

Simulations guiding on-demand services: The use of digital twins to shape service optimisation

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1. Introduction

The use of simulations and digital twins is contributing to the ability to understand how on-demand transit system performance can be optimized using service parameter adjustments. This paper demonstrates the use of a digital twin to replicate an active on-demand transit service in Auckland, New Zealand. It then shows the use of simulations to explore opportunities to adjust service parameters to improve service outcomes. It then demonstrates the impact of service adjustment on service delivery, showing increases in ridership. Finally, it outlines potential use cases for simulations and digital twins to explore on-demand transit systems.

1.1. What is on-demand transit?

On-demand transit systems are flexible transport services which offer an alternative to the traditional timetabled route-based public transport (Laws et al., 2009). Rather than travelling the same path every time, on-demand transit involves a small fleet of vehicles moving around within a zone, picking up and setting down multiple passengers in response to individual passengers' travel requests.

Due to the inherent flexibility of these services, they can be adapted for many different purposes and user types. Traditionally, dial-a-ride or paratransit services have offered flexible transport to a specific set of users (Bearse et al., 2004). The advent of routing algorithms and their incorporation into the design phase of a transport service is allowing transit authorities increased control over where, when, how, and why they introduce these types of services.

In this paper we explore the role of digital twins in the optimisation of on-demand services. This technology allows simulation of potential services and allows the transport planners to test a variety of variables prior to launch (Li & Quadrifoglio, 2009). Simulations also allow transport analysts to “re-run” aspects of a service in order to optimise service design (Rudskoy et al., 2021).

1.2. Routing Engines

On-demand services use routing engines to dictate movement patterns of vehicles based on rider demand and vehicle supply. They are key to any on-demand system and control service parameters. Inherent in any on-demand service routing engine is control over the amount of time different aspects of a trip take. Boarding and alighting times, route deviation, and road network speed must be calibrated in a digital twin to properly represent that service. Fine-tuning these parameters is pivotal in providing the best outcomes for riders and transport agencies.

1.3. Use of digital twins:

Digital twins are a “module that reproduces a detailed digital model of the road” and its associated transport networks, allowing for the testing of “solutions and the ability to simulate different situations” (Rudskoy et al., 2021). Digital twins provide valuable insight into the operation of an on-demand service, allowing for increased understanding of network and fleet behaviour. Digital twins are useful during the service ideation process, when evaluating a recently launched service, and when optimising a service’s parameters to improve performance.

1.3.1. Service Design

Digital twins can be very useful during the service ideation process, allowing different service concepts to be tested in a virtual environment. Representation of different service designs, fleet configurations, and routing parameters can be deployed and then evaluated against different demand levels to test performance. This allows service designers to explore behaviours on a service prior to launch, or in the case of this research project to test adjustments in service configuration post-launch.

On-demand service simulations conducted with digital twins by Liftango Labs fall under two main categories: input simulations and random trip generation simulations.

Input simulations are completed by taking service data from an active service, either from a Liftango On-demand service or by ingesting data from another service, and running those trips through a service configuration.

Random trip generation simulations are completed by creating trips within a service design to meet expected rider behaviour patterns. They can be used to test new service designs or stress-test fleet configurations by simulating higher demands.

The remainder of this paper will explore the use of Input Simulations on AT Local, an active Liftango on-demand service in Auckland, New Zealand.

1.3.2. Service Improvement Case Study: AT Local

Figure 1: Screenshot from the AT Local webpage ([Auckland Transport, 2023](#))

Where you can travel

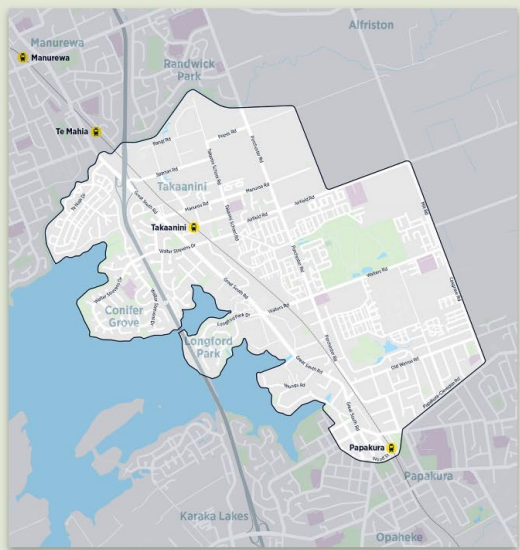
You can use AT Local to travel anywhere in the Service Zone shown on the map, which includes:

- Waiata Shores
- Conifer Grove
- Takaanini
- Kauri Flats
- Papakura Town Centre

AT Local cannot pick you up or drop you off outside the Service Zone.

There are almost 400 pick-up and drop-off points in the Service Zone. Your pick-up and drop-off points will be confirmed when you book.

There will be a short walk (around 120 metres or 3 minutes) to and from your pick-up and drop-off points. AT Local is not a door-to-door service.



[Download the full map \(PDF 370KB\)](#)

Paying with AT HOP

The on-demand service, AT Local, covers 16 sq km in Papakura, a suburb of Auckland, New Zealand. It operates with 4 fully electric vehicles (two 3-seater vehicles and two 7-seater vehicles) whose service design is demonstrated in Figure 1, above. The AT Local service replaced a diesel fixed-route service which previously covered part of the on-demand zone (Kaufman et al., 2022).

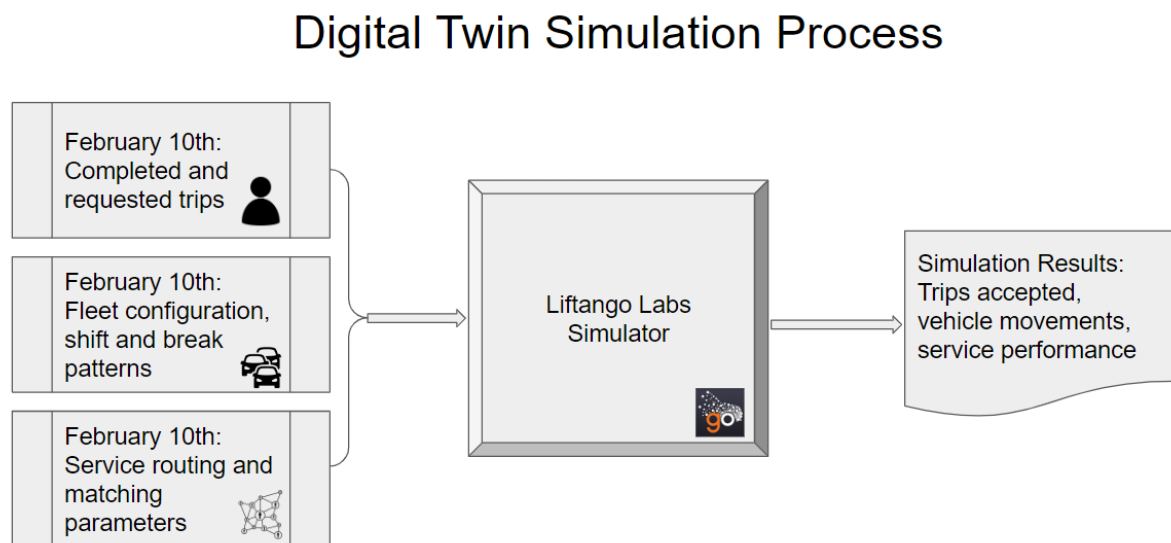
Since launch in November, 2021 ridership grew consistently, even through strong covid-related movement restrictions in New Zealand. However, by March of 2023, patronage had plateaued while demand continued to grow. Auckland Transport asked Liftango to explore opportunities for increasing patronage without sacrificing user experience.

The Liftango Labs simulator was chosen to explore service adjustments' impacts on ridership. Changes such as reducing allocated boarding times and increasing fleet size were suggested for exploration.

2. Methods

Using the Liftango Labs Simulator, a digital twin of the AT Local service in Papakura was developed. The model was trained and tested on data from February 10th, one of the busiest days on the service to date at that time. After configuring the service parameters and fleet to meet those of live AT Local service on the 10th of February, completed and requested trips were exported from the database.

Figure 2: Digital twin simulation process flowchart.



These trips were then uploaded into the calibrated digital twin which returned a 98.28% accuracy for trips accepted compared to the live service. As this was deemed to be sufficiently accurate (over 95% accurate, comparable with research performed by Argota Sánchez-Vaquero, 2021), the team was happy to move forward with simulations with adjusted service parameters to evaluate impact.

As this work was conducted to explore impacts on a live service, simulations were completed exploring potential real-world solutions, rather than exploring every possible service adjustment. Parameter adjustments were limited to potential adjustments that could be made

with the agency, Auckland Transport, limiting the optimisation problem space. Optimisation tests included reducing standard passenger boarding and alighting times; and adding a standard 3-seater vehicle to the fleet.

3. Results

The results of the simulation tests are in Table 1, below. Cells filled with “Base” reference the real service data, whose specific values have been omitted to protect intellectual property. However, all other results in each column are in comparison to the base value, demonstrating the relation to service before adjustment and the impact of each adjustment.

Table 1: Simulation Test Scenarios

Test Scenario	Boarding/ Alighting Time	Vehicles	Successful Trip Rate	Successful Trips
<i>Ground Truth Live Service</i>	<i>Base</i>	<i>4</i>	<i>80.18%</i>	<i>Base</i>
Digital Twin Base Scenario	Base	4	78.80%	98.28%
Decrease Boarding/Alighting Time Scenario	Reduced	4	92.63%	115.52%
Increase Fleet Scenario	Base	5	85.71%	106.90%
Decrease Boarding/Alighting Time + Increase Fleet Scenario	Reduced	5	95.39%	118.97%

The most successful service adjustment included both a reduction in boarding/alighting time and the purchase of an additional vehicle (an 18.97% increase in ridership). Decreasing boarding and alighting time alone was also successful, leading to a 15.52% increase in ridership. Adding an additional vehicle while maintaining the current design led to a 6.90% increase in trips.

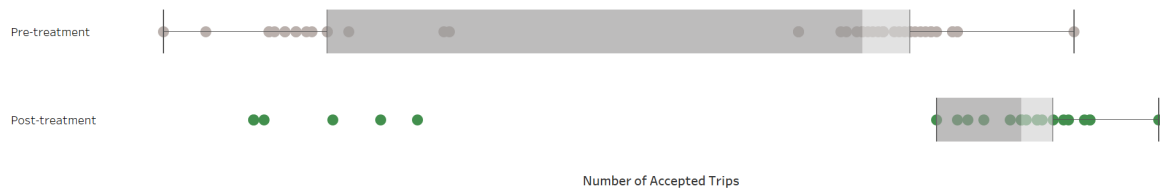
Based on these results, Auckland Transport accepted Liftango Labs’ advice to decrease the boarding and alighting time. This was chosen due to the increase in value for the customers without having to procure an additional vehicle and fund additional driver hours.

3.1. Impact of Service Changes

Since service adjustment, max daily ridership has grown, achieving a maximum increase of 14% compared to the historical maximum reached. This is close to the predicted expansion of 15.52%, which may be reached with more days of service and the associated data collection. After the change, passengers-per-vehicle-hour increased by 15% compared to the two weeks prior to the change. Impacts on the number of accepted trips pre and post-optimisation are shown below in Figures 2 and 3, with Figure 2 showing the distribution of daily accepted trips and Figure 3 demonstrating the relationship of trip requests on accepted trips. Overall, the change has led to all-time highs for daily and weekly ridership without incurring additional costs or reducing customer experience.

Figure 3: AT Local treatment analysis of service parameter adjustment

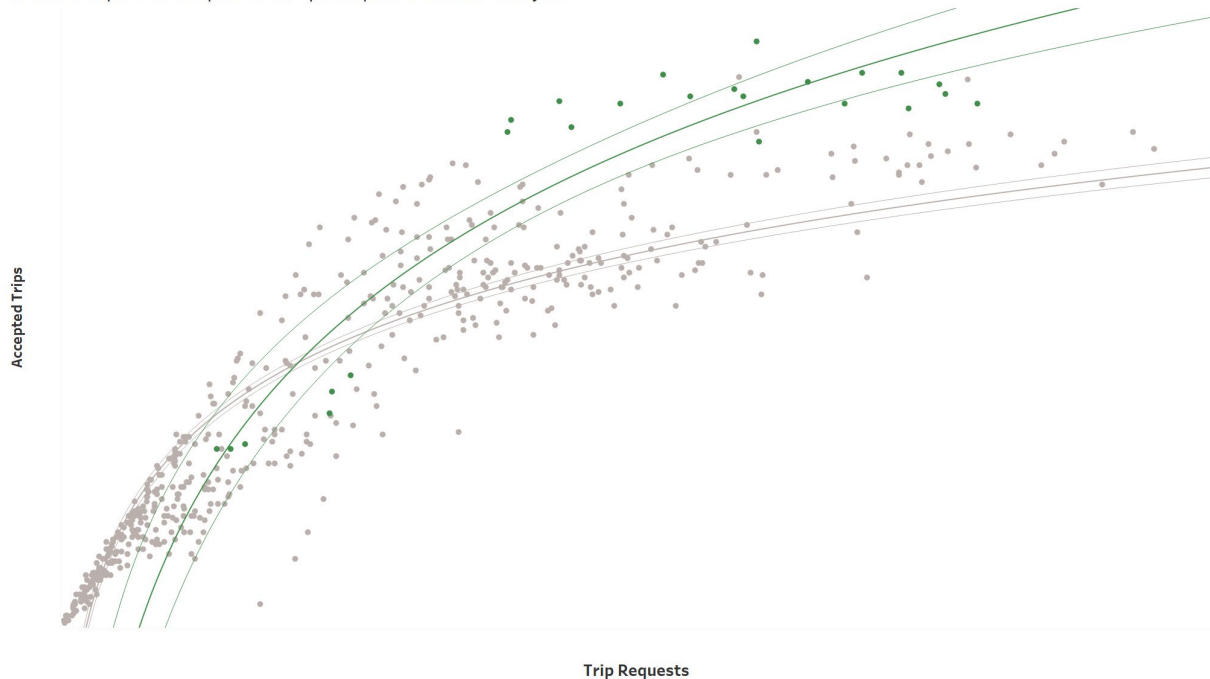
AT Local - Treatment effect on number of accepted trips



The relationship between accepted and requested trips is logarithmic with an asymptote that represents the upper capacity of the service. A logistic curve was chosen over a linear model due to a better R squared statistic and its ability to better describe the natural pattern within the data.

Figure 4: Relationship between successful trips and requested trips.

AT Local - Impact on accepted ride requests post-treatment Analysis



4. Discussion

The use of digital twins and simulations will be key to launching and improving on-demand services. They provide agencies with data on which to launch new services. Using real world data to adjust and improve services after testing in a simulation environment will be key.

The value that agencies place on different constraints should guide their service development, not a preconfigured solution with limited levers for adjustment. Furthermore, understanding changes that can be made to a service and their impact on both operational and user experience will assist when making decisions about service design and adjustment.

Limitations of this research include the finite trip set, reducing maximum impact of potential changes. If larger requested trip sets were used, greater improvements may have occurred in the results. In future research, additional days of trips, combinations of days of trips, and randomly generated trip sets can be used to explore impacts of changes. Additional limitations include the limited number of experiments deployed using this method. Due to the nature of

creating changes in live services and not in an experimental environment, readers must exercise patience and not expect widespread application of this novel technology.

There are also many other levers that can be used to impact service changes. This study only explored two small changes which had large impacts on ridership. Changes in service design as well as greater adjustments in the routing engine might produce better results. These areas were not explored in this study, offering opportunities for further expansion of this research.

4.1. Real world constraints for optimization

Using simulations can help explore many potential avenues for service optimisation. These questions can be configured in a simulation environment and explored using digital twin technology.

Some example operational questions that simulations can help explore include:

- Managing driver shortages: what impact would a reduced number of shifts have on a service?
- Fleet size: What would happen if another vehicle is added to the service?
- Vehicle seating: is demand high enough to use larger vehicles? How many vehicles do we need that meet accessibility requirements?
- EV Limitations: What does our break schedule need to look like to allow vehicle recharging? When purchasing an EV fleet, how large should the batteries be?

Similarly, user experience is impacted by service adjustments. Agencies look to meet specific service criteria, and adherence to those goals should be incorporated into any service design or adjustment. Questions about user experience that simulations can help answer include:

- Rider Deviation Time: How many more trips can be provided if our riders stay on the vehicle for longer? How would this impact passengers per vehicle hour?
- Booking Request Adherence: How would reducing adherence to user requested times impact trip acceptance?
- Service Zone and Destination Design: How would switching from a point-to-point service to a point-to-hub service increase efficiency and ride production?

These are just a few of the questions that digital twins and simulations can help provide guidance to answering. Any adjustment will inherently impact user behaviours, so simulations should be used as guidance, not perfect predictions of results.

4.2. Real world impacts of service adjustments

When adjusting any service, agencies must be thoughtful and careful with changes they make as they impact real people. This inherently produces boundaries on potential service adjustments. While it may be best for KPIs to allowing routing engines to collect as many riders as possible, this could lead to disastrous user experiences.

Agencies must start to develop a balance in user expectations and service delivery to guide on-demand technology providers when setting service parameters. Simulations give us guidance into exploring what this balance might look like in alternative scenarios, helping shift gears towards service designs that optimally serve both passengers and agencies alike.

5. References

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