Optimized travel options with a Flexible Mobility on Demand System *FMOD*

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Agenda

- Motivation and background
- Concept of FMOD
- Modeling framework
- Simulation experiments
- Conclusions and future directions

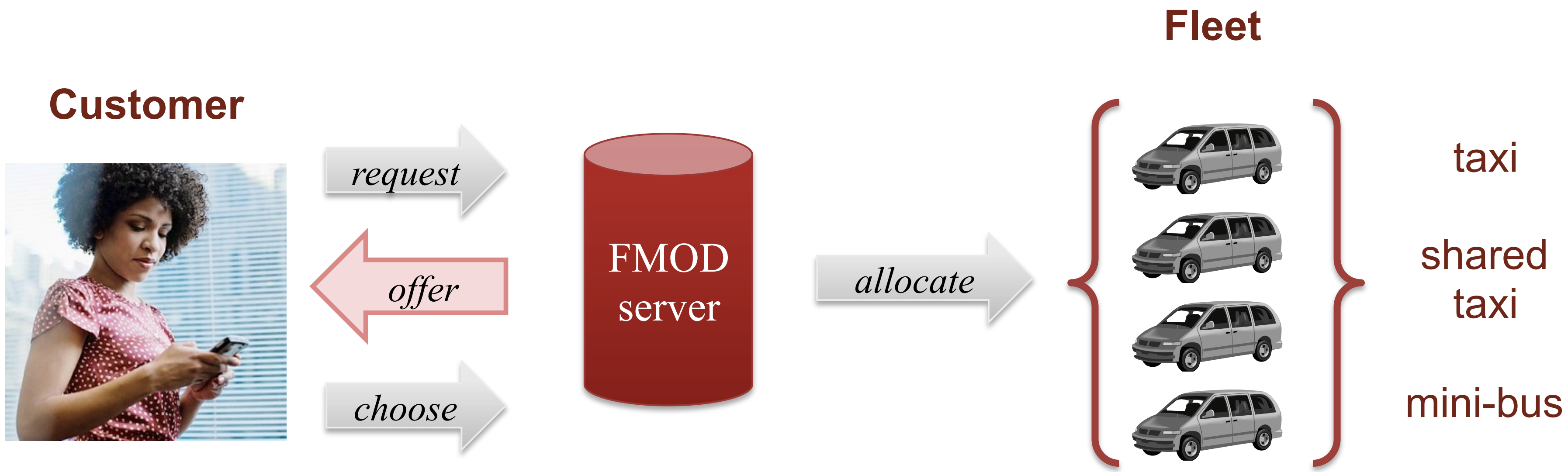
Motivation and background

- Personalized services using smartphone apps are emerging for taxi:
  - Uber, Lyft, SideCar, GoMyWay, etc.

- Why not apply similar technologies to also DRT and fixed route public transportation?

Concept of FMOD

- **Real-time** system
- **Personalized** demand responsive system that gives the traveler an **optimized menu**
- **Dynamic allocation** of vehicles to services



Concept of FMOD (cont.)

- **Taxi:** Flexible route, flexible schedule, private

- **Shared-taxi:** Flexible route, flexible schedule, shared

- **Mini-bus:** Fixed route, flexible schedule, shared

Concept of FMOD (cont.)

Supply Demand

FMOD Server

optimization

Request:
Origin: A, Destination: B
Preferred Departure Time: 8:00 – 8:30
/ Preferred Arrival Time: 8:45 – 9:00

request

offer

Offer:

taxi:	DT: 8:25/AT: 8:45, $20
shared-taxi:	DT: 8:27/AT: 8:57, $10 as the 4th passenger
mini-bus:	DT: 8:14/AT: 8:59, $5 as the 6th passenger

choose

Choice:
service: shared-taxi
DT: 8:27/AT: 8:57, $10

Modeling framework

- **Product**
  - A service on a vehicle departing at a certain time period
- **Feasible product**
  - A product that satisfies the capacity and scheduling constraints
    - Vehicle capacity
    - Existing schedule
    - Preferred time window
      - Maximum schedule delay
- **Offer**
  - A list of feasible products presented to the customer (max 1 product for each service)

Modeling framework (cont.)

Phase1. Feasible product set generation

Set of feasible products to be offered to the customer taking into account:

– Capacity constraints

– Scheduling constraints based on the request

Phase 2. Assortment optimization

Optimized list to be offered to the customer from the feasible set

– Maximize operator's profit and/or consumer surplus based on a choice model

Assortment optimization model

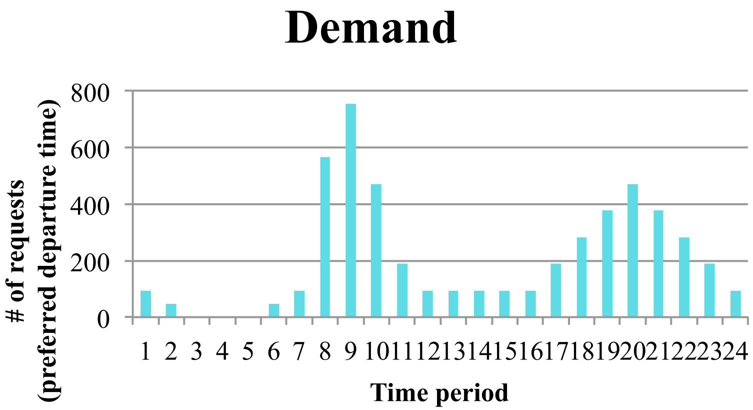
- Optimizes the list to be offered to each customer request among all the feasible products
- Choice model is integrated into the optimization model in order to represent shares of services
- Formulated as a mixed integer linear problem
- Myopic vs dynamic

- Different versions of the model are considered:
  - maximize consumer **surplus** (logsum)
  - maximize **profit**
  - maximize profit + consumer surplus: **total benefit**

Simulation experiments
Case study

- Simulation time: 24 hours
- Network
  - Hino city in Tokyo (approx. 9km×8km)
- Supply
  - Fleet size: 60
  - Bus line: actual route
- Demand
  - 5000 requests / day
  - OD: station, hospital etc. (population density)
  - VOT: from \$6/h to \$30/h
- Fare
  - Taxi: \$5 (base) + \$0.5 (per 320m)
  - Shared-taxi: 50% of taxi fare
  - Bus: \$3 (flat)
- Operator Cost
  - \$200 / day / vehicle + \$0.2 per km

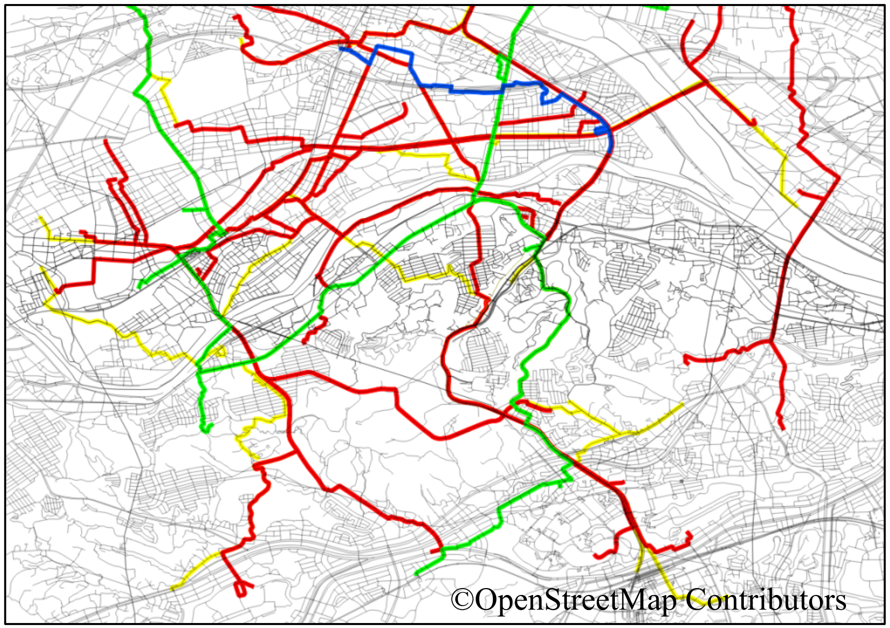
(Yellow: Bus line)



Simulation experiments

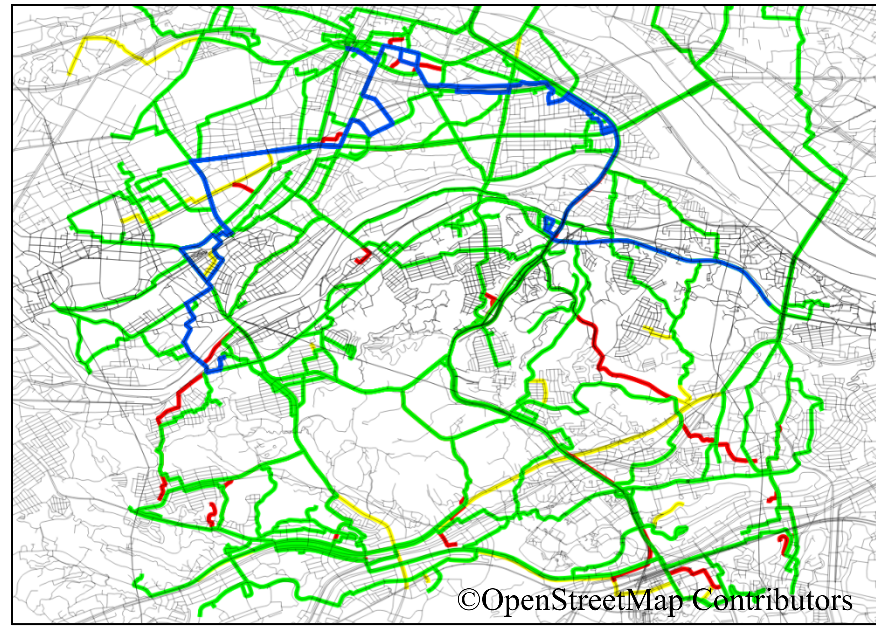
Snapshots

Red: Taxi, Green: Shared taxi, Blue: Mini-bus, Yellow: empty



Off-peak (AM 6:00)

Taxi is dominant

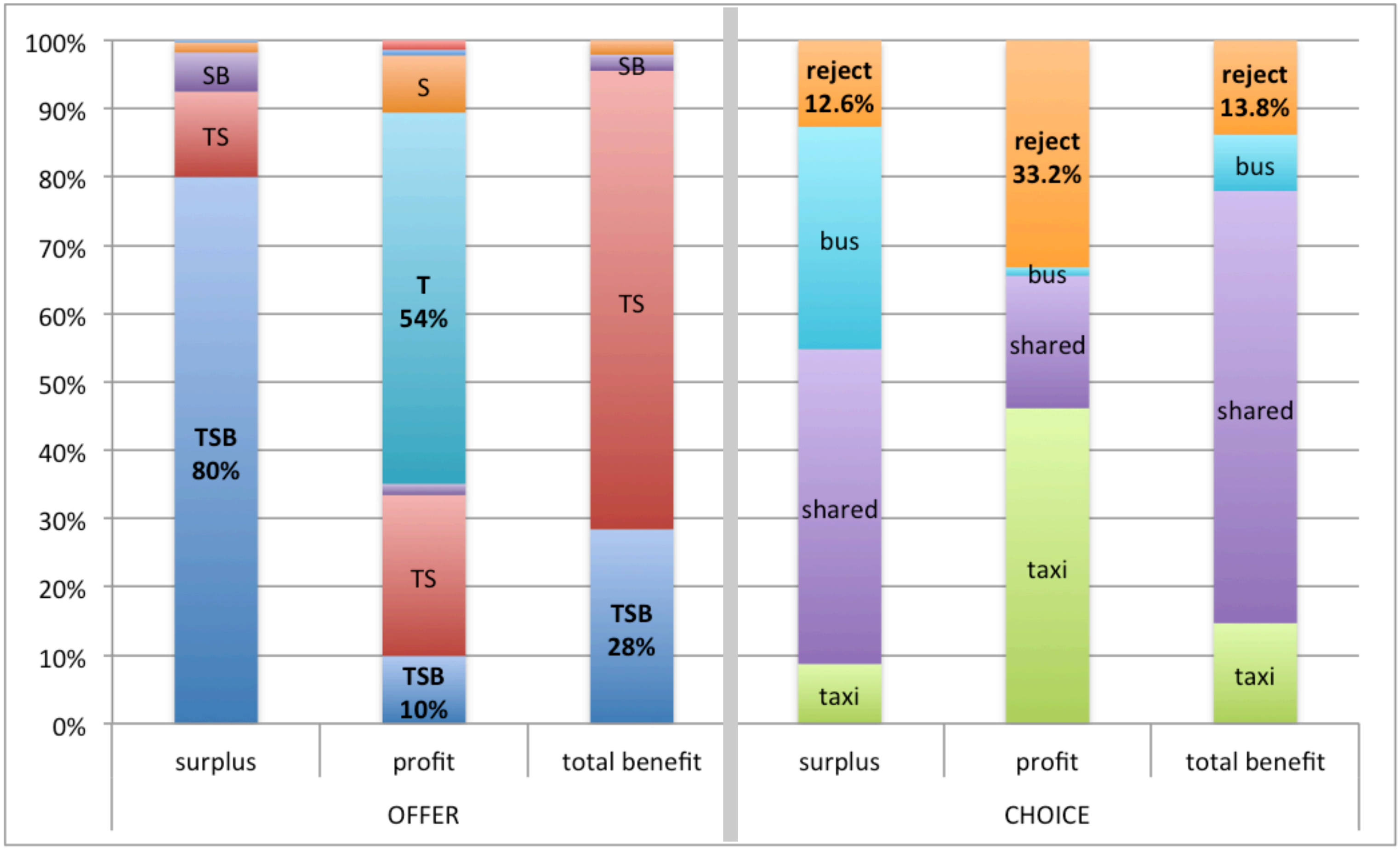


Peak (AM 8:00)

Shared taxi / Mini-bus are dominant

Simulation experiments
Comparison of models

T:taxi, **S**:shared-taxi, **B**: mini-bus



Simulation experiments
Main findings

- The offer given by FMOD is significantly affected by the objective function.
- Total benefit case compared to profit maximization:
  - Significant increase in consumer surplus without much decrease in profit
- Dynamic allocation of vehicles provides significant improvements over static allocation

Conclusions and future directions

- FMOD has a potential to increase operator's profit and improve passenger satisfaction

- Ongoing and further research directions include:
  - Field test
  - Estimation of future demand
  - Real life conditions (e.g. traffic)
  - Learning the behavior of customer through repeated visits

Thank you for your attention!

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