22 June 2022

Replacement Bus Patronage Counting and Wait Time Measurement: Final Report

Replacement Bus Patronage Counting and Wait Time Measurement: Final Report

Prepared for

Level Crossing Removal Project (LXRP)

Prepared by

Swinburne University of Technology

1 John Street Hawthorn Victoria 3122, PO Box 218, Australia

T +61 3 9214 8000 www.swin.edu.au

ABN 13 628 586 699

20 July 2022

Document Information

Document	Replacement Bus Patronage Counting and Wait Time Measurement – Final Report
Ref	\Research\Projects\iMOVE\LXRP
Date	20 July 2022
Prepared by	Chris McCarthy, Adin Tan, Udi Weizman, Felip Marti Carrillo, Prem Jayaraman, Franz Fuss, Hadi Ghaderi, Hussein Dia

Revision History

Revision	Revision Date	Details	Authorised	
			Name	Signature
0	22 June 2022	DRAFT for LXRP Review and Comments	Hussein Dia	
1	20 July 2022	Final version	Hussein Dia	

Executive Summary

This report provides an overview of results and outcomes, as well as recommendations for future development of deployment of the two technologies considered for rail replacement bus automatic passenger counting and associated analytics: the pressure-sensor based Sensor Mat, and the camera-based Video Analytics system, both developed at Swinburne University of Technology . Over the course of two field trials, held as part of two LXRP rail line occupations, the technologies were deployed and evaluated for the task of counting passengers boarding rail replacement bus services. The table below summarises the accuracy achieved by each technology with respect to counts of passengers who boarded a bus, for each venue across the two trials.

Summary		Accuracy (%)	
	Venues	Sensor Mat	Video
Field Trial 1	Reservoir	80.00	**98.38**
	Parliament	84.45	**98.89**
Field Trial 2	Pakenham	**87.25**	72.91
	Dandenong	**99.57**	95.31

Field trial results confirm both approaches offer high accuracy counts when operating within their expected working conditions. For Video Analytics, sufficient visibility is key, whereas for Sensor Mat, sufficient guidance of passenger traffic over the mat is essential. As such, both technologies offer trade-offs that must be considered in the context of the intended use-cases.

The table below summarises these trade-offs, along with other points of comparison for the two technologies.

Comparison Point	Sensor Mat	Video Analytics
Key advantages	Very high accuracy and consistency. Primarily supports counting.	High accuracy and versatility of positioning, supports per-bus counting, and numerous other use-cases.
Primary limitation	Requires passengers to step on mat, Positioning critical to get high value data.	Performance subject to sufficient visibility of passengers.
Use-cases supported	Real-time passenger counting and flow analysis. Feeding into live occupancy counts, and modelling for future disruption planning and costing.	1. Real-time passenger counting flow analysis for per-bus occupancy counts and on-site crowd counts. 2. Passenger wait time and behaviour analytics. 3. Real-time Bus Run ID recording 4. Space utilisation. All feeding into live bus occupancy and passengers waiting counts, and into modelling for future disruption planning and costing.
Endurance	Mat replacement after 6 months of consistent use. Repeated install/un-install may damage wires/accelerate wear-and-tear	Camera and electronics within device housing – 10 years Battery – 1 year Repeated install/uninstalls should pose no substantive wear and tear
Maintenance needs	Battery replacement Mat surface cleaning	Battery replacement Lens cleaning
Installation	Time: 10-15 minutes Requires:	Time: 5-10 minutes Requires:

	- placement in centre of expected passenger traffic - configuration of walkway to guide passengers over. - Taping of edges to ground surface - Electronics box placement away from foot traffic	- Placement of camera mount (a suitable camera mount e.g., tripod if camera is moved on a day to day basis) - Configuration of line of interest for counting (app provided)
Un-installation	10 minutes, reverse of above	2 minutes, reverse of above
Development time (for full deployment)	>= 9 months	6 months
Estimated cost per unit (fully deployed solution)	<= $470	<= $360
Staff Training to operate solution	Minimal-Moderate	Minimal

Based on field trial results, and the above listed considerations, below lists the recommended technology with respect to the primary LXRP relevant use-cases:

LXRP Relevant Use Case	Most Suitable Technology
Use Case 1 – Passenger Counting	Sensor Mat
Use-Case 2 – Passenger Counting per Bus	Video Analytics
Use-Case 3 – Wait Prediction	Video Analytics
Use Case 4 – Bus Run ID Detection	Video Analytics

A fully contained *live per-bus passenger counting solution* requires Use-Cases 1, 2 and 4. Thus, a solution using exclusively video analytics, or one in combination with Sensor Mat, is the recommendation of this report.

Both technology options offer the possibility of feeding real-time edge-computed data to cloud-based services for data storage and further analysis, and dashboarding. The report includes a summary of possibilities for such cloud service support (including costs). The report also makes clear the pathway and timeline for full development of the trialed technologies to deployment ready systems.

This study also used video-analytics to compute passenger waiting times for a replacement bus service. The camera captured video from Field Trial 1 (Camera 2, Reservoir-Parliament Occupation, May 2021) provided partial images of queuing passengers, thereby allowing a demonstration of this use-case to be provided. This was done over 2 hours of footage taken from Day 2 of Field Trial 1. From the recorded data, dwell times for each passenger were calculated, and the distribution of these times were analysed as shown below.

Summary	Min	1st Quartile	Median	3rd Quartile	Max
7am-8am	00:06	00:07	00:08	00:12	03:19
8am-9am	00:06	00:07	00:08	00:13	02:35

As can be observed, the time durations indicate that the median time a passenger spent in the queue was 8 seconds for both hour long time blocks. The maximum time a passenger spent in the queue was 3:19 over the two hours, however it is clear that the maximums for both time blocks are outliers compared to the overall distribution

GLOSSARY

Item	Description
Accuracy	The performance of solution in counting the number of passengers boarding the bus against ground truth.
Precision	The statistical variability of the system's accuracy, providing a measure of how consistent the accuracy level is, and the range of error.
Video analytics	The solution that incorporated vision-based systems (e.g. camera) to count the number of passengers
Sensor Mat	A pressure sensor-grid mat that records the number of passengers using an algorithm that calculates the centre of pressure movement.
Pilot trial	An initial in-lab trial to validate to prepare the proposed technologies and identify any technical issues in preparation for field trials.
Field trial	The performance evaluation of proposed technologies under the conditions in which it will be used in future.
Milestone	An important deliverable of the research determined by the project contract.
Disruption	Stoppage of rail service as the result of removal of level crossing

CONTENTS

Replacement Bus Patronage Counting and Wait Time Measurement

Final Report

Project Overview

Background

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. The Level Crossing Removal Project (LXPR) and its alliance partner MTM are responsible for replacement bus 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 data and partial records from previous disruptions. While this data is 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 and long wait times.

During a disruption, the responsibility of determining patronage numbers falls on customer service staff who may have to multi-task. Without reliable and timely information for patronage on replacement buses, there is a real challenge for the control centre to respond quickly to the changing real demand in the field. This has motivated consideration of alternative technology options to achieve autonomous, reliable, accurate and real-time measures of bus passenger patronage.

Swinburne University of Technology (SUT) have developed technologies for the automatic counting of people, which have been identified as possible options for LXRP to explore. Specifically, a floor-based pressure sensor known as Sensor Mat, and a camera-based video analytics solution (referred to as video analytics in this report). Both offer low cost solutions and the potential for the real-time automatic counting of passengers, as well as potential value-add options with respect to the analysis of passenger flow.

AIMS AND SCOPE

This project aimed to test and evaluate SUT's passenger counting technologies for automatic patronage counting for replacement bus services during rail disruptions. The project intended to compare both potential solutions and determine the strengths and limitations of each solution. Sand cost were both also identified as primary points of focus for the evaluation.

The project, through the design and completion of two extensive field trials, set out to achieve the following aims:

1. To evaluate the accuracy of the Swinburne-developed Sensor Mat and Video Analytics solutions for the automatic counting of bus passengers on-board rail replacement bus services

2. To compare the accuracy of both technology options according to a common ground truth – i.e., per bus passenger occupancy

3. To identify technology-specific strengths and weaknesses in the context of in-the-field use

4. assess the accuracy and feasibility of using video analytics to automatically recognise Bus Run ID and Bus registration

5. explore the potential for other value-add options such as estimating passenger wait time.

METHODOLOGY

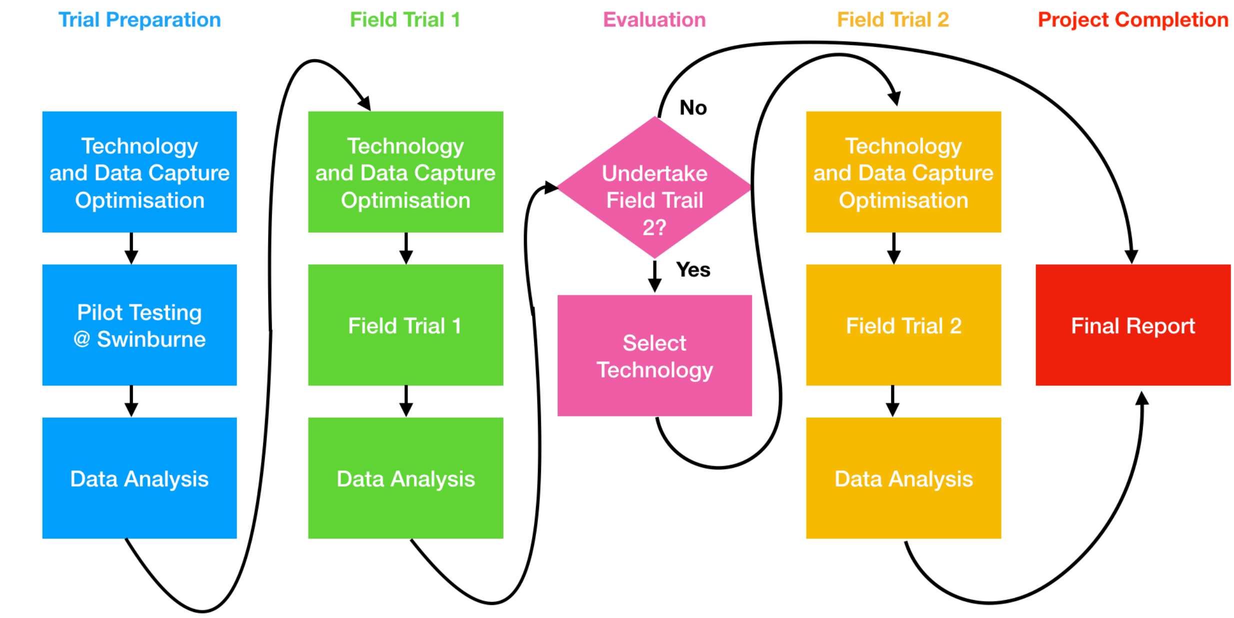


Figure 1 Trial Methodology Overview

Figure 1 above provides an overview of the trial methodology designed and employed for this project. Most prominent of the phases are the two field trials, titled Field Trial 1 and Field Trial 2. Field Trial 1 was conducted over 4 days between May 6 and May 11, 2021 (weekdays only), with 8 hours of data capture per day at two separate locations (Reservoir and Parliament Stations). Field Trial 2 was similarly conducted for both technology options, over 3 days between March 9th and March 15th, 2022 at Pakenham and Dandenong Stations. Both trials involved installing the technology options at Express Rail Replacement Bus pickup zones for the primary purpose of counting passengers boarding bus services during planned LXRP occupations. Details of both field trials can be found in previously submitted milestone reports. Figures 2 and 3 below show example images of the technologies in use during the trials.

FIGURE 2 SENSOR MAT AND INSTALLATION SETUP (FOR FIELD TRIAL 2)

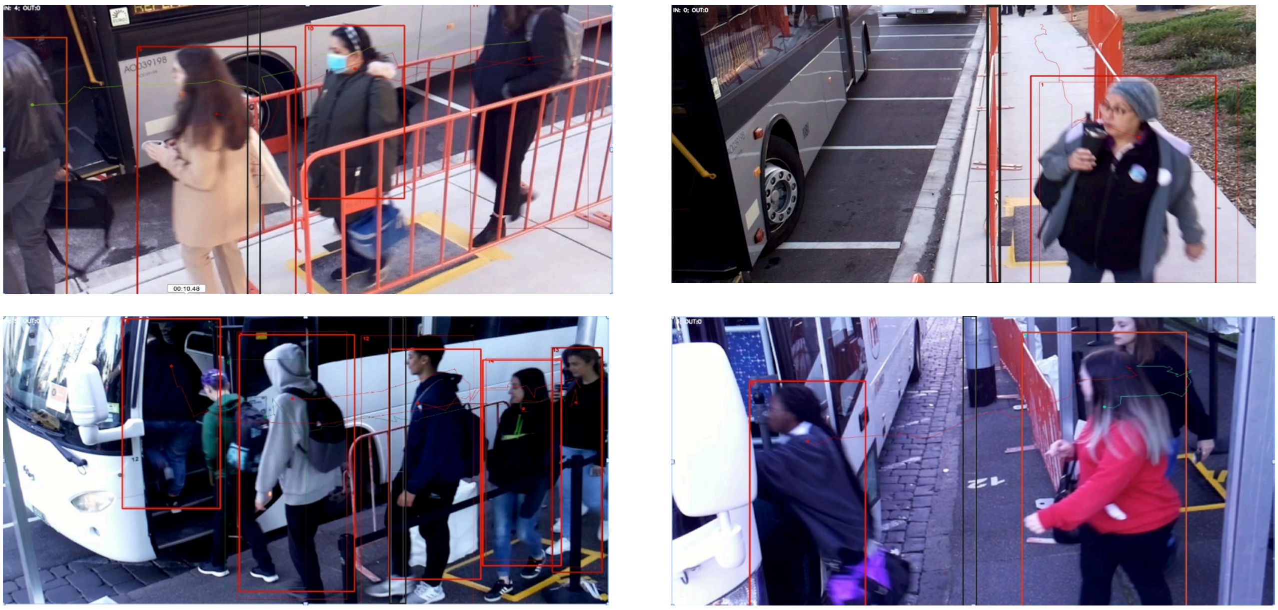


FIGURE 3 SAMPLE OUTPUT FRAMES FROM THE VIDEO ANALYTICS SYSTEM SHOWING PERSON DETECTIONS, TRACKING (AS LINE TRACKS), AND THE REGIONS OF INTEREST FOR COUNTING (SHOWN AS GREY LINES)

SUMMARY OF DATA COLLECTED

Table 1 below summarises the total hours of data collection undertaken as part of both Field Trial 1 and 2, with respect to both technologies, and the use-case being examined.

TABLE 1 SUMMARY OF DATA COLLECTED

Technology	Trial/Event	Hours
Sensor Mat	Field Trial 1 – counting	24
Sensor Mat	Field Trial 2 – counting	22
Total Sensor Mat (counter) data collection		46 hours
Video (Cam 1)	Field Trial 1 – counting	26.25
Video (Cam 2)	Field Trial 1 – counting	14.5
Video (Cam 1)	Field Trial 2 – counting	22.5
Total Video (counter) data collection		63.25 hours
Video (Cam 1)	Bus Run ID Model Training (Dandenong)	8
Video (Cam 2)	Field Trial 2 – Bus Run ID	24
Total Video (Bus Run ID) data Collection		32 hours
Total hours of data collection for project		141.25 hours

SUMMARY OF RESULTS

Table 2 below summarises and compares the accuracy performance of both technologies for the task of counting passengers who boarded a bus. Results are shown for all four locations in which data capture took place across both field trials.

TABLE 2 SUMMARY OF ACCURACY WITH RESPECT TO TOTAL BOARDING PASSENGERS AT EACH VENUE OVER FIELD TRIAL 1 AND 2

Summary		Accuracy (%)	
	Venues	Sensor Mat	Video
Field Trial 1	Reservoir	80.00	**98.38**
	Parliament	84.45	**98.89**
Field Trial 2	Pakenham	**87.25**	72.91
	Dandenong	**99.57**	95.31

Figure 2 below presents a comparison of raw bus occupancy estimates across all data sessions in both trials. Ground Truth is also shown.

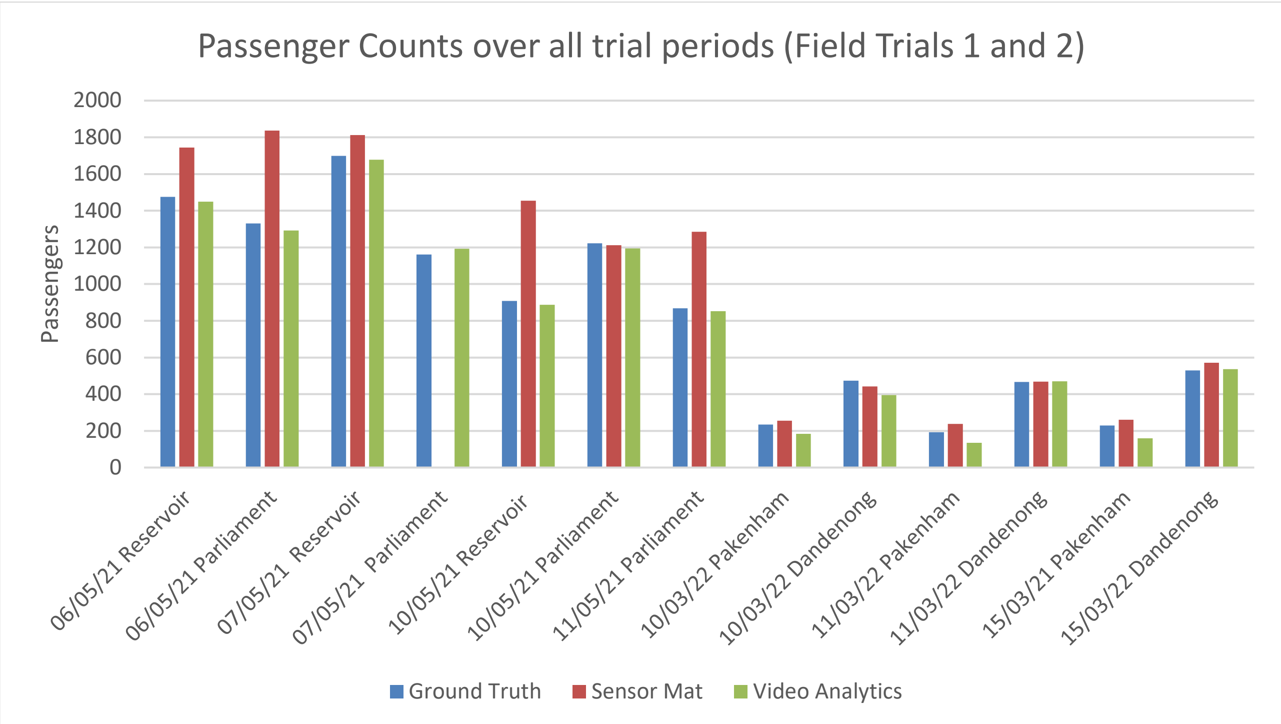


FIGURE 4 COMPARISON OF ACCURACIES WITH RESPECT TO TOTAL NUMBER OF PASSENGERS WHO BOARDED A BUS ACROSS ALL SESSIONS, IN BOTH TRIALS

For completeness, Appendix A provides Tables A.1 and A.2 which presents the same information as in Figure 4 above, but in tabular form, and with accuracy scores for each session:

In Field Trial 1, video analytics achieved the highest accuracy with respect to boarding passenger counts, while in Field Trial 2, Sensor Mat exhibited stronger accuracy in this regard. Reports for Field Trial 1 and 2 provide detailed reasons for the difference in performance of both technologies across the two trials, which we summarise here:

Sensor Mat: the placement of the mat was found to be critical to its ability to accurately capture bus occupancy. In Field Trial 1, its location was further away from the exact boarding location (due to practical considerations around the variability of bus stopping location). While this allowed flexibility in this regard, it also allowed non-bus travellers to walk on the mat, causing a generally higher count to be recorded. In addition, on-sight barriers providing guidance to passengers did not always succeed in guiding passengers over the mat. In Field Trial 2 both issues were addressed, thus resulting in higher accuracy overall (though false positive bus passenger counts remained a slight issue).

It is important to note that Sensor Mat's accuracy with respect to people who walked on the mat was very high across both trials (i.e. ~99%). Thus, the mat itself proved to be very accurate in counting who walked on it, however leveraging this benefit for the purpose of bus occupancy estimation requires placing the mat appropriately, as demonstrated in Field Trial 2 results.

Video Analytics: adequate lighting is a critical component of the video-based solution. While in Field Trial 1, both locations provided adequate lighting, Field Trial 2 saw lighting issues arise in the early morning at Pakenham (between 6am and 7am). Thus, approximately 25% of the data collection period at this location occurred under unworkable conditions for the technology, and during a period of generally high patronage and bus frequency compared to later in the same period (where passenger numbers and bus frequency dropped significantly, i.e. after 9am).

Overall, the video analytics solution demonstrated its ability to provide high accuracy so long as lighting conditions are maintained. Moreover, the solution demonstrated a high versatility and flexibility in how it is deployed, with respect to camera, and its ability to be moved and adjusted throughout any given occupation with minimal fuss.

Bus Run ID and Vehicle Registration Recognition

FIGURE 5 BUS RUN ID AND VEHICLE REGISTRATION RECOGNITION

Field Trial 2 also included development and evaluation of video analytics-based Bus Run ID recognition, as part of a video analytics-based solution for automated bus occupancy estimation. Full details of setup, data capture and analysis are provided in the Milestone 4 supplementary report, along with a direct comparison of the accuracy of this system to recognise both Bus Run ID and vehicle registration, and pair this with estimated per-bus occupancy (also estimated via SUT's video-based solution). Training data was captured over multiple occupations, during both Decembers 2021, and over the three days of Field Trial 2: March 10th, 11th and 15th 2022, during a scheduled Pakenham Line LXRP Occupation.

Tables 3 below summarise the accuracy of the system to recognise vehicle registration and Bus Run ID.

TABLE 3 SUMMARY OF ACCURACY RESULTS FOR BUS RUN ID AND VEHICLE REGISTRATION RECOGNITION

Labels	*Accuracy*
Vehicle registration number	*66%*
Bus Run ID	*71%*

Inspection of results at each venue indicated that Bus Run ID recognition accuracy achieved a mean of ~73% at Dandenong compared with ~70% for Pakenham. Vehicle registration recognition accuracy, however, exhibited a larger difference with respect to venue, achieving a mean of 71% at Dandenong compared to just over 60% for Pakenham – a likely result of poor lighting as noted earlier.

Results overall demonstrate feasibility for the use-case, but also highlight a need for further development and evaluation. However, the issues causing error are clear, and solutions readily available. Most prominent is sensor positioning and choice of lens – a camera view providing closer inspection of the bus frontage would likely improve results considerably. Notably, detection and localisation of Bus Run ID and vehicle registration plate was very accurate suggesting that further video analytics development work should focus on the subsequent character recognition once detected.

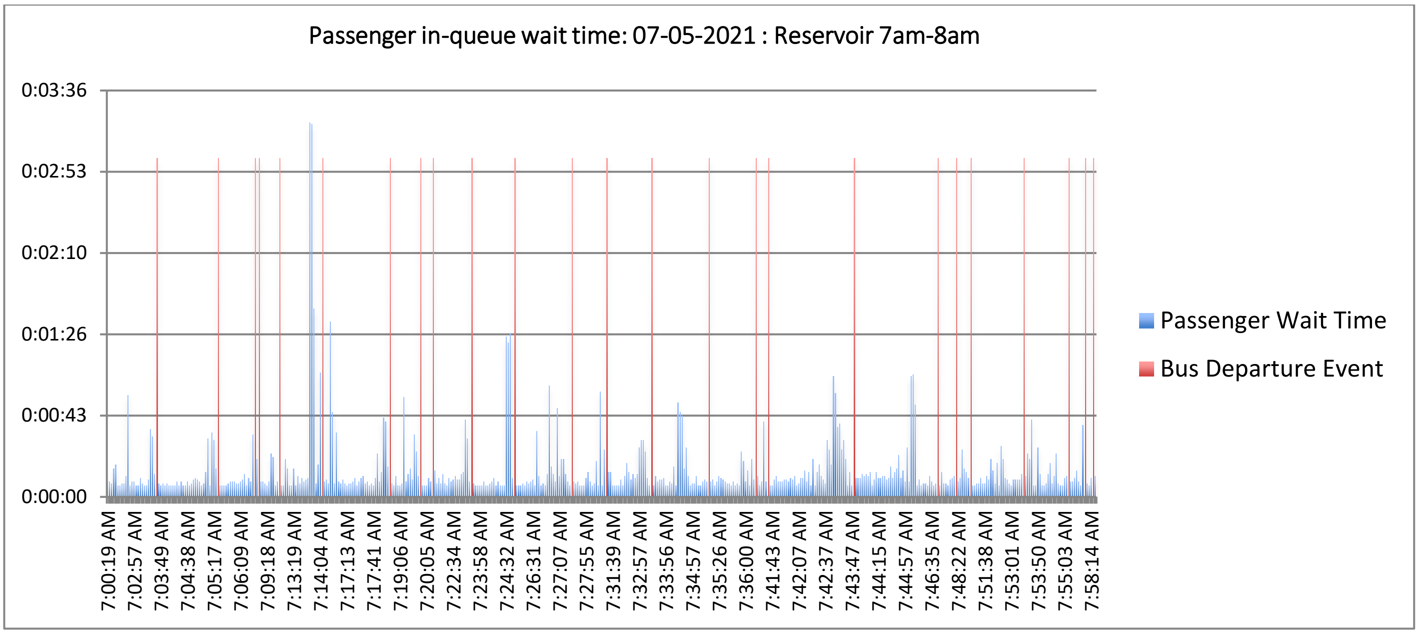
Passenger Wait Time Analysis

Video-analytics offers the substantive advantage of serving other passenger flow analytics needs. One identified use-case is computing time passengers spend waiting for a replacement bus service. While wait time was not a primary aim of the field trials undertaken, the camera captured video from Field Trial 1 (Camera 2, Reservoir-Parliament Occupation, May 2021) provides partial images of queuing passengers, thereby allowing a demonstration of this use-case to be provided. This was done over 2 hours of footage taken from Day 2 of Field Trial 1. For this, the video analytics system was configured to maintain constant tracks (using the same people detector and tracker used for counting), and time stamps of passengers within the camera's field of view. From this recorded data, dwell times for each passenger were calculated, and the distribution of these times analysed. Table 16 below provided quartile "in-queue" wait times for all passengers detected and tracked over the two hours.

Table 4 Distribution of in-queue passenger wait times at Reservoir (Field Trial 1) - 07/05/2021 - 7am-9am

Summary	Min	1st Quartile	Median	3rd Quartile	Max
7am-8am	00:06	00:07	00:08	00:12	03:19
8am-9am	00:06	00:07	00:08	00:13	02:35

As can be seen, the time durations indicate that the median time a passenger spent in the queue was 8 seconds for both hour long time blocks. The maximum time a passenger spent in the queue was 3:19 over the two hours, however it is clear that the maximums for both time blocks are outliers compared to the overall distribution. This is further illustrated in plots of wait-times for every passenger detected over the two hours in Figure 17 below. Note that the red line indicates the time that a bus departed.



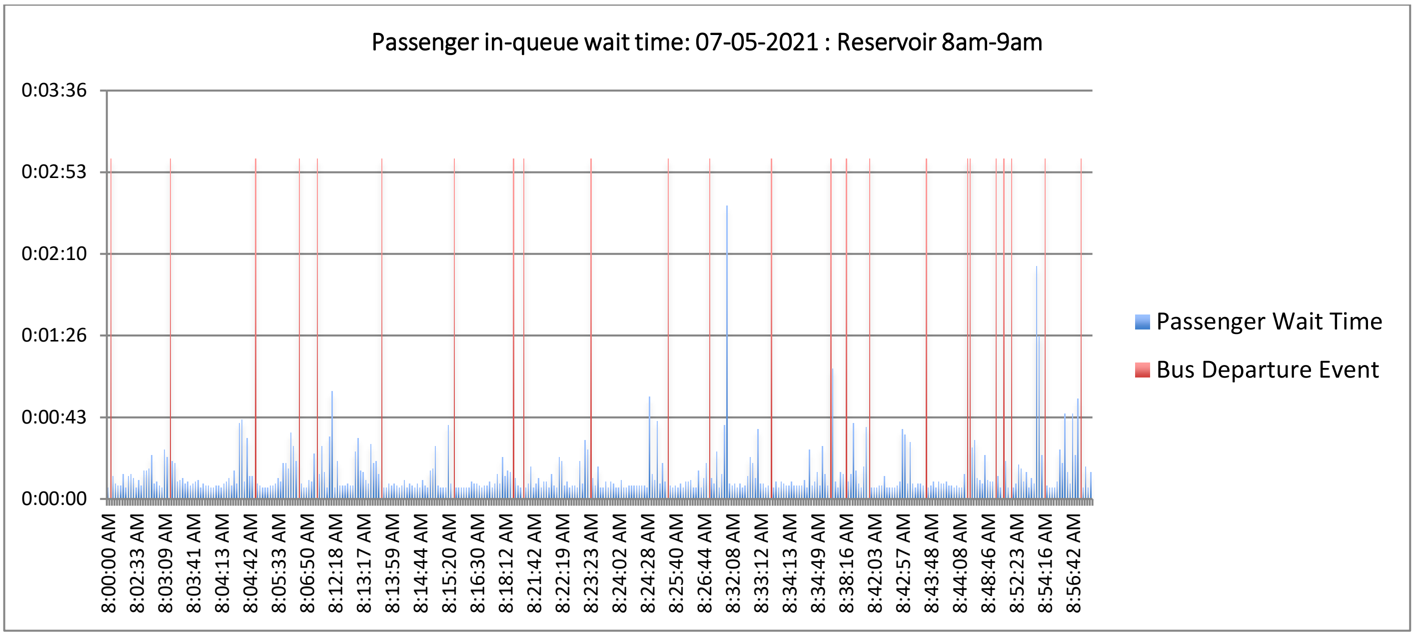


Figure 6 Plots of wait times from Field Trial 1, Reservoir for 7am-8am, and 8am-9am

As can be seen, spikes of greater than 1-minute wait time are rare, compared to the number of spikes below 1 minute, indicating that overall, passengers rarely had to wait in line before entering a bus.

Technology Deployment Considerations

The following section outlines, for both technology options, the envisaged pathway to further development and deployment of the technology for passenger counting. Included is a description of what the technology could consist of, as well as considerations around installation/de-installation, maintenance and endurance. Each technology also provides an estimated timeline for achieving this, noting also further research and development.

Deployment, Installation and Maintenance: Video Analytics

As the video analytics counter is an algorithmic solution applied to standard RGB camera feeds, it can either be deployed for use with existing CCTV cameras, or with installed-for-purpose video cameras as per the field trials. Regardless of sensor choice, an envisaged system for deployment would maintain the key tenants of self-powered, low cost computation on the edge, and network connectivity. To this end, the envisaged system for deployment would consist of:

- Embedded microprocessor with CPU, SDCard, WiFi, and USB ports (e.g., Raspberry Pi 4)
- Heat sink
- Movidius USB compute stick (GPU acceleration)*
- GPS adapter for bus tracking
- 15K mAh powerbank

As with the system used for the trials, the device would be housed in a weatherproof casing design, including a tilt-adjustable camera, and be either tripod mountable, or attachable to vertical railing.

Installation and un-installation

Where dedicated cameras are used, the fully integrated video computation box could be mountable on existing poles using bolt adjustable fastening brackets, or as a stand-alone system using a robust and stable tripod. Further development would investigate product design engineering solutions to further ensure ease of installation, in-built lighting, and weather proofing of the device.

The system software would provide a tablet/phone-based app for calibration of the system to ensure the camera position and tilt is calibrated for the passenger counting at a given site and camera location. Further research and development will seek to optimise this process for maximum efficiency, seeking a calibration time of no more than 1 minute per camera. A prototype app for this purpose has already been developed.

Power and operational requirements

Power requirements: Both Field Trials and pre-trial experimentation showed that a battery providing no more than 10K mAH is more than sufficient to power the system for a full working day (12 hours). This was calculated with a camera capture rate of 25 frames per second, which is required for a passenger detection and tracking system. However, this test did not include wireless data transfer, which will need to draw from the same power source. It is expected that 10K mAH would provide more than enough power for all components, for a day's operation. The design of the box would allow for quick battery swapping at the end of the day.

Note that if head-counting only is performed (i.e., not tracking for wait time calculations), then frames per second may be substantially reduced, and with it, computational and power requirements.

Endurance

The camera system involves no moving parts, with the exception of the camera's tilt adjustable mount, which over time may be subject to wear and tear as a result of adjustment. However, with appropriate design, the system should operate without the need for replacement for 5+ years.

Note that Lithium Ion battery lifespan is less than this and will likely require replacing (assuming regular daily use and recharging) once a year to maintain. A lifespan of between 300-500 full recharge cycles is commonly cited. However, if only deployed periodically, then batteries may provide up to 2+ years, though power storage capacity will gradually degrade.

Live data transfer, storage and analytics

Real-time edge-computed data will be periodically transmitted to dedicated servers over the 3G/4G (and at some point 5G) cellular network. The time frequency of updates is configurable, based on the needs of the user.

As an edge residing IoT solution*, no video data is required to be stored or transferred over the network*, however if desired, video frames can be locally stored and downloaded directly from each device via WiFi at the end of the day (and/or SD-Card obtained for direct copy of video files).

Note that where there is a need for obtaining recorded video data from the system (or streaming it to a different location), then automatic facial blurring may also be integrated and optionally applied to mitigate against any privacy or security concerns.

Key technical issues to address before full deployment

Key issues/challenges to address (and how they can be addressed) in order to realise a deployable version of the video analytics solution:

Improved training of passenger detection classifier: the trialed system deployed a pre-trained Convolutional Neural Network (CNN), trained to detect 90 different generic object classes using crowd-sourced annotated image data. One of these classes is people, however the visual conditions under which detection is required for bus travel is not adequately captured in such pre-trained models. As such, data obtained from the trials, and/or further data collection will be annotated and used to train a contextually relevant passenger detection system. This will improve the accuracy of detection, particularly for exiting passengers

Calibration: the current algorithm requires manual calibration to determine regions of interest. A fully deployed system will require an accompanying app or built in functionality to facilitating easy user calibration of the system when installed. This will enable a staff member to deploy the solution and configure it as required in the field.

Time to deployment

Duration of key work components (may be in parallel):

1. Algorithm refinement (including neural network training): 1 – 2 months
2. Data model design, development and cloud pipeline development: 2 – 3 months
3. Software Engineering of full software system (including calibration app): 2 – 3 months
4. Product Design Engineering and Fabrication: 2 – 4 months
5. Cloud Dashboard Development: 2 to 4 month

Assuming sufficient resources to address items 1-4 in parallel, and allowing for delays and unforeseen issues, a ready to deploy system is estimated to be achievable within 6 months.

Deployment, Installation and Maintenance: Sensor Mat

Description of envisaged fully deployed system

Parts/ components (usage per 1 day):

A sensor mat (24 sensing nodes in the mat (900 x 500 mm), in-house design and built, placed at centre and as close as possible to the edge of the bus step (in/outdoor).

Electronic box (83 x 54 x 31 mm), placed behind the opening doors, connected to the mat with electronic wiring, secured (taped) to the floor an.

50mm yellow gaffer tape to tape and secure the mat and wires

micro SD card (1GB) to record continuous pressure data output from the mat (8-10 hours of data, approx. 60MB)

3.7 V, 2000mA/h Lipo (uidhLithium-polymer) rechargeable battery

INSTALLATION AND UN-INSTALLATION

Installation

- Place the mat at centre and as close as possible to the edge of the entrance/ exit of the bus
- Secure edges of the mat to the floor with yellow Gaffer tape
- Place electronics box behind door and tape it to the wall.
- Secure the wires between the mat and the electronics box with yellow Gaffer tape to the floor.
- Insert SD card to electronics box
- Switch on electronics box

Un-installation

- Switch off electronics box
- Remove SD card
- Remove all Gaffer tape
- Remove mat and electronics box

POWER AND OPERATIONAL REQUIREMENTS

Based on current configuration for per day operation:

- micro SD card (1GB) to record continuous pressure data output from the mat (8-10 hours of data, approx. 60MB)
- 3.7 V, 2000mA/h Lipo (Lithium-polymer) rechargeable battery

ENDURANCE

Endurance tests were not conducted for this study. We can only base the estimate on previous trials and the total of 10 days of trialling as part of Field Trial 1 and 2. However, based on this and our theoretical understanding of the materials used, we estimate the life expectancy of the system with proper care to be 6 months.

Potential modes of failure:

- Ruptured wires
- Dysfunctional sensor nodes
- Failure of any electronic components – e.g. SD card, battery, microcontroller
- Water leakage

Factors that would contribute to the wear-and-tear of the solution

- Repeated installation and un-installation of the mat may damage the wires and the connection to the electronics box. In addition, the seal of the mat may be compromised allowing water to penetrate.
- Removed Gaffer tape from wires may result in ruptured wires
- Repeated loading on the mat may cause damage to the sensors over time.

MAINTENANCE REQUIREMENTS

Maintenance procedures/processes

- Ensure that the system can be powered up at the start of the day
- Ensure the data is correctly stored on the SD card at the end of the day

Real-time data transfer: passenger counting

Based on the current system:

- Data collected on SD card
- Passenger count is post processed
- Raw data collected at 10 Hz

Prospective improvements to the system:

- Data processing to be done on Microcontroller
- Data can be transmitted via Wi-Fi module and mobile hotspot
- Estimated sampling rate: 1 Hz

Key technical issues to address before full deployment

- Current system is built in-house. Manufacturing has to be outsourced.
- probably, the mat cannot be of uniform size, owing to different designs of buses e.g. size of wheelchair ramps and doors
- Above mentioned Prospective improvements to the system had not been implemented and tested

Time to deployment

Key stages to deployment

- Manufacturing method to be discussed with company that will produce the mats
- Electronics optimisation
- Algorithm
- Real time processing
- Implementation of wireless solution
- GPS data interface
- Improvement of sensing method, e.g. additional sensors

Estimated time: 9 months.

SOFTWARE ENGINEERING: REQUIREMENTS FOR CLOUD SUPPORT

Both technologies offer the possibility of providing real-time edge-computed passenger counts which can be sent over the cellular network for storage and further analysis. Below lists some of the additional requirements to realise a Cloud-supported passenger analytics system incorporating one or both of these technologies.

PASSENGER COUNT - DATA MODEL DESIGN, DEVELOPMENT AND DEPLOYMENT: A passenger count data model needs to be designed and developed to support the needs of the live passenger counting solution. This data model will need to take into consideration several requirements including location of the camera (e.g. Dandenong station), passenger information (entry, exit), Bus Run ID as well as other requirements from LXRP's team including supporting marshals on the ground.

CLOUD PIPELINE DEVELOPMENT*:* A Cloud pipeline needs to be designed and deployed to support the streaming of data from the cameras to the cloud. This will require the cloud pipeline to be robust as well as scalable.

CLOUD DASHBOARD DEVELOPMENT: A passenger counting dashboard has to be designed and developed to present live data from the field to various stakeholders.

Note: For the above full deployment, cloud platform providers such as Amazon could be a suitable choice to meet the robustness and scalability requirement of such a solution.

Business Considerations and Implications

Although a detailed benefit-to-cost analysis was outside the scope of this study, the technology-based approach for automatic passenger counting is expected to lead to substantial productivity and efficiency gains. As shown in the cost comparisons section below, the total cost per unit including cloud infrastructure is not expected to exceed $500 dollars per device. The benefits in terms of savings in the number of replacement bus services, better utilization of buses also enhanced traveler experience and satisfaction are expected to far outweigh the initial investment and maintenance costs of deployment of these devices. They will also reduce reliance on manual methods and reduction in labor costs which will also lead to further costs savings and benefits to operators.

Cost Evaluation

For the purpose of this report, we divide the cost components into fixed hardware and variable network connectivity and cloud infrastructure expenses. The expenses are reported in the following sections are based on the purchase price of items in small quantities and for controlled trials. In other words, it is likely that the cost could vary significantly when both hardware and software components are procured in larger quantities and/or custom built for industrial and commercial use. For example, power banks could be eliminated if the technology is deployed as fixed infrastructure using Alternating current (AC). The following table summarizes the cost of key hardware components of each technology option.

Technology	Components	Total unit cost
Sensor Mat	Hardware Costs per mat: 1Sensor fabrication, Electronics, Plywood, Waterproofing, Protective Rubber Mat - $400 PowerBank (power source) - $40	<= $440
Video Analytics	Raspberry Pi 4B+ (2Gb) - $80 RPi Camera Module v2 - $40 PowerBank (power source) - $40 Intel Movidius Compute Stick - $150	<= $330

Estimated Costings for Development of Full System

It is not possible to provide a detailed costing of development work to be undertaken for either technology, as this requires more detailed discussions regarding the specific requirements, and the funding framework under which the development would take place. However, as a rough guide we list the estimated personnel requirements to undertake the stated work, along with rough estimates of total development costs associated with this.

Video Analytics Development Costings (total estimated duration: 9 months)

The video analytics algorithm is relatively mature having undergone extensive testing in a variety of field trials. Remaining work, as stated in the previous section, would be focused on engineering the solution for real-time processing, and resolving of the device's housing requirements, and cloud infrastructure support.

1. Algorithm refinement (including neural network training): 1 – 2 months
2. Data model design, development and cloud pipeline development: 2 – 3 months
3. Software Engineering of full software system (including calibration app): 2 – 3 months
4. Cloud Dashboard Development: 2 to 4 months
5. Product Design Engineering and Fabrication: 2 months

6. Testing 2-3 months
7. Supervision:
8. Fabrication costs (to be negotiated, and determined based on numbers of sensors)

Personnel:

- 1x Research Fellow – Data Science – Level C
- 1x Software Engineer – Level B
- 1x Research Assistant – Level A
- 0.5 FTE – Project Manager – HEW 10

Assuming a 9-month project* and accounting for additional on-costs, development of a minimum viable deployable solution (assuming within a research project framework) would be <u>*expected to be $670-$700K*</u>. If pursued as a research project, then the possibility of co-funding and grant support may exist.

** Actual duration of project subject to resource availability*

Sensor Mat Development Costings (Total Estimated Duration: 12 months):

It is important to note that Sensor Mat exists currently as a lab-based research prototype, with substantive research and development still required. The development of the technology to a minimum viable deployable solution is estimated to require:

1. 2 x Research Fellows (Level B) FT over 12 months
2. Level E Supervisor 0.2 FTE over 9 to 12 months
3. 0.5 FTE – Project Manager – HEW 10
4. Cost of materials (~$400 per mat)
5. Manufacturing cost unknown – by negotiation and based on volume

Assuming a 12-month project** the estimated cost of development for the Sensor Mat itself, and assuming the same cloud infrastructure needs as outlined for Video Analytics (Items 2-4), then total costing including cloud infrastructure would be <u>*expected to be not less than $800K*</u>.

<u>*Please note that these costings are provided as guides only and based on the needs of minimum viable deployable solution under a research project agreement. Additional costs would likely be incurred for any further field testing and evaluation.*</u>

*** Actual duration and ability to undertake project subject to resource availability*

Network Connectivity

Both video analytics and sensor mat solutions require network connectivity for data transition and device management. For the trials, we considered a Mobile Hotspot subscription of $30 per month. In the case of commercial deployment, other connectivity technologies (e.g. Wi-Fi and Bluetooth) could be considered to synchronize multiple devices in the same location to minimize the Mobile Hotspot subscription cost per device. Note that a possible alternative to a Mobile Hotspot is to integrate 3G/4G connectivity within the Raspberry Pi board used for edge computing of video, which can support a potentially cheaper network connectivity option (~$10 per month per SIM card).

Cloud infrastructure

Both technologies currently operate outside of any cloud-based storage or dashboarding services. To support network connected operation, and dashboarding, it is recommended that a fully deployed system leverage cloud services for relational database storage (e.g. AWS RDS). If scaling deployment of the technologies over multiple sites simultaneously, then IoT edge runtime cloud services such as AWS IoT Greengrass may also be used to manage software deployment and maintenance remotely. Below provides an estimated costing for these services:

Service	Purpose	Cost
AWS IoT Greengrass	Remote IoT edge device monitoring and maintenance	$0.26 per month (up to 1000 devices)
AWS Relational Database Service (RDS)	MySQL managed database for storage of device generated data (eg passenger counts, Bus Run IDs, timestamps of detections etc)	$58.17 per month for a small instance (which this would be)
AWS EC2	For dashboard hosting	$45.50

INTEGRATION WITH 3RD PARTY SERVICES

For both the solutions (Video-based and Sensor Mat), due consideration needs to be provided to integrate the data produced by these solution with other 3rd Party services currently in use by LXRP. The solutions specifically, the cloud-based database that will be developed will provide access to data via standard application programable interfaces (APIs). APIs allow easy and convenient means for the Video-based/Sensor Mat solution to communicate with and integrate with other 3rd party services. These APIs can be hosted on the cloud service provider (e.g. Amazon) or on LXRP servers. The design of the APIs have to be undertaken as part of further solution development once the 3rd party services, their role and their data requirements are identified.

COMMERCIAL DEPLOYMENT AND UTILISATION IMPLICATIONS

The proposed passenger counting solutions of Video Analytics and Sensor Mat have different deployment and utilisation implications, which are briefly discussed here. The video analytics solution benefits from established and commercially available off-the-shelf hardware components, supported by advanced machine learning and software tools. The use of off-the-shelf components is beneficial as it reduces the cost of large-scale deployment and minimizes the risk of failure and low reliability. In summary, both solutions require some level of modification in design and supporting elements, if they are being selected for a larger trial and real-time passenger counting.

DEMAND MONITORING POST COVID-19

In the context of the current transition from remote work-from-home under COVID-19 settings to a post-COVID hybrid and flexible work place setting, automatic passenger monitoring combined with AI-powered passenger analytics is likely to offer increasingly high value both as a source of understanding these workplace patterns for planning, but also in ensuring rail replacement services, as a disruption to normal public transport operation, are responsive enough so as not to too severely interrupt this pattern. In the current climate it is likely that workers avoid going into the office precisely because rail replacement buses are in use on their train line. If bus services can both demonstrate high real-time responsiveness to demand, while also giving passengers access to real-time, up-to-date information on expected capacity, then the negative impact of rail disruptions on worker mobility may be reduced. Analytics in this regard may not just serve the need of optimising buses to the demand of passengers but also offer insights into how bus pick up and drop-down sites may be best organised to increase efficiency in the transition between transport modalities.

VALUE-ADDING FEATURES OF EACH TECHNOLOGY OPTION

This section presents potential value-adding features of both technology options. For a better understanding of value-adding options in a time horizon (mainly in terms of implementation and value creation), in this report, we have classified them into two time frames of short, and medium terms. Short-term is defined as 6-12 months, medium-term as 1-3 years. These time frames are indicative and may vary depending on each technology and its application.

Technology	Short-term	Longer-term
Sensor Mat	Crowd direction	Monitor crowd movements and patterns over day/night periods
Video Analytics	Multi-purpose data analytics: counting, wait time, passenger flow, demographics	Support on-demand service

SENSOR MAT

CROWD DIRECTION: The Sensor Mat solution is provided to count the number of passengers who pass over it in either direction, and therefore detect the direction of movement. Yet, within a short-term, value-adding data are combined with a time stamp and inform of the speed of boarding and exiting, and therefore inform of the efficiency of the planned bus replacement service.

CROWD ANALYTICS: In the longer term, sensor mats can be used at any location at train stations, bus and tram stops, to anonymously monitor crowd movements as a function of day/night-time, and thereby provide invaluable data for upgrading of transport services and infrastructures.

VIDEO-BASED COMMUTER TRACKING AND ANALYTICS

WAIT TIME AND SPACE UTILISATION ANALYSIS: This project has already demonstrated the capability of the video analytics system to capture dwell time of passengers (i.e., how long passengers spend in view). The capability to accurately estimate how long a passenger who did not board a bus, had to wait before either boarding a bus, or deciding to exit the queue, is a capability well within reach of the current system. Paired with this is the ability to analyse space usage and the flow of people through an area. Indeed, such analytics may be used in conjunction with fixed-in-place technologies such as the Sensor Mat, to identify strategic locations for the mat to be installed. It may also provide insight into the placement of barriers and signage to guide passengers.

ON-DEMAND OFF-PEAK BUS SERVICE: Leveraging the value-add above, real-time video analytics can also be used to determine when specific pick up locations require service, through analysis of waiting passenger counts and dwell times. This can be realised using the existing system's capabilities embedded within a network connected system. In the longer term, real time demand data on location, time and number of passengers can be captured and analysed to provide the right bus service solution to customers for specific locations and seasonal contexts. Accordingly, accurate information on demand point results in enhanced design and utilisation of transport network. In the context of the current post COVID-19 transition from remote work-from-home to a more hybrid model, such analytics is likely to be highly valuable for understanding the evolving demand for such services.

WIDER-AREA PASSENGER FLOW MAPPING: the existing video analytics systems is capable of combining counts across a network of cameras, however a step beyond this is to monitor passenger movement across such a network. Numerous state-of-the-art video analytics methods for multi-camera, multi-object tracking are emerging, which could be used to greatly expand the virtual field of view of the system (e.g. to an entire bus passenger pickup and put down site). This could allow a deeper analysis of *transport modality interchange questions* such as how many passengers transfer from trains to buses, or vice versa, or who opt for alternative transport, as well as statistics on total time spent, and paths taken by passengers during the transfer. The Swinburne video analytics team is currently developing a range of network-connected multi camera, multi object tracking systems for both municipal roadside asset monitoring, and for freight vehicle origin-destination monitoring. These developments can also feed into a scale up of our passenger analytics capability to the networked multi camera, wide area coverage context.

Anomaly/incident detection: SUT's passenger analytics system provides a platform for a host of detection and prediction use-cases. In its simplest form, video analytics can be used to determine patterns of crowd behaviour in terms of movement within the scene while waiting (or transitioning between transport modalities) and allow data to be compared over time (with cloud service support). More purposeful detection and prediction may also be supported. For example, the detection of anti-social behaviour, and/or violence is an active area of research and development.

.

SUMMARY

This report has provided an overview of key results and outcomes achieved as part of the LXRP and Swinburne University of Technology project: “Replacement Bus Patronage Counting and Wait Time Measurement”. Accuracy comparison results from two proposed automatic passenger counting technologies, obtained from two field trials conducted during two LXRP line occupations have been presented. In these results it was shown the Sensor Mat overall achieves the highest accuracy for passenger counts, however video analytics provides only a marginally reduced accuracy, but simultaneously offers more versatility and flexibility in its use, and the use-cases it can support. From these results, this report makes the following recommendations with respect to the LXRP use-cases.

LXRP Relevant Use Case	Most Suitable Technology
Use Case 1 – Passenger Counting	Sensor Mat
Use-Case 2 – Passenger Counting per Bus	Video Analytics
Use-Case 3 – Wait Prediction	Video Analytics
Use Case 4 – Bus Run ID Detection	Video Analytics

Overall, both technology options prove viable for the task of counting, with video analytics offering additional use-case support. Both technologies offer clear paths to full deployment within months (as little as 6 months for video analytics, and approximately 9 months for Sensor Mat (assuming adequate resourcing).

The report also outlined costings for both technologies to be fully realised, and an assessment of additional factors to be considered for the use-case of temporary use at rail replacement pick up sites, including power needs, installation and de-installation, maintenance and endurance.

Finally, this report has also identified value-add opportunities offered by each technology. For Sensor Mat, more sophisticated analytics of passenger behavior can be derived from the raw pressure contact information captured by the device. This may offer further insights into the movement patterns at different times of day, or over other time periods of interest. Video analytics offers myriad of value-add possibilities by virtue of the rich visual data upon which the analytics is based. Passenger flow patterns, space utilisation, wait time, Bus ID recognition (including improving the performance of the preliminary system trialed here), demographics analysis represent just some of the possibilities. Video from multiple networked camera systems may also be combined to expand the area of interest. Such possibilities are being actively explored in other application domains across a range of projects at Swinburne.

APPENDIX A

TABLE A.1 ACCURACY WITH RESPECT TO BUS OCCUPANCY COUNTS - FIELD TRIAL 1

Summary		Passenger Counts			Accuracy (%)	
		Total Passengers (GT)	SM raw count	Vid raw count	SM	Vid
May 6, 2021 - Day 1	Reservoir	1475	1745	1450	84.53	**98.3**
	Parliament	1330	1836	1292	73.40	**97.14**
May 7, 2021 - Day 2	Reservoir	1698	1812	1678	**93.71**	98.82
	Parliament	1162	-	1193	-	**97.33**
May 10, 2021 – Day 3	Reservoir	909	1454	888	**62.52**	97.69
	Parliament	1223	1211	1195	**99.02**	97.71
May 11, 2021 – Day 4	Reservoir	-	-	-	-	-
	Parliament	868	1286	852	**67.50**	98.16

TABLE A.2 ACCURACY WITH RESPECT TO BUS OCCUPANCY COUNTS - FIELD TRIAL 2

Summary		Passenger Counts			**Accuracy (%)**	
		Total Passengers (GT)	SM raw count	Vid raw count	SM	Vid
Mar 10 - Day 1	Pakenham	234	255	184	**91.76**	78.63
	Dandenong	473	442	395	**93.45**	83.51
Mar 11 - Day 2	Pakenham	193	238	135	**81.1**	69.95
	Dandenong	467	469	470	**99.57**	99.36
Mar 15 – Day 3	Pakenham	230	260	160	**88.46**	69.57
	Dandenong	530	571	536	92.82	**98.88**