Improving the repositioning operation for bike sharing system

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Motivation: Background

- Dock based bike
  - repositioning is driven by the demand on bikes & docks
  - limited by the facility's locations
- Dockless bikes
  - repositioning is only driven by the demand on bikes
  - increased cost of finding a bike
- Mixed bike service
  - Nice Ride

Motivation: Research Questions

Due to a potential mismatch of rental/return demand versus availability in dock-based/dockless system, operating an inventory rebalancing strategy could be beneficial.

- Find out the difference in the optimal rebalancing strategy and the optimal cost between two bike systems
- Utilizing empirical information to evaluate proposed policy performance

Literature Review

[1] Inventory Repositioning in On-Demand Product Rental Networks

- Motivating example: car2go.
- State variable: $(\boldsymbol{x}, \gamma)$
- Key assumption 1: return probability consists of "rental length" and "return location"

  $$p_{t,ij} = p_t q_{t,ij}$$

  Rental period can be greater than one.
- Key assumption 2: lost sales cost outweighs the repositioning cost

  $$\rho c_{\max} - c_{\min} \leq p_{\min}(\beta - c_{\min})$$
- Utilize approximate dynamic programming approach to approximate the convex objective function.
  - Finding lower bounding hyperplanes to a convex function.

Literature Review (contd.)

[2] Robust Repositioning for Vehicle Sharing

- Motivating example: car2go.
- State variable: $\boldsymbol{x}$
- Key assumption: lost sales cost outweighs the repositioning cost

$$\overline{p}_{it} \geq \sum_{j \neq i} s_{ji(t+1)} \alpha_{ijt}$$

- A stochastic dynamic programming can be solved optimally with 2 region and the assumption of temporal independence among demands.
- Introduce distributionally robust optimization approach (DRO) to deal with uncertainty in the distribution, resulting in a multi-period robust optimization problem.
- An enhanced linear decision rule (ELDR) approximation is used to promote computational tractability.

[3] BRAVO: Improving the Rebalancing Operation in Bike Sharing with Rebalancing Range Prediction.

- Motivating example: Nice ride
- Rebalancing interval: Utilizing the data sets to predict the demand on bikes/docks for each station.
- Routing: approximate algorithm for TSP where each path's weight is the Euclidean distance
- Rebalancing Amount Algorithm
    - reduces the total amount of loading/unloading bikes
    - "robbing Peter to pay Paul" problem

Model Description

- To compare the performance/repositioning policy between dock-based/dockless system, we adopt the stochastic dynamic programming model in [2] to analyze results for 2-region system.
- Modeling dockless system: the original model in [2]
- Modeling the dock-based system: adding respective capacity limit at each location in the formulation.

Model Settings for two locations

- Total bike numbers: N.
- State variable: number of bikes in location 1: x_t ($N - x_t$ for location 2).
- Reposition qunatity r_t, where $r_t \geq 0$ represents reposition from location 1 to 2, and $r_t \leq 0$ represents otherwise.
- Return probability α_{ijt}, where $\sum_j \alpha_{ijt} = 1$ implies **one-period rental**.
- Unit repositioning cost per trip: s_{12t} and s_{21t}.
- Average lost sales cost in location 1 and 2:

$$\overline{p}_{1t} = p_{11t}\alpha_{11t} + p_{12t}\alpha_{12t}$$
$$\overline{p}_{2t} = p_{22t}\alpha_{22t} + p_{21t}\alpha_{21t}$$

Model Settings for two locations: Capacity limits

- Capacity limits: $C = C_1 + C_2$.
- Holding cost: h_{1t} and h_{2t}
  - Instead of using hard constraint, we add it as an additional cost when return capacity is violated.

DP formulation for dock based counterpart

$$V_t(x_t) = \min_{x_t - N \le r_t \le x_t} \{\underbrace{s_{12t} r_t^+ + s_{21t} r_t^-}_{\text{Repositioning cost}} + \mathbb{E}_{\mathbb{P}}[J_t(y_t, \boldsymbol{d}_t)]\}$$

where

$$J_t(y_t, \boldsymbol{d}_t) = \min_{w_{1t}, w_{2t}} \{\underbrace{\overline{p}_{1t}(d_{1t} - w_{1t}) + \overline{p}_{2t}(d_{2t} - w_{2t})}_{\text{The lost sale cost}} +$$

$$\underbrace{h_{1t}(x_{t+1} - C_1)^+ + h_{2t}(N - x_{t+1} - C_2)^+}_{\text{The holding cost}} + V_{t+1}(x_{t+1})\}$$

$$\begin{aligned} \text{s.t.} \quad x_{t+1} &= y_t - \alpha_{12t} w_{1t} + \alpha_{21t} w_{2t}, \\ w_{1t} &\le \min(y_t, d_{1t}) \\ w_{2t} &\le \min(N - y_t, d_{2t}) \end{aligned}$$

where $a^+ = \max(0, a)$ and $a^- = -\min(0, a)$

- Terminal cost $V_{T+1}(x_{T+1}) = 0$.

Optimal Policy Structure

- Assumption: $\overline{p}_{it} \geq \alpha_{ijt}(h_{jt} + s_{ji(t+1)})$, for $j \neq i$ and $i, j \in \{1, 2\}$.
- Policy structure: a two threshold policy $[\underline{x}_t, \overline{x}_t]$:

$$
\begin{aligned}
y_t^*(x_t) &= \underline{x}_t, \quad x_t \in [0, \underline{x}_t) \\
y_t^*(x_t) &= x_t, \quad x_t \in [\underline{x}_t, \overline{x}_t] \\
y_t^*(x_t) &= \overline{x}_t, \quad x_t \in (\overline{x}_t, N].
\end{aligned}
$$

where $y_t(x_t) = x_t - r_t$ is the target inventory level after repositioning, and $\underline{x}_t, \overline{x}_t$ is the optimal reposition up-to and down-to level solved by the following convex programs:

$$
\begin{aligned}
\underline{x}_t &= \arg\min_{0 \leq y \leq N} \{s_{21t} y + \mathbb{E}_{\mathbb{P}}[J_t(y, \boldsymbol{d}_t)]\} \\
\overline{x}_t &= \arg\min_{0 \leq y \leq N} \{-s_{12t} y + \mathbb{E}_{\mathbb{P}}[J_t(y, \boldsymbol{d}_t)]\}
\end{aligned}
$$

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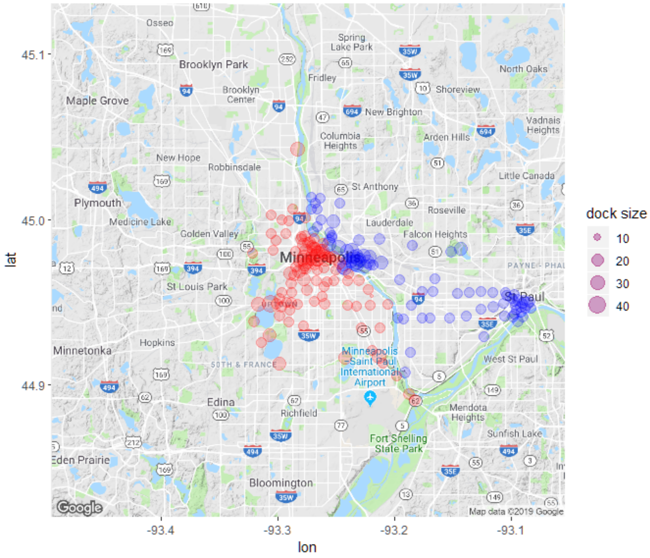
Optimal Policy Structure (contd.)

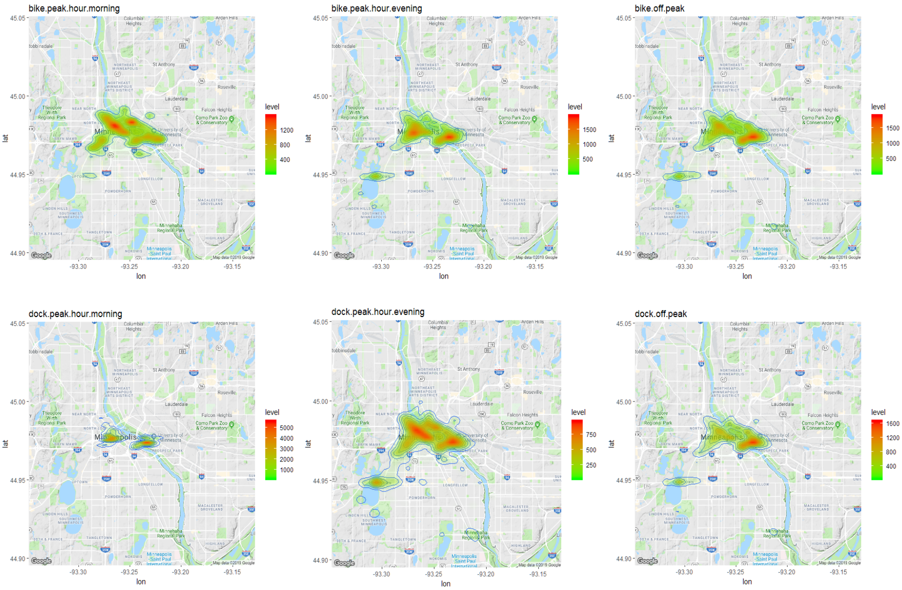
- The structure is the same as the original dockless settings, by seeing that adding terms $h_{1t}(x_{t+1} - C_1)^+ + h_{2t}(N - x_{t+1} - C_2)^+$ to J_t doesn't change the convexity of the function.
- However, the upper and lower threshold do change comparing to its dockless counterpart.

Data



lat
45.1
45.0
44.9
lon
-93.4
-93.3
-93.2
-93.1
dock size
10
20
30
40
Minneapolis
St Paul
Map data ©2019 Google

Data: Bike demand & Dock demand



Data: Observation

- Nice ride checkin/checkout records for September,October and November
- Spatial feature: The active region can be divided into 2 parts
- Time & Direction feature:
  - In the morning, the bike move from residential area(low bike density) to workplace (high bike density)
  - In the morning, the bike move from workplace (high bike density) to residential area (low bike density)
  - Off-peak time doesn't have clear trend

Simulation Settings

- Study: The impact of different (total capacity)/(total bike number) ratio on the thresholds and optimal cost.
- Ratio: 0.2,0.4,0.6,...,2. Balanced capacity in two locations.
- Total number of bikes: 178. (scaled by 10)
- Total period: 3.
- α: one period

$$\alpha_t = \begin{pmatrix} 0.82 & 0.18 \\ 0.22 & 0.78 \end{pmatrix}$$

- p: Lost sales cost

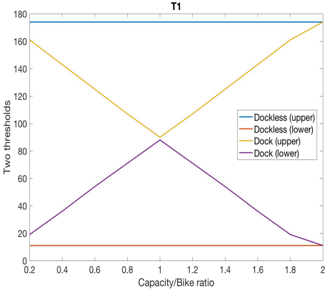
$$p = \begin{pmatrix} 0.8176 & 0.9412 \\ 0.9956 & 0.53 \end{pmatrix}$$

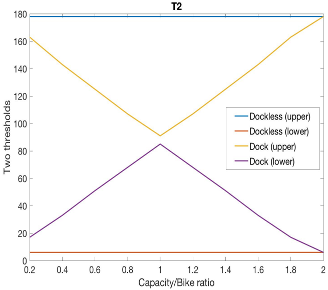
Simulation Settings (contd.)

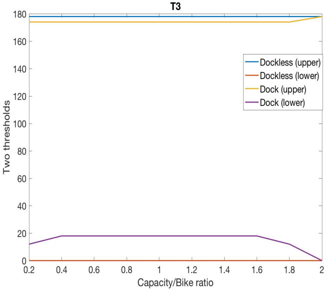
- Repositioning cost: 1.5
- Holding cost: 1
- Demand mean :

$$\mu = \begin{pmatrix} 12.02 & 31.25 & 22.94 \\ 7.81 & 29.61 & 16.54 \end{pmatrix}$$

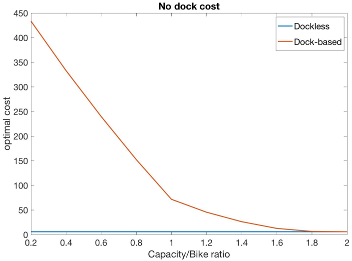
Results - Two thresholds

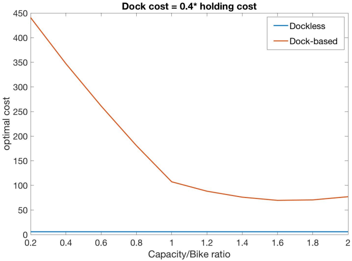






Results - Optimal cost





Remarks

Threshold policy:

- Dockless:
  - Large no-repositioning region: Large return-to-same-place probability $(\alpha_{11}, \alpha_{22})$
- Dock-Based:
  - Similar thresholds for extreme capacity ratio $\Rightarrow$ large repositioning region
  - Repositioning becomes efficient when capacity ratio$\approx$1 $\Rightarrow$ small no-repositioning region
  - T3:Larger no-repositioning region in last period$\Rightarrow$ similar to dockless system.

Optimal cost

- Due to the lack of holding cost, the dockless system outperforms the dock-based one.
- By adding the dock cost, there exits an optimal capacity ratio

Sensitivity Analysis - Settings

Holding cost h:

- Ratio: 0.5,0.6,...,2. Holding cost = ratio*[1,1].

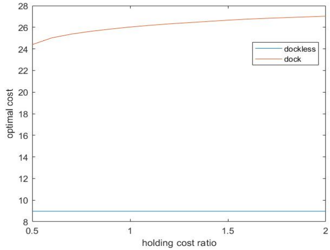
Repositioning cost s:

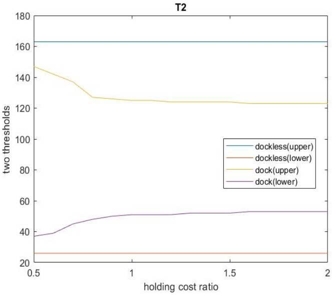
- Ratio: 0.5,0.6,...,2. Repositioning cost = ratio*1.5.

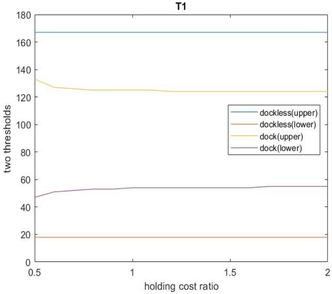
Unbalanced dock numbers in two locations:

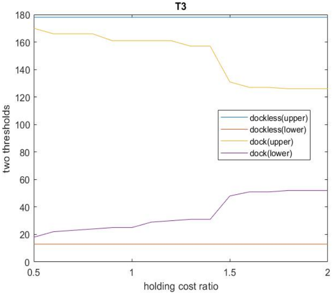
- Fixed total docks = 1.4* total bikes.
- $C_1/C_2 = 0.5, 0.6, ..., 2.$

Sensitivity analysis - holding cost





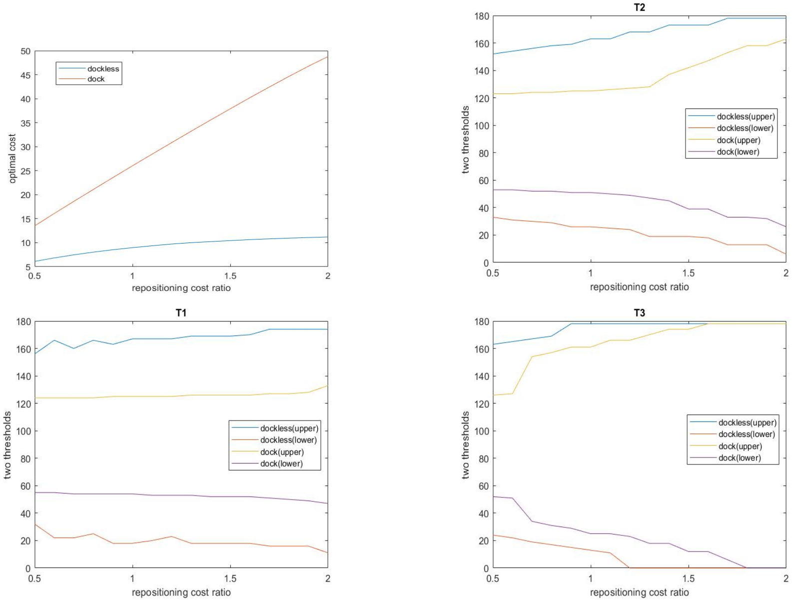




Remarks

- Higher holding cost$\Rightarrow$ more incentive to reposition $\Rightarrow$ small no-repositioning region.
- By assumption $\overline{p}_{it} \geq \alpha_{ijt}(h_{jt} + s_{ji(t+1)})$, for $j \neq i$ and $i, j \in \{1, 2\}$,the holding cost needs to be bounded, thus limiting the impact on the system.
- The thresholds in the later period are less sensitive to the increasing holding cost.

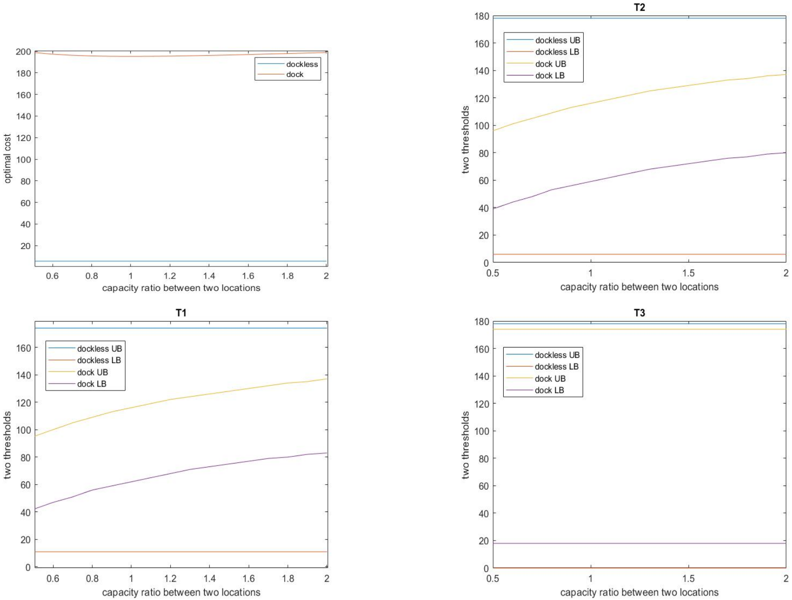
Sensitivity analysis - Reposition cost



Remarks

- Higher repositioning cost $\Rightarrow$ larger no-repositioning region.
- The total cost of the dock-based system is more sensitivity to the repositioning cost
- As opposed to $t = 3$, where the system tends to not reposition, in $t = 1$ the system tends to reposition more to account for the cost in future periods, hence the increased repositioning cost has less impact on the thresholds policy.

Sensitivity analysis - Imbalanced docks between stations



Remarks

- The optimal cost is less sensitive to the change of the ratio C_1/C_2.
- The size of no-repositioning region doesn't change, but the target inventory level in location 1 increases as the ratio C_1/C_2 increases.

Conclusion

- The project serves as an initial step to analyze the impact of capacity constraints on the repositioning policy in bike-rental system.

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- In general, one can view capacity (docks) as complement of products (bikes): too many bikes in a station implies few docks, both creating more incentive to reposition. Thus adding capacity cost reduces the no-repositioning region.

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- Due to large state/action space, a repositioning policy with more theoretical basis (such as in [1] or [2]) becomes unsolvable when problem size grows larger. To apply in real scenario, certain aggregation methods need to be tested. However,some crucial effects could be cancelled out in a aggregated system.

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- In recent years, the "capacity constraints" in similar systems vanishes away as evolving to "dockless" settings. Needs to find new motivating examples for such research. For example: electric charging station.

[1]Benjaafar, Saif and Jiang, Daniel and Li, Xiang and Li, Xiaobo, Inventory Repositioning in On-Demand Product Rental Networks (December 18, 2018). Available at SSRN: https://ssrn.com/abstract=2942921 or http://dx.doi.org/10.2139/ssrn.2942921

[2]He, Long and Hu, Zhenyu and Zhang, Meilin, Robust Repositioning for Vehicle Sharing (March 31, 2018). Forthcoming in Manufacturing Service Operations Management. Available at SSRN: https://ssrn.com/abstract=2973739 or http://dx.doi.org/10.2139/ssrn.2973739

[3]Wang, S., He, T., Zhang, D., Shu, Y., Liu, Y., Gu, Y., Liu, C., Lee, H., Son, S.H. (2018). BRAVO: Improving the Rebalancing Operation in Bike Sharing with Rebalancing Range Prediction. IMWUT, 2, 44:1-44:22.