Broken Bike Recycling Planning for Sharing Bikes System

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Abstract

Cycling as a green transportation mode has been promoted by many governments all over the world nowadays and bike-sharing systems have been widely used in urban public transportation, because of their convenience and environmental friendliness in recent years. However, due to the high daily usage and lack of effective maintenance, vast piles of broken bikes appear in many big cities. Therefore, building an effective broken bike collection model becomes a crucial task to promote the cycling behavior. In this paper, we build a broken sharing bike recycling planning model to collect the broken bikes based on the large scale real-world sharing bike data. We incorporate the realistic constraints to formulate our problem. Finally, we provide extensive experimental results to demonstrate the effectiveness of our approach.

1 Introduction

Bike-sharing systems have been widely used in urban public transportation due to their convenience and environmental friendliness in recent years, with over 1000 active systems and more than 300 in planning or under construction [1]. As a representative product of the sharing economy, it is often hailed as a good helper to solve the ‘last mile’ in citizen transportation. However, due to the randomness of use and the wide range of services, the system faces enormous challenges in the operation and maintenance of bikes. Especially, a fully station-less bike-sharing system like the Mobike, which offers a more flexible system, where the users can pick up and drop off their bikes at arbitrary locations. Bike-sharing took off in China, with dozens of bike-sharing companies quickly flooding city streets with millions of brightly colored rental bicycles. However, the rapid growth vastly outpaced immediate demand and overwhelmed Chinese cities, where infrastructure and regulations were not prepared to handle a sudden flood of millions of shared bicycles. Vast piles of broken bikes have become a familiar sight in many big cities (as illustrated in Figure 1a). A worker untangles a rope amid piled-up bicycles in a lot in Xiamen, Fujian province, China.

Aworker from the bike-share company ofo puts a damaged bike on a pile beside a makeshift repair depot for the company. Thousands of derelict bikes are being kept in the depot after coming off the road on March 29, 2017, in Beijing). Although the bike-sharing companies are collecting their unusable bicycles lying on streets and in 'bike graveyards' in many cities (as illustrated in Figure 1a), most of them cannot do so because they don’t have enough money. Since shared bikes have a lifespan of roughly three years, most of them ought to be decommissioned next year. So broken bikes collection problem will become more serious. Fortunately, the user sharing the bicycle can report the situation of the broken bicycle through the app as shown in 2(a), which provides relevant data for determining the state of the bicycle. When the user finds a problem with the bike, the user can upload the problem to the App. After the background recognition is passed, the user will remotely issue the command through the Internet of Things to remotely lock the broken bicycle. Even if the user encounters the broken bike, the user cannot scan the code and unlock the bicycle. Traditional approaches to collect broken bicycles in a city rely mainly on site inspection by operation and maintenance personnel as shown in Figure 3(a). However, existing work merely focuses on the identification and search of the broken bicycle reported by the user while ignoring the realistic constraints and requirements.

As a result, many broken vehicles failed to be repaired and restored in time. This has caused the current situation that the public "difficult to find a sharing bike" and "difficult to scan a sharing bike".

In this paper, we implement a broken bike recycling path...
planning system based on data mining results from the massive sharing bikes’ user orders, riding trajectories, and vehicle recycling. The system consists of two main modules: 1) data pre-processing, which filters outlier order data and GPS points, performs map-matching, and builds map griding; and 2) prediction and recycling model, which studies a method to model the current status for each sharing bike, extracts the features of bikes’ order-data and trajectories and infers the malfunction possibility of sharing bikes. The main contributions of the paper are summarized as follows:

We formulate the broken bike recycling problem by considering various recycling constraints, and the problem proves to be NP-hard.

We propose a multi-step collection algorithm, which provides a scalable and approximate solution to the broken sharing bike recycling problem.

The rest of the paper is organized as follows: Section 2 describes the problem and the system overview. Section 3 gives the solution of broken sharing bike recycling routing problem. Experiments and case studies are given in Section 4. Related works are summarized in Section 5. Finally, Section 6 concludes the paper.

2 Overview

In this section, we model and define the broken bike recycling routing problem for Sharing Bike, and outline our solution framework.

2.1 Problem Definition

In a city, its fully station-less bike-sharing system, including bikes that can ride normally and broken bicycles. The distribution of broken sharing bikes naturally forms a directed graph, which is called the distribution diagram of broken bikes (in short, the distribution diagram), and is defined as follows.

Definition 1 (Distribution Graph) A distribution graph $G = (V, E)$ where a vertex set $V = \{X_1, X_2, \cdots, X_n\}$ represents the longitude and latitude coordinates of broken sharing bikes and arc set $E = \{e_{ij} = (X_i, X_j) | X_i, X_j \in V, X_i \neq X_j\}$ represents all relevant road segments between broken sharing bikes.

Definition 2 (Time Cost) The dockless sharing bike can be at any location in the city, e.g., hiding in the residential area or close to the road network, where the parking location of collecting vehicles is usually along the road network. As a result, the distance between them varies significantly, which we employ to driving time, walking time, and area search time to better characterize the individual bike-collecting events.

Driving time is the time taken by the maintenance personnel to drive the vehicle to the designated location. The following inequality eq.(1) reflects this definition of $t_{ij}$:

$$t_{ij} = \frac{s_{ij}}{v_c}$$

Where $s_{ij}$ is the navigation distance from the nearest road to $X_i$, to the nearest road to $X_j$, $v_c$, is the average speed of the operation and maintenance personnel driving.

Walking time is the time spent on the maintenance personnel to walk to the broken sharing bikes (e.g., The distance of the $X_i$ from the nearest road is denoted by $d_i$). Assume that the average speed of the maintenance personnel is $v_p$. Based on the notations above, we can formulate the walking time $tw_i$ as

$$tw_i = \frac{2d_i}{v_p}$$

Area Search Time. There is a time cost $tas_i$ associated with each broken bike $X_i \in V$, to find and scan code registration for it (e.g., the occlusion of the building and the strength of the regional signal).

Finally, the time cost of collection broken bike $i$ can be defined as follows.

$$T_i = t_{ij} + tw_i + tas_i$$

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1https://en.wikipedia.org/wiki/Mobike
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The problem of collecting broken sharing bikes is an NP-hard problem. We develop a multi-step collection algorithm based on self-organizing neural network to tackle the issue.

2.2 System Overview

Figure 5 gives an overview of our system, which consists of two main components:

Data Pre-processing. This component takes the user order data, the trajectories, worker recycling data, and the road network as input, and performs the following three tasks: 1) Data Cleaning, which removes invalid order data and the outlier GPS points; 2) Map-Matching, which projects the bike trajectories onto the corresponding road segment and finds the nearest road segment to the bicycle location; and 3) Map Griding, which partitions the map into equal side-length grids to assess the time spent on finding a bicycle in different areas.

Recycling planning Model. This component recommends the appropriate collection route by evaluating the distribution of bikes. Main task is performed: broken bike recycling routing model, which takes the parameters of the bike maintenance personnel, e.g., the capacity of the recycling vehicle, and output the recommended route for recycling the broken bike. (detailed in Section 3).

3 Broken Bike Recycling planning Model

In this section, we describe the overall framework of the a multi-step collection algorithm based on self-organizing neural network for collection broken sharing-bike.

3.1 A Multi-step Collection Problem

In our broken bike collection problem, each temporary parking point has its own service range. The departure and return locations of the maintenance workers are the same temporary
parking points in the area. If the capacity of collecting vehicles is not limited, the problem of collecting broken bicycles can be transformed into a problem to minimize the entire collection path, which can be transformed into a TSP problem. However, due to the limited capacity of the collection vehicle, this problem can be described as the limited capacity of K maintenance personnel to collect all broken bicycles, which can be translated into VRP problem. Our goal is to minimize the time cost for each staff member to collect broken shared bicycles and to make their working hours as average as possible. In our broken bicycle collection task, we use self-organizing neural network to solve our problem [2–4].

**Main Idea.** The intuition of the multi-step collection algorithm based on self-organizing neural network is to create a mechanism that can put the associated output of similar inputs as much as possible close to each other. Our broken bike collection problem has a common temporary parking spot, the adaptation procedure must ensure that all collection broken bikes are connected with the temporary parking spot. Therefore, a winner node from each ring is selected and adapted to the temporary parking spot. After that, other broken sharing bikes are presented to the network in a random order and the winner node is selected from all noninhibited nodes. The network continues to evolve until every broken shared bicycle has a winner node close enough.

### 3.2 A Multi-step Collection Algorithm Framework

The self-organizing neural network for VRP[15] uses two-layered competitive learning networks, where each network contains two-dimensional input vector and an array of output units. In our multi-step collection task, the input vector \( X_i \) represents coordinates \((b_i^{\text{longitude}}, b_i^{\text{latitude}})\) of the broken sharing bike \( X_i \) and weights \( W_j = (W_j^{\text{longitude}}, W_j^{\text{latitude}})\) can be interpreted as coordinates of the node \( W_j \). The node connects to a ring representing a broken bicycle task and creates a separate ring for each maintainer, as shown in Figure 6. The broken sharing bikes are presented to the network in a random order and the winner node is selected from all noninhibited nodes. The network continues to evolve until every broken shared bicycle has a winner node close enough.

\[
J = \arg\min_j |X_i - W_j| \cdot (1 + \frac{T_r - T_{\text{avg}}}{T_{\text{avg}}}) + \gamma C_r \tag{5}
\]

where \( X_i \) is the coordinates of broken sharing bike \( i \), \( W_j \) is the coordinates of node \( j \) in ring \( r \) and \(|\cdot|\) is the Euclidean distance.

\( T_r \) is the time cost of the ring \( r \) to which node \( j \) belongs, and \( T_{\text{avg}} \) is the average time cost of the rings. Basicly, the rule prefers nodes from shorter cost time rings and thus it aims to minimize the longest cost time ring (collection task). \( T_r, T_{\text{avg}} \) and \( C_r \) are according to the following equations:

\[
T_r = \frac{\sum T_i - \min(T_i)}{\max(T_i) - \min(T_i)} \tag{6}
\]

The intuition of the multi-step collection algorithm based on self-organizing neural network is to create a mechanism that can put the associated output of similar inputs as much as possible close to each other. Our broken bike collection problem has a common temporary parking spot, the adaptation procedure must ensure that all collection broken bikes are connected with the temporary parking spot. Therefore, a winner node from each ring is selected and adapted to the temporary parking spot. After that, other broken sharing bikes are presented to the network in a random order and the winner node is selected from all noninhibited nodes. The network continues to evolve until every broken shared bicycle has a winner node close enough.

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where $W_j$ denotes the node $j$ in route $r$ [2]. $G$ is the gain parameter and $d$ is the cardinal distance measured along the ring between nodes $j$ and $J$. $\| \cdot \|$ represents absolute value.

Algorithm Design. Algorithm 1 gives the pseudo-code of our multi-step collection algorithm. In the initialization stage, the algorithm first divides the vertex set of the broken shared bicycle node $V$ into $k$ rings, each ring contains $M$ nodes. In the initialization stage, the algorithm first partition the vertex set of broken sharing bike nodes $V$ into $k$ rings. Each of the ring which contains $M$ nodes. The starting node and the ending node of rings is the temporary parking spot. Then, Initial the error of node and broken sharing bike $\delta = 0$. (Line 1-3). In each iteration of the Winner selection and Adaptation stage (Line 3-16), the broken bike collection task has a common temporary parking spot, the adaptation procedure must ensure that all collection broken bikes are connected with the temporary parking spot. Therefore, a winner node from each ring is selected and adapted to the temporary parking spot. After that, other broken sharing bikes are presented to the network in a random order and the winner node is selected from all noninhibited nodes. In the Winner selection to broken sharing bike, the algorithm chooses the nearest node from the temporary parking spot $X_d$ through a competition process according to equation 5. The competition only takes place between the nodes that are not selected as winners in this iteration (Line 6-7). We update the node $J$ and its adjacent nodes in the $r$ ring. Temporary parking space $X_d$ uses the equation 10 to ensure that all tasks of collecting broken bicycles are connected to the same temporary parking space. In the Randomizing, the algorithm randomize the order of broken sharing bikes and label them (Line 10-11). In the next step, we select the closest node to broken sharing bike through a competitive procedure according to equation 5 and update the node and its neighborhood coordinates according to equation 10. Finally, when the error between node and broken sharing bikes is smaller than the maximal allowable error $\Delta$ or the number of iterations of the algorithm reaches $N$, the algorithm terminates, and $k$ broken sharing-bikes collection ordered sets $BO$ and path $RP$ is returned as the recommended broken bike recycling plan.

4 Experiments

In this section, we conduct extensive experiments to evaluate the effectiveness of our system. We first describe the real dataset used in the paper. Then, we give experiment results of maintenance workers’ collection broken sharing bike time cost. Finally, a set of real case studies are presented to test our broken bike and collection route algorithm.

4.1 Datasets

Road Networks. Road network of Beijing, China is from Open Street Map 2.

Mobike Broken Bikes Data. Each Mobike broken bikes data contains a bike ID, latitude and longitude data of bikes. The dataset used in the paper is the area near Zhichun Road, Dazhongsi, and Beitucheng subway station in Haidian District, Beijing as shown in Figure 7.

Mobike Collection Data. Each Mobike collection data contains a bike ID, a maintenance personnel ID, start time to collect bikes (when the employee uses the device to control the bicycle smart lock ringing), end time to collect bikes (When the employee uses the device scan code to open the bicycle), smart lock ringing locations, and scan code locations. The dataset used in the paper is the full Mobike collection data in the City of Beijing, with the time span of 06/01/2017 - 31/12/2018.

\[ d = \min(||j - J||, M - ||j - J||) \]
4.2 Effectiveness Evaluation

In this subsection, we study the effects of different parameters in our system. Unless mentioned explicitly, the default parameters used in the experiments are: recycling vehicle capacity $cap = 25$, the average speed of the maintenance personnel's walking is $v_p = 1m/s$, and the average speed of the maintenance personnel's driving is $v_p = 25km/h$.

The evolution of the broken sharing bike problem by the multi-step collection algorithm is shown in Figure 8. Figure 8 illustrates the initial status of rings, after 50, 200 and 250 iterations as well as the final result. As shown in the figure, the starting and ending points of 27 rings are defined as temporary parking spaces, which are formed in the same way as the elastic network. Furthermore, the rings are elongated by an iterative process until settlement. Experimental result for our multi-step collection algorithm is shown in Table 1. As can be seen from the table, the algorithm divides the 538 broken sharing bikes in the area into 27 groups. Without exceeding the capacity limit of the recycling vehicle, the working time of each group of recycling tasks is relatively average, and the working time of each task is about 3 hours. The total recovery time of all tasks is the shortest.

To better understand the effectiveness of our bike prediction and recycling model, we conduct a field case study. We choose to visit the area near Zhichun Road, Dazhongsi, and Beitucheng subway station in Haidian District, Beijing. Figure 9 gives the path that Mobike operators use to collect broken bikes in this area. The total recycling path of the broken sharing bike is shown in Figure 9. All recycling tasks depart from the same temporary parking spot and eventually return to that spot. The four small images in figure 9 show the recovery paths of four groups of recovery tasks.

5 Related Work

Problems of bike-sharing systems correlate to the route planning problems and wireless sensor networks security problems (especially IoT security problems). The former problems involve the Vehicle Routing Problem (VRP) [5–8], the Multiple Traveling Salesman Problem (mTSP) [9, 10] and Orienteering Problem (OP) [11–13]. And the later one involves attack detection [26, 27, 30], trust management [30], and key management problems [31, 32, 35].

mTSP and OP can be considered as a relaxation of our problem, with the capacity or working time restrictions re-
In this paper, we introduce an approach to recommend the appropriate bicycle recycling path to the maintenance personnel based on the real sharing bikes data collected from Mobike. Our system can address the problem of recycling efficiency of broken sharing bicycles in a more realistic way, considering the constraints and requirements from sharing bike maintenance personnel’s perspective: 1) vehicle capacity constraint, 2) minimize the time to collect broken bikes and 3) The time cost of collection broken bike task for each maintenance personnel is as equal as possible. The formulated problem is proven to be NP-hard, thus we propose a multi-step collection algorithm based on self-organizing neural network. We perform experiments on a large scale Mobike data and demonstrate the effectiveness of our proposed broken bike recycling routing model.

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