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 → 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

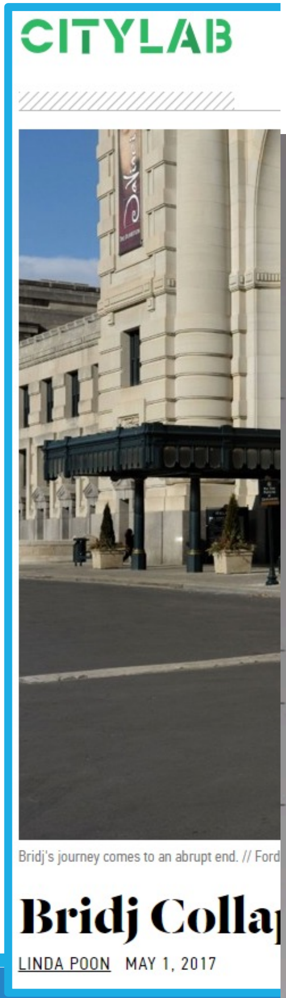
So many great benefits of **shared-ride MOD services!**

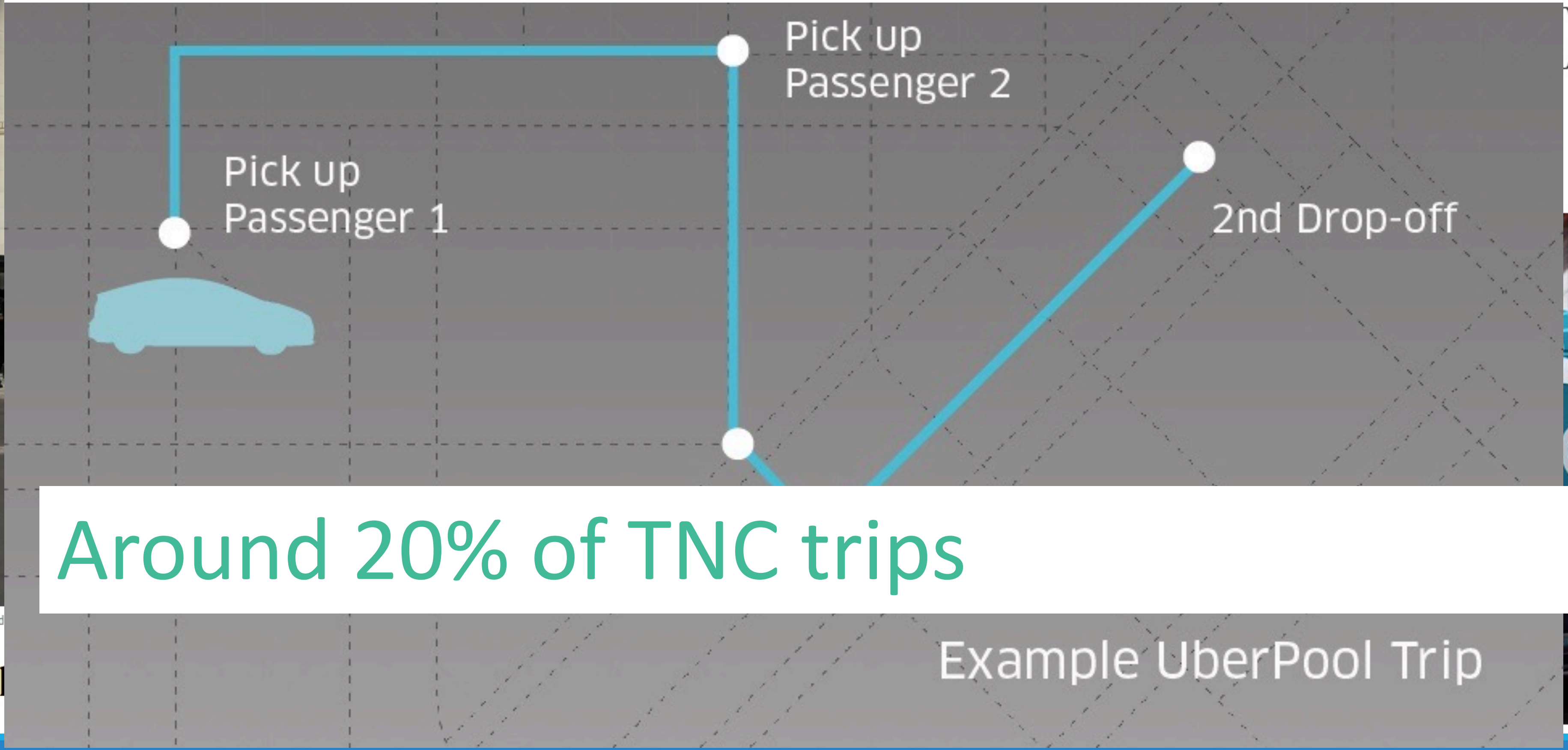
- **Individuals:** Reduced travel costs
  - Splitting operational – fuel and labor (~$0 for AVs) – costs
  - Capture capital/depreciation cost reduction from…
- **Mobility Service Providers (MSPs):** Reduced 'fleet' size and operational costs
- **Society:** Reduce vehicle miles travelled (VMT), traffic congestion, fuel consumption, harmful emissions

Yet…

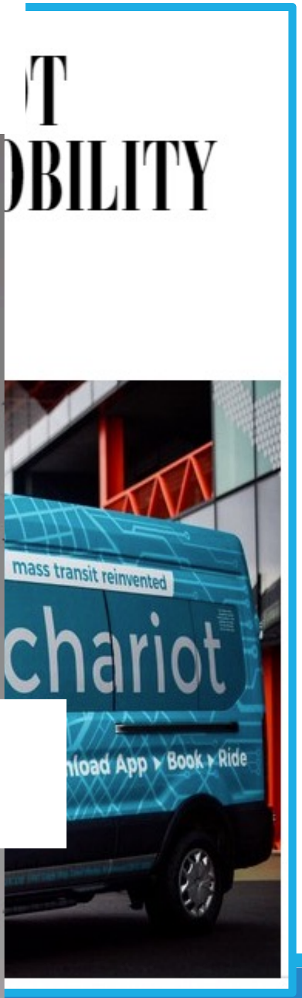
Mo

But what about Uber Pool and Lyft Line?





Around 20% of TNC trips



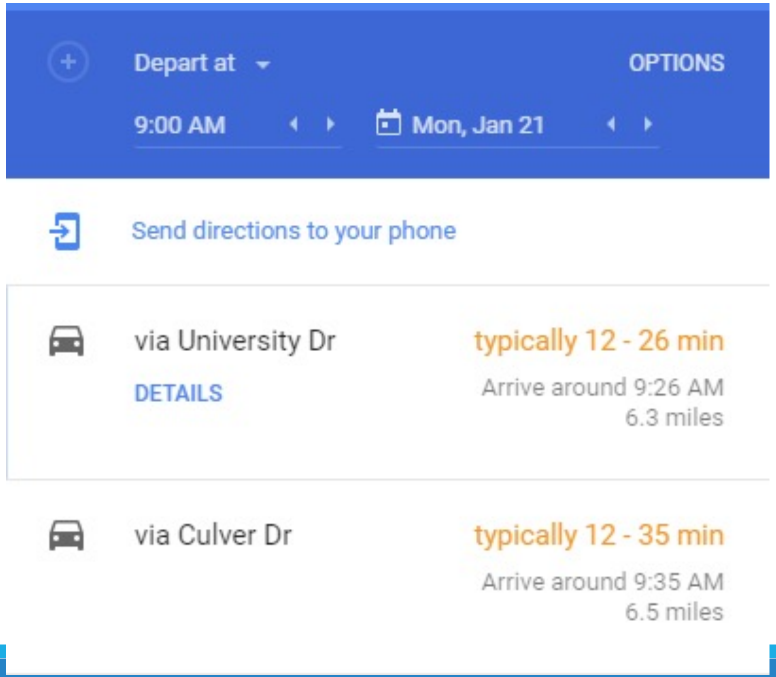
Motivation

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:

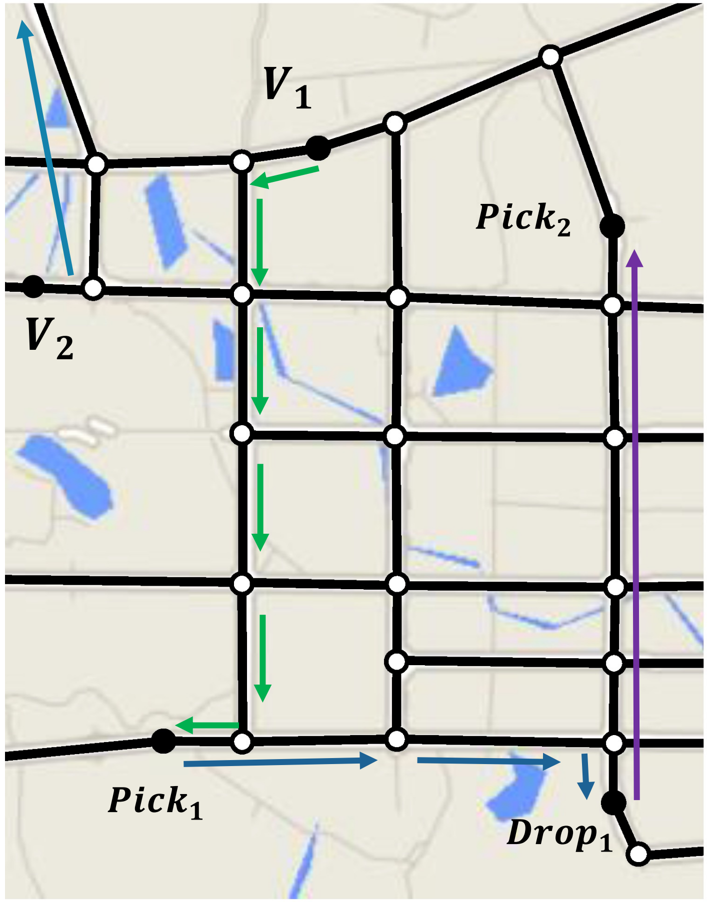
- Conceptualizes bi-criteria path-finding for shared MOD vehicles
- Develops a modeling framework for the static and dynamic bi-criteria best-path problems for shared-ride vehicles
- Proposes a solution algorithm (i.e., operational policy) for bi-criteria path assignment
  - In addition to algorithms/policies 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"

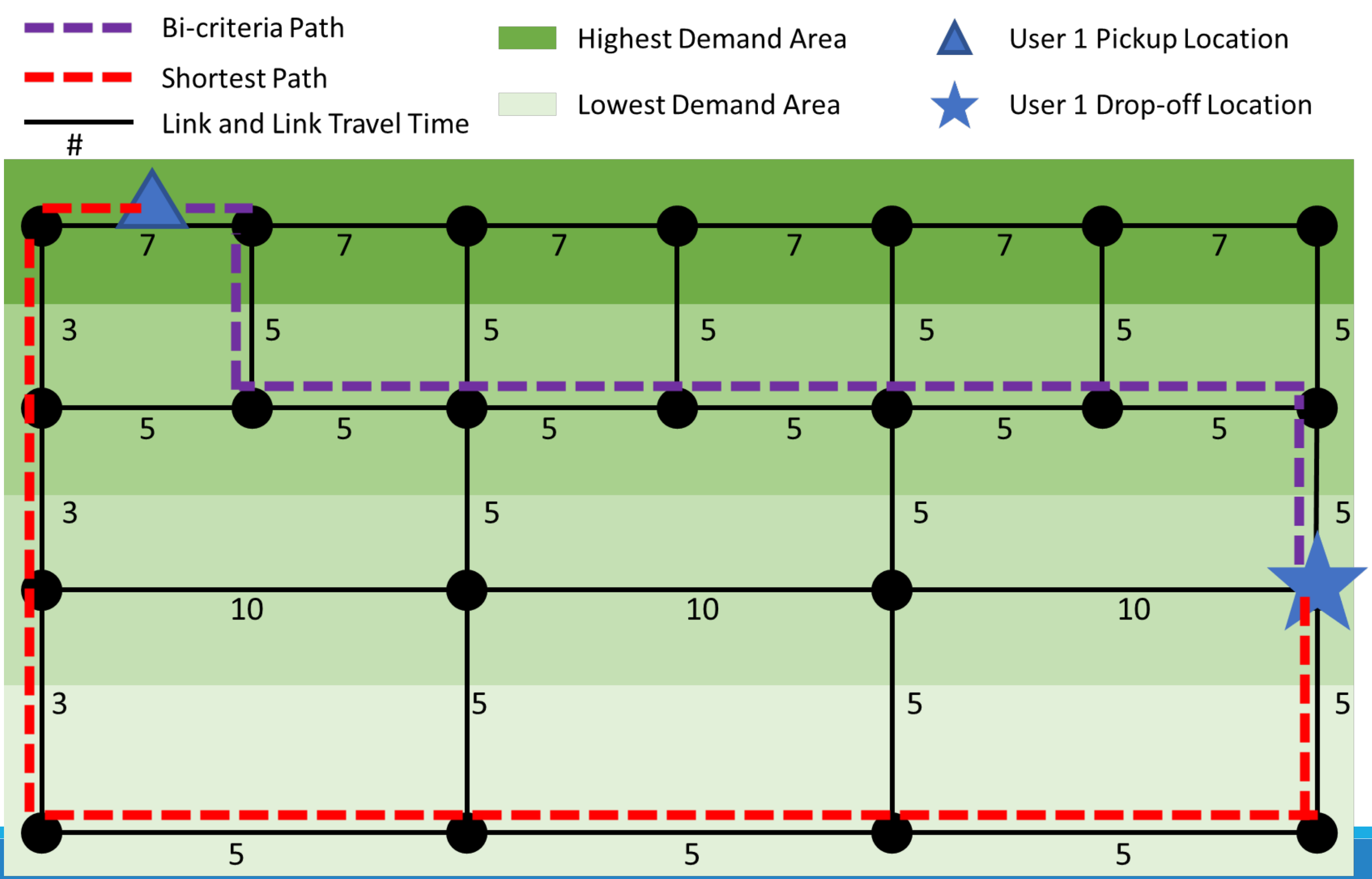


Research Hypothesis

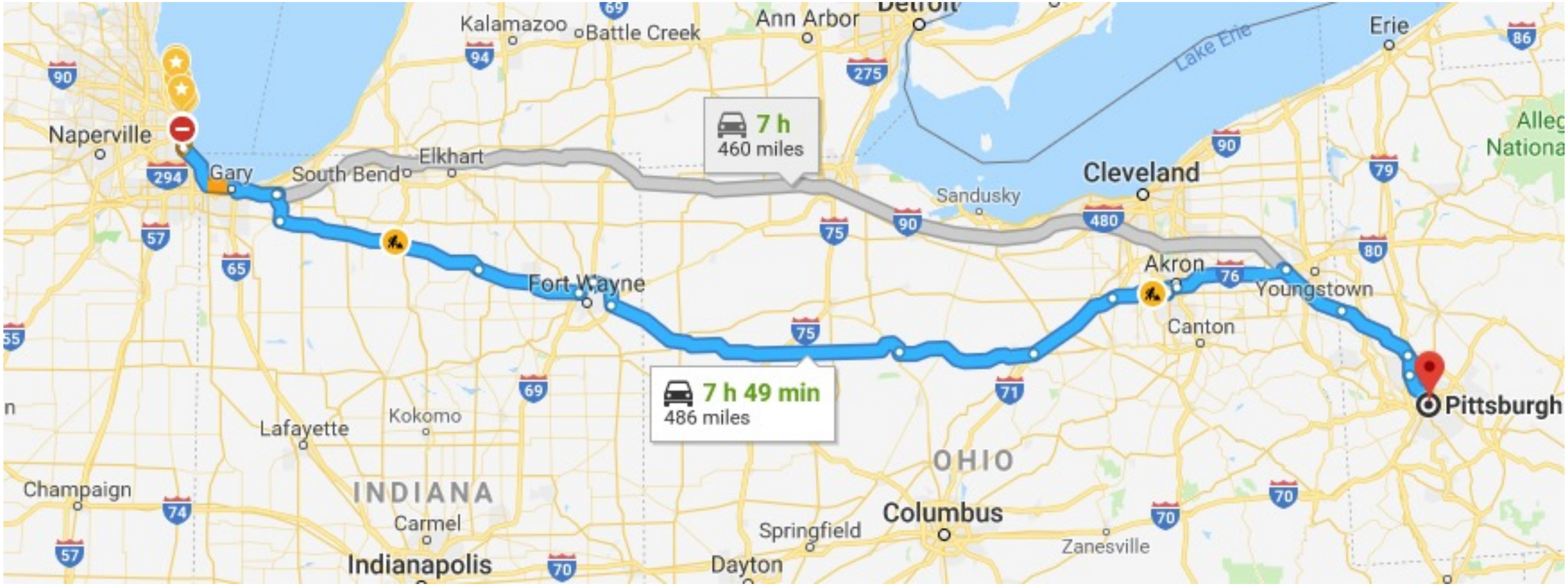
Assigning vehicles to **shortest paths** between pickup and drop-off locations may result in **suboptimal** fleet performance

- Vehicles may incur avoidable mileage when responding to new requests, since **pathfinding** process does **NOT consider future demand**

Key Idea: Bi-criteria Pathfinding



Key Idea: Bi-criteria Pathfinding



Goals and Research Questions

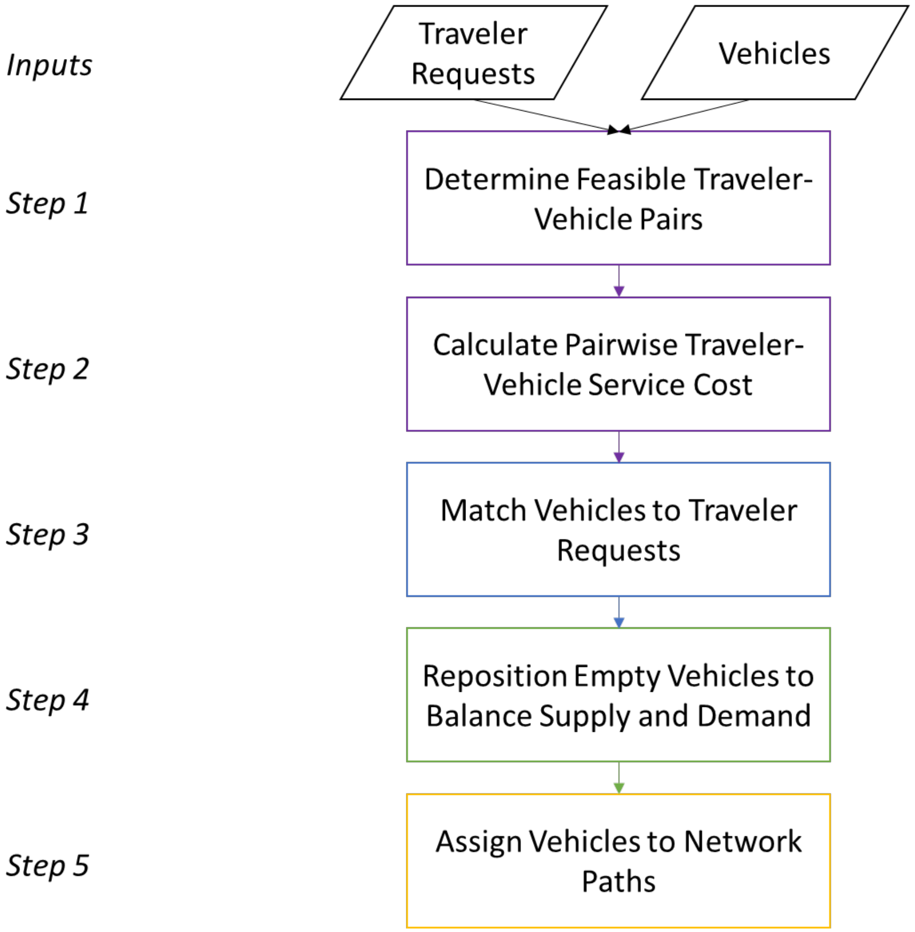
This research project aims to develop an efficient operational policy for shared-ride MOD services that efficiently:

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

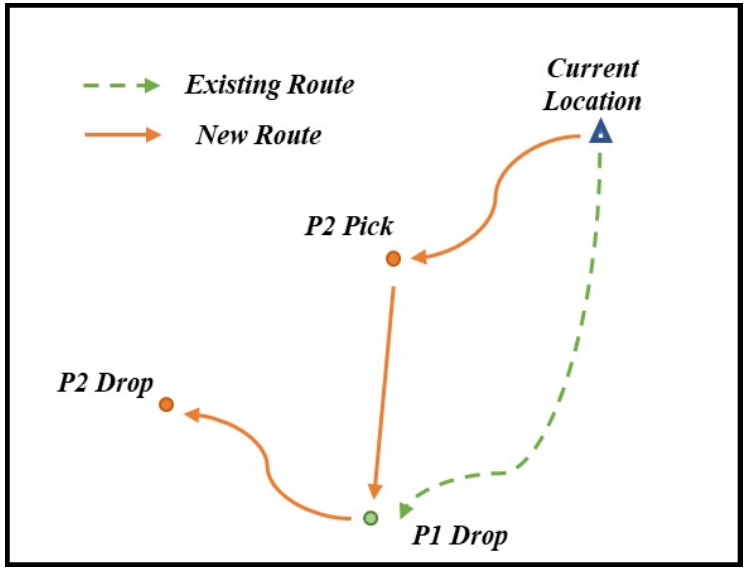
- Does bi-criteria pathfinding improve the operational efficiency of shared-ride MOD services?
- If yes, when should shared-ride MOD vehicles be assigned to bi-criteria paths?
- What are the major exogenous and endogenous factors that impact the effectiveness of bi-criteria pathfinding?

Methodology: Architecture Overview



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)

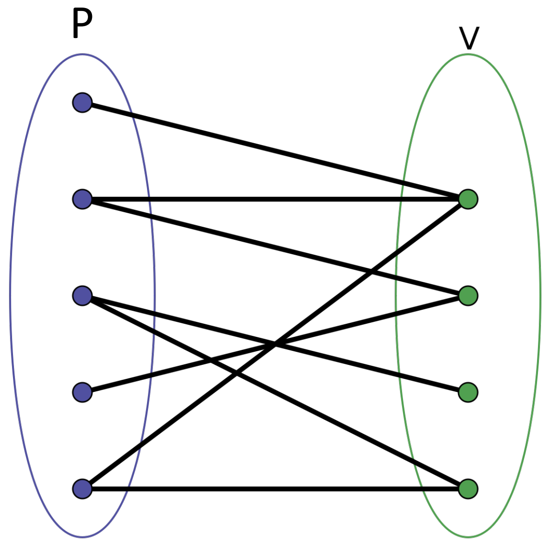
$$\boldsymbol{\underset{x_{pv}}{Max} \sum_{v \in V} \sum_{p \in P} (r_p - c_{pv}) \times x_{pv}} \quad \mathbf{(1)}$$

subject to:

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

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

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



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

Methodology: Step 5 -- Path Assignment

Routing a vehicle (formulated as a multi-criteria shortest path problem)

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

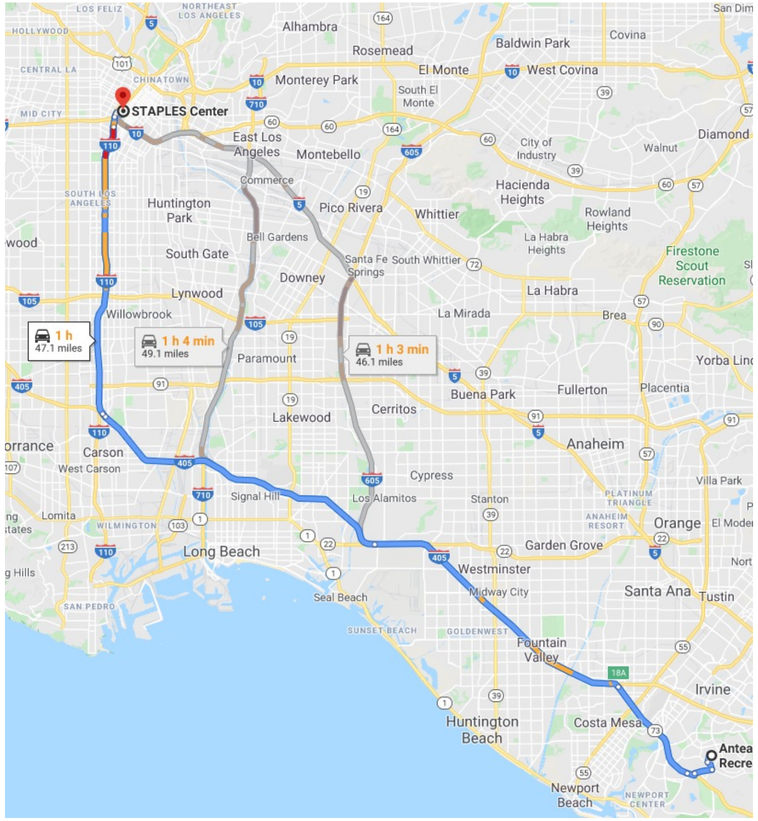
Subject to:

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

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

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)

$$\max_{x_{ij}} \sum_i \sum_j (w_r r_{ij} - c_{ij}) \times x_{ij} \quad (9)$$

- $w_r = f(occupancy, time\ slack)$

- *Reward term,* r_{ij}
- *Related to potential link demand*

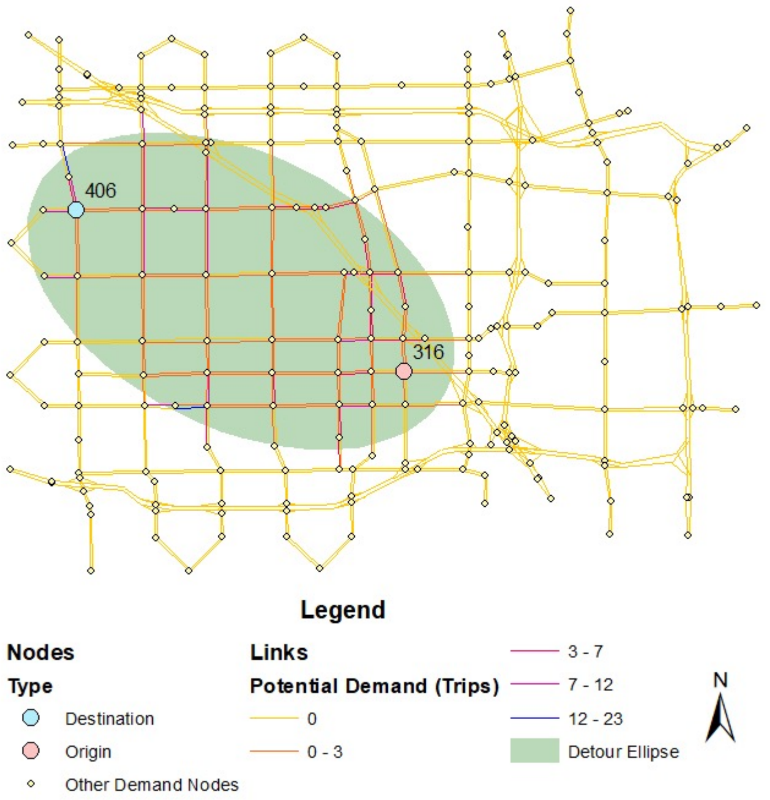
- We test bi-criteria routing under three conditions
  1. **The vehicle has only one drop off task remaining**
  2. **The vehicle has two drop-off tasks and no pickup tasks remaining**
  3. **The vehicle has two drop-off tasks and no pickup tasks remaining OR the vehicle is empty and en-route to a pickup task**

Methodology: Link reward calculation (Potential Demand on Links)

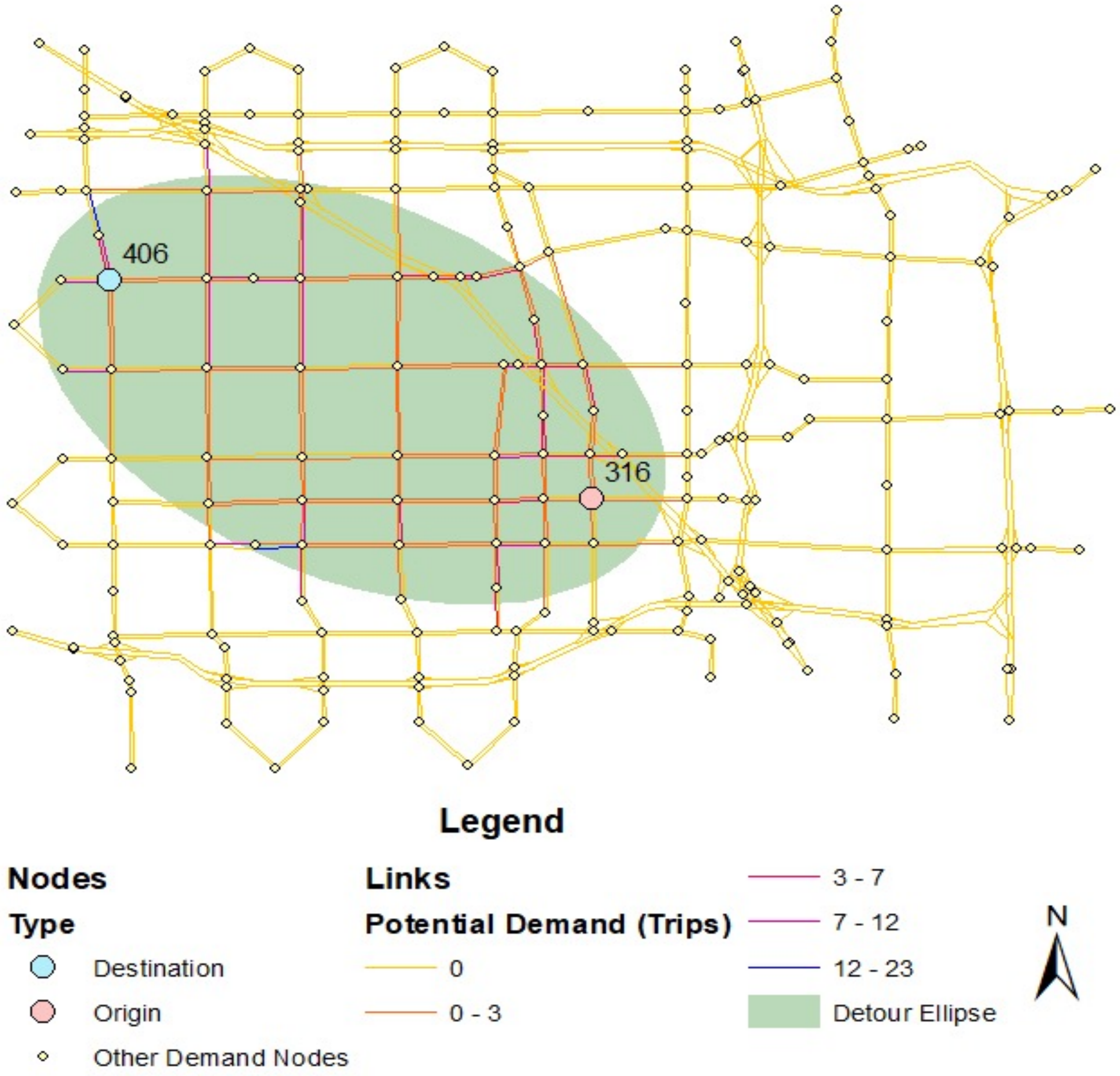
1. Construct a ‘Detour ellipse’
   - Vehicle’s current location (316) and Destination (406) as focal points
   - ‘Distance + Max Detour’ as major axis length

2. For each **Origin** node in the Detour ellipse region:
   - Find Destination nodes <u>within</u> the region.
     - Store **Origin** to Destination demand
   - Find Destination nodes <u>outside</u> 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



Potential Demand on Links for a Sample O-D pair



Case Study

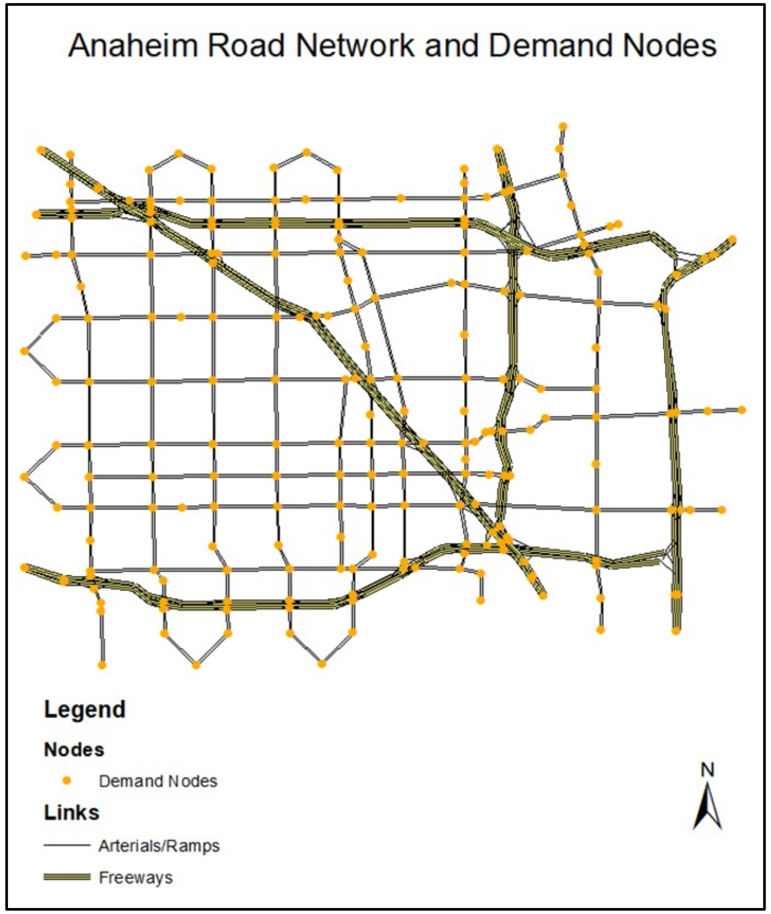
Case Study

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_r: 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



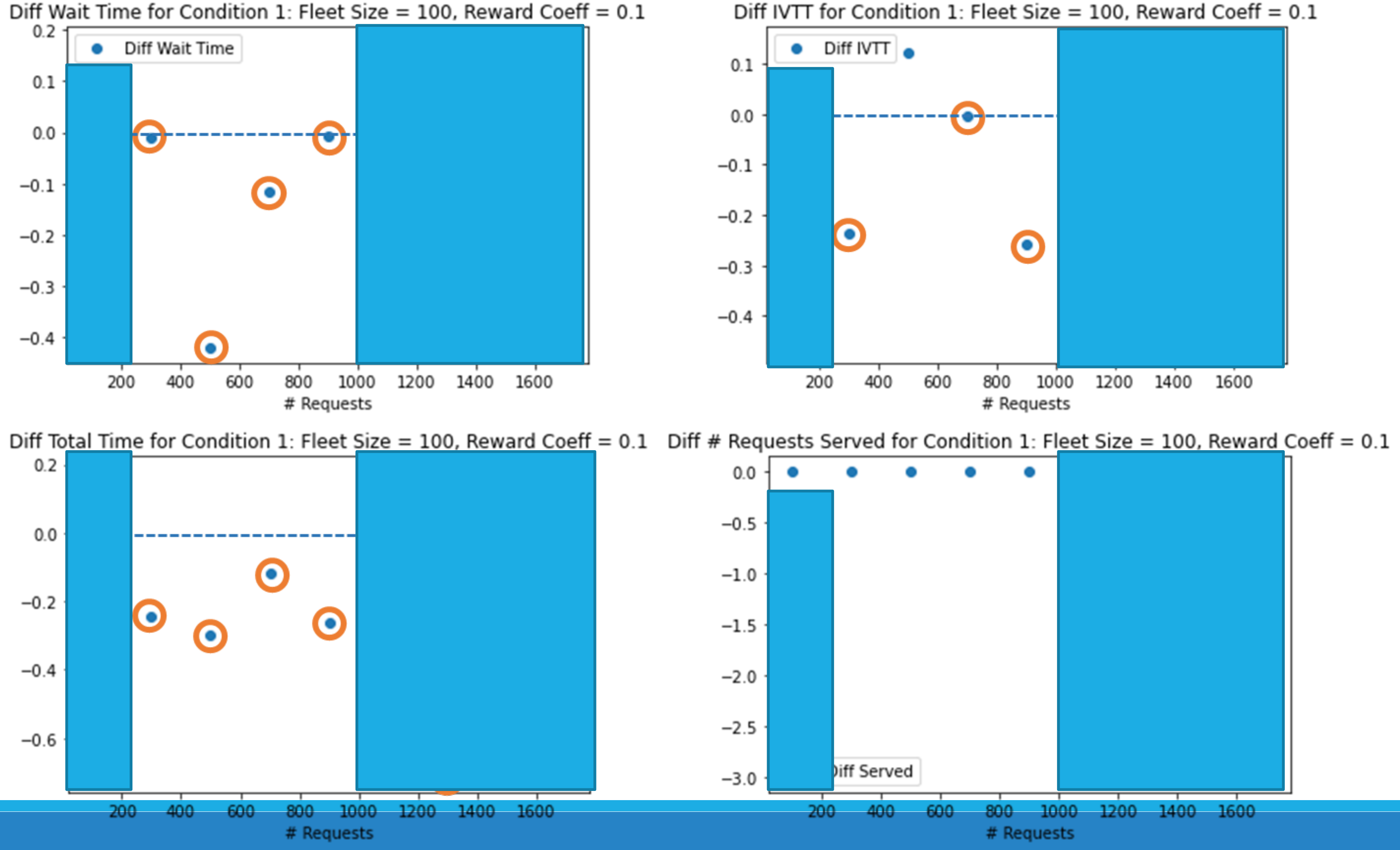
Results

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

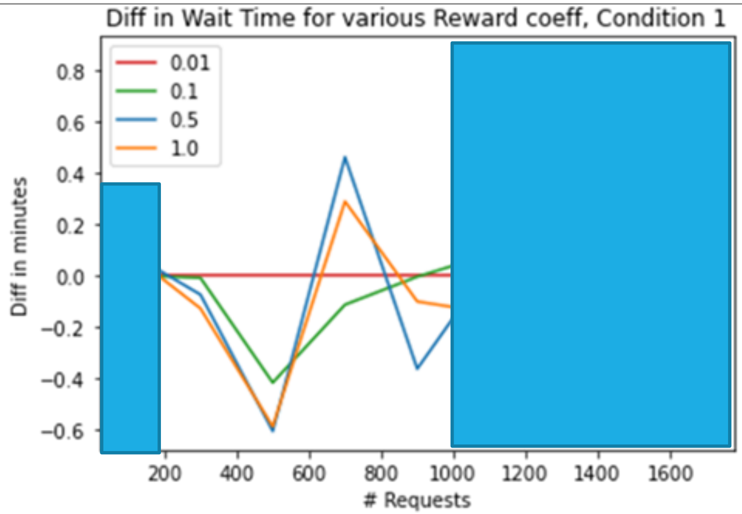
High variance in the results

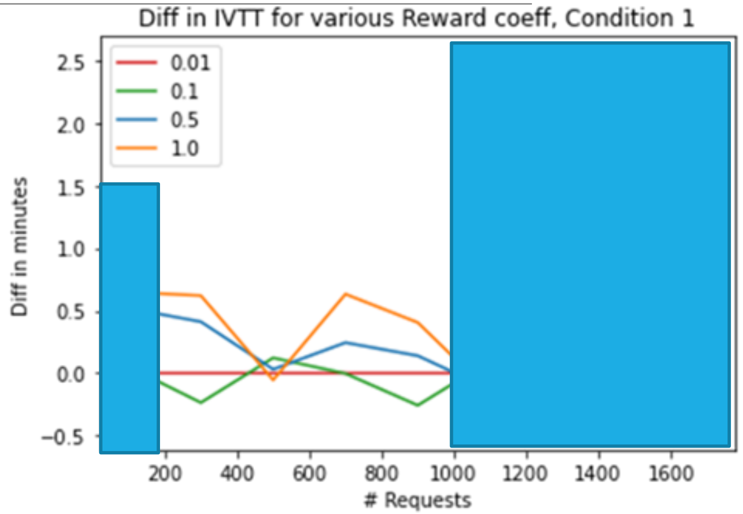
- Indicates an area of future research
- Need to be selective when using bi-criteria pathfinding

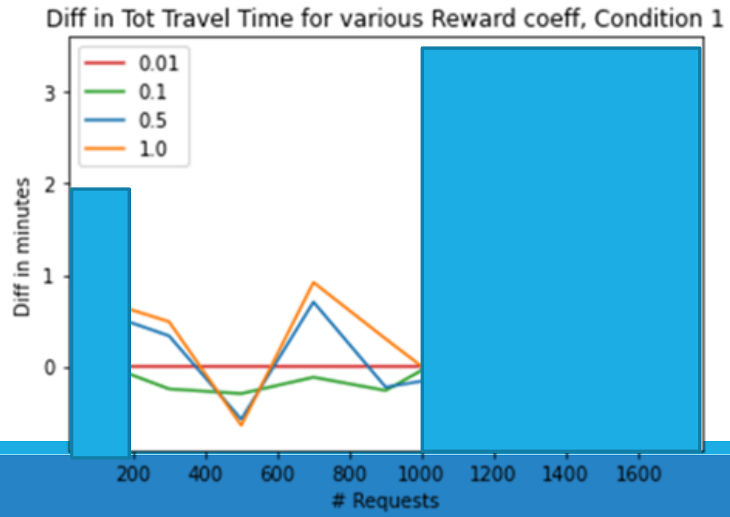
Using reward coefficient of 0.1 outperforms others

- 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.

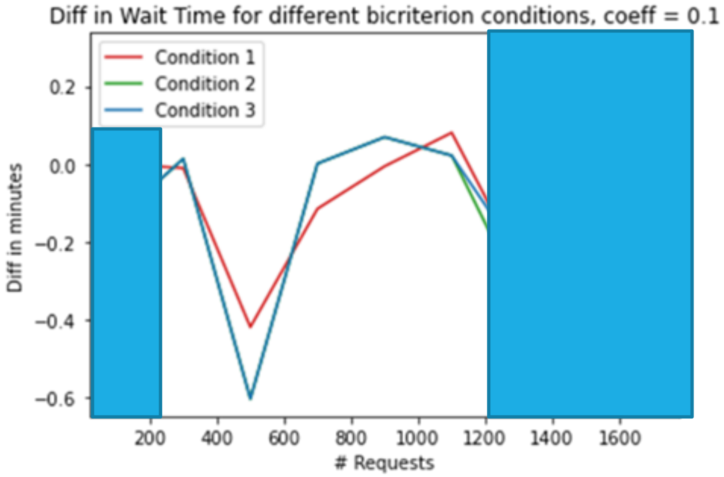


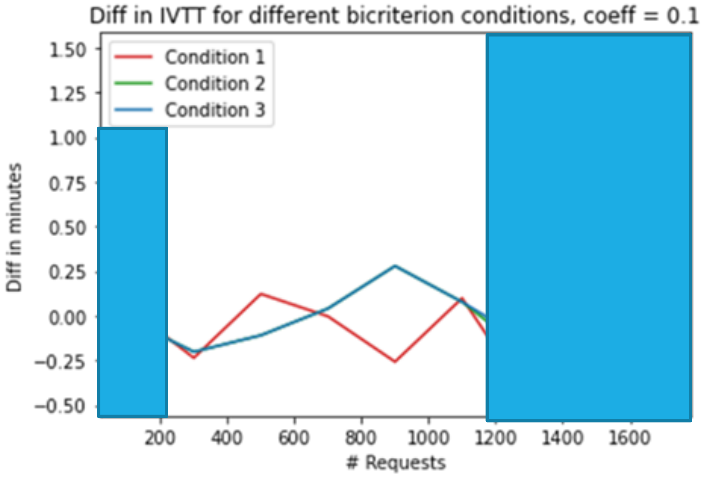


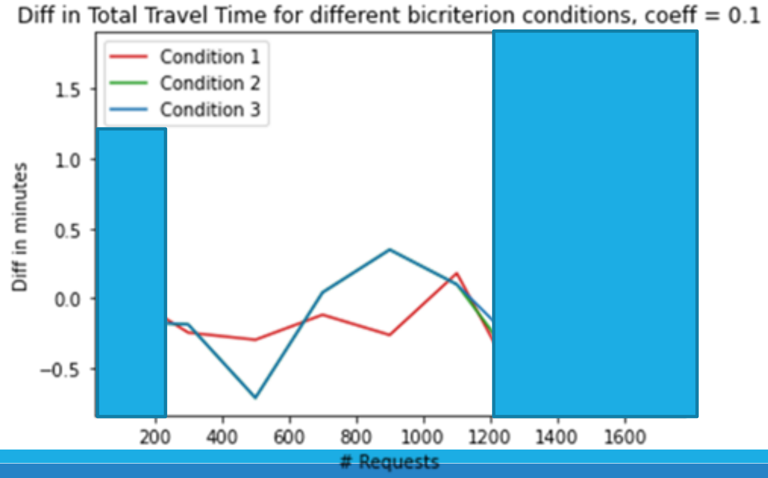


Testing Conditions for Bi-criteria Paths

- 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 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!

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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