Improving Customer Satisfaction in Bike Sharing Systems through Dynamic Repositioning

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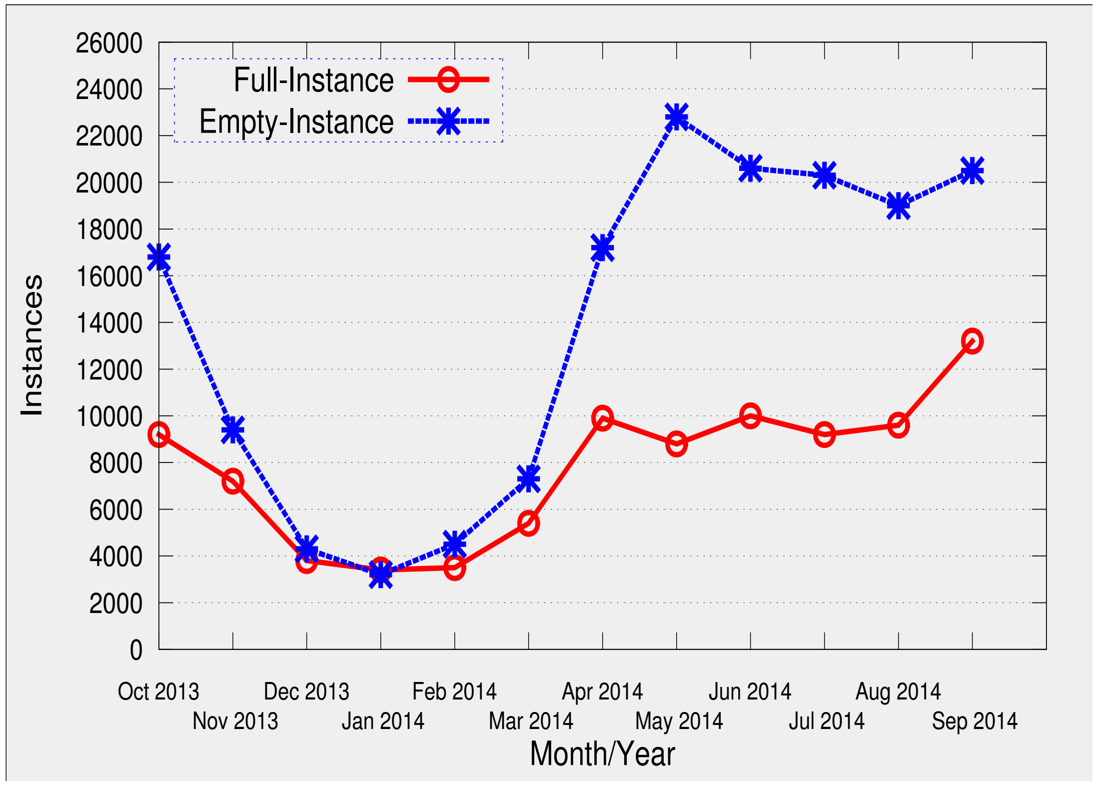
Motivation: Bike Sharing Systems

- **Bike Sharing Systems (BSS)**
  - 1700 active systems all over the world
  - Attractive alternative to private vehicles
  - Reduce traffic congestion, green house gas emission and air pollution

World view of bike sharing systems

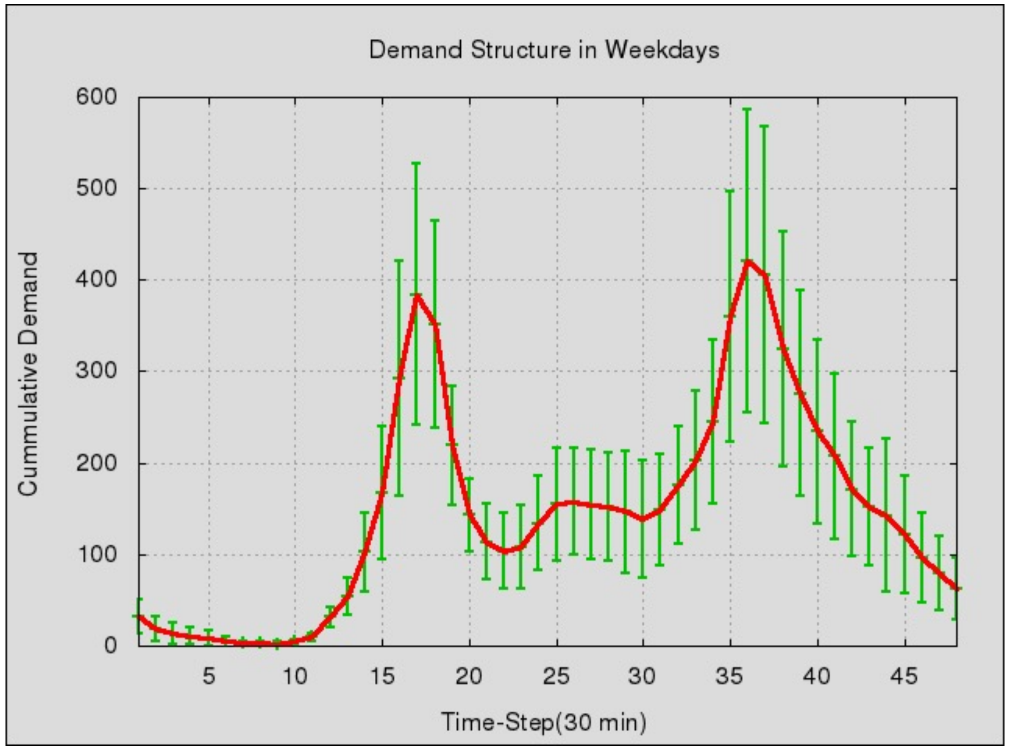
- **Problem**: Starvation or congestion of bikes at stations
  - Increase usage of private vehicle and carbon emission
- **Goal:** Repositioning of bikes during the day to address availability issues



Starvation/congestion in Capitalbikeshare

Background: Repositioning in Bike Sharing

- 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)
- Repositioning using incentives
  - Singla et. al. (2015), Ghosh et al. (2017)
- Robust repositioning under demand uncertainty
  - Ghosh et. al. (2016)
- Our contribution:
  - Using satisficing approach to tackle the demand uncertainty



Uncertainty (higher variance) in demand

Satisficing Approach

- Tractable satisficing approach [Jaillet et. al. 2016]
  - Constraints are defined over uncertain variables.
  - Maximize the probability of satisficing feasibility constraints.

$$\max \ \rho(\boldsymbol{\alpha})$$
$$\text{s.t. } \boldsymbol{A}(\boldsymbol{z})\boldsymbol{x} \geq \boldsymbol{b}(\boldsymbol{z}) \ \forall \boldsymbol{z} \in \mathcal{U}(\boldsymbol{\alpha})$$

Family of uncertainty set

Uncertain parameter

Uncertain variable

- Taking satisficing approach to bike-sharing system
  - Support set for station s:

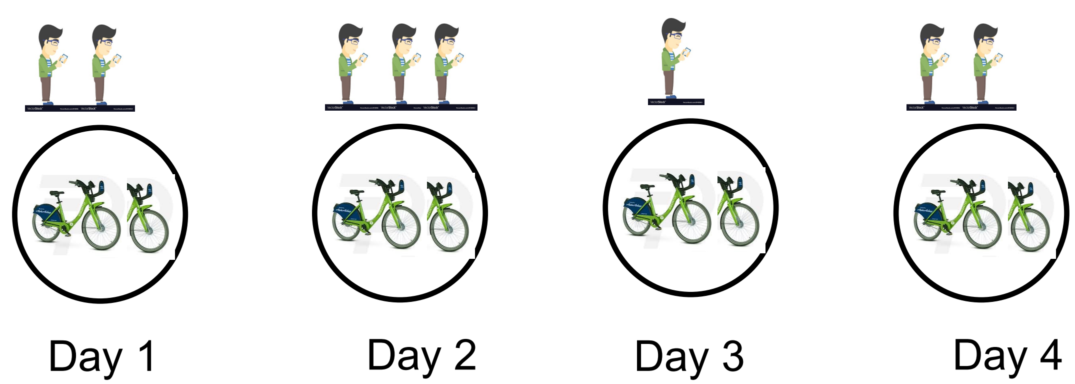
$$W_s = \{\zeta_s^1, ..., \zeta_s^n\} = \{1, 2, 3\}$$

  - Realization probability:

$$\lambda_s^2 = P(\bar{z}_s \leq 2) = 3/4$$

  - Objective:

$$\max \sum_s \log(P(\bar{z}_s \in W_s))$$



Optimization Model

- Input tuples: $\mathcal{S}, \mathcal{V}, \boldsymbol{C}^{\#}, \boldsymbol{C}^{*}, d^{\#,0}, \{\sigma_v^0\}, \boldsymbol{P}, \boldsymbol{F}$

  - $\mathcal{S}$: Stations
  - $\mathcal{V}$: Vehicles
  - $\boldsymbol{C}^{\#}$: Station Capacities
  - $\boldsymbol{C}^{*}$: Vehicle Capacities
  - $d^{\#,0}$: #bikes in stations
  - $\{\sigma_v^0\}$: #vehicles in stations
  - $\boldsymbol{P}$: Routing Costs
  - $\boldsymbol{F}$: demand Scenarios

- Outputs: Repositioning & routing strategy

- Decision Variables:

$$\alpha_s^l \in \{0,1\} : 1 \text{ if } \zeta_s^l \text{ is selected as demand bound}$$

$$y_s^+, y_s^- : \text{Total number of biles picked up and dropped off from station s}$$

$$z_{s,v}^r \in \{0,1\} : \text{ Set to 1 if vehicle } v \text{ is stationed at } s \text{ at episode } r$$

- Objective:

$$\max_{\boldsymbol{y}^+, \boldsymbol{y}^-} \sum_s \sum_l \alpha_s^l \log(\lambda_s^l)$$

Realization probability of *l-th* demand entry in support set (λ_s^l)

Maximize log-likelihood of meeting realized (uncertain) demand

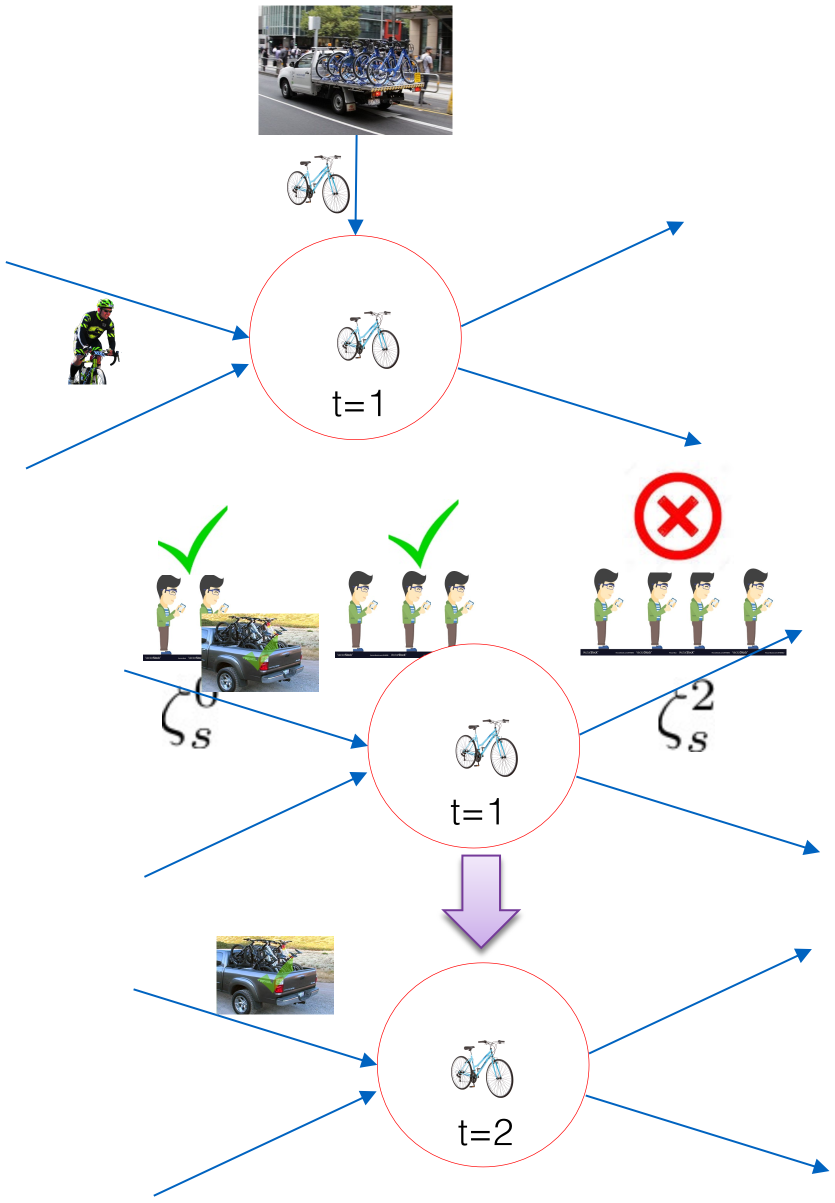
Problem Constraints

- Feasibility constraints

$$\sum_l \zeta_s^l \alpha_s^l \leq d_s^{\#} + y_s^- - y_s^+ + \rho_s \quad \forall s$$

$$\sum_l \zeta_s^l = 1 \; ; \quad \sum_s \rho_s \leq \rho$$

- Routing constraints:
  - A vehicle can only be at one station at any episode.



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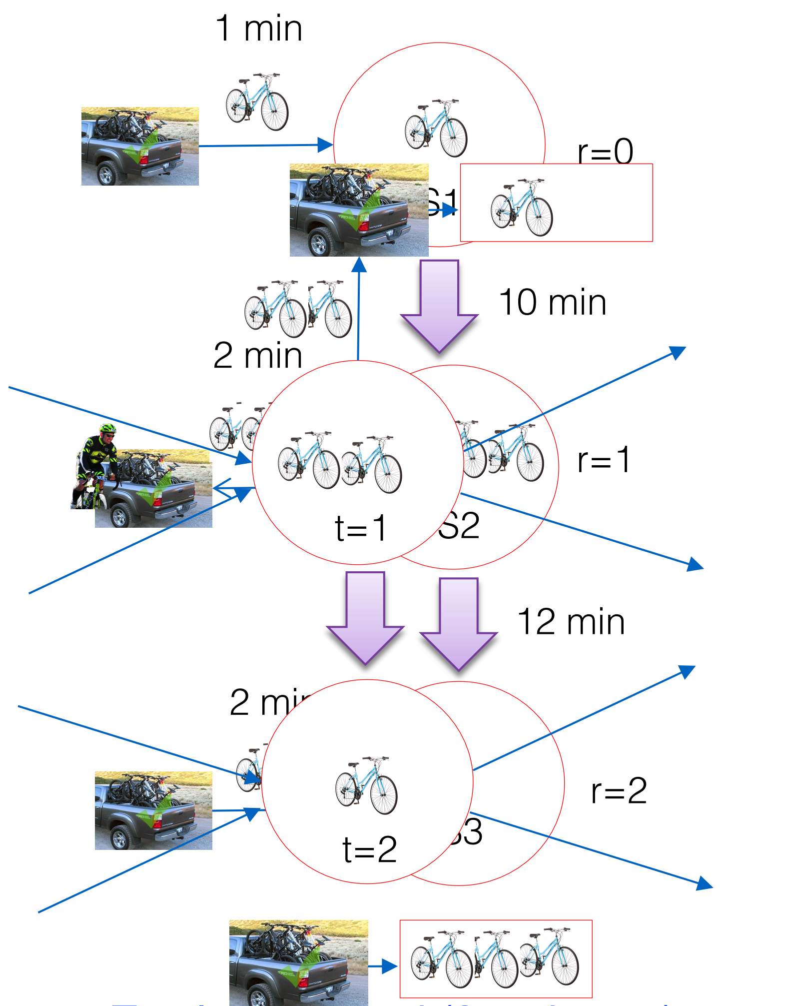
- Routing constraints:
  - A vehicle can only be at one station at any episode.
  - Time spend in routing & repositioning is bounded by duration of decision period.
- Repositioning constraints
  - Flow preservation of bikes at vehicles.
  - Reposition at a station is possible only if a vehicle is present there.

$$y_{s,v}^{+,r} + y_{s,v}^{-,r} \leq C_v^* \cdot z_{s,v}^r \qquad \forall s, v, r$$

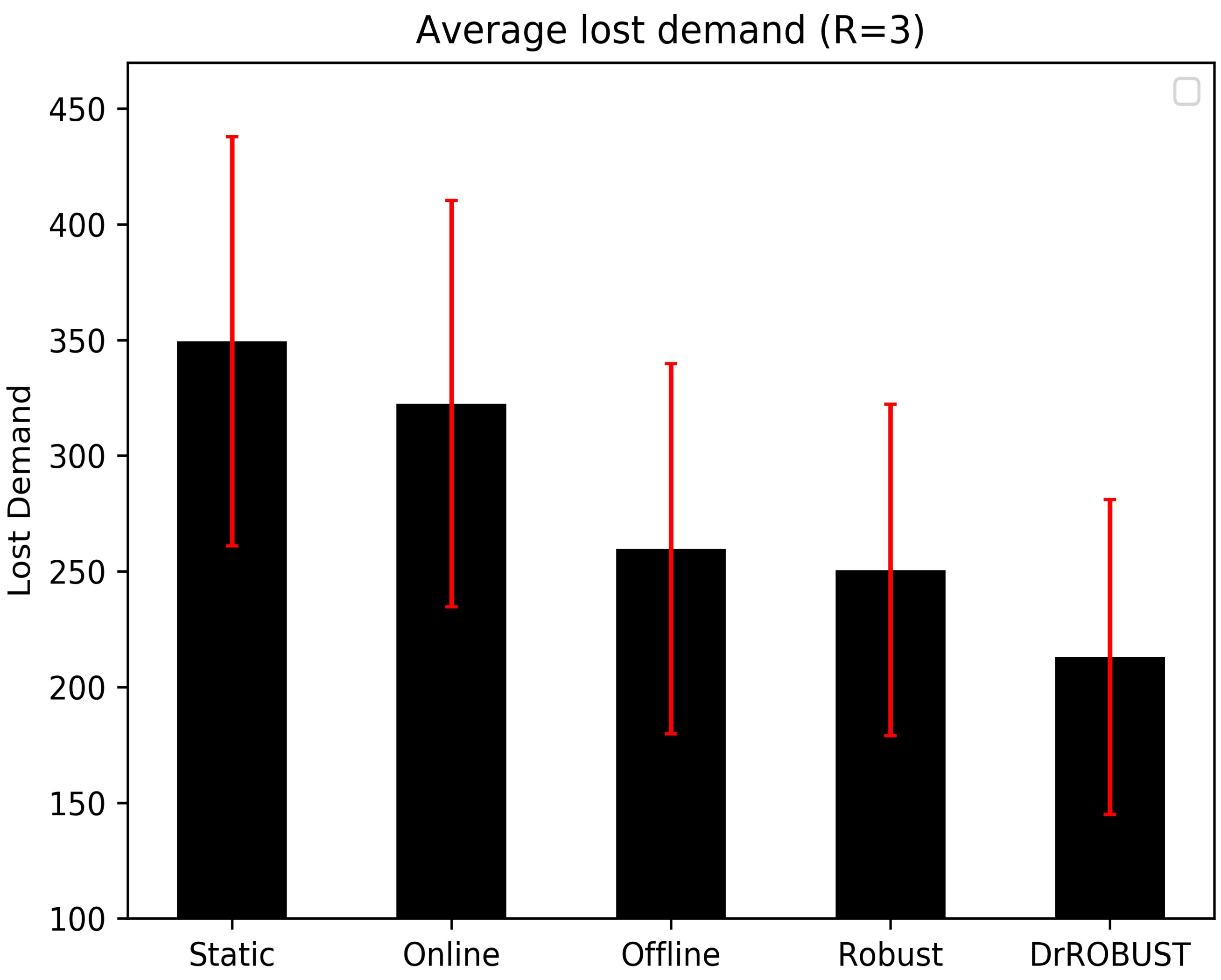


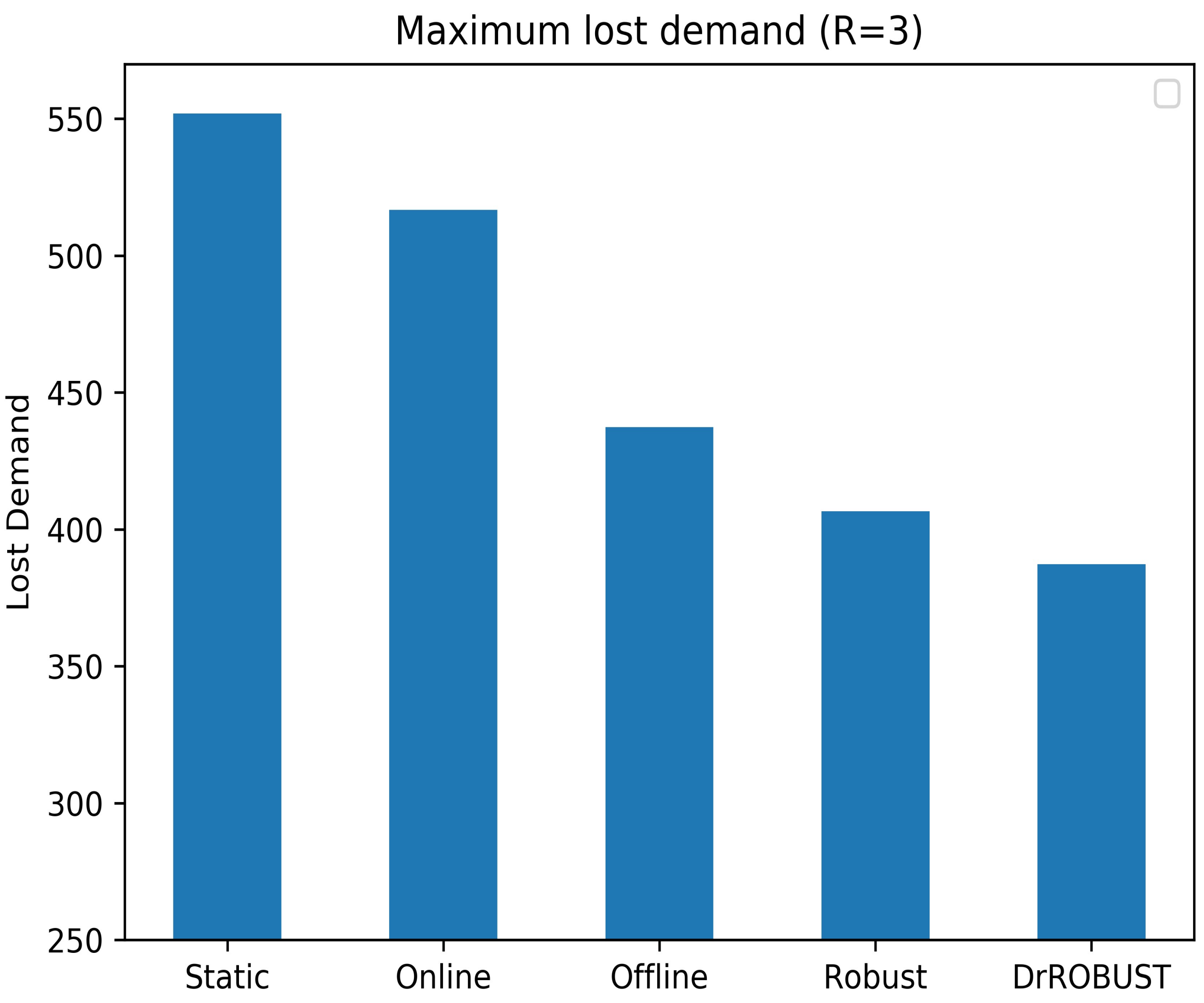
Experimental Setup

- **Dataset:**
  - Hubway (95 stations, 3 carrier vehicles)
  - Trip history data for 3 months
  - Planning period: 6AM-12PM (each decision epoch is 30 minutes)
  - Training data: 20 days of demand scenarios
  - Testing data: 40 days of demand scenarios
- **Evaluation Metrics:** Average and worst-case lost demand over all testing demand scenarios.
- **Approaches:**
  - Static (Redeployment at the end of day)
  - Offline approach [Shu *et. al.,* (OR Journal, 2013)]
  - Online approach [Schuijbroek *et. al., (EJOR Journal,* 2017)]
  - Robust approach [Ghosh *et. al.,* (IJCAI, 2016)]
  - DrROBUST (our approach using satisficing)

Experimental Results

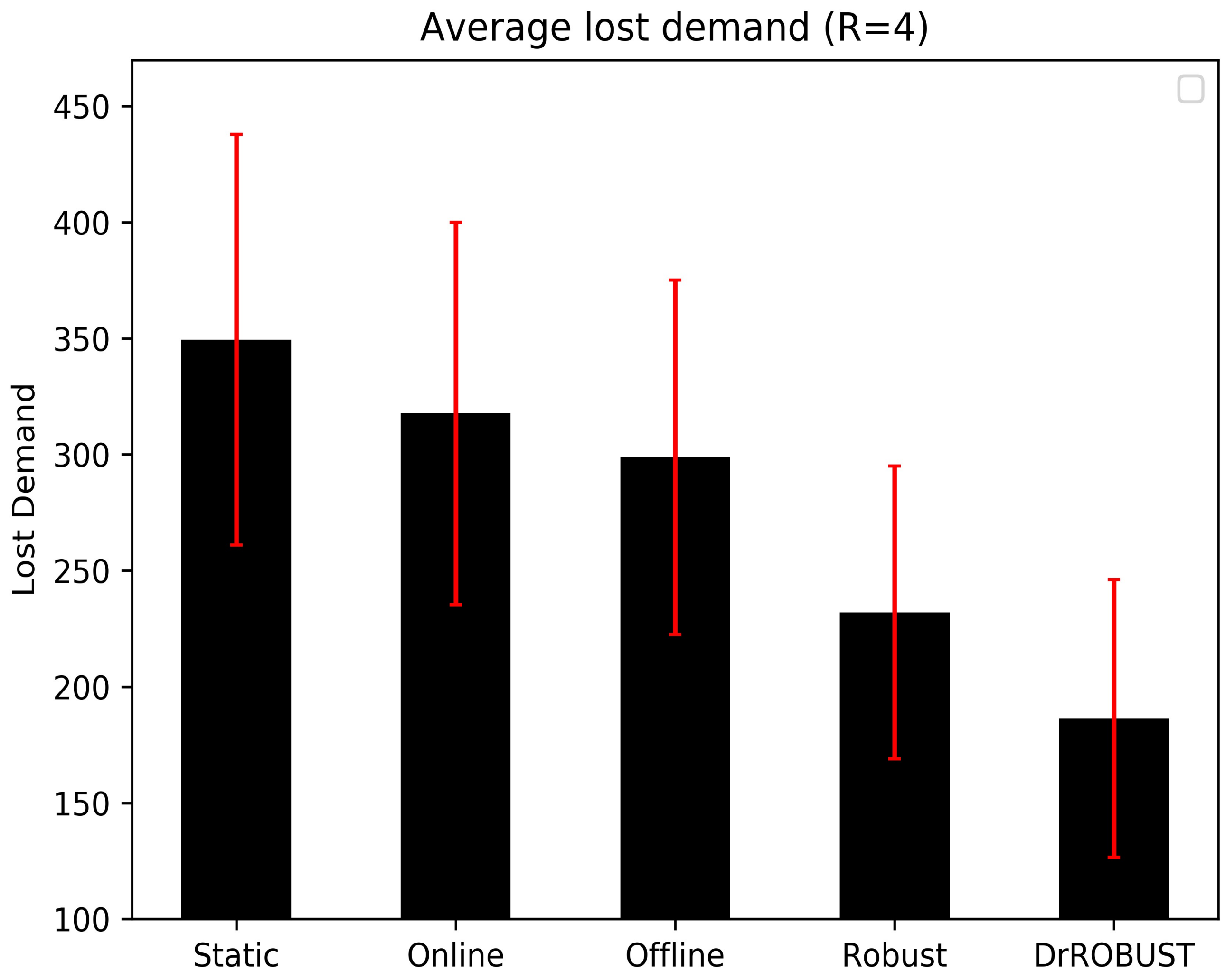
- A vehicle is allowed to visit a maximum of 3 stations (R=3):
  - Our Satisficing approach reduces the average lost demand by at least 15% over all the benchmarks.
  - The worst-case lost demand is reduced by at least 5%.

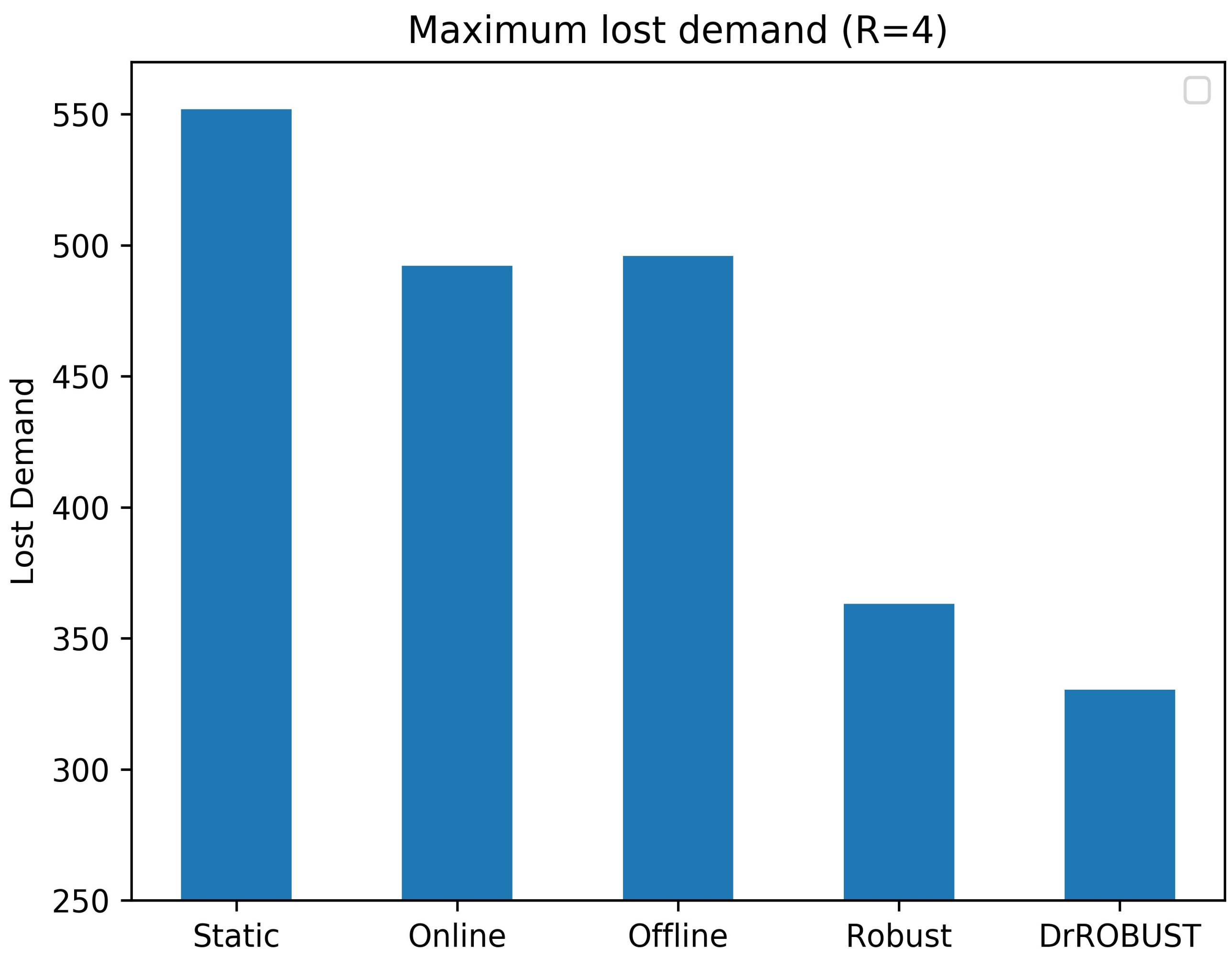




Experimental Results

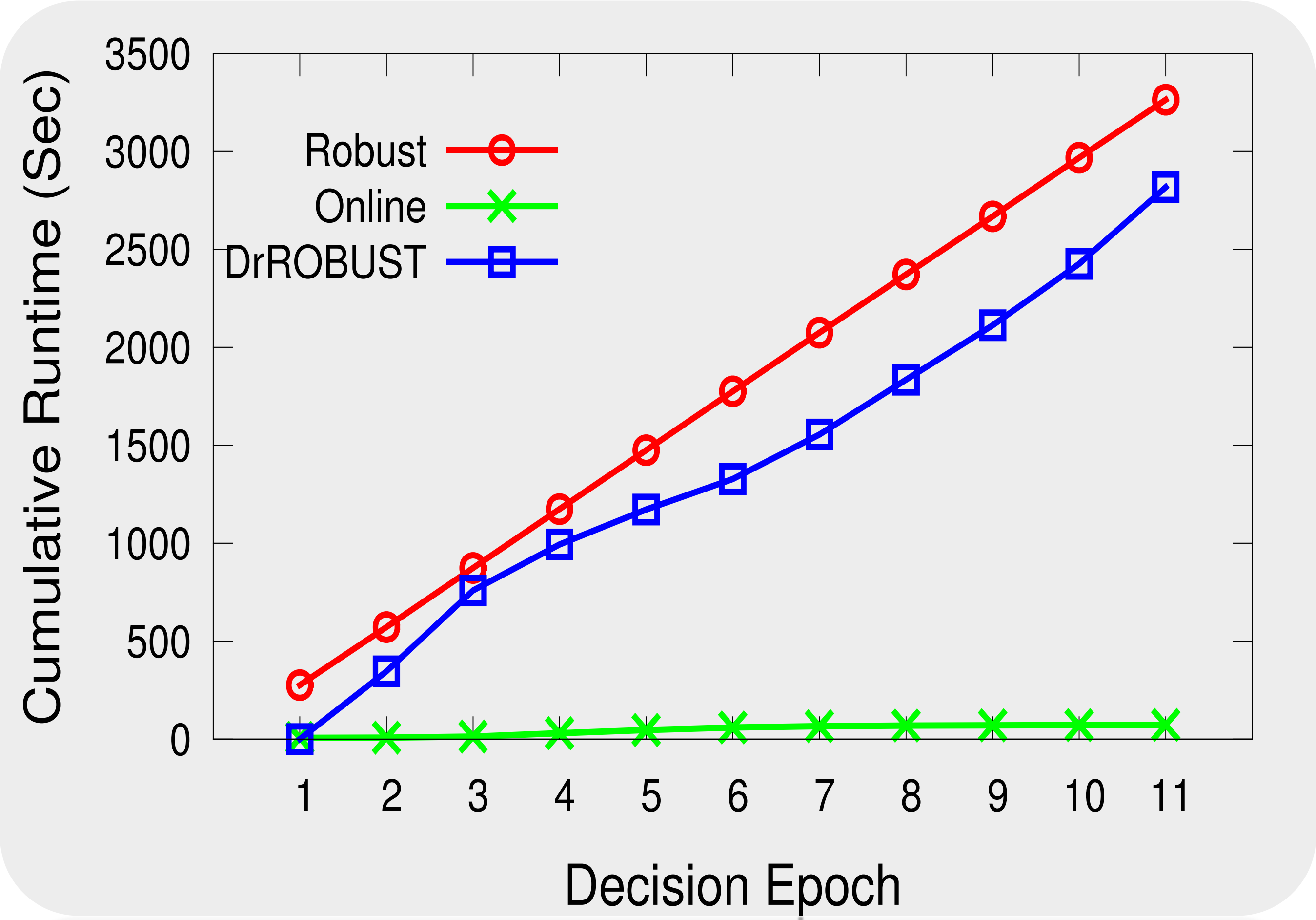
- A vehicle is allowed to visit a maximum of 4 stations (R=4):
  - Our Satisficing approach reduces the average lost demand by at least 19% over all the benchmarks.
  - The worst-case lost demand is reduced by at least 9%.

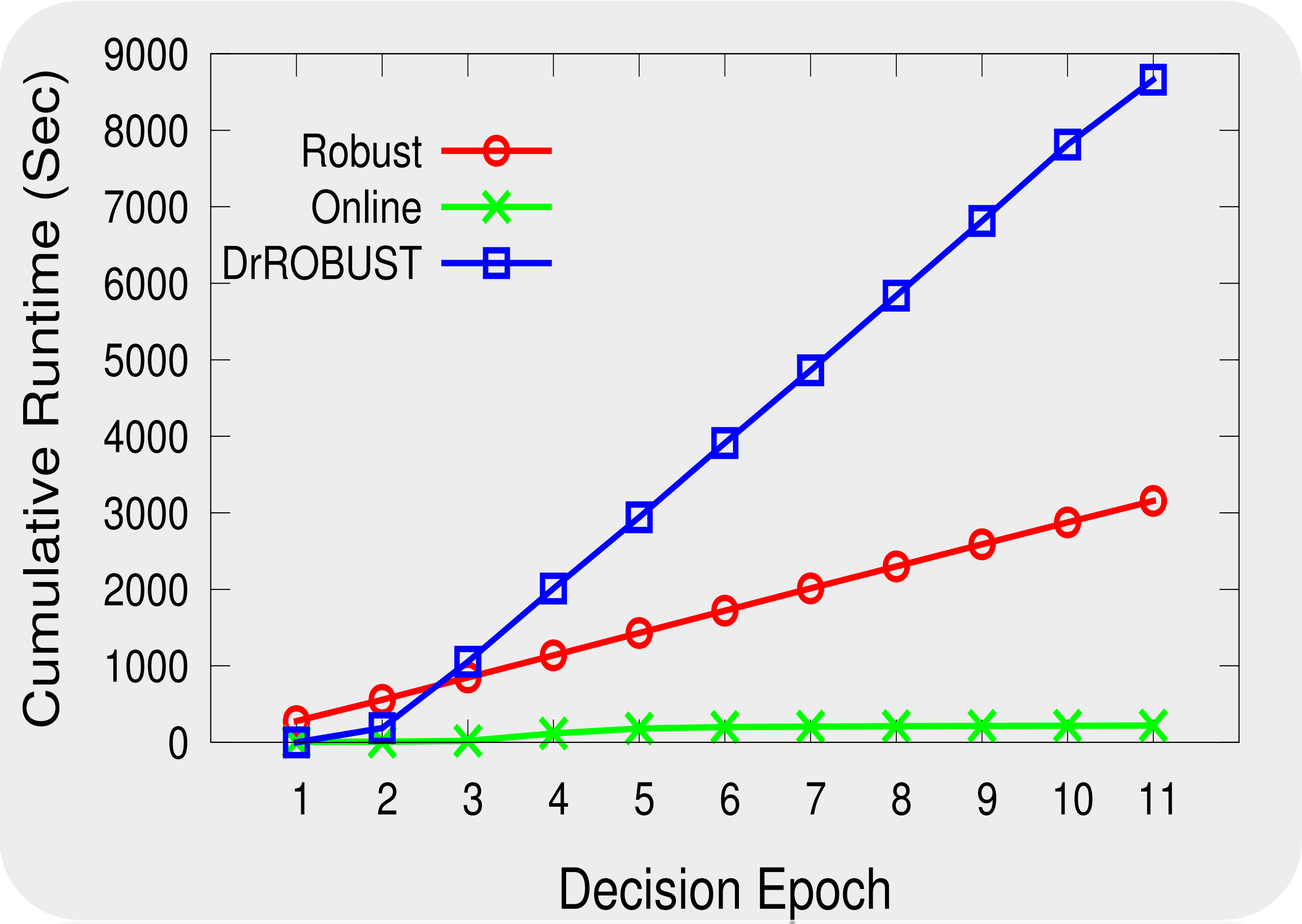




Runtime performance

- DrROBUST is more computationally attractive than Robust approach for 3 episodes per decision epoch.
- For 4 episodes per decision epoch, DrROBUST has highest runtime complexity, but runtime is always bounded by 15 minutes.





Concluding Remarks

- **Robust repositioning in Bike Sharing Systems**
  - A practically important and challenging problem.
  - A tractable satisficing approach is adopted to maximize the log-likelihood of meeting uncertain future demand.
  - Solutions are validated on a simulator built on a real-world data set.
  - Lost demand (average) is reduced by at least 15%.
  - Solution is robust to uncertainty in future demand.

- **Future Direction:**
  - How to adapt the solution approach to tackle the problem in the context of dockless bike sharing systems?
  - How to consider future demand for multiple time-steps to further reduce the lost demand?

Supplementary Slides

Simulation Model

- Compute flows of customers between stations given the distribution of bikes

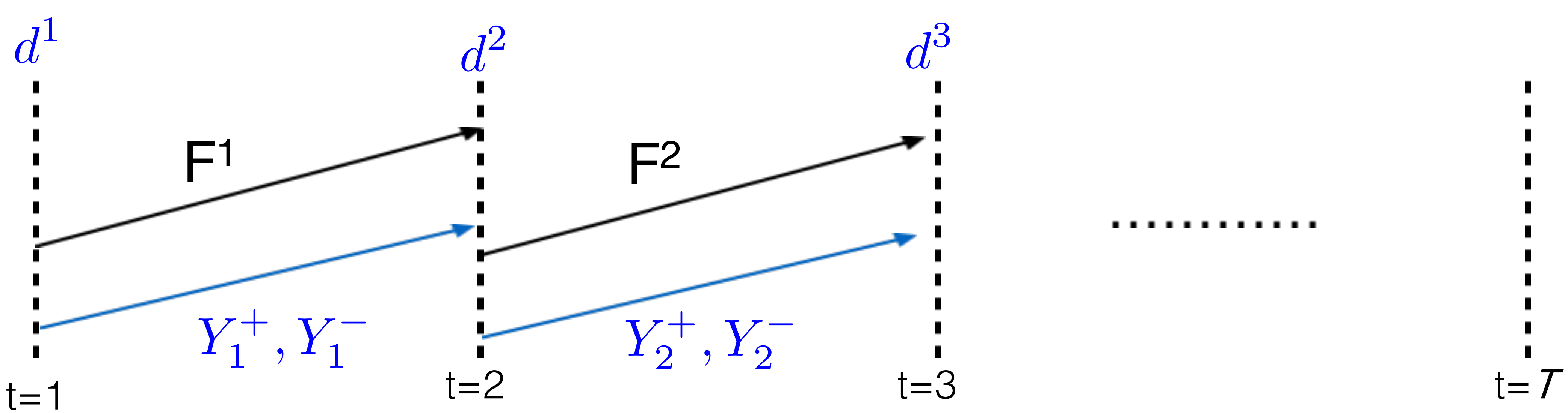
Demand — Supply

$$x^t_{s,s'} = \begin{cases} f^t_{s,s'} & \textbf{if } \sum_{s'} f^t_{s,s'} \leq d^{\#,t}_s \\ \frac{f^t_{s,s'}}{\sum_{\tilde{s}} f^t_{s,\tilde{s}}} \cdot d^{\#,t}_s & \textbf{Otherwise} \end{cases}$$

Actual flow depends on demand and supply of bikes

- Compute distribution of bikes for next decision epoch

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



Routing Distance Comparison

- Robust approach reduces the average and worst-case lost demand by at least 18% and 17% over all the benchmarks.
- Satisficing approach further reduces the average and worst-case lost demand by 26% and 14% over the Robust approach.