ON-DEMAND POOLING IN CHRISTCHURCH: BENEFIT OR BANE?

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ABSTRACT

New Zealand cities tend to be low-density, and public transportation may not be easily accessible in some areas. On-demand pooled-ride services can offer convenient transportation solutions, either through direct door-to-door trips or as first- and last-mile connections to public transportation networks. However, as the market for on-demand transportation expands, it is important to consider the impacts of on-demand vehicles on network performance and sustainability. This study employs agent-based mesoscopic simulation to explore the potential effects of a large-scale on-demand pooled-ride service operating in Christchurch's Central Business District (CBD) during the morning peak period. The network, modelled in Aimsun Next, covers an area of approximately 6.3 square kilometres, comprising around 1,550 links and 490 nodes. It contains 102 signalised intersections, with signal timings configured as fixed cycles based on observations of the Sydney Coordinated Adaptive Traffic System (SCATS) in Christchurch. Bus routes, stops, and timetables are set using realistic data from Metro, Christchurch's public bus service provider. Car traffic demand is generated using 199 × 203 origin-destination pairs based on real data sourced from the Christchurch Assignment and Simulation Traffic (CAST) model maintained by the Christchurch City Council. The on-demand service is modelled using a modified insertion algorithm that prioritises user experience while maintaining computational efficiency. Fleet sizes ranging from 2,500 to 12,500 vehicles were tested with a demand of 11,032 requests (representing a 25% modal shift from private vehicles). Analysis using Network Macroscopic Fundamental Diagrams (NMFDs) revealed that the on-demand service increased effective network capacity by approximately 20% and maintained steady network flow as vehicle accumulation increased, while the network without the on-demand service experienced reduced flow due to congestion. This suggests that large on-demand pooled-ride services may stabilise traffic flow patterns and increase the effective capacity of the network, potentially decreasing congestion during peak periods.

AUTHOR CONTRIBUTION STATEMENT

Cameron Davis: development of ideas/thoughts, interpretation of results, principal author, prepared the paper, reviewed the paper

Mehdi Keyvan-Ekbatani: development of ideas/thoughts, reviewed the paper, supervision

INTRODUCTION

Many cities worldwide have struggled with increasing levels of traffic congestion as vehicle numbers rise. This has multiple negative impacts, including higher time costs for travellers and increased emissions. According to Auckland Transport (2025), congestion in 2026 is expected to cost $1.9 billion in time delays, with the average Auckland driver experiencing 66 hours of delay. Transportation systems are therefore required that can cope with increasing travel demand without exacerbating congestion. Public transport offers one solution; however, New Zealand cities tend to be low-density, and public transportation may not be easily accessible in some areas.

On-demand pooled-ride services have the potential to increase the sustainability and accessibility of mobility while maintaining a level of convenience competitive with private vehicle use. These services can operate for profit or within a larger public transit system. When operated as public transit, they can increase service coverage and accessibility within their service area and through first- and last-mile connections to fixed-route services (Willcox, 2023). Use of on-demand services has increased yearly, with a 2024 penetration rate of 23.1% globally and 24.7% in New Zealand (Statista, 2024). However, as the market for on-demand transportation expands, it is important to consider the impacts of on-demand vehicles on network performance and sustainability (Davis, Tran and Keyvan-Ekbatani, 2025).

Modelling Approaches for On-Demand Services

There are two main streams of modelling for on-demand transportation: the first is analytical, where the service optimisation problem is modelled with a complete mathematical formulation and feasibility constraints, and the second is heuristic, where the model relies on the implementation of a heuristic solution algorithm to ensure feasibility. Analytical models can be solved exactly to guarantee an optimal solution; however, the often non-linear interactions between variables and the complexity of the formulation mean they tend to be limited in terms of problem size (Cordeau and Laporte, 2007; Ho *et al.*, 2018). On the other hand, heuristics are designed to quickly identify near-optimal feasible solutions and have been implemented on extremely large networks (Jin *et al.*, 2024). For this reason, the service presented in this study is modelled heuristically, with a modified insertion algorithm used to quickly identify feasible solutions.

An on-demand service operates within the context of a wider transportation system, which introduces additional difficulties into the modelling and optimisation of realistic service operations. Tools are required to model the interactions between the service and other components, such as diverse transportation modes and dynamically changing link conditions (Tran, Jiang and Keyvan-Ekbatani, 2026). Agent-based simulation models are particularly suited to this purpose, as they can simulate multiple (user or vehicle) agents with complex behaviours and interactions (Zhou *et al.*, 2024; Agriesti, Roncoli and Nahmias-Biran, 2025). This study employs Aimsun Next, a state-of-the-art software capable of simulating highly detailed networks with complex vehicle behaviours driven by stochastic individual agents (Casas et al., 2010).

Study Objectives

To explore the potential effects of a large-scale on-demand pooled-ride service operating in Christchurch, this study uses a mesoscopic simulation approach in Aimsun, where vehicles are modelled as individual agents, similar to a microscopic model, but with simplified lane-changing and car-following behavioural models. Mesoscopic simulation was chosen to incorporate detailed agent-based traffic modelling while maintaining computational tractability. On-demand service operations are simulated during the morning peak period in order to assess impacts on traffic flow, network performance, and service efficiency across different fleet sizes. The key contribution of this study is an exploration of on-demand pooled-ride service operations in the context of Christchurch.

METHODOLOGY

The on-demand service has been implemented in Aimsun via the Aimsun Ride API. This is a plug-in that connects to the Aimsun Next simulator and enables simulation of an on-demand service within a realistic traffic context. The on-demand operator uses this API to send service offers and vehicle routes, as well as to request information, such as shortest path travel times.

On-Demand Service Design

The service in this study allows for pooled rides, where two or more unrelated users may share a vehicle. Users are assumed not to transfer between vehicles, i.e., each on-demand request is served by at most one on-demand vehicle. Optimisation of the service prioritises the user experience, with the objective of minimising user travel time (including wait and detour time).

Several constraints restrict service operations to ensure solution feasibility and define the minimum allowable level of service. First, for route feasibility, pooled requests are subject to vehicle capacity. Second, limits are imposed on the user's maximum waiting time and their maximum trip duration. (1) ensures that the waiting time a user experiences is not more than α times their minimum possible waiting time $W_{\min}$, calculated as the shortest time for a service vehicle to reach the user's pick-up from its current location. An absolute maximum waiting time is also applied to prevent users from waiting excessively if no vehicles are nearby. (2) limits the user's total trip time, calculated as the duration between making the request and being dropped off. Their trip time must be no more than β times the minimum direct trip time, representing the service a user would receive if a vehicle were immediately dispatched to their pick-up location and travelled directly from pick-up to drop-off, with driving time $t_{p,d}$ (i.e., without detours for pooled requests).

$$W \leq \alpha W_{\min} \tag{1}$$

$$T \leq \beta\left(W_{\min} + t_{p,d}\right) \tag{2}$$

Insertion Algorithm

Decisions of the on-demand service are made using a modified insertion algorithm as outlined in Figure 1. This approach prioritises computational efficiency at the cost of solution optimality, aiming to quickly assign a feasible route for each user request. The algorithm first sorts all vehicles in order of increasing travel time from their current location to the request pick-up. It then iterates through the vehicles, checking the feasibility of inserting the request into each vehicle's existing route. If the constraints are met for all requests in a proposed route, where the new pick-up is inserted after the vehicle's existing stop i and the new drop-off after stop j, it is feasible to insert the request into the vehicle's pre-existing route. Once a feasible insertion position has been identified, the request is accepted, and the proposed route becomes the vehicle's new planned route.

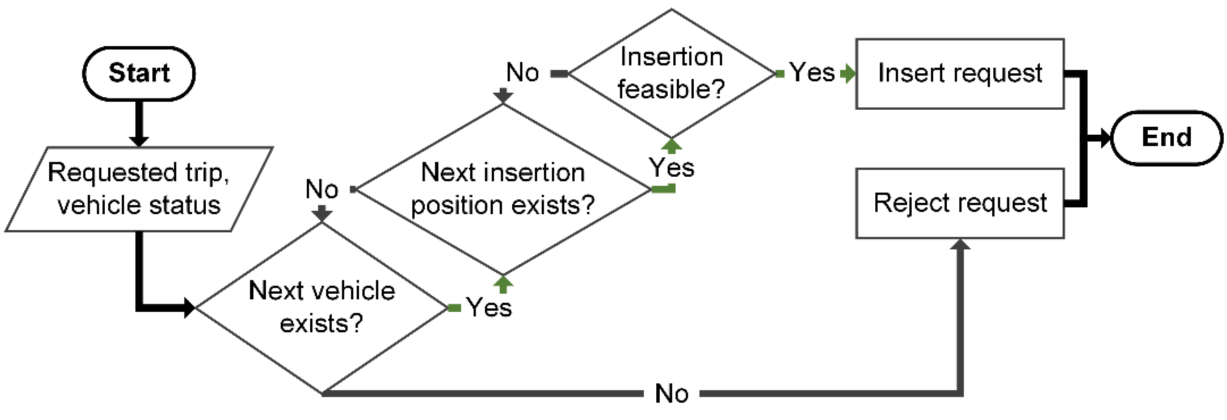

Figure 1. Flowchart outlining the decisions and processes of the implemented insertion algorithm.

NETWORK MODEL AND SIMULATION SETTINGS

This study implements the described on-demand service within the network of the Central Business District (CBD) in Christchurch, New Zealand (Figure 2). The network consists of 1,554 links and 488 nodes, covering an area of 6.3 km^2. There are 102 signalised intersections, with signal timings configured as fixed cycles based on observations of the Sydney Coordinated Adaptive Traffic System (SCATS) in Christchurch. Bus routes, stops, and timetables were defined using realistic data from Metro, Christchurch's public bus service provider. Total car traffic demand is generated using 199 x 203 origin-destination pairs based on real data from the morning peak period sourced from the Christchurch City Council's Christchurch Assignment and Simulation Traffic (CAST) model (Figure 3). This comprehensive network model closely mimics real-world conditions in the Christchurch CBD (Lee *et al.*, 2020). Private and on-demand vehicle route choice is modelled stochastically, with each vehicle using a C-logit model to select a route from their three shortest paths. Link costs, and thus the shortest paths, are recalculated every 5 minutes. Vehicles conduct route choice upon departure from origin/request nodes, as well as en route whenever the shortest paths have been recalculated. All scenarios used the same random seed to ensure comparable results.

Figure 2. Christchurch CBD network modelled in Aimsun with the intersections in yellow and the centroid connections in blue.

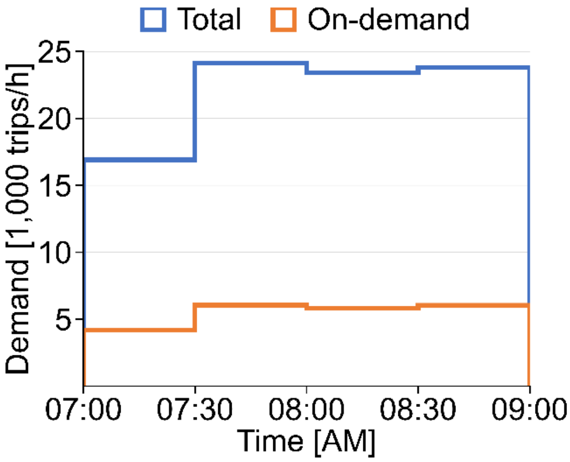

Figure 3. Demand profile for car trips in the morning peak period.

On-Demand Service Parameters

During a simulation, Aimsun stochastically generates private car arrivals based on the provided origin-destination demand matrix. To approximate realistic demand for the on-demand service, it was assumed that one private car trip was equivalent to one on-demand request. The simulated car arrivals were then randomly sampled so that 25% of car trips were replaced with on-demand requests, resulting in a total of 11,032 requests with a profile that matched the total car demand (Figure 3), while the remaining 75% of private car demand (33,094 trips) was unchanged. The arrival time of a request was defined as the time the sampled car arrived in the simulated network. Each request's pick-up and drop-off locations were defined as the midpoint of the internal network link closest to the corresponding trip's origin and destination centroids, respectively. This approach allowed fleet vehicles to serve requests without using the source and sink links, which can cause path infeasibility since they are dead ends.

Each request had a vehicle load of one passenger, and the capacity of on-demand vehicles was set to three passengers. The maximum wait time threshold was set to 150% of the time it would take the closest vehicle to reach the pick-up location ($\alpha = 1.5$), with the absolute maximum waiting time set to 10 minutes. The maximum trip time threshold was likewise set to 150% of the shortest possible trip duration ($\beta = 1.5$). If a user's request is rejected by the service operator, it is assumed that they will use public transport to complete their trip; therefore, the trip is not considered in the private car demand. This means that the number of private vehicle trips is fixed and does not vary with the number of requests served by the on-demand fleet in any given scenario.

RESULTS AND DISCUSSION

Several scenarios were tested, encompassing a range of on-demand fleet sizes. These range from 2,500 vehicles, approximately one quarter of the number of requests, to 12,500 vehicles, which exceeds the total number of requests. For each scenario, Table 1 displays the percentage of the fleet that was idle during the simulation, the percentage of requested trips that were rejected by the insertion algorithm due to infeasibility, and the mean wait time experienced by served requests.

	Fleet size [veh]				
	2,500	**5,000**	**7,500**	**10,000**	**12,500**
Idle vehicles [%]	40.6	57.6	65.4	70.4	73.4
Rejected requests [%]	85.3	79.4	75.0	71.4	68.2
Mean wait time [s]	33.0	23.3	19.3	18.4	18.1

Table 1. Performance of the on-demand service across different fleet sizes.

From Table 1, it is clear that while the insertion algorithm ensures that served requests receive a high quality of service, it does not make effective use of the entire fleet. Notably, many requests are rejected while the service maintains a high level of idle vehicles, indicating that requests are being rejected due to violating the time constraints, not due to a lack of capacity. This is likely due to the relative time limits, as if there is a vehicle near the requested pick-up, then W_{min} will be small, resulting in tight time windows if the nearby vehicle is unable to serve the request itself. The mean waiting time is well under the absolute limit of 10 minutes, supporting the finding that (1) and (2) tend to be the active time constraints limiting the service of requests. Additionally, it is observed that increasing the size of the on-demand fleet offers diminishing returns in terms of reducing mean waiting time, particularly beyond 7,500 fleet vehicles. This indicates that while increasing fleet size may allow for the service of more requests, the quality of service is likely to plateau.

Network Performance Impacts

The network delay time is plotted in Figure 4 to examine network performance during the operating period. As expected from the demand profile, the delay increases from 8:00 am. The scenario without on-demand vehicles (where all demand is modelled as private vehicle trips) additionally shows a large spike in delay between 8:30 am and 9:00 am, indicating higher levels of congestion. All of the on-demand scenarios show slightly lower levels of delay throughout the operating period. However, due to the high rates of rejection and the assumption that rejected requests use public transport, this reduction in delay may be due to a reduction in total simulated trips, rather than the active operations of the on-demand fleet.

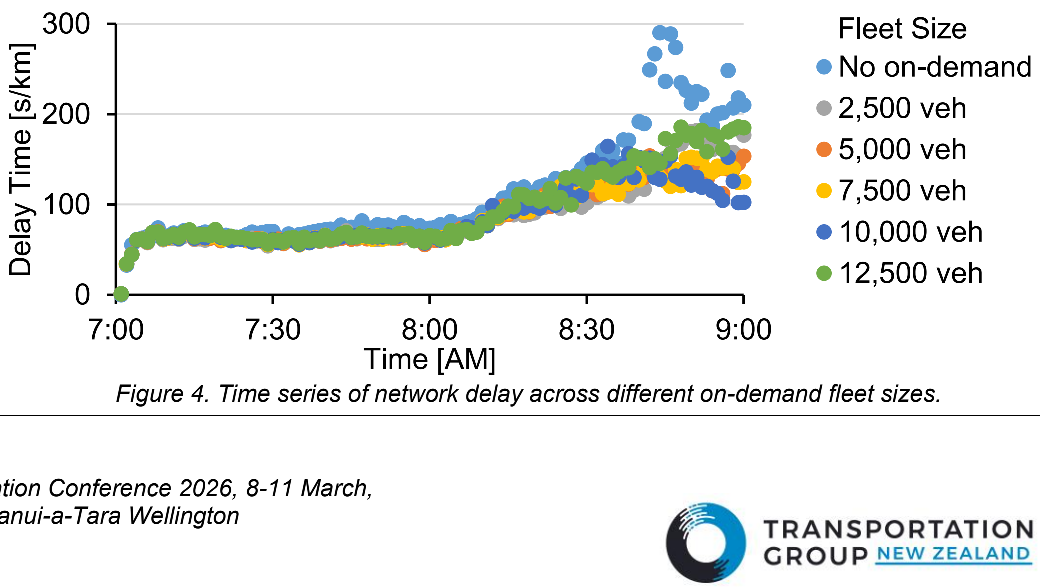

Figure 4. Time series of network delay across different on-demand fleet sizes.

Network characteristics, such as the capacity flow and critical accumulation, can be obtained from observations of Network Macroscopic Fundamental Diagrams (NMFDs) (Johari *et al.*, 2021; Mousavizadeh and Keyvan-Ekbatani, 2024). **Error! Reference source not found.** plots network f low against the number of vehicles inside the network for the scenario without an on-demand service (**Error! Reference source not found.**a), and for the scenario where the on-demand s ervice operates a fleet of 12,500 veh (**Error! Reference source not found.**b). While both diagrams display a clear free-flow branch where the flow is linearly increasing with the number of vehicles, their shape is quite different once they reach the accumulation capacity range. With only private vehicles, the NMFD indicates a network capacity of around 2,500 veh, beyond which the network becomes oversaturated. However, with the inclusion of the on-demand fleet, the network capacity appears higher, around 3,000 veh, and the network remains at a steady level of flow, even as vehicle accumulation approaches 7,000 veh. This suggests that on-demand services may help stabilise traffic flow patterns and potentially extend the capacity range of the network.

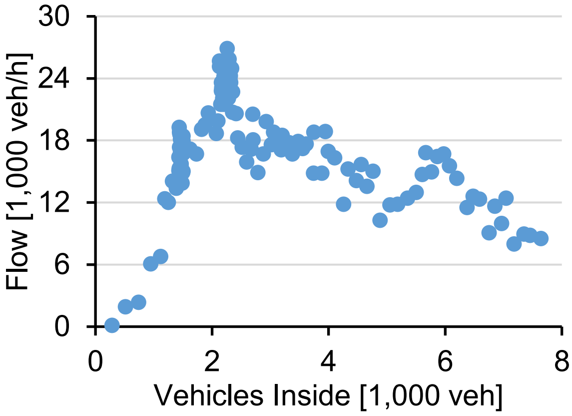

Figure 5a. NMFD without the on-demand service.

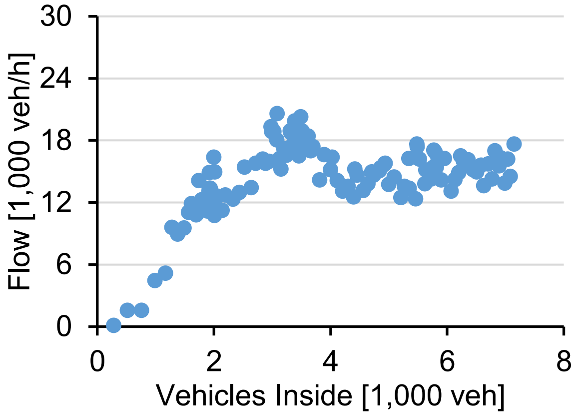

Figure 5b. NMFD with an on-demand fleet of 12,500 veh.

Figure 5. Network macroscopic fundamental diagrams demonstrating the relationship between traffic flow and the number of vehicles in the network, without (a) and with (b) the on-demand service.

To explore how the stabilising effect occurs over time, the two axes of the NMFD have been plotted as time series. These display the evolution of traffic flow (Figure 6) and the number of vehicles in the network (Figure 7) over the simulated morning peak period. When there is no on-demand fleet, and all trip demand is being modelled as private vehicle trips, network flow rapidly increases until 8 am, when it begins to decline (Figure 6a). Figure 7a confirms that this decrease in network flow is due to worsening congestion in the network, not a lessening of the demand flow. As expected from the NMFD (Figure 5b), flow in the network with the on-demand fleet does not show significant signs of congestion, remaining relatively stable between 12,000 and 18,000 veh/h from 8 am (Figure 6b), even as the number of vehicles in the network increases (Figure 7b).

In addition to plotting the total vehicle accumulation, Figure 7b displays separate lines for the number of private cars and the number of on-demand vehicles in the network. This demonstrates that the number of active on-demand vehicles increases linearly throughout the simulation period, with the active fleet outnumbering private vehicles at 8 am, even though on-demand requests make up only 25% of total trip demand. The presence of the on-demand fleet also increases the total number of vehicles in the network compared to when all trips are completed by private vehicles (Figure 7a), possibly because of deadheading. This merits further investigation, as if the fleet is completing significant deadheading, it may result in higher transport emissions. However, despite the higher vehicle accumulation, the network with the on-demand fleet maintains a steady flow, indicating that network capacity has not been exceeded.

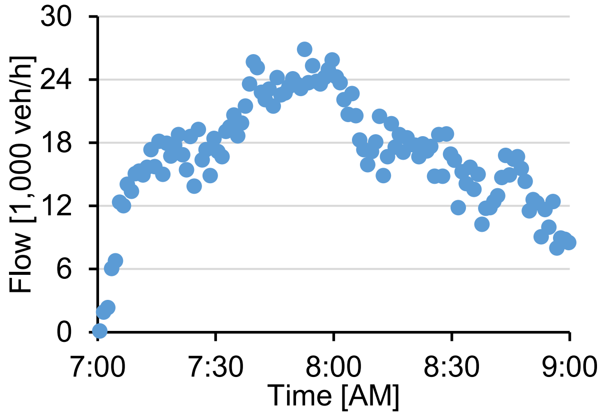

Figure 6a. Flow without the on-demand service.

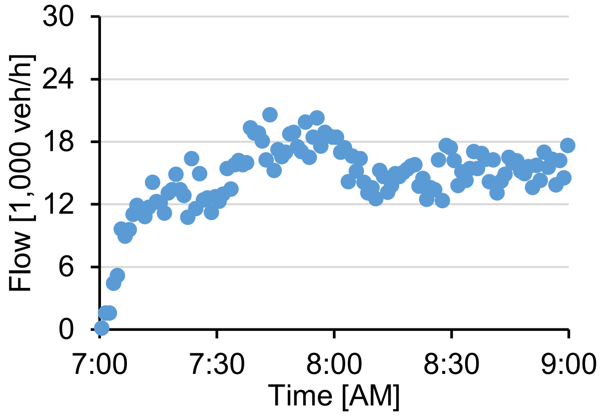

Figure 6b. Flow with an on-demand fleet of 12,500 veh.

Figure 6. Time series of traffic flow over the course of the simulation, without (a) and with (b) the on-demand service.

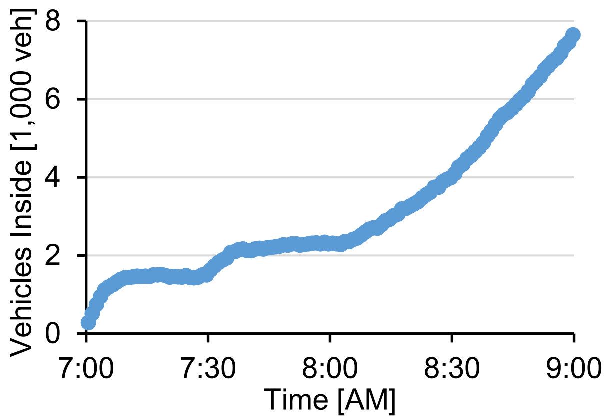

Figure 7a. Vehicle accumulation without the on-demand service.

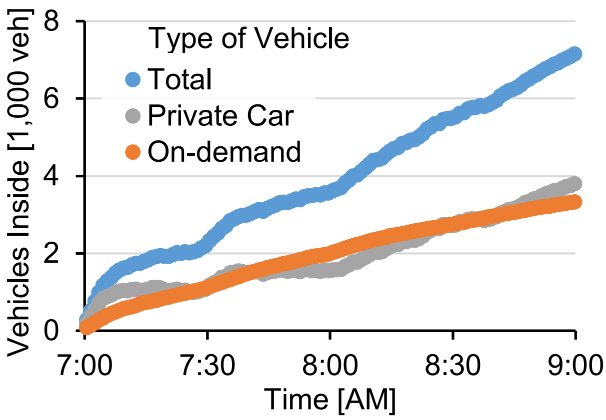

Figure 7b. Vehicle accumulation with an on-demand fleet of 12,500 veh.

Figure 7. Time series of the accumulation of vehicles inside the network over the course of the simulation, without (a) and with (b) the on-demand service.

The observed stabilising effect of the on-demand service could be due to on-demand vehicles having shorter trip legs than a private car travelling directly from origin to destination. If a fleet vehicle departs from multiple request nodes within 5 minutes (i.e., leaving its idle position, then serving pick-ups and drop-offs), then this would allow the fleet vehicle to choose between three shortest path options more frequently than a private vehicle with a 5-minute en route update interval. This more frequent route choice selection may allow for more efficient use of network resources, as the fleet may be better able to avoid aggravating congested areas. However, this is only an initial theory, and further investigation is required to understand the underlying mechanisms of the observed network impacts.

CONCLUSIONS

This study provides a preliminary investigation into the impacts of a large on-demand pooled-ride service on the Christchurch CBD network. The insertion heuristic described is highly efficient, capable of being used with large fleets and trip demands. Initial results indicate that on-demand services may promote smoother traffic flow and increase the effective capacity range of the network, potentially reducing congestion during peak periods. However, the findings also highlight the trade-off between service quality and fleet utilisation, as the strict time constraints resulted in rejection rates of 68-85% despite 41-73% of the fleet remaining idle. Additionally, diminishing returns were observed above fleet sizes of 7,500 vehicles, highlighting that increasing the fleet size does not necessarily improve the quality of service.

These preliminary tests of the simulation implementation were conducted using the Christchurch CBD as the study area. Ongoing work aims to investigate the impacts of an on-demand service using the much larger test bed of the greater Christchurch network. This will require further refinement of the insertion algorithm to ensure the simulations are computationally feasible. The objective of the insertion algorithm should also be carefully considered, as the current priority on high service quality resulted in many rejections. If a lower quality of service were allowed, it is likely that more requests could be feasibly matched to fleet vehicles. Another aspect that will be addressed in future work is the modelling of user mode choice and trip conservation. In the current simulation, rejected users are assumed to use public transport, and so are not considered in the total car trip demand. However, some users may instead choose to use private vehicles if rejected by the on-demand service. This may result in decreased network performance compared to the current assumption, as these rejected requests would then become private car demand, maintaining the total number of simulated trips.

This model may be extended to further explore the long-term impacts of a large on-demand service operating in New Zealand cities. One possibility is to explicitly model on-demand transportation operating as a first- and last-mile service for existing public transit systems. This may be especially interesting in cities connected by rapid transit systems, such as Hamilton and Auckland, as the modelling framework could be used to explore how the catchment for these systems may expand through working with an on-demand feeder service. Another possibility is to investigate whether it would be possible to satisfy the majority of transport demand through a combination of on-demand services and public transit. If most intra-city trips can be adequately served by shared modes of transportation, this could reduce the need for private car ownership.

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