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Rail Replacement Bus Patronage: counting and forecasting

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Abstract

Rail services in Melbourne are at times replaced by bus services due to scheduled track works and/or maintenance (planned disruptions), but also due to network incidents (unplanned disruptions). The cost of replacement services for such disruptions is significant.

PT disruptions can negatively affect passengers' nominal and perceived journey time as a consequence of longer waiting times due to missed connections, additional transfers, and longer in-vehicle times, dramatically altering travel behaviour. To enhance the connectivity of transport networks during disruptions and minimize the severity of potential negative impacts on service quality and operation costs, the Level Crossing Removal Project (LXRP) provides rail replacement buses, which has been recognized as one of the most critical components of effective disruption responses in metro networks.

LXRP seeks to better manage rail replacement bus allocations via the use of travel demand forecasting for planning and real-time monitoring and tracking of replacement buses utilization for operations. To capture the dynamic influence of the station disruption on passenger flow demand to some extent, having access to real-time passenger occupancy data proves to be useful. This approach should provide sustainable and optimized public transport services with high quality customer service while being cost efficient.

This project intends to identify potential uses of artificial intelligence methods and sensor technologies to for automatic real-time passenger counting, as well as conduct trials and utilize the data for prediction of potential rail replacement bus travel demand.

1. Introduction

Melbourne's multi-level transport network consists of various functional modes including metropolitan train, regional train (V/Line), tram, bus and the road network. The majority of trips rely on rail for high-demand routes and journeys, therefore, understanding important factors to minimise the impact of construction-base capacity restrictions to guarantee smooth rail operations is required. In addition, passengers of railway networks are not as resilient as road users. Often a common solution to addressing disrupted commuters' travel needs is to provide alternative transportation modes, such as buses, which are required to step into a much more prominent and 'structural' role overall and do some of the heavy lifting in transit and overall transport terms during disruptions.

Generally, 'disruption' means a serious deviation from the planned operations in the rail transit context. Station disruption is a typical case of a disruption on the metropolitan network, and it can strongly affect both the service and demand of the metro system. At the supply level, a station disruption means that the trains, which are planning to stop at the closed station, have to adopt other alternative routes to detour the closed station and at the demand level, the station disruption may cause significant changes in passenger flow demand. LXPR and its alliance partner Metro Trains Melbourne (MTM) are responsible for rail replacement bus (RRB) services for planned disruptions caused by level crossing removal works, and desire to provide these with minimal impact on commuters.

Currently, the planning of the replacement bus allocations relies primarily on predicting travel demand based on Myki ticketing data and partial records from previous disruptions. While this data are useful, the lack of full and accurate data on replacement bus patronage does not enable LXRP and its alliance partners to effectively plan for actual travel demand. This current lack of data also means there is not an effective feed-back loop through which an evidence-base can be used to estimate both current performance and future service level needs. This means that there is currently a risk of 1) over-procurement of replacements buses (which are then under-utilised by customers), or 2) under-procurement of replacement services, resulting in a negative customer experience, through crowding or long wait times.

Currently, during a disruption, the responsibility of determining patronage numbers falls on customer service staff who may have to multi-task. Without reliable and extensive real-time information on patronage on replacement buses, there is a real challenge for the control centre to respond quickly to the changing real demand in the field.

In order to design an efficient RRB network, a localized metro-bus integration approach that deploys the dynamic passenger flow demand under station disruption and considers commuter travel demand at the time of the disruption is required.

The replacement service travel demand forecasting tool predicts usage of replacement buses based on outputs from the Department of Transport's (DOT) Train Service Usage Model (TrainSUM), a passenger assignment model that estimates historical loads for individual train services. The tool adjusts the TrainSUM outputs by using a combination of traditional timeseries forecasting methods and results from disrupted passenger surveys to account for growth (or decline) in future patronage and changes in behaviour respectively.

However, the current lack of comprehensive real-time data on replacement bus patronage limits the ability to implement operational adjustments, while also restricting an effective feed-back loop through which an evidence-base can be fully used to estimate current performance and future service level requirements.

2. Methodology

In this project, the main aims are to identify and trial suitable systems for automatic patronage counting for replacement bus services during rail disruptions, which would enable LXRP to understand real-time statistics including entry/exit counts and vehicle occupancy, and potentially utilise this data for replacement service travel demand forecasting tool calibration and validation. The project builds on previous work undertaken by this study's research team (McCarthy et al, 2021).

This study also included trials (Figure 1) that were intended to test two passenger counting technologies in operating conditions and determine the strengths and limitations of each solution. The test systems should be trialled on a basis that they can be scalable for wider implementation at reasonable cost.

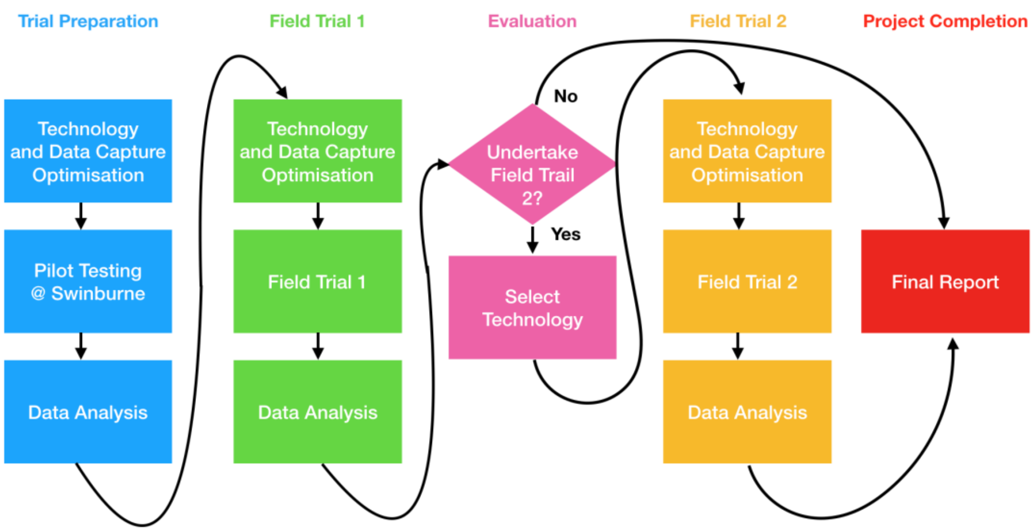

Figure 1: Trial methodology overview

Field Trial 1 was undertaken between 6-11 May 2021, and Field Trial 2 was undertaken on March 10th, 11th and 15th in 2022. Field trials consisted of a data capture period, conducted over 4 days, followed by post-processing and analysis of the captured data, with a primary focus on the accuracy of both technology options: the floor-based Sensor Mat, and the camera-based video analytics system, both developed at Swinburne University of Technology.

Each technology team captured data independently, however a common ground truth for per bus occupancy was created and used to facilitate direct comparisons of accuracy. In addition, each technology team undertook independent analysis of technology-specific questions, issues and observations to inform future use and development of the technologies, as well as to identify potential value-add opportunities

2.1. Proposed Technologies

2.1.1. Floor-mounted Sensor Mat System

This method practices an algorithm that calculates the centre of pressure movement when passengers step on and off a mat placed on the floor of the vehicle. This allows for the detection of the direction of movement over the mat and the achievement of accurate counting of the number of passengers stepping over the mat.

For the field trials, two sensor mats (Figure 1) with sensing nodes designed and built at Swinburne University were deployed. A sensor mat (4 sensing nodes in the mat), in-house design and built, was taped down to the ground at the passenger line-up point (see images below). The mat was centred and placed at the end of the line-up point, approx. one meter before the entrance of the bus. The corresponding electronic box, connected to the mat with electronic wiring, was taped to an adjacent rail pole away from the passenger's path. The electronic box contained a SD card to record continuous pressure data output from the mat (4 hours of data, approx. 20MB).

Figure 1: The Sensor Mat prototype used for passenger counting

2.1.2. Computer vision-based people counter

This technology offers a versatile range of configurations based on key priorities, with numerous systems already in use in both public transport, and other industrial settings including retail, and security. Swinburne has previously developed a low-cost solution for video-based people counting, capable of operating with images from a standard RGB camera. Swinburne's system utilises deep learning technology; specifically, a pre-trained convolutional neural network (CNN) for people detection. It is included as a system deployable with dedicated cameras, or with pre- installed cameras (e.g. CCTV) assuming access to the video stream is available and the CCTV footage is of sufficient resolution (e.g., 640x480 pixels or more), and from an angle providing adequate coverage of passengers (which is generally true to their primary purpose of passenger surveillance).

The video-based passenger counter (Figure 2) requires calibration of both the Region of Interest (ROI) for counting, and the error model. The ROI for counting was configured separately for each session of data capture. This was to account for changes of camera position, as well as the physical setup of the passenger pick up locations. Once configured for a session, the ROI was applied without modification across the entire video captured for that session

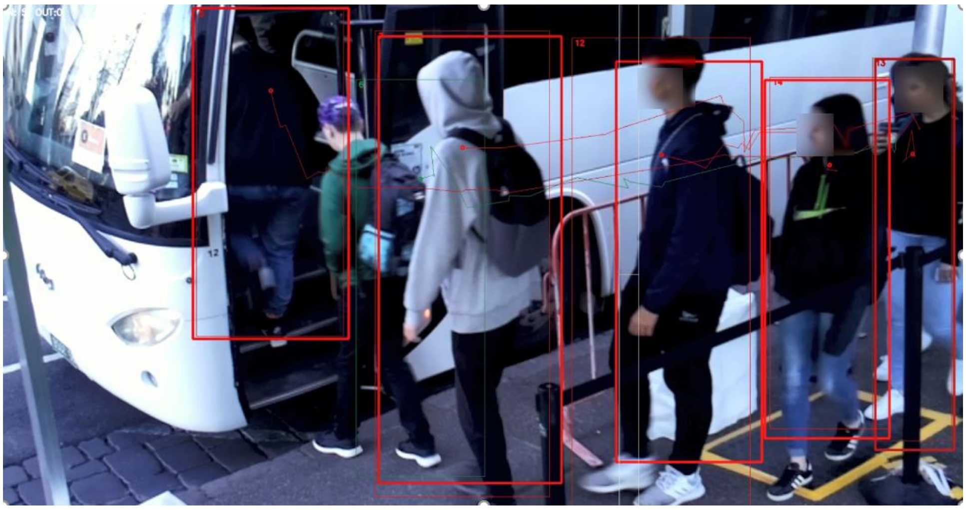

Figure 2: Passenger counting in operation. Red boxes indicate detected passengers being tracked and counted as entering or exiting a bus when the cross a virtual line of interest.

2.2. Ground truth data collection

2.2.1. Floor-mounted sensor Mat System

The initial intention for Sensor Mat accuracy evaluation was to rely on camera data captured by the video analytics team. However, observations on day one indicated that the Sensor Mat counts the people that walk/run over the mat; e.g. people coming from the car park rather than from the train did not queue up and did not walk over the mat. Also, video capture and Sensor Mat data was not synchronised, thus making the registration of sensor mat data to the manually annotated passenger counts from video difficult. For these reasons, a smart phone app was quickly developed and used to obtain manual counts. This was employed from Day 2 onwards. The app was developed to count by touch, and saves the split counts (i.e. lap counts/after each wave of people) together with the corresponding split (lap) time stamp. Lap counts are important for understanding the dynamics of the counting algorithm of the Sensor Mat.

2.2.2. Computer vision-based people counter

Ground truth for the video-based bus passenger count evaluation was obtained from the manual inspection of time-stamped video recordings of all data capture sessions. Individual passenger bus entries were manually logged, as well as bus arrival and departure times. From this, per-bus passenger counts were obtained for each bus and recorded with the departure time of each bus. Summary of technologies is presented in Table 1.

Table 1: Summary of technologies

Video-based commuter tracking and analytics	Applying advanced computer vision techniques and machine learning algorithms to recognize and count passengers passing through areas covered by visual sensors	• Easily installed and generally applicable to any bus or environment of interest. • Multi-modal data analytics: e.g., passenger counts, waiting time, passenger flow. • Narrow or wide visual coverage. • Established approach already being used in commercial systems • Portable	From A$200-A$1,000 per unit (depending on sensor/computing and deployment location choices) plus rechargeable battery (~A$100) and up to A$35 for additional services.	> 80%
Ground-based sensing (Sensor Mat)	Installing piezo-resistive sensing mats at the entrances of the bus which can count the number of boarding passengers as they step on the mats.	• Detachable, rechargeable batteries. • Invisible to passengers. • Little maintenance. • Capture anonymous data. • Robust to weather conditions	Up to A$200 per prototype plus rechargeable battery ~A$100 and up to A$35 for additional services.	> 90%

3. Results

3.1. Technology results comparison

The following tables present accuracy scores for both technology options with respect to total passenger counts across each session. The columns GT(SM) and GT(Vid) indicate the total number of passengers manually counted for Sensor Mat and Video Analytics respectively, for each comparison event. SM (Sys) and Vid (Sys) report the system calculated counts for Sensor Mat and Video Analytics respectively. Finally, SM (acc) and Vid (acc) report the percentage accuracy. Table 2 and Table 3 report accuracies of each data collection session, and for each location (i.e., the total of all sessions at each location) . Lastly, Table 6 reports accuracies over all data captured from the field trial.

Table 2 Accuracy comparison of Field Trial 1 - Total passengers per session over data collection period

		GT (SM)	GT (vid)	SM (sys)	Vid (sys)	SM (acc)	Vid (acc)
May 6 - Day 1	Reservoir	-	1475	1745	1450	-	98.3
	Parliament	-	1330	1836	1292	-	97.14
May 7 - Day 2	Reservoir	1815	1698	1812	1678	99.83	98.82
	Parliament	1155	1162	-	1193	-	97.33
May 10 – Day 3	Reservoir	1426	909	1454	888	98.03	97.69
	Parliament	1196	1223	1211	1195	98.75	97.71
May 11 – Day 4	Reservoir	-	-	-	-	-	-
	Parliament	1265	868	1286	852	98.34	98.16
All Days	Reservoir	3241	4082	3266	4016	99.23	98.38
	Parliament	2461	4583	2497	4532	98.54	98.89

Table 3 Accuracy comparison of Field Trial 2 - Total passenger per session over data collection period

		GT (SM)	GT (vid)	SM (sys)	Vid (sys)	SM (acc)	Vid (acc)
Mar 10 - Day 1	Pakenham	233	234	255	184	**96.57**	78.63
	Dandenong	436	473	442	395	**98.62**	83.51
Mar 11 - Day 2	Pakenham	236	193	238	135	**99.15**	69.95
	Dandenong	483	467	469	470	97.1	**99.36**
Mar 15 – Day 3	Pakenham	261	230	260	160	**99.62**	69.57
	Dandenong	568	530	571	536	**99.47**	98.88
All days	Pakenham	730	657	723	479	**99.04**	72.91
	Dandenong	1487	1470	1482	1401	**99.66**	95.31

3.2. Per-Bus Occupancy Estimation

In the previous Accuracy Comparison section, we reported total bus patronage estimates for each session, location and over all data collected. Here we focus specifically on the LXRP identified use-case of per-bus occupancy estimation as a feature of the video analytics approach. While the trialled system does not currently perform automatic bus detection, time-stamped passenger entry/exit events were registered with manually recorded bus departure times from ground truth data to establish system-derived estimates of occupancy numbers per bus.

To better understand the performance of the video-based solution for per-bus occupancy counts, quartile accuracies were calculated for each bus pick-up event – that is, the total number of passengers on board each bus at its point of departure. Accuracy for each bus pickup event was thus calculated as:

$$\text{Accuracy} = (1 - |GT\_occ - SYS\_occ|/GT) \times 100 \qquad \text{(Equation 1)}$$

where GT_occ is the Ground Truth bus occupancy and SYS_occ is the video-analytics estimated occupancy. Means and quartile accuracies were then determined from the distribution of per-bus accuracy scores across time periods and locations of interest. Below we present these accuracy results for both cameras in use during the trial. To understand the impact of different days, locations etc, we report our results per day/session, per location and overall, all data collected.

Table 6 Per-bus occupancy quartile accuracies (%) for each data capture period each day - Field Trial 1

[redacted]

		AM	PM	Day	AM	PM	Day	AM	PM	Day	AM	PM	Day	AM	PM	Day
May 6 – Day 1	Cam 1	91.8	83.5	86.3	29.1	35.0	17.6	87.4	80.0	83.2	96.3	86.7	91.1	100	97.3	98.9
	Cam 2	91.8	73.9	79.5	25.9	26.7	15.0	86.1	64.8	69.5	94.5	72.2	84.9	100	85.4	96.5
May 7 – Day 2	Cam 1	76.0	86.2	80.7	16.4	16.5	29.6	64.7	80.9	75.2	85.1	88.9	84.4	95.5	95.2	93.9
	Cam 2	83.4	79.3	82.0	13.6	0.98	0	76.6	71.4	77.4	89.2	84.8	83.7	95.5	94.9	92.8
May 10 – Day 3	Cam 1	88.9	89.1	88.3	24.7	10.5	17.8	84.9	86.0	84.8	92.7	94.7	92.8	99.6	99.6	98.8
	Cam 2	71.0	83.2	75.5	0	53.6	0	61.3	73.5	61.4	66.0	85.1	74.8	88.2	95.1	92.8
May 11 - Day 4	Cam 1	-	80.1	-	-	12.6	-	-	71.6	-	-	83.7	-	-	95.0	-
	Cam 2	-	87.3	-	-	62.0	-	-	81.8	-	-	87.6	-	-	96.3	-

4. Conclusions

Rail services in Melbourne are at times replaced by bus services due to scheduled track maintenance or upgrades (planned disruptions), but also due to network incidents (unplanned disruptions). During disruptions, passengers are often provided a solution to reduce the impact on travel needs. The solution is normally based on two strategies: short-turning train services on a disrupted route and providing rail replacement bus services at stations where trains cannot be reached. These strategies seem to be effective to enhance the connectivity of a railway network and minimize passenger delays

This project not only provides solutions with novelty, but also the comparative analysis informs industry on these automatic passenger counting solutions and assists them in selecting the best solution-based purpose and limitations. In this project we tested two passenger counting technologies in operating conditions and determined the strengths and limitations of each solution.

It is also anticipated that if a successful alternative technology can be identified and trailed, this may present other “value-add” options or opportunities for consideration by the DoT or LXRP. These opportunities would potentially relate to the creation of a new dataset of travel behaviours and insights into a market segment (i.e. disrupted commuters) that currently remains “hidden” from existing data sources. There may be service integration opportunities which may arise from potentially having a “real-time” feedback of customer patronage of replacement bus services and tracking replacement bus services. This could allow more tailored services to respond promptly to unanticipated “peaks” and “troughs” in patronage on replacement services, improving both the efficiency of service provision and responsiveness to customers.

5. Acknowledgements

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6. References

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