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Publication date
2022

Document Version
Final published version

Citation (APA)
Alves Beirigo, B., & Atasoy, B. (2022). *To wait or not to wait? A-learning-based approach for on-demand ride-pooling water transport systems*. Abstract from INFORMS Transportation Science and Logistics Workshop , Bergen, Norway.

To wait or not to wait? A learning-based approach for on-demand ride-pooling water transport systems

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Ride-pooling is a key component of modern *transportation network companies* (TNCs), as it can result in substantial advantages to all urban mobility stakeholders. By combining overlapping itineraries in the same journey, on-demand ride-pooling services like UberX Share (Uber, 2022) decrease passengers' costs, increase operators' revenue, and, most importantly, improve vehicle utilization, which ultimately reduces congestion in cities as fewer vehicles can fulfill the same number of trips (Storch, Timme, and Schröder, 2021).

Due to its potential to make better usage of vehicle space, efficient ride-pooling can further benefit on-demand systems where vehicles are traditionally larger. For example, the request-based on-demand water transport system operating in Rotterdam, the Netherlands (Watertaxi Rotterdam, 2022) uses a 12-seat vessel fleet to pick up and deliver passengers throughout 50 docks along *Nieuwe Maas* river (see Figure 1). In this setting, individual trips tend to be neither cost- nor space-efficient — a captain is required to sail a nearly-empty vessel. Besides, history data by the service operator shows that most requests take on average 6 min (Flying Fish, 2022). As a result, ride-pooling preferably occurs before departure; more directed routes with fewer detours presumably render higher quality on-trip experience, as also assumed by (Lo and Morseman, 2018).

The ride-pooling problem, where vehicles (empty or not) must be dynamically assigned to different passengers while complying with their service quality requirements, has been widely studied in the literature. Typically, many ride-pooling systems also address the rebalancing problem where vehicles preemptively move to promising areas aiming to fulfill future demand. Robust approaches that integrate ride-pooling and rebalancing to solve real-world instances include reoptimization methods (see, e.g., Beirigo et al., 2022), lookahead algorithms (see, e.g., Alonso-Mora, Wallar, and Rus, 2017), and learning-based policies (see, e.g., Shah, Lowalekar, and Varakantham, 2020; Gueriau et al., 2020). Proposed approaches, however, consider departure occurs as soon as vehicles pick up passengers. No study evaluates the extent to which non-empty waiting at the pickup location can increase sharing, which may yield considerable benefits for mobility services using higher-capacity vehicles.

Besides ride-pooling, better vehicle utilization also depends on adequately setting the vehicle capacity to the demand. However, operational costs for small-capacity vehicles and vessels are currently prohibitive due

Figure 1 Rotterdam water taxi transport operating area (Watertaxi Rotterdam, 2022).

to human labor. The development of automated technologies can help overcome this barrier, allowing the deployment of a more diverse mix of vehicles. For example, a heterogeneous fleet of *autonomous surface vessels* (ASVs) suited to the service area could be considered once captains are out of the loop. For example, Duarte, Johnsen, and Ratti (2020) show how using small-sized electric ASVs (called "Roboats") could reduce on-street parking spaces and traffic in Amsterdam, the Netherlands, if passenger transportation could also be carried out throughout the city's waterway network. However, the dynamic fleet management of heterogeneous fleets has been mostly overlooked in shared mobility literature (Narayanan, Chaniotakis, and Antoniou, 2020).

Aiming to improve vehicle utilization in on-demand ride-pooling water transport systems, this study proposes a learning-based approach to determine the best policy to route a heterogeneous fleet of vessels servicing dynamic and stochastic pickup and delivery requests. Similarly to (Beirigo et al., 2022), we leverage users' waiting tolerance to increase service rate (i.e., the rate of completed requests). However, in contrast to most related literature, where service levels are commonly defined in terms of pickup and ride time delays, we define service levels solely in terms of maximum total delay. We consider the system has the leeway to strategically take advantage of this delay to decide how long users wait at any phase of the trip fulfillment process.

Contributions

We make three contributions:

- We are the first to assess the effect of allowing partially occupied vessels (of different capacities) to wait at pickup locations — in anticipation of future demand — such that more travelers can embark before departure.
- We propose a route-based *Markov Decision Process* (MDP) model (see Ulmer et al., 2020) that considers both rebalancing (empty) and waiting (empty or not) decisions besides the conventional routing and matching decisions while addressing dynamic and stochastic demand.
- In contrast to most related studies on dynamic stochastic transportation problems, which predominantly use linear *value function approximations* (VFAs) to capture the downstream impact of decisions, we approximate value functions through a Deep Neural Network in order to address the inherent non-linearity entailed by rich ride-pooling system states.

Example

Figure 2 illustrates how an on-demand ride-pooling water transport system can harness anticipatory decision-making to improve service levels. We consider two vessels, V2 and V4, of capacity two and four, respectively, operating on a one-dimensional service area comprised of five dock locations $l = \{A, B, C, D, E\}$. These vessels are required to service pickup-delivery request list $R = \{$B-C, B-C, B-D, C-D, D-E, E-D, E-D$\}$, appearing throughout decision epochs $t = \{0, 1, 3, 4, 5\}$. Vessels and requests depicted across locations at each decision epoch t represent the post-decision state of the system at t, that is, the state resulting from the decisions taken based on information arriving between epochs $t-1$ and t. Each request can be represented at three stages: (i) not requested yet, (ii) requested, and (iii) serviced. Requests at stage (i) are uncertain but may be forecasted by the system. As soon as a request appears, it can be assigned to a vessel seat, therefore, entering the vessel's route plan (upper left tuple), featuring the next locations to visit. By taking advantage of requests' stochastic

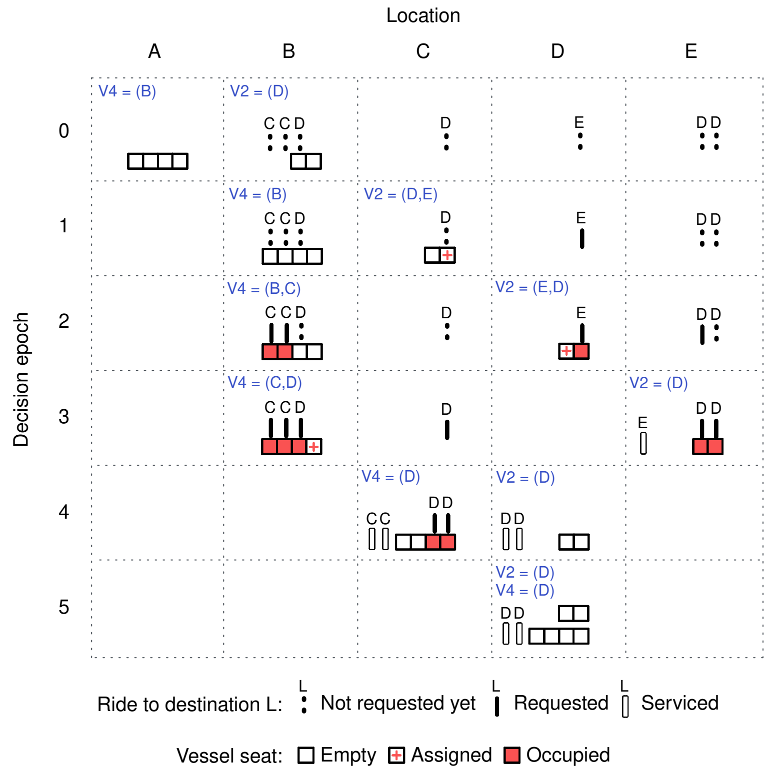

Figure 2 **Example of an on-demand ride-pooling water transport system working on a one-dimensional service area throughout time. Besides picking up riders, the two-seat vehicle V2 and the four-seat vehicle V4 may wait (empty or not) at their current locations or rebalance to different locations in anticipation of future demand.**

information, at $t = 1$, V4 rebalances to B, and V2 rebalances to D. Passengers at locations B and D are yet to appear, but the system anticipatorily routes vehicles to these locations such that they can promptly service requests as soon as they emerge. The rebalancing route plan is also motivated by the vessel sizes: V2 could not adequately fulfill the demand expected at B, being better suited for the demand forecasted at C, D, or E. Later, at $t = 1$, V4 waits at B, whereas V2 is matched to a request from D to E that appeared between $t = 0$ and $t = 1$. At $t = 2$, two B-C requests are picked up by V4, which updates its plan to add destination C, but delays its departure expecting to accommodate predicted requests at B. In the meantime, V2 picks up request D-E and is matched to an E-D request. Subsequently, at $t = 3$, requests B-D, C-D, and E-D appear. Then, at $t = 3$, while V4 picks up B-D and is assigned to pick up C-D, V2 drops off a user at E and picks up two E-D requests. Next, at $t = 4$, V4 delivers two users and picks up the previously matched request C-D, whereas V2 drops off all its passengers. Finally, at $t = 5$, both vehicles are completely unoccupied and plan to wait at location D.

Experiments

We benchmark our VFA-based model against state-of-the-art reoptimization and lookahead algorithms, using a subset of the New York City taxi trip record data (NYC Taxi and Limousine Commission, 2022) consisting of the transportation demand arising within Manhattan's 64 taxi zones over a day. Besides, we evaluate our learning-based approach on real-world data from Rotterdam's water transport service (Watertaxi Rotterdam, 2022), assuming similar operational settings (eighteen 12-seat boats and 50 docks). Finally, we provide managerial insights on (i) trading off operational costs and waiting times and (ii) using a heterogeneous ASV fleet to fulfill Rotterdam's water transport demand.

Acknowledgments

This research is supported by the project "Sustainable Transportation and Logistics over Water: Electrification, Automation and Optimization (TRiLOGy)" which is (partly) financed by the Dutch Research Council (NWO). We also thank Flying Fish and Watertaxi Rotterdam for providing the data.

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