Robust Repositioning to Counter Unpredictable Demand in Bike Sharing Systems

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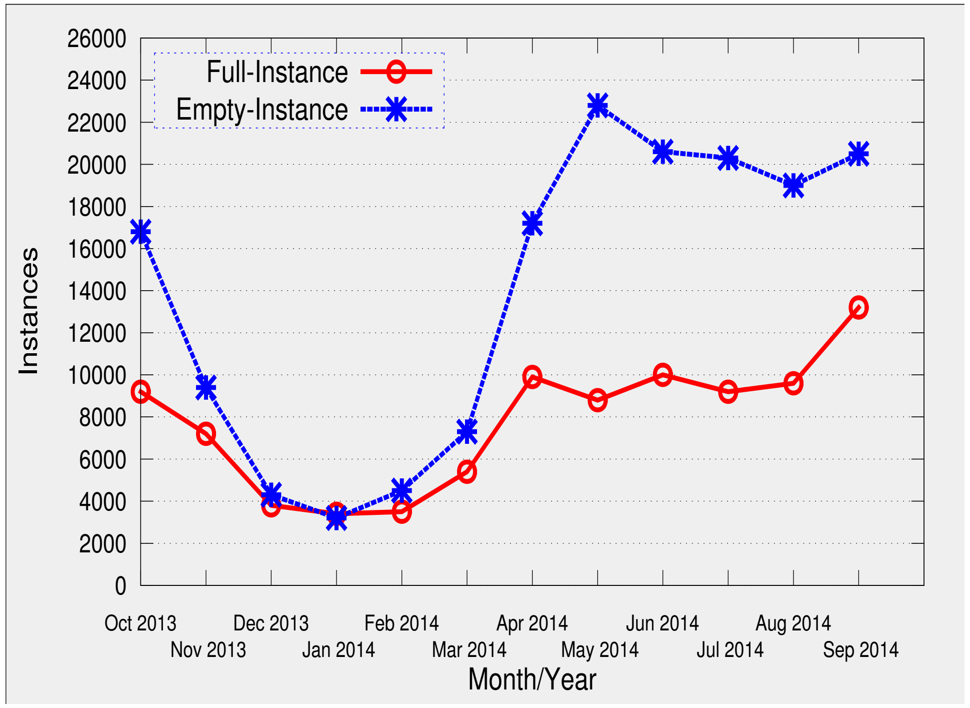
Motivation: Bike Sharing Systems

- Bike Sharing Systems
  - 1,070 active systems all over the world.
  - Ex: Capital Bikeshare (Washington DC), Hubway (Boston), Vélib'(Paris)
- **Problem**: Low availability of bikes at base stations due to uncoordinated movements.

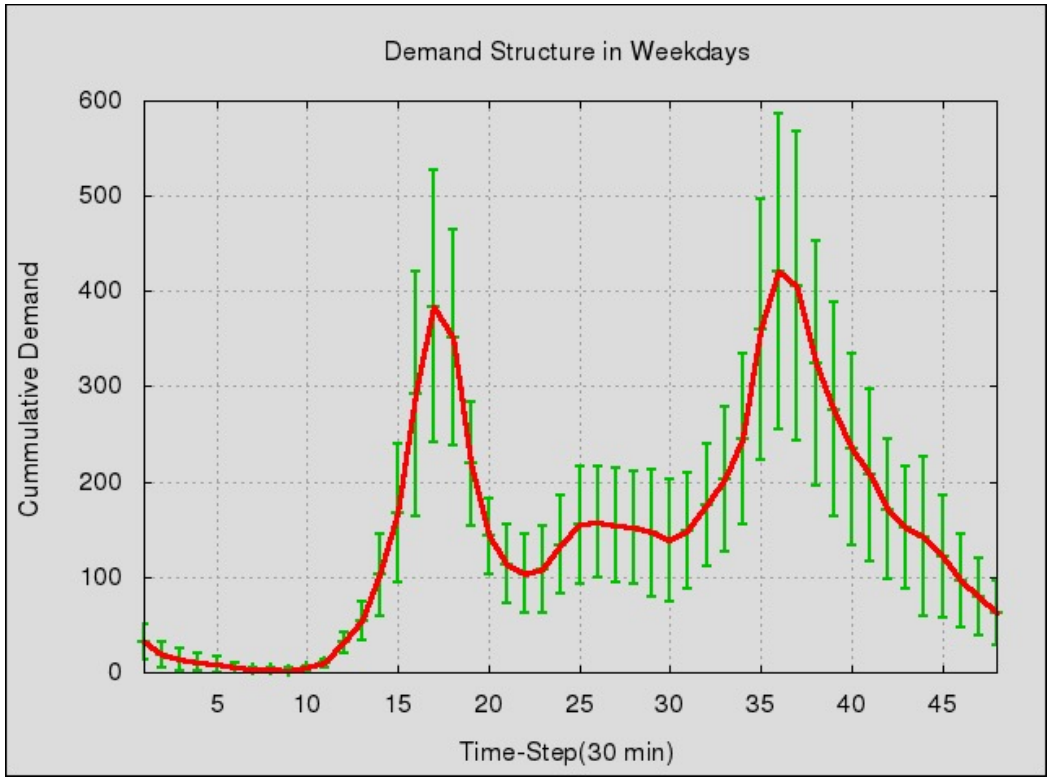


Starvation/congestion in Capitalbikeshare

- **Goal:** Robust & dynamic repositioning to address availability issues

Background & Contributions

- Static repositioning (at the end of day)
  - Raviv and Kolka (2013), Raidl et al. (2013)
- Dynamic repositioning (myopic & offline)
  - Schuijbroek et al. (2013), Shu et al. (2013)
- Existing solutions do not capture uncertainty in future demand
- Demand has higher variance for densely populated cities

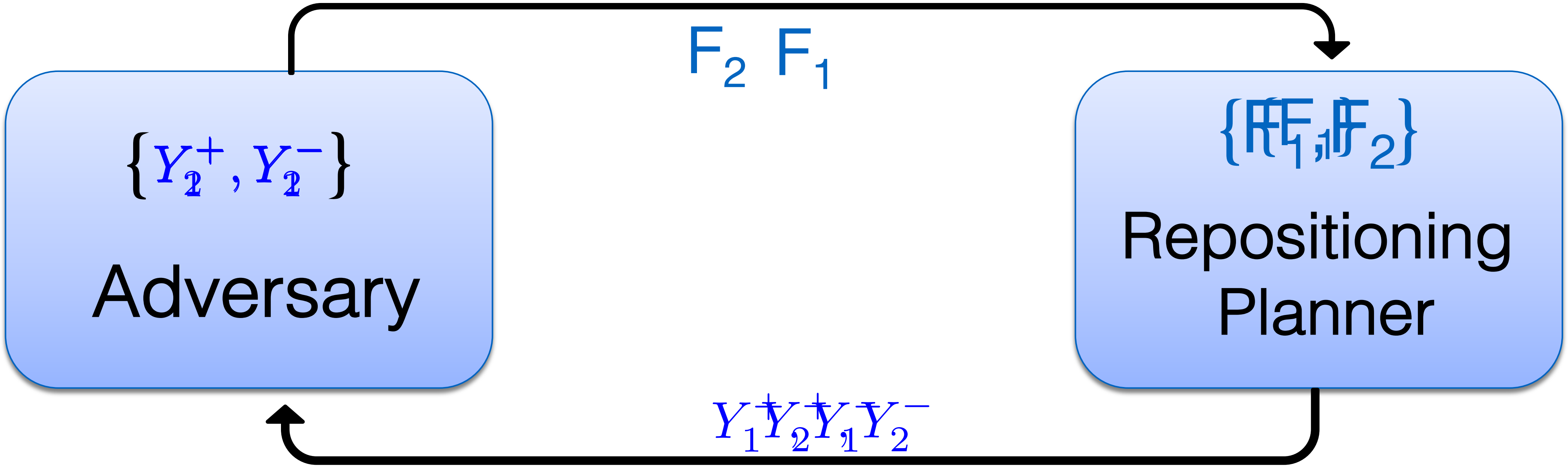


Uncertainty (higher variance) in demand

- **Contributions:**
  - We formally represent the **D**ynamic **R**epositioning and **R**outing **P**roblem under demand **U**ncertainty [**DRRPU**]
  - Propose an iterative two player game between the decision maker and the environment acting as an adversary to solve the *DRRPU*.
  - Execute the policy online using a simulation built on real world data set.

Solution Methodology

- Input: **DRRPU** tuple $< \mathcal{S}, \mathcal{V}, \mathbf{C}^{\#}, \mathbf{C}^{*}, \mathbf{d}^{\#,\mathbf{0}}, \mathbf{d}^{*,\mathbf{0}}, \mathbf{P}, \check{\mathbf{F}}, \hat{\mathbf{F}} >$
- Outputs: Repositioning & routing strategy $< \mathbf{Y}^{+}, \mathbf{Y}^{-}, \mathbf{Z} >$



F_2 F_1

$\{Y_2^+, Y_2^-\}$ / $\{Y_1^+, Y_1^-\}$

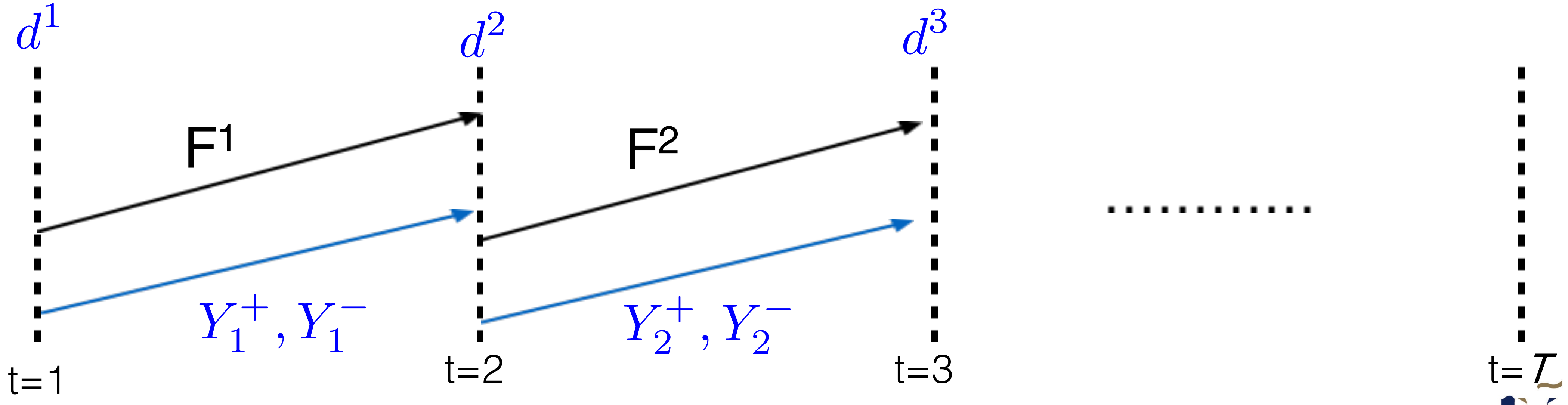
Adversary

$\{F_1, F_2\}$

Repositioning Planner

$Y_1^+ Y_2^+ Y_1^- Y_2^-$

- **Policy execution:** Simulate policy along with flow of bikes by customers



Adversary Model

Redeployment Strategy

Demand Bounds

Distribution of bikes

Inputs: $d^{\#}, \overbrace{Y^{+}, Y^{-}}, \overbrace{\check{\mathcal{F}}, \hat{\mathcal{F}}}$

MILP:

$$\max_{F} \sum_{s} L_s$$

Maximise lost demand

$$s.t. \quad L_s = \underbrace{max(0, \sum_{s'} F_{s,s'} - (d^{\#}_s + Y^{-}_s - Y^{+}_s))}_{LostDemand}, \forall s$$

Compute lost demand

$$F \in [\check{\mathcal{F}}, \hat{\mathcal{F}}] \Rightarrow \boxed{\begin{array}{ll} \check{F}^t \leq \sum_{s,s'} F_{s,s'} \leq \hat{F}^t & \\ \check{F}^t_s \leq \sum_{s'} F_{s,s'} \leq \hat{F}^t_s, & \forall s \\ \check{F}^t_{s,s'} \leq F_{s,s'} \leq \hat{F}^t_{s,s'}, & \forall s, s' \end{array}}$$

Demand scenario follows input bounds on demand

Repositioning Model

Inputs: $d^{\#}, \overbrace{F^1, F^2, ..., F^k}$

k demand scenarios

Distribution of bikes

MILP:

$$\min_{y,z} \ \max_{k} \sum_{s} L_s^k$$

Minimise worse case Lost demand

$$s.t.\ L_s^k \geq \underbrace{\sum_{s'} F^k_{s,s'}}_{Demand} - \underbrace{(d_s^{\#} + \sum_{\hat{t},v}(y_{s,v}^{-,\hat{t}} - y_{s,v}^{+,\hat{t}}))}_{Supply}, \ \forall s, k$$

Compute Lost Demand

$$y^{+}, y^{-} \in \phi(z, d^{\#})$$

Follow additional routing constraints

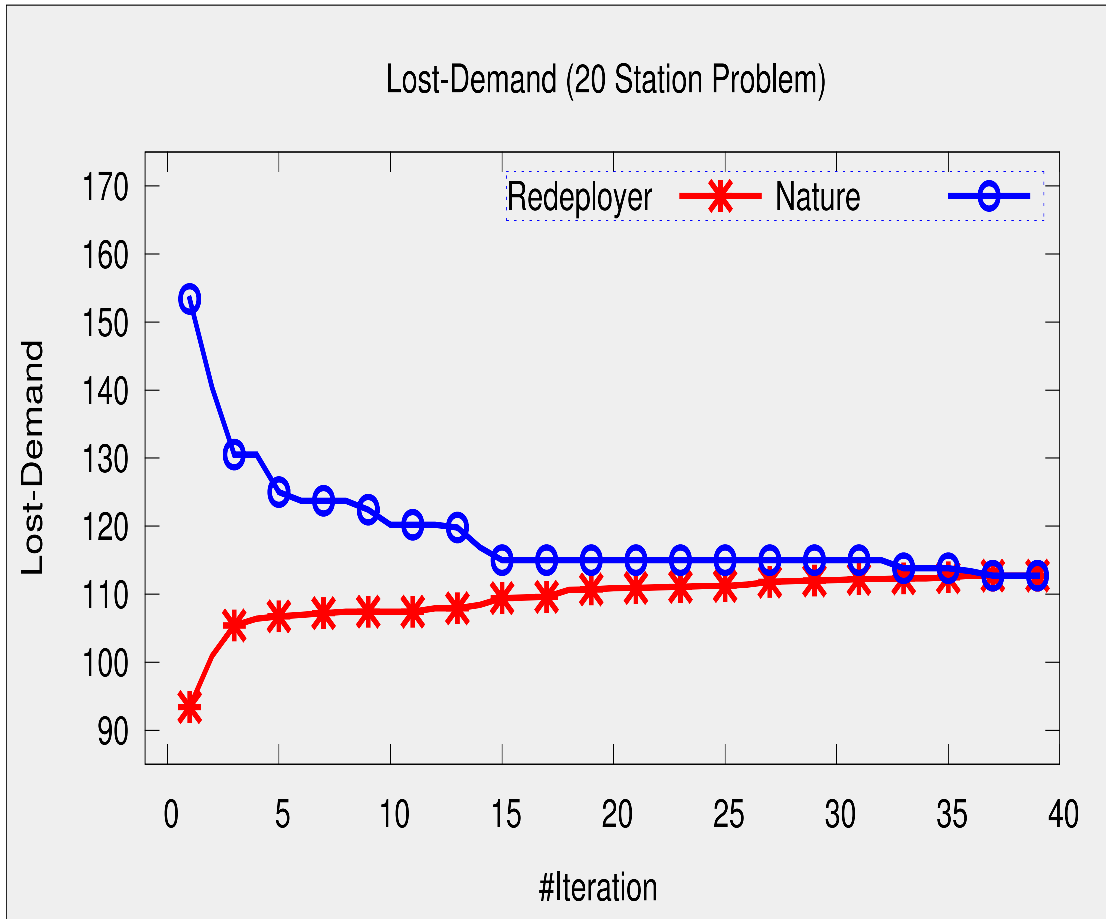
1. Carrier vehicle flow (routing) preservation constraints.
2. Routing distance of carrier is bounded by a threshold value.
3. Carrier can pickup/drop-off bikes if it is present in the station.
4. Bike flow preservation in the carriers.

Experimental Results

- **Dataset:** Hubway BSS of Boston (95 stations, 3 carrier vehicles)
  - Trip history data for 3 months
  - Planning period: 6AM-12PM (each decision epoch is 30 minutes)
- **Evaluation Metrics:** Average, standard deviation and maximum lost demand (computed over 100 demand scenarios)

- **Benchmark Approaches:**
  - Static (Redeployment at the end of day)
  - Myopic (Fill a fixed percentage of the station inventory)
  - Online (Schuijbroek *et. al.*,2013)

- **Scenario Generation approach:**
  - Gap reduces monotonically
  - At convergence, guarantees an upper bound on the lost demand



Convergence of scenario generation approach

Lost Demand Statistics on Hubway Data set

1. **Real world demand scenarios** (18% & 10% reduction in average and worse case lost demand)

	Static	Myopic	Online	Robust
Average	329	407	303	248
STDEV	98	109	99	83
Maximum	562	667	544	490

2. **Demand follows Poisson at each station** (27% & 19% reduction)

Average	198	281	183	133
STDEV	27	40	32	28
Maximum	276	367	260	211

3. **Demand follows Poisson for each OD pair** (18% & 16% reduction)

Average	231	314	205	167
STDEV	37	50	34	33
Maximum	309	428	290	244

Conclusion

- **Online and robust repositioning in BSS**:
  - A practically important and challenging problem.
  - A two-player iterative game approach to counter unavailability of bikes (with unpredictable demand).
  - Employed a simulation build on real-world data set for policy execution and performance validation.
  - Lost demand (average) is reduced by at least **18%**.
  - Solution is robust to uncertainty in future demand.

Q & A

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Redeployment planner

$$\min_{y,z} \max_{k} \sum_{s} L_s^k$$

Minimise worse case lost demand

$$\textbf{s.t.}\ L_s^k \geq \underbrace{\sum_{s'} F_{s,s'}^k}_{Demand} - \underbrace{(d_t^{\#} + \sum_{\hat{t},v}(y_{s,v}^{-,\hat{t}} - y_{s,v}^{+,\hat{t}}))}_{Supply},\ \forall s, k$$

Compute Lost Demand

$$\underbrace{\sum_{k\in S} z_{s,k,v}^{\hat{t}}}_{Outflow} - \underbrace{\sum_{k\in S} z_{k,s,v}^{\hat{t}-1}}_{Inflow} = \sigma_v^t(s), \qquad \forall \hat{t}, s, v$$

Carrier Flow Preservation

$$d_v^{*,\hat{t}} + \sum_{s\in S}[(y_{s,v}^{+,\hat{t}} - y_{s,v}^{-,\hat{t}})] = d_v^{*,\hat{t}+1}, \qquad \forall \hat{t}, v$$

Bike Flow Preservation
in Carriers

$$y_{s,v}^{+,\hat{t}} + y_{s,v}^{-,\hat{t}} \leq C_v^* \cdot \sum_{i\in S} z_{s,i,v}^{\hat{t}}, \qquad \forall \hat{t}, s, v$$

Redeployment Constraints

$$\alpha \underbrace{\sum_{\hat{t},s,s'} D_{s,s'} z_{s,s',v}^{\hat{t}}}_{TravelTime} + \underbrace{M \sum_{\hat{t},s}(y_{s,v}^{+,\hat{t}} + y_{s,v}^{-,\hat{t}})}_{Pickup/DropoffTime} \leq T, \qquad \forall v$$

Physical Consequence
of Routes

Simulation Model

- Compute the flow of bikes by the customers

$$x^t_{s,s'} = \left\{ \begin{array}{ll} f^t_{s,s'} & \textbf{if } \sum_{s'} \overset{\text{Demand}}{f^t_{s,s'}} \leq \overset{\text{Supply}}{d^{\#,t}_s} \\ \frac{f^t_{s,s'}}{\sum_{\tilde{s}} f^t_{s,\tilde{s}}} \cdot d^{\#,t}_s & \textbf{Otherwise} \end{array} \right\}$$

- Compute distribution of bikes for next decision epoch

$$d^{\#,t+1}_s = d^{\#,t}_s + \underbrace{\Big[\sum_{\tilde{s}} x^t_{\tilde{s},s} - \sum_{s'} x^t_{s,s'}\Big]}_{\text{Net inflow of bikes by customers}} + \underbrace{\Big[Y^{-,t+1}_s - Y^{+,t+1}_s\Big]}_{\text{Net drop-off bikes by carrier vehicles}}$$