Pathfinding for Shared-ride Vehicles: Bi-criteria pathfinding considering travel time and proximity to demand

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Agenda

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Preliminaries

**Mobility-on-demand (MOD) services without shared rides**
- E.g. UberX, Conventional Lyft, Taxis
- Automated MOD $\rightarrow$ AMOD

**Shared-ride MOD services**
- E.g. Uber Pool, Lyft Line, Via, Chariot, Bridj
- Microtransit, Demand-responsive transit, Dial-a-ride Problem

**Network Paths vs. Vehicle Routes**
- Network Paths: the sequence of nodes/links a vehicle traverses in a road network
- Routes: the ordered sequence of user pick and drop locations for a vehicle
Motivation

So many great benefits of **shared-ride MOD services**!

- **Individuals**: Reduced travel costs
  - Splitting operational – fuel and labor (~$0 for AVs) – costs
  - Capture capital/depreciation cost reduction from...

- **Mobility Service Providers (MSPs)**: Reduced ‘fleet’ size and operational costs

- **Society**: Reduce vehicle miles travelled (VMT), traffic congestion, fuel consumption, harmful emissions

Yet...
But what about Uber Pool and Lyft Line?

Around 20% of TNC trips
Motivation

Challenges/Problems

1. Travelers have an aversion to sharing rides

2. Operating shared-ride vehicle fleets is challenging
   ◦ Trade-offs between sharing opportunities, detours, and price
   ◦ Uncertainties/Stochasticity everywhere
     ◦ New traveler requests
     ◦ Link travel times
     ◦ Pickup times (and to a lesser extent) drop-off times

3. What policy interventions would be helpful?
   ◦ Considering equilibrium at mode choice and route choice levels
Research Scope

This research study:
- Conceptualizes bi-criteria path-finding for shared MOD vehicles
- Develops a modeling framework for the static and dynamic bi-criteria best-path problems for shared-ride vehicles
- Proposes a solution algorithm (i.e., operational policy) for bi-criteria path assignment
  - In addition to algorithms/policies for matching vehicles and requests, and sequencing user pickups and drop-offs
- Tests and validates the solution algorithm/policies and models, using the Anaheim, CA network
Background

The **operational process** for **shared-ride MOD services** usually includes two/three interconnected parts:

1. **Matching** passengers with service vehicles
2. **Routing/Sequencing** vehicles to pick-up/drop-off customers
3. **Repositioning** empty vehicles

**Pathfinding** largely overlooked – “just assign vehicles to shortest network paths”
Research Hypothesis

Assigning vehicles to **shortest paths** between pickup and drop-off locations may result in **suboptimal** fleet performance

- Vehicles may incur avoidable mileage when responding to new requests, since **pathfinding** process does **NOT** consider future demand
Key Idea: Bi-criteria Pathfinding
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Goals and Research Questions

This research project aims to develop an efficient operational policy for shared-ride MOD services that efficiently:

1. **Matches** new requests to vehicles
2. **Sequences** traveler pickups and drop-offs for individual vehicles
3. **Repositions** empty vehicles
4. **Assigns** vehicles to **paths** through a network, considering both travel time and potential future demand

To answer the following questions:
- Does bi-criteria pathfinding improve the operational efficiency of shared-ride MOD services?
- If yes, when should shared-ride MOD vehicles be assigned to bi-criteria paths?
- What are the major exogenous and endogenous factors that impact the effectiveness of bi-criteria pathfinding?
Methodology: Architecture Overview

**Inputs**

- Traveler Requests
- Vehicles

**Step 1**

Determine Feasible Traveler-Vehicle Pairs

**Step 2**

Calculate Pairwise Traveler-Vehicle Service Cost

**Step 3**

Match Vehicles to Traveler Requests

**Step 4**

Reposition Empty Vehicles to Balance Supply and Demand

**Step 5**

Assign Vehicles to Network Paths
Methodology: Step 2 – Cost Measure

For each feasible passenger-vehicle pair, this study defines the cost ($c_{pv}$) as the travel time/distance differential between the vehicle route without the new request and the vehicle route with the new request.

The cost of matching ($c_{pv}$) for the vehicle and Passenger 2 in the picture is the difference between the travel distance/time of the orange route and the green route.
Methodology: Step 3 -- Matching

Passenger-vehicle assignment problem (bi-partite matching)

\[
\text{Max} \sum_{v \in V} \sum_{p \in P} (r_p - c_{pv}) \times x_{pv} \quad (1)
\]

subject to:

\[
\sum_{v} x_{pv} \leq 1, \forall p \in P; \quad (2)
\]

\[
\sum_{p} x_{pv} \leq 1, \forall v \in V; \quad (3)
\]

\[
x_{pv} \in [0, 1] \quad (4)
\]

In the above formulation:

\(x_{pv}\): Binary decision variable, equal to 1 if traveler \(p\) is served by vehicle \(v\)

\(r_p\): Reward for serving traveler \(p\)

\(c_{pv}\): Cost of serving traveler \(p\) with vehicle \(v\)
Routing a vehicle (formulated as a multi-criteria shortest path problem)

\[
\min_{x_{ij}} \sum_i \sum_j c_{ij} x_{ij} \quad (5) \quad \max_{x_{ij}} \sum_i \sum_j r_{ij} x_{ij} \quad (6)
\]

Subject to:

\[
\sum_j (x_{ij} - x_{ji}) = \begin{cases} 
1, & i = O \\
0, & i \neq O, D \\
-1, & i = D 
\end{cases} \quad (7)
\]

\[x_{ij} \in [0,1] (8)\]

In the above formulation:

- \(x_{ij}\): Binary decision variable, equal to one if link \((i, j)\) traversed by vehicle
- \(r_{ij}\): Potential reward for travelling on a link \((i, j)\)
- \(c_{ij}\): Cost of traversing link \((i, j)\)
Methodology: Step 5 -- Path Assignment

Combine the two objective functions (5) and (6)

\[
\max_{x_{ij}} \sum_i \sum_j (w_i + r_i - c_{ij}) \times x_{ij} \tag{9}
\]

- \( w_r = f( \text{occupancy, time slack} ) \)
- Reward term, \( r_{ij} \)
- Related to potential link demand

- We test bi-criteria routing under three conditions
  1. The vehicle has only one drop off task remaining
  2. The vehicle has two drop-off tasks and no pickup tasks remaining
  3. The vehicle has two drop-off tasks and no pickup tasks remaining OR the vehicle is empty and en-route to a pickup task
Methodology: Link reward calculation (Potential Demand on Links)

1. Construct a ‘Detour ellipse’
   ◦ Vehicle’s current location (316) and Destination (406) as focal points
   ◦ ‘Distance + Max Detour’ as major axis length

2. For each Origin node in the Detour ellipse region:
   ◦ Find Destination nodes within the region.
     ◦ Store Origin to Destination demand
   ◦ Find Destination nodes outside of the region, where the shortest path from the Origin to the Destination passes through the current vehicle Destination (406).
     ◦ Store Origin to Destination demand
   ◦ Assign Origin to Destination demand to Origin outbound link on Shortest Path from the Origin node to the Destination (406) node
     ◦ The summation of all this demand is the Link Reward $r_{ij}$
Potential Demand on Links for a Sample O-D pair

Legend

Nodes
- Type
  - Destination
  - Origin
  - Other Demand Nodes

Links
- Potential Demand (Trips)
  - 0
  - 0 - 3
  - 3 - 7
  - 7 - 12
  - 12 - 23

Detour Ellipse
Case Study
Case Study

Inputs:
- Anaheim Network
  - 401 nodes (223 nodes with demand) and 854 links
- Fleet size: 20, 50, 100, 200
- Number of Requests: [100 to 2,100]
- Reward coefficient $w_x$: 0.01, 0.1, 0.5, 1
- Bi-criteria Conditions
  1. The vehicle has only one drop off task remaining
  2. The vehicle has two drop-off tasks and no pickup tasks remaining
  3. The vehicle has two drop-off tasks and no pickup tasks remaining OR the vehicle is empty and en-route to a pickup task

Outputs:
- Shortest path vs. Bi-criteria pathfinding, difference in:
  - Customer waiting time
  - In-vehicle travel time
  - Combination of customer waiting time and in-vehicle travel time
Results
Base Case: Condition 1, Fleet Size 100, Reward Coeff = 0.1

Bi-criteria pathfinding is reasonably effective when # Requests is between 300 and 1000
- This represents moderate oversupply to moderate undersupply

Bi-criteria pathfinding is ineffective in extreme undersupply and oversupply cases
Impact of Reward Coefficient: $w_r$

High variance in the results
- Indicates an area of future research
- Need to be selective when using bi-criteria pathfinding

Using reward coefficient of 0.1 outperforms others
- It works especially well when request are between 300 to 1000.

Giving large weights to reward terms does not make bi-criteria path more effective.
Testing Conditions for Bi-criteria Paths

- Condition 1 outperforms 2 and 3
- Simple policy is better than complex ones
- Need to be selective about employing bi-criteria pathfinding

1. If a vehicle has only one drop off task assigned.
2. If a vehicle has two or less drop off tasks assigned.
3. Condition 2 & if a vehicle is empty and en-route to a pickup task
Conclusions
Conclusions

Bi-criteria path usage is effective for reducing both customer waiting time and in-vehicle travel time

- The reduction of total time for passengers with bi-criteria path is 3-5%

Bi-criteria pathfinding works best in cases where the supply of vehicles and request demand are relatively balanced

Link reward weights impact performance

- This study uses a fixed weight across all system states; future research should make the weight a function of system state

Condition 1 outperforms Condition 2 and 3

- Only consider bi-criteria paths when vehicle is empty or has one remaining drop-off
Future Enhancements

Improve link reward estimation method to better estimate potential demand

Improve pickup/drop-off resequencing when the vehicle is on a bicriterion path

Incorporate remaining travel time buffer of in-vehicle passengers and current vehicle occupancy during bi-criteria path choice

Account for spatial and temporal availability of VEHICLES (in addition to demand) when assigning vehicles to paths

Optimal dispersion of vehicles through multiple bi-criterion paths, instead of assigning all vehicles on the same path

Make reward term in objective function, conditional on state of system
- Supply-demand imbalance, vehicle occupancy, etc.
Thank You!

Acknowledgements:

- This research was funded by the Pacific Southwest Region University Transportation Center (PSR UTC). The PSR UTC is the Region 9 UTC funded under the US Department of Transportation’s University Transportation Centers Program.

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Extra Slides
Benefits of Bi-criteria pathfinding

Passengers/Users:
- Reduce user wait time
- More affordable

Service Providers:
- Reduce operational costs
- Reduce necessary fleet size
- Potentially increase ridership

Society:
- Decrease VMT, congestion reduction, energy consumption, and emissions
- Increase mobility and accessibility, particularly for car-less households

Public Sector:
- Better utilization of roads
- Potential reduction of infrastructure maintenance cost