Non-myopic pathfinding for shared-ride vehicles: A bi-criteria best-path approach considering travel time and proximity to demand

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The goal of this research project is to improve the operational efficiency of shared-ride mobility-on-demand services (SRMoDS). SRMoDS ranging from UberPool to micro-transit have the potential to provide travelers mobility benefits that are comparable to existing ride-hailing services without shared rides such as UberX, but at a lower cost and with fewer harmful externalities. To meet the project's goal, this study proposes a bi-criteria network pathfinding approach that considers proximity to potential future traveler requests in addition to travel time. This pathfinding approach was built on top of a state-of-the-art dynamic vehicle routing and matching modules. The study tests the proposed pathfinding approach using the network of the City of Anaheim. The results indicate that the proposed bi-criteria pathfinding can potentially reduce both traveler waiting and in-vehicle travel time; however, the effectiveness depends on several factors. Important factors include the relative supply-demand imbalance as well as several hyperparameters in the optimization-based control policy. Moreover, the results indicate that the bi-criteria policy is only advisable when the SRMoDS vehicle has one or fewer in-vehicle passengers. Although the operational benefits found in this study are relatively small, future research efforts related to tuning hyperparameters should allow bi-criteria pathfinding to significantly improve SRMoDS.

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Pacific Southwest Region UTC
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Contents

About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

The PI Michael Hyland along with graduate student researchers Dingtong Yang and Navjyoth Sarma conducted this research titled, "Non-myopic pathfinding for shared-ride vehicles: A bi-

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Abstract

The goal of this research project is to improve the operational efficiency of shared-ride mobility-on-demand services (SRMoDS). SRMoDS ranging from UberPool to micro-transit have the potential to provide travelers mobility benefits that are comparable to existing ride-hailing services without shared rides such as UberX, but at a lower cost and with fewer harmful externalities. To meet the project's goal, this study proposes a bi-criteria network pathfinding approach that considers proximity to potential future traveler requests in addition to travel time. This pathfinding approach was built on top of state-of-the-art dynamic vehicle routing and matching modules. The study tests the proposed pathfinding approach using the network of the Anaheim, CA. The results indicate that the proposed bi-criteria approach can potentially reduce both traveler waiting and in-vehicle travel time; however, the effectiveness depends on several factors. Important factors include the relative supply-demand imbalance as well as several hyperparameters in the optimization-based control policy. Moreover, the results indicate that the bi-criteria policy is only advisable when the SRMoDS vehicle has one or fewer in-vehicle passengers. Although the operational benefits found in this study are relatively small, future research efforts related to tuning hyperparameters should allow bi-criteria pathfinding to significantly improve SRMoDS.

Non-myopic pathfinding for shared-ride vehicles: A bi-criteria best-path approach considering travel time and proximity to demand

Executive Summary

Mobility-on-demand (MoD) services have become a relatively popular mode of transportation in urban areas. MoD service providers such as Lyft and Uber leverage the empty space inside private vehicles and provide convenient and affordable mobility to travelers. Shared-ride MoD services (SRMoDS) provide additional benefits to travelers, namely, lower costs and possibly shorter wait times, at the expense of slightly longer travel times compared to MOD services without shared rides. Moreover, SRMoDS provide additional societal benefits compared to MoD services without shared rides, such as increased vehicle occupancies thereby potentially reducing traffic congestion and vehicle emissions. Studies in the literature suggest that compared with MoD services without sharing, SRMoDS can reduce vehicle miles traveled (VMT) and vehicle hours by 20% to 30%, respectively (*1*).

While the benefits for travelers and society associated with SRMoDS are clear and significant, these services have not seen the market share of MoD services without shared rides. The reasons for this are many but undoubtedly the operational challenges associated with SRMoDS, compared with non-shared-ride services, play an important role. As such, the goal of this study is to improve the operational efficiency of SRMoDS with a focus on using a bi-criteria pathfinding approach to assign vehicles to network paths between traveler pickup and drop-off (PUDO) locations.

To serve a set of traveler requests, a SRMoDS operator usually considers the following operational subproblems: (a) Filtering available vehicles for each traveler request; (b) Estimating a 'cost' for each feasible traveler-vehicle combination; (c) Matching vehicles to travelers; and (d) Sequencing traveler PUDO tasks for individual vehicles to serve travelers. Additionally, many SRMoDS try to actively reposition vehicles to balance supply and demand. In subproblems (b) and (d) as well as the repositioning subproblem, the service provider almost exclusively, in the literature and in practice, assigns vehicles to the path with the shortest travel time. Using the shortest time path minimizes travel time for in-vehicle passengers in the myopic (i.e., short-sighted) sense but may not be the most efficient choice for overall system performance. Since the shortest path often consists of highway links where new demands do not originate, traveling on highway links and on the shortest path limits a vehicle's potential to pick up new requests en-route to its next PUDO location. This study aims to improve the operational performance of SRMoDS via considering both travel time and proximity to future demand when assigning vehicles to network paths. This approach is referred to as the bi-criteria pathfinding approach.

There are several potential benefits of a bi-criteria pathfinding approach. First, considering future demand when assigning vehicles to paths can potentially reduce waiting time for incoming travelers. Second, considering demand proximity can increase the possibility that a vehicle is shared, thereby increasing vehicle occupancies, and decreasing VMT. Third, combining the above two points, bi-criteria pathfinding can increase system-wide service efficiency and reduce negative environmental impacts of MOD services.

SRMoDS have received considerable attention in the recent academic literature (*1–5*). However, to the best of the authors' knowledge, all the operational studies that incorporate road networks assign vehicles to the shortest path between their current location and next PUDO location. The major research questions addressed in this study on bi-criteria pathfinding include: (a) When should a vehicle consider bi-criteria paths? (b) How should the bi-criteria paths be decided? and (c) What are the benefits of using bi-criteria pathfinding? To answer these questions, this study employs an agent-based dynamic stochastic simulation to test several different bi-criteria pathfinding policies against a conventional shortest path approach for SRMoDS.

In the shortest path approach, the only data needed to compute the optimal path are the link travel times. Conversely, the bi-criteria pathfinding approach requires both link travel times and a measure of demand proximity (or a reward) for each link. To obtain a reward on each link, the study first needs to determine the potential origin-destination demand 'flows' a vehicle can reasonably serve given its current location and its planned sequence of PUDO tasks. This directional demand eventually needs to be converted to a reward on each link. This study develops and presents a new algorithm (Algorithm 1) to estimate the potential demand on links, as well as the combined 'cost' of travel time and potential demand on links.

To test the effectiveness of bi-criteria pathfinding, this study simulates the operations of a SRMoDS using travel demand and roadway network data for Anaheim, California. Simulation results illustrate the benefits of bi-criteria pathfinding while at the same time unveiling the conditions that limit the effectiveness of bi-criteria pathfinding. Results indicate that bi-criteria pathfinding can reduce traveler waiting and in-vehicle time under certain conditions. The study also finds that the supply of vehicles and total number of demand requests have a large impact on the effectiveness of bi-criteria pathfinding. In general, bi-criteria pathfinding is more effective when the system is mildly undersupplied to mildly oversupplied. Moreover, rather than always assigning vehicles to paths using the bi-criteria approach, when the number of passengers currently inside a vehicle exceeds one, the shortest path approach is superior.

As this represents the first study to consider non-shortest-paths when assigning SRMoDS to network paths, there is significant potential to improve the bi-criteria pathfinding control policies and algorithms proposed in this study. While there is significant variance in the performance gap between bi-criteria path assignment and shortest path assignment, improved control policies and properly tuned hyperparameters should both decrease the performance gap variance across scenarios and also increase the mean performance gap measure under most conditions.

Introduction

The ubiquity of wireless mobile internet and smartphones has led to the proliferation of mobility-on-demand (MoD) services offered by companies like Uber and Lyft. The growth and market share of MoD services suggest they are already providing significant mobility benefits to individual travelers in terms of cost and/or convenience relative to other travel options. Moreover, shared-ride MoD services (SRMoDS), via increasing vehicle occupancy relative to individually owned and operated vehicles, may be able to simultaneously benefit society through decreases in vehicle miles traveled (VMT), traffic congestion, and vehicle emissions. However, the market share of SRMoDS, such as Uber Pool and Lyft Line, appear to be significantly lower than MoD services without shared rides such as UberX and conventional Lyft (*6*). Moreover, the demand for SRMoDS offered by transit agencies (e.g., flexible, demand-adaptive, and demand-responsive transit) and microtransit companies also pale in comparison to taxi services and the MoD services of Uber and Lyft without shared rides. There are many reasons for this, but one of them is certainly the operational inefficiency of existing SRMoDS.

The overarching goal of this study is to improve the operational efficiency of SRMoDS. Several research studies in the recent literature address SRMoDS operational problems (*4*, *7–11*). However, the primary focus has been on dynamically assigning new user requests to shared-ride vehicles and then inserting each user's pickup and drop-off (PUDO) locations within his/her assigned vehicle's existing route/schedule. This research study addresses a separate and often overlooked subproblem associated with operating SRMoDS, namely, the assignment of vehicles to network paths as the vehicles move between PUDO locations. A network path is an ordered sequence of nodes or links in a road network that a vehicle should traverse between PUDO locations. To the best of the authors knowledge, this network path subproblem has not been examined in the context of MOD services, and given only scant attention in dynamic freight pickup and delivery literature (*12*).

In practice and in the academic literature, individual shared-ride vehicles are assigned to the shortest travel time paths between PUDOs, in the same way drivers of personal vehicles and taxis take the shortest path between trip origins and destinations. However, this intuitive strategy is myopic for shared-ride vehicles because it does not consider the (high) likelihood of new users requesting service during the time the shared-ride vehicle travels between PUDOs. The bi-criteria network pathfinding strategy proposed in this study considers both travel time and proximity to expected future demand when assigning a shared-ride vehicle to a network path. While the MoD fleet controller should certainly still aim to minimize each vehicle's travel time between PUDO locations, to increase sharing opportunities and prevent the shared-ride vehicle from needing to detour from high-speed, low-demand areas back to lower speed, high-demand areas to pick up new user requests, the MoD controller should consider the proximity of network paths to expected future demand.

To meet the goal of improving the operational efficiency of shared-ride MoD services, this study conceptualizes, defines, models, and develops solution algorithms for the bi-criteria shared-ride best-path problem, considering travel time and proximity to demand. The study compares the bi-criteria pathfinding approach with the shortest path approach, within the context of operating a SRMoDS in Anaheim CA.

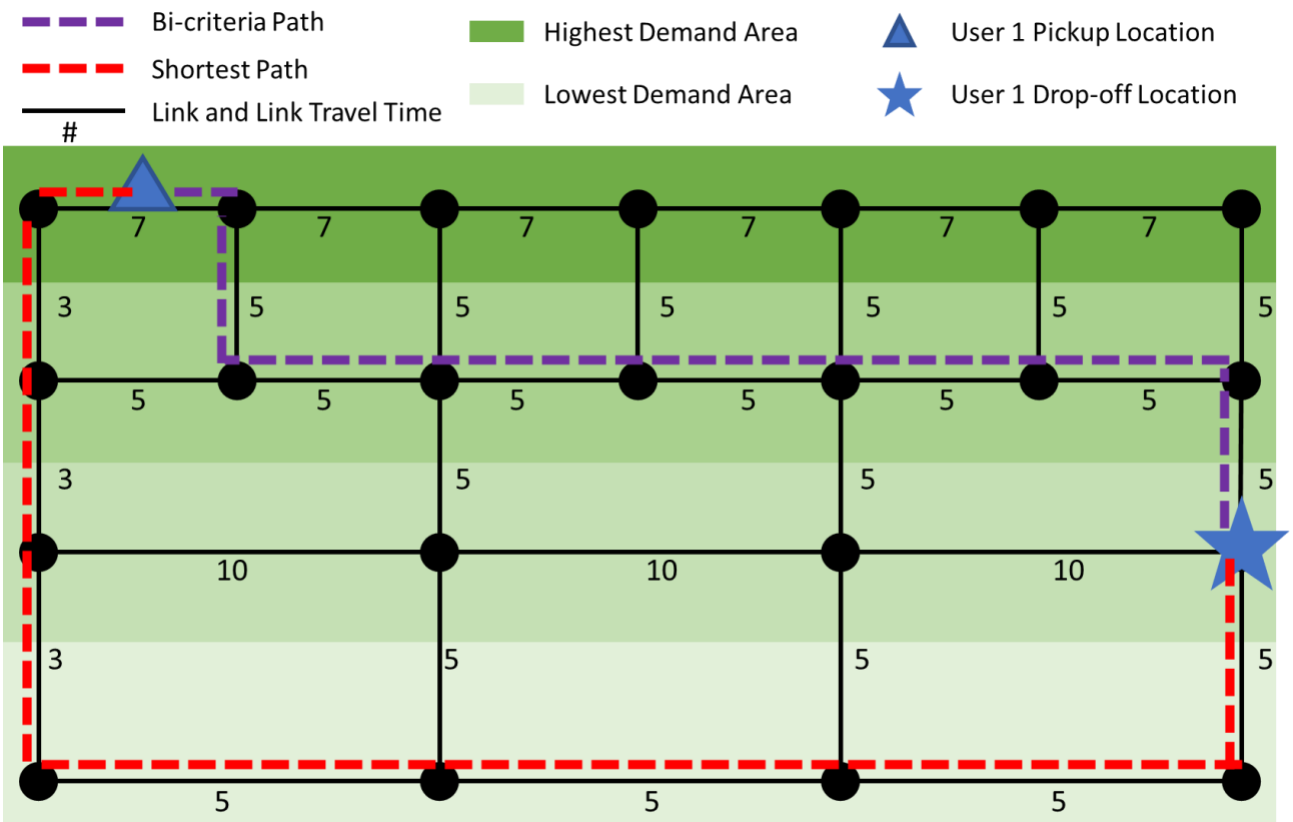
The remainder of the report is structured as follows. The next section provides a conceptual framework and visualization of the bi-criteria pathfinding approach. The following section provides relevant background information and reviews relevant studies in the literature. The following two sections present the formal problem statement as well as the proposed solution methodology. The penultimate section presents a case study and then discusses the computational results comparing the bi-criteria and shortest path approaches. The final section concludes the paper with a summary and a discussion of future research objectives.

Conceptual Framework

Error! Reference source not found. displays pictorially the static bi-criteria best-path problem, considering travel time and proximity to demand. The MoD fleet controller must assign a shared-ride vehicle to a network path to connect the traveler's pickup (blue triangle) and drop-off (blue star) locations. The MoD controller's bi-criteria objective involves minimizing travel time and maximizing proximity to expected future demand. In **Error! Reference source not found.**, the link travel times are displayed below the links, whereas the darkness of the area represents the expected future demand rate—darker implies a higher demand rate. The minimum travel time component of the objective drives the controller to assign the shared-ride vehicle to the shortest path in terms of travel time. Conversely, the maximum proximity to demand component of the objective drives the controller to assign the vehicle to the links in the dark-green portion of the region.

The red dashed line in **Error! Reference source not found.** displays the conventional shortest travel time path between the PUDO locations. Essentially, the controller immediately moves the vehicle from the user's pickup location in the high-demand, low-speed area (e.g., a business district) directly to the low-demand, high-speed area (e.g., a highway running parallel to the business district). From there, the vehicle takes the highway to the exit nearest the user's drop-off location. Once the vehicle gets on the highway, it is either unlikely to be assigned to a new user request before the next drop-off location, or it would require a significant detour to pick up a new request.

Figure 1. Paths for shortest path (red) and bi-criteria (purple) strategies



The purple dashed line in **Error! Reference source not found.**, displays a possible bi-criteria network path a vehicle may take between the user's PUDO locations if the controller considers proximity to demand in addition to travel time. Rather than immediately moving to the low-demand, high-speed area, the bi-criteria vehicle moves to the moderate-demand, moderate-speed area from the high-demand, low-speed area. Under this approach, if a new demand request arises in the moderate-demand area, the vehicle may not even need to divert its path to pick up the new request. Similarly, if a new request arises in the high-demand area, the bi-criteria vehicle can easily divert to this portion of the network and pick up the new request. The exact network path a controller using the bi-criteria approach assigns to a vehicle depends on several factors including the remaining occupancy of the vehicle and weight of *proximity to demand* relative to *travel time* in the objective function.

Lastly, it is important to note that in **Error! Reference source not found.** the setting is static and deterministic, whereas in the SRMoDS operational problem presented in this study, the setting is dynamic and stochastic. This means that as the vehicle traverses a path, either purple or red, new requests will enter the system that may or may not be assigned to the vehicle. If the requests are assigned to the vehicle, it will likely need to divert from its current path to pick up the newly

assigned request. Hence, the network paths for vehicles in a SRMoDS often require updating as the real-world operation or simulation advances through the day.

Background and Literature Review

Ridesharing, Shared-rides, and Pooled Rides

Shaheen and Cohen present a taxonomy of rideshare services (*1*). In their categorization, rideshare services include three major classes, namely core pooled services, ridesharing, and on-demand ride services. Core pooled services define a broad set of services that encompass pooling services without smartphone apps (e.g., public transit). Ridesharing consists of general carpool/vanpool of family members or coworkers, in which smartphone apps are also not necessarily involved. The last category, on-demand ride services, utilize smartphone apps for matching drivers and riders in real-time. On-demand ride services are further classified into four sub-classes, including ride sourcing (Uber, Lyft), ride splitting (Uber pool, Lyft Line), taxi share, and micro transit. Ride splitting is the focus of the study; however, this study refers to ride-splitting services as SRMoDS.

The literature illustrates several ways in which SRMoDS services have large social and economic benefits. Survey results indicate that pooled services have an average occupancy of 2.1 passengers per trip (*13*). Moreover, Ridesharing services reduce VMT, costs for traveler, and road network congestion (*14*). In an early study, Levin et al. simulate the city traffic of Austin with and without dynamic ridesharing (another name for a SRMoDS) and find that dynamic ridesharing can reduce empty vehicle repositioning trips (*15*).

Shared-ride Mobility-on-Demand Service Fleet Operations

Despite the clear social and economic benefits of SRMoDS, operating SRMoDS is complicated and challenging. As new requests want to be served immediately, the system is highly dynamic. And because the mobility service provider does not know where and when future requests will arise, the system is also highly stochastic. Moreover, in this highly dynamic and stochastic setting, the following four computational subproblems require substantial computational resources: (i) assigning new requests to vehicles, (ii) sequencing PUDO locations for each vehicle, (iii) assigning vehicles to network paths, and (iv) repositioning idle vehicles to achieve a better spatial balance between supply and demand. The remainder of this subsection reviews literature and/or provides background information related to these four subproblems.

The first subproblem, matching/assignment of traveler requests to vehicles, is usually referred to as a “single driver, multiple rider arrangement”; i.e. a vehicle can simultaneously serve multiple riders, while riders will not switch between vehicles (*16*). The literature models the traveler-vehicle matching/assignment problem as well as its objective function and constraint set in multiple ways. Several objective functions are considered in previous studies, such as minimizing total VMT (*5*, *17*), minimizing total delays and waiting time (*18*), and maximizing the total VMT saved (*19*). Besides the difference in objective functions, the formulation of the problem also

differs in terms of the decision variables and constraint set. One stream of models involves an integer programming (IP) formulation known as the assignment problem or bi-partite matching problem (*5*, *18*, *20*). A second stream of models involves a mixed-integer programming formulation known as the dial-a-ride problem (DARP) (*21–23*). The DARP actually integrates sequencing PUDO locations (subproblem two) with assigning requests to vehicles. This study employs the bi-partite matching problem formulation for the vehicle-traveler assignment problem and uses the objective of minimizing VMT.

The second subproblem, sequencing of PUDO locations, is often modeled as a vehicle routing problem (VRP) or more specifically, a DARP or pickup and delivery problem (*5*, *11*). Unlike the bi-partite matching problem, the VRP and DARP are computationally intensive optimization problems. However, if the sequencing of PUDO locations only needs to be done for a single vehicle and a few requests, then the problem can be solved quickly. Conversely, if the sequencing of PUDO locations is done alongside the assignment of travelers to vehicles, the problem becomes impractical to solve exactly in a dynamic/real-time context for even a few vehicles and a couple dozen requests. Hence, this study assumes the assignment problem is solved first and then the sequencing problem is solved for each individual vehicle.

The third subproblem, the assignment of vehicles to network paths, has largely been overlooked in the academic literature. Many studies do not even include a real road network and in studies that do, researchers almost exclusively assign vehicles to the shortest travel time path. In the freight, less-than-truckload literature, Thomas and White present seminal work that considers non-shortest travel time network paths between PUDO locations (*12*). They refer to their approach as anticipatory route selection. The current study uses the term *network path* rather than *route* to differentiate between the third subproblem (i.e., network pathfinding) and second subproblem (i.e., sequencing PUDO locations, which is a type of vehicle routing problem).

The fourth subproblem, vehicle repositioning, can be employed to address spatial imbalances between supply and demand, where the spatial mismatch in supply and demand arises from a spatial imbalance between trip origins and destinations. To reposition vehicles, some operators directly dispatch empty vehicles to the highest demand area. On the contrary, Lei suggests that the relocation activities could be more productive if pricing strategies are used to influence path choices of riders (*24*). Lei suggest that lower prices could be assigned to paths that travel through areas with high demand to encourage riders to choose those paths (*24*).

The potential of shared-ride MoD services to enhance mobility and sustainability has motivated several researchers to address the problem recently. To further improve the sustainability of SRMoDS, Jung et al. examine SRMoDS with electric vehicles and address the operational problem considering re-charging constraints (*10*). Qian et al. model the taxi group ride problem, and try to group travelers with similar origins, destinations, and departure times into the same taxi (*19*). Hence, they do not allow the shared-ride vehicle to pick up other travelers after grouping requests together in the origin region. This limits the solution space and the applicability of the proposed bi-criteria path-finding approach.

Related Dynamic Stochastic Operational Problems in Transportation

In the case of stochastic dynamic pathfinding, the controller must constantly reconsider the best paths of shared-ride vehicles as they traverse the network. This problem falls under the general class of stochastic dynamic vehicle routing problems (*25*). Similarly, the bi-criteria approach falls under the general class of anticipatory (or pro-active) approaches to stochastic dynamic problems (*12*, *26*, *27*), in contrast to reactive approaches.

Much of the existing research on anticipatory routing is in the freight transportation literature and it uses stochastic information about user demand to solve the dynamic vehicle fleet routing and scheduling problem (*26*, *28*), rather than the individual vehicle path-finding problem. Most of the research on stochastic dynamic vehicle routing problems does not consider path-finding in networks (*27*, *28*); this is often because the models do not include physical networks and/or congestion effects. Fleischmann et al. present seminal work on stochastic dynamic routing that incorporates road networks, congestion, and online traffic information; however, the study assigns vehicles to the shortest network paths between PUDO locations (*29*).

Other research shows that not forcing vehicles to travel on the shortest network path between two points when rebalancing can nearly eliminate the congestion effects of empty vehicle trips in MoD systems (*30*). Conversely, another study considering a real network with a realistic spatial-temporal demand distribution shows that empty rebalancing trips will increase congestion (*31*).

Many existing formulations and operational policies in the dynamic freight/courier vehicle routing literature do not allow decisions to be made until vehicles stop at pickup or delivery points (*27*). Under this modeling approach, shortest travel time paths are optimal; however, this modeling assumption should be relaxed to allow vehicles to be diverted between PUDO locations.

Bi-criteria Pathfinding

The bi-criteria best-path problem considering travel times and proximity to demand can be thought of as an inverse hazardous materials routing problem (*32*). In the hazardous material transportation problem, the routing decision combines both safety and cost concerns (*33*, *34*). From the safety perspective, hazardous materials should be routed away from populous regions. From the cost saving perspective, the total travel distance should be minimized. In the hazardous materials case, unlike the SRMoDS case, paths near population centers are penalized rather than rewarded (*35*). Early work models the hazardous material routing problem on a Euclidean Plane (*36*). Later research model the problem in a network with stochastic, time-varying travel times (*37*). The solution approaches of multi-objective problems are well-discussed in literature, which includes the constraint method (*38*), convex combination of multi-objectives (*33*), and dynamic programming (*39*). Recent research also considers equity along with proximity to population centers in the transportation of hazardous goods (*40*). Including equity in the bi-criteria best-path problem for MoD shared-ride vehicles is an interesting future research direction that is beyond the scope of this study.

Problem Statement

The section presents the SRMoDS operational problem with bi-criteria pathfinding; the model is similar to the one presented in Hyland and Mahmassani's study of a SRMoDS with automated vehicles that does not consider pathfinding (*2*).

The SRMoDS operational problem is characterized by a fleet of m vehicles $V = \{v_1, v_2, v_3, \dots, v_m\}$ that aim to serve customers $C = \{c_1, c_2, \dots c_i, c_{i+1} \dots, c_{|C|}\}$ who request service during the finite time horizon $T = [0, t_{max}]$, in network $G = (N, L)$ where N is the node set and L is the link set. A link from $Node\ i$ to $Node\ j$ is represented as (i, j).

At time $t = 0$, vehicles may be located at one or several depots, or they may be dispersed throughout the entire network. Traveler requests follows a stochastic process with a Poisson distribution for interarrival times, wherein the demand rate parameter for each node N is a function of the origin-destination input demand. Each traveler request c_i comes with a request time $t_r^i \in T$, pickup location $l_p^i \in N$, and drop-off location $l_d^i \in N$, a group size g^i, and a time window for travel—the latest pickup time $t_p^i \in T$ and latest drop-off time $t_d^i \in T$.

The SRMoDS operator must pick up travelers at their requested pickup locations and drop them off at their requested drop-off locations. However, the vehicles can pick up additional requests, even if there is a traveler currently inside the vehicle. The goal of the SRMoDS operator is to efficiently serve the traveler requests via (i) dynamically assigning vehicles to travelers, (ii) dynamically sequencing PUDO locations for the assigned requests, (iii) assigning vehicles to network paths, and (iv) repositioning idle vehicles requests. Efficiently serving traveler requests refers to minimizing wait time, in-vehicle travel time (IVTT), and fleet mileage as well as maximizing the number of requests served.

This study assumes that vehicles do not need to refuel as the analysis period in the study represents a peak period of the day, where it should be reasonable to assume that prior to the peak period, the vehicles can be refueled and then operate without refueling during the entire peak period.

This paper defines a *vehicle task* as either picking up or dropping off a traveler. This paper also defines a *vehicle job* as completing the service for a traveler, i.e., a job includes a pickup task and a drop-off task.

Modeling the Dynamics

Rather than a detailed model of the entire simulation framework, this section presents the state variables considered in the simulation model. The state variables needed to model each vehicle from the current time period t to the end of the analysis period t_{max} include each vehicle's current location, current occupancy, planned sequence of PUDO task locations, and planned network path from its current location to its next PUDO task location. The state variables needed to model each travel request include the request's elapsed wait time and its current status.

Possible traveler statuses include not yet requested, requested but unassigned, assigned but not picked up, in-vehicle, and served. The model also captures the current imbalance between supply and demand in subregions of the network.

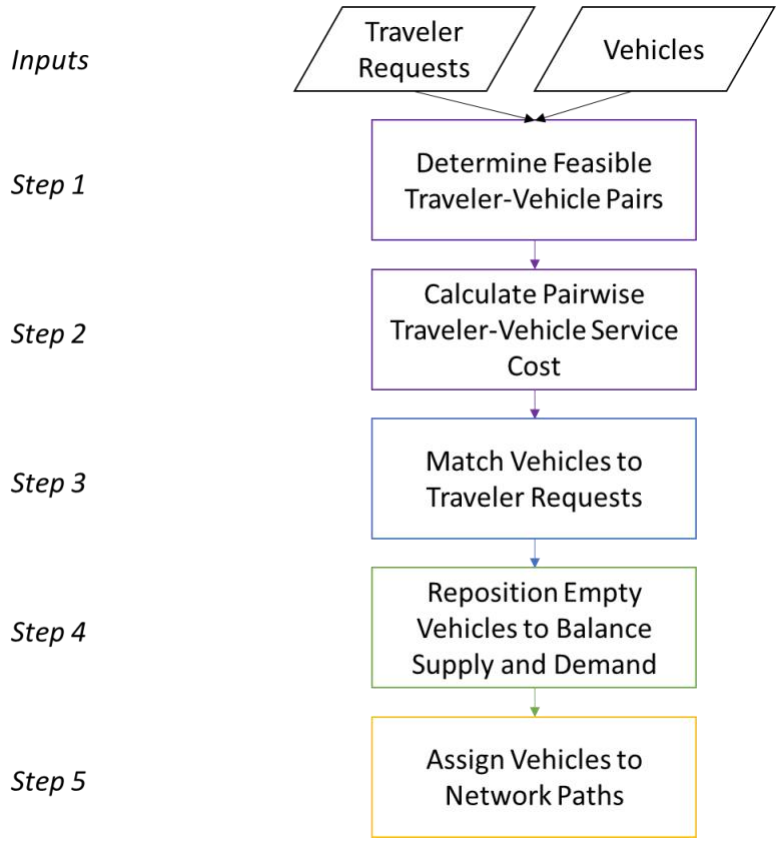
Solution Methodology

Overview

Error! Reference source not found. summarizes the operational approach for solving a SRMoDS operational problem (*5*, *18*) in five steps. The five steps are detailed as follows:

0. **Input:** Determine the set of unassigned/open traveler requests and the status of every vehicle in the fleet. A vehicle's status includes its current location, occupancy, planned sequence of PUDO task locations, and planned network path.
1. Construct a set of feasible traveler-vehicle pairs from the unassigned requests and vehicles. The location of a request and a vehicle's location, occupancy, and time window constraints associated with previously assigned requests are used to determine the feasibility of traveler-vehicle pairs. This study assumes that a maximum of one traveler request can be assigned to a vehicle in one time step. Hence the traveler-vehicle pairs are always one-to-one matching.
2. Calculate a 'cost' metric for each feasible traveler-vehicle combination from Step 2. This study defines the cost for a traveler-vehicle combination (c_{pv}) as the total added cost for the in-vehicle passengers (i.e., detours) in vehicle v and the cost to serve the new potential request p (i.e., remaining wait time if assigned). This step implicitly determines the optimal insertion point for a new request p within vehicle v's planned sequence of PUDO tasks.
3. Solve the traveler-vehicle assignment problem, using the cost metric c_{pv} and the objective function and constraints displayed in Formulation 1 below.
4. Reposition empty unassigned vehicles to rebalance supply and demand spatially throughout the region. In this study, if a vehicle has been idle for more than 5 minutes, the system will search the node with highest demand that is within 2.5 miles of the current vehicle location and direct the vehicle toward that node.
5. Assign vehicles to network paths between their current location and their next PUDO or repositioning location using the proposed bi-criteria approach.

Figure 2. Solution approach for the Shared-ride mobility-on-demand operating problem with bi-criteria pathfinding



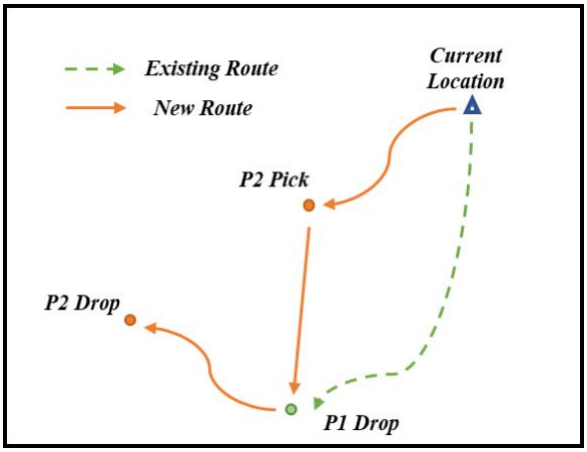
Pairwise Traveler-Vehicle Service Cost

Let n_t denote the set of passengers/travelers $P = \{p_1, p_2, p_3, \dots, p_n\} \subset C$ who request a ride at time t. These travelers can potentially be served by each of the m vehicles in the fleet. Steps 1-3 in **Error! Reference source not found.** output a 'service cost' estimate for all feasible pairs of vehicles and travelers. The cost term for each traveler-vehicle pair, denoted c_{pv}, could be implemented in multiple ways under different scenarios. Typically, c_{pv} is calculated as the shortest path cost (either distance or time) between a vehicle's current location and the traveler pickup locations (*41*). This method is most common when shared rides are not offered. In the SRMoDS matching problem, the cost term could be treated as the summation of detours and wait times for previously and newly assigned travelers where the objective function also includes a fixed cost for each request left unassigned (*18*). In addition, the cost could be also expressed as the total cost/time duration for a vehicle v to serve scheduled travelers and the new request p (*5*).

To determine the pairwise service cost, this study computes the minimum cost to complete the existing assigned tasks and the potential pickup. The pairwise service cost for each traveler-vehicle pair is obtained by solving a single vehicle pickup and delivery problem. When adding a

new traveler to the vehicle, the existing sequence of PUDO locations of the vehicle may change. For example, in Figure 3, the vehicle has one assigned passenger in the vehicle, and the current task is to drop off passenger 1 (the green dashed route). When the potential new job (Traveler 2) appears, the cost of serving traveler 2 is calculated as the entire orange route. The sequence of serving the tasks is also optimized (pick up P2, drop off P1, drop off P2).

Figure 3: Routing vehicle with a new job



Traveler-Vehicle Assignment Problem

After calculating the costs for each traveler-vehicle combination, the next step involves solving the assignment/matching problem. The general form of traveler-vehicle assignment problem is displayed in Formulation 1.

Formulation 1

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

subject to:

$$\sum_{v} x_{pv} \leq 1, \qquad \forall \boldsymbol{p} \in \boldsymbol{P} \tag{2}$$

$$\sum_{p} x_{pv} \leq 1, \qquad \forall \boldsymbol{v} \in \boldsymbol{V} \tag{3}$$

$$x_{pv} \in [0, 1] \qquad \forall \boldsymbol{p} \in \boldsymbol{P}; \ \forall \boldsymbol{v} \in \boldsymbol{V} \tag{4}$$

Where:

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

Constraint (2) ensures that each request is served by one or no vehicle. Constraint (3) guarantees that a vehicle is matched with at most one traveler. In a dynamic setting, the problem will be solved every time step to handle new traveler requests and previously unmatched travelers. This formulation has the feature of total unimodularity. The binary decision variable can be relaxed to linear, and the solution algorithm will still return binary values. This property drastically reduces the computational complexity of integer programming problem.

Simonetto et al. (*5*) write the objective function using a minimization form without a reward term and Constraint (3) as a equality constraint. The current study allows travelers to be unmatched for a maximum number of s time steps, and therefore the inequality constraint is used. The reward term for serving traveler p, denoted r_p increases by a given amount if the traveler is not serviced at the current time step.

Assigning a Vehicle to a Network Path

The bi-criteria pathfinding approach considers potential future demand when assigning a vehicle to a network path. For a given origin (O)--destination (D) node pair in a directed graph, the bi-criteria pathfinding problem could be formulated as shown in Formulation 2.

Formulation 2:

$$\min_{x_{ij}} \sum_i \sum_j c_{ij} x_{ij} \tag{5}$$

$$\max_{x_{ij}} \sum_i \sum_j r_{ij} x_{ij} \tag{6}$$

Subject to:

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

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

In the above formulation:

x_{ij}: Binary decision variable, equal to one if a link (i, j) is traversed by the vehicle

r_{ij}: Potential reward for travelling on a link (i, j)

c_{ij}: Cost of traversing link (i, j)

In formulation 2, the bi-criteria pathfinding problem has two objectives. Objective function (5) is the same objective function as in a conventional shortest path problem, which is to minimize the path travel time. Objective function (6) incorporates the potential future demand through a reward term r_{ij}. The method to determine r_{ij} for each link (i, j) given a particular vehicle and its

state is presented in the next subsection. Constraint set (7) represents the standard flow conservation constraints for the shortest path problem. Formulation 2 also has a totally unimodular constraint matrix.

In order to present a bi-criteria formulation, this paper combines the two objectives into one combined objective by assigning a weight to the reward term. The combined objective function is presented as follows:

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

In the combined objective, this paper introduces a linear combination term of reward and cost by applying a weight coefficient w_r, which is a function of the vehicle's current occupancy and time slack associated with the vehicles existing PUDO tasks.

$$w_r = f(occupancy, time\ slack) \tag{10}$$

For example, if a vehicle is full or has little time slack for existing tasks, then $w_r = 0$ for the current task, i.e., bi-criteria paths will not be considered. On the other hand, if the vehicle has one passenger inside and considerable time slack for detouring, w_r will take a positive value, and bi-criteria pathfinding is active.

This study presents several sub-policies for when to employ bi-criteria pathfinding. The hypothesis being that when vehicle occupancy is high, bi-criteria pathfinding becomes less desirable. Therefore, the following bi-criteria conditions are considered.

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.

Future Demand and Link Reward for Bi-criteria Pathfinding

This section presents the method to determine the expected future demand or potential reward parameter on each link (i, j) in the network, r_{ij}. This study assumes that all demand requests are between nodes in the network, and the future demand (O/D table) is known.

For a SRMoDS vehicle, when it attempts to detour to acquire additional demand, it considers both the future demand requests' origins and destinations. It is meaningless to consider future potential trips requests with locations that are far away from the vehicle's current path. Therefore, the reward r_{ij} is vehicle dependent, and it depends on the vehicle's current location and its next PUDO task location. This research proposes the following method to compute potential demand on links (reward) given a vehicle's current location (i.e., origin) and next PUDO task location (i.e., destination).

Algorithm 1: Link Demand Estimation Algorithm

Input:
An Origin/Destination Pair $[o, d]$
Time Window t
N = Set of all Nodes in the Network
N_D = Set of all Demand Nodes in the Network
$L = \{l_{ij}\}$ Set of links in the network from node i to node j. $i, j \in N$
$Demand = \{Demand_{mnt} \ \forall \ [m, n] \in N_D \times N_D\}$
Output:
Set of potential demand on all links in the network for the given o, d, t
$R_{odt} = \{r_{ij} \ \forall \ l_{ij} \in L\}$
Initialization:
$R_{odt} = \{0 \ \forall \ l_{ij} \in L\}$
Procedure:
Draw an ellipse with its foci at (o, d) and major axis length: $d_{od} + detour_{max}$
d_{od} = Euclidean distance between o, d
$detour_{max} = \min(5, 0.25 * d_{od})$ (Distances in miles)
Select all demand nodes that fall within the ellipse: these are the intermediate nodes.
I = Set of all Demand Nodes that fall within the ellipse
Select all O-D pairs between demand nodes within the ellipse excluding intranodal trips
$S = I \times I - \{ (i, i) \ \forall \ i \in S \}$
Also add O-D pairs that have their origin in I but destinations in $N_D - I$ but shortest path passes through d

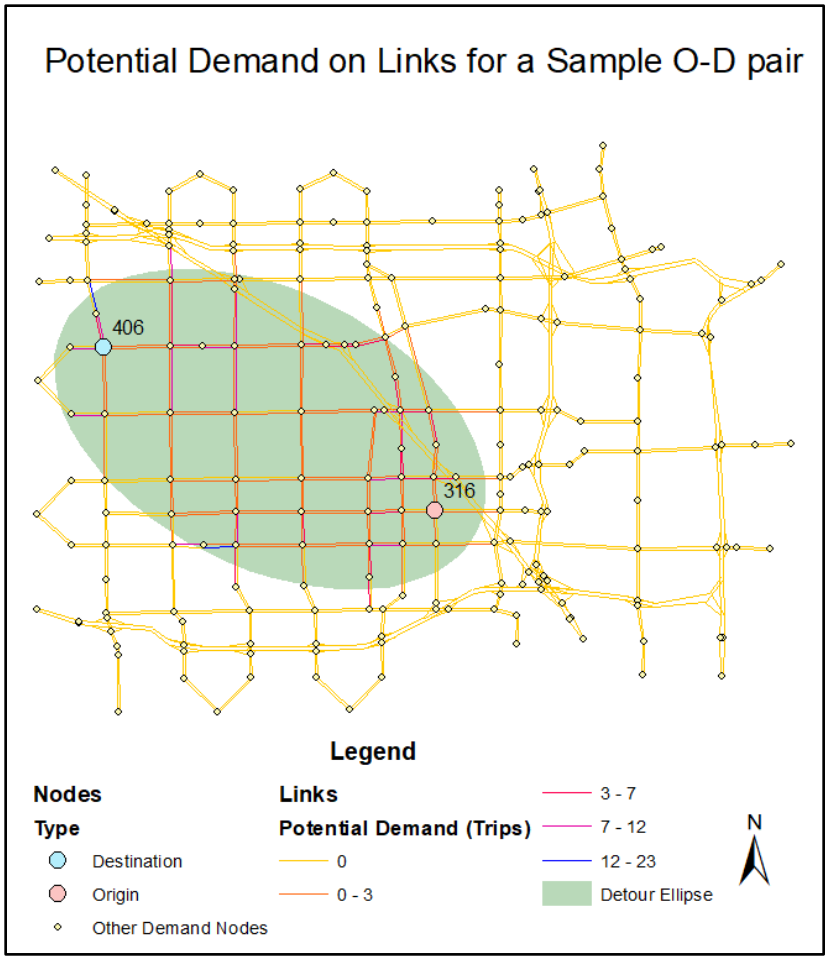
```
For m ∈ I
    For n ∈ N − I
        SP_mnt = Shortest Path between (m, n) in time window t
        If d ∈ SP_mnt
            S = S ∪ { (m, n) }
        End If
    End For
End For
```

Assign demand from origin nodes in S to outgoing links that are on the Shortest Path to their destination nodes in S

```
For (m, n) ∈ S
    L_m = Set of all outgoing links from m
    For l_ij ∈ L_m
        If l_ij ∈ SP_mnt
            r_ij = r_ij + Demand_mnt
        End If
    End For
End For
Return: R_odt
```

Figure 4 illustrates the above algorithm for calculating potential future demand on the links of the Anaheim network for a sample Origin-Destination Pair. Here, the vehicle is currently at Origin Node 316 and heading to Destination Node 406. The ellipse represents the maximum Euclidean detour range for the vehicle.

Figure 4: Illustrative Example of Calculating Potential Demand on Links



Under a shortest path approach, the shared-ride vehicle takes the shortest path from Node 316 to Node 406. The potential link demands illustrated in 4 indicate the demand a shared vehicle is likely to receive while traversing the link. The motivation behind assigning a vehicle to a non-shortest path to its destination is to make the vehicle travel through a path in which trips in the direction of the vehicle are likely to get requested. This is done by evaluating the trade-offs between the cost of traversing a link, and the potential benefit or reward of additional demand/requests that are likely to be generated on the link. This is done by calculating a bi-criteria cost function that subtracts the potential reward of traveling on a link from the cost of traveling the link.

$$c_{ij}^{b} = \alpha \times c_{ij} - \beta \times r_{ij} \tag{11}$$

where,

c_{ij}^{b} is the combined bi-criteria cost of traversing link connecting nodes (i, j)

α is the cost coefficient parameter

c_{ij} is the cost of traversing the link i, j (Travel time/Distance)

β is the reward/demand coefficient

r_{ij} is the potential reward/demand of traversing link connecting nodes (i, j)

The reward coefficient parameter β can be thought of as the marginal monetary benefit that the vehicle fleet owner receives for every additional demand/request. Similarly, the cost coefficient parameter α can be considered as the marginal cost incurred for every additional unit distance or time of traversing on a link. Links that see very high demand may have a zero or negative combined weighted bi-criteria cost. The weighted costs of such links are rescaled to have a small positive value in the range of [0.001, 0.002] in order to have all links have positive costs to solve Formulation 2 using standard algorithms that assume non-negative link costs. The optimization algorithm returns a bi-criteria path for the vehicle between its current location and the destination it is heading to that has the optimal demand versus cost trade-off value.

Computational Results

Case Study Overview

To analyze the proposed bi-criteria pathfinding approach, this study applies the proposed approach to the Anaheim, CA network. The network information, including origin-destination (OD) demand data, was downloaded from an open data source in GitHub (Access Date: February 1, 2021). Additional information on the network and demand data is provided in the 'Data Management' section. The "Data Management" section also lists the software developed for this research.

At the beginning of the simulation, each traveler is assigned a random request time. Each traveler's PUDO locations are assigned to reproduce the OD demand distribution. Each traveler also has a maximum tolerance of waiting time before pickup of 10 mins. If the traveler has not been picked up by any vehicle before the maximum waiting time, the traveler will leave the system and be marked as a 'lost' customer. Vehicles are randomly dispersed throughout the network to begin the simulation. A vehicle has a capacity of 3 unique requests (rather than 3 travelers), as each request may include more than one traveler.

The Anaheim network consists of 401 nodes (223 nodes with demand) and 854 links. The network is shown in Figure 5. The analysis period for the study is 3 hours, representing a peak period. To evaluate the effectiveness of bi-criteria pathfinding, the study analyzes the bi-criteria pathfinding

approach under different fleet sizes (20, 50, 100, 200 vehicles), different number of traveler requests (ranging from 100 to 2,100), and different reward coefficients for potential demand (0.01, 0.1, 0.5,1). In most cases, the computational results compare the bi-criteria pathfinding approach with the shortest path approach. The study also compares the performance of the bi-criteria approach under three different conditions. The conditions vary in terms of when bi-criteria pathfinding is activated. The three conditions include:

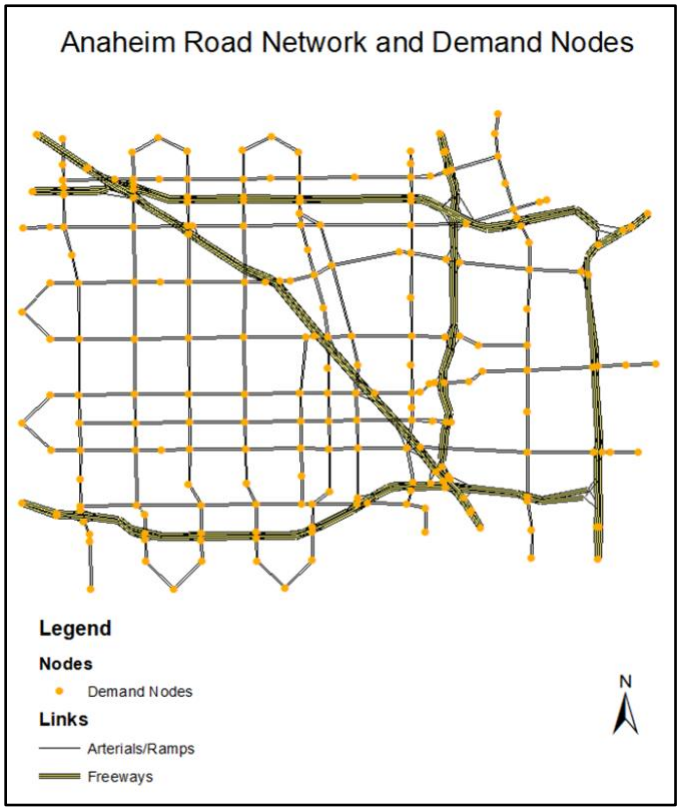
1. The vehicle has only one drop off task remaining.
2. The vehicle has two drop-off tasks and no pickup tasks remaining.
3. The vehicle has two drop-off tasks and no pickup tasks remaining OR the vehicle is empty and en-route to a pickup task.

In total, the study simulates 160 scenarios to compare shortest-path-only pathfinding and bi-criteria pathfinding.

Three performance metrics are deployed to evaluate the effectiveness of bi-criteria pathfinding approach. The specific definitions of the performance metrics are as follows.

- **Average Waiting Time:** The average time duration for a traveler after making a request until being picked up by a service vehicle.
- **Average In-Vehicle Time (IVTT):** The average time duration for a traveler after being picked up until service completion.
- **Average Total time:** The average total time duration for a traveler between requesting service and service completion.

Figure 5: Anaheim Network



The Impact of Fleet Size and the Number of Requests

The fleet size (supply of vehicles) and the number of requests (demand) are the fundamental factors that impact the performance of the SRMoDS and pathfinding approaches. In addition, the impact of fleet size is also correlated with the network size. Either a large network with few vehicles (a sparse case) or a small network with numerous vehicles (a dense case) will result in poor performance metrics. In order to better measure the impact of vehicle supply and travel demand, this study introduces the *supply ratio* metric, to measure the relative sufficiency of supply. Given the total number of SRMoDS vehicles and the total demand size, the supply ratio is calculated as follows:

$$supply\ ratio = \frac{Fleet\ size \times Simulation\ Time}{Average\ Service\ Time\ for\ a\ Passenger \times Demand\ size}$$

When the supply ratio is close to 0, it means the current fleet size is undersupply for the current demand size. When supply ratio is a large number, it is an indication of oversupply.

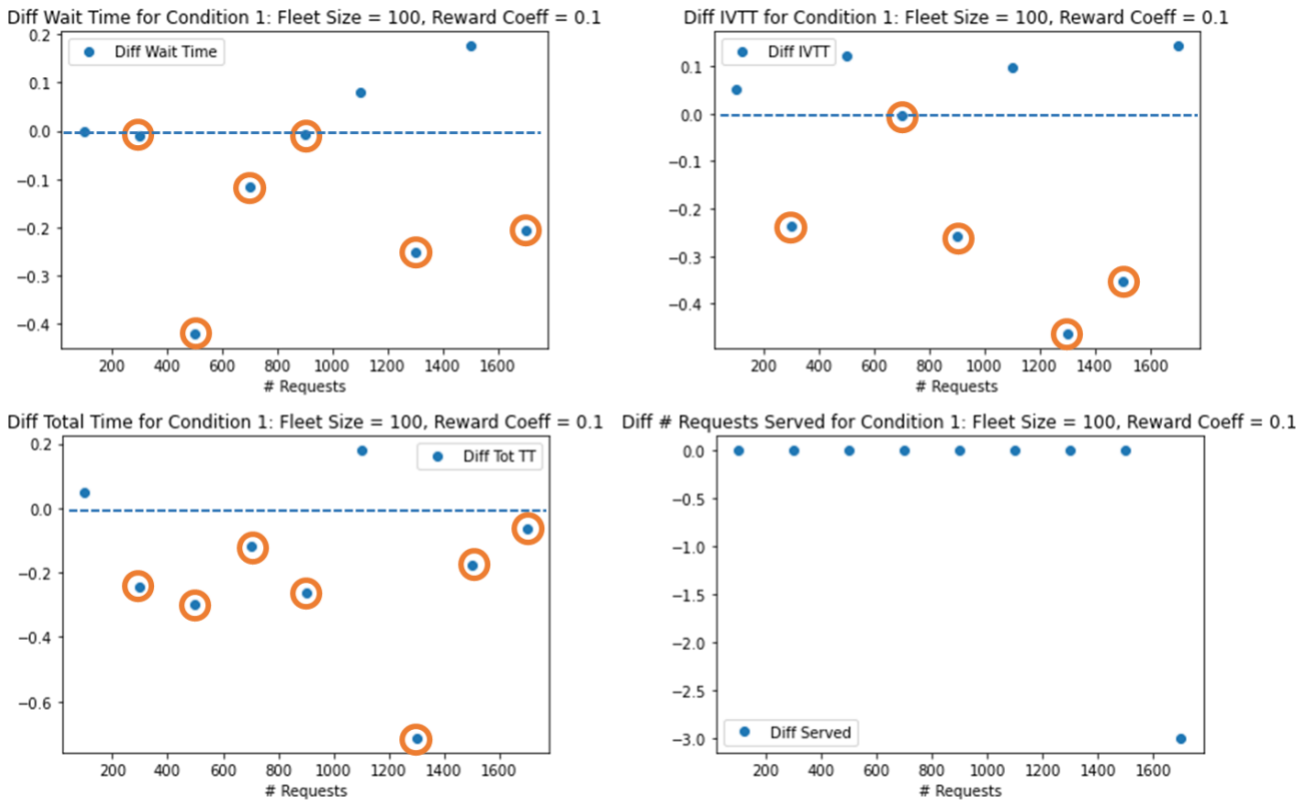
In this subsection, we use a fleet size of 100 to demonstrate the effectiveness of bi-criteria pathfinding. Figure 6 includes the differences in waiting time, IVTT, total time, and travelers served between bi-criteria pathfinding and short path approaches. By analyzing the wait time, we find that for a fleet size of 100 and a reward coefficient of 0.1, bi-criteria pathfinding reduces

both waiting time and IVTT for the cases where the total request is between 300 and 1300. The corresponding supply ratio for this range is between 2.78 to 0.55. Qualitatively this supply ratio range represents a slight undersupply to slight oversupply. On the other hand, when the fleet size is relatively larger (extreme oversupply) or too small (extreme undersupply) with respect to the demand size, bi-criteria pathfinding may actually increase waiting time and/or IVTT. Similar trends are seen for Vehicle Hours Travelled (VHT).

A potential explanation for the impact of fleet size on the effectiveness of bi-criteria path could be as follows. When the fleet size is relatively large, especially for an extreme oversupply case, a new traveler request would often be surrounded by a considerable number of available vehicles, which could also be empty (i.e., directly available). Under these cases, using bi-criteria pathfinding may cause the in-use vehicles to unnecessarily detour, and therefore increase the waiting time and IVTT for travelers relative to always assigning vehicles to the shortest path. However, when the supply ratio is within a normal range (0.55 to 2.78 for the 100-vehicle case), encouraging the usage of bi-criteria pathfinding would proactively send vehicles to potential high demand locations, which would result in a reduction in waiting and IVTT.

Notably, the results in Figure 6 show a non-monotonic relationship between demand or supply ratio and the performance gap between bi-criteria paths and shortest paths. The lack of monotonicity and the variance in the results indicate that there are other important factors that influence the performance of both the bi-criteria paths and shortest paths. We believe both endogenous factors like hyperparameters in the operational policy and exogenous factors like the spatial distribution of demand are impacting the pathfinding algorithms performance. Hence future research should examine how internal factors, external factors, and the interaction between internal and external factors impact fleet performance in the context of bi-criteria pathfinding.

Figure 6: Difference between shortest path and bi-criteria approaches for different fleet sizes and number of requests (time in mins).

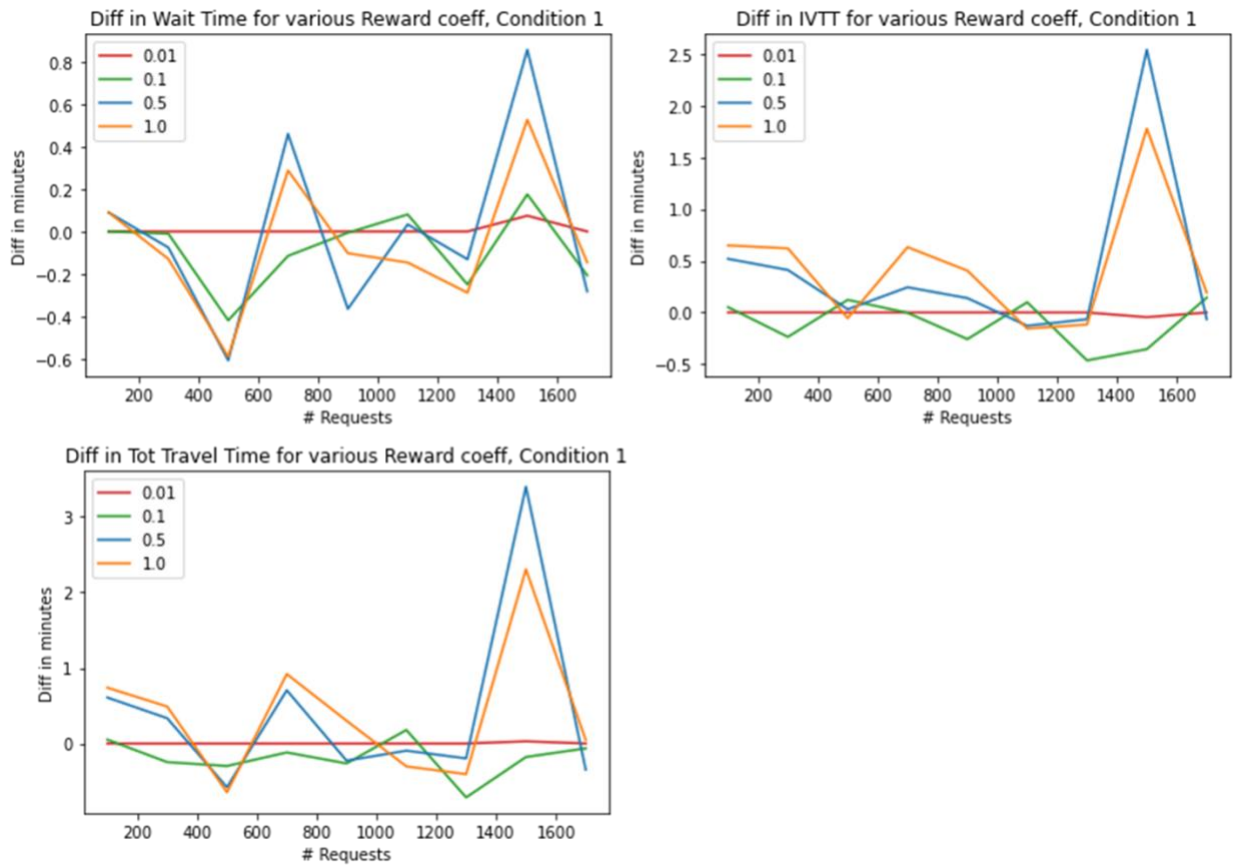


The Impact of Reward Coefficient

The reward coefficient represents the weight assigned to potential future demand on links relative to link travel times. The magnitude of the reward coefficient indicates the relative importance of assigning vehicles to paths in high-demand areas compared to shortest time paths. When the reward coefficient equals zero, the bi-criteria approach becomes the shortest travel time approach. In this section, we test the impact of the reward coefficient on the effectiveness of bi-criteria pathfinding.

Figure 7 displays the differences in waiting time, IVTT, and total travel time for fleet size = 100 and bi-criteria condition 1 under different demand levels. Figure 7 indicates that for the fleet size of 100, the reward coefficient of 0.1 outperforms the other coefficients. The reward coefficient of 0.1 saves travel time for the cases where total requests are between 300 and 1300. On the other hand, larger reward coefficients, e.g., 0.5 and 1, do not perform well when demand is relatively high.

Figure 7: Comparison of shortest path and bi-criteria approaches under different reward coefficients and number of requests (fleet size = 100).



The results in Figure 7 once again show quite a bit of variance. Although the reward coefficient of 0.1 regularly outperforms the shortest path approach, the relative gap is non-monotonic with the number of requests and the variance is relatively high. Moreover, the variance with the larger reward values is much greater.

These results indicate that the reward coefficient should probably not be static throughout the entire simulation period but actually be responsive to the current state of the system. Moreover, the reward coefficient should like vary with each individual vehicle based on the vehicle's status and the status of the system.

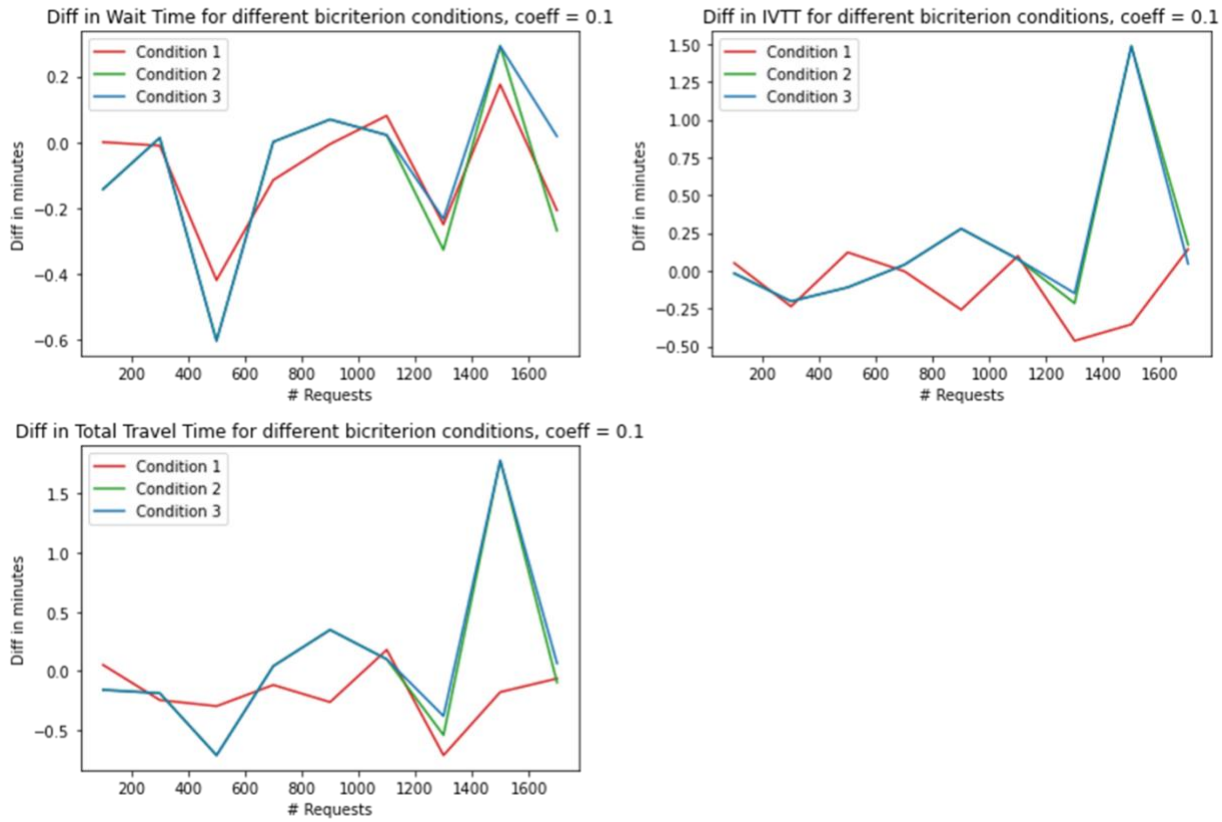
The Impact of Bi-criteria Conditions

This subsection presents the comparison of the three bi-criteria conditions. In general, Condition 3 implements bi-criteria pathfinding more often than Condition 2 and Condition 2 implements bi-criteria pathfinding more often than Condition 1.

Figure 8 indicates that in most cases, Condition 1 outperforms both Condition 2 and 3 in terms of both waiting time and IVTT. All conditions have similar trends over waiting time saved, but

Condition 1 is more stable in terms of IVTT. It is worth noting that Condition 1, as the simplest policy, leads to the best performance of bi-criteria pathfinding. The possible explanation could be as follows. Under Condition 2 and 3, though a vehicle is assigned to bi-criteria path, it may not be able to serve additional requests due to time window constraints. This finding provides managerial insights that when travelers have a low tolerance of waiting and travel duration, bi-criteria pathfinding should only be considered in the case where the vehicle is relatively empty. In future studies, time window constraints of vehicles could be incorporated directly into bi-criteria pathfinding.

Figure 8: Comparison of different bi-criteria conditions across different number of requests (fleet size = 100).



Summary of Key Findings and Limitations of Methodology

From the above discussion, we find that bi-criteria pathfinding outperforms the shortest path approach in several cases. The effectiveness of bi-criteria pathfinding depends on various factors, including fleet size, demand size, the choice of reward coefficient, and bi-criteria conditions.

In summary, bi-criteria pathfinding could save both waiting time and IVTT for travelers. The total saving is around 3% to 5% of the total service time on average under Condition 1 and a reward coefficient of 0.1, but there is considerable variation in the performance. The results also indicate

that in order for bi-criteria pathfinding to be effective, the balance between supply and demand should not be highly uneven in either direction.

Due to the complexity of the problem, there are certain limitations of this study. First, the method of estimating demand, r_{ij}, on links could be improved. The current method of estimation incorporates the directionality of vehicles, but additional information on vehicles should receive consideration, such as, occupancy and detour time limitation. More importantly, it might make sense to not only consider expected future demand on each link but actually the expected difference between future demand and supply on/around the link. For example, if an area of the network, call it area A, tends to have high demand but a lot of vehicles are already in area A and/or will travel through area A, vehicles from other areas should not detour into area A.

The second possible improvement mentioned previously is the hyperparameters in the bi-criteria pathfinding objective function (i.e., the weight for expected future demand) should not be static over the entire simulation and should not necessarily be the same across all vehicles. Rather the hyperparameters should likely be a function of the state of the vehicle (e.g., occupancy level, remaining trip distance, proximity to demand) and the state of the system (e.g., supply ratio).

Another relevant factor is the vehicle density in the region, measured as either vehicles per node or vehicles per square kilometer/mile. If vehicle density is quite high, it is unlikely that bi-criteria pathfinding is beneficial as there will always be vehicles relatively near potential future demands. Conversely, if vehicle density is low or moderate, the bi-criteria pathfinding may provide benefits as it will push the few vehicles in the network toward locations that are likely to generate demand.

Conclusion

This study proposes an operational policy for a shared-ride mobility-on-demand service (SRMoDS) service that involves assigning vehicles to network paths considering the paths' travel time and their proximity to potential future demands. One subcomponent of this operational problem involves assigning expected potential future demand to links. This study formulates the assignment of vehicles to bi-criteria paths as an optimization problem. The study evaluates the effectiveness of the bi-criteria pathfinding approach using the network and demand data for Anaheim, CA.

Simulation results indicate that bi-criteria pathfinding can reduce both waiting time and in-vehicle travel time for travelers. However, the average improvement is relatively small and there is pretty large variance regarding the performance gap between bi-criteria and shortest path approaches. The study also finds that the effectiveness of bi-criteria pathfinding is determined by multiple factors, including the number of vehicles, the number of requests, network size, bi-criteria conditions, and reward coefficients. Simulation results indicate that the bi-criteria pathfinding approach performs best with a slight under- or over-supply of vehicles relative to demand. The study also finds that bi-criteria pathfinding works best when vehicles are empty or only have one remaining drop-off task and no pickup tasks.

This research provides evidence that bi-criteria pathfinding can improve the operational effectiveness of SRMoDS and likely other ride-sharing services. However, further research, particularly tuning hyperparameters in the optimization model as a function of the state of individual vehicles and each region's spatial imbalance between supply and demand, will likely indicate significantly larger operational benefits associated with bi-criteria pathfinding.

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Data Management Plan

Products of Research

1. Data
    a. Anaheim Road Network data
    b. Anaheim Demand data
    c. Anaheim Link Demand
2. Software/Algorithms
    a. Shared-ride mobility-on-demand service fleet simulation model
    b. Vehicle-traveler assignment model and solution algorithm
    c. Pickup and drop-off task sequencing model and solution algorithm
    d. Bi-criteria pathfinding model and solution algorithm

Data Format and Content

1. Anaheim Road Network data:
    a. anaheim_nxgraph.pickle - Contains the Anaheim road network data encompassing nodes and links stored in a serializable pickle format.
        of a python networkx object.
    b. Anaheim_SPskims.pickle - Contains the shortest paths as well as shortest travel time costs between all Origin-Destination pairs in the Anaheim network, stored as a Python dictionary object in a serializable pickle data type.
2. Anaheim Demand data:
    a. anaheim_odtable.csv - Contains total person trip travel demand between Origin and Destination Nodes in the Anaheim Network for 1 hour period.
3. Anaheim Link Demand data:
    a. t_180_mins_uniform_anaheim_demtime_30_modeshare_0.05.pickle - Contains potential shared ride trip demand data for all links in the network in the direction of an O-D pair for each time period, for a uniform demand distribution.

Data Access and Sharing

The data and software are available at the following link:
https://datadryad.org/stash/share/Wz0uJ9u9eeq4S_thyKofuzcEgbQjIE0IuA3bOBj_t70