Achieving Location Truthfulness in Rebalancing Supply-Demand Distribution for Bike Sharing*

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Abstract. Recently, station-free Bike sharing as an environment-friendly transportation alternative has received wide adoption in many cities due to its flexibility of allowing bike parking at anywhere. How to incentivize users to park bikes at desired locations that match bike demands - a problem which we refer to as a rebalancing problem - has emerged as a new and interesting challenge. In this paper, we propose a solution under a crowdsourcing framework where users report their original destinations and the bike sharing platform assigns proper relocation tasks to them. We first prove two impossibility results: (1) finding an optimal solution to the bike rebalancing problem is NP-hard, and (2) there is no approximate mechanism with bounded approximation ratio that is both truthful and budget-feasible. Therefore, we design a two-stage heuristic mechanism which selects an independent set of locations in the first stage and allocates tasks to users in the second stage. We show analytically that the mechanism satisfies location truthfulness, budget feasibility and individual rationality. In addition, extensive experiments are conducted to demonstrate the effectiveness of our mechanism. To the best of our knowledge, we are the first to address 2-D location truthfulness in the perspective of mechanism design.

Keywords: Location truthfulness · Bike sharing · Mechanism design

1 Introduction

Bike sharing as a convenient, health-promoting, and eco-friendly form of transportation, has been widely adopted in more than 1000 cities across the world [1]. It substantially contributes to the reduction of traffic congestion and

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air pollution. In recent years, a new type of bike sharing, called station-free bike sharing, has been deployed in many cities[1] and attracted increasing attention.

Compared with traditional bike sharing, users of a station-free bike sharing system can pick up and drop off bikes at any valid locations rather than at designated stations. This new system brings new challenges. The foremost challenge is a more serious imbalance of bike distribution as compared to the traditional bike sharing, due to the much less restriction on parking locations and the asymmetry of bike demand. For instance, suppose a hospital is short of bikes while a nearby shopping mall has many redundant bikes. Without a proper rebalancing mechanism, subsequent shoppers would still go to the shopping mall to park for convenience, leading to a more and more serious imbalance.

To tackle this problem, a plausible solution is to design an incentive mechanism to motivate users to park their bikes in desirable locations. However, there are two challenges. First, there is a limited budget for the bike sharing platform to use as the incentive, and hence it should be used to the maximal efficiency. Second, there is a continuum of possible parking locations and a large number of bikes, making computation tractability a practical issue.

This paper addresses the bike rebalancing problem and our main contributions are as follows:

- We characterize the imbalance between bike demand and supply using the Kullback-Leibler (KL) divergence, and formulate an optimization problem under a crowdsourcing framework.
- Pertaining to this model, we prove two impossibility results: (1) the optimization problem is NP-hard, and the traditional VCG mechanism cannot be applied; (2) there is no truthful and budget-feasible mechanism for this problem that can achieve a bounded approximation ratio.
- Thus, we propose a two-stage heuristic mechanism as an alternative solution, which achieves both location truthfulness, budget feasibility, and individual rationality. To the best of our knowledge, we are the first to study the 2-D location truthfulness in the perspective of mechanism design.
- We conduct experiments using real-world data, and demonstrate the effectiveness of our mechanism as a viable solution.

2 Related Work

Optimizing bike sharing systems has attracted much research effort [2–4]. For station-based bike sharing, Singla *et al.* [5] proposed a crowdsourcing mechanism that incentivizes users in the bike repositioning process, where users report their destination stations and the system provides an offer that consists of recommended stations and corresponding incentives. Ghosh *et al.* [1] generated repositioning tasks with trailers using an optimization method. For station-free bike sharing, a deep reinforcement learning algorithm is proposed in [6]. In that work, the platform learns to determine the payment based on their behaviors. It takes spatial

[1] https://mobike.com/cn/about/

and temporal features into consideration, but the proposed mechanism does not guarantee truthfulness. In contrast, our work achieves truthfulness and budget feasibility simultaneously.

In the field of crowdsourcing [7] and crowdsensing [8], a large body of works study the allocation and payment of spatial tasks [9, 10], and especially some papers take the quality into consideration [8, 11] which are similar to our work in a sense. In these works, users report their cost for tasks directly, but in reality, users may not know their exact cost. In our work, users only need to report their respective destinations, which would be a more practical approach.

3 The Model

In the bike rebalancing problem as illustrated in Fig. 1, there is a set of n users $N = \{1, 2, 3, \cdots, n\}$, and a set of m discrete locations $M = \{1, 2, 3, \cdots, m\}$. We assumed that the demand distribution $D(l)$ at all the locations $l \in M$ and the current bike distribution A_0 are known to the system (e.g., through the mobile apps and GPS), where A_0 means the set of the existing parked bikes and their respective locations. In this model, each user i who uses a bike needs to indicate or report her intended destination d_i on the map. The destinations of users are continuous in the 2-D area, but locations of tasks M are discrete points, each of which indexes a grid (see Fig. 1). We focus on bikes that are being in use and have not been parked (the parked ones are accounted for by A_0).

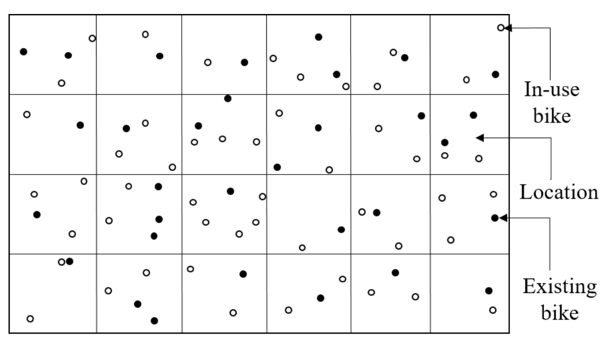

Fig. 1. Bike rebalancing problem: existing (parked) bikes, in-use bikes (to be parked), and locations (grids) for parking tasks.

As explained earlier, serious imbalance of bike distribution can happen if all the users park their bikes exactly at their destinations. Hence, the bike sharing platform would like to allocate a system-desired location l_i (rather than d_i) to user i for her to park her bike in order to match demand of bikes. In return, the platform offers an incentive p_i to user i if she takes that task. We employ an crowdsourcing framework as follows. Each location $l \in M$ corresponds to a task and each user $i \in N$ reports her destination as her bid. The distance between any two points x and y is denoted by H_{xy} and can be retrieved by the platform. The cost of user i for parking her bike at location l_i rather than her intended destination d_i is denoted by C_i or $C_{d_i l_i} = c * H_{d_i l_i}$, where the constant c is the unit travel cost. Hence, the utility of user i who takes a task of location l_i is $u_i = p_i - C_i$. In addition, we assume that a user does not accept a task whose location is outside range h of d_i, where h is a constant.

The platform has a budget B, within which it aims to design a mechanism to allocate desirable locations to users for balancing the demand and supply of bikes. The mechanism should satisfy the following properties:

- *Location truthfulness*: the utility of each user bidding truthfully should be no less than the utility of misreporting, i.e., $u_i(d_i, d_{-i}) \geq u_i(d'_i, d_{-i}), \forall d'_i \neq d_i$.
- *Budget feasibility*: the payment to all users should not exceed the budget limitation, $\sum_i p_i \leq B$.
- *Computational efficiency*: the algorithm should terminate in polynomial time.
- *Individual rationality*: the utility of any user should be nonnegative, i.e., $p_i \geq C_i$.

3.1 Problem Formulation

We characterize the imbalance of bike distribution using KL divergence, which measures the expected logarithmic difference between two probability distribution X and Y, as defined by

$$KL(X||Y) = \sum_i X(i) log \frac{X(i)}{Y(i)}.$$

The smaller the KL divergence is, the smaller the gap between X and Y is, and $KL(X||Y) = 0$ means that X and Y are identical probability distributions. In our case, we substitute $Q(l) = \frac{D(l)}{\sum_{l' \in M} D(l')}$ for $X(i)$ (demand), and $\frac{|A(l)|}{|A|}$ for $Y(i)$ (supply), where A is the set of all the parked bikes including existing bikes and bikes with allocated tasks, and $A(l)$ is defined the same way but for location l only. We assume $|A_0(l)| > 0$ for all locations[2] to avoid singularity.

Thus, the KL-divergence is

$$KL(A) = \sum_l Q(l) log \frac{Q(l)|A|}{|A(l)|} \tag{1}$$

where we omit Q on the left hand side for notational convenience. Now, let A_i denote the set of all the parked bikes before user i parks her bike. If user i takes the task of parking a bike at location l_i, then we have

$$KL(A_i \cup (i, l_i)) = \sum_{l \neq l_i} Q(l) log \frac{Q(l)(|A_i| + 1)}{|A_i(l)|} + Q(l_i) log \frac{Q(l_i)(|A_i| + 1)}{|A_i(l_i)| + 1} \tag{2}$$

[2] This is generally ensured as long as a grid is not too small.

In this work, our goal is to minimize the imbalance of bike distribution, namely the KL divergence, so we define the contribution of user i as the difference between $KL(A_i)$ and $KL(A_i \cup (i, l_i))$. Based on equation (1) and (2), we have

$$\begin{aligned} \xi_i &= KL(A_i) - KL(A_i \cup (i, l_i)) \\ &= log \frac{|A_i|}{|A_i| + 1} + Q(l_i) log \frac{|A_i(l_i)| + 1}{|A_i(l_i)|}. \end{aligned}$$

Denote

$$\xi_i^1 = log \frac{|A_i|}{|A_i| + 1}, \quad \xi_i^2 = Q(l_i) log \frac{|A_i(l_i)| + 1}{|A_i(l_i)|}.$$

We can observe that the sum of the first item only depends on the total number of users $|N|$. Since our objective is to minimize the KL divergence, which is the total contribution of all the users, we can omit the first term ξ_i^1 because the sum of ξ_i^1 is a constant. Thus, we let $\xi_i = \xi_i^2$ in the following. Moreover, note that the sequence of task allocation influences users' contribution, because $A_i(l_i)$ and A_i are evolving when we sequentially calculate each user's contribution.

Based on the above, the bike rebalancing problem can be formulated as:

$$\begin{aligned} \mathbf{max} \quad & \xi = \textstyle\sum_{i \in U} \xi_i \\ \mathbf{s.t.} \quad & \textstyle\sum_{i \in U} p_i \le B \\ & p_i \ge C_{d_i l_i} \quad \forall i \in U \end{aligned} \tag{3}$$

where U is the subset of users that are chosen to park in particular locations (namely, to perform parking tasks), p_i is the payment given to user i, which should be no less than her cost of performing the task. For users who are not selected (i.e., $N \setminus U$), they can just park at their intended destinations and the system does not allocate tasks to them.

3.2 NP-hardness

We prove that the problem (3) is NP-hard.

Theorem 1 *The bike rebalancing problem is NP-hard.*

Proof. We prove the decision version of the bike rebalancing problem is NP-hard. In the decision version, the question is whether there exists a subset of items U that satisfies both $\sum_{i \in U} \xi_i \ge K$ and $\sum_{i \in U} p_i \le B$ for a given constant K.

We use reduction to NP-hardness from the *0-1 knapsack problem* which is a classic NP-complete problem, and is defined as follows.

Definition 1 (An Instance of 0-1 Knapsack Problem) *Given a set of n items, each with a positive weight w_i and a positive value v_i. Given a maximum weight capacity W and a constant K, the question is whether there exists a subset of items U that satisfies $\sum_{i \in U} v_i \ge K$ and $\sum_{i \in U} w_i \le W$.*

We simplify the decision version of our problem to an instance where the acceptable range h is small enough such that there is only one choice of $\hat{l}_i$ for each user i and all the $\hat{l}_i$'s are non-overlapping. Thus, the quantities v_i, w_i, and W in the 0-1 knapsack problem correspond to ξ_i, p_i, and B in our case, respectively. Hence, the solution to the instance of the 0-1 knapsack problem is exactly the solution to the instance of our problem. In addition, the above reduction ends in polynomial time, which completes the proof. □

4 Impossibility of Approximate Mechanisms

Theorem 1 shows that VCG mechanism is unusable due to the exponential time complexity of finding an optimal solution. One possible direction is to make use of the available results in [14,15] where the authors proposed budget-feasible approximate mechanisms for *submodular* functions which are defined as follows:

Definition 2 *[17] A function $V : 2^{[n]} \to \mathcal{R}_+$ is submodular if $V(S \cup \{i\}) - V(S) \geq V(T \cup \{i\}) - V(T), \forall S \subseteq T$.*

In short, it means that the marginal contribution of a user decreases when the chosen user set becomes larger. However, our problem does not satisfy submodularity: when the set of chosen users expands from S to T, the (additional) user i's marginal contribution may *increase* because the user i may have multiple choices of tasks and the task allocated to her (and hence her contribution) may change when S changes to T. Therefore, the mechanisms introduced in [14,15] cannot be directly used. In fact, we prove that there does not exist an approximate mechanism with bounded approximation ratio for our problem.

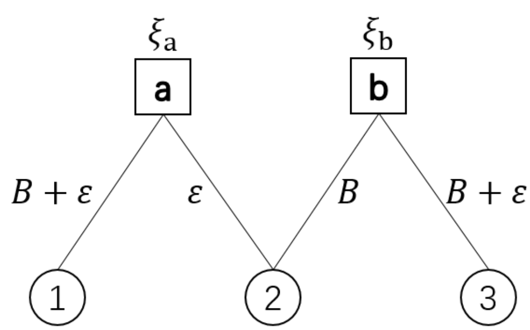

Fig. 2. An example showing impossibility where circles denote users and boxes denote tasks.

Theorem 2 *There is no approximate mechanism with a bounded approximation ratio that is truthful, budget-feasible and individually rational simultaneously for the bike rebalancing problem.*

Proof. Let us consider an example shown in Fig. 2, where the bid of location has been easily converted to the bid of cost by calculating the distance. The bidding profile is $x = \{(B+\epsilon, \infty), (\epsilon, B), (\infty, B+\epsilon)\}$, where ϵ can be any positive number less than B. ξ_a and ξ_b are the contribution of fulfilling task a and b respectively, and $\frac{\xi_b}{\xi_a}$ can be arbitrarily large. In the optimal solution, location b should be allocated to user 2, leading to a total contribution of ξ_b. We now show that any truthful, budget feasible and individually rational mechanism can achieve at most a total contribution of ξ_a.

Assume for the purpose of contradiction that there exists a mechanism f that satisfies these properties and guarantees a bounded approximation ratio. Let's consider the case of bidding profile $y = \{(B+\epsilon, \infty), (\epsilon, B+\epsilon), (\infty, B+\epsilon)\}$, where user 2 declares $B+\epsilon$ instead for location b. In this case, the optimal solution will allocate location a to user 2, so does the mechanism f. The reason is that (1) if f allocates location b to user 2, the cost of user 2 is above B, so it is neither budget feasible nor individually rational, and (2) if none of the locations a and b is allocated to user 2, then the total contribution is 0, and thus f can not guarantee a bounded approximation ratio. Given this allocation, to achieve truthfulness, the payment to user 2 for parking at location a has to be B because, otherwise, user 2 can misreport B for location a. Now, we can compare the bidding profiles x and y. In the case of y, the utility of user 2 is $B-\epsilon$. In the case of x, if mechanism f allocates location b to user 2, the utility of user 2 is at most 0, so she has incentive to misreport $B+\epsilon$ for location b to change the bidding profile into y to get better utility. Therefore, to ensure truthfulness, mechanism f has two choices in the case of x: allocating location a to user 2 or allocating nothing. In either case, the approximation ratio of total contribution is $\frac{OPT}{\sum_{l \in M} \xi_i} \geq \frac{\xi_b}{\xi_a}$ which can be arbitrarily large. Therefore, the mechanism cannot guarantee bounded approximation ratio, which constitutes the contradiction.

□

5 A Two-stage Incentive Mechanism

Due to the impossibility result of approximate mechanisms, we propose a heuristic mechanism in this section for the bike rebalancing problem.

The main idea is to convert the problem into a submodular problem and then employ techniques for submodular functions. We choose some representative locations that are not overlapping, and restrict each user to choose one of these locations or none (not participating). This way, the function of total contribution becomes a submodular function. Note that this method is not impractical because in the real world there are typically some sparse locations that are short of bikes, such as subway stations or residential areas.

However, there are still two challenges in designing a heuristic mechanism: (1) the selection of locations is a maximum weighted independent set problem, which is an NP-complete problem [16], and (2) allocating tasks to users to achieve truthfulness and budget feasibility simultaneously is a difficult problem.

Algorithm 1: The Two-stage Mechanism

Input: N, M, A_0, $Q = \{Q(1), Q(2), \cdots, Q(m)\}$, set of bids $d = \{d_1, d_2, \cdots d_n\}$, and the conflict network $G = (V, E, W)$.

Output: set of winning allocation $(i, l_i) \in U$, and payment p_i, for winning user i.

1: $U_l \leftarrow \emptyset$, $L \leftarrow \emptyset$, $TC \leftarrow 0$, $N_l \leftarrow 0$;
2: **for** $l \in V$, $i \in N$ **do**
3:     **if** $H_{d_i l} \leq h$ **then**
4:         $N_l \leftarrow N_l \cup i$;
5:     **end if**
6: **end for**
7: **for** $l \in V$ **do**
8:     $\overline{\xi_l(A_0)} = Q(l) \log \frac{|A_0(l)|+1}{|A_0(l)|}$;
9: **end for**
10: Sort locations based on the contribution $\overline{\xi_l(A_0)}$ into a list M' in descending order;
11: **while** $M' \neq \emptyset$ **do**
12:     Let l' be the head of the list, and $G_{l'}$ be the neighbor set of l';
13:     $L \leftarrow L \cup \{l'\}, M' \leftarrow M' \backslash \{G_{l'} \cup l'\}$;
14: **end while**
15: **for** $l \in L$ **do**
16:     $B_l = \frac{|N_l| \cdot B}{\sum_{l' \in L} |N_{l'}|}$;
17:     Sort users in set N_l into a list N'_l based on $C_{d_i l}$ in nondecreasing order, and let j be the head of N'_l;
18:     **while** $C_{d_j l} \leq \frac{B_l}{|U_l|+1}$ **do**
19:         $U_l \leftarrow U_l \cup (j, l), N'_l \leftarrow N'_l \backslash i$;
20:         Let j be the new head of N'_l;
21:     **end while**
22:     **for** $(i, l) \in U_l$ **do**
23:         $p_i = \min\{C_{d_j l}, \frac{B_l}{|U_l|}\}$;
24:     **end for**
25: **end for**

We propose a two-stage incentive mechanism. In the first stage, we construct a conflict network among locations by adding an edge of two locations if the distance between them is no more than $2h$, and we assign the weight of each location to be the contribution of the first user who parks at the location. Then, we use a greedy method to find the maximum weighted independent set of locations. In the second stage, the budget is divided for selected locations, and users are chosen for each location using the critical price mechanism. The complete procedure is presented in Algorithm 1.

In Algorithm 1, line 2-6 is to determine the candidates that are adjacent to each location. Line 7-14 determines a maximum weighted independent set of locations and proportionally divides the budget to each location based on the number of users. Line 15-25 is to find the optimal set of winners in a greedy manner for each location, where the critical price $\min\{C_{d_j l}, \frac{B_l}{|U_l|}\}$ is used as the payment for the first unselected user j.

In the following, we prove four important properties of our proposed mechanism: truthfulness, individual rationality, budget feasibility and computation efficiency. For proving truthfulness, we give a definition of symmetric modular function and a lemma presented below.

Definition 3 *[17] A function $V : 2^{[n]} \rightarrow \mathcal{R}_+$ is symmetric submodular if there exist $r_1 \geq \cdots \geq r_n \geq 0$, such that $V(S) = \sum_{i=1}^{|s|} r_i$.*

Intuitively, a function is *symmetric* if the value of the function is only determined by the cardinality of the set, and it is *submodular* if the marginal value is monotonously non-increasing.

Lemma 1 *[14] For a symmetric submodular function with a given budget, the above mechanism of determining winners (line 17-24) is truthful.*

Theorem 3 *The two-stage incentive mechanism is location truthful.*

Proof. In the first stage, it's obvious that users cannot manipulate the selected locations because the sorting of locations only relies on the condition of locations rather than the bids of users. So, let user i be a candidate of location l, if she misreports her destination $d'_i \neq d_i$, it must fall into one of following cases:

Case 1: $H_{d'_i l} > h$. In this case, user i either becomes a candidate of another location $l' \neq l$, or fails to be a candidate. In the former scenario, based on the non-overlapping characteristic between different selected locations, we have $H_{d_i l'} > h$, so it's beyond the acceptable range of user i. In the latter scenario, we easily have that user i's utility $u_i(d'_i, d_{-i}) = 0 \leq u_i(d_i, d_{-i})$.

Case 2: $H_{d'_i l} \leq h$ and $d'_i \neq d_i$. In this case, we use Lemma 1. Due to the monotonicity of function $\log \frac{x+1}{x}$, if $S_l \subseteq T_l$, we have

$$\begin{aligned}
\xi_l(S_l \cup \{i\}) - \xi_l(S_l) &= Q(l) \log \frac{|A_0(l)| + |S_l| + 1}{|A_0(l)| + |S_l|} \\
&\geq Q(l) \log \frac{|A_0(l)| + |S_l| + |T_l \backslash S_l| + 1}{|A_0(l)| + |S_l| + |T_l \backslash S_l|} \\
&= Q(l) \log \frac{|A_0(l)| + |T_l| + 1}{|A_0(l)|} - Q(l) \log \frac{|A_0(l)| + |T_l|}{|A_0(l)|} \\
&= \xi_l(T_l \cup \{i\}) - \xi_l(T_l).
\end{aligned}$$

Moreover, the function of total contribution $\xi_l = Q(l) \log \frac{|A_0(l)|+|U_l|}{|A_0(l)|}$ depends on cardinality only. Therefore, the contribution of a single location is a symmetric submodular function, and by Lemma 1, the above mechanism is truthful. □

Theorem 4 *The two-stage incentive mechanism satisfies individual rationality.*

Proof. For an unselected user i, her payment and cost are both zero, so the utility $u_i = p_i - C_i = 0$. For a winning user i, by the line 18 in the algorithm, we have $C_i \leq \frac{B_l}{|U_l|}$, and by the nondecreasing order of N'_l, we can get $C_i \leq C_j$, where j is the first unselected user. Therefore, we have that $u_i = \min\{C_j, \frac{B_l}{|U_l|}\} - C_i \geq 0$. □

Theorem 5 *The algorithm of the two-stage incentive mechanism has a polynomial-time computation complexity.*

Proof. The complexity of allocating users to adjacent locations (line 3-7) is $O(|V| \cdot |N|)$. The operation of sorting locations (line 10) is $O(|V| \cdot \log |V|)$. The computation complexity of determining winners for single location (line 17-24) is $O(|N_l| \cdot \log |N_l|)$, so for all selected locations, it's at most $O(|N| \cdot \log |N|)$. Since we have $|N| > \log |V|$ and $|V| > \log |N|$ in reality, the overall complexity of the two-stage mechanism is $O(|V| \cdot |N|)$. □

Theorem 6 *The two-stage incentive mechanism is budget feasible.*

Proof. In the mechanism, the given budget is divided for each selected location, so we only need to prove the mechanism for each single location is budget feasible. For location l and the set of selected users A_l, the price is $\min\{C_{d_j l}, \frac{B_l}{|U_l|}\}$ where j is the first unselected user, so we have

$$\begin{aligned}\sum_{i \in N} p_i &= \sum_{l \in L} \min\{C_{d_j l}, \frac{B_l}{|U_l|}\} \cdot |U_l| \\ &\leq \sum_{l \in L} \frac{B_l}{|U_l|} \cdot |U_l| \\ &= B\end{aligned}$$

which proves the budget feasibility. □

6 Performance Evaluation

We evaluate the effectiveness of our proposed mechanism using a real-world dataset from Mobike[3], which is a popular bike sharing company in China. We build a simulator that generates parking users and demand users based on the dataset of Beijing city from 10th to 14th May 2017.

The parameter values are set as follows. The cost of unit distance for each user is $c = 1RMB/km$, and the maximum acceptable range $h = 2km$. Unless otherwise specified, the number of existing bikes is 4000, the number of parking users is 1700, and the number of demand is 5000. We perform each experiment for 30 times and present the average value.

Three mechanisms are compared: our proposed two-stage heuristic mechanism (TSH), a randomized mechanism (RAN) and a randomized mechanism with selected locations (RAN-SL). In RAN, one user is chosen randomly in each round, and the platform picks all of nearby locations with higher demand than her affiliated location, then randomly chooses one to allocate to the user and pays her the maximum possible cost $p_i = c * h$ for performing that task. RAN-SL is similar to TSH in that it selects an independent set of locations the same

[3] https://mobike.com/global/

way as in our mechanism. However, the platform randomly chooses a location and a candidate user for that location in each round, and the payment for each task is also the maximum cost $p_i = c * h$.

We use *successful service ratio* (SSR) as the evaluation metric, which is defined as the proportion of demand that is satisfied, formally,

$$SSR = \frac{\sum_{l \in M} \min\{D(l), |A_0(l)| + |U_l|\}}{\sum_{l \in M} D(l)}.$$

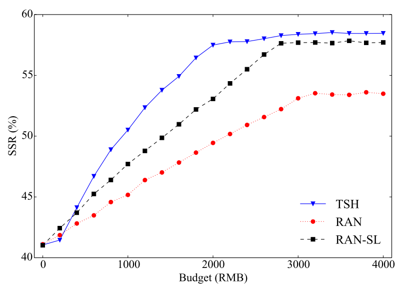

Fig. 3. Comparison on SSR with varying budget.

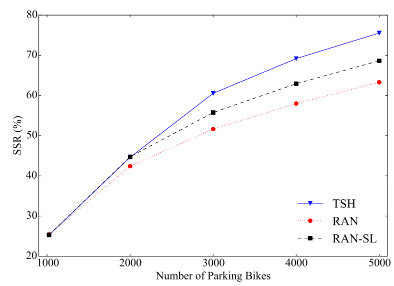

Fig. 4. The effect of the number of parking users.

The comparison of the successful service ratio (SSR) with varying budgets is illustrated in Fig. 3. We observe that SSR of all the three methods increases with the increase of budget until a threshold value. This is because all the candidate users have been selected and there is a remaining budget. Our method TSH outperforms the other methods in general. In addition, we see that the threshold of our method is about 2000 whereas the threshold of RAN and RAN-SL is about 3000, which indicates the *budget-saving* advantage of our mechanism.

7 Conclusion

In this paper, we have studied the bike rebalancing problem in station-free bike sharing. We have proved two impossibility results for optimal and approximate mechanisms, respectively. Therefore, we have proposed a two-stage heuristic mechanism as an alternative solution, and showed that it is effective and outperforms other choices through our extensive experiments based on a real-world dataset. In future work, we plan to explicitly incorporate the temporal factor into an online model, and conduct pilot experiments in a real city.

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