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Testing request prioritization strategies to improve the quality of a shared autonomous vehicles service: A Melbourne case study

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Abstract

Shared autonomous vehicles (SAVs) have the potential to revolutionize urban transport by offering a mobility service that combines the benefits of autonomous vehicles and ride-hailing systems. However, one of the main limitations of these services is the handling of all request types in a singular way, which can increase biases towards a fixed type of passengers who have different properties and accessibility-based constraints. This study proposes a prioritization approach based on different request properties and the urgency of the request. The study uses the MATSim simulator to evaluate the prioritization schemes and implements five different scenarios to assess the collective and individual effects of the schemes. The case study focuses on Melbourne Metropolitan Area, and the prioritization is done based on the existing public transport (PT) service and pre-calculated SAV demand of the network. The study considers different performance measures, such as service efficiency, externalities, and provision equity, to estimate the benefits of the prioritization.

The results indicate that prioritization can improve overall equity by spreading wait times evenly across the network. The prioritization approach improves the service with more riders finding the service attractive, resulting in more served rides with lower average vehicle kilometers traveled per ride. In addition, the study shows that the PT mode share is increased in multiple scenarios, demonstrating the positive effect of considering accessibility when prioritizing requests.

1. Introduction

Conventional public transport (PT) is designed to cater to densely populated urban areas with predictable travel patterns through fixed schedules and routes. Nonetheless, due to suburban expansion, the dispersal of the population, and socioeconomic changes, there is a growing demand for flexible transport alternatives (Koffman, 2004). Ride-hailing services provide efficient and quick service in these low-mobility locations. However, the average vehicle occupancy in these services is low, which can contribute to an increase in congestion, CO2 emissions, and fuel consumption. As a more sustainable alternative, ride-hailing services can allow users to share rides by matching users going in the same direction to the same vehicle. Known as ridesplitting, these services can leverage the convenience of ride-hailing while increasing vehicle occupancy and consequently reducing the total number of vehicles on the network (we refer to the broader category of services that encompass ride-hailing and ridesplitting as ridesharing).

The development of fully automated vehicles (AV), which do not require human drivers, is likely to further increase the feasibility and advantages of ride-hailing and ridesplitting systems. This is because AVs can reduce the operational costs of shared fleets by increasing efficiency and removing current constraints associated with human drivers. These services are known as shared autonomous vehicles (SAVs) and are the focus of the current study. They are an on-demand transport service with a fleet of AVs requiring no human intervention (level 5 automation) or minimal human intervention (level 4 automation on select suitable roads).

Potts et al. (2010) show that ridesharing services have the potential to enhance mobility, lower costs, and incentivize the adoption of PT, especially when coupled with traditional PT networks in low-mobility areas. One specific form of integration, the first-mile/last-mile (FMLM) service, commonly serves regions with lower population densities and offers a more adaptable approach to connecting individuals with regional PT systems. Integrating these services with PT provides an improved solution to accessibility and mobility, especially for segments of the population that are unable to drive, such as older adults and/or disabled people. Such segments are likely to benefit the most from SAVs.

Recently, software-based solutions have been incorporated into these flexible transport services to improve their functionality and focus on serving requests based on the FCFS approach, where the overall goal is to look for solutions to minimize costs. A significant challenge to this service is ensuring reasonable waiting times in less densely populated areas, where demand may be comparatively lower than in urban centers. A priority order to serve requests can be used to solve this problem. These prioritizations may be based on the urgency and importance of the request based on specific decision criteria. This study examines different decision criteria that can be used to prioritize requests for SAVs services. We apply the insertion-based ride-matching strategy used in MATSim and test the prioritization of some types of passengers over others based on their and the network's properties.

The remainder of the paper is organized as follows: Section 2 discusses the background and previous literature related to the study. Section 3 includes the methodology, which explains the case study, the proposed model, and the scenarios used in the study. Section 4 explains the key performance matrices used in the study. Section 5 discusses the simulation results, followed by the conclusion and future work in Section 6.

2. Background

Matching and dispatching algorithms significantly impact ride-hailing systems' overall performance and efficiency (Wang & Yang, 2019). Most works in the domain of assignment of passengers to vehicles and planning the optimal drop-offs are based on an FCFS approach. It is common for trips of different types to have varying degrees of flexibility. There are only a few studies that focus on prioritizing requests based on their properties and time flexibility.

Trip prioritization is not a common topic in literature. The prioritized ridesharing problem is similar to the fixed route traveling salesman game, also known as the routing game (Levinger et al., 2021). Previous studies focus on deciding the order as optimal order by minimizing the total cost (Potters et al., 1992). Alonso-Mora et al. (2017) developed a sampling-based algorithm for their vehicle routing problem, where lower priority was given to the predictive trip requests, reducing delays. In one of the recent studies, Pouls et al. (2022) developed an algorithm that prioritizes different requests based on different weight types in the objective functions. These weights help prioritize requests in high-demand areas in case not all requests can be covered simultaneously. Tiwari et al. (under review) proposed multiple ride-matching strategies for ride-hailing services, where the trips without parallel PT routes were prioritized, eventually increasing the PT ridership. Unlike these studies, our priority order follows multiple criteria developed based on the information of the network and historical demand in the network.

Despite the high-tech environment, ride-hailing services do not serve all neighborhoods and regions equally. The potential distribution of impacts across populations and equity considerations is absent from most ride-hailing modeling efforts. The literature has given limited attention to measuring the impact of different policies on inequalities across various ride-hailing services. Many equity measures have been proposed in the literature focusing on transport projects. The most widely used measure is the Gini Index (Gini, 1921), which measures the relative difference between actual and ideal situations (Jin et al., 2019; Yan & Howe, 2019). To the best of our knowledge, no studies show how prioritization schemes for specific types of trips affect system performance and equity outcomes. Addressing these inequalities is crucial for ensuring equitable access to these services, yet there is a lack of research on how to do so effectively.

The prioritization-based matching problem in this article differs from the cases discussed above in two main aspects. First, the studies discussed above focus on designing the services based on a single prioritizing criterion, which can lead to better service performance in that one aspect. In contrast, the current study considers using multiple criteria individually and combinedly based on the properties of the requests and network. Second, most studies are optimization-based and focus on optimizing different objectives, such as PT ridership, delays, and costs, and do not include equity. The current study is not an optimization study and considers equity as the key performance indicator and objective for the efficiency of the service. In summary, instead of proposing a ride-matching strategy to prioritize different request types, this study changes the FCFS approach to a prioritization-based approach.

3. Methodology

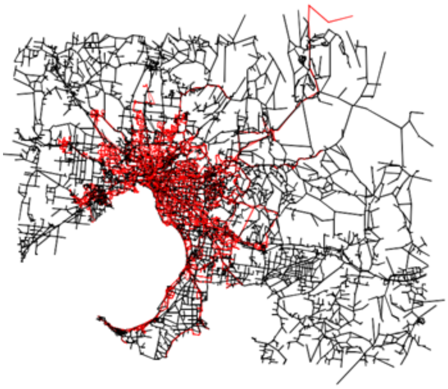
3.1. Multi-Agent Transport Simulation

MATSim is an open-source, agent-based simulator of travel demand and supply implemented in Java (Horni et al., 2016). It uses a simple and computationally efficient queue-based approach to represent the traffic flow. MATSim is based on a co-evolutionary principle, where each agent optimizes daily activity schedules by maximizing daily plan scores by changing their routes, modes, activity times, and locations over the configurable number of iterations. The input population file includes each agent's initial set of daily plans with their location, transport mode, and travel time. At the end of each iteration of the entire day, the performance of the plan is calculated using a score based on the successful engagement in activities and travel. The co-evolutionary algorithm is run during the replanning module, where a share of all agents is allowed to search for a new plan according to predefined evolution strategies. At the end of each iteration, the agents choose the plans with maximum scores. The DVRP extension was designed to simulate dynamic transport services (Maciejewski & Nagel, 2012). Bischoff et al. (2016) proposed a demand responsive transit (DRT) framework to serve several passengers at the same time. These extensions were used and modified in the current study to investigate the effects of trip prioritizations.

3.2. Case study

This study uses an existing synthetic MATSim model of Melbourne's Metropolitan Network. The network file of the study area (Melbourne) and the config file were taken from the base scenario, and the config file was modified according to the requirements. A typical General Transit Feed Specification (GTFS) data was used to create a PT network map mapped with the existing Melbourne Model network file. Transit schedules that have not been mapped do not provide details about the routes taken by vehicles but only show the sequence of stops for each transit route. When mapping these schedules, only links labeled as "bus" or "car" can be used for transit routes that operate on a bus schedule, while transit routes that operate on a rail schedule can only use rail links. If a scheduled transport mode is not assigned, artificial links between stops are created for all transit routes that use that mode. Figure 1 shows the PT network mapped on the MATSim Melbourne model network. The population file was generated using the VISTA 2016 (Victorian Integrated Survey of Travel and Activity) and census datasets. The population contains ten percent of the sample size of the entire population. Scaling down the population has been applied in most of the MATSim studies in the literature, where ten percent population has been used (Ben-Dor et al., 2021).

Figure 1: Metropolitan Melbourne PT network mapped on the MATSim model network



The scoring functions in MATSim allow the addition of travel time models by applying utility and monetary values to the trips and activities. These scoring functions are used to simulate activity scheduling and travel mode choices. KPMG and Infrastructure Victoria (Victoria, 2017) have estimated the calibration parameters for the Melbourne Activity-Based Model (MABM). The final calibrated parameter values from the KPMG report (Victoria, 2017) were used in the simulations in this study.

Different fleet sizes were tested to achieve acceptable service quality, and finally, 3500 vehicles were used in this study, where each vehicle has a maximum capacity of 4 passengers. Each scenario consists of 100 iterations, each being a simulation for a weekday day. In the replanning step of the MATSim model, for the first 80 iterations, 10% of agents could change their modes, and 10% of agents were allowed to change their routes. In the last 20 iterations, replanning is not allowed, and agents choose their plans based on existing plans and scores. The demand and mode shares keep changing over the 100 iterations based on the new plans that the agent creates each iteration. The wait time and detour constraint were kept constant for all the scenarios. The results shown in the study are after 100 iterations, and each started from iteration 0 from a fixed plan file.

3.3. Prioritization model

The model uses the insertion-based heuristics algorithm from MATSim to serve the requests (Bischoff et al., 2018). The algorithm inserts each request in all vehicles and finds the best suitable vehicles within the specified wait time and detour constraints. The proposed model differs from the MATSim base model in the sense that MATSim uses an FCFS basis approach, where the vehicles are found for each request as they come. In contrast, the model presented in this study focuses on a request distribution and prioritization approach, where the requests are divided into different lists based on their properties and served in the same order that they were distributed.

Let τ_n be the nth dispatching interval of the day, which has total r_m requests. The origin and destination of the request r_i is O_i and D_i respectively, which are inside the zone $Z_{i,O}$ and $Z_{i,D}$ of the network. At the start of each dispatching interval, the model finds the number of lists (L_p) from the last dispatching interval and serve each list one by one. Each list L_i has multiple requests, and each request from the list (r_j) is considered, and a suitable vehicle is found for the request, which satisfies the wait time and detour constraints. Figure 2 explains the process for serving the lists from the previous dispatching interval first and later distributing the requests of the current interval in different lists based on the model presented in Figure 3. The dispatching interval was kept as 60 seconds in this study. Figure 3 shows the flow chart of the distribution of all the requests based on different prioritization schemes. The demand-based prioritizations, indirect rebalancing, and accessibility-based prioritizations (which are presented in detail in Section 3.4) use parts of the flow chart and are later served in those orders. The detailed prioritization schemes are explained in the next section in detail.

Figure 2:Assignment process in the prioritization scenario

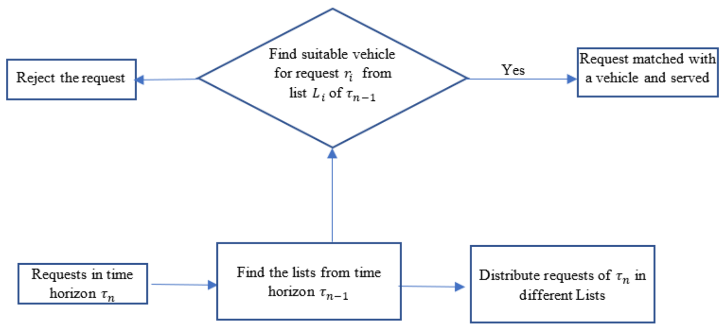
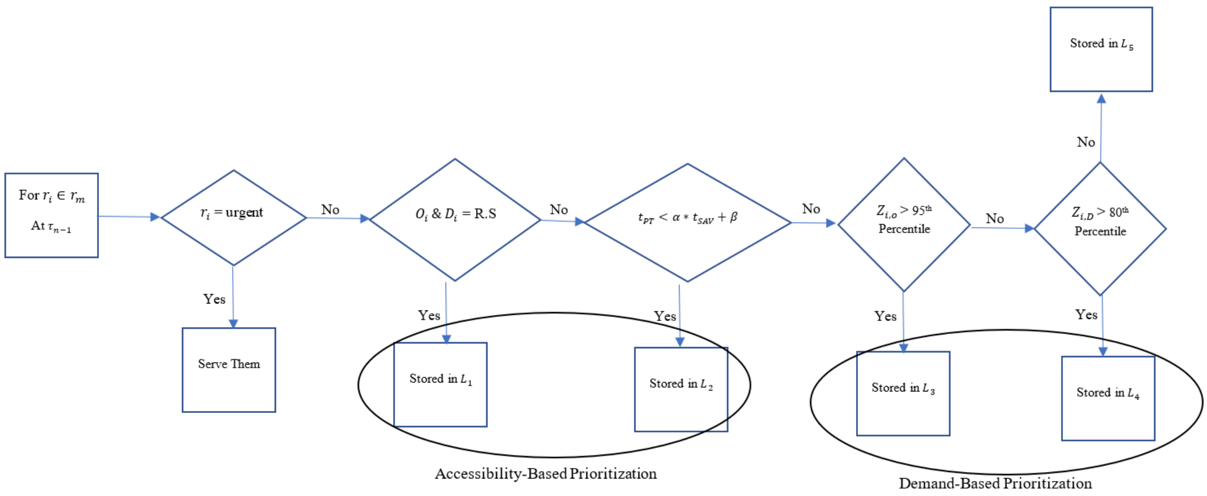


Figure 3: Flow chart of the model distributing requests under different prioritization schemes



3.4. Prioritization schemes

This section explains the prioritization criteria used in the model. We have developed six lists or criteria that serve the requests in an order, where the requests inside each list are served on a first-stored/first-served basis.

3.4.1. Urgent requests

This list considers the requests for impaired and mobility-disabled people. While SAVs may pose challenges to PT systems, some segments of the population, such as older adults and/or disabled people, can hugely benefit from these services. This is because these groups usually cannot drive and may face challenges accessing or using PT services. Literature suggests that

12-13% of the population are transport disabled in some way, which is they experience issues accessing some or all modes of transport (Wilson, 2003). There were 17.7% of people in Victoria with some form of impairment, among which 5.7% of the Victorian population had a profound or severe disability in 2018 (ABS, 2019). This study randomly assigns 5.7% of requests to be considered as mobility impaired and urgent requests.

3.4.2. Accessibility-based prioritization

(a) FMLM requests

The requests that are assumed to be accessing the PT stop are considered under this criterion. MATSim does not differentiate between door-to-door and intermodal requests and considers both similarly. Railway stations tend to be characterized by substantially larger catchment areas than stops of slower PT modes, making ridesharing services an attractive access mode compared to walking (Keijer & Rietveld, 2000; Martens, 2007). Therefore, most of the intermodal trips using SAVs as an FMLM mode are completed using trains. This criterion estimates the closest PT stop to the origin and destination of the request, and if the PT stop is a railway station (the acronym "R.S." is used in the flowchart), the request is considered to be used for a multimodal trip and is served under this criterion.

(b) PT inaccessibility

This criterion refers to the low accessibility of PT in some of the locations around the network. The PT accessibility was estimated by comparing the travel times by PT and SAV and estimating if there are any possible alternative travel routes that PT could serve at a similar level of service. This study uses the relationship developed by Tiwari et al. (2023) to evaluate the accessibility of PT. If $t_{PT} > \alpha * t_{SAV} + \beta$, then the trip is considered as inaccessible by PT and those requests are collected in this list and the list is prioritized over other requests. The alpha and beta values, which are 1.4 and 120 sec, respectively, were taken from the same study, where these values were estimated for the case study of Melbourne Metropolitan.

3.4.3. Demand-based prioritizations

This study uses the zonal aggregation model in MATSim, which divides the network into smaller zones. The network was distributed into zones of squares of 2.5 km x 2.5 km, and the SAV demand based on the available historical data from past simulations was estimated. The base simulation with no rejection was run to estimate the demand for the network. The simulation was run for 100 iterations, and the number of requests in each zone was estimated at the end of the simulation. We had requests from 0 to 2600 per zone in the historical demand data. The demand data were sorted based on the number of requests in each zone.

(a) High-demand zones

As the demand for SAVs varies based on spatial and temporal properties of the requests, some locations have higher demand throughout the day compared to other locations. That is why it is important to serve those requests originating from these locations with a priority in order to improve the service quality. This criterion considers the zones with a number of requests higher than the 95th percentile to be considered high-demand zones. The criterion selects those requests originating in these zones, considers them a high priority, and serves them.

(b) Indirect rebalancing

Indirect rebalancing refers to serving requests with their destinations in high-demand zones. Sometimes, the undersupply of vehicles in some locations causes significant waiting times in those regions and unattractive service. When not using any rebalancing strategy with the matching, it is better to prioritize requests with destinations in the zone of high demand requests, ensuring indirect rebalancing and vehicle availability to serve the upcoming requests. This criterion uses the zones with a number of requests higher than the 80^{th} percentile to be considered high-demand zones for requests to be prioritized. The main objective of this criteria is to send the vehicles to the zones with potentially high demand so that a higher number of vehicles will be available in these zones.

3.4.4. Deprioritized

The requests that do not fulfill the mentioned criteria are considered under this list and served after serving all the requests. The main aim of this list is to deprioritize the requests satisfying no criteria. This list of requests is served at last after serving all the requests.

3.5 Simulation scenarios

We have used five scenarios to see the impact of the prioritizations in MATSim. All of the scenarios differ in the sequence of requests in which the passenger will be matched with the vehicle.

Scenario 1: Base Case Scenario: The base scenario serves all the requests collected at the end of each dispatching interval of 60 seconds. The scenario focuses on serving requests based on the FCFS approach at the end of each dispatching interval.

Scenario 2: Trip-Based Prioritization: The proposed prioritization focuses on distributing and storing the requests in each dispatching interval and later serving them in the same sequence of the schemes. The scenario includes all the prioritization schemes and follows the approach in Figure 3.

Scenario 3: Demand-Based Prioritization: This scenario focuses on three types of lists, high-demand zones, indirect rebalancing, and deprioritized lists.

Scenario 4: Indirect Rebalancing-Based Prioritization: This scenario uses a part of scenario 3, where only the requests ending in the high-demand zones are prioritized. This scenario focuses on two types of lists, indirect rebalancing and deprioritized lists.

Scenario 5: Accessibility-Based Prioritization: This scenario focuses on prioritizing requests based on the PT accessibility of the network. This scenario focuses on three types of lists, FMLM requests, alternative PT route availability, and deprioritized lists.

4. Key performance indicators (KPIs)

There are multiple ways to assess and evaluate the performance of the SAVs. This study includes different perspectives from various stakeholders, such as fleet operators, users, and PT operators. The overall performance of a model can be examined from three main perspectives: service efficiency, service externalities, and service provision equity. The KPIs used under different categories are explained below.

4.1. Service efficiency

Service efficiency can be defined from the perspective of the service provider as well as the user. The main indicators included in the user's perspective of service efficiency include **average passenger wait times**. The key parameters that are included in the service providers' perspective are the **empty ratio** (i.e., the ratio of empty kilometers traveled and total VKT) and the **number of total rides served**.

4.2. Service externalities

SAV's service externalities refer to the costs and benefits that impact those not utilizing the service directly, such as environmental consequences or modal share. This study focuses on using **average VKT per ride** and **PT mode share** as indicators of environmental effects.

4.3. Service provision equity

The equity dimension relates to how the service's costs and benefits are allocated among various population groups. This study uses multiple inequality measures to measure the performance of the model and the number of served rides to see the effect of improved equity over the network. This study uses Gini, Theil, and Atkinson indices using the zonal average wait times as the income variable because they are the most used indicators in literature. Chakravorty (1996) delineated three distinct categories for indices that serve as appropriate measures of inequality, which corresponded to the indices he identified. These categories are defined by the approach used in their construction, namely: those that rely on deviations (such as the **Gini Index**), those based on entropy or information theory (such as the **Theil Index**), and those derived from normative social welfare considerations (such as the **Atkinson Index**).

4.3.1. Gini index

The Gini coefficient measures income distribution that gauges the extent to which a policy is progressive or regressive and is commonly used to evaluate inequality (Gini, 1921). Despite being one of the commonly-known equality measures, the Gini coefficient of inequality is little used in literature in the cases of on-demand services (Souche et al., 2016). For the distribution of income in a population of *N* individuals, if $i = 1,2, \ldots., n$, y_i is the income of individual *i*, y_j is the income of individual *j*, and μ is the mean income, the Gini coefficient, denoted by *G*, is written as follows:

$$G = \frac{1}{2N^2\mu}\sum_i \sum_j |y_i - y_j|$$

Another way to estimate the Gini index is by using the Lorenz curve. The Lorenz curves represent the cumulative distribution function of income across the population (Lorenz, 1905). The greater the Gini coefficient, more is the more inequality. The closer the Lorenz curve is to the line of equality or the diagonal, the greater the equality.

4.3.2. Theil index

The Theil index calculates the difference in population size and income share among groups, with a positive value indicating higher income than the population mean and a negative value indicating lower income (Theil, 1967). For a population of *N* individuals, y_i is the income of individual belonging to the population and μ is the mean income, the Theil index, noted T, can be written as follows:

$$T = \frac{1}{N}\sum \frac{y_i}{\mu} log \frac{y_i}{\mu}$$

Using a negative value with the Theil Index is impossible because the logarithm induces a non-null value. Although Theil Index is sensitive to extrema values, it is more sensitive to changes in high-income groups and income transfers from the poor to the rich.

4.3.3. Atkinson index

The Atkinson index adds an ethical judgment made by society to evaluate inequalities (Atkinson, 1970). It reveals the value judgments that are made when the parameters of the social well-being function are chosen. Atkinson's social well-being index, denoted by AT, is written as follows:

$$AT = 1 - \left[\sum_i \left(\frac{n_i}{N}\right)\left(\frac{y_i}{\mu}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}$$

Where N is the number of individuals, n_i the number of individuals in each income category, $i = 1,2, \ldots, n$, y_i is the income of individual i, and μ is the mean income, $\varepsilon \geq 0$ is a parameter that defines the relative aversion in inequality. Atkinson index is very sensitive to the choice of the parameter ε, where $\varepsilon = 0$ means there is no aversion to inequality, and when ε tends to infinity, the index only considers the poorest observation. Like Theil Index, Atkinson Index is sensitive to extrema values, especially to small incomes. Consequently, the Atkinson Index gives more importance to inequalities between the poor than between the rich. This preference is accented with the increase of ε parameter.

These indices are used to establish an analogy between inequalities and SAVs, where zonal average wait time is used as the income, and the inequalities are measured.

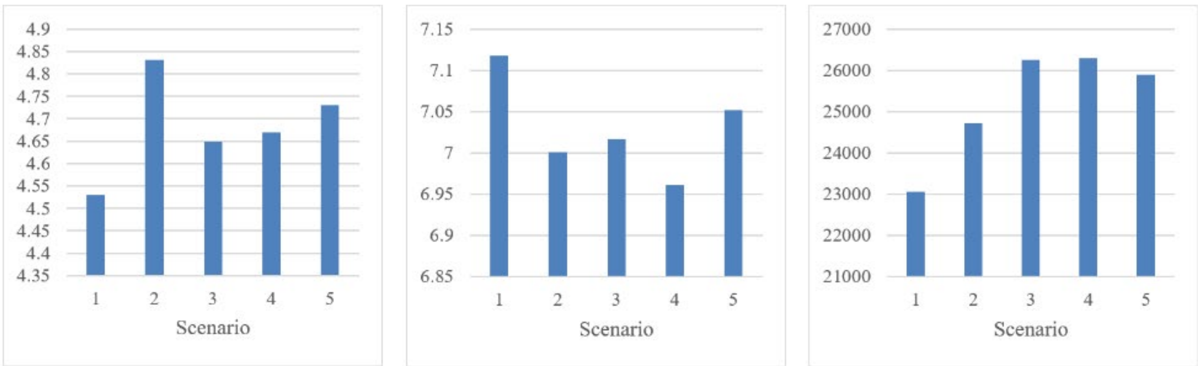
5. Results and discussions

The results are shown in three categories based on the abovementioned properties. The effects of different prioritization schemes are assessed for three categories of KPIs.

5.1. Service efficiency

Figure 4a shows the average wait times for different scenarios. The average wait times for all the prioritized scenarios are slightly higher than the base scenario. As the number of requests served is higher in the case of prioritized scenarios, as shown in Figure 4c, the overall wait time increases slightly. The model takes some time to distribute the requests into different categories, which eventually increases the average wait times by a fraction. The larger number of served requests with higher average wait times indicates that the requests from further zones are also being served. Figure 4b indicates the empty ratio. The empty ratio is decreasing in the prioritized scenarios as the scenarios focus on prioritizing requests from high-demand zones and indirectly relocating vehicles in those zones.

Figure 4: (a) average wait time (min); (b) empty vehicle ratio (%); (c) the total number of rides served.



(a) (b) (c)

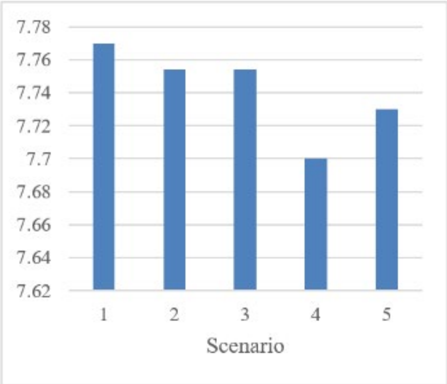
5.1.1. Summary

Regarding service efficiency, it can be summarized that the demand-based and indirect rebalancing scenario leads to better wait times and a lower empty ratio. A large number of requests come at the cost of higher wait times compared to the base case scenario. The wait times are best in the scenarios of demand-based prioritization and indirect rebalancing, which indicates the benefit of prioritizing requests from the high-demand zones.

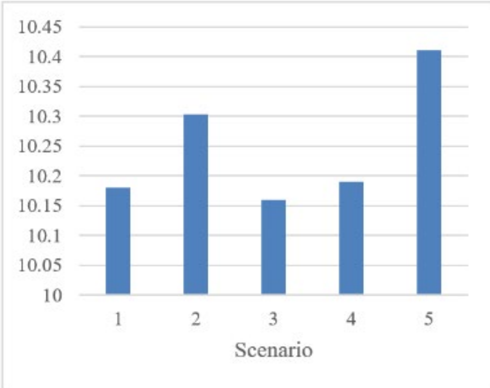
5.2. Service externalities

The externalities of prioritizations are analyzed for two aspects: (1) Average VKT per ride and (2) PT mode share. Different type of prioritizations leads to different VKT per ride and PT mode share. The VKT per ride is improved in all scenarios compared to the base scenario, as seen in Figure 5a. Due to the inclusion of the demand of upcoming requests, the requests originating and destined in high-demand zones are prioritized, which eventually decreases the average VKT per ride as a higher number of vehicles are available to be matched with the upcoming requests.

Figure 5: average VKT per ride (km); (b) PT mode share



(a)



(b)

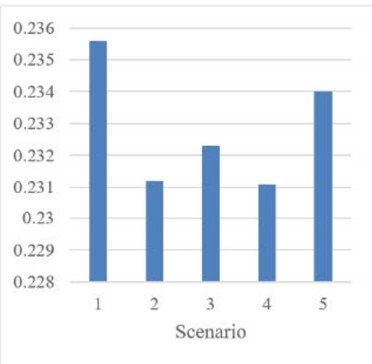
5.2.1. Summary

The externality measures indicate that accessibility-based prioritization leads to the highest increase in PT mode share. The demand-based and indirect rebalancing pose positive externalities in the case of VKT per ride as they reduce the additional kilometers traveled from further distances to serve the requests because of receiving prioritized vehicles in the high-demand zones.

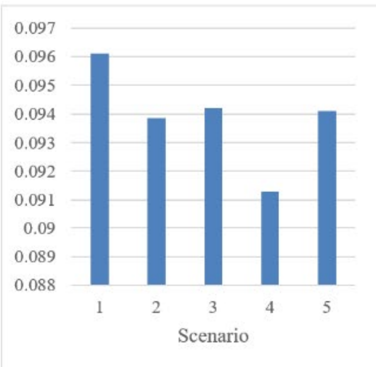
5.3. Service provision equity

This study considers the distribution of average wait times per zone throughout the network to analyze the service provision equity for the SAVs. Three different indices, the Gini index, Theil index, and Atkinson index, are considered for the zonal average wait times throughout the network. The fourth KPI shows the zonal average wait time spread throughout the network to show the distribution.

Figure 6: (a) Gini index for different scenarios; (b) Theil index for different scenarios; (c) Atkinson index for different scenarios



(a)



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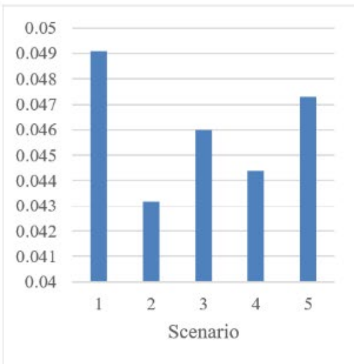


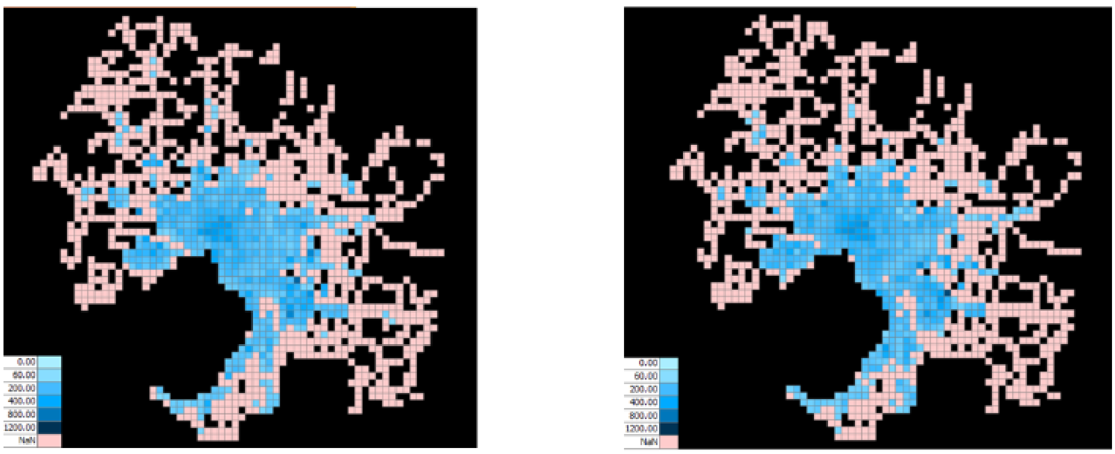
(c)

Figures 6a, 6b and 6c show the values of the Gini index, Theil index, and Atkinson index for all five scenarios, respectively. The Gini index shows an improvement in the overall equity in the network. The Gini Index for the base case scenario was 0.2356, which comes down to 0.231 to 0.234 for all other prioritized scenarios, which shows an improvement in the equitable distribution of the wait times. Similarly, the Theil index for the base case scenario was 0.0961, which comes down from 0.0913 to 0.0942, showing an improvement in the distribution. The results of the Atkinson index show the results where the value for the base scenario was 0.0491 for a value of ($\varepsilon = 0.5$), which comes down to 0.0431 to 0.0473, which is a positive trend towards equity.

5.3.1. Mapping zonal average wait times across the network

Figures 7a and 7b show the zonal average wait times per distribution for the base case and trip-based prioritization scenarios. It can be seen from Figure 8a that the base scenario has a more significant number of zones with higher average wait times, which goes down in the trip-based prioritization scenario, as can be seen in Figure 8b. The wait time is distributed better in the prioritized scenario as the number of zones with extreme average wait times is less than the base scenario.

Figure 7: Zonal average wait times in the base scenario (sec); (b) Zonal average wait times in the trip-based prioritization scenario (sec)



(a) (b)

5.3.2. Summary

Regarding service provision equity, three of the considered indices indicate that prioritization can improve equity and evenly spread the network's average wait times. The best results were received for indirect rebalancing as the availability of vehicles, which can be seen from the average wait times in both scenarios, which was less compared to the other scenarios.

6. Conclusion and future research

The increasing levels of vehicle automation are predicted to significantly affect transport systems, which could create a new way of transport known as the SAV, a combination of shared on-demand services and AVs. One of the main limitations of these studies is the different wait times in different locations as they consider all the requests with similar priority and do not focus on improving the service for the passenger with urgency and time-inflexibility. This study considers the properties of the request and the network for prioritizing different request types to improve overall service quality. This study uses MATSim to differentiate between the properties of different request types and serve them individually. The different prioritization schemes consist of serving urgent requests, improved accessibility, and improved service in high-demand zones. The effects of these schemes were evaluated using multiple scenarios, which include all schemes and part of the schemes to evaluate their total or individual effect on the service.

This research paper analyzed the impact of different prioritization schemes on service efficiency, externalities, and provision equity of a SAVs service. The results indicate that demand-based and indirect rebalancing scenarios lead to better wait times and lower empty ratios. However, prioritization may come at the cost of longer wait times, particularly for scenarios with a high number of requests served. Accessibility-based prioritization creates a positive impact on PT mode share, whereas undesired and negative externalities in terms of PT ridership can be noticed in the demand-based and indirect rebalancing scenarios. The demand-based and indirect rebalancing pose positive externalities in the case of VKT per ride. The prioritization improves the service provision equity, measured as the zonal average wait times, with the best results observed for indirect rebalancing. Overall, the findings suggest that prioritizing requests can improve service efficiency and equity. These findings provide insights for policymakers and stakeholders in deploying and managing SAVs.

While this study has shed light on the potential benefits of prioritizing different request types in SAV services, several avenues remain for further research in the field. First, future studies could explore the trade-offs between wait times, travel time, and cost in greater detail to better understand the factors influencing user preferences and willingness to pay. Additionally, it may be useful to examine the impacts of prioritization schemes on different demographic groups, such as those with disabilities or those living in underserved areas. Future research can also explore the effectiveness of different prioritization schemes in various urban contexts and with different levels of SAV penetration. Finally, there is a need for further research on the environmental and social impacts of SAV services with different prioritization schemes, as well as their economic feasibility and implications for public policy. These recommendations could help to guide future research in the field and inform policymakers and stakeholders on the best practices for deploying and managing SAV services.

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