Repositioning of Ride-pooling Fleets using Machine-Learning Methods

Master‘s Thesis of Shyam Twanabasu

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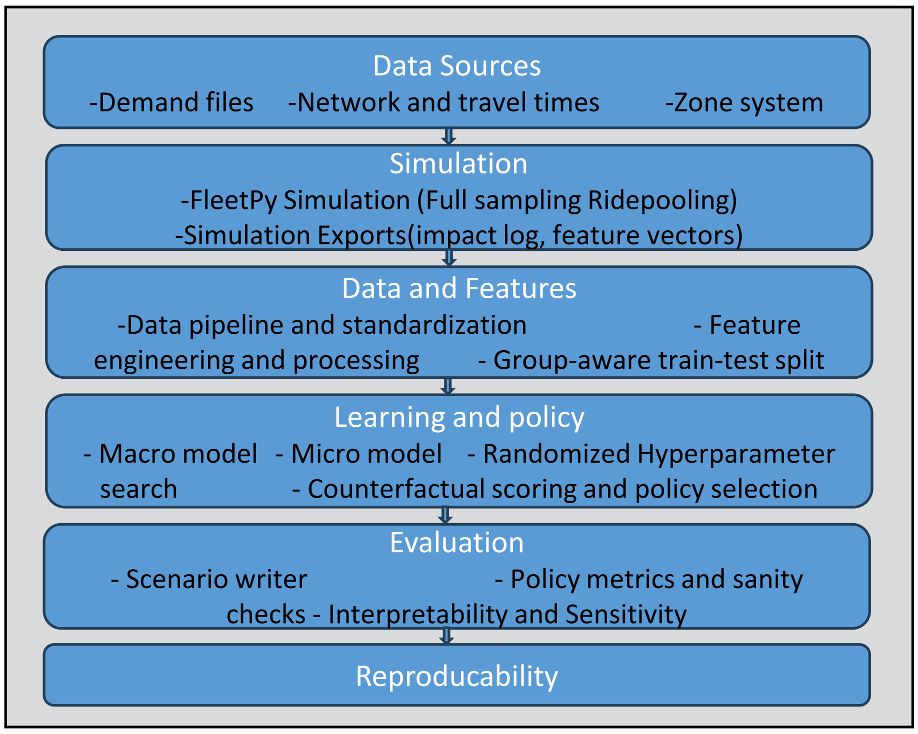
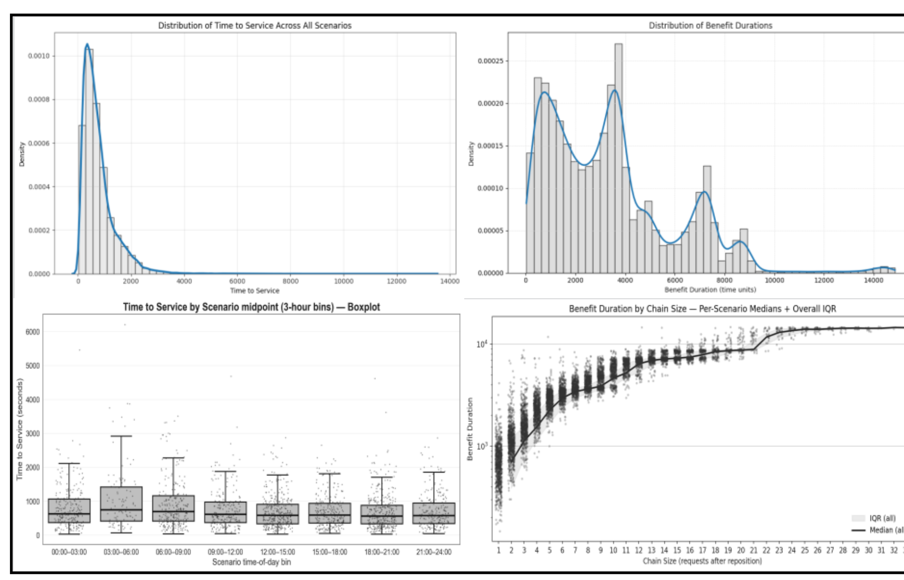


Problem Statement
Non-stationary demand in ride-pooling → need for adaptive, proactive repositioning.

Objective
Develop a reproducible, machine–learning–based framework within FleetPy to optimize repositioning horizons in ride-pooling fleets, balancing service efficiency and vehicle kilometres travelled (VKT).

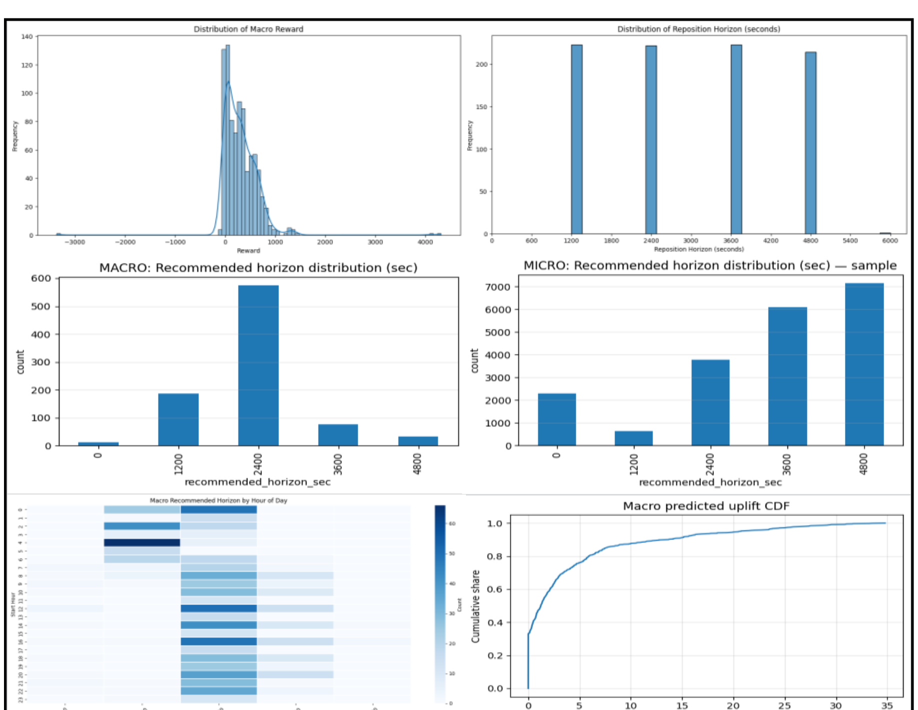
Research Question
Focus on what drives repositioning performance, how horizon decisions can be improved, how time affects them, and how stable these improvements are across scenarios.

Methodology
1. Designed a data pipeline transforming simulation logs into macro (scenario-level) and micro (decision-level) datasets.
2. Trained Random Forest models to predict proxy rewards and select optimal repositioning horizons.
3. Conducted feature importance analysis, sensitivity testing, and counterfactual uplift scoring.
4. Validated predictions across 883 scenarios and over 49,000 decisions.



Key Results
- Macro model achieved $R^2 = 0.675$ (RMSE = 183.26).
- Micro model achieved $R^2 = 0.398$ (RMSE = 1.63).
- Medium horizons (2400 s) performed best overall in macro simulations, while longer horizons (3600–4800 s) in micro simulations
- Horizon choice stable across scenario families
- 73% (macro) and 88% (micro) positive predicted uplift
- Key drivers: destination-side demand, OD identity, feasible travel time

Discussion & Insights
- Repositioning reduces idle time: time-to-service » 8–12 min, benefit duration » 57 min. (the time in the graph is in seconds)
- Demand concentration and OD travel times drive horizon choice.
- Joint tuning of horizon and rebalancing step (Δt) is critical for stability.
- ML-driven policies outperform static heuristics, offering contextual adaptability.



Conclusion
Adaptive horizon selection via supervised ML improves ride-pooling efficiency and service balance. The framework provides an interpretable, reproducible foundation for integrating data-driven repositioning strategies in real-world fleet operations.

Contributions
•Reproducible FleetPy-ML pipeline
•Interpretable counterfactual policy selector
•Context-aware horizon recommendation.

Future work
•Joint tuning with rebalancing timestep (Δt),
•Integration with demand forecasting, multi-objective control with an improved reward function and other ML methodologies.

Repository Link
All source code, simulations, and results and thesis document:
https://syncandshare.lrz.de/getlink/fiCuvhpDMAU9fSh6XZuExP/

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