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
- ...

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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

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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

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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 (in 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
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
- -l ≤ m ≤ l
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., neg., and zero pieces
- Visit each pair following the seq. in the cycle

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

(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

(Average per bike repositioning distance in km)


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

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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

L. Pan et al, A Deep 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 $\delta$
- 0 in original rent/return region
- $\eta \delta^2$ in neighbor regions
- $+\infty$ otherwise

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

Mobike Shanghai trace data
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:

Optimality of the two rounds of matching

\[ \Sigma ou \leq \Sigma ou' \]
\[ \Sigma (so + ud) \leq \Sigma (s'o + ud') \]

Triangle inequality

\[ \Sigma ud' \leq \Sigma (uu' + u'd') \]
\[ \Sigma uu' \leq \Sigma (ou + ou') \]

Combining

\[ \Sigma (so + ou + ud) \leq \Sigma (s'o + 3ou' + u'd') \leq 3OPT \]
5. Spatial and Temporal Complexity

Traffic dynamic: NYC Citi Bike dataset

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

**Global state**
- Local state
- Transition state
- *Cut*: a re-balancing event goes across two slots

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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

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

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

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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, 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

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

Mobike Shanghai Dataset (08/01/16-08/31/16)
6. Challenges and Opportunities

Model extensions
- Models with “cut”
- Repositioning spanning over one slot

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

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

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