Preference-Aware Dynamic Ridesharing

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Abstract. Smart mobility and, in particular, automated ridesharing platforms, promise efficient, safe and sustainable modes of transportation in urban settings. To make such platforms acceptable by the end-users, it is key to capture their preferences not in a static manner (by determining a fixed route and schedule for the vehicle) but in a dynamic manner by giving the riders the chance to get involved in the routing process throughout a journey. To that end, this work provides a toolbox, enabling riders to interact with the ridesharing service and have a say in the routing process.

Keywords: Dynamic Ridesharing · Preference Elicitation · Agent-Oriented Smart Mobility

1 Introduction

Ridesharing is a promising means towards reducing carbon emissions and mitigating climate change [5]. Integrating preference-awareness into ridesharing systems enhances the satisfaction of the end-users and, in turn, enables the efficient use of spare capacity in urban transportation services [14]. However, although the potential gains are known, some traditional urban transportation systems—such as bus services—are not benefiting from preference-aware ridesharing technologies. Our buses are still operating based on fixed schedules and, in the best cases, use historical data on the behaviour of riders to improve their routes. However, determining routes based on data about *past* users does not necessarily fit how *present* riders want to use the service. For example, arguably, bus schedules generated based on travellers' behaviour in 2019 (i.e., before the COVID-19 pandemic) do not satisfy what we want for riders in 2022. While gathering data more frequently and then fixing a static schedule is an option, in this work, we go a step further and suggest dynamic schedules that are determined based on the preferences of the *current* users/riders. Doing this will allow buses to provide customised services to riders, avoid wasting resources by visiting unnecessary stations, and find compromises for pickup and drop-off locations that users see preferable.

Ridesharing can be considered a vehicle routing problem that is typically solved by optimising a given global objective function. Most studies focused on optimising operational-based objective functions [11] which usually benefit the ridesharing service provider rather than the passengers. Optimising based on the provider's incentives

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would not lead to widespread adoption of this service, as passengers' preferences are not taken into consideration. Thus, recently, there have been studies regarding incorporating passengers' preferences or incentives into the ridesharing problem. These studies specified constraints such as passengers' maximum travel distance and maximum waiting time to ensure some level of quality of service, as well as incorporating new terms in the objective function, encapsulating the overall satisfaction of passengers [11]. This method, however, does not guarantee fairness among the passengers. For example, a ridesharing system might choose route *A* because it minimises the total waiting time and travelling time of all passengers. However, route *A* might lead to a longer travel time for a subset of passengers; for the sake of minimising the overall objective function, their preferences have been neglected, such that route *A* results in more inconvenience to them. In principle, assuming that the ideal route needs to be optimal merely based on the characteristics of the city in an objective sense (e.g., in terms of distances), ignores how satisfied riders are in a subjective sense. In such a view, ridesharing is approached and accordingly solved as a merely *technical* problem with no intention to take into account the *social* and preferential dimensions. In view of human-centred AI techniques and the need for developing trustworthy human-AI partnerships [13], we see ridesharing as an inherently sociotechnical problem and argue that its acceptance by society depends on the ability to capture riders' preferences throughout the journey.

Against this background, this is the first contribution that develops algorithms for determining ridesharing routes in participation with riders, allows dynamic routing through the journey by integrating voting mechanisms, and relaxes the expectation that riders need to compromise their privacy by sharing information with other riders. The current work focuses on riders with temporal preferences; however, all presented algorithms can handle complex utility functions, a capability we intend to employ in future work.

2 Main Approach

We consider the case of generating a route for a single bus that is part of a 24-hour ridesharing service. The route generated is a sequence of visited stations, taking into account the temporal preferences of the current riders. The map is defined as a graph that links bus stations. The riders are fully satisfied when their most preferred departure and arrival time is met, and suffer a disutility when the schedule deviates from that. Additionally, the riders have different senses of urgency and patience. We present 3 different algorithms, capturing various aspects of this problem. The algorithms are evaluated using simulation-based experiments.

The main building block of our schedules is the notion of *TourNode* as a list. The i-th TourNode defines the location of the i-th station in the schedule, as well as arrival and waiting times and the sets of riders for pick-up and drop-off. The list of TourNodes should meet certain constraints; the locations of two adjacent TourNodes should be different, as well as the arrival time at the i-th TourNode should be no smaller than the departure time of the $(i-1)$-th TourNode.

Our first approach, the *Randomized Greedy Algorithm* examines the riders according to a random ordering, and builds a list of TourNodes, as the bus schedule. More specifically, consider the case where the i-th rider is examined. A provisional schedule of TourNodes has been constructed when the previous riders were examined. At this point, the algorithm first creates a temporary set of valid TourNodes (these could be new or already exists in the provisional schedule) for the departure and the arrival of the rider. Then, the algorithm finds two valid TourNodes, one for the departure and one for the arrival, which maximize the utility for rider i and assigns rider i to them. If any of these two TourNodes does not exist in the provisional schedule, it is then added by the algorithm. The final route of the bus is the sequence of TourNodes created this way.

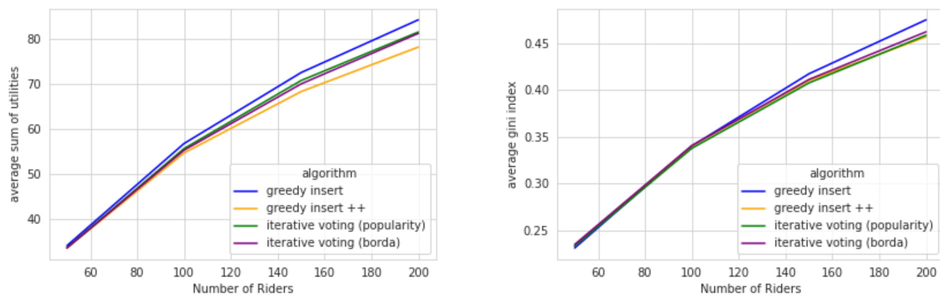
While this algorithm takes preferences into account, it does not consider any fairness aspects. The riders assigned first benefit the most from the scheduling, since the schedule for the first riders is not dense, and there is a higher chance of allocating a departure and arrival TourNodes to maximize the early scheduled riders' utility. To mitigate this impact, we firstly propose the *Randomized Greedy ++ Algorithm*. This algorithm works similarly to the Randomized Greedy Algorithm, with a slight modification: it firstly assigns TourNodes for the departure of the riders according to a random ordering, and then allocates TourNodes for the arrival, according to the reverse order. This form of allocation is also known as *picking sequences* [3]. This way, a rider whose departure was scheduled late, gets more flexibility in the scheduling of her most preferred arrival time.

A second algorithm designed to enhance fairness is the *Iterative Voting* algorithm. This algorithm follows a voting procedure that is repeated until all riders are allocated in a departure and an arrival TourNode. At each iteration, and given a provisional schedule of TourNodes, all unallocated riders propose the TourNode that suits them the best, first for their departure and then for their arrival, in a pool of candidate TourNodes. Observe that the proposed TourNodes should respect any constraints imposed by the previously scheduled TourNodes. After the pool of candidate TourNodes is built, the riders vote to select one of them to be added to the schedule. The voting is done either using the Borda method or plurality voting [3]. When all riders are allocated (i.e. they are allocated in a TourNode for departure and a TourNode for arrival time) the final sequence of TourNodes is returned, as the bus route.

3 Evaluating Fairness and Efficiency

We evaluate the performance of the algorithms experimentally. As a measure of efficiency, we focus on the sum of utilities [10]. To measure fairness we follow [8] and use the Gini Index [6, 10], a popular measure of equity in the transportation literature [16]. We use the locations of 66 bus stations in Westminster, London from the Naptan dataset [4] to create a fully connected graph. Finally, we generate riders with different patience levels and various departure and arrival times, simulating peak and off-peak demand.

Our preliminary observations on fairness and efficiency are presented in Figure 1. The Randomized Greedy algorithm worked the best with respect to efficiency, while all fairness-aware algorithms performed the best with respect to the Gini index, with small differences between them.



(a) Sum of Utilities (b) Gini Index

Fig. 1: Sum of Utilities and Gini index vs Number of Riders.

4 Future Directions

In this work, we presented preliminary algorithms and results from an ongoing project on preference-aware dynamic ridesharing, aiming to promote rider participation. Such algorithms can be implemented in ridesharing services to improve riders' satisfaction and, in turn, foster the financial and environmental benefits of smart mobility. Future work can build on these algorithms to explore more realistic preference models.

Our approach is also privacy-conscious as it intentionally neither assumes that riders have complete knowledge about other riders nor expects them to share such sensitive information with others. While this perspective respects privacy concerns in general, in some specific settings (e.g., sharing a ride with others in a social network), sharing information may lead to improved performance of the service. As an extension of this work, we aim to integrate methods for sharing more information with other trusted riders on the service (e.g., using multiagent negotiation techniques [9]) to achieve meaningful consent over a shared route [15, 1]. Another extension is to work towards the design of sustainable preference-aware dynamic ridesharing systems by applying mechanism design methods [12], (e.g., as in [7]). Under this perspective, the riders are represented by computational agents [2] which act in real time on their behalf.

Data Access Statement This study was a re-analysis of data that are publicly available from the national public transport access nodes (NaPTAN) [4].

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