

1. Background & Motivation

The Problem: Bike Sharing Systems (BSS) face two critical challenges:

- **Demand-Supply Imbalance:** Stations become empty or full, causing user dissatisfaction
- **Broken Bikes:** Barcelona: 12% severe + 55% light damage; NYC: 2% need daily repairs

Research Gap: No existing study jointly optimizes:

1. Vehicle-based repositioning (usable & broken bikes)
2. **Labor-based on-site repairs**



On-site repairs

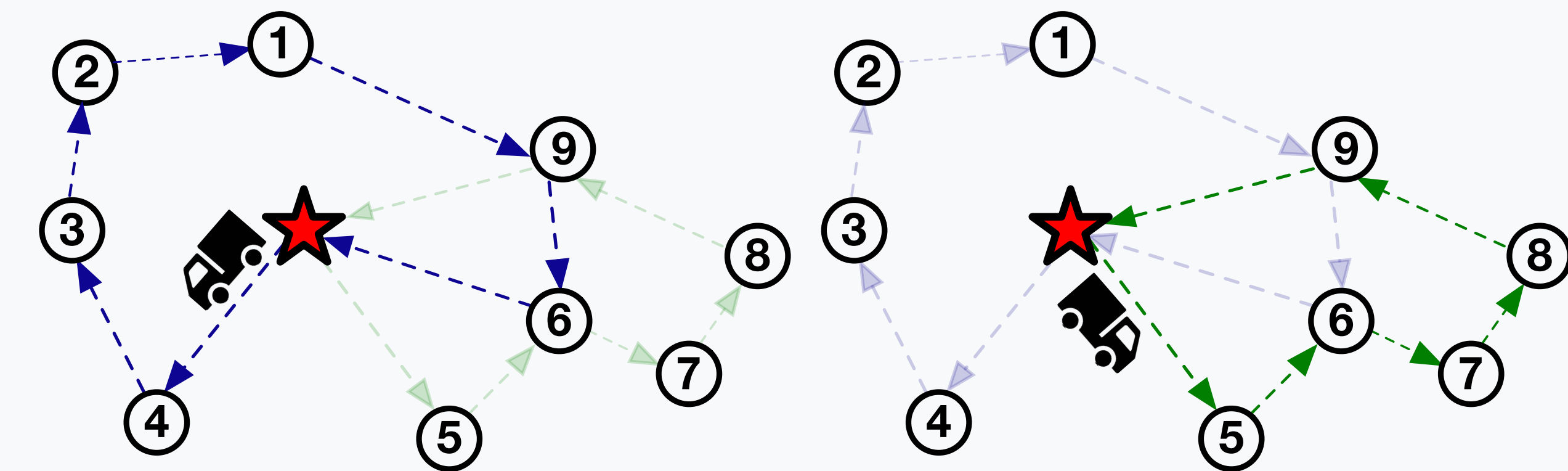


Off-site repairs

2. Contributions

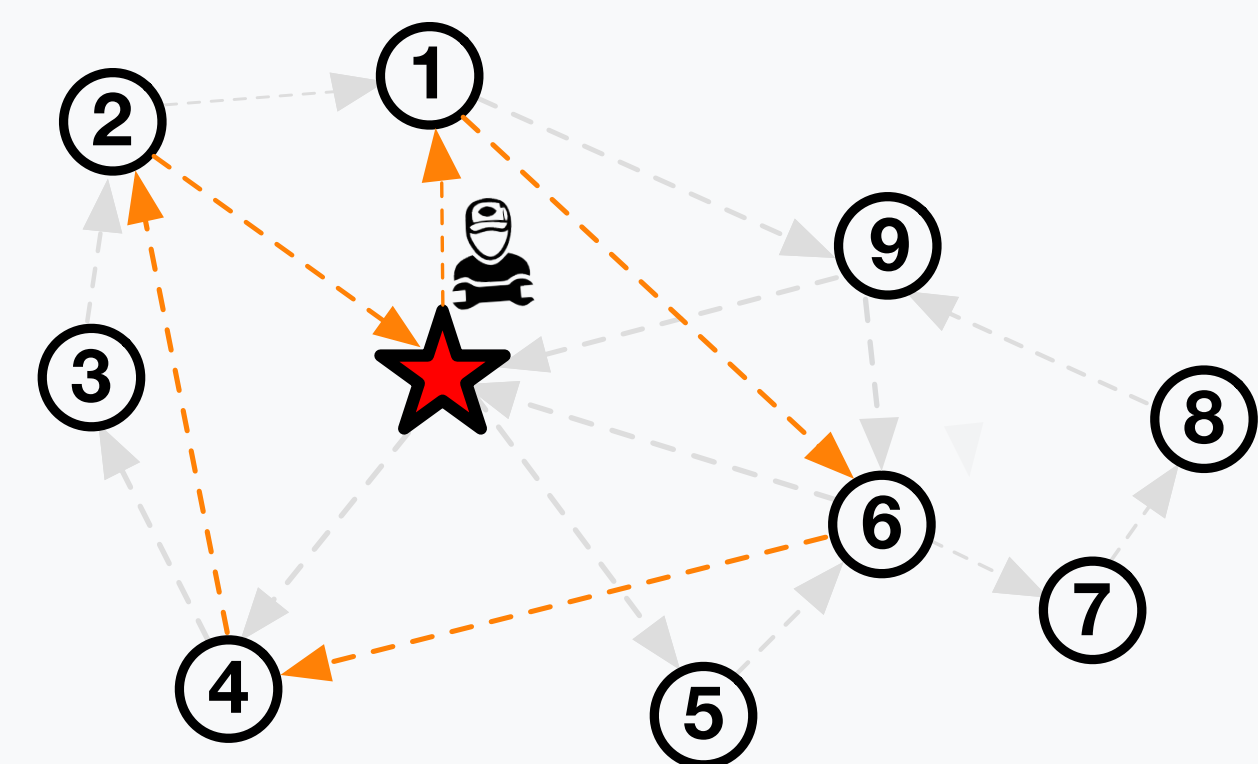
1. **Novel Problem:** First study to integrate on-site repairs with vehicle-based repositioning operations
2. **MILP Model:** Time-indexed formulation minimizing user dissatisfaction + CO₂ emissions
3. **HGSDAC-SBC:** Hybrid Genetic Search algorithm with Station Budget Constraint for large-scale instances
4. **Managerial Insights:** Cost-effectiveness analysis framework for repairer deployment decisions

3. Problem Illustration



Truck 1 route: 0-4-3-2-1-9-6-0

Truck 2 route: 0-5-6-7-8-9-0



Repairer route: 0-1-6-4-2-0

Fig. 3.1: Network with 10 stations, 2 trucks, 2 repairers. Shows vehicle routes and loading/unloading quantities.

4. Mathematical Model

Objective: Minimize total penalty cost (dissatisfaction + emissions)

$$\begin{aligned} & \text{minimize } c^p \sum_{i \in S} F_i(p_{i,t}, b_{i,t}) + c^e \sum_{i \in S_0} \sum_{j \in S_0} \sum_{t=t_{ij}+1}^T \sum_{k \in K} e_{ij,t-i_j} k^+ \\ & \left(\sum_{i \in S_0} \sum_{j \in S_0} \sum_{t=t_{ij}+1}^T \sum_{k \in K} (x_{ij,t-i_j}^y \cdot x_{ij,t-i_j}^y) + \sum_{i \in S_0} \sum_{t=t_{ij}+1}^T \sum_{k \in K} e_{ij,t-i_j}^{\text{load}} \cdot (y_{i,t,k}^u + y_{i,t,k}^w + y_{i,t,k}^b + y_{i,t,k}^h) + \right) \end{aligned}$$

6. HGSDAC-SBC Algorithm

Hybrid Genetic Search with Adaptive Diversity Control + Station Budget Constraint

Algorithm 1: HGSDAC-SBC

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1 Initialization: Generate a population Pop consisting of a feasible subpopulation Popf and an infeasible subpopulation Popi
2 Set iter_no_imp = 0 and current_best_value = +∞
3 while iter_no_imp < ItNI and cpu_time < Tmax do
4 Randomly select two individuals Ind1 and Ind2 from Pop
5 Generate the routes of offspring C1 and C2 using ordered crossover on the routes of Ind1 and Ind2, then apply the SBC heuristic on the routes to determine the (un)loading and repairing quantities for C1 and C2
6 Educate on both C1 and C2 by applying local search procedures to generate new routes and using the SBC heuristic to determine the (un)loading and repairing quantities
7 if Ci (i = 1, 2) is feasible then
8 Add Ci to the feasible subpopulation Popf
9 else
10 Add Ci to the infeasible subpopulation Popi and repair Ci with the probability Prepair using local search procedures and the SBC heuristic
11 end if
12 if the individuals become feasible after repairs then
13 The repaired individuals are added to the feasible subpopulation Popf
14 else
15 The repaired individuals are discarded, and the original infeasible solution is kept in the infeasible subpopulation Popi
16 end if
17 if the size of Popf or Popi reaches the maximum subpopulation size then
18 Select survivors from the corresponding subpopulation
19 end if
20 Set bs = the solution with the best fitness value from Popf and set bv = the fitness value of bs
21 if bv ≥ current_best_value then
22 Set iter_no_imp = iter_no_imp + 1
23 Else
24 Set current_best_value = bv, current_best_sol = bs, and iter_no_imp = 0
25 end if
26 if iter_no_imp ≥ Itdiv then
27 Diversify the population consisting of Popf and Popi and adjust the penalty parameter
28 end if
29 end while
30 return current_best_sol, current_best_value

```

7. Station Budget Concept (SBC)

Key Innovation: Prevents over-allocation of service time to early stations

Benefit-Cost Ratio Function (BCRF):

$$BCRF_s^t(p, b) = \frac{F_s(p, b) - F_s(q, 0)}{t^{\text{load}} \cdot (|q - p| + b)}$$

- Quantifies dissatisfaction reduction per unit service time
- Higher BCRF stations receive larger time budgets
- Unused time redistributed dynamically to later stations

8. BCRF Illustration

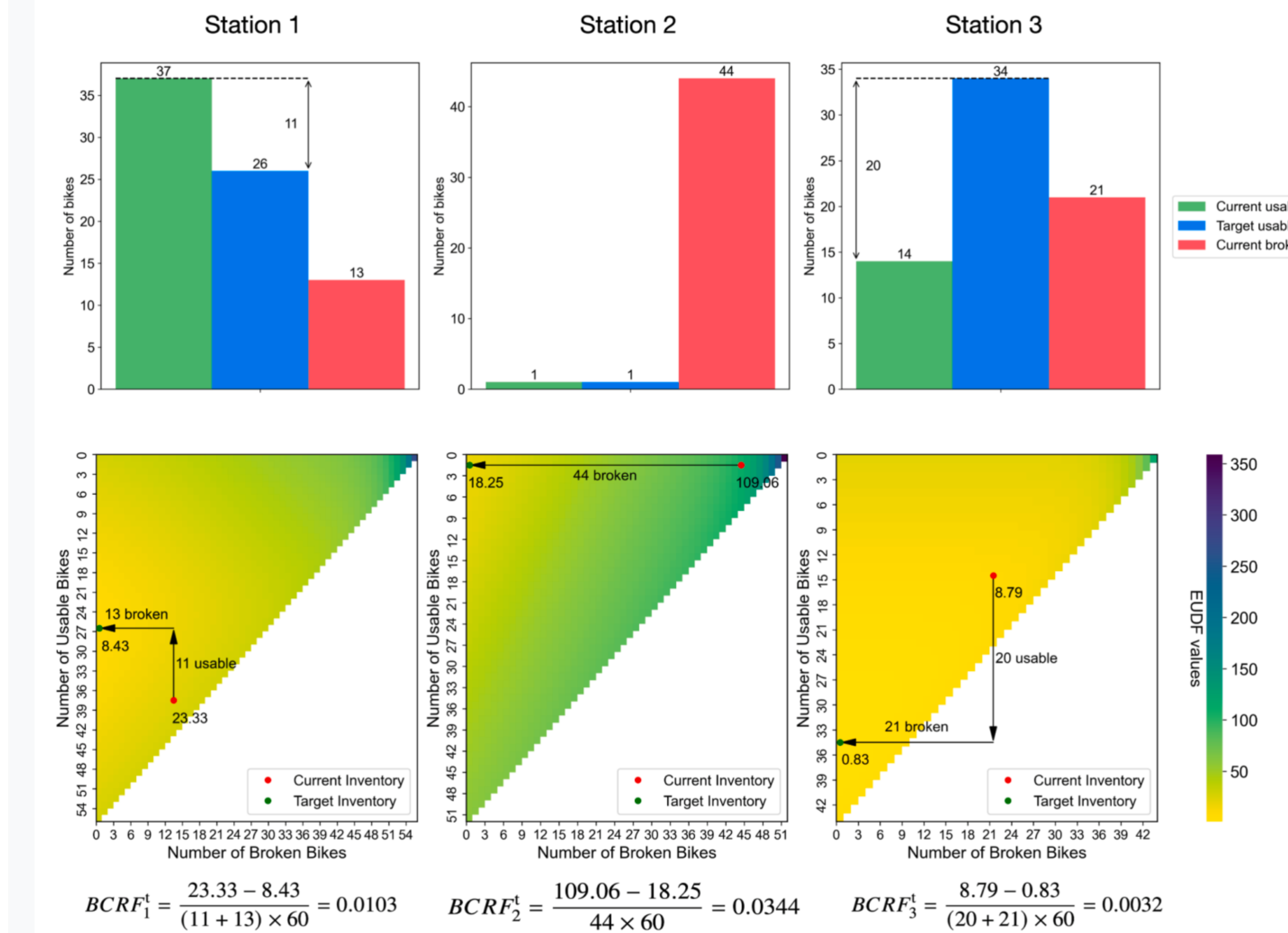


Fig. 4.1: BCRF calculation for 3 stations. Top: inventory status; Bottom: EUDF heatmaps.

9. Computational Results

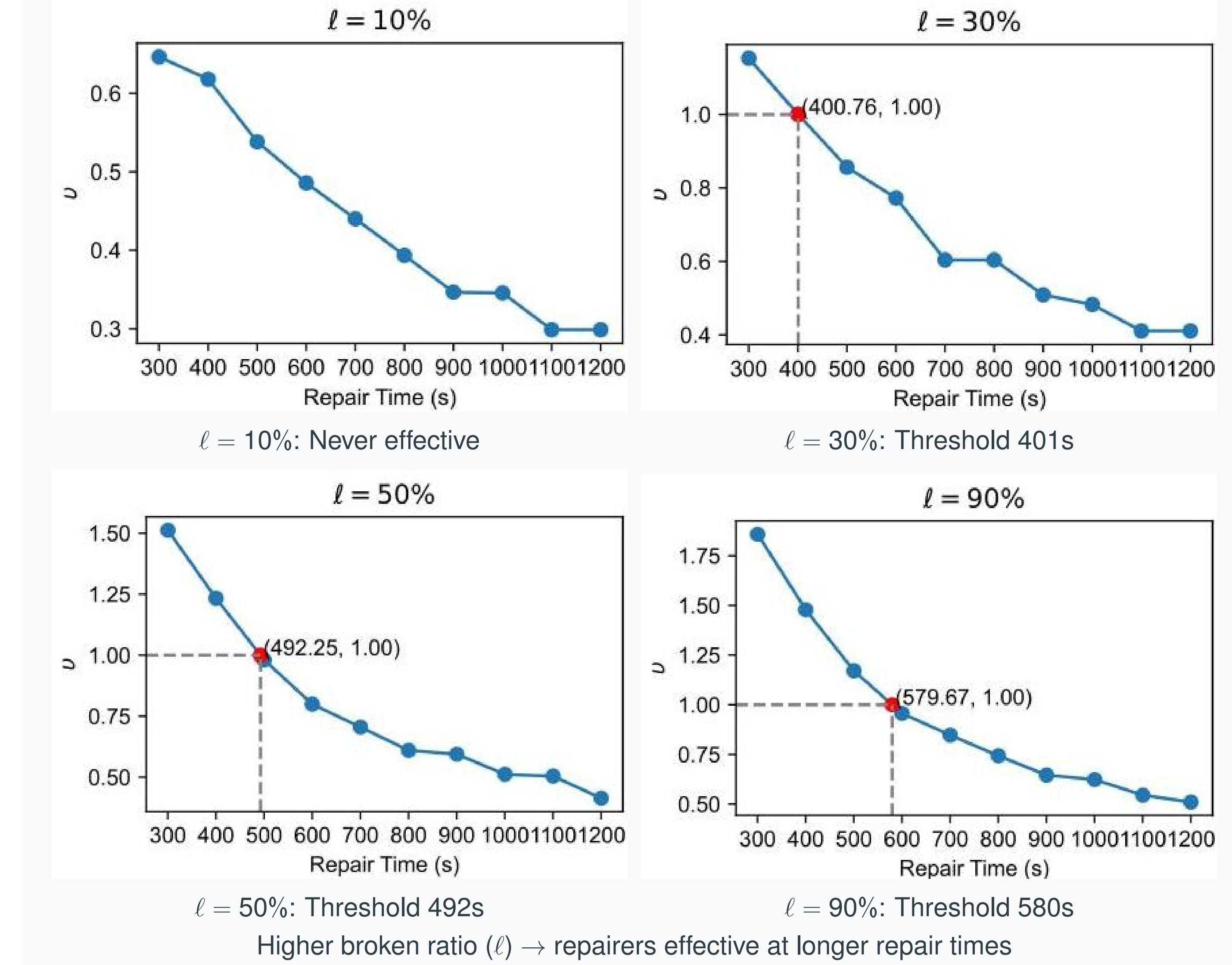
Comparison vs Gurobi (T=2h, $\tau=600$ s, 20 runs)

10. Cost-Effectiveness of Repairers

Indicator ν : Ratio of dissatisfaction reduction to repairer wage

$$\nu = \frac{c^p \sum_{i \in S} (\hat{F}_i - \hat{F}_i')}{\varpi \cdot T / 3600}$$

$\nu > 1$: Cost-effective $\nu < 1$: Not cost-effective



11. Key Managerial Insights

- **Critical Threshold:** Repair time > 645s \Rightarrow **never** cost-effective
- **Low damage ($l < 20\%$):** Trucks alone sufficient; repairers not justified
- **High damage ($l \geq 30\%$):** On-site repairers become economically justified
- **Preventive maintenance** crucial to keep repair times below threshold

12. Conclusions

1. HGSDAC-SBC is **scalable** for real-world BSS (up to 500 stations)
2. Station Budget Constraint effectively balances time allocation across route
3. Dynamic repairer deployment should adapt to daily damage levels

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References

Hu, R., Szeto, W.Y., & Ho, S.C. (2025). Repositioning in bike sharing systems with broken bikes considering on-site repairs. *Transportation Research Part E*, 104155.

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