‘Public Transport Innovations in the Time of Covid-19’: Crowdsourcing and Bus Telematics for Promoting Fuel Efficiency and Eco-Driving Practices on the EDSA Busway

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Abstract: Crowdsourcing through telematics and mobile platforms has been heavily researched for transport applications in the last decade falling in the realm of intelligent transport systems (ITS). The value of crowdsourced data is in allowing participation of the “crowd” for a human-centric, reliable information system. There is a need for robust systems beyond traditional data collection methods especially in public transport services. On the other hand, telematics is generally understood as a method of monitoring cars, trucks, equipment and other assets by using GPS technology and on-board diagnostics (OBD) to plot the asset’s movements on a computerized map. In this study, the power of crowdsourced open data for promoting fuel efficiency and eco-driving practices on bus operations is demonstrated through the pilot implementation of the EDSA Bus Efficiency Analysis and Monitoring System (BEAMS). The platform is integrated with the *SafeTravelPH* public transport crowdsourcing app and information exchange platform. Through collaboration with operators and drivers, the prototype platform was used to collect and analyze real-time data on vehicle location, boarding and alighting and bus occupancy feeds. Moreover, vehicle operating parameters including engine RPM, speed and fuel level were captured and processed with the implementation of image processing and AI techniques.

Keywords: Public transport crowdsourcing, bus telematics, ITS, eco-driving, AI

1. INTRODUCTION

1.1 Background

The manifestation of the COVID-19 pandemic in 2020 grossly affected the Philippine economy and prompted an emergency response from the national government to slow down the spread of the virus. On March 15, 2020, the President announced the Enhanced Community Quarantine (ECQ), a national lockdown that stirred all sectors of the country including public transportation. Travel restrictions were placed all over the country that severely disrupted all forms of transportation except for essential travel. At the time of the lockdown, only private vehicles were allowed, while a few shuttle services were deployed under special permits to facilitate healthcare workers reach their work destinations.

It was then that the Department of Transportation (DOTr) found it opportune to move through with its Public Utility Vehicle Modernization Program (PUVMP) by implementing 31 rationalized bus routes in Metro Manila through Memorandum Circular 2020-019 of the Land Transportation Franchising and Regulatory Board (LTFRB). Among these 31 routes was the EDSA Carousel - a dedicated bus route along the EDSA corridor running from Monumento to the Pasay Integrated Terminal Exchange (PITX) physically set at the median lane. The route is designed to ensure that EDSA buses operate at reliable travel time and consistent headways without the ramifications of mixed traffic congestion along EDSA. Bus stops were also placed along the median lane, most of which were placed either below pedestrian footbridges or aligned with the MRT-1 stations.

The initiative has been met with several challenges. Firstly, travel demand remains largely uncertain brought about by varying levels of quarantine restrictions. Secondly, the infrastructure was largely an ad hoc augmentation to the EDSA-MRT3 services. As such, a lot of bus stops were placed under the footprint of the existing MRT stations with constrained waiting area and pedestrian footbridges that are not designed to carry queues of commuters. Lastly, the basis of travel demand on EDSA was based on the MMUTIS Update and Capacity Enhancement Project (MUCEP) conducted back in 2015, which does not capture more recent travel demand patterns. Currently, the EDSA busway runs with about 300 operating units out of the 550 authorized units from 31 bus operators.

It is argued that the success of the EDSA busway, being the backbone route of the metropolis, is crucial to improving the rest of Metro Manila's transportation system. Incremental improvements in the service can best be achieved with effective monitoring and data systems. It is in this context that key performance indicators should be regularly captured and monitored towards improving the operational efficiency and at the same time achieve financial sustainability of bus operations.

During the nationwide lockdowns, the University of the Philippines Pandemic Response Team, housed under the UP Resilience Institute (UPRI), was established as the University's initiative in providing knowledge and proposing solutions to the pandemic. The *SafeTravelPH* mobile application[1] and information exchange platform was borne out of the need to support contact tracing in public transportation alongside providing a long-term more sustainable solution to the data needs of transport planning and operations. At the same time, an Energy Research Fund (ERF) project[2] was undertaken to promote fuel efficiency and eco-driving practices for bus operations along EDSA.

1.2 Research Objectives

This paper aims to establish the use case for crowdsourced data platforms for Philippine road public transport by evaluating the performance of the EDSA busway operations from the viewpoint of fuel efficiency and eco-driving principles. The overarching goal of the research is to propose a robust approach in bus telematics in view of the national goal of modernizing public transport technology and operations in the Philippines.

2. EDSA BUSWAY

2.1 Study Area

About 30% of the total number of the public utility buses (PUB) in the Philippines is operating in Metro Manila, majority of which are city buses plying the stretch of Epifanio de los Santos Avenue or EDSA. As such, EDSA is considered the prime route among bus operators because of the exclusion of jeepneys for most of its stretch, wide carriageways appropriate to bus

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[1] Google Play Store. https://play.google.com/store/apps/details?id=ph.safetravel.app

[2] University of the Philippines Diliman Office of the Vice-President for Academic Affairs (OVPAA) Energy Research Fund (ERF) Project on "EDSA Bus Efficiency Analysis and Monitoring System (BEAMS): Promoting Bus Fuel Efficiency Through Promotion and Incentivization of Eco-driving Practices"

operations, and the largest number of passenger flows generated by business districts (Makati and Ortigas) as well as several malls (Ayala Center, Megamall, SM City, Araneta Center). The use of public transport is continuously threatened by growing car ownership and deteriorating levels of service of public transportation. The EDSA Carousel is designed as a 28-km route from Monumento (North of Metro Manila) to the SM Mall of Asia (South of Metro Manila) before terminating into the PITX. EDSA has six (6) lanes with a maximum width of over 20 meters per direction, and since implementation, the median lane has been dedicated to the EDSA Carousel.

Figure 1. Image of the EDSA Busway

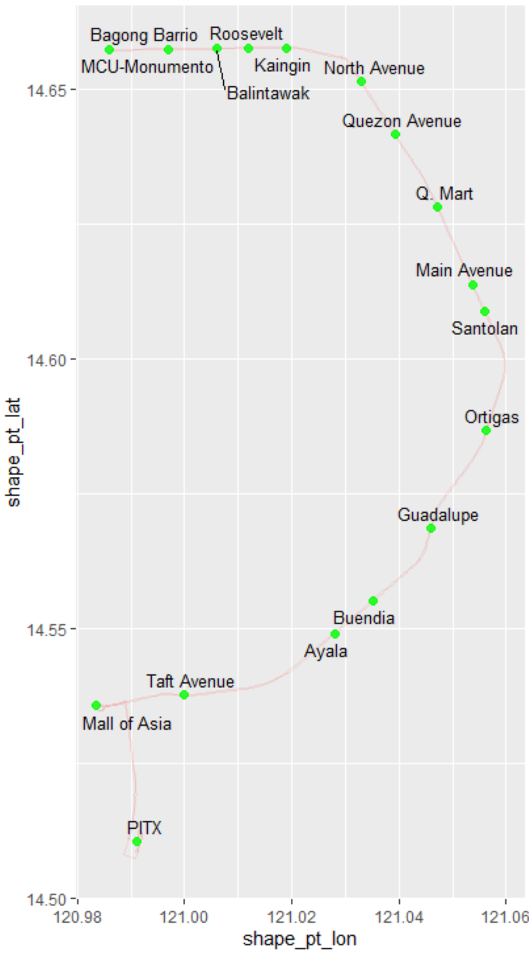


Figure 2. EDSA Busway Route and Stations

Surveys were conducted in Jan-Feb 2021 in order to determine headways and occupancies of buses that were part of the initial implementation of the EDSA Carousel. It is observed that bus arrivals and headways at the time of the survey have been quite erratic (Figure 3 and Figure 4). The average bus headway is 4.1 minutes for the northbound direction while it is 2.2 minutes for the southbound direction. While this is so, it can reach up to 62 minutes before a bus arrives. On the other hand, it seems pretty clear from the survey that bus operators were complying with restrictions with average occupancies meeting the 50% passenger load limit (Figure 5 and Figure 6).

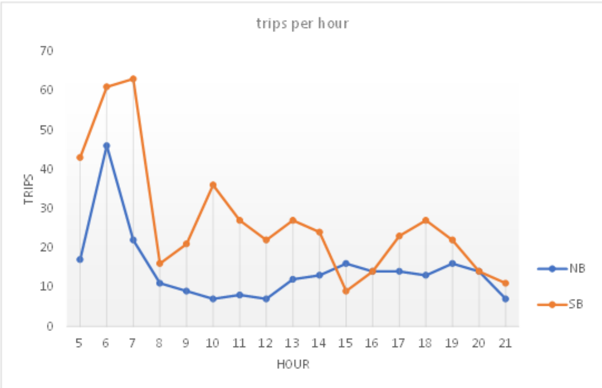


Figure 3. Bus arrivals per hour

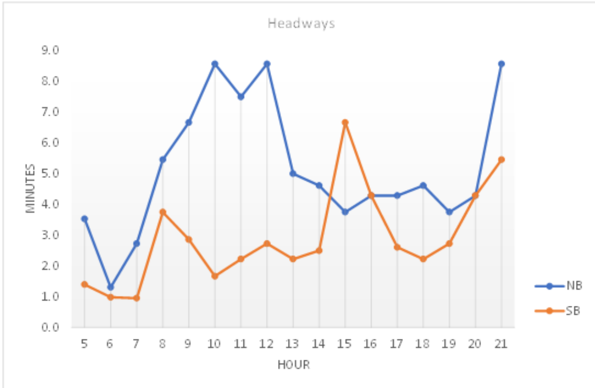


Figure 4. Bus headways per hour

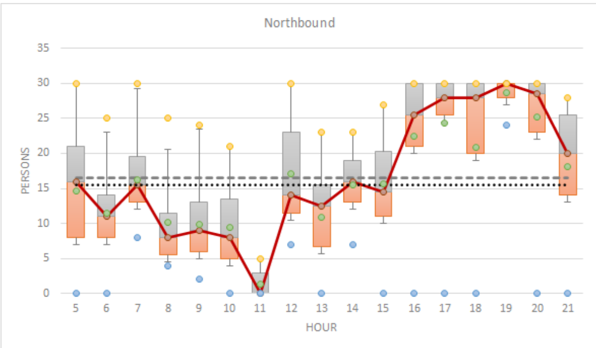


Figure 5. Boxplot of observed occupancies of southbound trips per hour

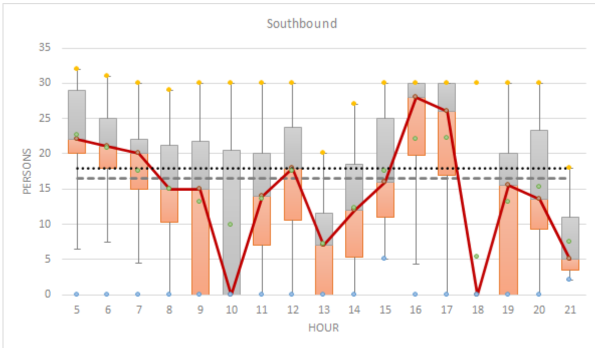


Figure 6. Boxplot of observed occupancies of southbound trips per hour

Source: ERF Bus Survey 2021

2.2 Need for Bus Efficiency Monitoring

There is a need to continuously analyze and monitor the operation of buses along EDSA with a view towards improving the planning and control systems of concerned agencies as well as bus industry stakeholders and general commuters. Bus telematics have often relied on Automatic vehicle location (AVL) and automatic passenger counter (APC) systems that are capable of gathering an enormous quantity and variety of operational, spatial, and temporal data. If such data are captured, archived, and analyzed properly, it holds substantial promise for improving public transport performance by supporting improved management practices in areas such as service planning, scheduling, and service quality monitoring.

Based on the recent data from the Department of Energy, the transport sector is 35% of total final energy consumption, growing at a rate of 4.1% per year. The sector emits 28% of greenhouse gases. Recent literature points out that operators can achieve a reduction of up to 25% of their fuel consumption by training their drivers on eco-driving. This requires estimating parameters (such as speed, speed variation, acceleration/deceleration) where the vehicle would operate at optimal fuel efficiency, also called a "green area" and continuously improve using real-time data.

According to Huertas, et al. (2018), the main obstacle of implementing the green area concept is the lack of an engine load gauge to guide drivers to operate the engine preferentially within this green area, and therefore the green area concept has been reduced to the RPM green band concept in traditional eco-driving techniques.

3. LITERATURE REVIEW

3.1 Eco-driving

Existing literature points out that operators can achieve a reduction of up to 25% of their fuel consumption by training their drivers on eco-driving. While there is no exact definition for eco-driving, there are established elements from best practices around the world. Sivak and Schoettle (2012) in their presentation of information about effects on driver behavior on fuel economy of light vehicles classified three (3) decision levels: Strategic decision (vehicle selection and maintenance); Tactical decision (route selection - road type, grade, congestion and vehicle load) and Operational decisions (idling, speed, engine rpm, cruising, aggressive driving, air-conditioning)

Xu et al (2017) found that the savings from eco-driving were comparable and better in some cases to the fuel consumption and emission improvements that can be achieved in switching to compressed natural gas (CNG) powered vehicles, a popular energy conservation strategy. While policies aimed at reducing CO2 emissions thru eco-driving practice are effective, with impacts from 5% to 45% depending on the locations and kind of interventions, there are still conflicting views on the effectiveness of eco-driving in improving emissions and fuel consumption in congested city centers.

Sanguenitti et al (2017) synthesized prior research on eco-driving behaviors that results to varying fuel consumption saving and outlined six (6) typology of driver's (and shop's/operator's) behaviors that can be the basis of interventions for holistic fuel savings in fleet management:

1. Driving (acceleration/deceleration, cruising, waiting, parking)
2. Cabin comfort (air-conditioning, ventilation, appliances)
3. Trip planning (travel routes, road types, time of the day of the travel)
4. Fueling (fuel type, time of day and temperature when fueling)
5. Load management (occupancy, cargo, aerodynamics of vehicle selected)
6. Maintenance (changing oil, oil selection, tires selection and inflation, engine maintenance schedule)

3.2 Fuel consumption savings and parameters

Limiting the discussion to engine operations, these eco-driving techniques can be re-stated as the techniques of reducing fuel consumption by restricting the engine to work within recommended operational ranges ("green area"), where the engine exhibits its highest energy efficiency (minimum fuel consumption). Usually, this range has been expressed as a constant range for RPM and it is referred as the engine RPM green band (DFT, 2009).

In a field trial with 1156 trips in two cities, deceleration rate, engine RPM and speed, as well as external factors such as congestion and road slope have a direct influence on fuel consumption. (Lois et al, 2019). Similarly, driving styles can reveal the differences among drivers of the same vehicle that can vary up to 5.5% fuel consumption reduction, with significant contribution from braking, acceleration, and standstill behavior (Ayyildiz et al, 2017). Meanwhile, around 50% of fuel consumption of a city bus is consumed during acceleration (Ma et al, 2015).

Conversely, when deceleration is minimized during smoother rides with less braking (negative deceleration), a decrease in fuel consumption in urban area can be achieved observed. The fuel savings, however, depends on the type of the road and the reduction of maximum speed on each road type, but not on the number of stops per kilometer (Coloma et al, 2018). Recent work shows that engine energy efficiency also depends on engine load. Therefore, the engine RPM green band concept of eco-driving can be extended to an engine load—RPM green area which corresponds to the load vs. RPM area where engines exhibit highest energy efficiency.

A multiple regression analysis is one simple way of correlating vehicle information as independent variables to the fuel consumption as dependent variable (Lee and Son, 2011). Results from previous studies can be used to create a model based on relationships of variables that are proven to be significant in predicting fuel consumption. However, predicting accurately the fuel consumption level within the dynamics of driver's behavior, road conditions, and engine and vehicle performance can be too complex, due to human bias and randomness (Delice et al, 2007), and non-linearity of diesel engine dynamics and control system (Chiara et al, 2011).

In their study of interaction of driving behavior and external factors, Lois et al (2019) employed a sequential method in data analysis comprising of factorial analysis, regression analysis, and path analysis, for a dataset of 1,156 trips, 8,150 kilometers of travel, and 128 variables. Factorial and regression analyses were done to determine empirically important variables, while path analysis model the relationships among internal (engine RPM, negative acceleration, vehicle speed) and external (congestion, road slope) factors, and fuel consumption. At $p<0.001$, the multiple regression method has an r-squared of 0.702, which indicates strong correlation between independent variables and fuel consumption.

Meanwhile, the fuel consumption level and driving style evaluation model developed by Ma et al (2015), departing from the regression and continuous variables modeling from other studies, used a decision tree-based classification modeling algorithm called C4.5. The following reasons are the advantages C4.5 over other data science methods:

- Its ability to get good classification predictions while requiring minimal computational resources is significant to low-cost, low-capacity embedded system/telematics equipment of a vehicle. This can also encourage the widespread use of the technology to enhance datasets and data randomness.
- Statistical significance and relative significance of factors among each other can be outputted by decision trees methods and could inform drivers and fleet managers to optimize their operations.
- This decision tree method can process continuous input from driver's telematics data.

This model used 7500 acceleration samples, which were based on recorded initial and shifting threshold velocities, gear shifting for acceleration, and acceleration/deceleration times. The accuracy of a two-level discrete classification driver evaluation model ("Good" or "Bad" driver) was 86.47%, while a five-level model reached 50% accuracy. Generally, the more classification levels, the lower the accuracy rate.

3.3 Crowdsourcing and Co-production

Monitoring and analysis of driver's performance via mobile phone GPS is quite novel in the Philippine public transport regime, although several attempts have been done elsewhere. The study of Shinde and Ansari (2017) proposed an intelligent bus monitoring system for accident detection, emergency fail switch, and drunk and drive authentication using GPS and RFID sensing. The study of Sultan et. al (2017) exploited crowdsourced user-generated data, namely GPS trajectories collected by cyclists and road network infrastructure generated by citizens, to extract and analyze spatial patterns and road-type use of cyclists in urban environments. Spatial data handling processes including data filtering and segmentation, map-matching and spatial arrangement of GPS trajectories with the road network were used to address data deficiencies.

Mobile phone applications for transportation, in fact, have been around for some time. Waze© has been a known brand as a decision support system for road navigation and trip making for private cars. Google provides web-based navigation with mode options. In fact, Waze itself utilizes machine learning and crowdsourcing in its backend navigation models. In the Philippines, several applications already exist that apply real-time monitoring but mostly for deliveries (Grab, Food Panda) or taxi services (Grab, Uber (defunct)). Few in so far provides specifically for public transport. Sakay.ph since its creation has attempted building itself as a multimodal platform for commuters.

Poblet et al. (2017) presents a comprehensive review of crowdsourcing platforms and methods and provided a very useful typology in understand the role of the crowd based on the type of data be participation involved. This leads to four types of crowdsourcing roles based on i) type of data processed (raw, semi-structured, and structured data), ii) participants' level of involvement (passive or active) and, (iii) skills required to fulfill the assigned task (basic or specialized skills).

Recently, Falco and Kleinhans (2019) provides a review of over 100 digital participatory platform (DPP) and provides a more comprehensive picture of the availability and functionalities of DPPs. They reported that a renewed interest has appeared in citizen co-production of public services, especially in view of the financial pressures currently facing governments around the world. Co-production generally refers to the public sector and citizens making better use of each other's assets and resources to achieve better outcomes and improved efficiency. In line with this stance, mobile applications and platforms created by professional developers through government challenges, prizes, apps competitions, and hackathons - where governments make their data available to produce new ideas and solutions - are widespread and common.

It is argued that there is a need to actively explore collaborative governance mechanisms as innovations to the decades-old public transport policy in the Philippines. Firstly, there is a need to identify policy gaps in the PUVMP implementation as there may be underlying structural constraints and bottlenecks in the policy environment. Secondly, there is a need to evaluate the institutional capacity of concerned national and local government agencies involved in the roll-out of the PUMVP. Lastly, there is a need to take stock of the responses of concerned public transport operations and the commuters at large with respect to the policy performance of the PUVMP. Overall, there is a need to explore a multi-stakeholder approach in terms of sense-making as well as evaluating the present state of the public transport system in the country.

Collaborative governance (CG) as a strategy has been used by governance scholars and practitioners for decades to explore solutions of cross-boundary governance problems, but without a clear analytical framework to explain its mechanisms, especially the collaborative dynamics. Emerson et al. (2012) proposed a pioneering integrated framework that defines collaborative governance broadly as "the processes and structures of public policy decision making and management that engage people across the boundaries of public agencies, levels of government, and/or the public, private, and civic spheres to carry out a public purpose that could not otherwise be accomplished". This provides a broad conceptual approach for situating and exploring components of CG systems, ranging from policy or programme-based intergovernmental cooperation to place-based regional collaboration with nongovernmental stakeholders to public-private partnerships. This integrative framework consists of three nested dimensions, representing the general system context, the CG regime (CGR), and its collaborative dynamics and actions.

According to Howlett and Ramesh (2015), co-production, like other collaborative governance arrangements, discounts the fact that it is often practiced without knowing exactly under what conditions and constraints it is likely to succeed or fail. The authors say that each arrangement has its own prerequisites in terms of governing capabilities and competences from both governments and non-state actors. To take a significant step forward in understanding co-production, it is necessary to clarify what resources are required at the individual, organizational and systemic levels.

3. METHODOLOGY

3.1 Public Transport Crowdsourcing

This study utilized crowdsourcing and co-production approaches to gather real-time monitoring data on participating drivers and operators in the EDSA busway route. The researchers collected data from two sources. First, the collection of real-time vehicle location and occupancy data involved the pilot deployment of the *SafeTravelPH* app that allows commuters to report and view transport conditions and monitor Public Utility Vehicle (PUV) availability and locations, arrival times at transit stops, and vehicle occupancies, as well as rate and record the quality of their trips. At the same time, the app allows PUV operators to better calibrate their routes, monitor their operations and improve their overall systems.

SafeTravelPH as an information exchange platform emphasizes the importance of co-design and crowdsourcing through strong partnerships between the system developers, government, and private institutions in the creation of systems, data collection, and policy development. The development of the *SafeTravelPH* public transport crowdsourcing app was guided by the various challenges in public transport operations during the pandemic which include serious capacity constraints and needs to ensure that safety protocols are in place to limit the spread of COVID-19, namely:

- Lack of real-time transit information restricts citizens' mobility and leads to longer waiting lines and overcrowding inside public transport vehicles;
- Lack of proper management on route-based fleet schedules increases citizens' exposure due to packed stops waiting for public transport vehicles to arrive;
- Lack of safe public transport contact tracing mechanisms increases risk of transmission; and
- Lack of monitoring and feedback systems reduces government and operators' ability to ensure compliance of operations with safety and sanitary protocols.

SafeTravelPH is anchored on the principle that the quality of a public transport system can be measured by the service's availability, reliability, comfortability, predictability, safety, and timeliness. In order to achieve these, four (4) components must be considered in a public transport system: technology, data analytics, user feedback, and partnerships.

Figure 6. Structure of SafeTravelPH app and platform

The platform provides vehicle location feeds by the second and allows drivers to log boarding and alighting. At the time of writing, four (4) buses have been monitored, although the deployment was aimed for thirty (30) buses. Monitoring lasted from 30 October 2020 to 15 December 2020, and each day drivers were allowed to monitor anytime during their operating hours, typically between 4AM and 7PM. Second, wide-angle web cameras installed on the vehicle dashboards captured speed, RPM, and fuel levels at a sensing frequency of up to four images per second. Images are subject to computer processing to translate the dashboard images into values for RPM, speed, and gas. Image processing was developed via Python. Although this method of collecting RPM data.

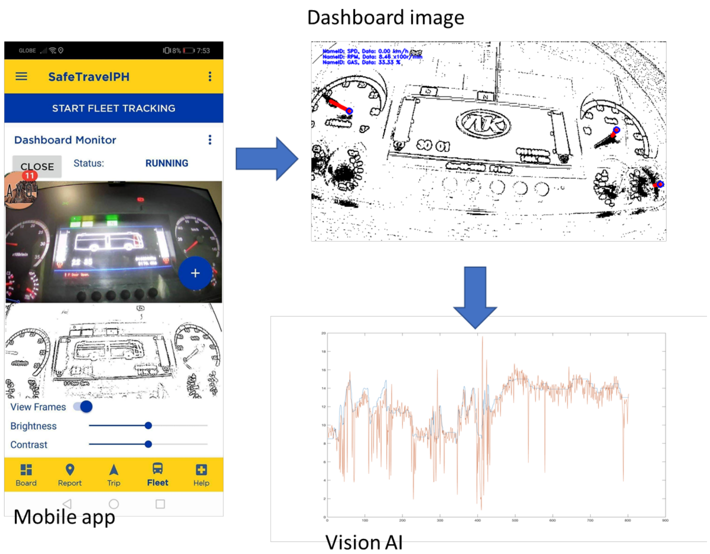


Figure 7. Image processing example

This paper uses a subset of the monitoring data from 23 November 2020 to 29 November 2020. Data prior to this period were a result of testing and calibrating the platform to suit the operational characteristics of the participating operators and drivers. A week of data is used to provide a snapshot of a week-long monitoring. There are several factors that contribute to the data quality that need to be addressed lest be wary of for further research and development. First, the accuracy of vehicle locations (Long, Lat) depends on the smartphone GPS and different cover types like buildings and trees. Second, occupancy depends highly on drivers keying boarding and alighting accurately, thus the need for incentives, training and quick feedback. Lastly, missing data tends to occur under poor connectivity, when phone battery runs out, or when the driver turns off the phone during operating hours.

3.2 Pilot Implementation

A pilot implementation was of the proposed EDSA Bus Efficiency Analysis and Monitoring System (BEAMS) was conducted from October 20 to December 5, 2020 where a target of 5 drivers of the HM Transport, Inc. company was engaged to install and operate the propotype device during actual bus operations. The prototype platform consists of the following devices: Xiaomi POCO X3 (64 GB storage, 6 GB memory, Android 10), USB to Type-C adapter and Web camera.

Figure 12. Prototype BEAMS platform

The relationship between RPM and eco-driving has been described by Coloma, Garcia, and Wang (2018) that said average RPM is lower in eco mode than non-eco mode, and that negative acceleration are also lower in eco mode. The preceding paper also concluded that there is strong correlation between fuel consumption and various parameters such as sloping, RPM, and speed. This research examined how RPM readings can effectively be monitored via dashboard image processing and explore how such a system can be utilized for eco-driving behavior analysis. However, the method posed challenges in also monitoring fuel consumption that could be useful in correlating consumption and speed at various points on the bus corridor.

4. DASHBOARD AI SSYTEM

4.1 Main Process

The Dashboard AI aims to provide real-time insight on the current performance of the vehicle (i.e. RPM, speed, and fuel levels) by directly observing the readings from the vehicle dashboard, and provide analysis and insights afterwards. With the help of computer vision, the analog displays of the speedometers are converted to digital information and are then processed to become a meaningful insight.

At the level of the driver, the application aims to provide an event detection system throughout the vehicle operation – whether an event of over-speeding occurs or perhaps a low fuel is detected. Additionally, it can also provide a general insight to the driver's behavior – how generally fast he drives or how much fuel is consumed in a span of time. On a collective scale, and with the help of GPS and other location services already available, the data gathered from different vehicles may provide insights on the average speed and RPM based on a certain street, path, or highway; as well as the invention may provide insight on the fuel consumption based on the vehicular model used (i.e., bus, car, van, etc.).

Figure 8 depicts the general workflow of the Dashboard AI. The operation starts by capturing an image of the vehicular dashboard and pre-processing it for transmission. Depending on the parameter, these pre-processed images are then grouped together and are sent as a batch, for lesser transmission overhead. On the server side, the transmitted image frames are then read and post-processed to numerical data and interpreted depending on pre-defined parameters (e.g., maximum angular reading for speedometer, minimum angular reading for speedometer, etc.). The interpreted data are then sent back to the local side for display to users.

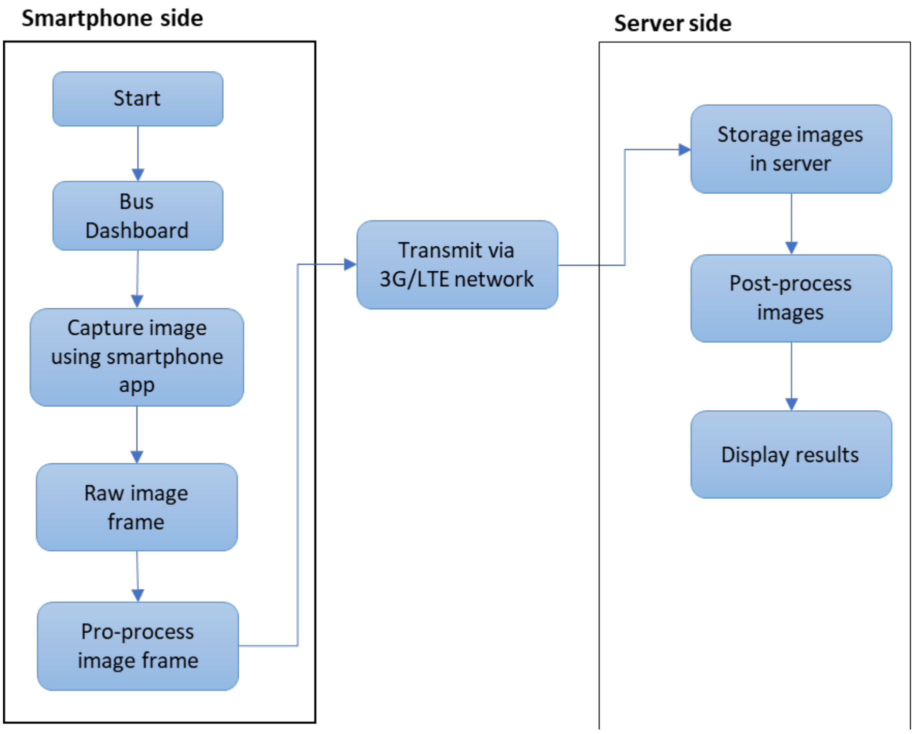


Figure 8. General Workflow of the Dashboard AI

4.2 Pre-Processing

The structure of separating the processes into two parts (one in local and one in server) stems from two main underlying principles:

- To lessen the load of processing on smartphones, which consequently allows for wider device compatibility (both high-end and low-end smartphones will ideally be able to use the smartphone app)
- To aggregate the data collected from multiple vehicular monitoring systems which may be used for larger-scale analytics (i.e., general traffic speed at a certain road, general speed of a certain vehicle type, etc.)

Figure 9 depicts the pre-processing for a raw image captured by the OTG camera. The main principle for doing the pre-process stage before transmission is to ease the process load on the server side, without compromising the local side as well. The methods and processes contained are comparatively less intensive in terms of resources and runtime.

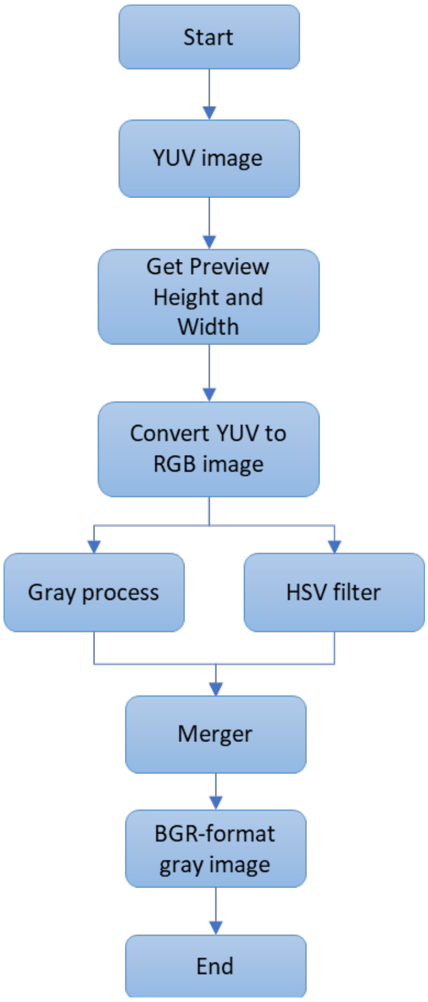


Figure 9. Pre-processing Workflow

Figures 11 and 12 show the raw image and processed image, respectively. It is noted that the calibration of the Dashboard AI depends much on the image capture conditions and the resulting raw image quality. This would include lighting conditions, image orientation and occlusion levels. If these factors are controlled for, then it is expected that results will be more than satisfactory. On the other hand, the pilot implementation necessitated the incorporation of smoothing algorithms in order to address spurious readings. This was achieved through post-processing steps.

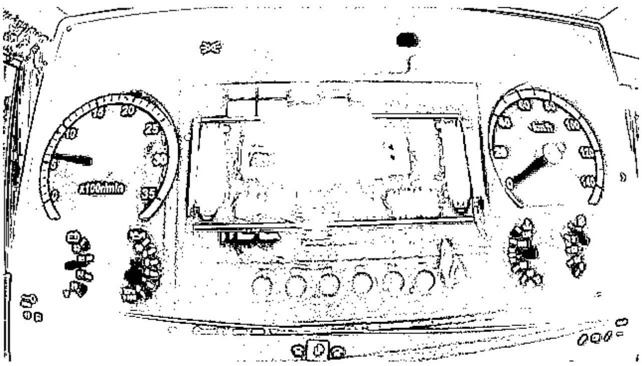


Figure 11. Raw image

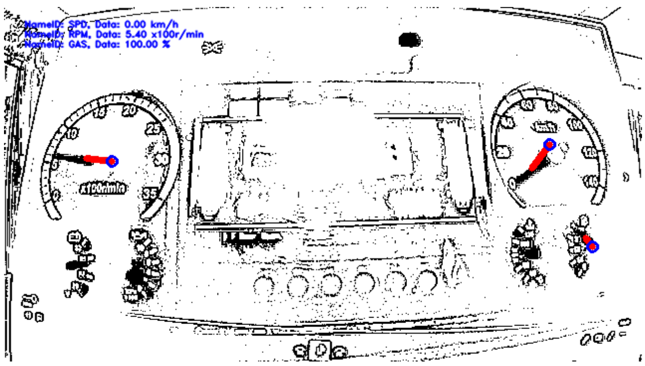


Figure 12. Processed image

Figure 13 presents the automated file management and process workflow to generate AI readings from a batch of raw images. The automated process is necessary since there is a big number of raw images to be processed due to the high frame rate. The prototype system has been tested at 10 frames per second although the final data sets were sampled at 2 frames per second to reduce data size.

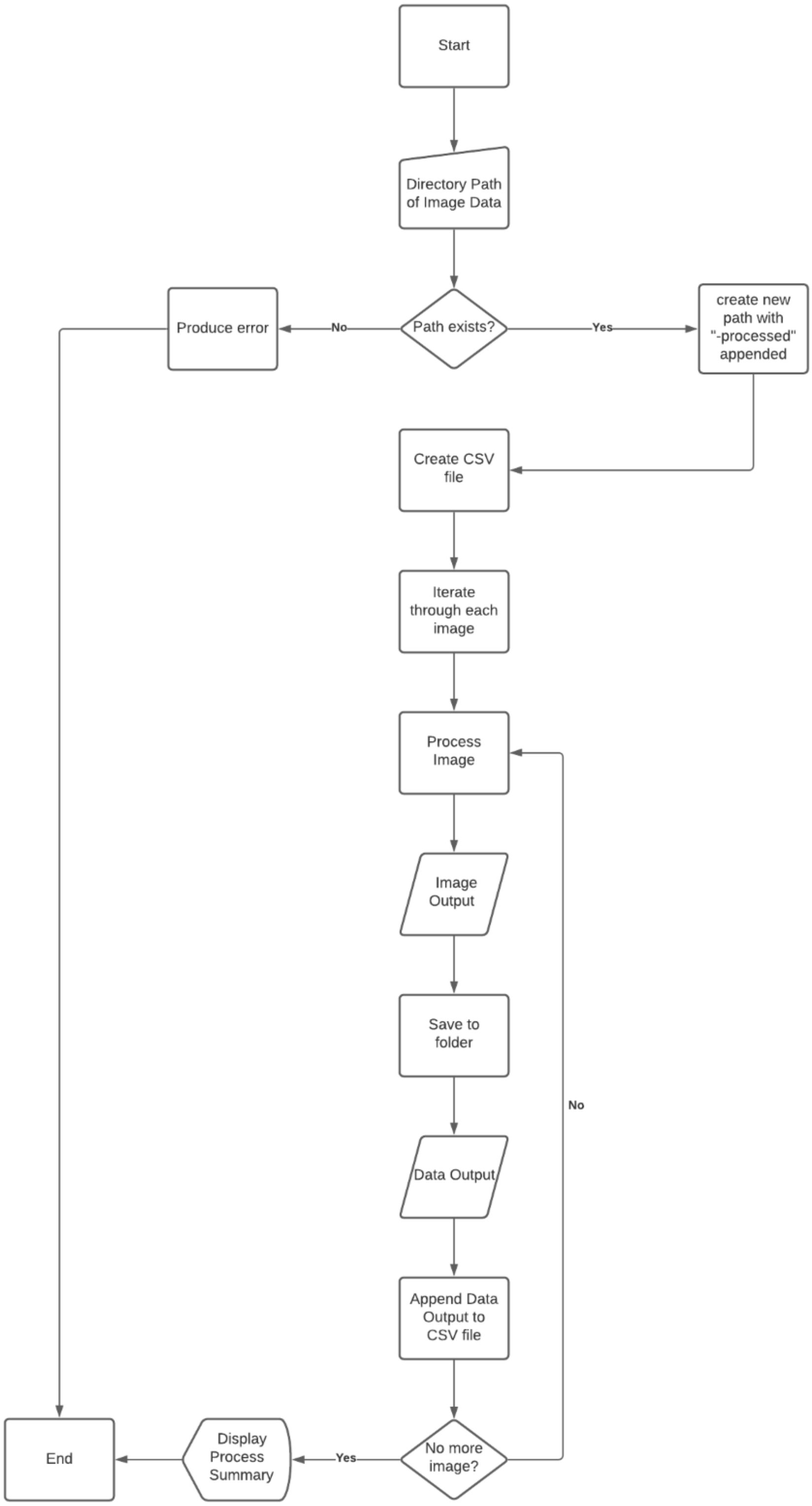


Figure 13. File Processing Workflow

4.3 Post-Processing

Figure 14 depicts the post-processing of batched image data transmitted via 3G network. The server's process workflow produces primarily two (2) outputs: a CSV file containing the value readings per frame, and a directory of processed images for validation. For the post-process of the AI readings, a smoothener is added to further smoothen the data acquired. Two modes are available for such: (a) Thresholding, and (b) EWMA.

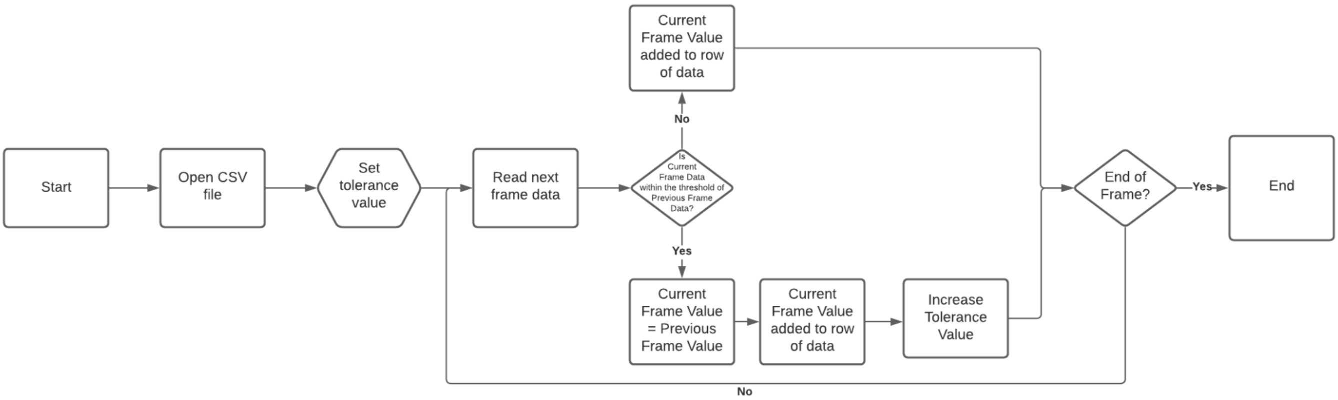


Figure 14. Post-processing Workflow

Mode 0: Thresholding

The thresholding method lies on the principal assumption that the dial reading cannot jump at a very high reading within a split second. With such a basis, it means that the next frame reading should be within a threshold from the previous frame; and a big jump on a reading indicates error in reading. In the case that such a scenario happens, the current reading is discarded and the reading from the previous frame is rather accepted as the correct current reading. The tolerance threshold is then increased. The complete workflow is show in the figure below: Currently, the base tolerance for RPM, SPD and GAS are 1.25, 8, and 16 respectively; while the steps for each encountered error reading are 0.5, 1.2 and 4. These figures are very specific to the current bus model used for prototyping.

Mode 1: EWMA

The second available mode for smoothening a dataset is with the use of Exponential Weighted Moving Average. Using the CSV-formatted dataset, Mode 1 will convert the dataset to a panda DataFrame, and feed it to a library function `ewma().mean()` with the following parameters: *alpha = 0.7* and *ignore_na = True*.

4.4 Accuracy Assessment

The following improvement has been observed from a sample dataset of a Manguiran bus trip. Originally, without the smoothening post-process, the accuracy of the reading is at 48.9%. Figure 15 shows the comparison between the manual reading and the AI reading.

For Mode 0, which uses the Thresholding approach, a significant increase in the accuracy of the readings has been observed. Except for the time duration wherein occlusion has heavily occurred, the data generally seemed to be closer to the true readings. In this method, the accuracy has gone up to 71.2% as shown in Figure 16. As for Mode 1, which uses EWMA for smoothening, there was a further decline in accuracy of the AI reading, with a rate of 44.8%. Although, to note, as compared to Mode 0, the recovery of EWMA from an occlusion (particularly in the 5:43:00 mark) is more rapid. This is shown in Figure 17.

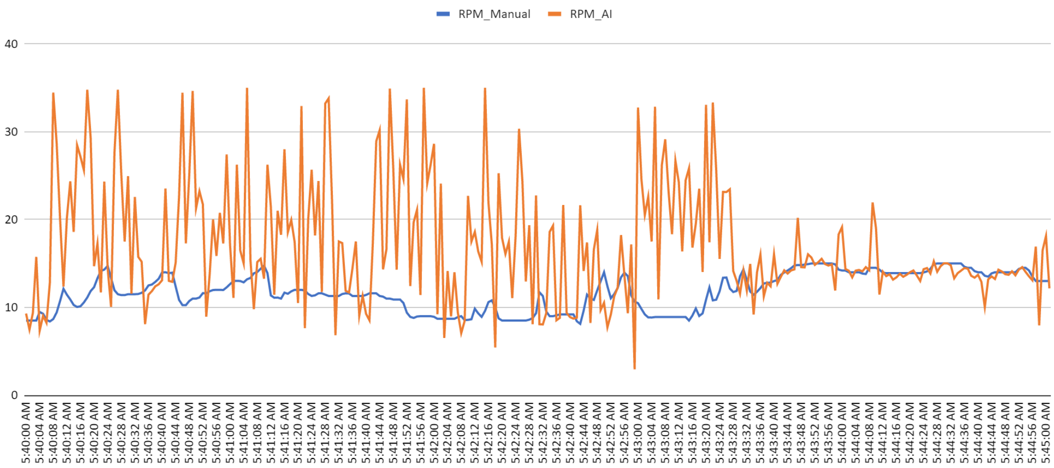


Figure 15. Comparison of Manual and Original AI Results

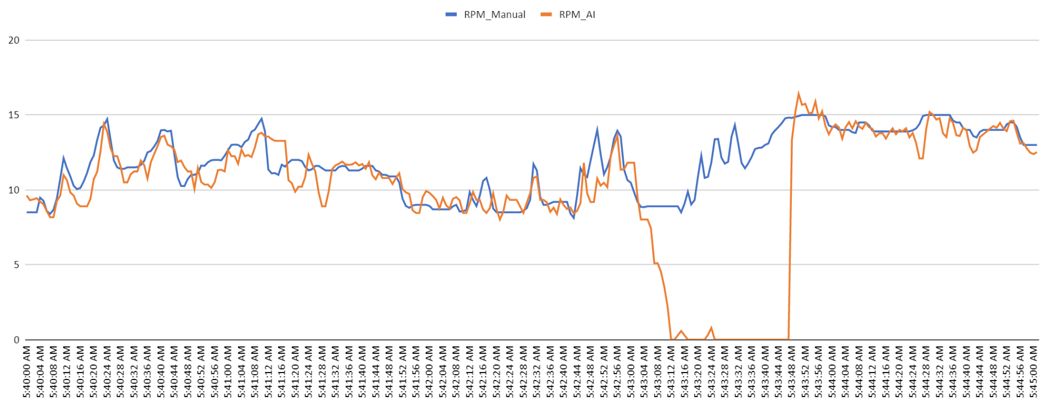


Figure 16. Comparison of Manual and Smoothened AI Results- Mode 0

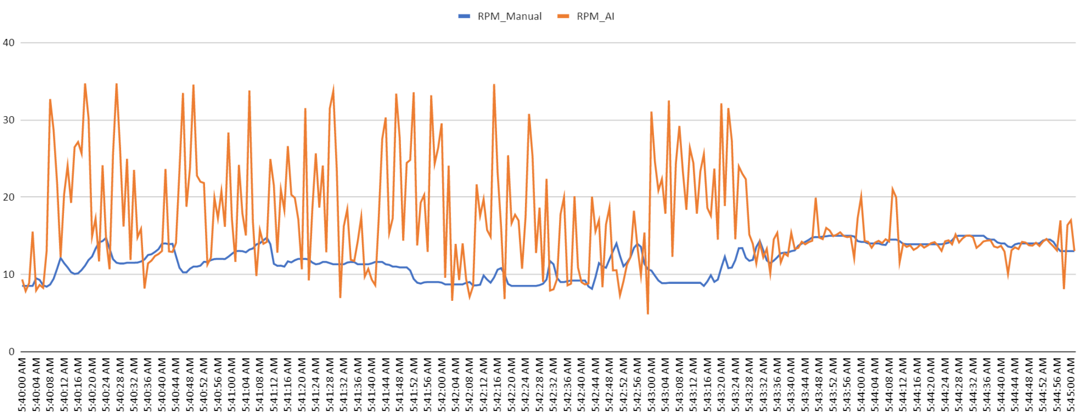


Figure 17. Comparison of Manual and Smoothened AI Results- Mode 1

4.5 Real-time RPM Monitoring and Eco-Driving

Although the speed detection has been already commercially available such as the Waze app, the Dashboard AI tries to integrate the vehicular behavior detection as close as possible to the driver, literally. With a camera in front of the dashboard, the process of monitoring is straightforward and does not require a transmission of location (which generally is power-consuming) to deduce the speed and other parameters via server. Essentially, with dashboard AI, monitoring is localized.

With the application in place, the detection system for vehicular driving is improved by lessening the burden for the drivers to look up the street and down the dashboard routinely. Ideally, with the Dashboard AI, the driver will be able to focus on the street and will just be notified when certain events (over-speeding, low fuel) happen through an alarm or voice alert. It is noted that many public transport vehicles in the Philippines still exist under the analog system and therefore that application is expected to provide utility not only to drivers and operators but also regulators and policy makers.

5. INITIAL RESULTS AND DISCUSSION

Figure 18 presents the fuel monitor by driver on December 3, 2020 during the pilot implementation of the EDSA-BEAMS prototype. The fuel consumption and total kilometer reading were requested from actual company records. It is noted that there is a linear relationship between kilometers travelled and fuel consumption. It should be emphasized that one cannot make an instant determination of who among the drivers is the most fuel-efficient just by looking at the fuel monitor.

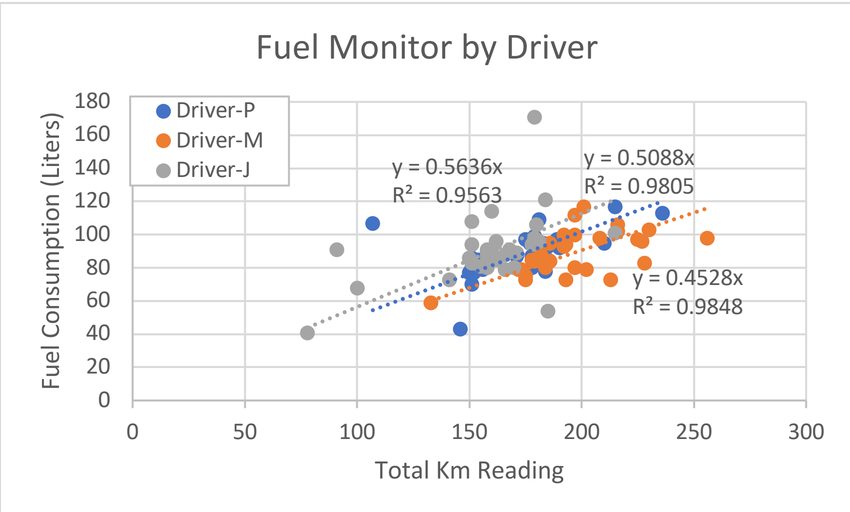
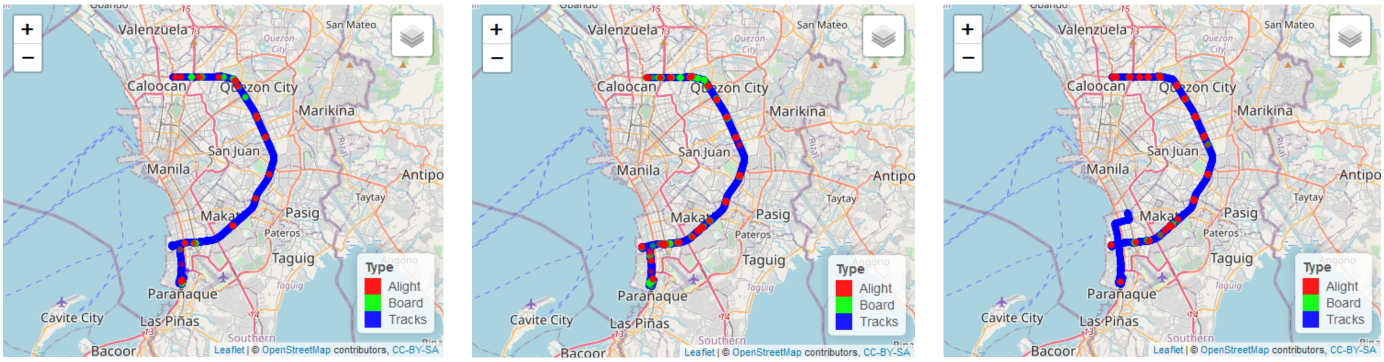


Figure 18. Fuel Monitor by Driver

Table 1 shows the performance statistics for the three drivers who participated in the pilot implementation of the BEAMS platform. Figures 19 and 20 present the GPS vehicle feeds and occupancy heatmaps per participating driver based on the SafeTravelPH public transport crowdsourcing app. Figure 21 presents the passenger load profile by driver. and passenger load profile captured using the SafeTravelPH app and platform. It is noted that data analytics platform is still under development and therefore might required re-validation.

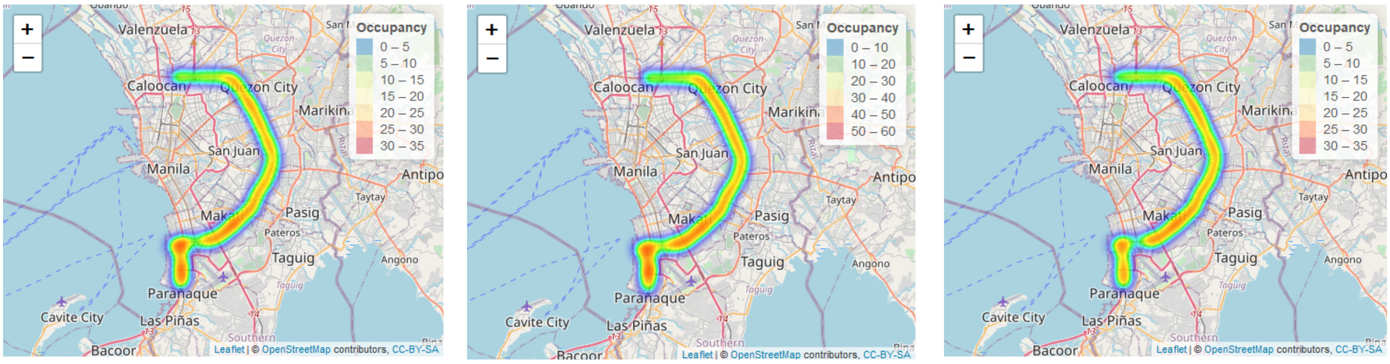
Table 1. Driver Performance Statistics on December 3, 2020

	Driver P	Driver M	Driver J
Time start	10:00:00	10:00:01	10:00:01
Time end	9:59:59	9:59:59	9:59:59
Time duration	12.5 hours	13.31 hours	13.93 hours
Total distance travelled	152.61 kms	167.79 kms	161.13 kms
Average speed	15.58 kph	16.96 kph	14.04 kph
Total boarding	68	451	204



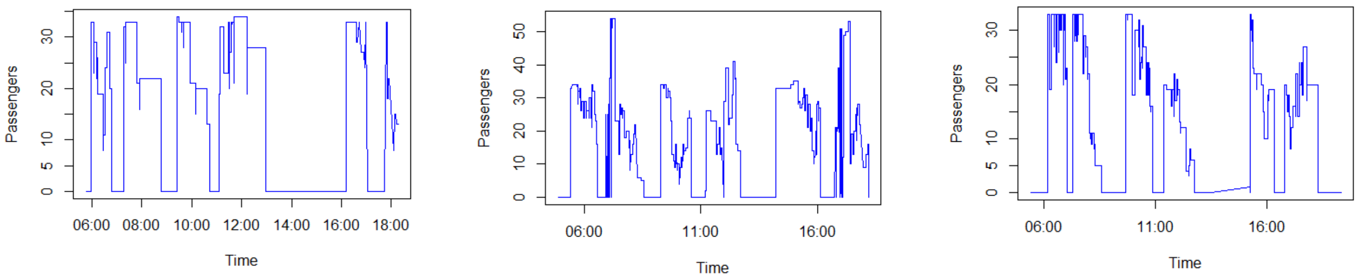
Driver P DriverM Driver J

Figure 19. SafeTravelPH GPS Vehicle Feeds by Driver



Driver P DriverM Driver J

Figure 20. SafeTravelPH Occupancy Heatmap by Driver



Driver P Driver M Driver J

Figure 21. SafeTravelPH Passenger Load Profile by Driver

Three Performance Parameters are proposed to provide the basis for an evaluation of the most fuel-efficient driving operation, namely:

- Total Distance Travelled;
- Weighted Occupancy which is computed as the total of hourly values of average number of passengers per hour multiplied by distance travelled within the hour; and
- Weighted Speed which is computed as the total of hourly values of average speed per hour multiplied by distance travelled within the hour

Based on the above parameters, the following Fuel Efficiency Indices are proposed to be evaluated using Fuel Consumption in liters as the numerator and the parameters as denominators:

1) Distance Index (DI) measured in liters/km;
2) Occupancy Index (OI) measured in liters/passenger; and
3) Speed Index (SI) measured in liters/kph

Table 2 presents the evaluation of the various performance parameters for each participating driver. Table 3 and Figure 22 present the computation of the various fuel efficiency indices for each driver. Based on the results, Driver M consistently exhibits the lowest values under each fuel efficiency index compared to Driver P and Driver J clearly indicating that Driver M has the lowest fuel consumption among other drivers and is deemed to be the most fuel-efficient.

Table 2. Performance Parameters

	Total Distance Travelled (km)	Weighted Occupancy (passengers)	Weighted Speed (kph)	Fuel Consumption (liters)
Drive P	152.6	17.8	16.1	95
Driver M	167.8	23.2	18.5	80
Driver J	161.1	16.6	17.3	96

Table 3. Fuel Efficiency Indices

	Distance Index (liter/km)	Occupancy Index (liter/pax)	Speed Index (liter/kph)
Driver P	5.3	5.9	0.62
Driver M	3.5	4.3	0.48
Driver J	5.8	5.5	0.60

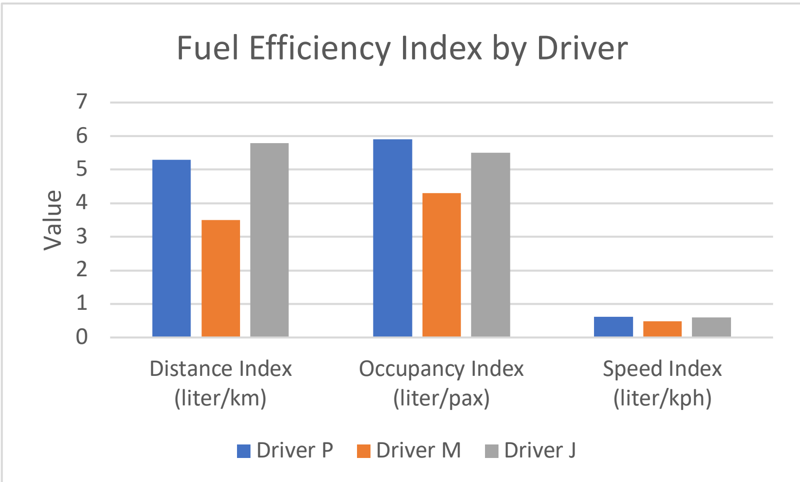


Figure 22. Fuel Efficiency Index by Driver

6. CONCLUSIONS

This study successfully demonstrated the use of bus telematics and big data analytics through crowdsourcing and open platforms in analyzing road public transport performance. In the case of EDSA Busway, this paper analyzed the performance of buses using the sample monitoring and crowdsourced data from December 3, 2020 from the viewpoint of fuel efficiency and eco-driving.

The success of this experiment falls on both technical soundness and effective partnerships, i.e. operators, drivers, commuters, and developers working together in providing, storing and analyzing data from an open platform that crowdsource from mobile phone data feeds. It is also important that the developers and analysts provide feedback on the analysis to incentivize the drivers to continue keying in the necessary inputs. Regular feedback to the data providers (drivers and operators) also motivates cooperation which is key to the crowdsourcing aspect of the platform.

There remains more research and development efforts needed for the AI methods deployed in this study towards a holistic decision support system aimed at improving bus planning and eco-driving policy. For instance, as demonstrated by the RPM readings, the dashboard readings should be efficiently matched with locational readings to relate consumption and driving behavior to the design of the bus corridor as well as bus operational decisions. Nonetheless, this research has shown promise in crowdsourced real time data processing for EDSA Carousel that can be further developed -an innovation that was hatched during the pandemic.

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