Conference Poster

Fleet control algorithms for automated mobility
A simulation assessment for Zurich

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Fleet control algorithms for automated mobility: A simulation assessment for Zurich

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1. Problem Statement

Autonomous Mobility on Demand (AMoD) service

Customers can request rides from the AMoD operator, who dispatches an empty autonomous vehicle to the respective pickup location. Then the vehicle drives the customer straight to the dropoff point. The operator decides which vehicle to assign to which request (dispatching strategy) and where to move unoccupied vehicles (rebalancing strategies).

Operator objectives

The operator produces (paid) customer mileage, empty pickup mileage and empty rebalancing mileage. Given a static demand, find optimal dispatching and rebalancing strategies that minimize the empty-pickup distance and empty rebalancing distance, respectively.

2. Algorithms

A1) Load-balancing heuristic (Bischoff et al., 2016)

For every dispatching time step check whether there are more available vehicles than requests. If so, assign the closest available vehicle and assign the closest available vehicle. Otherwise, assign the closest available vehicle and assign the closest available vehicle. Once assigned, unassigned vehicles cannot be assigned.

A2) Global Euclidean Bipartite Matching (“Hungarian Algorithm”)

Determine an optimal bipartite matching between all open requests and available vehicles in every dispatching time step, based on the Euclidean distance. Assignments may be changed in the next dispatching step.

A3) Feedforward Linear Program (Pavone et al., 2011)

On top of the previous algorithm, perform rebalancing: Given the customer arrival rates η and transition probabilities p, on a network of virtual nodes, solve Equation 1 to obtain optimal rebalancing flows $\eta_{ij}$ for a fixed-time dispatching period. Assign unoccupied vehicles to viable rebalancing destinations using Global Euclidean Bipartite Matching. Vehicles with a rebalancing task can only be controlled again once they reach their destination.

\[
\min \sum_{i} \eta_{i,j} \quad \text{subject to} \quad \eta_{ij} - \eta_{ji} = \lambda_{ij} \quad \forall (i,j) \\
\eta_{ij} \geq 0 \\
\lambda_{ij} \geq 0 \\
\eta \in \mathbb{V}
\]

A4) Feedback Linear Program

Instead of using precomputed request rates and transition probabilities, the Feedback Linear Program uses continuously measured counts of open requests as the desired number of vehicles at each node for each time interval. Then, the same system as in A3 is solved and bipartite matching is used.

3. Simulation Setup

MATSim

• Agent- and activity-based transport simulation framework
• Simulates daily travel plans of a population in a queue-based network
• Extensive library of principled Vehicles by Hof (2017)

Baseline Scenario: City of Zurich

• Cut from 8M agents Swiss Baseline Scenario (Bösch et al. 2010)
• 1% sample of agents that interact with the study area (City of Zurich, Figure 1)
• Detailed multi-stage daily activity chains
• Demand generation for the AMoD service

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4. Fleet Operation Results

Waiting time (Figure 2)

• The Load-balancing heuristic (A1) yields consistently the longest waiting times.
• The Feedback Linear Program (A4) performs best, but close to the other algorithms based on Hungarian matching.
• A wait time of 5 minutes (which is assumed to be acceptable) is reached with a fleet size of 9000 vehicles for the heuristic, but only with 4700 vehicles for the feedback dispatcher.

Fleet distance (Figure 3)

• Customer distance (left, dark) stays constant since demand is kept constant.
• Empty pickup distance (middle, light) decreases with larger fleet sizes and higher vehicle availability
• Empty rebalancing distance (right, dark) adds substantial mileage to the fleet. The total mileage is almost kept constant with rebalancing.

5. Financial Analysis

Cost Calculation (Bösch et al., 2017)

• Considered fleet capacity (idle time) and utilizations (empty miles)
• Price per passenger kilometer in Swiss Francs (CHF) for a profit margin of 3%

Results (Figure 4)

• The Feedback Linear Program (A4) is able to offer the cheapest rides if very low waiting times (<5 min) are desired.
• For longer waiting times (>5 min) the nonrebalancing matching (A2) outperforms the rebalancing ones.
• For almost any analyzed waiting time, there is at least one advanced algorithm with a competitive advantage over the simple heuristic (A1).

Conclusion & Outlook

We show that, in our scenario, an operator with an intelligent dispatching and rebalancing algorithm has a competitive advantage over others. What is the most beneficial strategy, however, depends on the willingness to pay (WTP) of the customer.

For future studies, we will use the possibility of MATSim to perform dynamic mode choice decisions. By incorporating survey results we will be able to further explore the tradeoff between WTP, customer cost times and AMoD supply. Furthermore, larger population samples will be used.

6. Acknowledgments

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Study Area

Virtual Nodes

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