Dynamic Intra-Cell Repositioning in Free-Floating Bike Sharing Systems

Xue Luo, Li Li, and Lei Zhao, Tsinghua University
Jianfeng Lin, Meituan

Freight Mobility Research Institute, Florida Atlantic University
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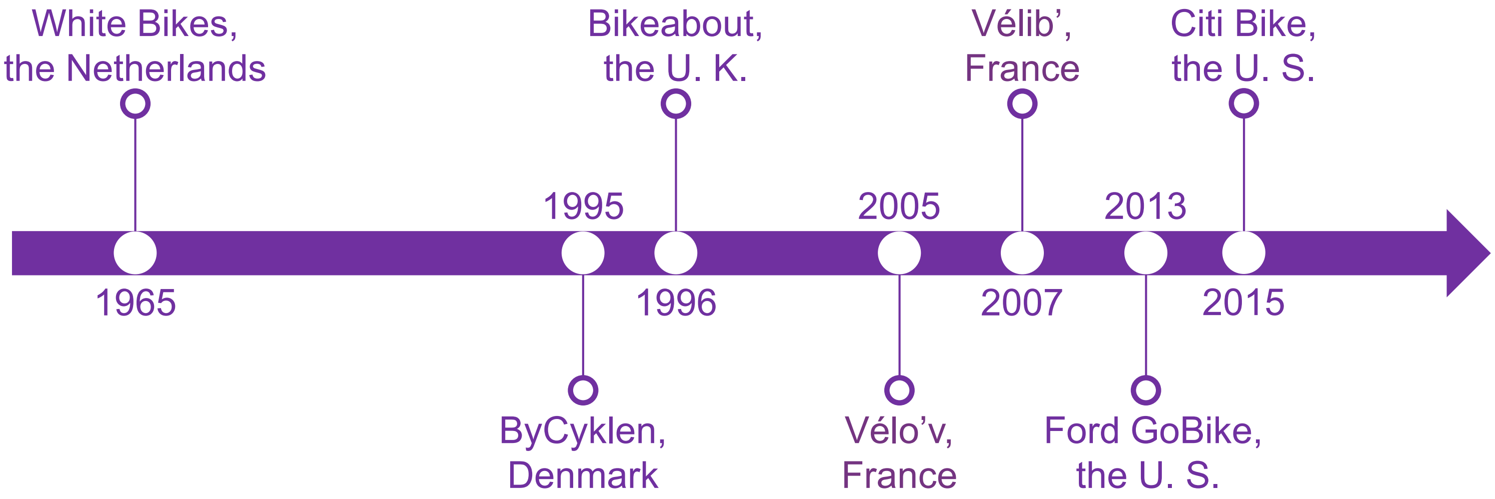
Operations & Services Research (TOpS) Laboratory
Department of Industrial Engineering
Tsinghua University, China

Introduction

Luo, X., L. Li, L. Zhao, and J. Lin (2021). Dynamic Intra-Cell Repositioning in Free-Floating Bike Sharing Systems using Approximate Dynamic Programming. *Transportation Science*, accepted.

Station-Based Bike Sharing Systems



White Bikes, the Netherlands

1965

1995

ByCyklen, Denmark

Bikeabout, the U. K.

1996

2005

Vélo’v, France

Vélib’, France

2007

2013

Ford GoBike, the U. S.

Citi Bike, the U. S.

2015

Source: DeMaio (2009), official sites

Bike Sharing Systems

	Station-based	Free-floating
Investment cost[1]	High	Low
User convenience[1]	Low	High
Scale	Over 7000 systems with 800,000 bikes in 2015[2]	74 systems with more than 23 million bikes in 2018[3]

Source: [1]Caggiani et al. (2018), [2]Laporte et al. (2015), [3]State Information Center (2018)
nypost.com (left figure), Seattle Department of Transportation (right figure)

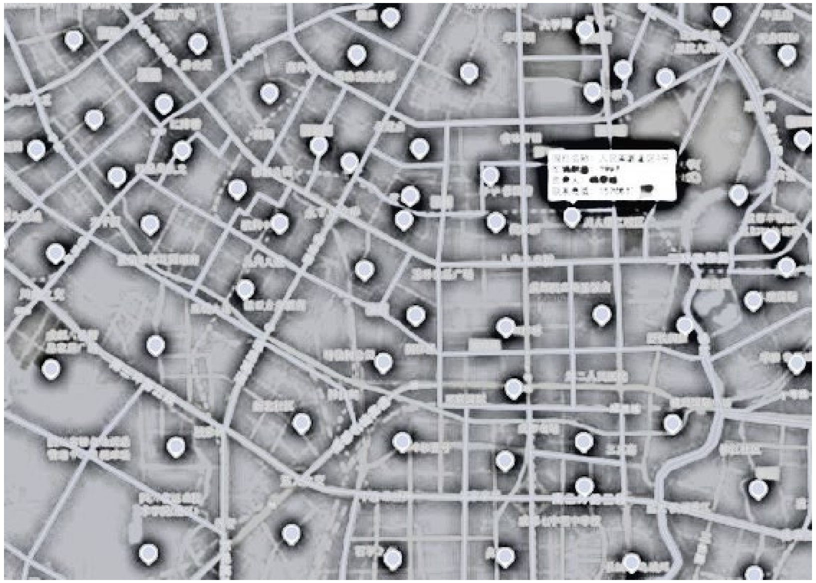
Free-Floating Bike Sharing Systems

□ Most users ride bikes for short trips.

	Li et al. (2020)	Xing et al. (2020)
Area	Downtown and surrounding areas of Shanghai, China	Metropolitan area of Shanghai, China
Time	August 2016	August 2016
Data set	A Mobike data set of 102,361 trips	A Mobike data set of 1,023,603 trips
Findings	The majority of bike trip distances are within 2 km. The most frequent trip has a length of 1.2 – 1.4 km.	The majority of bike trip distances are within 3 km. The average trip distance is approximately 1.8 km.

Free-Floating Bike Sharing Systems

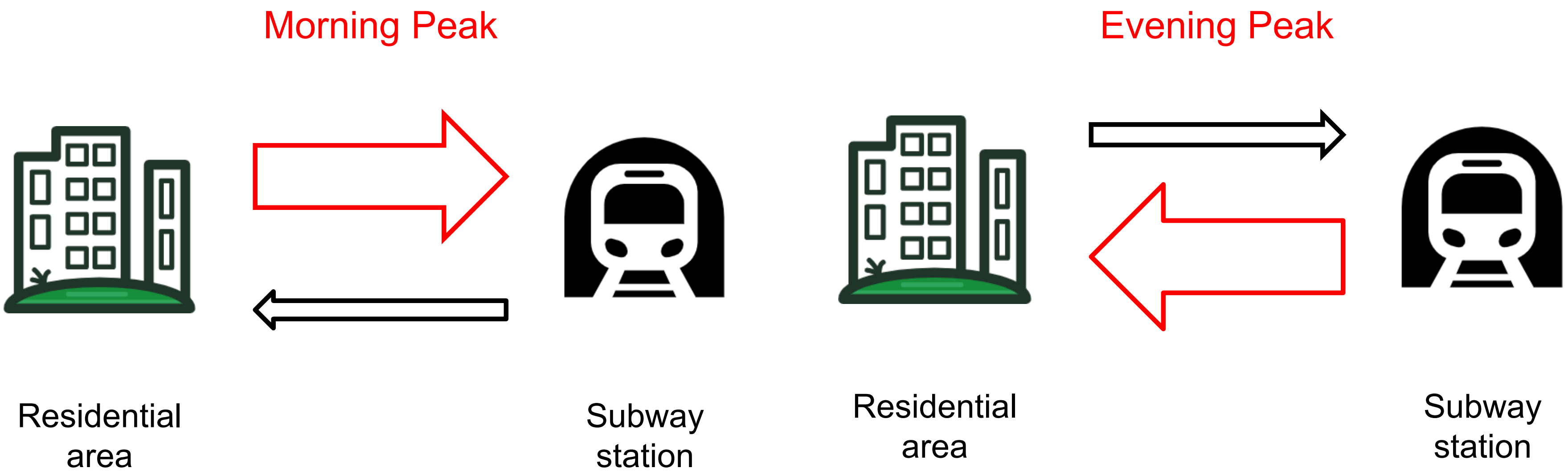
- □ Partition of cells
  - ■ A free-floating bike sharing company usually partitions the operating area into cells.
    - □ Factors to consider: demand density and distribution, trip patterns, geographic and demographic characteristics, etc.
    - □ Cell size: 2 km × 2 km (Hellobike), 3 km × 3 km (Meituan), etc.



Source: iResearch (2017), Hellobike (2018), Hellobike (2019), Xinhua News (2018)

Free-Floating Bike Sharing Systems

□ Spatiotemporal imbalance of bike flows



Morning Peak

Residential area

Subway station

Evening Peak

Residential area

Subway station

Shortage of bikes at some locations & overage at some others, depending on the time of the day

Bike Repositioning in Free-Floating Systems

- Static repositioning vs. dynamic repositioning
  - Static repositioning: during the night
  - Dynamic repositioning: during the daytime
- Intra-cell repositioning vs. inter-cell redistribution
  - In the design of cells, the company tries to contain the majority of bike trips within each cell.
  - Intra-cell repositioning
    - One or several movers to reposition bikes within each cell to counteract the spatiotemporal imbalance of bike flows within the cell.
    - Usually performed with electronic tricycles
  - Inter-cell redistribution
    - Bike trips traveling across cells → "escaping bikes" → needs to move bikes across cells.
    - Usually performed with a larger capacity vehicle, e.g., truck

Bike Repositioning in Free-Floating Systems

□ Intra-cell repositioning vs. inter-cell redistribution

- When a company enters a new market
  - □ Initial allocation of bikes may not match the user demand in the cells well.
  - □ Inter-cell redistribution plays a major role and is used frequently.
- When the market stabilizes
  - □ Allocation of bikes among the cells reasonably well, based on a good knowledge of the user demand.
  - □ Inter-cell redistribution is used less frequently.
  - □ Intra-cell repositioning becomes to play a major role.
- It is always necessary for the company to efficiently operate both intra-cell repositioning and inter-cell redistribution.

Bike Repositioning in Free-Floating Systems

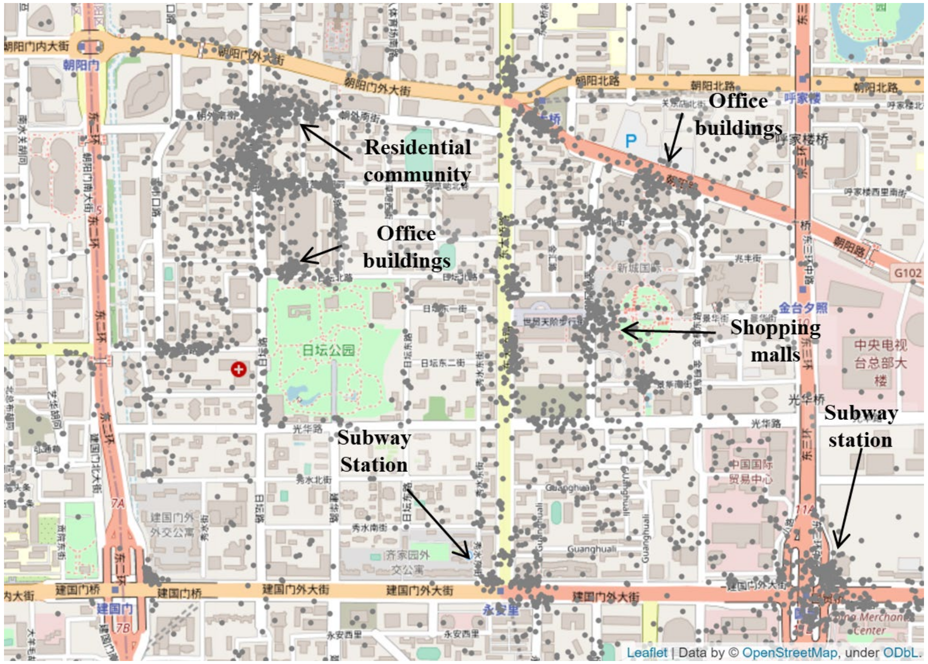
□ Intra-cell repositioning by a mover

Source: Photos taken by Xue Luo in 2019 and by Lei Zhao in 2021

Bike Repositioning in Free-Floating Systems

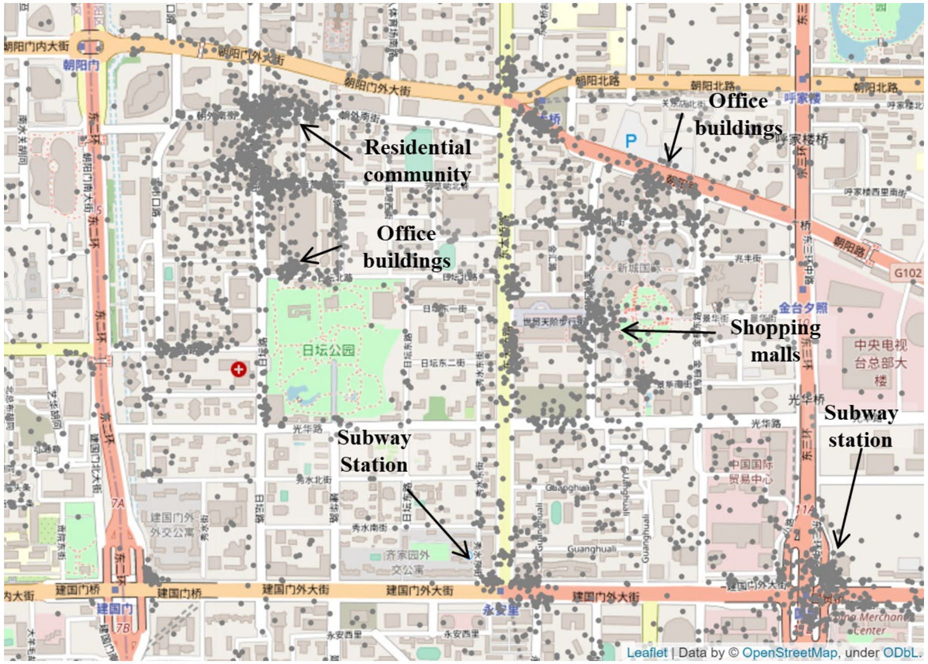
□ Intra-cell repositioning

- Clustered bikes around subway stations, office buildings, shopping malls, etc., referred to as gathering points.
- Scattered bikes along the paths between gathering points



Bike Repositioning in Free-Floating Systems

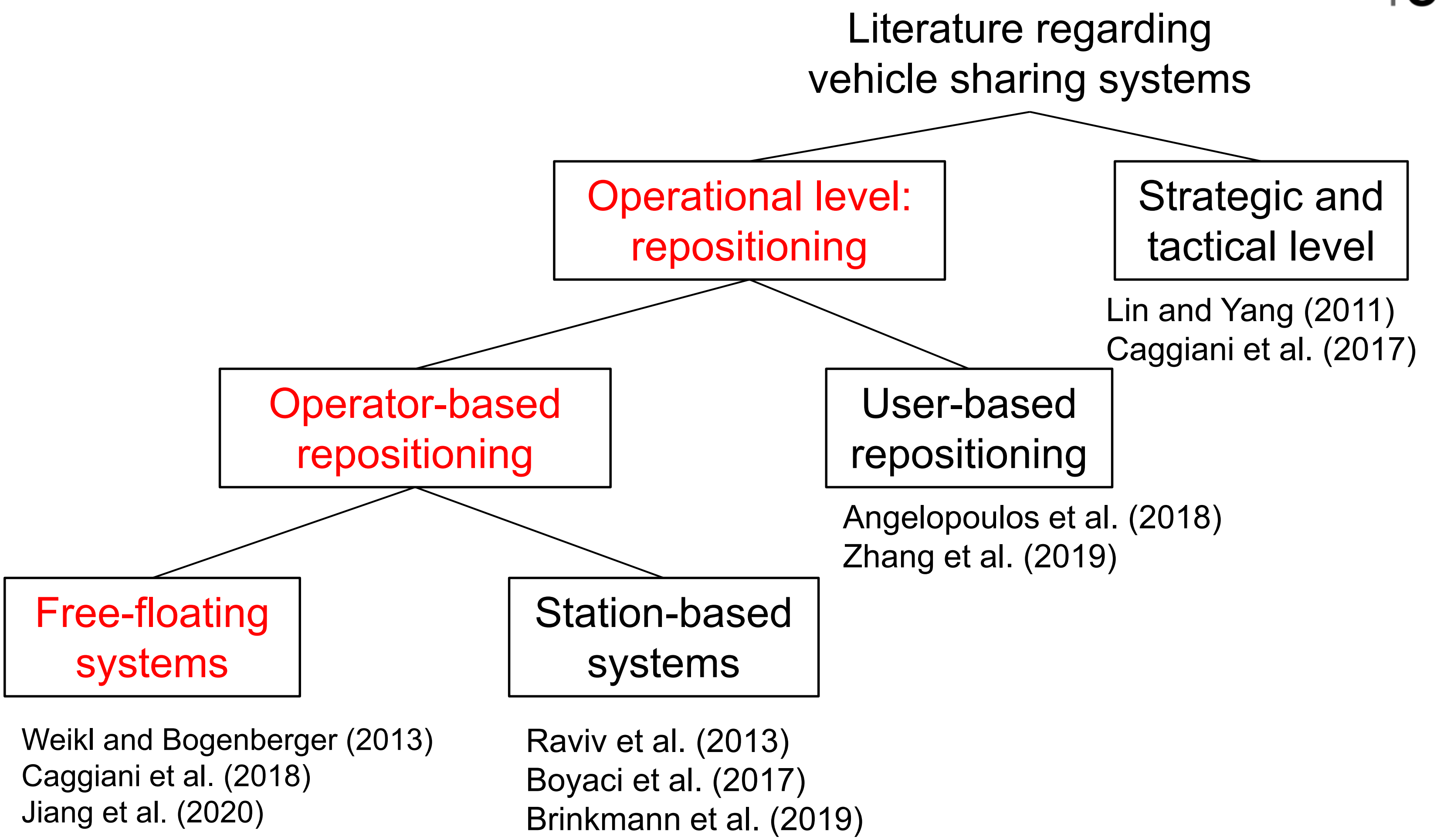
- Intra-cell repositioning
  - Reposition bikes among gathering points (pre-selected by the company)
  - Collect scattered bikes along the paths at the same time
  - To satisfy as many demand at the gathering points as possible



Leaflet | Data by © OpenStreetMap, under ODbL.

Literature Review

Literature Review



Literature regarding vehicle sharing systems

Operational level: repositioning

Strategic and tactical level

Lin and Yang (2011)
Caggiani et al. (2017)

Operator-based repositioning

User-based repositioning

Angelopoulos et al. (2018)
Zhang et al. (2019)

Free-floating systems

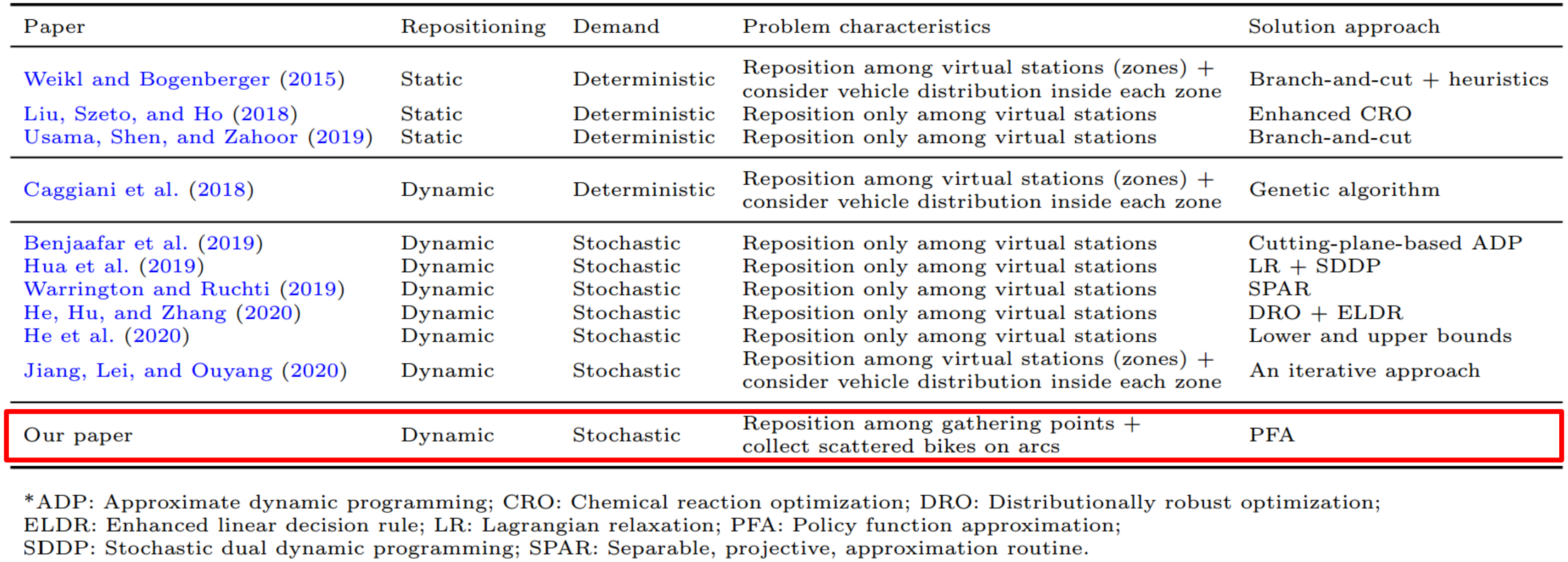
Station-based systems

Weikl and Bogenberger (2013)
Caggiani et al. (2018)
Jiang et al. (2020)

Raviv et al. (2013)
Boyaci et al. (2017)
Brinkmann et al. (2019)

Literature Review

□ Papers on repositioning in free-floating systems

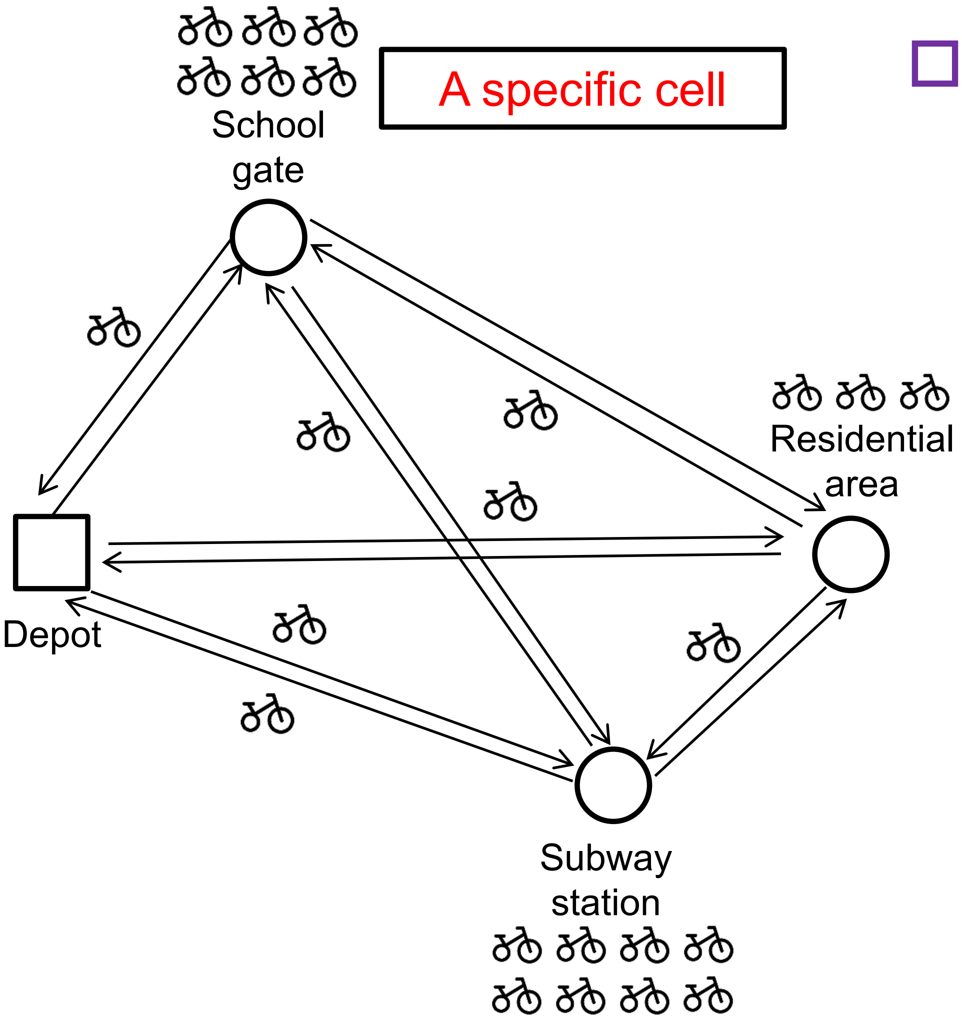


Paper	Repositioning	Demand	Problem characteristics	Solution approach
Weikl and Bogenberger (2015)	Static	Deterministic	Reposition among virtual stations (zones) + consider vehicle distribution inside each zone	Branch-and-cut + heuristics
Liu, Szeto, and Ho (2018)	Static	Deterministic	Reposition only among virtual stations	Enhanced CRO
Usama, Shen, and Zahoor (2019)	Static	Deterministic	Reposition only among virtual stations	Branch-and-cut
Caggiani et al. (2018)	Dynamic	Deterministic	Reposition among virtual stations (zones) + consider vehicle distribution inside each zone	Genetic algorithm
Benjaafar et al. (2019)	Dynamic	Stochastic	Reposition only among virtual stations	Cutting-plane-based ADP
Hua et al. (2019)	Dynamic	Stochastic	Reposition only among virtual stations	LR + SDDP
Warrington and Ruchti (2019)	Dynamic	Stochastic	Reposition only among virtual stations	SPAR
He, Hu, and Zhang (2020)	Dynamic	Stochastic	Reposition only among virtual stations	DRO + ELDR
He et al. (2020)	Dynamic	Stochastic	Reposition only among virtual stations	Lower and upper bounds
Jiang, Lei, and Ouyang (2020)	Dynamic	Stochastic	Reposition among virtual stations (zones) + consider vehicle distribution inside each zone	An iterative approach
Our paper	Dynamic	Stochastic	Reposition among gathering points + collect scattered bikes on arcs	PFA

*ADP: Approximate dynamic programming; CRO: Chemical reaction optimization; DRO: Distributionally robust optimization; ELDR: Enhanced linear decision rule; LR: Lagrangian relaxation; PFA: Policy function approximation; SDDP: Stochastic dual dynamic programming; SPAR: Separable, projective, approximation routine.

Problem Description and Model Formulation

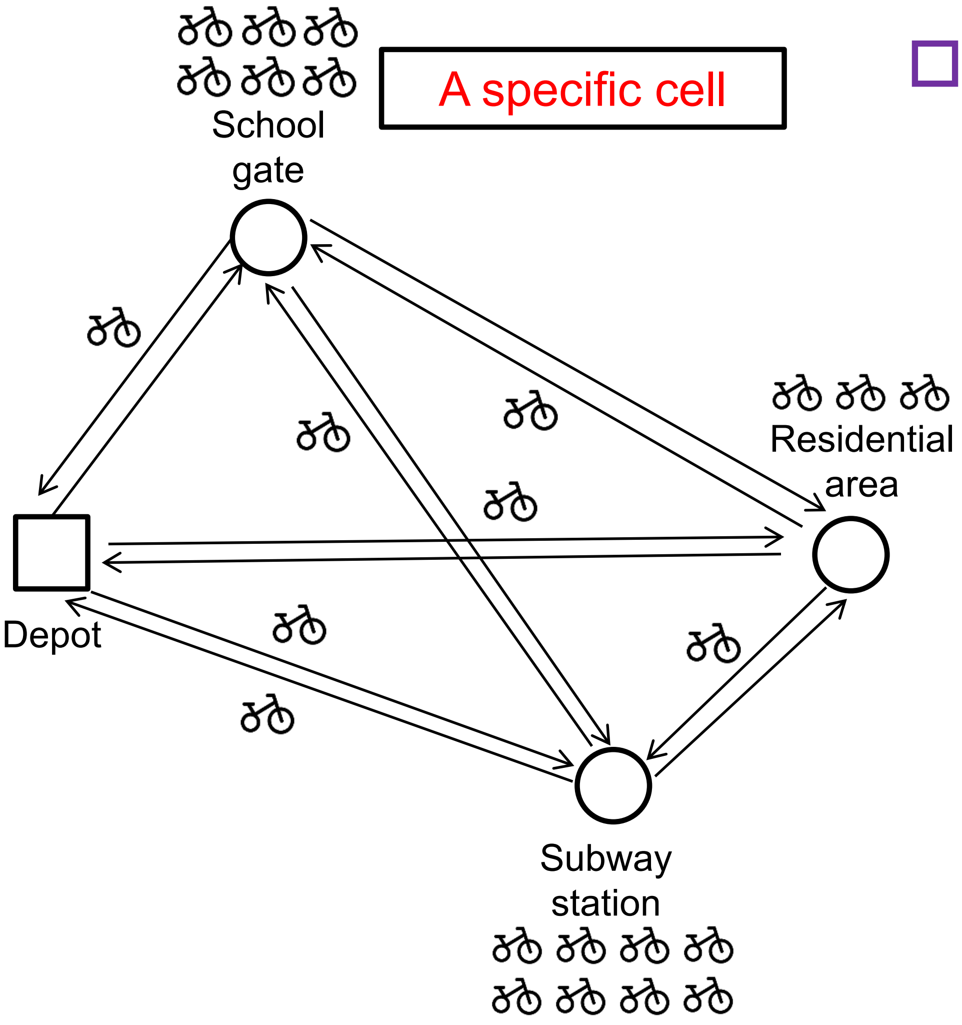
Problem Description



- □ Complete graph $G = (\mathcal{N}', \mathcal{A})$
  - ■ Node set $\mathcal{N}' = \mathcal{N} \cup \{0\}$
    - □ Gathering points $\mathcal{N}$, depot 0
    - □ Capacity q_i, $\forall i \in \mathcal{N}$
  - ■ Arc set $\mathcal{A}$
    - □ $(i, j) \in \mathcal{A}$: a path (where bikes are scattered) the mover travels between nodes i & j
    - □ No capacity limit
    - □ Deterministic travel time τ_{ij}

Bikes randomly arrive and depart at gathering points & on arcs

Problem Description



□ Mover

- A vehicle of capacity Q
- Loads bikes onto / unloads bikes from the vehicle at nodes
  - □ τ^N: unit loading / unloading time
- Loads bikes onto the vehicle on arcs
  - □ τ^A: unit loading time

Problem Description

- □ System dynamics during the mover's working time $\mathcal{T}$
  - The mover starts from the depot with an empty vehicle.
  - Each time arriving at a node (decision epoch), the mover decides
    - □ Inventory: # bikes to load onto (+) / unload from (-) the vehicle at the current node
    - □ Routing: the next node to visit
    - □ En route: # bikes expected to load onto the vehicle on the arc to the next node
  - The mover returns to the depot at the end of the working time.

To satisfy as many demand as possible
at all the nodes during the working time

Model: Markov Decision Process

□ Decision epoch k: upon arrival at a node

□ State variable $S_k = (t_k, L_k, N_k^N, N_k^A)$

- ■ Current time t_k
- ■ Vehicle attributes $L_k = (l_k, Q_k)$
  - □ Node l_k
  - □ Remaining capacity Q_k
- ■ Number of bikes at each node $N_k^N = (n_{ki})_{\forall i \in \mathcal{N}}$
- ■ Number of bikes on each arc $N_k^A = \left(n_{kij}\right)_{\forall (i,j) \in \mathcal{A}}$

Model: Markov Decision Process

- Decision variable $x_k = (x_k^L, x_k^D, x_k^R)$
  - Inventory decision $x_k^L \in \mathbb{Z}$: number of bikes to load onto (+) / unload from (-) the vehicle at the current node k
  - Routing decision $x_k^D \in \mathcal{N}$: the next node to visit
  - En route decision $x_k^R \in \mathbb{N}$: number of bikes expected to load on the arc to the next node
  - Constraints
    - Remaining capacity & bikes on the vehicle
    - Remaining capacity & bikes at the current node
    - Bikes currently scattered on the arcs
- Exogenous information $W_{k+1} = (\Delta D_{k+1}^N, \Delta D_{k+1}^A)$
  - $\Delta D_{k+1}^N = \left(\underline{\Delta d_{k+1,i}}\right)_{\forall i \in \mathcal{N}}, \ \Delta D_{k+1}^A = \left(\underline{\Delta d_{k+1,ij}}\right)_{\forall (i,j) \in \mathcal{A}}$

Number of net bike departures at node i

Number of net bike departures on arc (i,j)

Model: Markov Decision Process

□ Transition function

Time

$$t_{k+1} = t_k + \overbrace{\tau^N |x_k^L|}^{\text{Node loading time}} + \underbrace{\tau_{l_k, x_k^D}}_{\text{Travel time}} + \overbrace{\tau^A \hat{b}_{k+1}}^{\text{Arc loading time}},$$

$\hat{b}_{k+1}$: number of bikes actually loaded en route

Vehicle location & remaining capacity

$$\begin{aligned} L_{k+1} &= (l_{k+1}, Q_{k+1}) \\ &= (x_k^D, Q_k - x_k^L - \hat{b}_{k+1}), \end{aligned}$$

Bikes at each node

$$n_{k+1,i} = \begin{cases} n_{ki} - \Delta d_{k+1,i}, & \forall i \in \mathcal{N} \backslash \{l_k\}, \\ n_{ki} - \Delta d_{k+1,i} - x_k^L, & i = l_k, \end{cases}$$

Bikes on each arc

$$n_{k+1,ij} = \begin{cases} n_{kij} - \Delta d_{k+1,ij}, & \forall (i,j) \in \mathcal{A} \backslash \{(l_k, x_k^D)\}, \\ n_{kij} - \Delta d_{k+1,ij} - \hat{b}_{k+1}, & (i,j) = (l_k, x_k^D). \end{cases}$$

Model: Markov Decision Process

□ Contribution function

- Total demand satisfied at all the gathering points between decision epochs k and $k+1$

$$\hat{C}_{k+1}(S_k, x_k, W_{k+1}) = \sum_{i \in \mathcal{N}} f_{k+1,i}(S_k, x_k, W_{k+1})$$

□ Expected contribution $C_k(S_k, x_k)$

$$C_k(S_k, x_k) = \mathbb{E}\left\{\hat{C}_{k+1}(S_k, x_k, W_{k+1})|S_k\right\}$$

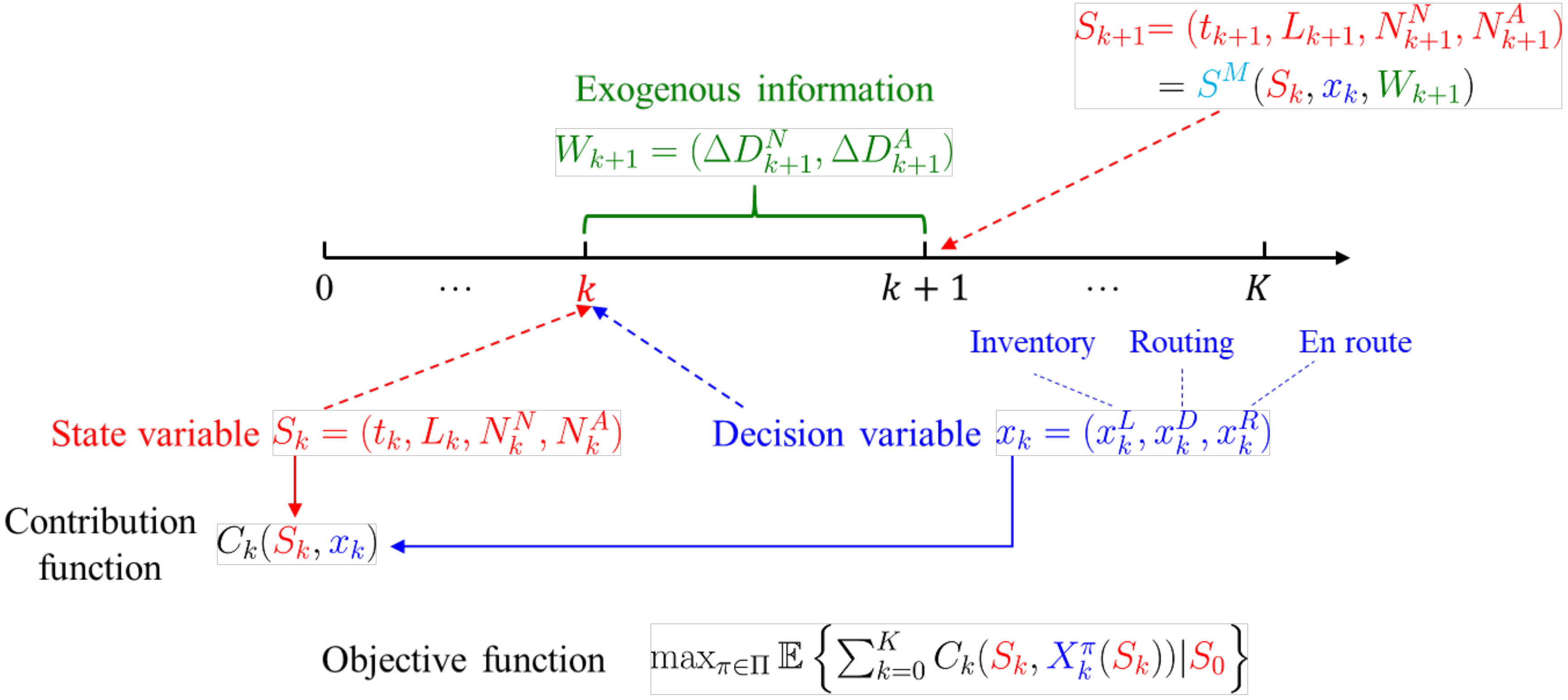
□ Objective function

- Maximize the expected total demand satisfied at all the gathering points during the working time

$$\max_{\pi \in \Pi} \mathbb{E}\left\{\sum_{k=0}^{K} C_k(S_k, X_k^{\pi}(S_k))|S_0\right\}$$

Model: Markov Decision Process

□ Illustration



$S_{k+1} = (t_{k+1}, L_{k+1}, N^N_{k+1}, N^A_{k+1})$

$= S^M(S_k, x_k, W_{k+1})$

Exogenous information

$W_{k+1} = (\Delta D^N_{k+1}, \Delta D^A_{k+1})$

$0 \quad \cdots \quad k \quad k+1 \quad \cdots \quad K$

Inventory Routing En route

State variable $S_k = (t_k, L_k, N^N_k, N^A_k)$

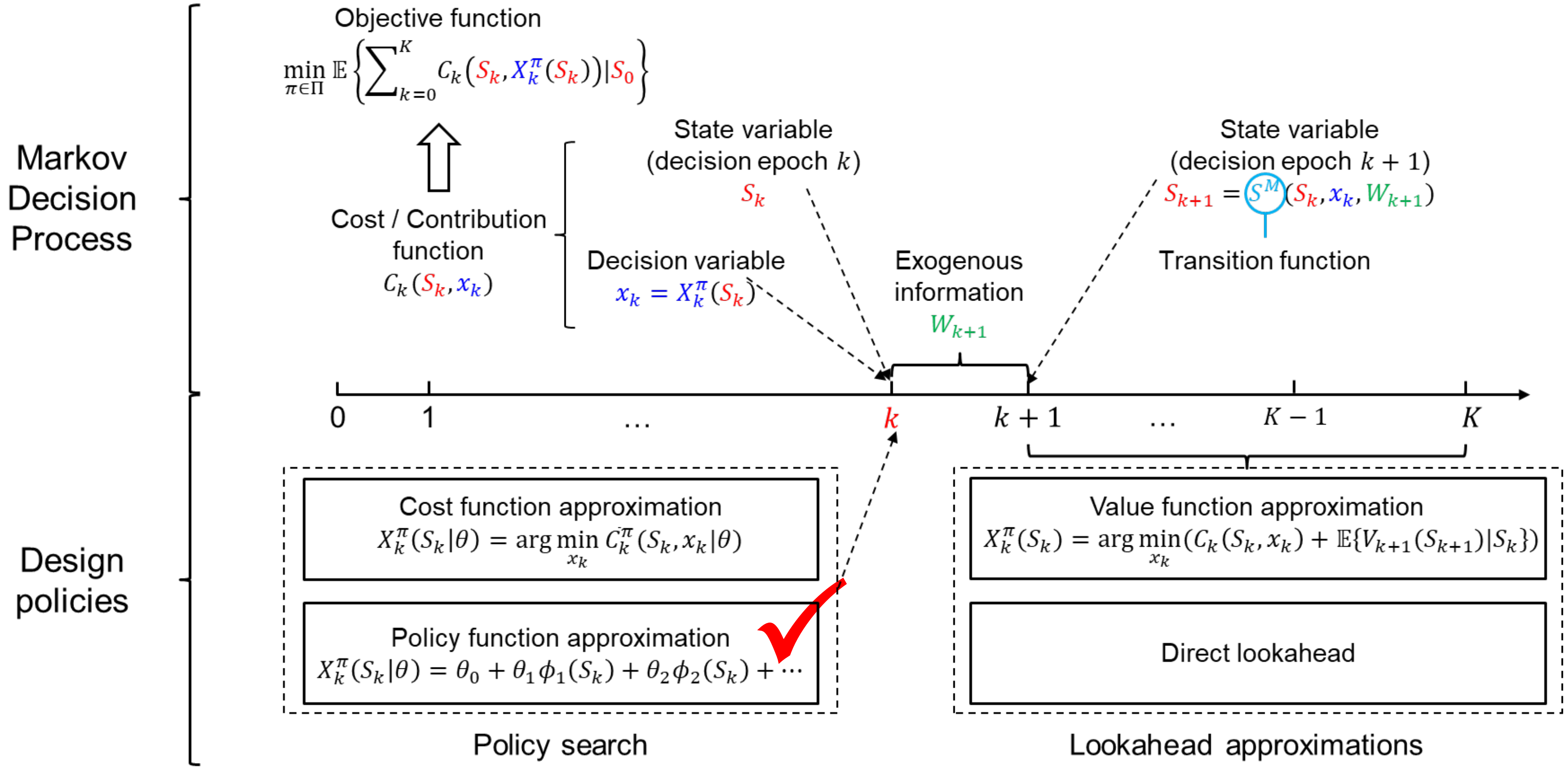
Decision variable $x_k = (x^L_k, x^D_k, x^R_k)$

Contribution function $C_k(S_k, x_k)$

Objective function $\max_{\pi \in \Pi} \mathbb{E} \left\{ \sum_{k=0}^{K} C_k(S_k, X^\pi_k(S_k)) | S_0 \right\}$

Solution Methodology

A Unified Framework for Stochastic Optimization



Markov Decision Process

Objective function

$\min_{\pi \in \Pi} \mathbb{E}\left\{\sum_{k=0}^{K} C_k\left(S_k, X_k^{\pi}(S_k)\right) | S_0\right\}$

Cost / Contribution function

$C_k(S_k, x_k)$

State variable (decision epoch k)

S_k

Decision variable

$x_k = X_k^{\pi}(S_k)$

Exogenous information

W_{k+1}

State variable (decision epoch $k+1$)

$S_{k+1} = S^M(S_k, x_k, W_{k+1})$

Transition function

$0 \quad 1 \quad \dots \quad k \quad k+1 \quad \dots \quad K-1 \quad K$

Design policies

Cost function approximation

$X_k^{\pi}(S_k|\theta) = \arg\min_{x_k} \bar{C}_k^{\pi}(S_k, x_k|\theta)$

Policy function approximation

$X_k^{\pi}(S_k|\theta) = \theta_0 + \theta_1\phi_1(S_k) + \theta_2\phi_2(S_k) + \cdots$

Policy search

Value function approximation

$X_k^{\pi}(S_k) = \arg\min_{x_k}(C_k(S_k, x_k) + \mathbb{E}\{V_{k+1}(S_{k+1})|S_k\})$

Direct lookahead

Lookahead approximations

Source: Powell (2019, 2021)

Policy Function Approximation

- □ Inventory decision
  - Two-threshold policy (L_{ti}, U_{ti})
    - □ Try to keep the number of bikes at node i at time t within $[L_{ti}, U_{ti}]$
  - At decision epoch k
    - □ Unload bikes if $n_{kl_k} < L_{t_k l_k}$, $x_k^L = -\min\{L_{t_k l_k} - n_{kl_k}, Q - Q_k\}$

      Bring the inventory level up to $L_{t_k l_k}$

      No more than the remaining bikes on the vehicle
    - □ Load bikes if $n_{kl_k} > U_{t_k l_k}$, $x_k^L = \min\{n_{kl_k} - U_{t_k l_k}, Q_k\}$

      Bring the inventory level down to $U_{t_k l_k}$

      No more than the remaining capacity of the vehicle
    - □ Do nothing otherwise

Policy Function Approximation

□ Inventory decision

- How to specify (L_{ti}, U_{ti}) for each node i at each time t?
  - □ Five parameters $(\underline{\theta}^{+}, \bar{\theta}^{+})$, $(\underline{\theta}^{-}, \bar{\theta}^{-})$, τ^{L}

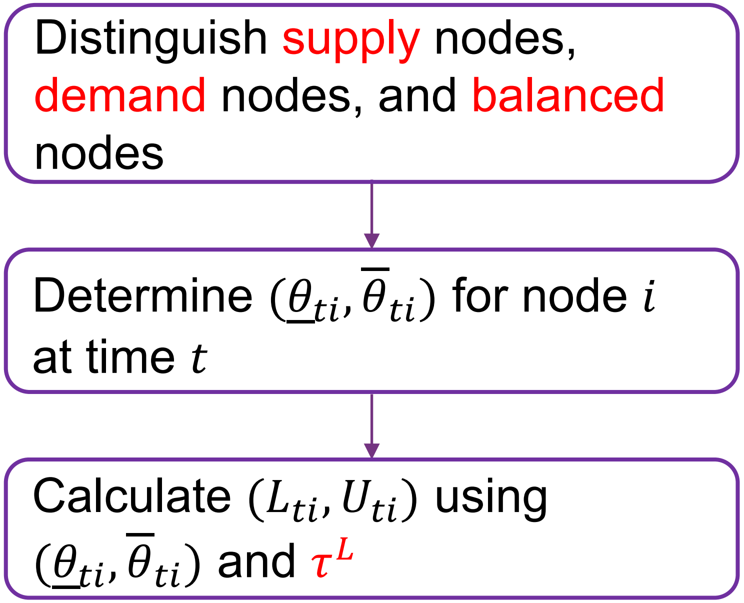
Distinguish supply nodes, demand nodes, and balanced nodes

$$\begin{cases} \text{Supply nodes: } \lambda_{ti}^{INST,+} > \lambda_{ti}^{INST,-} \\ \text{Demand nodes: } \lambda_{ti}^{INST,+} < \lambda_{ti}^{INST,-} \\ \text{Balanced nodes: } \lambda_{ti}^{INST,+} = \lambda_{ti}^{INST,-} \end{cases}$$

Notation	Definition
$\lambda_{ti}^{INST,+}$	Instantaneous bike supply rate at node i at time t
$\lambda_{ti}^{INST,-}$	Instantaneous bike demand rate at node i at time t

Policy Function Approximation

- □ Inventory decision
  - How to specify (L_{ti}, U_{ti}) for each node i at each time t?
    - □ Five parameters $(\underline{\theta}^{+}, \bar{\theta}^{+})$, $(\underline{\theta}^{-}, \bar{\theta}^{-})$, τ^{L}



Distinguish supply nodes, demand nodes, and balanced nodes

Determine $(\underline{\theta}_{ti}, \bar{\theta}_{ti})$ for node i at time t

Calculate (L_{ti}, U_{ti}) using $(\underline{\theta}_{ti}, \bar{\theta}_{ti})$ and τ^{L}

$$\begin{cases} \text{Supply nodes: } \lambda_{ti}^{INST,+} > \lambda_{ti}^{INST,-} \\ \text{Demand nodes: } \lambda_{ti}^{INST,+} < \lambda_{ti}^{INST,-} \\ \text{Balanced nodes: } \lambda_{ti}^{INST,+} = \lambda_{ti}^{INST,-} \end{cases}$$

$$(\underline{\theta}_{ti}, \bar{\theta}_{ti}) = \begin{cases} (\underline{\theta}^{+}, \bar{\theta}^{+}), & \text{if } i \text{ is a supply or balanced node at } t, \\ (\underline{\theta}^{-}, \bar{\theta}^{-}), & \text{if } i \text{ is a demand node at } t. \end{cases}$$

$$L_{ti} = \min\left\{ q_i, \int_{t}^{t+\tau^{L}} \alpha_{t'i} \underline{\theta}_{t'i} dt' \right\},$$

$$U_{ti} = \min\left\{ q_i, \int_{t}^{t+\tau^{L}} \alpha_{t'i} \bar{\theta}_{t'i} dt' \right\},$$

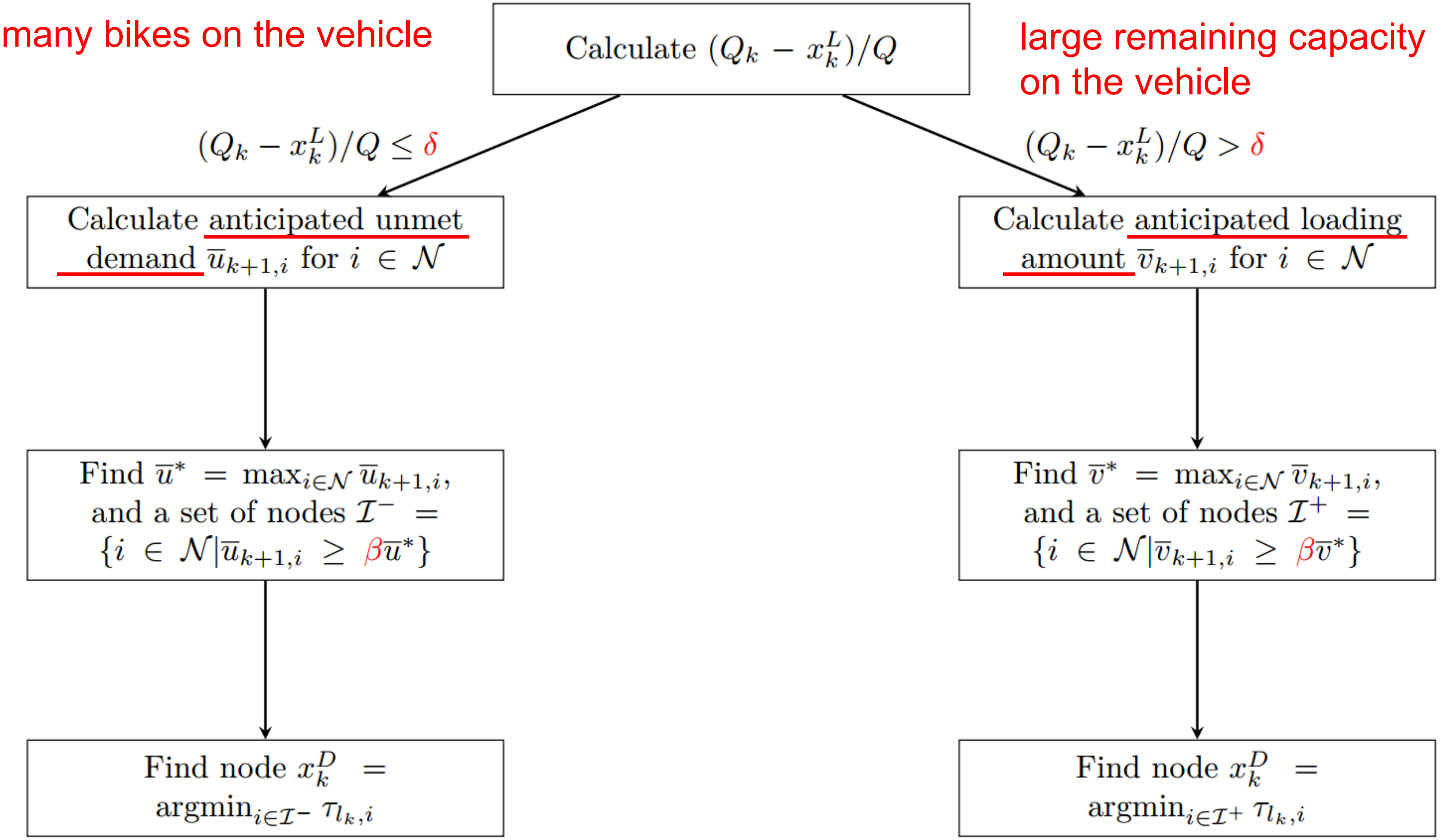
$$\text{where } \alpha_{t'i} = \begin{cases} \dfrac{1}{|\lambda_{t'i}^{INST,+} - \lambda_{t'i}^{INST,-}| + 1}, & \text{if node } i \text{ is a supply or balanced node at time } t', \\ |\lambda_{t'i}^{INST,+} - \lambda_{t'i}^{INST,-}| + 1, & \text{if node } i \text{ is a demand node at time } t'. \end{cases}$$

Policy Function Approximation

□ Routing decision

many bikes on the vehicle

large remaining capacity on the vehicle



Calculate $(Q_k - x_k^L)/Q$

$(Q_k - x_k^L)/Q \le \delta$

Calculate anticipated unmet demand $\overline{u}_{k+1,i}$ for $i \in \mathcal{N}$

Find $\overline{u}^* = \max_{i \in \mathcal{N}} \overline{u}_{k+1,i}$, and a set of nodes $\mathcal{I}^- = \{i \in \mathcal{N} | \overline{u}_{k+1,i} \ge \beta \overline{u}^*\}$

Find node $x_k^D = \mathrm{argmin}_{i \in \mathcal{I}^-} \tau_{l_k,i}$

$(Q_k - x_k^L)/Q > \delta$

Calculate anticipated loading amount $\overline{v}_{k+1,i}$ for $i \in \mathcal{N}$

Find $\overline{v}^* = \max_{i \in \mathcal{N}} \overline{v}_{k+1,i}$, and a set of nodes $\mathcal{I}^+ = \{i \in \mathcal{N} | \overline{v}_{k+1,i} \ge \beta \overline{v}^*\}$

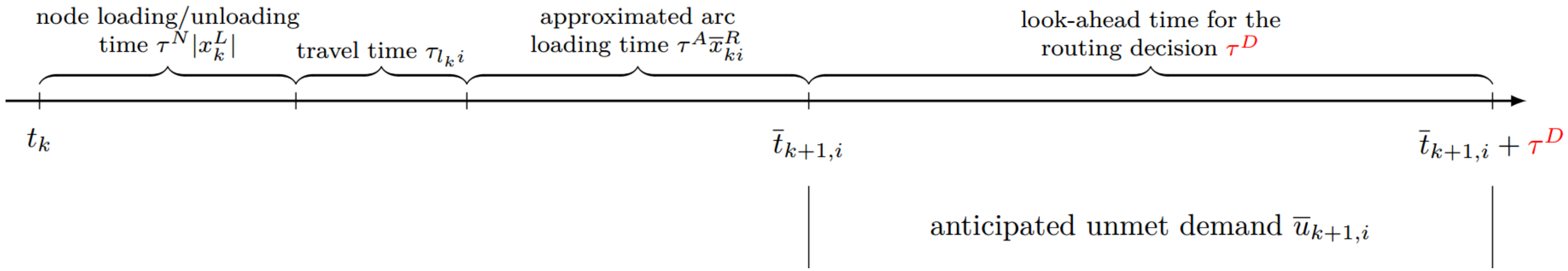
Find node $x_k^D = \mathrm{argmin}_{i \in \mathcal{I}^+} \tau_{l_k,i}$

Policy Function Approximation

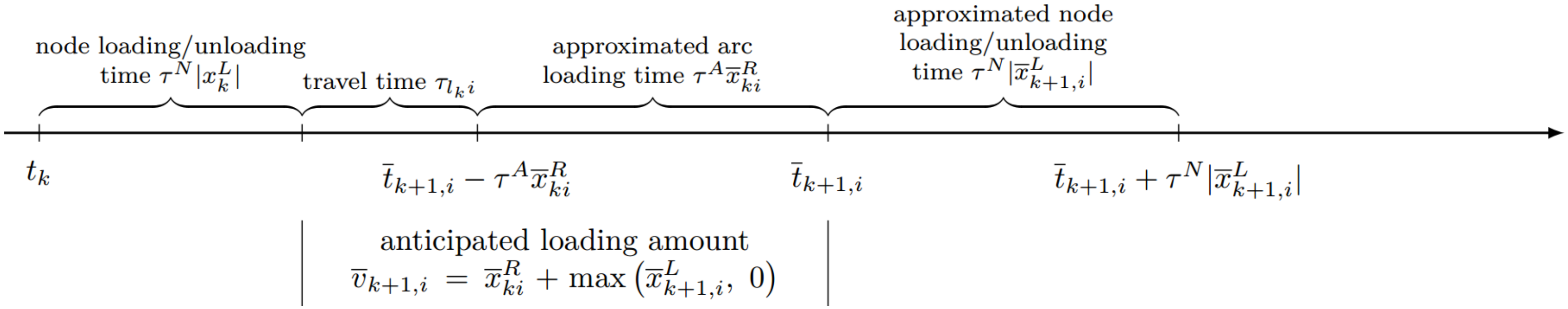
□ Routing decision

- Anticipated unmet demand $\overline{u}_{k+1,i}$

τ^D: look-ahead time for the routing decision


node loading/unloading time $\tau^N|x_k^L|$
travel time $\tau_{l_k i}$
approximated arc loading time $\tau^A \overline{x}_{ki}^R$
look-ahead time for the routing decision τ^D
t_k
$\bar{t}_{k+1,i}$
$\bar{t}_{k+1,i} + \tau^D$
anticipated unmet demand $\overline{u}_{k+1,i}$

- Anticipated loading amount $\overline{v}_{k+1,i}$


node loading/unloading time $\tau^N|x_k^L|$
travel time $\tau_{l_k i}$
approximated arc loading time $\tau^A \overline{x}_{ki}^R$
approximated node loading/unloading time $\tau^N|\overline{x}_{k+1,i}^L|$
t_k
$\bar{t}_{k+1,i} - \tau^A \overline{x}_{ki}^R$
$\bar{t}_{k+1,i}$
$\bar{t}_{k+1,i} + \tau^N|\overline{x}_{k+1,i}^L|$
anticipated loading amount
$\overline{v}_{k+1,i} = \overline{x}_{ki}^R + \max\left(\overline{x}_{k+1,i}^L, 0\right)$

Policy Function Approximation

□ En route decision

$$x_k^R = \min\left\{\phi\tau_{l_k,x_k^D}/\tau^A,\ n_{k,l_k,x_k^D},\ Q_k - x_k^L\right\}$$

Time limit on the arc loading time

Current number of bikes en route

Remaining capacity of the vehicle after the loading / unloading operation at l_k

Policy Function Approximation

□ How to efficiently choose among candidate parameters?

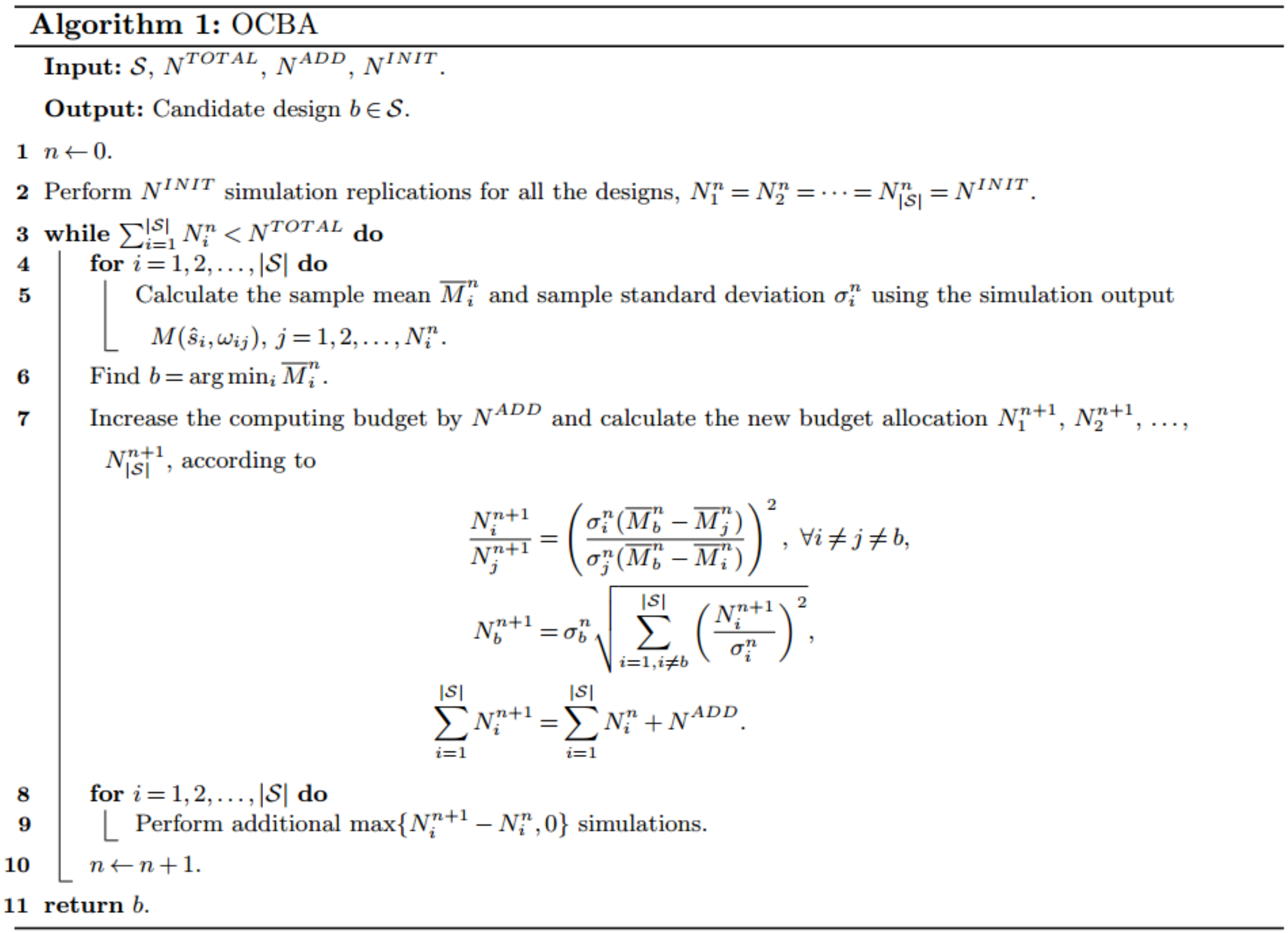
	Notation	Definition
Inventory	$(\underline{\theta}^{+}, \overline{\theta}^{+})$	Inventory threshold parameters for supply and balanced nodes
	$(\underline{\theta}^{-}, \overline{\theta}^{-})$	Inventory threshold parameters for demand nodes
	τ^{L}	Look-ahead time for the inventory decision
Routing	τ^{D}	Look-ahead time for the routing decision
	δ	Capacity threshold parameter
	β	Set size parameter
En route	ϕ	En route time limit parameter

Policy Function Approximation

- Optimal Computing Budget Allocation (Chen and Lee, 2011)
  - Maximize the probability of correct selection $P\{CS\}$ with a fixed computing budget N^{TOTAL}
  - Procedure
    - Allocate an initial number of simulation replications N^{INIT} for each candidate design
    - In each iteration, allocate N^{ADD} to the candidate designs, until the computing budget N^{TOTAL} is exhausted
      - Allocate more budget to the more promising candidate designs
      - For the simulation outputs of each candidate design, consider the sample mean and sample standard deviation

Policy Function Approximation

□ Optimal Computing Budget Allocation



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Algorithm 1: OCBA
Input: $\mathcal{S}$, $N^{TOTAL}$, $N^{ADD}$, $N^{INIT}$.
Output: Candidate design $b \in \mathcal{S}$.
$n \leftarrow 0$.
Perform $N^{INIT}$ simulation replications for all the designs, $N_1^n = N_2^n = \cdots = N_{|\mathcal{S}|}^n = N^{INIT}$.
while $\sum_{i=1}^{|\mathcal{S}|} N_i^n < N^{TOTAL}$ do
    for $i = 1, 2, \ldots, |\mathcal{S}|$ do
        Calculate the sample mean $\overline{M}_i^n$ and sample standard deviation $\sigma_i^n$ using the simulation output
        $M(\hat{s}_i, \omega_{ij})$, $j = 1, 2, \ldots, N_i^n$.
    Find $b = \arg\min_i \overline{M}_i^n$.
    Increase the computing budget by $N^{ADD}$ and calculate the new budget allocation $N_1^{n+1}$, $N_2^{n+1}$, $\ldots$,
    $N_{|\mathcal{S}|}^{n+1}$, according to
        $\frac{N_i^{n+1}}{N_j^{n+1}} = \left(\frac{\sigma_i^n(\overline{M}_b^n - \overline{M}_j^n)}{\sigma_j^n(\overline{M}_b^n - \overline{M}_i^n)}\right)^2, \ \forall i \neq j \neq b,$
        $N_b^{n+1} = \sigma_b^n \sqrt{\sum_{i=1, i \neq b}^{|\mathcal{S}|} \left(\frac{N_i^{n+1}}{\sigma_i^n}\right)^2},$
        $\sum_{i=1}^{|\mathcal{S}|} N_i^{n+1} = \sum_{i=1}^{|\mathcal{S}|} N_i^n + N^{ADD}.$
    for $i = 1, 2, \ldots, |\mathcal{S}|$ do
        Perform additional $\max\{N_i^{n+1} - N_i^n, 0\}$ simulations.
    $n \leftarrow n + 1$.
return $b$.
```

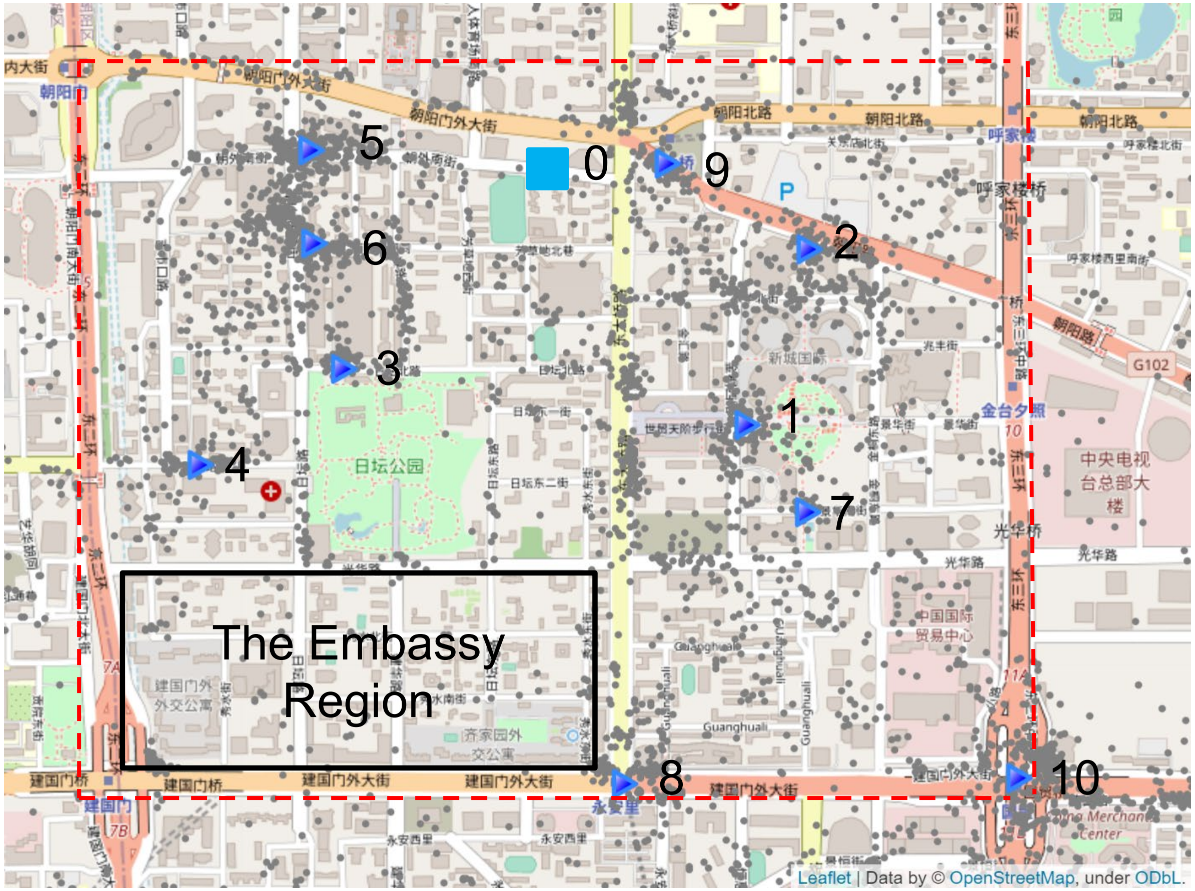
Numerical Experiments

Experimental Setting: Test Instances

- □ Nodes – location

■ Depot

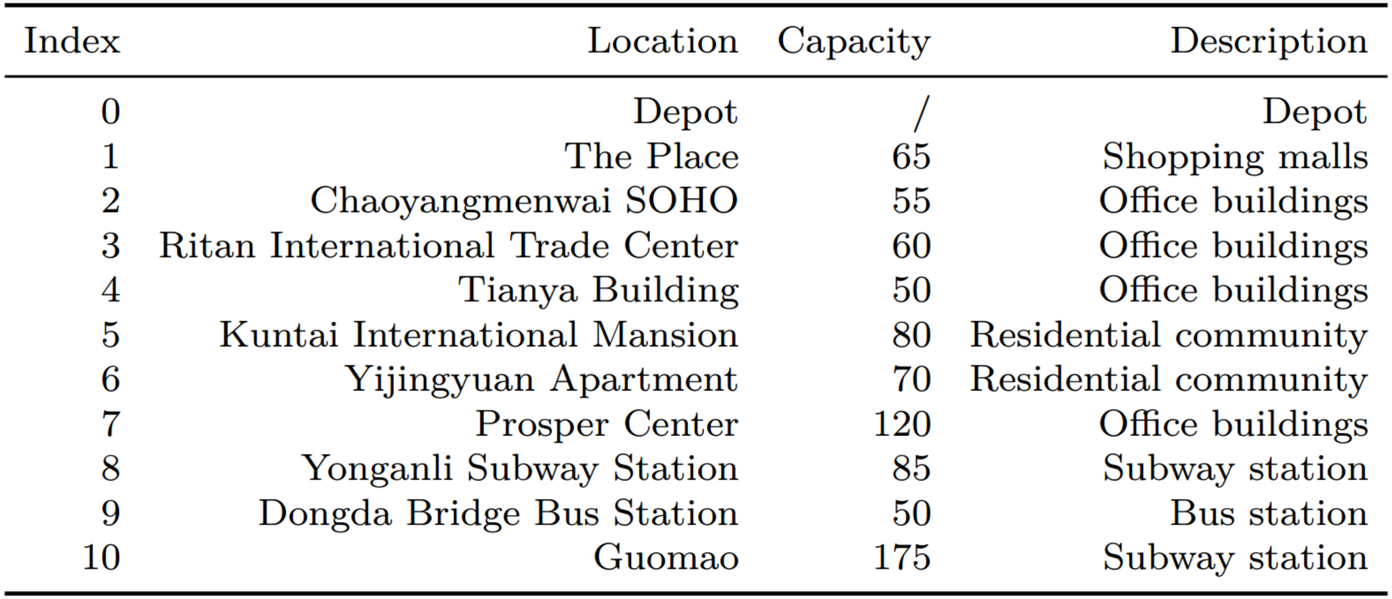
▲ Gathering point



Leaflet | Data by © OpenStreetMap, under ODbL.

Experimental Setting: Test Instances

- Nodes – capacity
  - Based on Mobike (2017) and expert opinions



Index	Location	Capacity	Description
0	Depot	/	Depot
1	The Place	65	Shopping malls
2	Chaoyangmenwai SOHO	55	Office buildings
3	Ritan International Trade Center	60	Office buildings
4	Tianya Building	50	Office buildings
5	Kuntai International Mansion	80	Residential community
6	Yijingyuan Apartment	70	Residential community
7	Prosper Center	120	Office buildings
8	Yonganli Subway Station	85	Subway station
9	Dongda Bridge Bus Station	50	Bus station
10	Guomao	175	Subway station

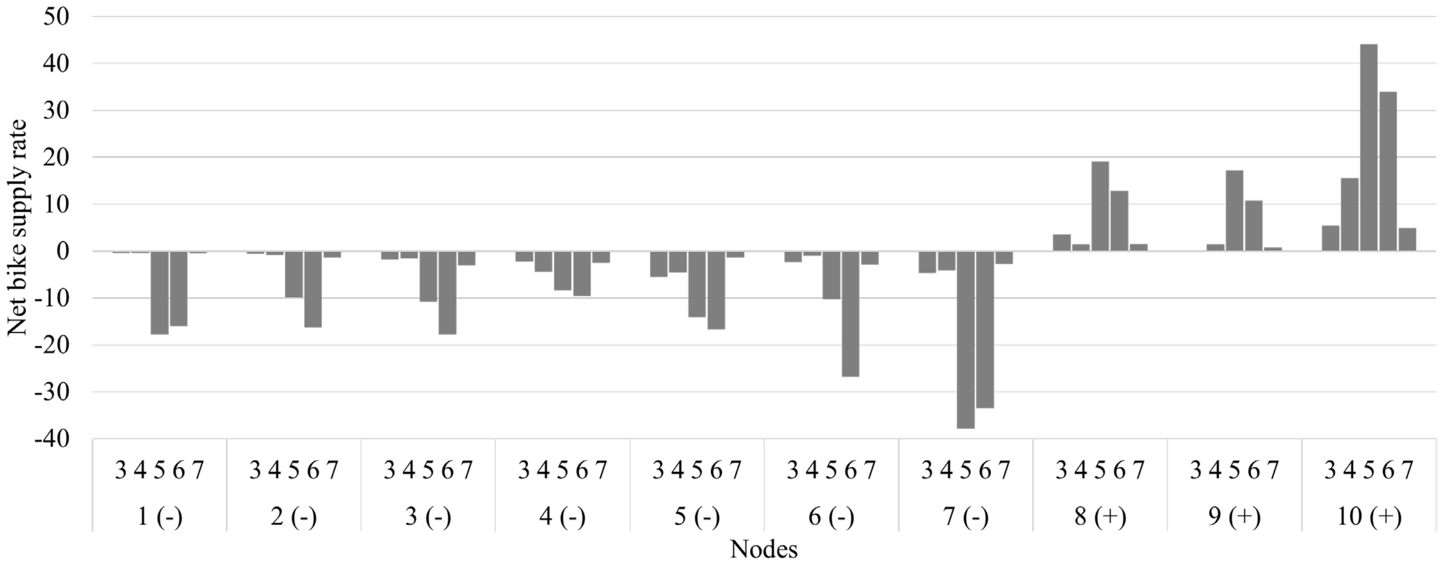
Experimental Setting: Test Instances

- □ Working time $\mathcal{T}$: afternoon shift, 3 pm – 8 pm
  - Discretized time: 5 minutes per time period
  - Time intervals
    - □ $\mathcal{E} = \{$3 – 4 pm, 4 – 5 pm, 5 – 6 pm, 6 – 7 pm, 7 – 8 pm$\}$.
    - □ Assume that within each time interval $e \in \mathcal{E}$, the bike supply and demand at each node or on each arc remain stationary and can be represented as independent Poisson processes.
      - λ_{ei}^{+} and λ_{ei}^{-} are estimated from Mobike (2017).

Notation	Definition
λ_{ei}^{+}	Bike supply rate at node i during time interval e
λ_{ei}^{-}	Bike demand rate at node i during time interval e
λ_{eij}^{+}	Bike supply rate on arc (i,j) during time interval e
λ_{eij}^{-}	Bike demand rate on arc (i,j) during time interval e

Experimental Setting: Test Instances

□ Nodes – bike supply and demand



3 – 5 pm: pre-evening-peak hours
5 – 7 pm: evening-peak hours
7 – 8 pm: post-evening-peak hours

+: evening-peak-supply nodes
–: evening-peak-demand nodes

Experimental Setting: Test Instances

- □ Arcs – bike supply and demand
  - During time interval e,
    - □ λ_e^+: the total bike supply rate in the network
    - □ ν_e^A: the proportion of bike supply rate to the arcs
  - Allocate $\nu_e^A \lambda_e^+$ to the arcs and the rest $(1 - \nu_e^A)\lambda_e^+$ to the nodes
    - □ In the base instances, $\nu_e^A = 50\%$, $\forall e \in \mathcal{E}$.
  - During time interval e, λ_{eij}^+ is set proportional to $\lambda_{ei}^+ + \lambda_{ej}^+$.
    - □ In the base instances, $\lambda_{eij}^- = \lambda_{eij}^+$.

Experimental Setting: Test Instances

- □ Arcs – travel time
  - ■ Divide the travel distance (from Amap) by a constant travel speed of 25 km/h.

- □ Initial bike allocation
  - ■ Allocate $\psi^A N^0$ bikes to the arcs and the rest $(1 - \psi^A) N^0$ bikes to the nodes
    - □ N^0: total number of bikes in the initial network
    - □ ψ^A: proportion of bikes on the arcs in the initial network
    - □ In the base instances, $N^0 = 300$, $\psi^A = 50\%$.

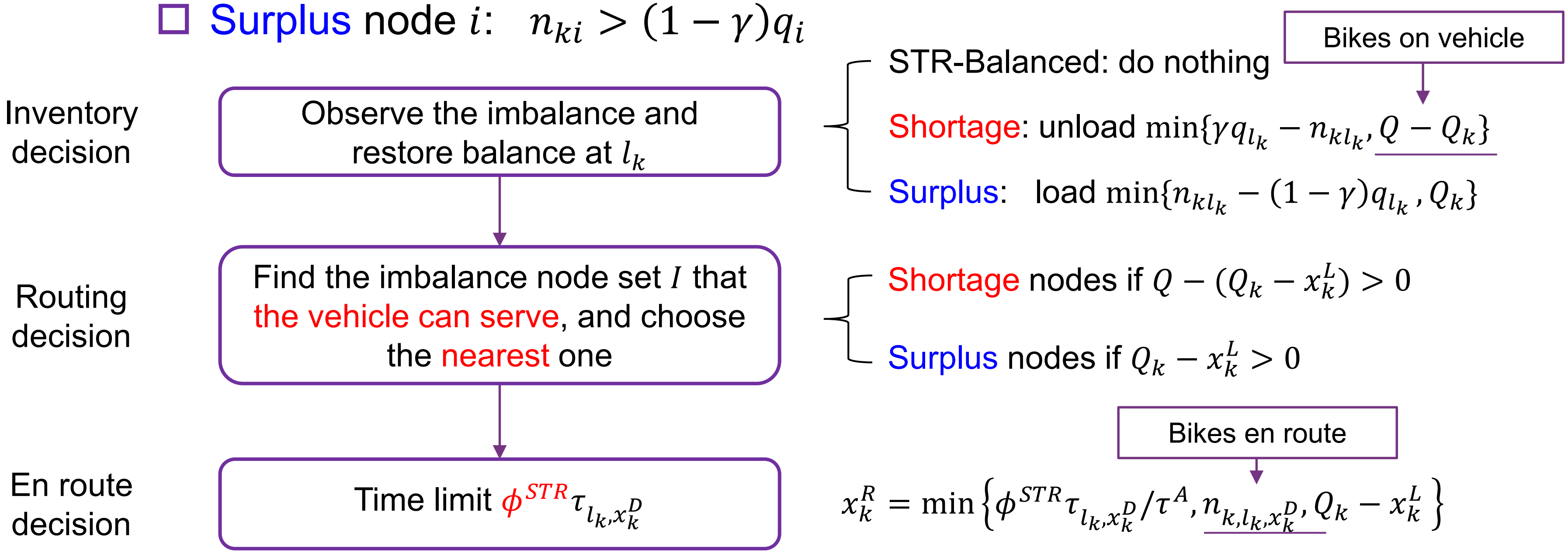
Experimental Setting: Benchmark Policies

- □ NRP (No-repositioning policy)
  - The mover stays at the depot and does nothing.
  - To identify the value of repositioning

- □ STR (Short-term relocation policy)
  - Brinkmann et al. (2015, 2019)
  - Based on the current bike shortage/surplus of nodes
  - Similar to our two-threshold policy in the inventory decision
  - Lacks anticipation and does not differentiate supply nodes and demand nodes in the routing decision

Experimental Setting: Benchmark Policies

- □ STR: parameter γ, ϕ^{STR}
  - Balance range $[\gamma q_i, (1-\gamma)q_i]$ for any node $i \in \mathcal{N}$
  - At decision epoch k
    - □ STR-Balanced node i: $\gamma q_i \le n_{ki} \le (1-\gamma)q_i$
    - □ Shortage node i: $n_{ki} < \gamma q_i$
    - □ Surplus node i: $n_{ki} > (1-\gamma)q_i$



Inventory decision

Observe the imbalance and restore balance at l_k

STR-Balanced: do nothing

Shortage: unload $\min\{\gamma q_{l_k} - n_{kl_k}, \underline{Q - Q_k}\}$

Bikes on vehicle

Surplus: load $\min\{n_{kl_k} - (1-\gamma)q_{l_k}, Q_k\}$

Routing decision

Find the imbalance node set I that the vehicle can serve, and choose the nearest one

Shortage nodes if $Q - (Q_k - x_k^L) > 0$

Surplus nodes if $Q_k - x_k^L > 0$

En route decision

Time limit $\phi^{STR}\tau_{l_k, x_k^D}$

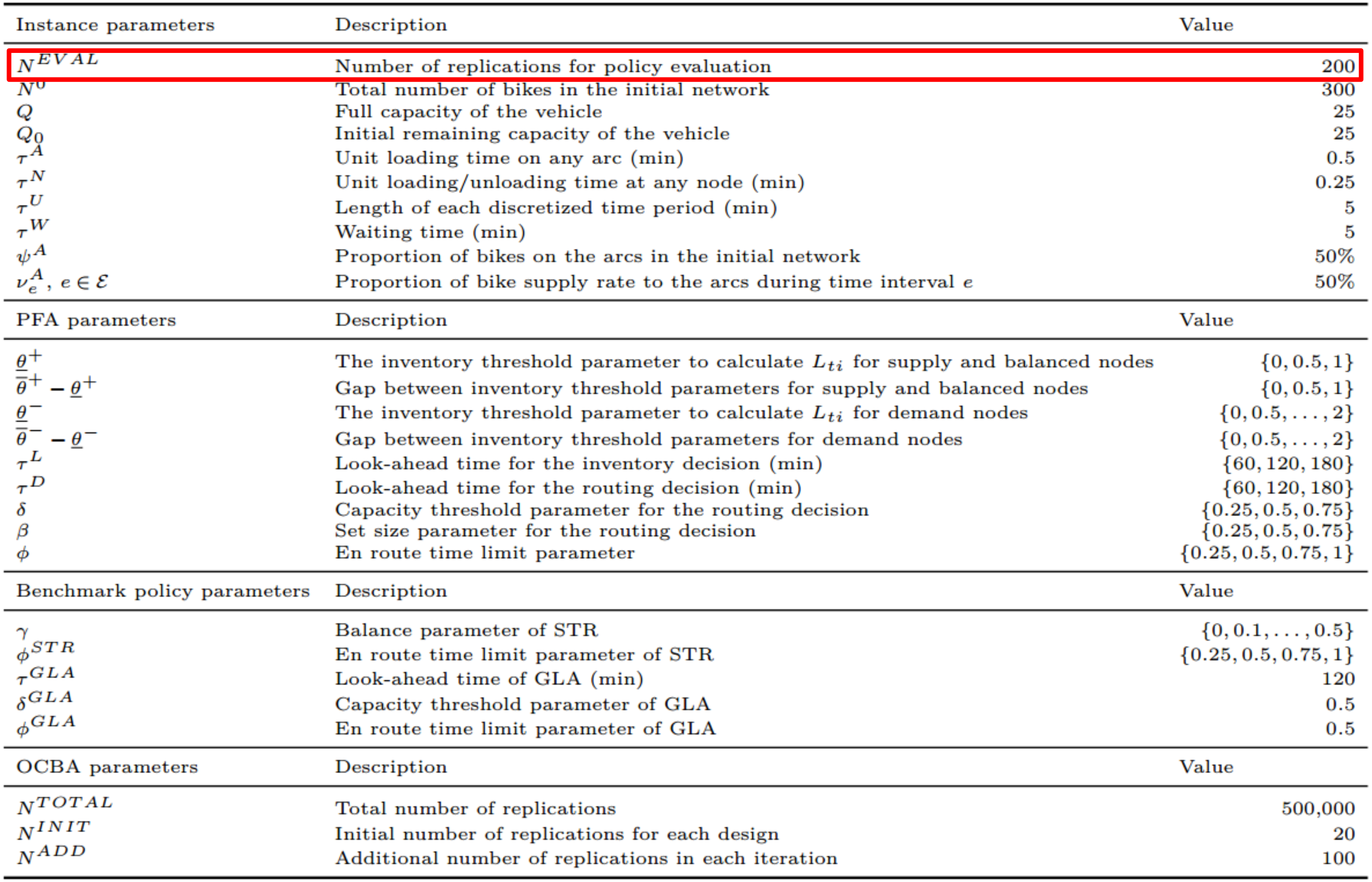
Bikes en route

$$x_k^R = \min\left\{\phi^{STR}\tau_{l_k,x_k^D}/\tau^A, \underline{n_{k,l_k,x_k^D}}, Q_k - x_k^L\right\}$$

Experimental Setting: Benchmark Policies

- □ GLA (Greedy look-ahead policy)
  - Mimics the mover's status quo practice in major free-floating bike sharing companies in China
  - Looks into τ^{GLA} time ahead
  - Makes the routing decision in a greedy way
    - □ The mover chooses the node either with the maximum number of bikes or in need of bikes the most.

Experimental Setting: Parameter Settings



Instance parameters	Description	Value
N^{EVAL}	Number of replications for policy evaluation	200
N^0	Total number of bikes in the initial network	300
Q	Full capacity of the vehicle	25
Q_0	Initial remaining capacity of the vehicle	25
τ^A	Unit loading time on any arc (min)	0.5
τ^N	Unit loading/unloading time at any node (min)	0.25
τ^U	Length of each discretized time period (min)	5
τ^W	Waiting time (min)	5
ψ^A	Proportion of bikes on the arcs in the initial network	50%
$\nu_e^A,\ e \in \mathcal{E}$	Proportion of bike supply rate to the arcs during time interval e	50%
PFA parameters	**Description**	**Value**
$\underline{\theta}^+$	The inventory threshold parameter to calculate L_{ti} for supply and balanced nodes	$\{0, 0.5, 1\}$
$\overline{\theta}^+ - \underline{\theta}^+$	Gap between inventory threshold parameters for supply and balanced nodes	$\{0, 0.5, 1\}$
$\underline{\theta}^-$	The inventory threshold parameter to calculate L_{ti} for demand nodes	$\{0, 0.5, \ldots, 2\}$
$\overline{\theta}^- - \underline{\theta}^-$	Gap between inventory threshold parameters for demand nodes	$\{0, 0.5, \ldots, 2\}$
τ^L	Look-ahead time for the inventory decision (min)	$\{60, 120, 180\}$
τ^D	Look-ahead time for the routing decision (min)	$\{60, 120, 180\}$
δ	Capacity threshold parameter for the routing decision	$\{0.25, 0.5, 0.75\}$
β	Set size parameter for the routing decision	$\{0.25, 0.5, 0.75\}$
ϕ	En route time limit parameter	$\{0.25, 0.5, 0.75, 1\}$
Benchmark policy parameters	**Description**	**Value**
γ	Balance parameter of STR	$\{0, 0.1, \ldots, 0.5\}$
ϕ^{STR}	En route time limit parameter of STR	$\{0.25, 0.5, 0.75, 1\}$
τ^{GLA}	Look-ahead time of GLA (min)	120
δ^{GLA}	Capacity threshold parameter of GLA	0.5
ϕ^{GLA}	En route time limit parameter of GLA	0.5
OCBA parameters	**Description**	**Value**
N^{TOTAL}	Total number of replications	500,000
N^{INIT}	Initial number of replications for each design	20
N^{ADD}	Additional number of replications in each iteration	100

Selected parameters of policies

□ Computational environment

- Implemented in Python 3.6.2
- Conducted on a PC with an Intel Core i7-7700 processor with 3.60 GHz CPU and 16 GB RAM

PFA parameters	Description	Value
$\underline{\theta}^{+}$	The inventory threshold parameter to calculate L_{ti} for supply and balanced nodes	0
$\overline{\theta}^{+}$	The inventory threshold parameter to calculate U_{ti} for supply and balanced nodes	0
$\underline{\theta}^{-}$	The inventory threshold parameter to calculate L_{ti} for demand nodes	0.5
$\overline{\theta}^{-}$	The inventory threshold parameter to calculate U_{ti} for demand nodes	1
τ^{L}	Look-ahead time for the inventory decision (min)	180
τ^{D}	Look-ahead time for the routing decision (min)	180
δ	Capacity threshold parameter for the routing decision	0.75
β	Set size parameter for the routing decision	0.75
ϕ	En route time limit parameter	1
Benchmark policy parameters	Description	Value
γ	Balance parameter of STR	0.4
ϕ^{STR}	En route time limit parameter of STR	1
τ^{GLA}	Look-ahead time of GLA (min)	120
δ^{GLA}	Capacity threshold parameter of GLA	0.5
ϕ^{GLA}	En route time limit parameter of GLA	0.5

Trained by OCBA

24 hours

4 hours

Fixed

Once the policy parameters are determined, the time to make a dynamic repositioning decision is negligible (in centiseconds for PFA).

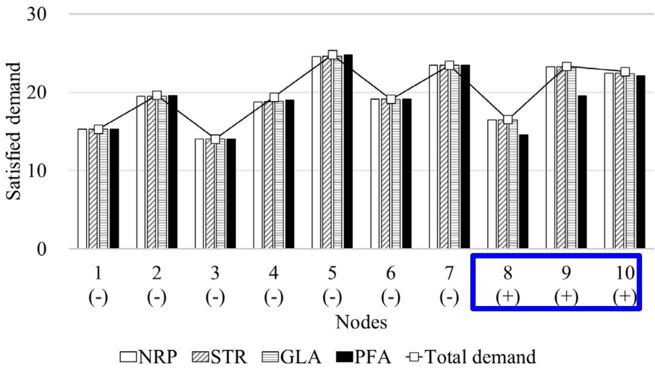
Value of Repositioning

- Overall performance
  - Demand satisfaction ratio: ratio of the satisfied demand to the total demand
  - Value of repositioning of a policy: improvement of the demand satisfaction ratio during the working time, compared with NRP

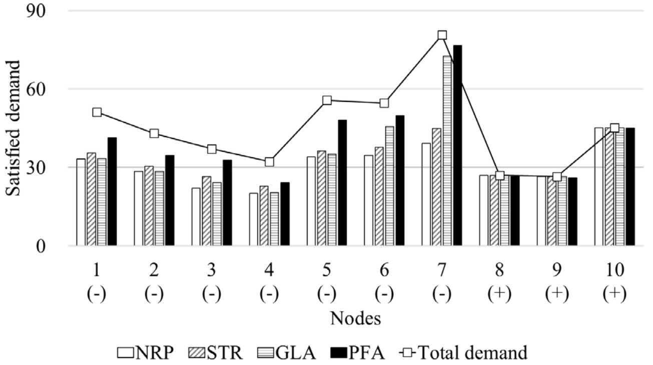
	Average demand satisfaction ratio	Standard deviation	Value of Repositioning
NRP	77.3%	3.0%	-
STR	81.1%	3.2%	**3.8%**
GLA	85.0%	2.9%	**7.7%**
PFA	91.2%	2.9%	**13.9%**

Value of Repositioning

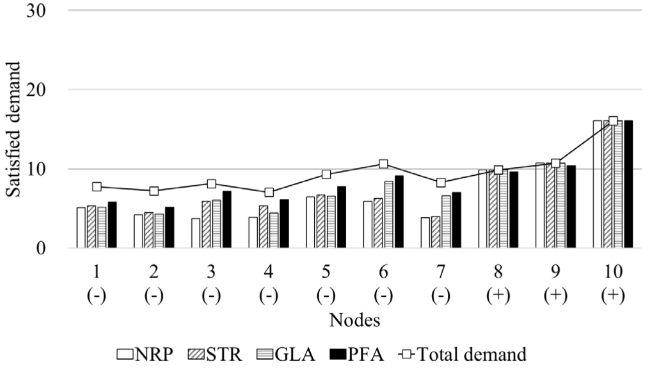
- □ Satisfied demand
  - ■ During pre-evening-peak hours
    - □ PFA results in small demand losses at the evening-peak-supply nodes.



Pre-evening-peak (3 – 5 pm)



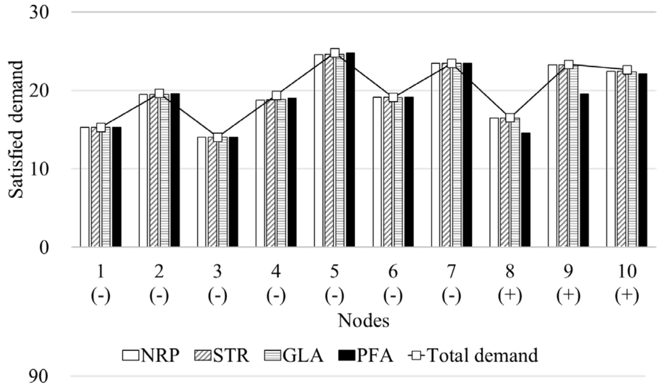
Evening-peak (5 – 7 pm)



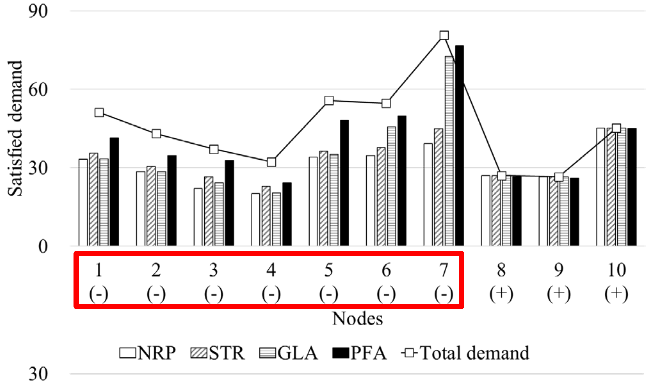
Post-evening-peak (3 – 5 pm)

Value of Repositioning

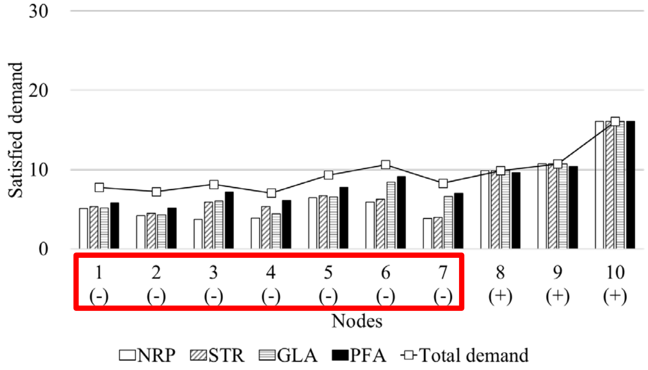
- Satisfied demand
  - During pre-evening-peak hours
    - PFA results in small demand losses at the evening-peak-supply nodes.
  - During evening-peak and post-evening-peak hours
    - Many more satisfied demand at the evening-peak-demand nodes.



Pre-evening-peak (3 – 5 pm)



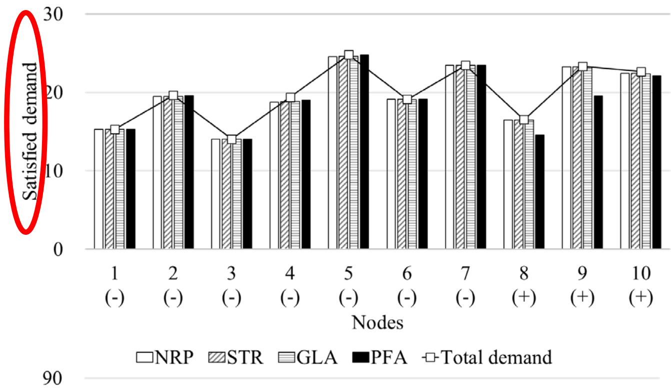
Evening-peak (5 – 7 pm)



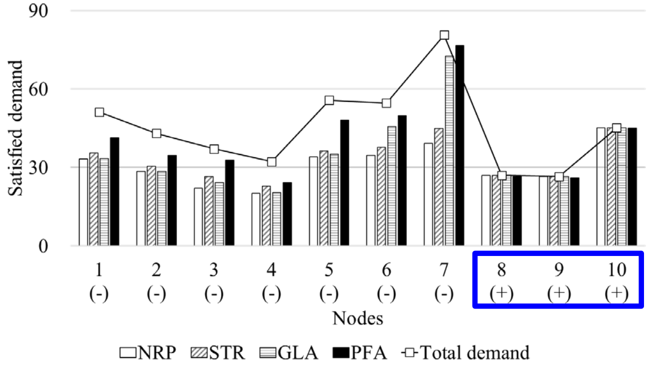
Post-evening-peak (3 – 5 pm)

Value of Repositioning

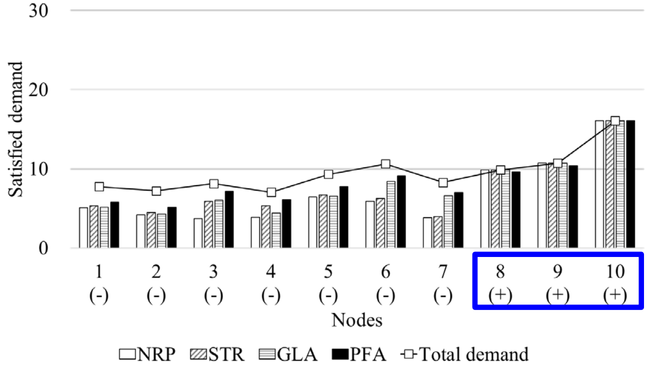
- Satisfied demand
  - During pre-evening-peak hours
    - PFA results in small demand losses at the evening-peak-supply nodes.
  - During evening-peak and post-evening-peak hours
    - Many more satisfied demand at the evening-peak-demand nodes.
    - Slightly less satisfied demand at the evening-peak-supply nodes.



Pre-evening-peak (3 – 5 pm)



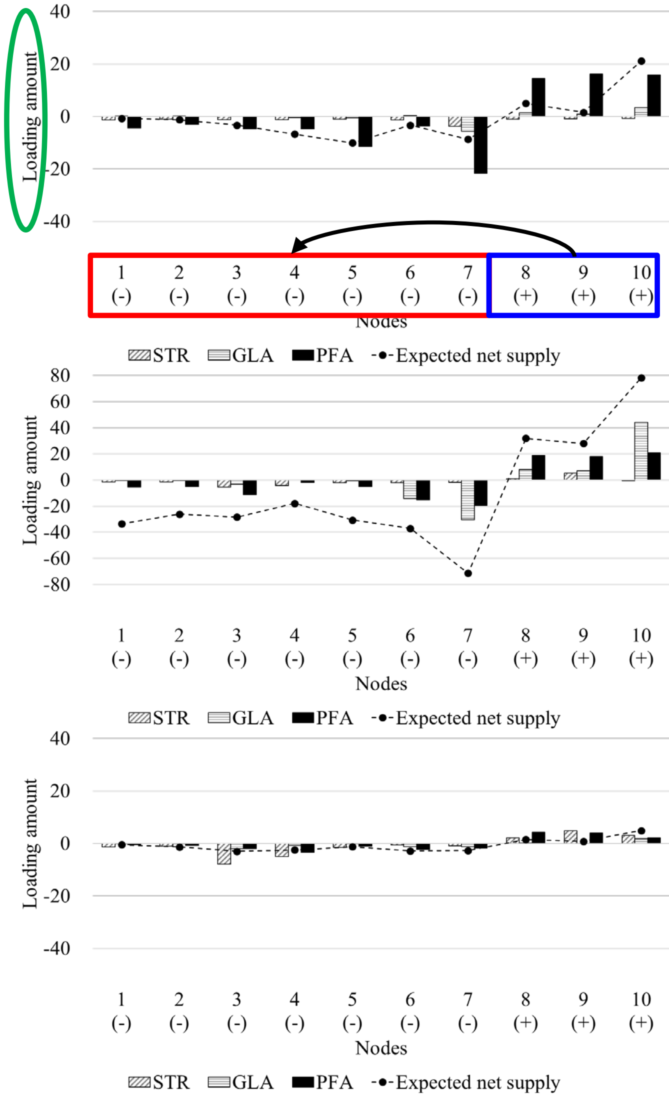
Evening-peak (5 – 7 pm)



Post-evening-peak (3 – 5 pm)

Value of Repositioning

- □ Policy behavior
  - During pre-evening-peak hours
    - □ PFA repositions many more bikes from the evening-peak-supply nodes to the evening-peak-demand nodes.



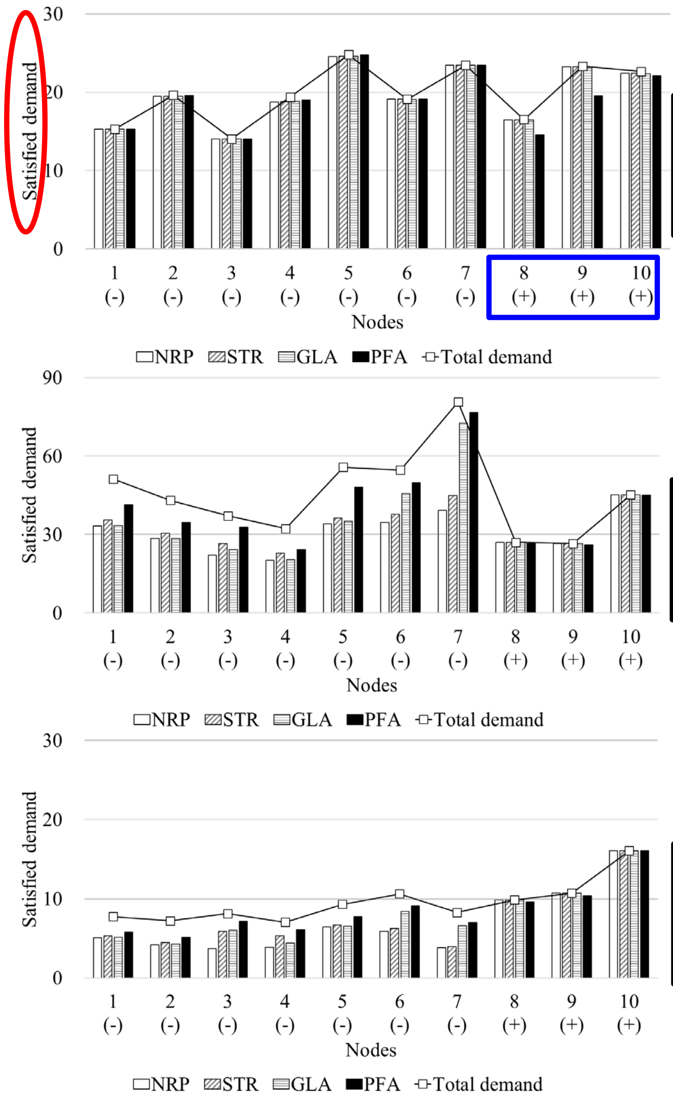
Pre-evening-peak (3 – 5 pm)

Evening-peak (5 – 7 pm)

Post-evening-peak (3 – 5 pm)

Value of Repositioning

- □ Policy behavior
  - During pre-evening-peak hours
    - □ PFA repositions many more bikes from the evening-peak-supply nodes to the evening-peak-demand nodes.
      - Small demand losses at the evening-peak-supply nodes during pre-evening-peak hours



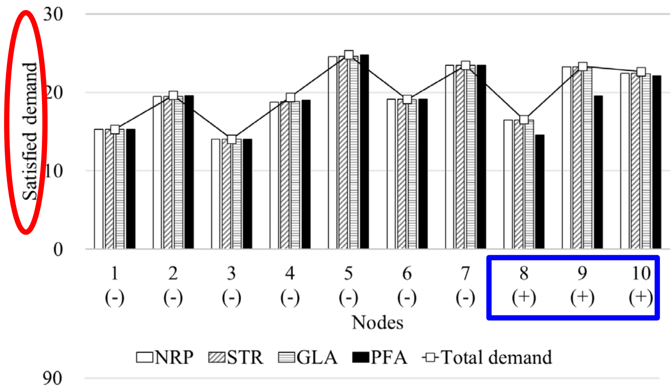
Pre-evening-peak (3 – 5 pm)

Evening-peak (5 – 7 pm)

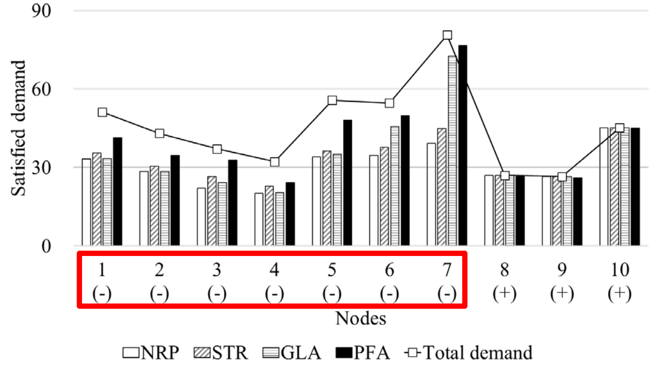
Post-evening-peak (3 – 5 pm)

Value of Repositioning

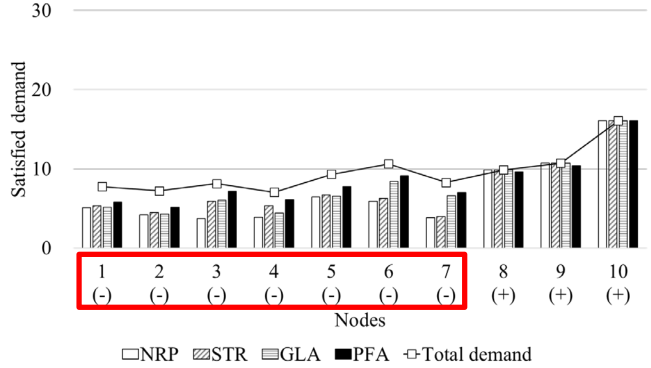
- □ Policy behavior
  - During pre-evening-peak hours
    - □ PFA repositions many more bikes from the evening-peak-supply nodes to the evening-peak-demand nodes.
      - Small demand losses at the evening-peak-supply nodes during pre-evening-peak hours
      - Many more satisfied demand at the evening-peak-demand nodes during and post evening-peak hours



Pre-evening-peak (3 – 5 pm)



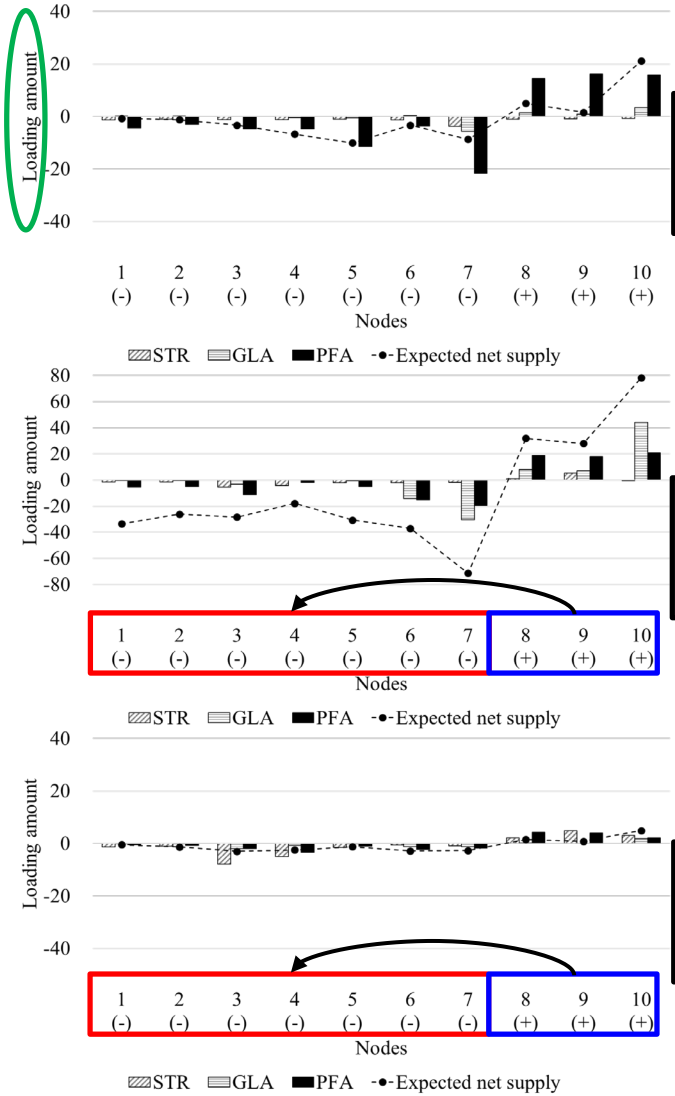
Evening-peak (5 – 7 pm)



Post-evening-peak (3 – 5 pm)

Value of Repositioning

- □ Policy behavior
  - ■ During evening-peak and post-evening-peak hours
    - □ All the policies load bikes from the evening-peak-supply nodes and unload bikes to the evening-peak-demand nodes.



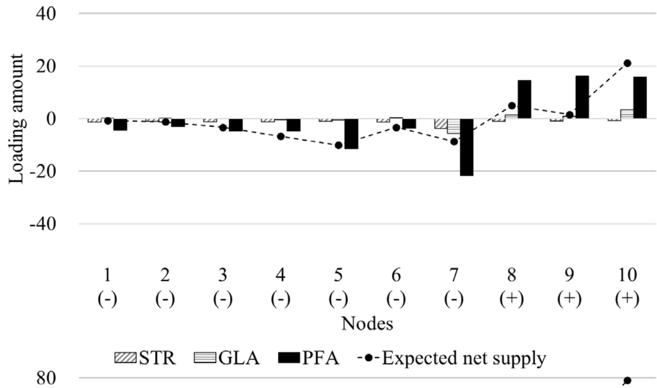
Pre-evening-peak (3 – 5 pm)

Evening-peak (5 – 7 pm)

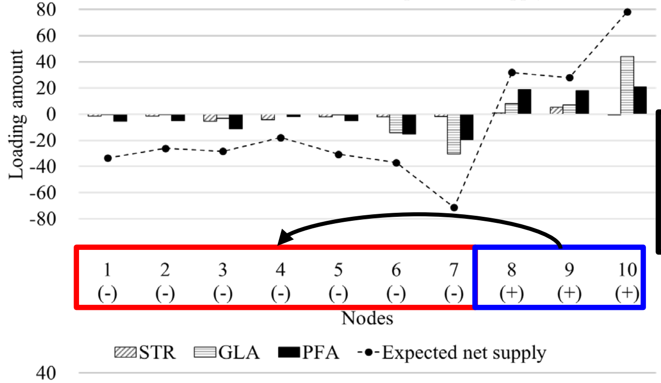
Post-evening-peak (3 – 5 pm)

Value of Repositioning

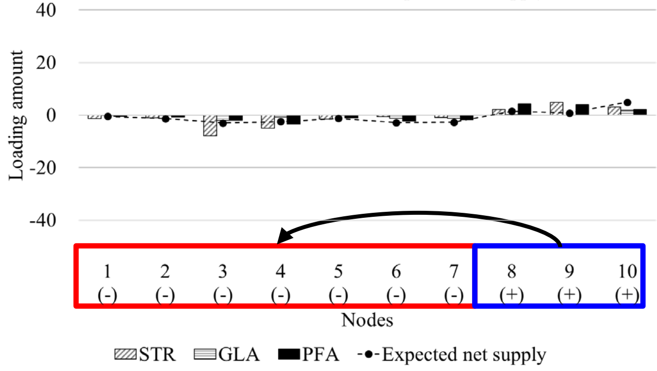
- □ Policy behavior
  - During evening-peak and post-evening-peak hours
    - □ PFA repositions bikes more efficiently, measured by the correlation between the expected net supply and the loading amount during 5 – 8 pm.
      - PFA (0.94) > GLA (0.93) > STR (0.58)



Pre-evening-peak (3 – 5 pm)



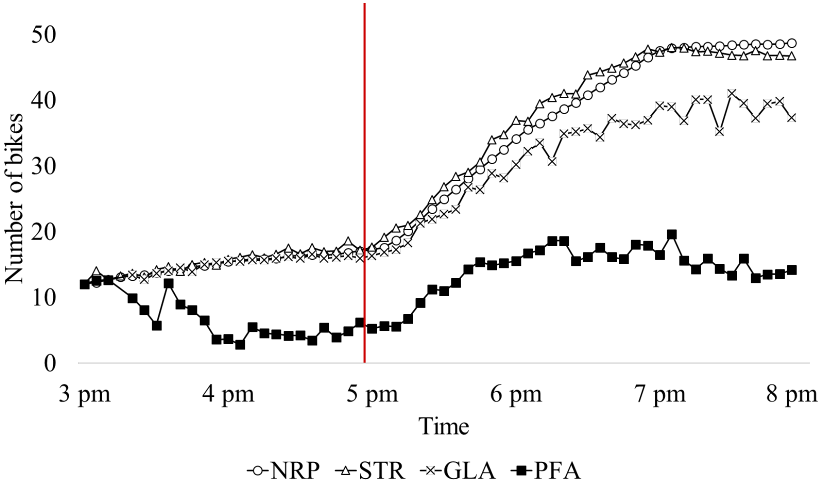
Evening-peak (5 – 7 pm)



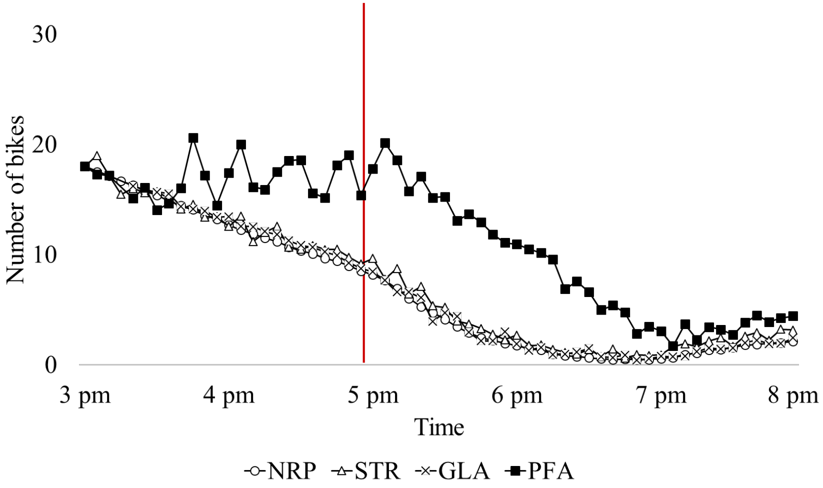
Post-evening-peak (3 – 5 pm)

Value of Repositioning

- □ Number of bikes over time
  - Compared with other policies, PFA
    - □ Accumulates fewer bikes at the evening-peak-supply node 8
    - □ Keeps more bikes at the evening-peak-demand node 5
    - □ Already starts repositioning during pre-evening-peak hours (3 – 5 pm), to prepare for evening-peak hours (5 – 7 pm).



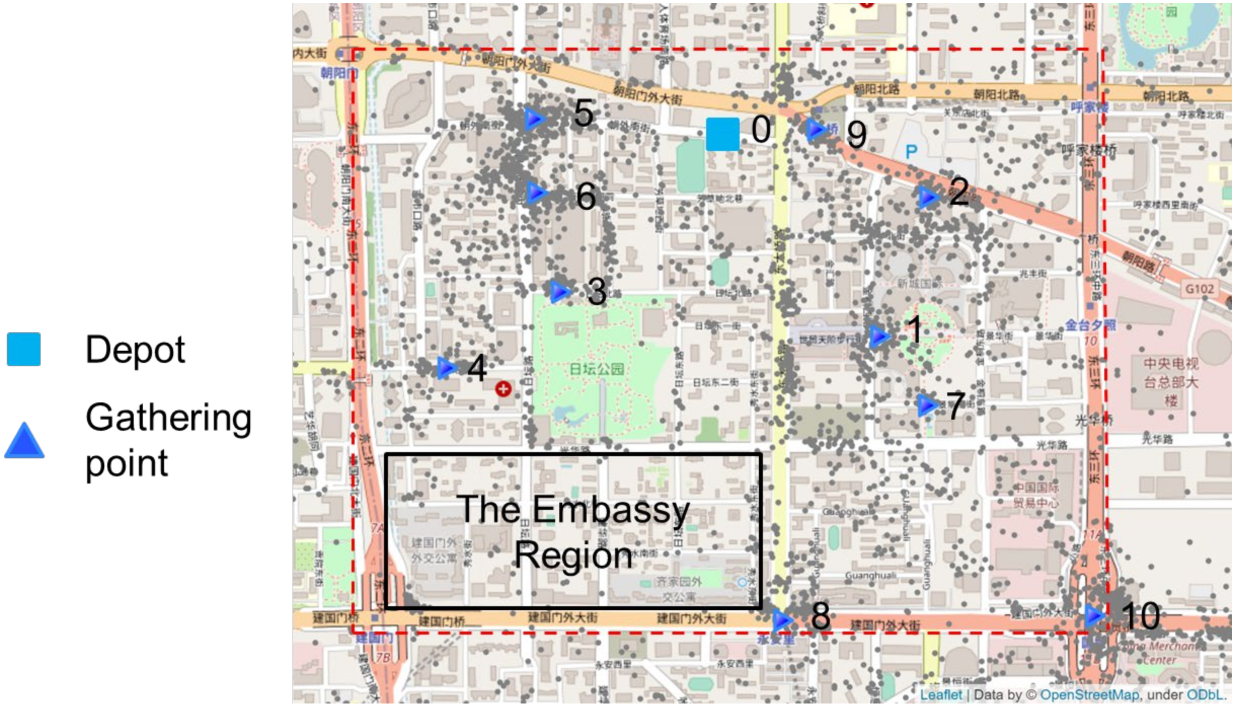
Node 8 (+)



Node 5 (–)

Impact of Bike Scatteredness

- In a free-floating bike sharing system
  - Bikes are not only located at the gathering points, but also scattered at other less popular locations.

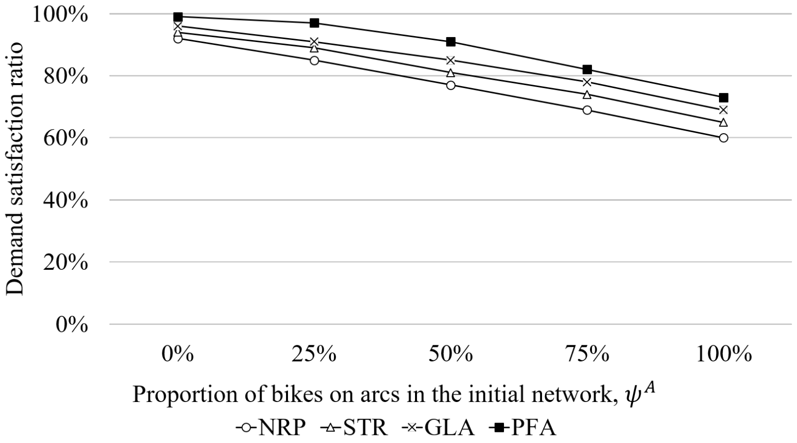


Impact of Bike Scatteredness

- □ Bike scatteredness
  - ■ ψ^A: proportion of bikes on the arcs in the initial network (i.e., at the beginning of the working time)
    - □ In the base instances, $\psi^A = 50\%$
    - □ Test range: $\{50\%, 60\%, 70\%, 80\%, 90\%, 100\%\}$

Impact of Bike Scatteredness

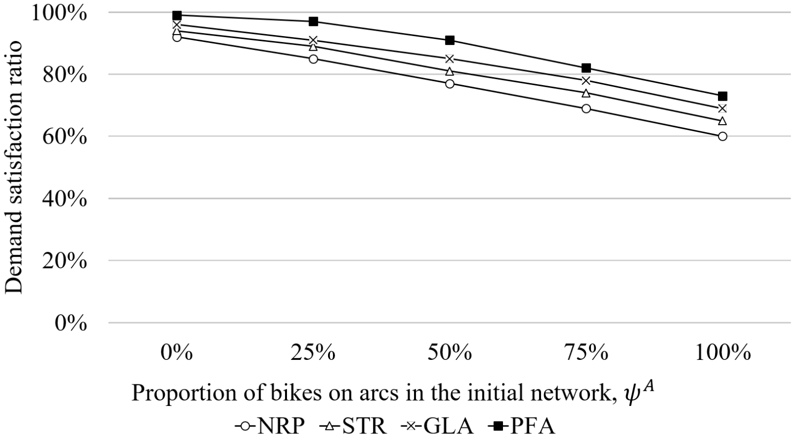
- Overall performance
  - The demand satisfaction ratio decreases in ψ^A under each policy.
  - PFA always achieves the highest demand satisfaction ratio.



Impact of Bike Scatteredness

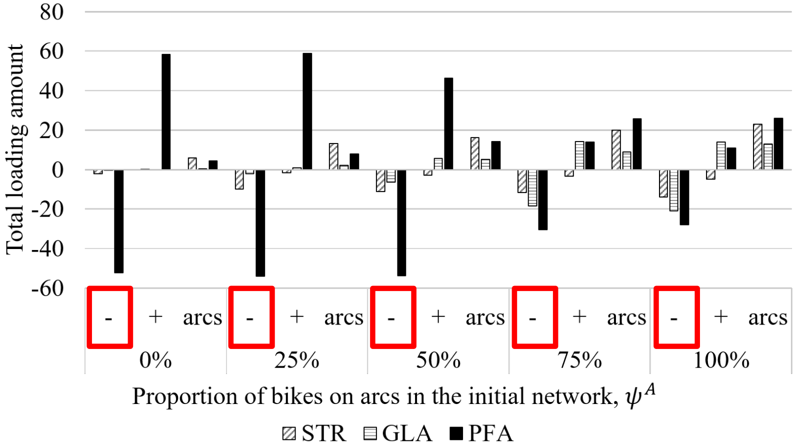
□ Overall performance

- Compared with NRP, the company can benefit from adopting any of the repositioning policies.
- Such benefit is not very significant when there are sufficient bikes at the nodes at the beginning of the working time ($\psi^A = 0\%$).



Impact of Bike Scatteredness

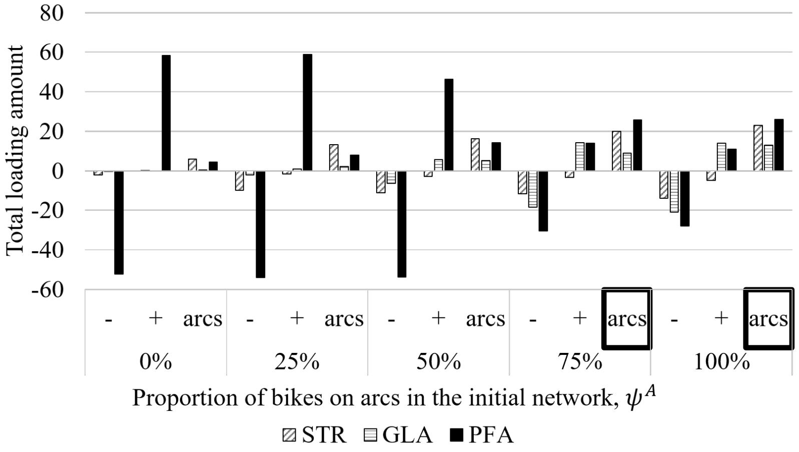
- Policy behavior
  - During pre-evening-peak hours
    - Compared with other policies, PFA always unloads more bikes to the evening-peak-demand nodes.



Pre-evening-peak
(3 – 5 pm)

Impact of Bike Scatteredness

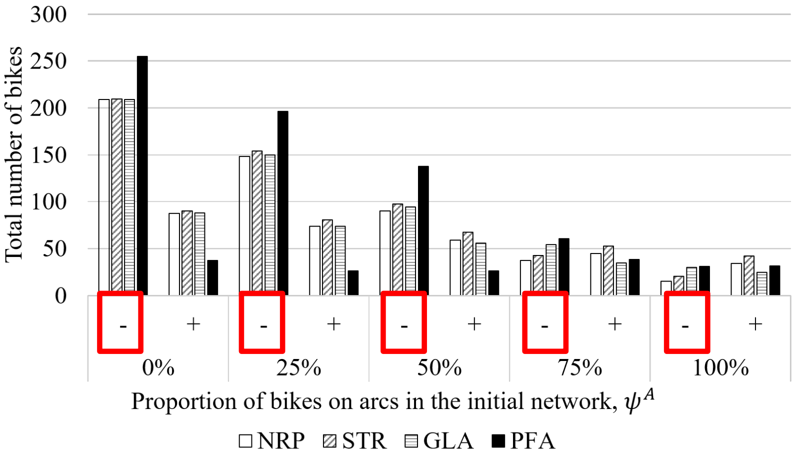
- Policy behavior
  - During pre-evening-peak hours
    - Compared with other policies, PFA always unloads more bikes to the evening-peak-demand nodes.
    - When there are few bikes at the nodes at the beginning of the working time (i.e., $\psi^A \geq 75\%$), PFA collects more scattered bikes from the arcs.



Pre-evening-peak (3 – 5 pm)

Impact of Bike Scatteredness

- Policy behavior
  - As a result, PFA prepares more bikes at the evening-peak-demand nodes at 5 pm.



5 pm

Summary

- □ Problem characteristics
  - ■ Dynamic intra-cell reposition of bikes among gathering points
  - ■ Collection of bikes scattered along the paths
  - ■ Under stochastic demands both at the gathering points and along the paths
- □ Model: Markov Decision Process (MDP)
- □ Algorithm: Policy Function Approximation (PFA)
  - ■ Optimal Computing Budget Allocation (OCBA) to search for optimal policy parameters
- □ Numerical experiments based on a real data set
  - ■ Outperformance of PFA against benchmark policies
  - ■ Value of repositioning
  - ■ Impact of bike scatteredness

References

- □ Aftabuzzaman, M., Currie, G., & Sarvi, M. (2010). Evaluating The Congestion Relief Impacts Of Public Transport In Monetary Terms. *Journal Of Public Transportation*, 13(1), 1-24.
- □ Agussurja, L., Cheng, S. F., & Lau, H. C. (2019). A State Aggregation Approach For Stochastic Multiperiod Last-mile Ride-sharing Problems. *Transportation Science*, 53(1), 148-166.
- □ Angelopoulos, A., Gavalas, D., Konstantopoulos, C., Kypriadis, D., & Pantziou, G. (2018). Incentivized Vehicle Relocation In Vehicle Sharing Systems. *Transportation Research Part C: Emerging Technologies*, 97, 175-193.
- □ Benjaafar, S., Jiang, D., Li, X., & Li, X. Dynamic Inventory Repositioning In On-demand Rental Networks. *Working Paper*.
- □ Boyacı, B., Zografos, K. G., & Geroliminis, N. (2017). An Integrated Optimization-simulation Framework For Vehicle And Personnel Relocations Of Electric Carsharing Systems With Reservations. *Transportation Research Part B: Methodological*, 95, 214-237.
- □ Brinkmann, J., Ulmer, M. W., & Mattfeld, D. C. (2015). Short-term Strategies For Stochastic Inventory Routing In Bike Sharing Systems. *Transportation Research Procedia*, 10, 364-373.
- □ Brinkmann, J., Ulmer, M. W., & Mattfeld, D. C. (2019). Dynamic Lookahead Policies For Stochastic-dynamic Inventory Routing In Bike Sharing Systems. *Computers & Operations Research*, 106, 260-279.
- □ Caggiani, L., Camporeale, R., Marinelli, M., & Ottomanelli, M. (2018). User Satisfaction Based Model For Resource Allocation In Bike-sharing Systems. *Transport Policy*.
- □ Caggiani, L., Camporeale, R., & Ottomanelli, M. (2017). A Dynamic Clustering Method For Relocation Process In Free-floating Vehicle Sharing Systems. *Transportation Research Procedia*, 27, 278-285.
- □ Chen, C. H., & Lee, L. H. (2011). *Stochastic Simulation Optimization: An Optimal Computing Budget Allocation*. World Scientific.

References

- □ DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of public transportation*, *12*(4), 3.
- □ Folkestad, C. A., Hansen, N., Fagerholt, K., Andersson, H., & Pantuso, G. (2020). Optimal Charging And Repositioning Of Electric Vehicles In A Free-floating Carsharing System. *Computers & Operations Research*, 113, 104771.
- □ Freund, D., Henderson, S. G., O'Mahony, E., & Shmoys, D. B. (2019). Analytics and bikes: Riding tandem with motivate to improve mobility. *INFORMS Journal on Applied Analytics*, *49*(5), 310-323.
- □ Hamilton, T. L., & Wichman, C. J. (2018). Bicycle Infrastructure And Traffic Congestion: Evidence From Dc's Capital Bikeshare. *Journal Of Environmental Economics And Management*, 87, 72-93.
- □ He, L., Hu, Z., & Zhang, M. (2019). Robust Repositioning For Vehicle Sharing. *Manufacturing & Service Operations Management*.
- □ He, L., Ma, G., Qi, W., & Wang, X. (2020). Charging An Electric Vehicle-sharing Fleet. *Manufacturing & Service Operations Management*.
- □ Hellobike. (2018). *Regulations and Protocols*.
- □ iResearch. (2017). *Report of Bike Sharing In China*.
- □ Laporte, G., Meunier, F., & Calvo, R. W. (2015). Shared Mobility Systems. *4or*, 13(4), 341-360.
- □ Legros, B. (2019). Dynamic repositioning strategy in a bike-sharing system; how to prioritize and how to rebalance a bike station. *European Journal of Operational Research*, *272*(2), 740-753.
- □ Li, L., Wang, S., Li, M., & Tan, J. (2018). Comparison Of Travel Mode Choice Between Taxi And Subway Regarding Traveling Convenience. *Tsinghua Science And Technology*, 23(2), 135-144.
- □ Li, M., Wang, X., Zhang, X., Yun, L., & Yuan, Y. (2018). A Multiperiodic Optimization Formulation For The Operation Planning Of Free-floating Shared Bike In China. *Mathematical Problems In Engineering*, 2018.

References

- Li, W., Wang, S., Zhang, X., Jia, Q., & Tian, Y. (2020). Understanding intra-urban human mobility through an exploratory spatiotemporal analysis of bike-sharing trajectories. *International Journal of Geographical Information Science*, *34*(12), 2451-2474.
- Lin, J. R., & Yang, T. H. (2011). Strategic Design Of Public Bicycle Sharing Systems With Service Level Constraints. *Transportation Research Part E: Logistics And Transportation Review*, 47(2), 284-294.
- Liu, Y., Szeto, W. Y., & Ho, S. C. (2018). A Static Free-floating Bike Repositioning Problem With Multiple Heterogeneous Vehicles, Multiple Depots, And Multiple Visits. *Transportation Research Part C: Emerging Technologies*, 92, 208-242.
- Mahmoodiana, V., Zhang, Y., & Charkhgarda, H. (2019). Hybrid Rebalancing With Dynamic Hubbing For Free-floating Bike Sharing Using Multi-objective Simulation Optimization. *Working Paper*.
- Mobike. (2017). *Mobike data mining competition at biendata*.
- Pal, A., & Zhang, Y. (2017). Free-floating Bike Sharing: Solving Real-life Large-scale Static Rebalancing Problems. *Transportation Research Part C: Emerging Technologies*, 80, 92-116.
- Powell, W. B. (2019). A unified framework for stochastic optimization. *European Journal of Operational Research*, *275*(3), 795-821.
- Powell, W. B. (2021). Reinforcement Learning and Stochastic Optimization. John Wiley & Sons, to appear.
- Raviv, T., Tzur, M., & Forma, I. A. (2013). Static Repositioning In A Bike-sharing System: Models And Solution Approaches. *EURO Journal On Transportation And Logistics*, 2(3), 187-229.
- State Information Center. (2018). *Annual Report Of Sharing Economy In China*.
- Usama, M., Shen, Y., & Zahoor, O. (2019). A Free-floating Bike Repositioning Problem With Faulty Bikes. *Procedia Comput. Sci*, 151, 155-162.

References

□ United Nations. (2018). *World Urbanization Prospects: The 2018 Revision*.

□ Warrington, J., & Ruchti, D. (2019). Two-stage Stochastic Approximation For Dynamic Rebalancing Of Shared Mobility Systems. *Transportation Research Part C: Emerging Technologies*, 104, 110-134

□ Weikl, S., & Bogenberger, K. (2015). A Practice-ready Relocation Model For Free-floating Carsharing Systems With Electric Vehicles–mesoscopic Approach And Field Trial Results. *Transportation Research Part C: Emerging Technologies*, 57, 206-223.

□ Xing, Y., Wang, K., & Lu, J. J. (2020). Exploring travel patterns and trip purposes of dockless bike-sharing by analyzing massive bike-sharing data in Shanghai, China. *Journal of transport geography*, *87*, 102787.

□ Xinhua News. (2019). *Delicacy management of bike sharing systems*.

□ Yang, Y., Heppenstall, A., Turner, A., & Comber, A. (2019). A Spatiotemporal And Graph-based Analysis Of Dockless Bike Sharing Patterns To Understand Urban Flows Over The Last Mile. *Computers, Environment And Urban Systems*, 77, 101361.

□ Zhang, J., Meng, M., & David, Z. W. (2019). A Dynamic Pricing Scheme With Negative Prices In Dockless Bike Sharing Systems. *Transportation Research Part B: Methodological*, 127, 201-224.