Optimal Re-balancing for Bike Sharing System

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I. Problem Characterization

In considering the current conditions of growing urban traffic and rising air degradation, bike sharing systems (BSS) are progressively being used as a method of public transit in Toronto. In this fast paced city, the demand of any public transportation is high hence people sometimes experience the shortage of available bikes at select stations. Many solutions from different perspectives are proposed, such as adding more stations or increasing the initial amount of bikes at each station. However, economically speaking, these are not the most sustainable and efficient way. As an alternative solution, the usage of bike redistribution trucks is mandatory to keep everything on the right track.

This study proposes a model that both predicts bike demands in different stations using regression analysis, as well as optimizes a route for redistribution using ACO. However, since the public environment is constantly changing, it's challenging to keep track of every movement and calculate the best route for such redistribution in a dynamic environment. Instead, we decided to focus our solution on the redistribution at night, where the movement of bikes is negligible. In addition, the usage for bikes are affected by the demand of commuting on weekdays and weekends. Therefore, we will analyze these two time zones separately.

II. Problem Formulation and Modeling

A. Bike Station Demand Prediction Notation

The bike station demand is defined as the number of bikes that a station needs. In this prediction, we do not consider the bike stations that are under maintenance or out of service.

The total number of the pick-up bikes in a station during a day, we denote s_{out}. The total number of the drop-off bikes in a station during a day, we denote s_{in}. Then, using the formulation:

$$s_{delta} = s_{out} - s_{in} \tag{1}$$

A positive s_{delta} means on this day, customers are mostly riding bikes from this station to other stations, which implies that the station has s_{delta} fewer bikes than its actual demand. Similarly, a negative s_{delta} would mean that the station has $-s_{delta}$ more bikes than its actual demand.

In this problem, since there are obvious distinct distributions during weekdays and weekends, we will use two predictions - one is the s_{delta} on weekdays, and another is the s_{delta} on weekends.

B. Bike Re-balancing Optimization Notation

We denote a set V_{total} to represent the s_{delta} in each $station_i$, where n_{total} is the total number of bike stations.

$$V_{total} = \{v_1, v_2, v_3, ..., v_{n_{total}}\} \tag{2}$$

V is used to denote the s_{delta} for each $station_i$ which has a non-zero s_{delta}. Given the number of stations n_total in total, stations that need more bikes n_{in}, and the number of stations that could provide more bikes n_out, in this problem, we denote:

$$V = \{v_1, v_2, ..., v_{n_{out}}, v_{n_{out}+1}, ..., v_{n_{out}+n_{in}}\} \tag{3}$$

$$n = n_{out} + n_{in} \leq n_{total} \tag{4}$$

n is the total number of bike stations that need to be re-balanced.

The next task is to find the best route r_{best} that could visit both of these two kinds of stations and balance the number of bikes with the least travel distance.

C. Bike Demand Prediction with Regression Analysis

In this problem, we choose the regression analysis method, using the data of station location and the corresponding input/output number of bikes, to predict the possible demand gap for each station. [1] We do a regression analysis for each station's demand during a day (from 0:00 to 23:59) on both weekdays and weekends. With that method, we obtain a prediction model for all of the stations, and using those models, the demand value for each station can be found.

After that, we could know whether each station's demand value $s_{predict}$ is positive or negative and do the following re-balancing route optimization.

D. Re-balancing Bike Optimization with Ant Colony Algorithm

We are using the ACO algorithm for each station to find the shortest tour. The ACO algorithm simulates the behavior of real ant colonies and the use of ant pheromone trails to determine the best route, in our case the shortest path to redistribute the bikes.

The truck (used for redistributing bikes) is considered an individual ant, and its route is built by incrementally selecting bike stations until all stations have been visited. The visited stations are stored in the visited list. The decision for choosing the best route is based on the ant's probabilistic formula.

The Ant Colony Optimization algorithm and formula: In the first step, each ant selects a path, i.e. the order in which every location is visited. In the second step, the different paths are compared, and in the last step, the ants update the pheromone levels on each edge.

- Edge selection: Each ant needs to construct a solution to traversing through all the locations of interest. To pick the next edge of the graph, the ant needs to consider the length of each edge linked to its current node, as well as the pheromone level of the edge. An ant moves from state x to state y, and $A_k(x)$ computes the set of feasible expansions to ant k's current position in the graph. For ant k, p_{xy}^k denotes the probability of moving from state x to state y computed with attractiveness η_{xy} of the move and the trail level τ_{xy} of the move. η_{xy} is computed by the heuristic indicating the prior desirability of the move and τ_{xy} indicates the proficiency this move has been in the past, representing a posterior indication of the desirability of the move. [2]
  The probability of the move from state x to state y of the k^{th} ant is:
  $$p_{xy}^k = \frac{(\tau_{xy}^{\alpha})(\eta_{xy}^{\beta})}{\Sigma_{z \in allowed_x}(\tau_{xz}^{\alpha})(\eta_{xz}^{\beta})} \tag{5}$$
  where τ_{xy} is the deposited pheromone from x to y, η_{xy} is the attractiveness of the state transition xy, i.e. the reciprocal of the distance d_{xy}, and α is a weighted parameter on τ_{xy}, β a weighted parameter on η_{xy}.

- Pheromone update: Pheromone update happens after the ants complete their tours by changing the trail level τ_{xy} based on whether it's a good or bad solution. One possible update rule is:
  $$\tau_{xy} \leftarrow (1-\rho)\tau_{xy} + \sum_{k}^{m} \Delta\tau_{xy}^k \tag{6}$$
  ρ is the pheromone evaporation coefficient, m is the total number of ants, and $\sum_k^m \Delta\tau_{xy}^k$ is the pheromone deposited by ant k.
  In a typical TSP problem,
  $$\Delta\tau_{xy}^k = \begin{cases} Q/L_k & \text{if ant } k \text{ makes the } xy \text{ move} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$
  where Q is a constant and L_k is the cost of the solution. In our case, we can update the pheromone by each edge's *task completeness level*, in other words, if this move contributes to the overall task of re-balancing the bike numbers across set V, then we may update τ_{xy}^k by:
  $$\Delta\tau_{xy}^k = \begin{cases} Q \cdot C_k/L_k & \text{if ant } k \text{ makes the } xy \text{ move} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$
  where C_k is the contribution to the overall re-balancing task, quantified by $\Delta \sum_{i=1}^n v_i$ where v_i is the initial demand gap defined in (2).
  To emulate the situation when a trucker makes decisions about which station to go to next, we are adding a local update to the trail level τ_{xy} when an ant makes a contribution to minimize the demand gap for y, e.g. if the ant currently at x carries 2 bikes and the station y needs 3 more bikes to fill its demand gap, after the ant arrives at y and drop the 3 bikes, τ_{xy} should be updated according to the following equation:
  $$\Delta\tau_{xy}^k = \begin{cases} P \cdot c_y^k/l_{xy}^k & \text{if ant } k \text{ makes the } xy \text{ move} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$
  where P is a constant and c_y^k is the *contribution coefficient* which equals to $2/3$ in this case. l_{xy}^k is the cost of the move from x to y, which can be defined with the distance d_{xy}.

III. Related Work

The research community have shown their interest in the realm of vehicle redistribution problems, especially with bikes since it's one of the most rapidly growing industry. In a nutshell, the redistribution of bikes is done by a vehicle, usually a truck that travels between different stations and rearranges the number of bikes by picking up and dropping off. This operation can be divided into two categories: static and dynamic. A static redistribution usually happens at midnight or any time slot where the change in the number of bikes in the majority of stations is minimal and negligible. In contrast, a dynamic redistribution assumes that user activities can strongly affect the demand of each station and has taken many factors into account. An example would be traffic analysis with respect to the change of time proposed by Chiariotti et al. [3], as well as the constantly changing weather conditions in the middle of the day. Compared with static re-balancing, dynamic re-balancing is expensive since the system is remarkably large and complex [4]. Considering the variety of disadvantages in dynamic redistribution problems, we decided to approach the bike re-balancing problem statically.

A. Demand analysis

To solve a redistribution problem for static bike-sharing systems, understanding the demand of customers at each station and their impact is vital. Alvarez-Valdes et al. approached this problem by forecasting the unsatisfied demand of each station for the next day [5]. The demand is divided into two categories: 1) the user willing to withdraw a bike but arrives at an empty rack, and 2) the user willing to return a bike but finds the station full. Inspired by this categorization, we used positive and negative numbers to quantify the demands at each station, in which a positive sign is "bikes needed" and its corresponding value represents the number of bikes.

B. Optimization operations

Many scholars proposed a solution to optimize the redistribution problem. Jia et al. approached this by finding the shortest routes for repositioning vehicles using the Artificial Bee Colony algorithm [6]. However, the demand for bikes varies by different factors such as traffic or commute purposes on weekdays and weekends. Therefore, we will analyze these two conditions separately. Another approach is using Ant Colony Optimization (ACO), which is first proposed to solve the Traveling Salesman Problem (TSP) [7]. Gaspero et al. combined ACO with Constraint Programming (CP) [8] and Bell et al. used multiple ACO to successfully find a solution for TSP that is known to be within the top 1% of optimal solutions [9]. It's shown that many scholars have used ACO to solve vehicle redistribution problems and have encouraging results, we will also approach this problem using ACO.

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