Potential of Anticipatory Decision-Making in Dynamic Fleet Management

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1. Introduction

In recent years, operators like UberPool offer innovative ride-sharing services that bundle travelers on their way to the destination (`https://www.uber.com/de/de/ride/uberpool/`). These ride-sharing services provide on-demand access, which is realized through automated booking processes that manage incoming requests dynamically. From a vehicle routing perspective, this is very challenging, since two types of dynamic decisions need to be taken. First, the operator needs to decide instantly whether to accept an incoming request (*acceptance decision*), and, second, a fleet of vehicles has to be managed dynamically in order to fulfill accepted requests efficiently (*routing*).

Since the stochastically incoming requests expect an immediate response from the operator and possibly a short-term fulfillment, decision support for acceptance and routing has to be made instantly and under uncertainty of future demand. However, many contributions in dynamic routing focus on the anticipation of only one decision type, namely request acceptance or routing, which is already challenging in a dynamic and stochastic environment. For instance, Bent and van Hentenryck (2004) introduce a multi-scenario approach in which predicted requests are implemented for an anticipatory routing. Ulmer et al. (2019) propose a value function approximation approach in order to make anticipatory decisions upon the acceptance of requests with respect to an efficient dynamic routing.

Focusing either on the acceptance or routing decision implies that the information on future demand is only partially used. However, it is not clear how the value of information differs for different types of anticipatory decision-making with respect to acceptance and routing decisions. The aim of this contribution is to assess the potential of anticipatory acceptance and/or routing decisions for the dynamic fleet management of ride-sharing services. To this end, we consider a

dynamic dial-a-ride problem (DARP) that represents acceptance and routing decisions faced by a typical on-demand ride-sharing service.

2. Problem Description

Let $\mathcal{L}$ be a set of locations in the service area of a ride-sharing service. For all pairs of locations $(i, j) \in \mathcal{L}$, it is assumed that a (deterministic) travel time of $c_{i,j}$ is known. The considered ride-sharing service faces a demand consisting of requests $r \in \mathcal{R}$. Each request $r \in \mathcal{R}$ is characterized by the receiving time of the request t_r, its origin $o_r \in \mathcal{L}$, its destination $d_r \in \mathcal{L}$, as well as its time window $[b_r, e_r]$, which defines the earliest pick-up time $b_r = t_r$ and its latest drop-off time $e_r = t_r + c_{o_r,d_r} + \alpha$. The parameter α defines the tolerance of travelers towards their accepted waiting time to be picked up and detours on the way to their destination. Detour times also include boarding and alighting of other travelers, for which a deterministic service duration s_r is assumed. In order to satisfy the demand, a fleet of identical vehicles $v \in \mathcal{V}$ is available.

The dynamic and stochastic problem can be modeled as follows. A booking process stretches over a series of decision epochs $\mathcal{K}$. In the initial state, each vehicle $v \in \mathcal{V}$ is waiting in idle mode at an initial location $l_v \in \mathcal{L}$. Each decision epoch $k \in \mathcal{K}$ is triggered through a new stochastically incoming request $r_k \in \mathcal{R}$. The pre-decision state is defined by this new request, its receiving time, the current location of the vehicles, their currently executed requests, and the accepted yet outstanding requests. Based on the pre-decision state, the acceptance of the new request has to be investigated followed by the determination of a feasible routing plan. The two decisions result in a post-decision state, in which the routing plan is executed until the next decision epoch $k + 1$ is triggered. The objective over all decision epochs $k \in \mathcal{K}$ is to maximize the number of accepted requests.

3. Anticipation Types

Dynamic request acceptance and routing may benefit from information on future demand. We investigate the potential of the following four anticipation types for acceptance and routing:

		Request acceptance decision	
		Request acceptance if feasible	Request acceptance if feasible & favorable
Routing decision	Routing considers accepted requests	*None Anticipatory*	*Anticipatory Acceptance*
	Routing considers accepted & future requests	*Anticipatory Routing*	*Fully Anticipatory*

The potential of these types of anticipation are evaluated by solving problem variants that differ in the level of available information on future demand as described below.

None Anticipatory: For each incoming request, the acceptance decision is made by checking whether an incoming request can be inserted into the incumbent routing plan. If the insertion is successful, the request will be accepted. Then, a new routing plan is determined by solving a static DARP for all accepted requests under the objective of minimizing the total travel time. Note that for both acceptance and routing decisions, only those parts of the routing plan can be considered that have not been executed yet.

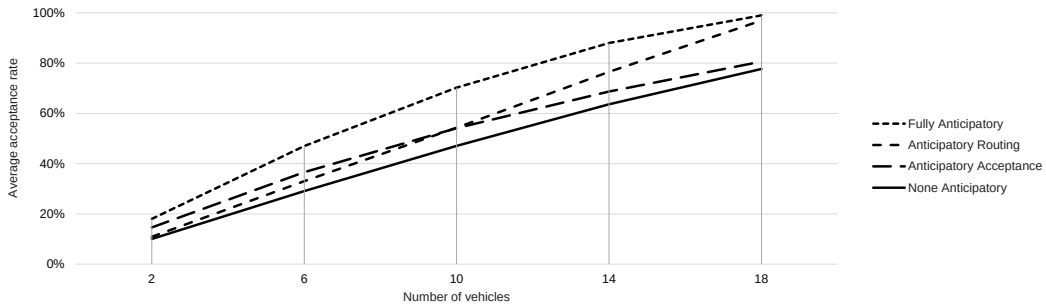
Anticipatory Acceptance: Following the principle of *none anticipatory*, it is analyzed whether an incoming request can be inserted into the incumbent routing plan. Then, the favorability of the request is investigated. To this end, a static team orienteering problem (TOP) with equal scores for each request is solved, considering the incumbent routing plan as well as all current and future requests. The request is accepted if it is contained in the best found solution, which also considers all already accepted requests. A new routing plan, however, is afterwards determined by solving a static DARP as in the case of *None Anticipatory*.

Anticipatory Routing: For this anticipation type, we assume that routing decisions can be postponed until all requests are known. Here, only decisions on request acceptance have to be made in the online environment by checking for each incoming request if a feasible solution can be found. The routing plan is then determined for the finale set of accepted requests by solving a static DARP.

Fully Anticipatory: We assume all information on future demand as given, allowing all dynamic decisions to be made in advance. For this purpose, the problem is solved as a static TOP with the same score for each request, resulting in a solution that specifies the requests to accept and the routing to perform.

4. Computational Experiments

To investigate the potential of anticipation, a large neighborhood search based on Ropke and Pisinger (2006) is used to solve problem instances of the described variants. We derive our instances from taxi trip data provided by the City of New York (`https://data.cityofnewyork.us/Transportation/2014-Yellow-Taxi-Trip-Data/gn7m-em8n`). Our instances differ in the sequence of the requests, the receiving times and the initial vehicle locations. Based on 180 trips, 100 instances with 40 potential initial vehicle locations and request times between 17:30 and 20:30 are created. The free flow travel times between all required locations were computed using GraphHopper (`https://github.com/graphhopper/graphhopper`) and adjusted to rush hour travel times by a factor $\beta = 3$. The tolerance of travelers regarding waiting times and detours is set to $\alpha = 15$ minutes. Below, we show first results of a demand coverage analysis. For this, the 100 instances were solved five times with a fleet size of 2 to 18 vehicles. We report the average acceptance rate, defined as the total number of requests accepted divided by the total number of requests received.



As expected, the average acceptance rate increases with increasing fleet size for all investigated variants. *None Anticipatory* serves as our lower bound, and always accepts the smallest number of requests on average. Similarly, *Fully Anticipatory* builds an upper bound, therefore always provides the highest potential compared to *None Anticipatory*. Particularly interesting are the results of the problem variants with partial anticipation. While for *Anticipatory Routing* the potential compared to *None Anticipatory* increases with an increasing demand coverage, the potential of *Anticipatory Acceptance* decreases.

So far, it can be concluded that the dynamic fleet management of ride-sharing services can highly benefit from anticipatory decision-making. In order to fully exploit its potential, *Fully Anticipatory* approaches are preferable. However, if only partial anticipation is practicable, the demand coverage can be an indicator for when acceptance or routing decisions have a bigger impact on the solution quality. Alongside with the results shown, our study will be covering more sensitivity analysis on temporal and geographical demand densities and service quality levels. In addition to the average acceptance rate, further metrics will be discussed that demonstrate the effects of the different anticipation types on the dynamic fleet management as well as the associated potential differences. Moreover, the impact on the service quality will be analyzed with regard to average waiting times and detours.

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