Optimal Bluebikes rebalancing strategies


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Executive summary

Bluebikes is Boston's bikeshare program, giving access to more than 4000 bikes across just under 450 stations. In August 2022, it reached a record of 500,000 monthly trips. With the rising popularity of the service, users regularly struggle to find bikes at rush hour.

In this study, we provide efficient **rebalancing strategies** using vans to relocate bikes considering estimated demand, **reducing unmet demand by 86%.**

Problem statement

A viable solution is to use vans to move bikes from one station to another, freeing up docks at full stations and refilling empty stations. For example, relocating bikes from MIT to surrounding residential areas enables more students to bike to class.

Bluebikes currently employs 4-5 rebalancing vans to dynamically redistribute bikes based on real-time system data. In this project, we aim to provide BlueBikes with data-driven rebalancing strategies, in order to **minimize unmet demand** while keeping **rebalancing costs reasonable**.

In this study, we focus on the **top 30 active stations** in terms of monthly trips, covering 50% of trips. We use **individual-level trip data** provided Bluebikes, as well as real-time information about the Bluebikes system provided in the context of the General Bikeshare Feed program (GBFS).

? Demand estimation

Estimating demand is critical in order to efficiently reallocate bikes between high and low traffic stations. While accurately estimating demand between pairs of station is a complex task, it can be **approximated** with a few assumptions.

- *Non-saturated* stations ⟶ Demand = actual #trips
- *Saturated* stations ⟶ Demand = actual #trips + ε

Optimization model

Decision variables: vans routing, users trips, bikes inventory

Multi-objective function:
We seek to minimize unmet demand, while keeping the total distance traveled by the vans reasonable (trade-off λ)

Minimize (demand - #trips) + $\lambda *$ distance

Constraints:

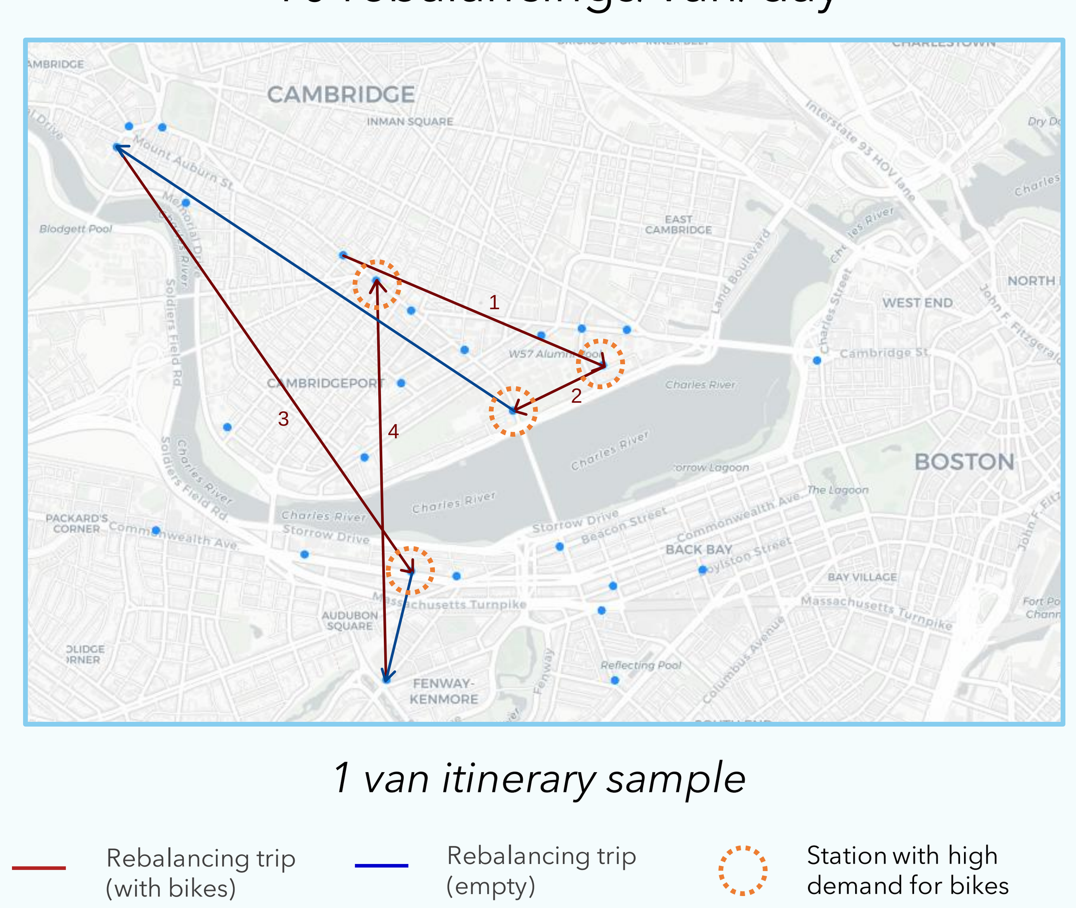
- **Stations capacity:** Each station has a limited capacity:
  $$\forall t:\ n_t \leq C$$
- **Stations flow balance:** The number of bikes at each station is balanced with the number of bikes picked up and dropped off by users (f_{out}, f_{in}) and by vans (r_{out}, r_{in}):
  $$\forall t:\ n_t = n_{t-1} - f_{out} + f_{in} - r_{out} + r_{in}$$
- **Bikes availability:** Users can only pick up bikes when available, and drop off bikes when docks are available
- **Vans capacity:** Vans can carry a limited number of bikes
- **Feasibility:** Vans can only rebalance neighboring stations
- **Granularity:** Max one rebalancing trip per van per hour

Granularity: hourly

Results

Simulation for 30 top stations and 5 vans:

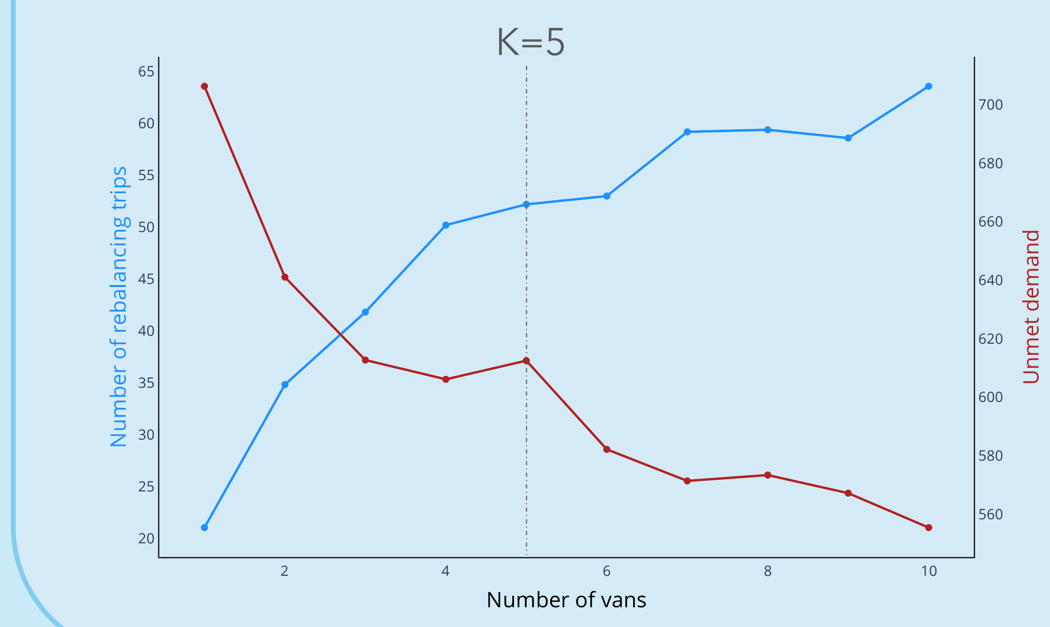
~10 rebalancings/van/day



1 van itinerary sample

Key findings

Simulations for different numbers of vans (K)



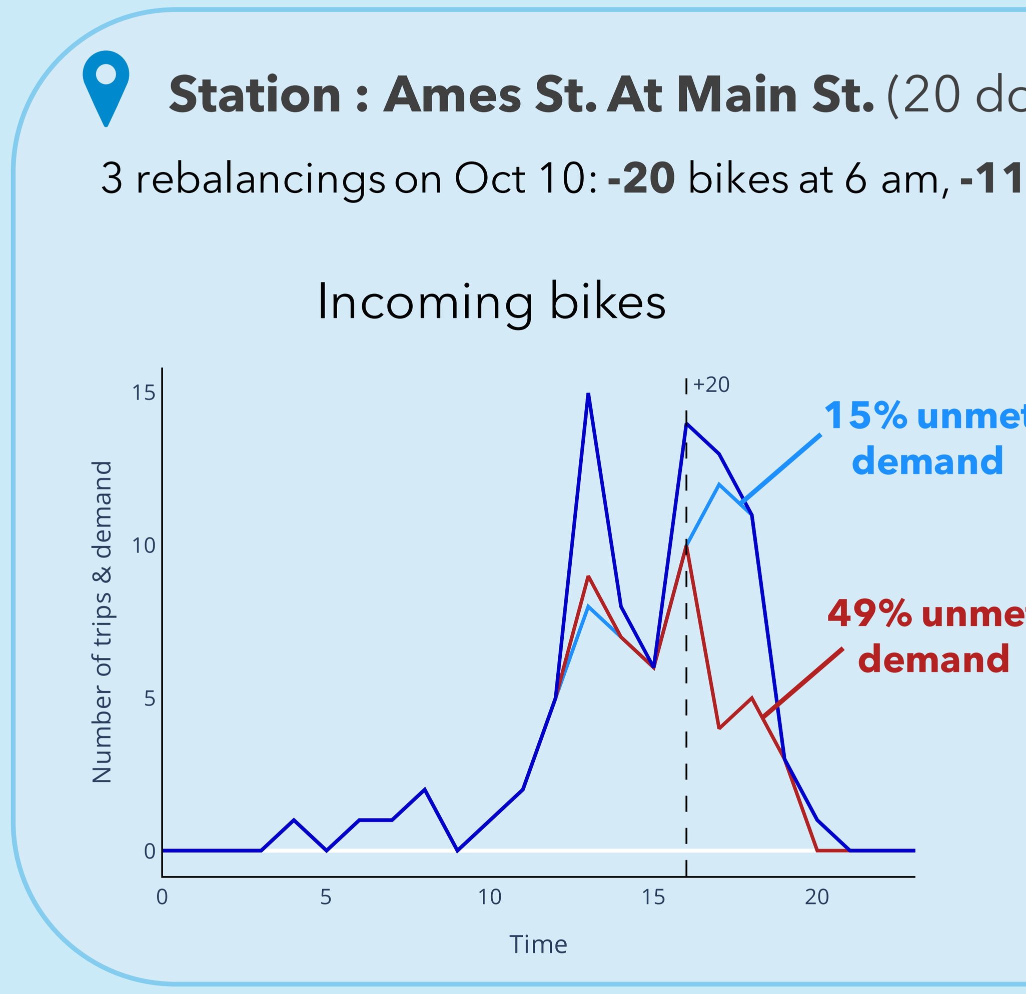
Our rebalancing strategies contribute to reducing unmet demand significantly

K=5 provides a good **trade-off** between **unmet demand** and **costs**

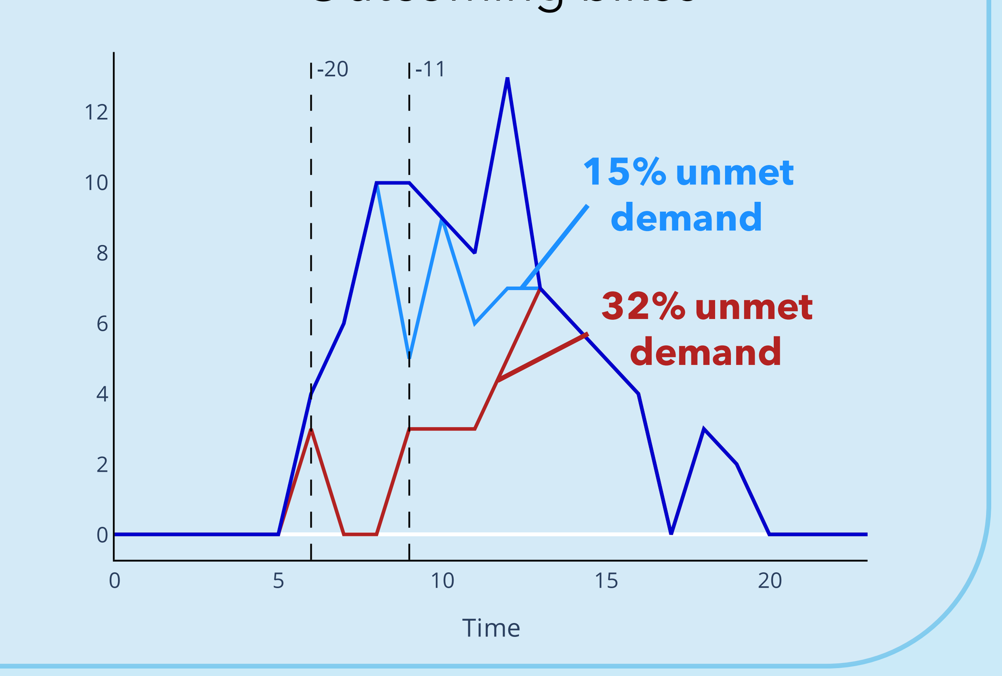
Station : Ames St. At Main St. (20 docks)

3 rebalancings on Oct 10: **-20** bikes at 6 am, **-11** bikes at 9 am, **+20** bikes at 4 pm

Incoming bikes



Outcoming bikes



Impact

Improve mobility by increasing access to sustainable and healthy transportation

- 47% Overall unmet demand reduction

+500 Additional user trips per day (+4%)

Next steps

- **Robustness:** Model uncertainty on trips demand to generate robust rebalancing solutions
- **Scaling:** Simulate optimal rebalancing over the 450 stations
- **Cost-effectiveness:** Penalize non-use of vans between two rebalancings to reduce labor costs
- **Granularity:** Increase time granularity to better model real-time demand between stations and need for rebalancings