Algorithmic Solutions for Re-Balancing in Bike Sharing: Challenges and Opportunities

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Road Map

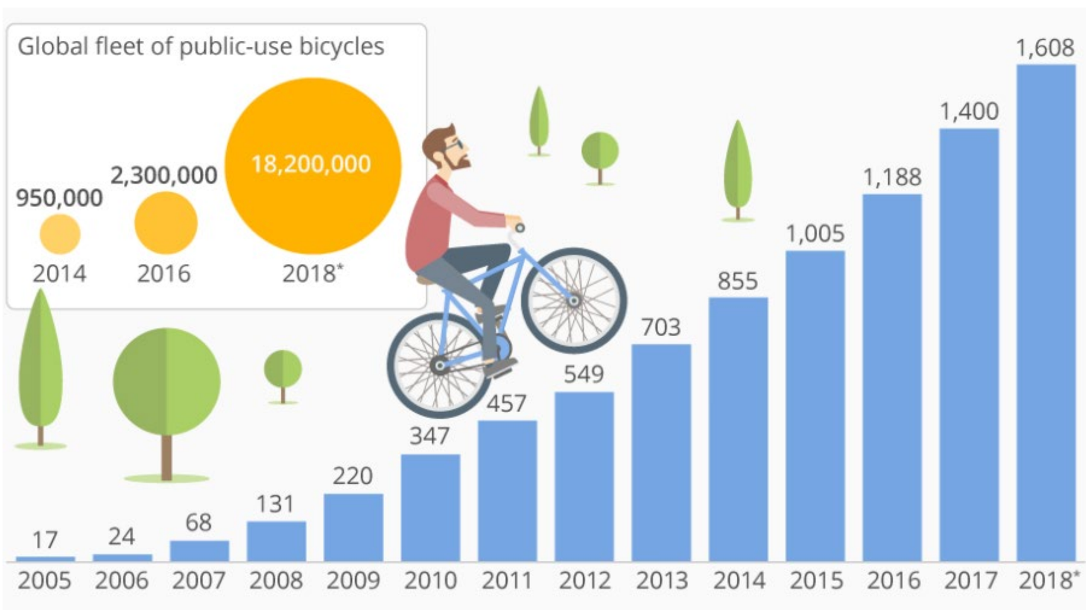
1. Introduction
2. Four System Components
3. Re-balancing Through Trucks
4. Re-balancing Through Workers
5. Spatial and Temporal Complexity
6. Challenges and Opportunities
7. Conclusion

1. Introduction

- Smart City
  - Collection of data
  - Management of assets, resources, and services
- Scope
  - Transportation
  - Power plants
  - Utilities
  - Water supply
  - Crime detection
  - School
  - Libraries
  - Hospitals
  - ...

Bike Sharing System (BSS)

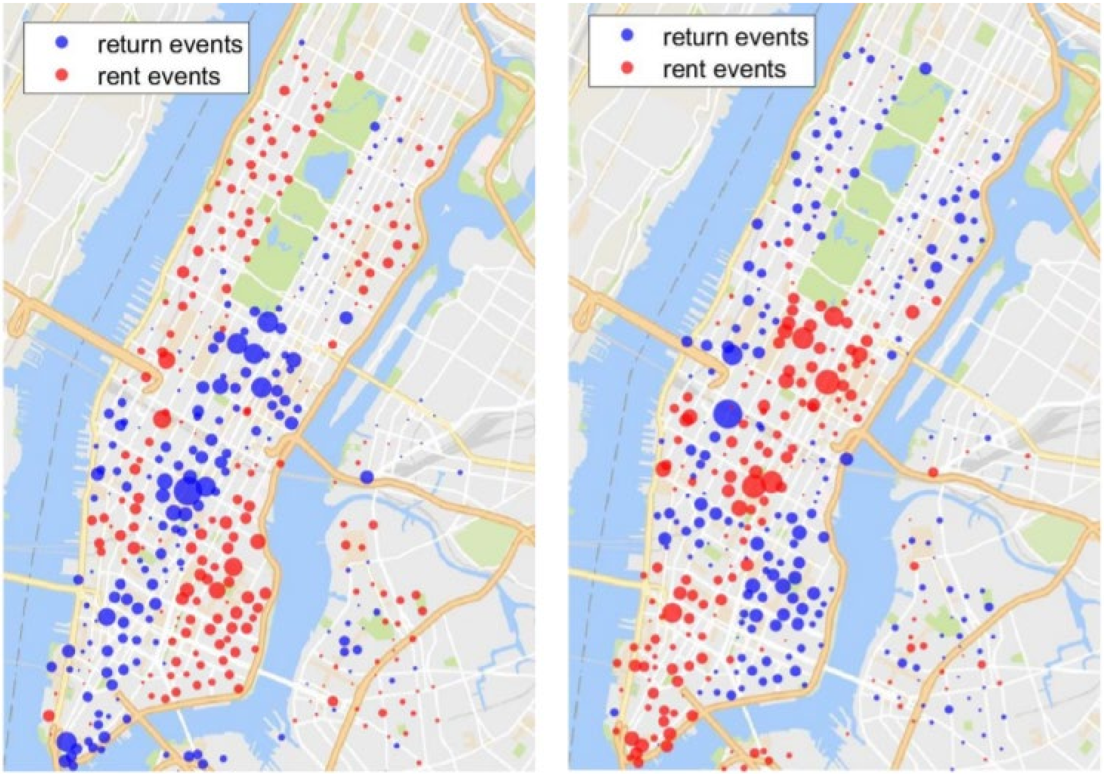
- BSS
  - First/last mile connection
  - Rent-Ride-Return
  - > 1600 BSSs in > 50 countries
- Benefits
  - Healthy lifestyle
  - Green transportation
  - 40% of BSS users drive less



Unbalanced Usage in BSS

- Unbalanced usage
  - Time
  - Space

- Capacity
  - Underflow (empty)
  - Overflow (full)



(a) AM rush hours: 8:00 - 10:00 AM (b) PM rush hours: 5:00 - 7:00 PM

Re-Balancing in BSS

Dock BSS

- Citi Bike (NYC), Indego (Philly), and GoBike (Bay Area)
- BikeMi (Milan), Bubi (Budapest)

Dock-less BSS

- ofo and Mobike (China)
- U-Bicycle and OV-fiets (Europe)
- LimeBike and JUMP (US)

Re-balancing (repositioning)

- Via trucks (not eco-friendly)
- Via workers (through crowdsourcing)

2. Four System Components

1. System design

- Station number, location, capacity, and bike number
- Facility location problem: area best for placing a station?

2. System prediction

- Mobility modeling
- Demand prediction

3. System balancing

- Dedicated truck service
- Incentive-based worker recruitment
- Route planning and scheduling

4. Trip advisor

- User guidance
- Re-balance via suggestions

AI Take-off

- X - AI convergence
  - AI blackbox
- However, DARPA: Explainable AI
  - Produce more explainable models
  - Enable human users to understand
- Back to fundamentals
  - Direct algorithmic/combinatoric solutions
  - Mixed with AI/ML solutions

3. Re-balancing Through Trucks

Hamiltonian circle (for TSP)

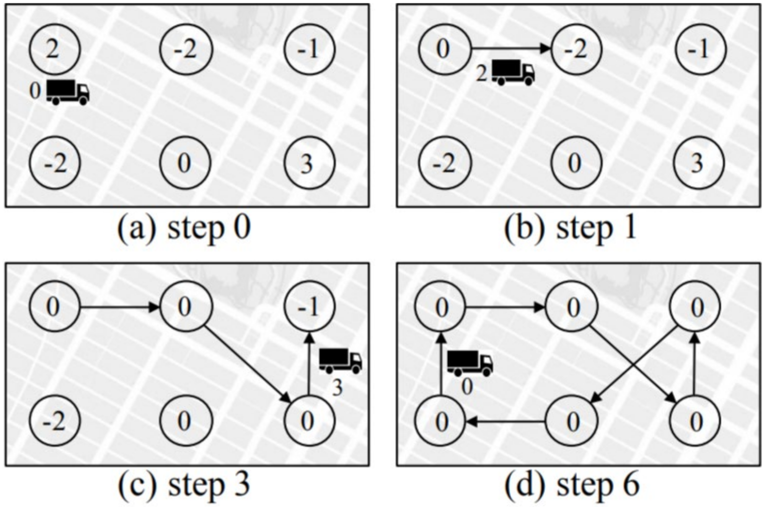
- Trucks move around stations to pick-up/drop-off bikes

Legitimate circle

- Alternating positive pieces and negative pieces s.t. capacity l

Notation

- +m: overflow by m
- -m: underflow by m
- l: truck capacity

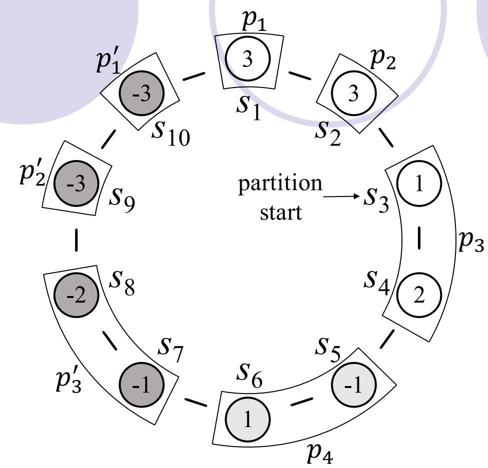


(a) step 0 (b) step 1 (c) step 3 (d) step 6

MATCH Method

Assumptions

- Predefined Hamiltonian cycle
- Piece length limit: l'

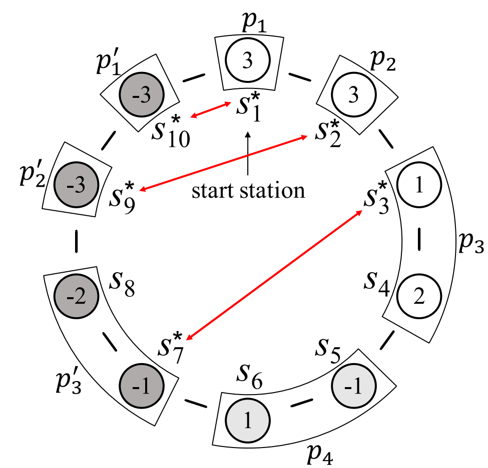


MATCH method

- l': l/2, complexity: $O(n^3)$, bound: 6.5
- Min-weight perfect matching:

  pos (l')., neg (l')., and zero pieces
- Visit each pair following the

  cycle clock-wise (random point)
- Cyclic-shift the sequence (real start)
- + and – initially balanced



l=6, l'=3, (**3**, 7, 8, 4, 5, 6, 9, 2, 10, 1)

Cyclic-shift: (**1**, 3, 7, 8, 4, 5, 6, 9, 2, 10)

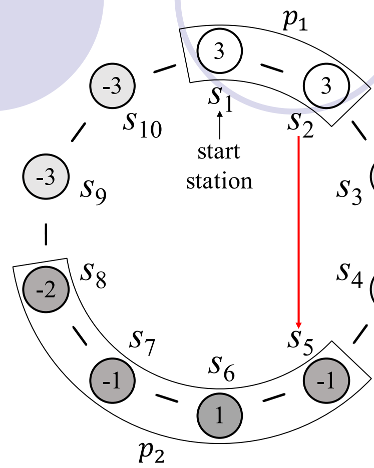
GREED Method

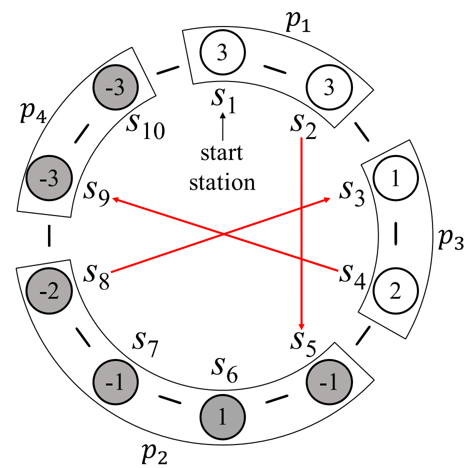
Assumptions

- Predefined Hamiltonian cycle
- Piece length limit: l'

GREED method

- l': l, complexity: $O(n^2)$
- Alternating pos. and neg. following the cycle clock-wise





(1, 2, 5, 6, 7, 8, 3, 4, 9, 10, 1)

HYBRID Method

MATCH

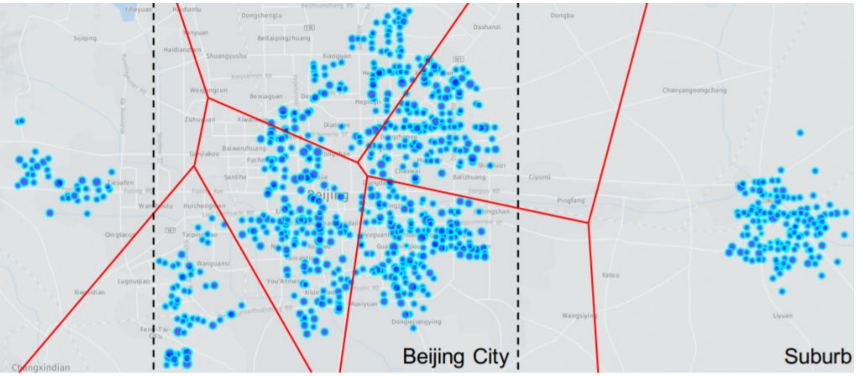
- Sparse mode (primary)
- Small geo-area (secondary)

GREED

- Dense model (primary)
- Large geo area (secondary)

HYBRID

- Two-level hierarchy
- MATCH for intra-cluster
- GREED for inter-cluster



(a) A sample distribution of dock stations in Beijing [26]

	MATCH	GREED	HYBRID
City	2.064	1.108	0.881
City+Suburb	3.016	1.923	1.080
City (Sparse)	1.435	1.781	1.342
City + Suburb (Sparse)	2.597	2.575	1.827

(b) MATCH, GREED, vs HYBRID

(Average per bike repositioning distance in km)

M. Charikar et al, Algorithms for capacitated vehicle routing, SIAM, 2001

Y. Duan, J. Wu, and H. Zheng, A greedy approach for vehicle routing, GLOBECOM, 2018

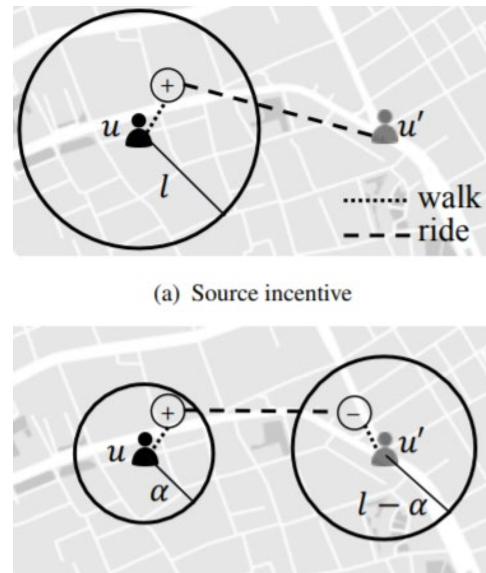
4. Re-balancing Through Workers

Through incentive

- Workers are BSS users
- Overflow: + and underflow: -
- Monetary award prop.to distance
- Reinforcement learning on setting the price

Dock-less incentive

- Source detour bounded by l
- Extensions with detour at both source and destination



(a) Source incentive

(b) Source and destination incentive

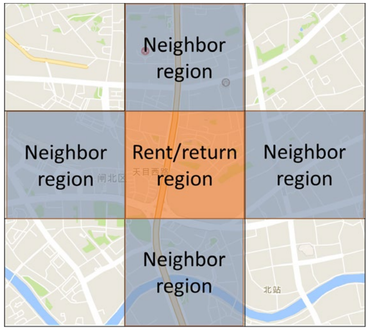
L. Pan et al, A Deeep Reinforcement Learning Framework for Rebalancing Dockless Bikesharing Systems, AAAI, 2019

Y. Duan and J. Wu, Optimizing Rebalance Scheme for Dockless Bike Sharing Systems with Adaptive Incentive, MDM, 2019

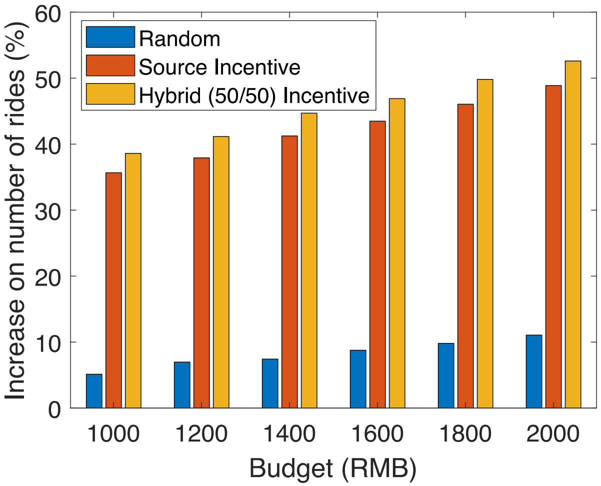
Incentive Simulation

Cost of detour δ

- 0 in original rent/return region
- $\eta\delta^2$ in neighbor regions
- $+\infty$ otherwise



Mobike Shanghai trace data



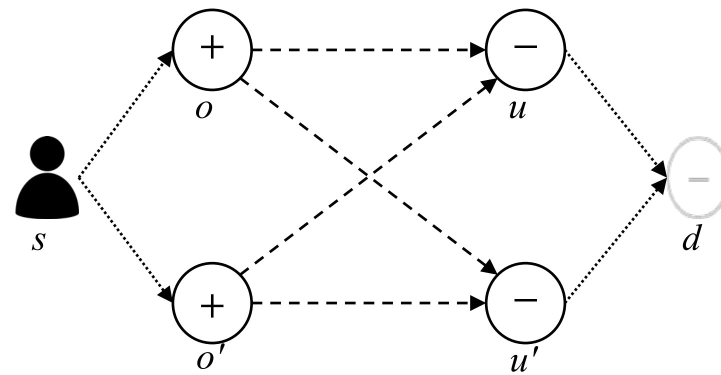
Incentive

- RL learns optimal prizing for different regions and slots
- Higher rent (return) incentive in overflow (underflow) regions

A Global Incentive Approach

Incentive

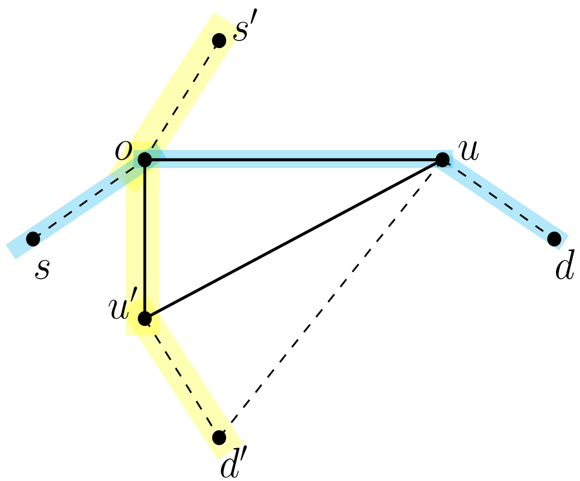
- For both dock and dock-less
- Deal with multiple workers
- Two rounds of perfect matching
  - Match overflow stations with underflow stations
  - Match users with station pairs



Y. Duan and J. Wu, Optimizing the crowdsourcing-based bike rebalancing scheme, IEEE ICDCS, 2019

Approximation

- 3-approximation
- Proof sketch:



Yellow: Optimal, Blue: 2-Round

Optimality of the two rounds of matching

$$\Sigma ou \le \Sigma ou'$$

$$\Sigma(so + ud) \le \Sigma(s'o + ud')$$

Triangle inequality

$$\Sigma ud' \le \Sigma(uu' + u'd')$$

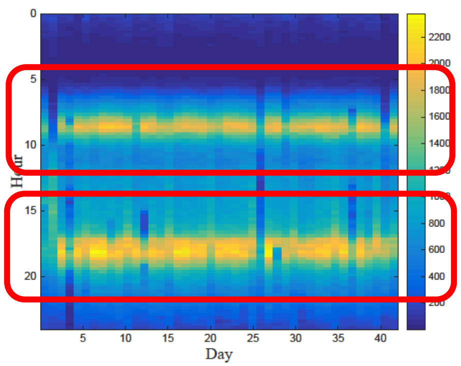
$$\Sigma uu' \le \Sigma(ou + ou')$$

Combining

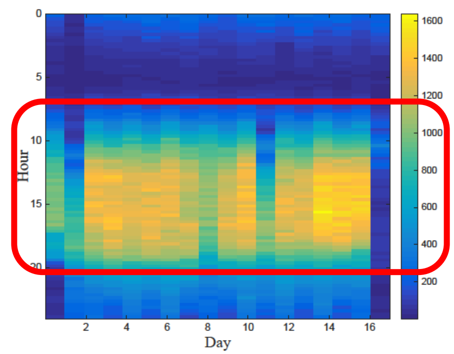
$$\Sigma(so + ou + ud) \le \Sigma(s'o + 3ou' + u'd') \le 3OPT$$

5. Spatial and Temporal Complexity

Traffic dynamic: NYC Citi Bike dataset

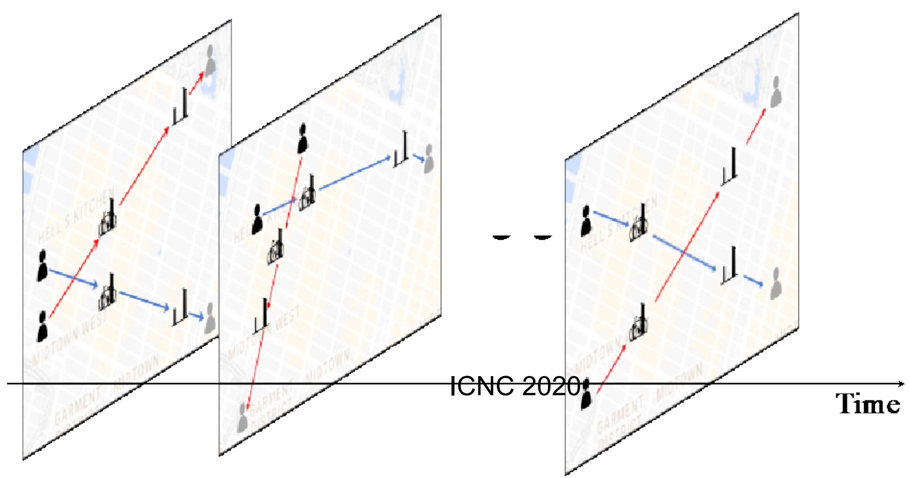


weekdays



weekends

Static vs. dynamic repositioning



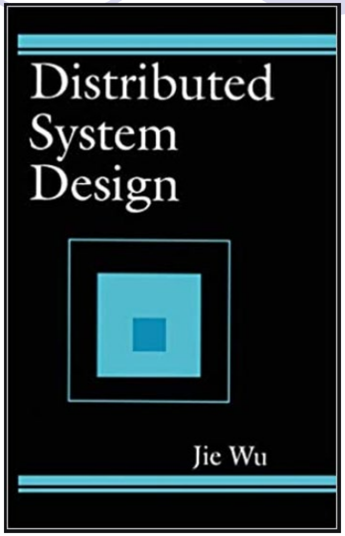
Time-Space View

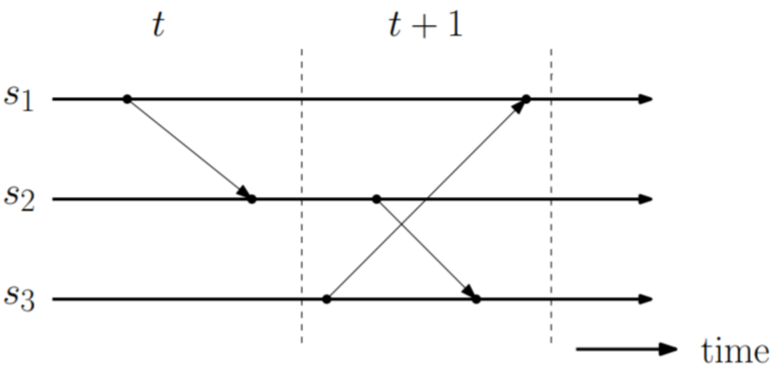
View

- Horizontal line
  - Status of local station
- Vertical dotted line (slot)
  - Time period between two slots
- Slanted arrow
  - Re-balancing event
- Cut: a re-balancing event go across two slots

Global state

- Local state
- Transition state

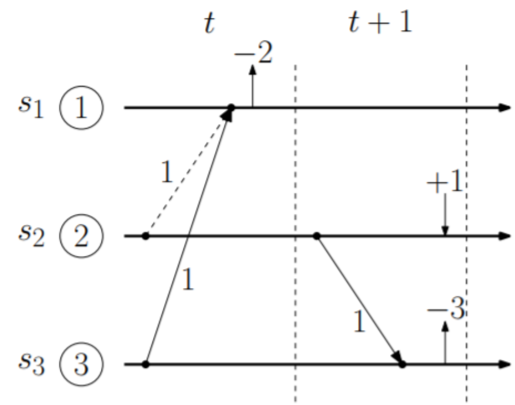




Frequency Reduction via Look-Ahead

K-hop look ahead

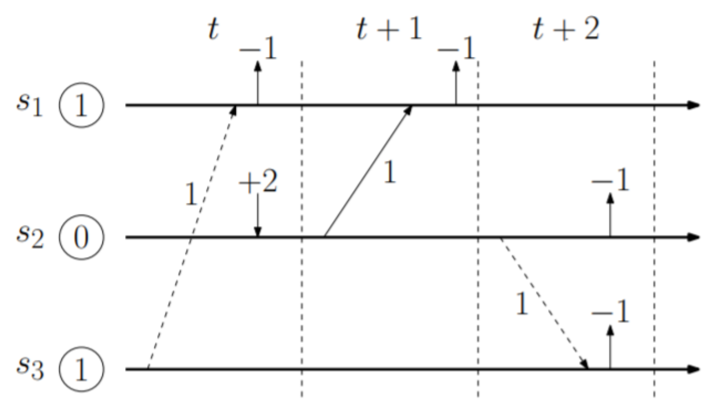
- Make minimum move in the current slot so that it can last at least k hops
- Reschedule after k slots



(a) An example of 2-hop look ahead outperforming 1-hop look ahead

Greedily look ahead

- Make move in the current slot so that it can last the longest (L)
- Reschedule after L slots



(b) An example of 1-hop look ahead outperforming greedily look ahead

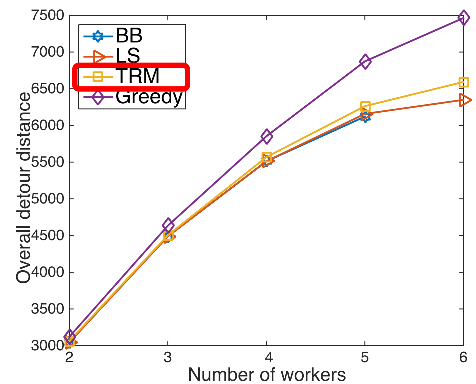
(a) and (b): solid lines for 1-hop

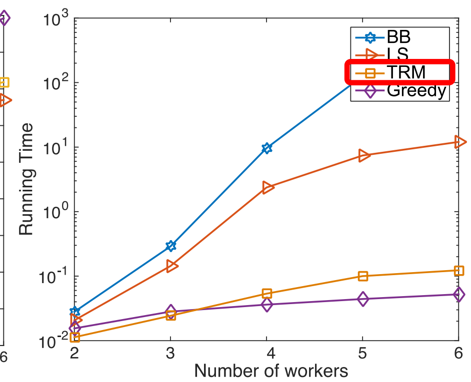
Spatial and Temporal Domain Simulation

Spatial domain

- On a single time slot
- Given rebalance targets
- Minimize worker detour

(BB: Branch & Bound , LS: Local Search, TRM: 2-Round Matching, Greedy: closest NYC Citi Bike)

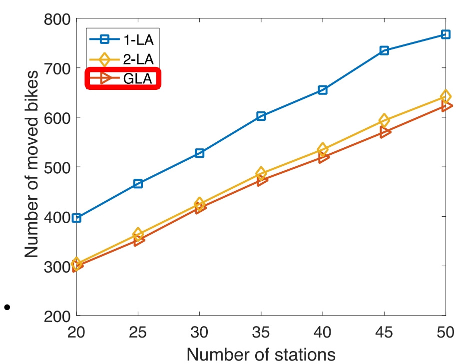


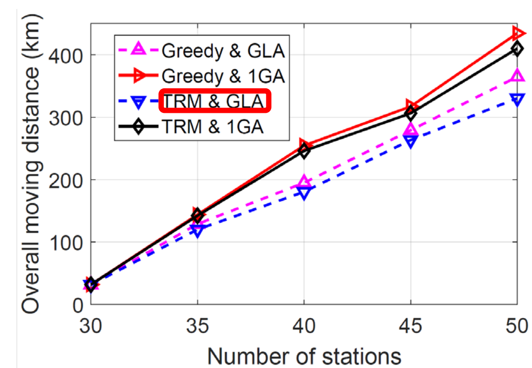


Temporal domain

- Over multiple time slots
- Minimize bike repositioning dis.

(1-LA: 1-hop, 2-LA: 2-hop, GLA: Greedily)

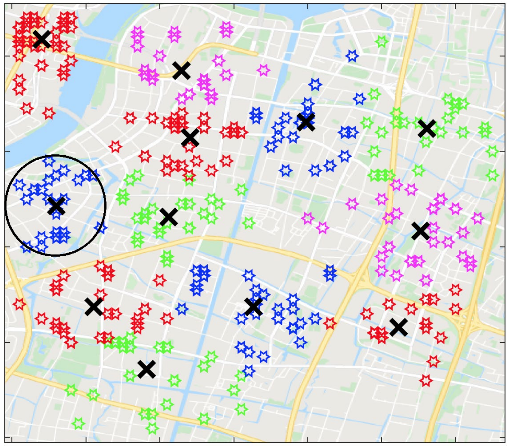




Extension to Dock-less Scenario

Virtual stations (VS)

- Mesh grid
- K-means
- Density-based clustering



Mobike Shanghai Dataset (08/01/16-08/31/16)

Rebalancing VS

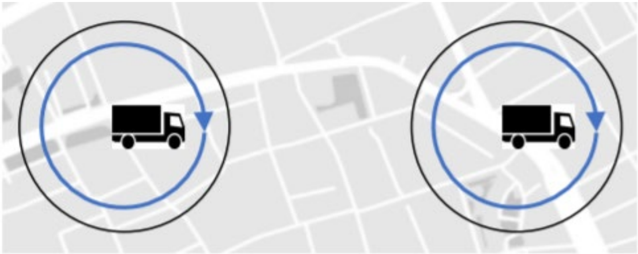
- Pick-up
  - nearest in starting VS
- Drop-off
  - nearest in destination VS

Y. Duan and J. Wu, Spatial-Temporal Inventory Rebalancing for Bike Sharing Systems with Worker Recruitment, accepted to appear in IEEE Transactions on Mobile Computing, 2020

6. Challenges and Opportunities

Model extensions

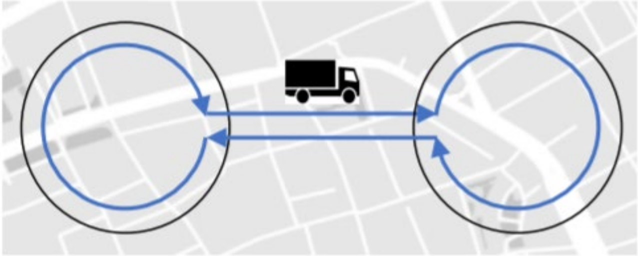
- Models with "cut"
- Repositioning spanning over one slot



(a) Two individual circles

Scalable design

- Geometric partitioning
- Clustering (k-means or density-based)
- Number of trucks used
- Scheduling of trucks



(b) One merged circle

J. Wu, Collaborative Mobile Charging and Coverage, JCST 2014

H. Zheng, N. Wang, and J. Wu, Minimizing Deep Sea Data Collection Delay With Autonomous Underwater Vehicles, *Journal of Parallel and Distributed Computing*, 2017

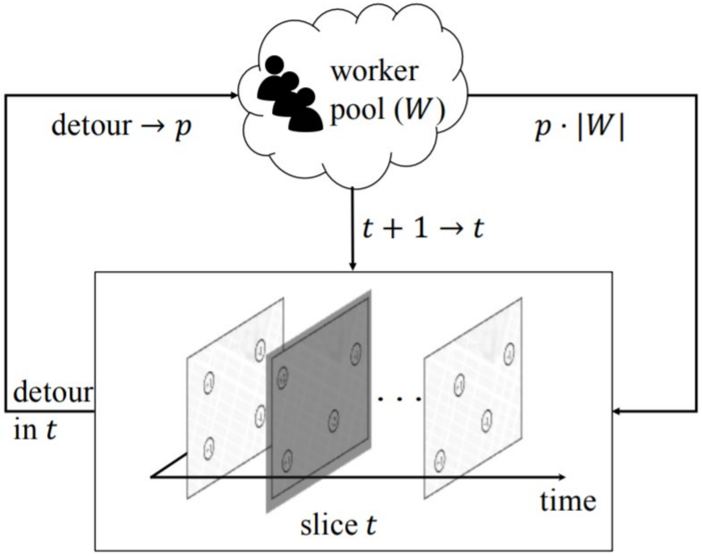
Challenges and Opportunities (Cont'd)

Other models

- Bike recycling (and usage balance)
- Robust solution (under data uncertainty)
- Economic models (mechanism design

Gaming and incentive

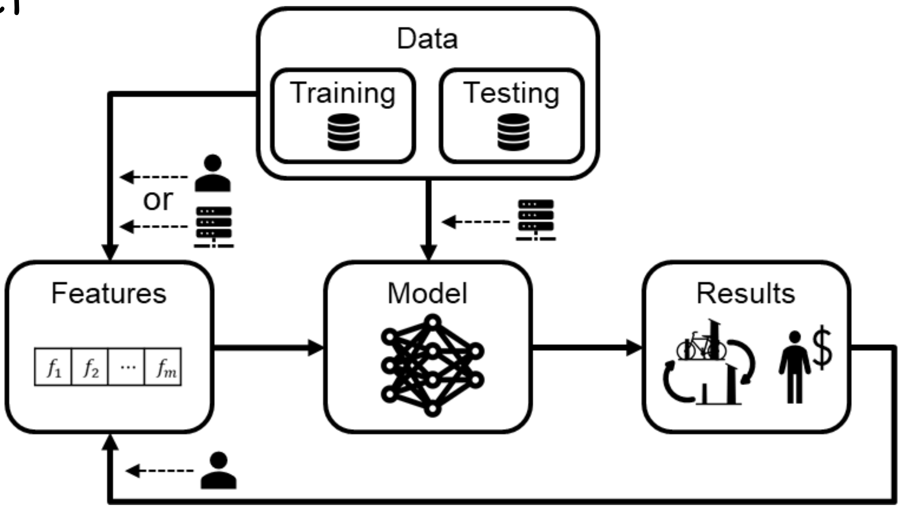
- Stakelberg and Nash games
  - Among BBS operators and workers
- Incentive
  - Reinforcement incentive



Challenges and Opportunities (Cont'd)

Machine Learning (ML)

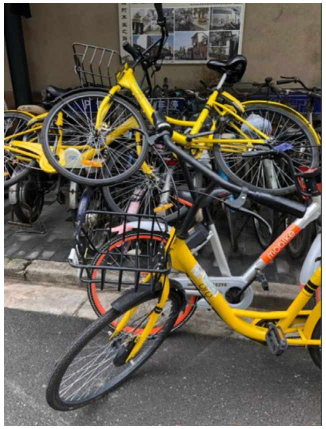
- Effectiveness
  - Learning from a large data set
  - Challenges: biased samples, data sparsity, data missing
- Robustness
  - Performance deviation due to the data perturbation
- Explainable AI
  - Hybrid approach



Challenges and Opportunities (Cont'd)

Dock vs. dock-less BSS

- Flexibility
- Manageability



Trends

- Dock-less BSSs have disappeared largely in US, JUMP from Uber
- Ofo, the largest dock-less BSS in China, suffered financially

A Bigger Picture: Classification

Active transportation

- Fixed (subway, bus, auto-shuttle)
- On-demand (taxi, Uber, DiDi, Lift)
- Hybrid (restricted on-demand)

Passive transportation

- ZipCar (first/last ten-mile)
- Bike/e-bike (first/last mile)
- Scooter/e-scooter (first/last mile)

J. Wu et al, Logarithmic Store-Carry-Forward Routing in MANETs, *IEEE Trans. on Parallel and Distributed Computing*, Aug. 2007..

A Bigger Picture: Future of BSSs

Future
- E-bike
- Two-wheeled e-scooters

Policy
- Shared responsibility
  - Credit systems
- Safety and regulation
  - Sidewalk, bike lanes, and car lanes
  - Scooter: sidewalk or bike lane?
  - How about folded-mini cars (MIT's CityCar Project)?
  - Regulation to enhance rebalancing?

7. Conclusions

- Bike Sharing Systems (BSSs)
  - Bike re-balancing issue

- Solutions
  - Algorithmic solutions
  - ML solutions with data analytics

- Future of BSSs
  - Policies and regulations
  - Role in a smart-city ecosystem

Questions

J. Wu, Challenges and Opportunities in Algorithmic Solutions for Re-balancing in Bike-Sharing Systems, *Tsinghua Science and Technology*, 2020.