Leveraging destination flexibility to increase ridesharing participation: an integrated model and case study

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1 Introduction

Recently, ridehailing companies such as Uber and Lyft have offered the option to share trips with other passengers for a discounted fare (Lawler, 2014a,b). Widespread adoption of these *ridesharing* services has the potential to limit the negative externalities caused by personal vehicle travel: carbon emissions and traffic congestion. Combining trips into one vehicle allows multiple passengers to be served with the same fuel expenditure and roadway occupancy as a single trip. Past research shows that ridesharing has the potential to dramatically reduce the vehicle-miles traveled (VMT) and carbon emissions generated by ridehailing platforms (Santi et al., 2014; Lokhandwala and Cai, 2018; Cai et al., 2019).

Unfortunately, ridesharing participation remains low (Schaller, 2018). One method of increasing ridesharing adoption is to operationalize destination flexibility. For certain trip purposes, travelers may be willing to visit an alternative destination if travel is more convenient. Destination flexibility is commonly observed; in fact, one attractive feature of urban life is the variety of available destinations (Van Loon et al., 2014). The degree of destination flexibility for a given activity is dependent on activity type, traveler preferences, land use and other factors (Hannes et al., 2008). Generally, discretionary trips are more flexible than work or school trips (Vilhelmson, 1999; Huang and Levinson, 2015).

Imagine that, when requesting a ridehailing trip, travelers may enter several destinations or even a general trip purpose. The platform would respond with the price and estimated duration for trips to alternative destinations that match the desired activity type. The operator can offer a lower price for trips that have a high probability of matching due to the lower operating cost of shared rides. Such a framework would allow the user to make a trade-off between price, travel time and destination preferences, then select the trip that provides the greatest value. Enabling multiple options would therefore have the effect of increasing ridesharing participation, as travelers would be incentivized through cost differential to choose trips with a higher probability of sharing.

What makes this problem particularly compelling is that the need and opportunity are coincident; traffic and emissions are highest in urban areas, which are also home to a large and diverse set of potential activity destinations.

Previous ridesharing literature is primarily concerned with developing algorithms for ridesharing platform operations and the social factors affecting traditional ridesharing systems (Agatz et al., 2012; Furuhata et al., 2013; Zhang and Zhao, 2018; Moody et al., 2019). Some recent papers have investigated ridesharing matching with flexible destinations. Wang et al. (2016) develops a matching algorithm that considers multiple destinations for each trip, but treats alternative destinations as equivalent from the traveler's perspective. Such a framework is not ridesharing adoption research, which shows that perceived utility is the primary driver of decisions about shared rides (Wang et al., 2019). Subsequent studies take a similar approach (Khan et al., 2017; de Lira et al., 2018; Mahin and Hashem, 2019).

To lay the groundwork for a destination-flexible ridesharing application, we have developed an integrated destination choice and ridesharing matching (DCRM) model to evaluate the potential for destination flexibility to increase ridesharing participation. This project addresses the gaps in the existing literature by formulating the DCRM model based on utility-maximization behavior among travelers. Allowing flexible destinations dramatically increases the problem size; several approximation techniques are proposed to improve tractability. In summary, this project will be the first to make the following contributions:

- Develop a utility-based destination choice and ridesharing optimization model.
- Propose new problem-specific approximation methods and compare those methods against the performance of a generic meta-heuristic.
- Quantify the benefits of destination flexibility for travelers and ridesharing platforms through empirical demonstration.

2 Methodology

The static DCRM model builds on the models developed in Zhang et al. (2019) and Caros et al. (2021), which are used to determine equilibrium network flows considering ridesharing and destination choice, respectively. In this case, we assume that ridehailing trips are a relatively small percentage of the overall traffic and do not impact link travel times. Like Zhang et al. (2019), we decompose the model into components and solve for the equilibrium states iteratively.

Destination choice is determined using a logit model that includes destination utility, travel time disutility and a monetary cost term to reflect the fare difference between trips. Total travel time and cost for ridesharing trips are functions of the characteristics of other trips, effectively creating a feedback loop between destination choice, ridesharing matching, travel cost and travel time as shown in Figure 1.

Given fixed origin-destination demand, the optimal ridesharing matching arrangement is found using an offline version of the algorithm proposed by Alonso-Mora et al. (2017). The model objective is to minimize total travel time, subject to constraints on vehicle capacity and a maximum detour restriction for individual trips. Once the set of ridesharing trips is determined, we update travel time and cost, thus completing the feedback loop in Figure 1.

Convergence to equilibrium states for the DCRM cannot be guaranteed as the travel time and travel cost functions are irregular and discontinuous due to the ridesharing matching component. A change in destination by one traveler could result in an entirely different optimal ridesharing

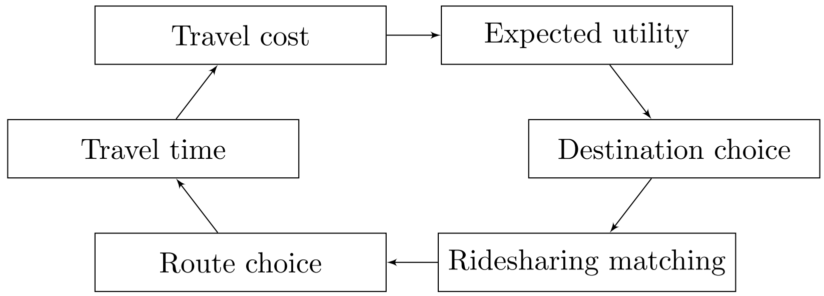

Figure 1: Diagram of the destination choice - ridesharing matching - travel time feedback system

arrangement with impacts on travel time and travel cost for other travelers. Enumeration methods are not practical, as the number of possible destination sets scales exponentially with the number of travelers.

Instead, we propose to use pruning, clustering and convergence methods to solve for the network equilibrium iteratively. Our research into solution methods is ongoing, therefore only the conceptual framework is reported here. We begin by initializing the model with only the equilibrium destinations that occur when no ridesharing is permitted. Non-competitive destination choices can be eliminated immediately due to low destination utility. The solution is then improved iteratively by strategic addition of alternative destinations and solving for the new equilibrium state.

First, any alternative destination that provides greater utility but does not affect the ridesharing matching is added to the decision set. Second, origins and destinations are clustered by proximity, and new destinations that permit a traveler to join a ridesharing trip with unused capacity between their origin and destination clusters are added to the decision set. Iterations continue until the total travel time converges. Convergence can be forced by fixing certain matches after each iteration (Zhang et al., 2019). The computation time and solution quality of the proposed solution method will be compared against the results of a greedy algorithm. Further improvements to the solution method, including finding the global optimal solution, are under investigation.

We propose to test our model on classical traffic assignment test networks. The DCRM model will be compared against a benchmark model that includes only the most preferred destination for each trip to isolate the benefits of destination flexibility. The reported results will include the societal benefit and how the efficiency gains of ridesharing are split between operators and travelers.

3 Expected results

At the time of this writing we have not progressed to the point of generating preliminary results. We expect that destination flexibility will provide a moderate increase in traveler utility coupled with a reduction in operating cost and VMT for the operator.

4 Conclusion

The key contribution of this paper is the development of a tractable model for estimating equilibrium traffic flows with ridesharing and destination flexibility. This framework will enable ridesharing platforms to test their own operating policies and evaluate the impact on service quality, costs and revenue. It will also provide policy makers with the ability to test destination-flexible ridesharing in order to estimate the reduction in emissions and congestion that would occur in their communities. Implementation of a ridesharing platform with multiple alternative destinations provides the opportunity for a rare Pareto improvement in urban transportation: a free, non-subsidized, voluntary program that provides benefits to the operator, the traveler and society.

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