost demand (or equivalently revenue from bike jobs) and cost of employing carrier vehicles, using the dollar value of both quantities and combine them into overall profit. The key to this formulation for solving DRRP are the following flow preservation, movement and capacity constraints for bikes, stations and carriers. (1) Flow of bikes in and out of stations is preserved. (2) Flow of bikes between any two stations follows the transition dynamics observed in the data. (3) Flow of bikes in and out of carriers is preserved (4) Flow of carriers in and out of stations is preserved. (5) Only one carrier can be in one station at a time step. (6) Carrier can pick up or drop off bikes from a station by being at the station. (7) Station capacity **and** Carrier capacity is not exceeded when redeploying bikes.

2.1 Decomposition Approach for Solving DRRP

We exploit the minimal dependency that exists in the global MILP between the routing problem and the redeployment problem , to decompose the global MILP into two slaves. The routing and redeployment problems have a separate structure except that they are coupled through the complicating constraint (6), i.e., the redeployment strategy is controlled by the routing decision of the carriers. Therefore, we dualize this complicating constraint using the well known Lagrangian Dual Decomposition **[LDD]** (Fisher 1985). Thus, we have a decomposition of the dual problem into two slaves, where each of the slaves has a simple structure and is easy to solve. To obtain the final dual solution, we solved the master optimization problem iteratively using sub-gradient descent on dual variables. The infeasibility in the dual solution arises because routes of the carriers (computed by routing slave) may not be consistent with redeployment of bikes (computed by redeployment slave). However, solution of the routing slave is always feasible and can be fixed in the global MIP to obtain a feasible primal solution.

2.2 Abstraction Approach for Solving DRRP

Even after applying LDD, we can only scale to problems with at most 60 stations, 38 time-step and 6 carriers. To ensure scalability for bigger cities, we propose a heuristic approach that employs abstraction. Specifically, we have used the following key steps (1) Create an abstract DRRP with abstract stations, each of which is a grouping of original base stations. (2) Solve the abstract DRRP using LDD and obtain routing and redeployment strategy over abstract stations. (3) Derive the routing and redeployment strategies for the original DRRP from the routing and redeployment strategies for abstract DRRP.

	Whole day (5am-12am)		Peak period (5am-12pm)	
	Revenue gain	**Lost demand reduce**	**Revenue gain**	**Lost demand reduce**
Mean	3.47 %	22.72 %	7.74 %	30.58 %
Mon	2.33 %	22.46 %	4.48 %	25.55 %
Tue	3.07 %	28.56 %	7.86 %	37.10 %
Wed	3.30 %	31.16 %	8.95 %	44.88 %
Thu	2.86 %	33.76 %	6.04 %	35.97 %
Fri	2.51 %	27.37 %	4.50 %	28.15 %
Sat	3.87 %	23.61 %	4.33 %	24.30 %
Sun	3.01 %	26.00 %	4.04 %	36.51 %

Table 1: Revenue and lost demand comparison on CapitalBikeshare Dataset

3 Experimental Results

We evaluate our approaches on real world data of *CapitalBikeShare* company from US which provides the following key information: (1) Customer trip records that are indicative of successful bookings. We predict demand from these trip records. (2) Number of active docks in each station (i.e. station capacity) and initial distribution of bikes in the station at the beginning of a day. (3) Geographical locations of base stations. From the longitude and latitude information of stations, we calculate the relative distance between two stations. (4) Revenue model of the agency and cost of fuel for carriers.

CapitalBikeShare data set has 305 active stations and we consider 50 abstract stations (obtained through k-means clustering). The planning horizon is 38 (30 minute intervals during the working hours from 5AM-12AM). To predict the demands we have used 3-months of trip history records (3rd quarter of 2013). We provide the performance comparison between our approaches and current practice (i.e., no redeployment during the day) with respect to lost demand and revenue generated for the bike-sharing company. We generate the overall mean demand as well as the demand for individual weekdays from historical data of trips. We compute the results for the entire time horizon 5 AM to 12 AM and also for one of the peak durations from 5 AM to 12 PM. Table:1 shows the percentage gain in revenue and the percentage reduction in lost demand in comparison with current practice. With respect to both revenue gain and lost demand, our approach (abstraction + LDD + MILP) was able to outperform current practice during the peak time as well as over the entire day. We reduce the lost demand in all the cases by at least 20%, a significant improvement over current practice.

References

Fisher, M. L. 1985. An applications oriented guide to lagrangian relaxation. *Interfaces* 15(2):10–21.

Shu, J.; Chou, M. C.; Liu, Q.; Teo, C.-P.; and Wang, I.-L. 2013. Models for effective deployment and redistribution of bicycles within public bicycle-sharing systems. *Operations Research* 61(6):1346–1359.