Citizen Centric Demand Responsive Transport

Doctoral Consortium

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ABSTRACT

This extended abstract outlines the benefits of implementing citizen-centric design principles into a demand-responsive transportation optimization system. Demand-responsive transportation systems work on flexible schedules to predict and react to user demand in real-time. Additionally, areas where social preferences can be incorporated into these methods, are identified. Then a comparison between a Tabu search heuristic and a simple greedy heuristic for passenger stop selection is outlined. An ant colony heuristic handled the primary vehicle routing. The results of these tests indicate a benefit to the users of the transportation system when these design principles are implemented. However, more work is required to add essential features, such as dynamic elements, to the model as well as improve the overall efficiency of the method. Finally, a path to these improvements as well as potential extensions to work is discussed, including focus groups, wider surveys and further experiments.

KEYWORDS

Routing; Optimization; citizen-centric; Accessibility; Smart City; Socially aware design

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1 INTRODUCTION

Current public transportation systems utilize static stops and timetables. This arrangement is not designed to serve the passengers individually but the community. Currently, if a user wishes to make a journey not covered by the current transportation network they must either book a taxi or use a ridesharing service such as Uber[1] or Lyft[2]. These ridesharing services have problems of their own, for example, surge pricing, controversial labour practices and lack of service in rural areas. These static systems are a necessity when the user base of the transportation has no interaction with the system. However, with modern technology, there is an opportunity to allow users to impact the transportation system [11]. This potential two-way interaction would require a substantial change to the organisation and scheduling of existing transportation systems.

When designing these changes to the system, there is the opportunity to make more citizen-centric choices that focus on the users' needs [1]. By providing a service that focuses on and serves the users' needs more than the existing system, the users are more likely to favour the public transportation system over personal transportation. This is the aim of improving the system as the use of buses and trains reduces the congestion on the road and reduces the total emissions of transport [9]. There are two main focuses that these improvements can have. First, a citizen-centric design where passengers' concerns, such as different accessibility needs, that passengers may have or the environmental impact of travel are incorporated when designing the methods. The second focus is to consider the entire passenger journey, from origin to destination [12]. For example, in a bus system, this includes the time the passengers must walk to and from the locations the bus stops at.

Demand-responsive transportation systems rely on the input of the passengers to book point-to-point trips [4]. These bookings include a starting location, a destination and a target arrival time. The demand-responsive system will have to route a fleet of vehicles around a set area, be it a region or city, to best complete each booking. This operation and adjustment of the route must be made in a short time frame as changes to the route must be calculated before the actual time frame of the change occurs. This problem is compounded by the NP-hard nature of the routing problem [3, 8, 10]. In addition to this problem, there is the aspect of the bus driver making changes to their route as new directions arrive, a possible distraction for the driver.

Next, the demand-responsive system must be flexible. One of these methods is to increase flexibility by removing the current static stops and replacing them with dynamic stops [7]. The system could also be made to predict the demand across the active region to preemptively route the bus fleet to the areas that will serve the most demand.

Finally, a system that is designed to be citizen-centric must have some mechanism to gauge how well the system is serving the needs of the passengers. There are three categories that passenger preferences can fall into economic, environmental and social. Each of these categories and preferences can be split further into individual objectives. These objectives, such as cost and emissions, can be quantified and compared [5]. However, social preferences are more nebulous and hard to quantify.

Many of these aforementioned social preferences relating to the accessibility of the transportation network. This accessibility relates to both physical and social aspects of accessibility. Some examples

[1]https://www.uber.com/
[2]https://www.lyft.com/

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of physical accessibility of transportation are wheelchair accessibility, walking to bus stops and waiting times [6]. In contrast, social accessibility preferences include objectives such as a level of safety, reducing contact with others or the fairness of the system. The ability to quantify these metrics and scale them to their importance to the passengers is crucial to the ability to compare and contrast these values meaningfully.

2 METHOD

The core problem of routing remains the same, optimizing the routing of a fleet of vehicles. However, when designing citizen-centric systems using the aforementioned objectives and preferences new challenges arise. In many routing systems, the key technique used to optimize the routing are Heuristics. Initial experiments were undertaken to evaluate if including a specific passenger cost value in the objective function of the evaluation step of the heuristics. These costs were generated using a random uniform distribution. An Ant Colony Heuristic (ACO) [13] was used for the overall routing of the vehicles. In the context of demand-responsive transport that considers the entire passenger journey, a second heuristic was used to route the passengers to the stop locations.

To test and compare two heuristics were compared for the routing of passengers to the stops, a Tabu search and a greedy search. These tests were undertaken in an environment created from Open Street Map data [1] of the city of Southampton. For this initial battery of tests, the passenger cost was implemented in a simple fashion by adding the cost of distance walked for each individual passenger to the objective function. However, future versions of the objective function aim to incorporate the different passenger preference categories outlined in the introduction.

In addition to integrating the passenger information into the objective function, we have begun investigating the other elements of a demand-responsive system to improve the passenger objectives. One of these experiments was exploring the addition of vehicle-to-vehicle transfers and the potential benefit this could have on the passenger journey. Using this simulator we implemented a heuristic based on a modified insertion [2] heuristic, one that additionally looked for stops where passengers could change from one vehicle to another mid-journey to better meet their requirements.

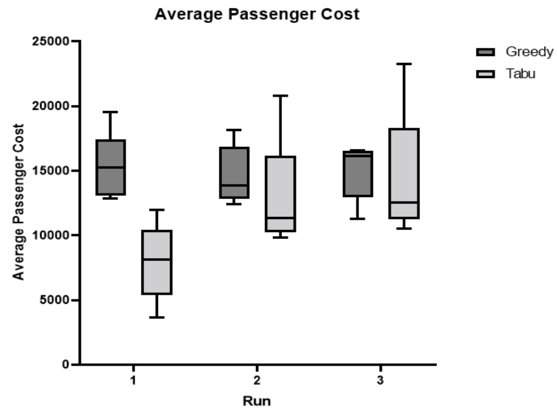

Figure 1: A graph of the average passenger cost

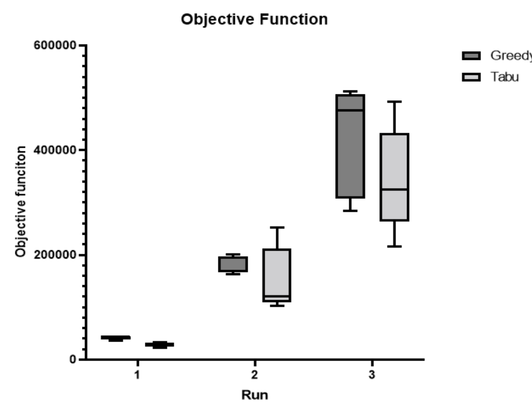

Figure 2: A graph of the objective function of the Heuristics

3 CONCLUSIONS AND FUTURE WORK

The tests undertaken indicated a benefit to considering the passenger as seen by an 18% decrease in the objective function, indicating an overall improvement to the system. However, the other measured metrics such as average passenger wait time and passenger cost improvements had less significant mean improvements, between 1-3%. This highlights that including a passenger cost on its own in the objective function of the optimization may have some benefit to the overall system. However, during the tests, it was clear that this method was insufficient to address the barriers in the transport systems.

One of these areas that were insufficient was the execution of passenger costs. In this simulation, the costs were a simple random distribution assigned to the passenger. To address this weakness I will be running a set of focus groups and interviews wherein a sample of the population will be asked about their current usage of transportation and the accessibility barriers that currently prevent their use of public transport. Using this information further wide-scale surveys that will aim to collect more quantitative data. Using this data a more complex system of multiple passenger costs and weights that cover a wide range of identified accessibility challenges will be implemented. In addition to this and adding dynamic elements to the simulator the passenger costs will also be dynamic and change as the simulation progresses.

Additionally, further work is needed in the investigation of vehicle-to-vehicle transfers both in the design of the heuristic and the method of selecting transfer windows. When selecting transfer windows we examined a very selective set of stops where both the vehicles stopped at the same stop and the passenger's destination was served by the later vehicle. This very limited set of transfer windows was very rarely met in the system.

[1] https://www.openstreetmap.org/

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[2] https://www.ccais.ac.uk/

[3] https://autotrust.org.uk/