Public Transport Crowdsourcing and Collaborative Governance for BRT in Transition: Monitoring and Analyzing the EDSA Carousel in Metro Manila for Strategic Planning and Policies

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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. In this study, the researchers harnessed the power of crowdsourced open data in building a fleet monitoring system for road-based public transportation using EDSA Carousel bus operations in Metro Manila as a use case. Through collaboration with operators and drivers, the *SafeTravelPH* platform was used to collect and analyze real-time data on vehicle location, boarding and alighting, and bus occupancy. Monitoring objectives were framed within the PUV Modernization Program of the Philippine government. The research found that crowdsourced data can effectively capture operational parameters through a combination of technology and active human participation.

Keywords: Crowdsourcing, telematics, big data analytics, collaborative governance, BRT

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. Travel demand remains largely uncertain, brought about by health risks confounded by the reopening of the economy. Second, the infrastructure was largely ad hoc augmentation of the existing MRT stations, and a lot of stops were placed under pedestrian footbridges that are not designed to carry queues of EDSA busway 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 especially with uncertainties, resulting in highly varied reliability and capacity of the busway. Currently, the EDSA busway runs with 273 operating units of the 550 authorized units from 31 bus operators. The EDSA busway's success, 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.

Around the same time as the nation-wide 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 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. In the platform's development, a collaborative research partnership was forged between the University, the LTFRB, and the Bus Consortium to promote and deploy the application.

1.2 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 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. According to the Metropolitan Manila Development Authority, traffic volume along EDSA – whose capacity is around 245,000 vehicles a day – has risen to 385,000 vehicles a day n 2019 from 321,000 a day in 2016[1].

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 (Figure 1). 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. The route has 23 official stops as per the LTFRB MC 2020-019 as shown on Table 1. By the end of 2020 there are 550 authorized units running on the route.

[1] https://www.philstar.com/nation/2019/07/02/1931192/edsa-traffic-acceptable-2022-dpwh

Table 1. Characteristics of the EDSA Busway

Route Length	28.1 km
No. of Stops	27 stops
Design Speed	30 kph
Number of Authorized Units (NAU)	550
Number of Operating Units (NOU)	428
Number of Operators	31
Average Headway (NB)	4.1 minutes
Average Headway (SB)	2.2 minutes

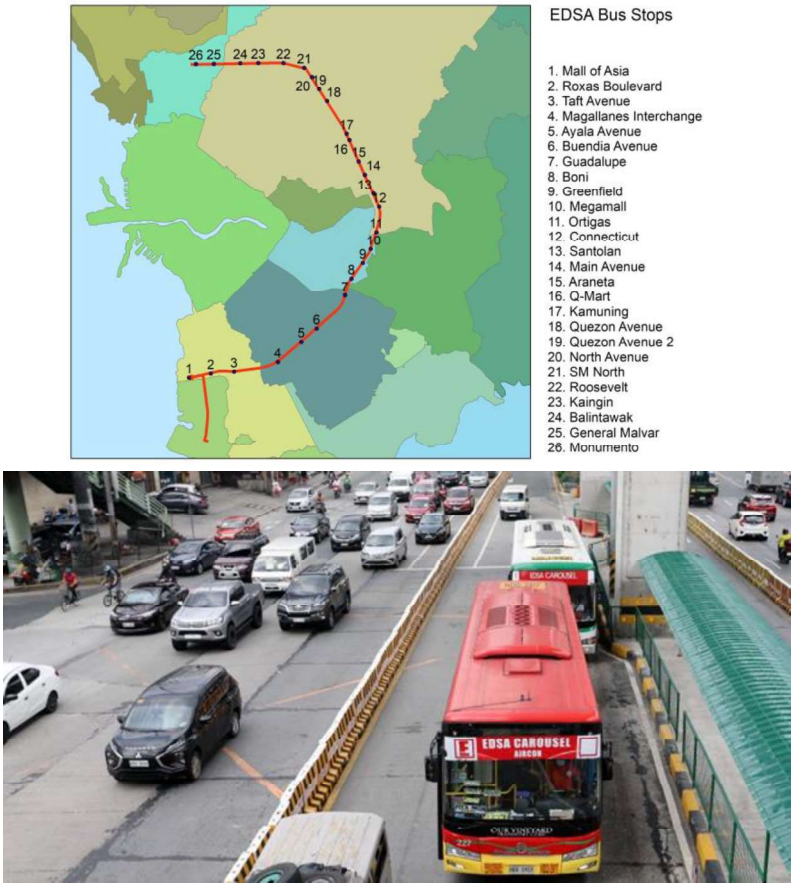


Image Source: Philippine News Agency

Figure 1. Map and Image of the EDSA Carousel

In a prior study on EDSA sponsored by the research team at a time when the Metro Manila lockdown was eased, a public transport survey was lodged to determine headways and occupancies of buses that were part of the initial implementation of the EDSA carousel. In that study, the researchers found that bus arrivals have been quite erratic, and while headways averaged at around 4 minutes per bus, it can reach up to 62 minutes before a bus arrives (Figure 2 and Figure 3). The EDSA carousel was in transition: operating buses were constrained by a cap on occupancy to ensure crowding did not occur, while the number of authorized units were restricted. Bus operators nonetheless complied with the restrictions in observance of public health risks, but it was clear from data (Figure 4 and Figure 5) that bus transport has been one of many sectors affected by the pandemic.

Figure 2. Bus arrivals per hour

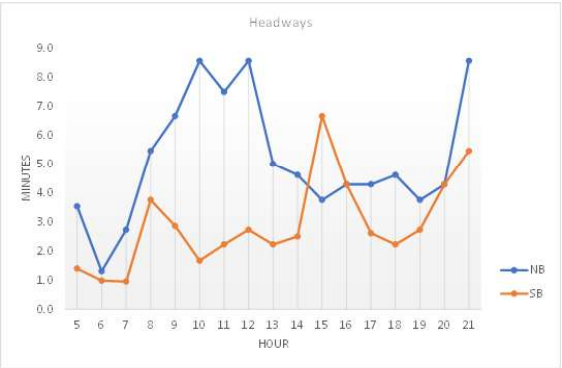


Figure 3. Bus headways per hour

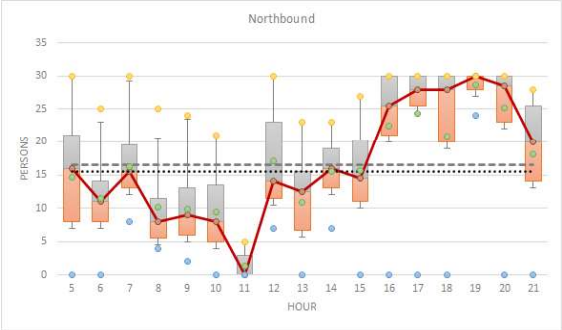


Figure 4. Boxplot of observed occupancies of southbound trips per hour

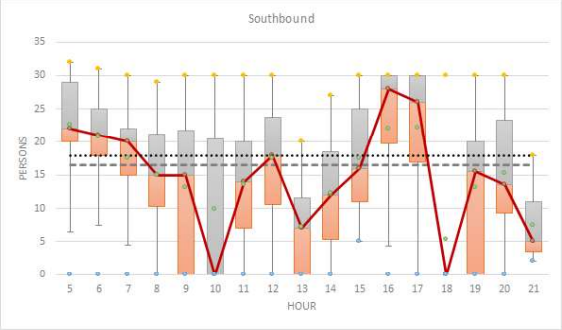


Figure 5. Boxplot of observed occupancies of southbound trips per hour

Source: Unpublished survey results. The surveys were part of preliminary research on the EDSA carousel service post-lockdown

1.3 Research Objectives

The following are motivations to this research:

1) There is a lack of robust non-commercial systems for monitoring road public transport performance that can provide reliable and consistent monitoring of public transportation in Metro Manila. This limits the capacity of government and private sector in creating strategies for improving service quality.
2) Upon the implementation of MC 2020-019 of the LTFRB, the EDSA busway has not been clear of challenges based on public feedback. There seem to be real-world issues such as reliability and capacity that need monitoring data to be addressed with proper response based on scientific data.
3) With the rationalization of bus routes, travel itself was shaken, with commuters adjusting to the new transfers and route coverages. Lack of information on the routes at the onset caused a lot of confusion from commuters. On the other hand, the fear of exposure to COVID19 affected travel demand. These two points led to low occupancies and consequently poor revenue for road public transportation.
4) At the time of writing, travel demand seemed to gradually return to pre-lockdown levels even without students commuting due to stay at home directives during the pandemic. However, route rationalization restricts the return to original public transport supply as the government handles revision and provision of new franchises.

5) When the restrictions brought by the pandemic expires, the problem of sparse monitoring data for fleet management and bus planning will persist without current options in public transport monitoring systems. Existing commercial tools as of yet lack integration, are costly, and do not seem to capture the needs of the public transport system during the pandemic and beyond.

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 using mobile phone application, Internet of Things (IoT), GIS and big data approaches at an operational level to inform strategic planning and eco-driving policy. At the macro-level, the research aims to identify key sections of the EDSA busway that are sources of inefficiency that would point authorities and stakeholders to further investigate, formulate strategies and innovate given that the EDSA busway is new. The busway was designed based on the EDSA BRT proposal and data analytics would be key in constantly improving the route's service.

The overarching goal of the research is to propose a robust approach in bus performance data collection and analytics in view of the National goal of modernizing public transport technology and operations in the Philippines.

2. LITERATURE REVIEW

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). Based on these, the role of crowd can be distinguished as follows:

a) *Crowd as sensors*: people generate raw data just because some processes are automatically performed by sensor-enabled mobile devices (e.g. processes run in the backend by GIS receivers, accelerometers, gyroscopes, magnetometers, etc.) which can be later on used for a purpose (i.e. mobile phone coordinates for positional

triangulation, traffic flow estimates, etc.). This type of data collection has been defined elsewhere as "opportunistic crowdsourcing". Opportunistic crowdsourcing requires very low data processing capabilities (if any) on the side of participants and is the most passive role in the contributing information chain.

b) *Crowd as social computers*: people generate unstructured data mostly by using social media platforms for their own communication purposes (e.g. sharing contents or socializing in social media). Social media users do not process information in any specific form, but these data can later be reused to extract semantically structured information. As in a) there is no explicit participatory effort in any crowdsourced initiative or project.

c) *Crowd as reporters*: people offer first-hand, real-time information on events as they are unfolding (e.g. they tweet about a hurricane making landfall and the reporting damages in a specific location). This user-generated content included valuable metadata added by users themselves (e.g. hashtags) than can be used as semi-structured, preprocessed data.

d) *Crowd as microtaskers*: people generate structured, high quality, interpreted data by performing some specific tasks over raw data (e.g. labeling images, adding coordinates, tagging reports with categories, etc.). This role requires an active participation of users in the effort and it may exploit special skills or require different levels of previous training.

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 Crowdsourcing Technology

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. Part of the research in its development was the conduct of a series of design thinking workshops with drivers, operators and government discussing user experience and proposing the process upon which the platform was built.

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.

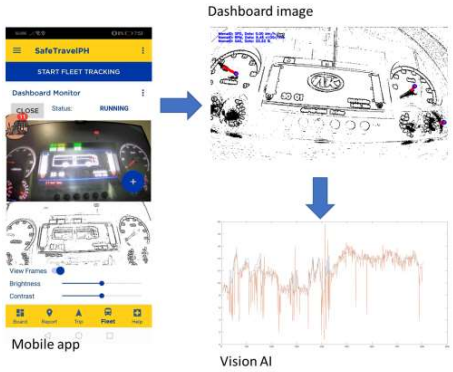


Figure 7. Image processing example

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 Analytical Framework

The monitoring and analytics framework of this research frame bus performance within the following service qualities:

- Safe and energy-efficient operating speeds and acceleration/deceleration
- Safe loads compliant with pandemic restrictions
- Reliable travel time and minimal idling

Because formal EDSA bus schedules do not exist at the time of this study, on-time arrivals cannot be monitored, although schedules can be developed hereafter. The EDSA busway is expected to have consistent travel time as a dedicated and protected bus lane. The study also postulates that aside from idling time, clustering of vehicle data feeds over space-time indicates waiting and/or idling and refines the monitoring framework.

Based on the monitoring objectives, the following parameters are monitored:

Table 2. Monitoring framework using crowdsourced and automatic vehicle data

Objective	Monitoring Parameter and Methodology	Unit	State in "Control"
Safe and energy-efficient operating speeds and acceleration/deceleration	Speed	Kilometers per hour (kph)	Bus Lane Speed Limit: 30 kph Highway Speed Limit: 60kph
	Critical speed (85th percentile)	Kilometers per hour (kph)	The critical speed is the speed by which the monitored vehicles operated on under which 85% of observed speed fall; the critical speed indicates the level of extreme speed
	Acceleration/deceleration over location	Meters per second squared	
	Speed by time curve	(control chart)	Stable speed with minimal variation
	RPM (over time and location)	Smoothed RPM	
Safe loads compliant with pandemic restrictions	Occupancy	passengers	Occupancy should not exceed the restrictions
	Occupancy over time	passengers/hour	Occupancy should be within bus capacity
Reliable travel time and minimal idling	Travel time	hours	
	Idling time	hours	
	Round trips	count	
	Clustering (DBSCAN)	Cluster size and radius	Clustering patterns should be sparse based on DBSCAN

3.3 DBSCAN Clustering and Analysis

Density-based spatial clustering with noise (DBSCAN) is a widely used methodology for spatial point data analysis and is well-documented in computing and statistical literature. The method is quite straightforward, albeit done iteratively by varying its two parameters: the maximum radius, and the minimum cluster size. In this study, the "optimum" clustering is decided when the chosen epsilon and cluster size arrives with the lowest number of changes in

cluster membership. At each iteration of epsilon and cluster size, the number of resulting clusters and the change in clusters are examined.

This study employed (DBSCAN) for multiple purposes:

1. Reveal underlying patterns of spatial point data over the EDSA trajectory;
2. Determine outliers that muddle spatial patterns;
3. Identify points of congestion (clusters) along the EDSA busway route; and
4. Segment EDSA based on an "optimum" clustering

DBSCAN is also capable of identifying segments of the transit corridor where congestion or idling is frequent. Note that the data comprise vehicle location feeds per second, thus, areas where data feeds are very dense (indicative of slow vehicle movement) tend to be members of the same cluster under DBSCAN. DBSCAN adds value to the monitoring by revealing patterns of clustering vehicle data feeds over space and time and presenting such patterns visually through GIS. A similar approach can be found in the paper by Sultan et. al. (2017).

4. RESULTS

4.1 Crowdsourced Data

The data used for this study covers 7 days starting November 23, 2020. There are four bus drivers who participated in the study. The drivers were trained to use the mobile app and record passenger boarding and alighting during their respective shifts. Table 3 and Figure 8 shows the availability of data for the drivers per monitoring day. As can be seen from the table, some drivers did not participate on certain days due to the shifting of work.

Table 3. Daily participation of each driver over monitoring days

	Participation in the Monitoring (hours)			
Date of Operation	DriverE	DriverJ	DriverM	DriverP
11/23/2020	12.9	13.1	12.5	4.2
11/24/2020	14.7	3.8	14.1	
11/25/2020	13.6		13.9	
11/26/2020	13.8		13.7	13.3
11/27/2020	11.9	5.1		11.9
11/28/2020	2.0			12.3
11/29/2020				5.5
TOTAL	68.9	22.0	54.3	47.2

4.2 Route Characteristics

The Figure 8 show the 85th percentile (also called the critical speed) of all the calculated spot speed values during collection of vehicle tracking data. It shows that the 85th percentile for the drivers lie mostly between 36 to 51 kph, with Driver P registering the highest critical speeds and Driver E registering the lowest recorded critical speeds. The 85th percentile in spot speed surveys are often used in planning as a guide to determine the highway speed limits (ITE, 2021).

The collected critical speeds from the four drivers exceed the 30 kilometers per hour design speed of the Department of Transportation for the bus lane. The results show us that the

separation of the bus lanes from the rest of the road traffic gave the buses more freedom to increase their speed to drive in between bus stops to serve their passengers more efficiently.

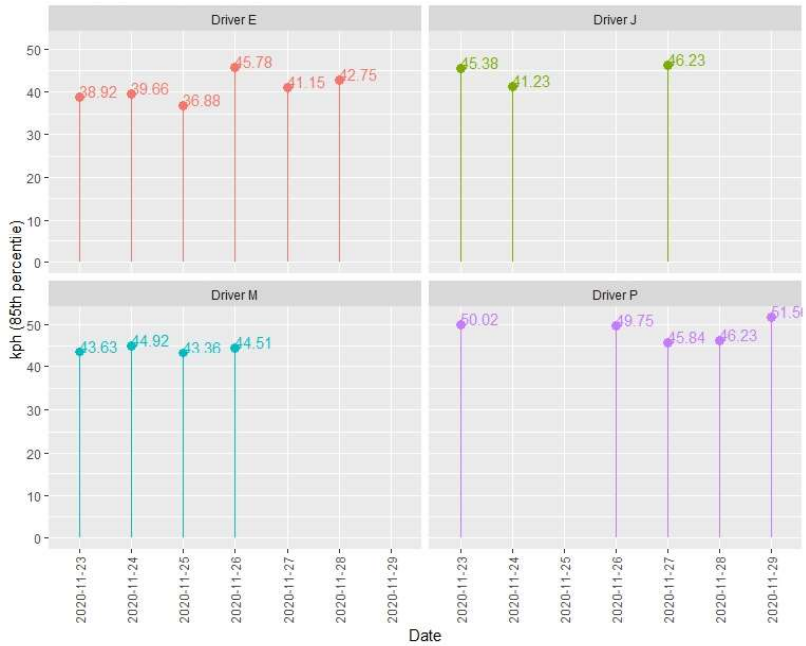


Figure 8. “Pin” chart of critical speed per day of each driver

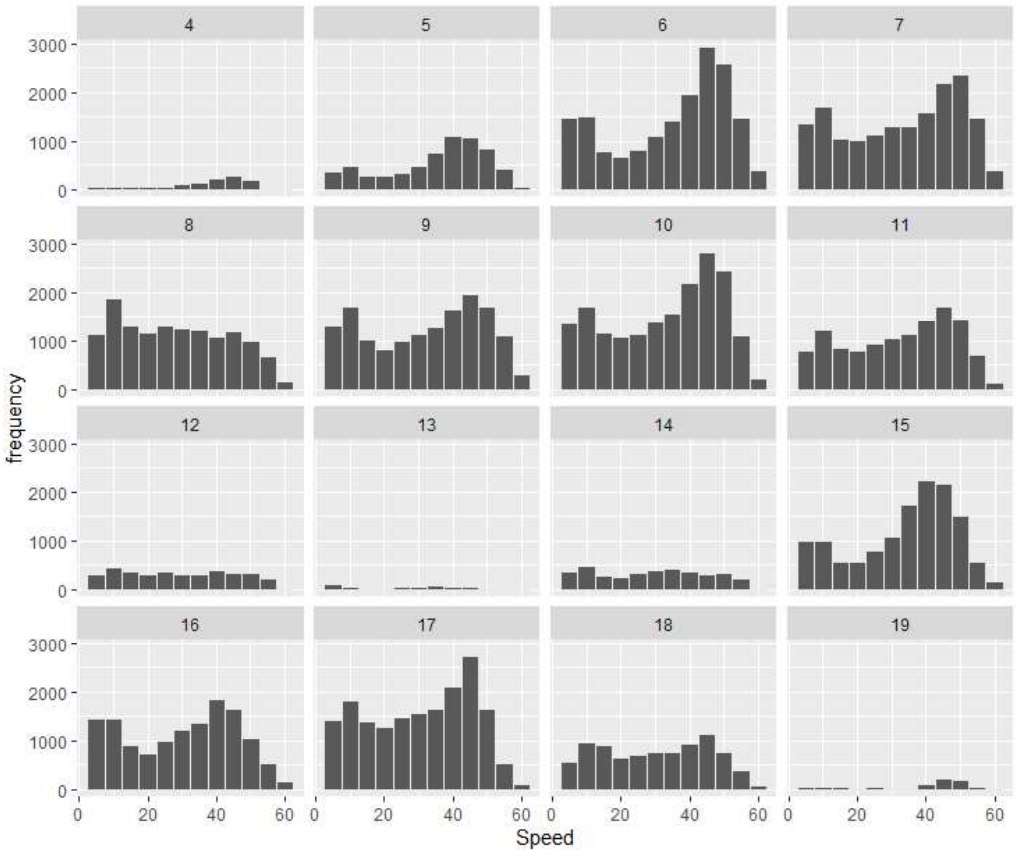


Figure 9. Histogram of monitored bus speed per operating hour

Figure 9 presents the distribution of observed bus speeds sans outliers and extreme observations. Most of the time, buses on the EDSA carousel route operate typically within 40 to 50 kph. The frequencies also illustrate how intense the vehicle feeds are per hour. The hours with the most speeds are from 5:00 to 7:00 during the morning hours and from 16:00 to 17:00 during the afternoon hours.

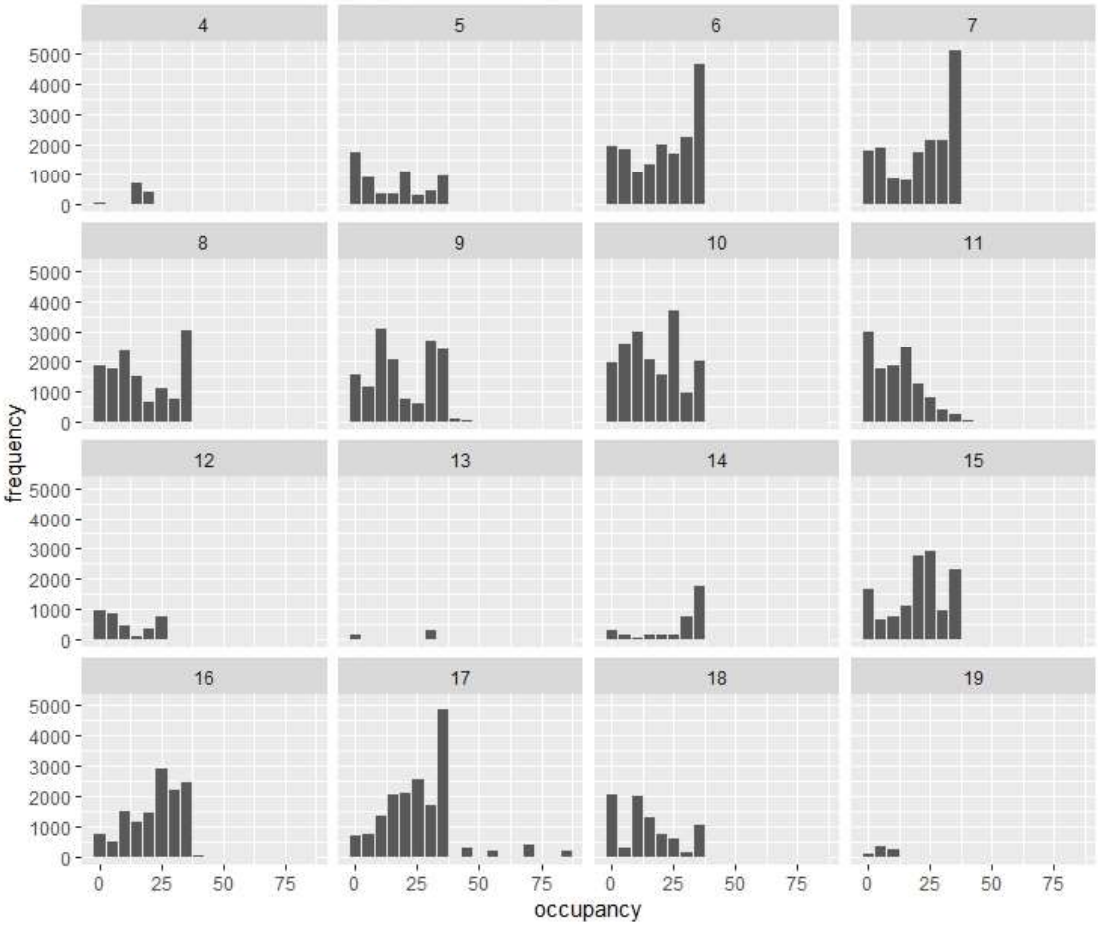


Figure 10. Histograms per hour of observed occupancies

The histograms (Figure 10) above show the frequency of the occupancy of the buses for all drivers starting 04:00 (4AM) and ending at 19:00 (7PM). Histograms show that highest occupancy times occur during morning from 6AM to 7AM and during the evening at 5PM as shown by the high frequency for the occupancy value of 30. Occupancy values begin to go low after these hours with the values going almost zero during the noontime.

The data also shows if the bus goes beyond the mandated capacity. The histogram at 17:00 (5PM) shows bars that are in values beyond the mandated 50% capacity for buses (33 passengers) during the General Community Quarantine that is being implemented at that time. While there are times that the bus is beyond allowable occupancy during the General Community Quarantine, these instances happen during the time where passenger demand also increases because of the end of work hours. Also, since occupation data is manually input by

the driver, human error cannot be ruled out even though these possible input errors only represent a negligible part of the whole vehicle tracking data.

4.3 Speed and Occupancy by Driver

Figures 11 to 15 show the disaggregate per second load profile and the speed profile of all the drivers for the day of November 23, 2020. The light blue bars and the black lines represent the spot speed of the bus and the number of passengers occupying the bus at a certain second, respectively. All data collection was conducted during their revenue runs from around 5:00 AM until 7:00 PM, except for Driver P who ran from 6:00 AM to 11:00 AM that day.

The number of trips done by Drivers E, J, M, and P are 6, and only 3 for Driver P who only ran for 5 hours and 13 minutes that day.

In examining the load profiles and the speed profiles of each driver, we can see that the areas where speed and the occupancy go high now mostly coincides, indicating that the buses now travel faster during their revenue runs.

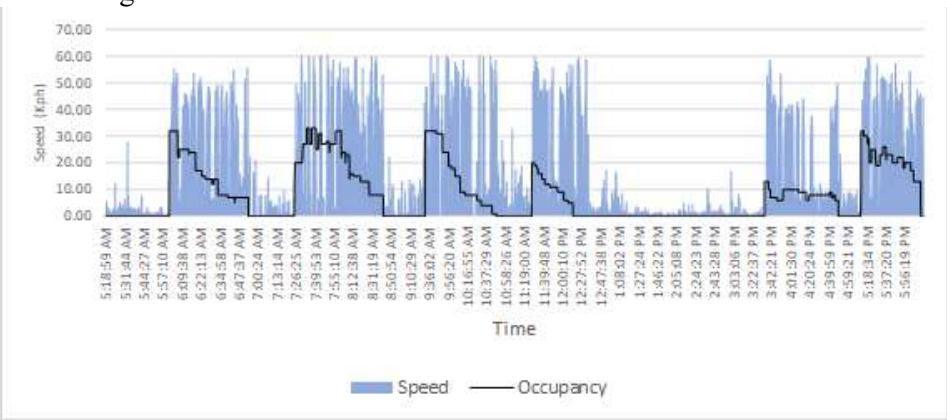


Figure 11. Speed and load profile over time – DriverE

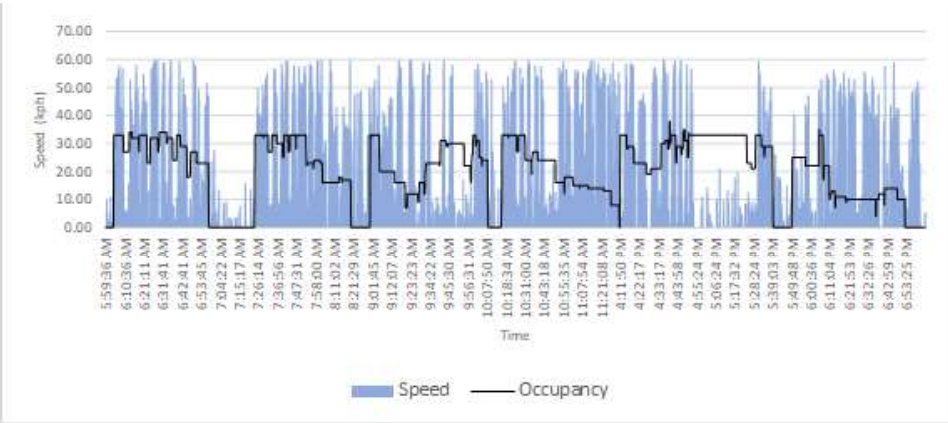


Figure 12. Speed and load profile over time – DriverJ

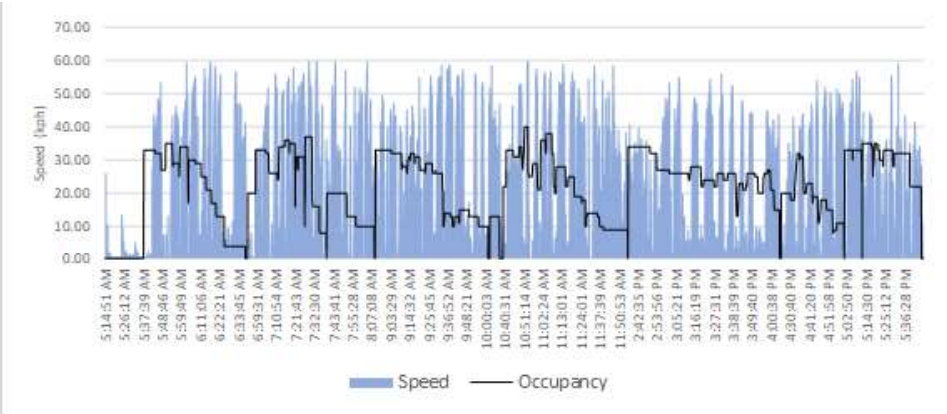


Figure 13. Speed and load profile over time – DriverM

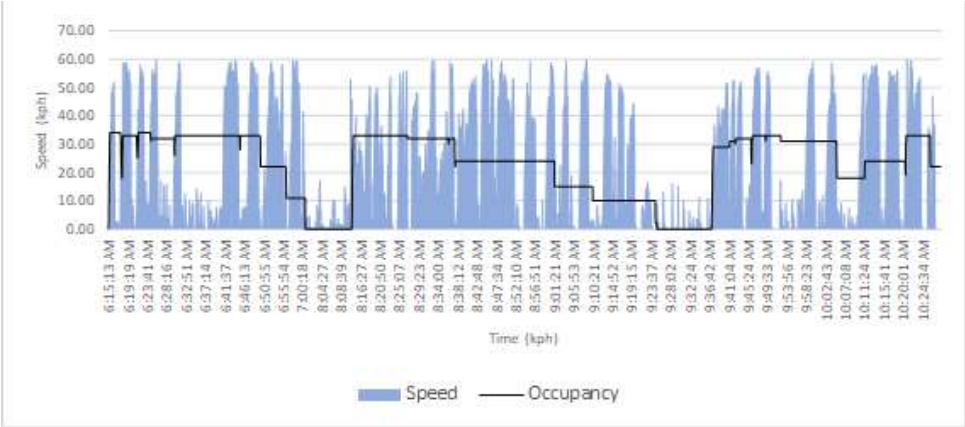


Figure 14. Speed and load profile over time – DriverP

The data also shows if the bus goes beyond the mandated capacity. The histogram at 17:00 (5PM) shows bars that are in values beyond the mandated 50% capacity for buses (33 passengers) during the General Community Quarantine that is being implemented at that time.

The line chart below (Figure 15) corresponds to the average hourly occupancies of each driver from 04:00 (4:00 AM) to 19:00 (7:00 PM) during the survey days. For all drivers, the occupancy goes up from 5:00AM to 6:00AM during the daytime peak and from 5:00PM to 6:00PM in the nighttime peak. The nighttime peak has higher average occupancies than the daytime peak.

For individual drivers, Driver E got the lowest daytime and nighttime peak than his peers while Driver P got the highest daytime and nighttime peaks of the four drivers who participated, respectively.

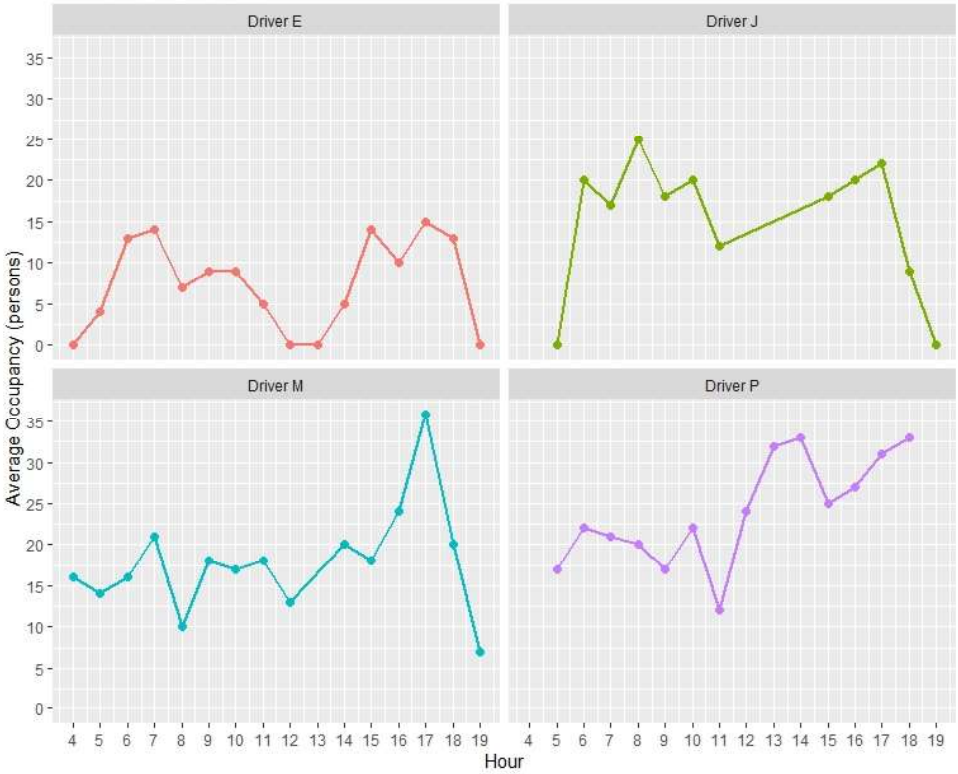


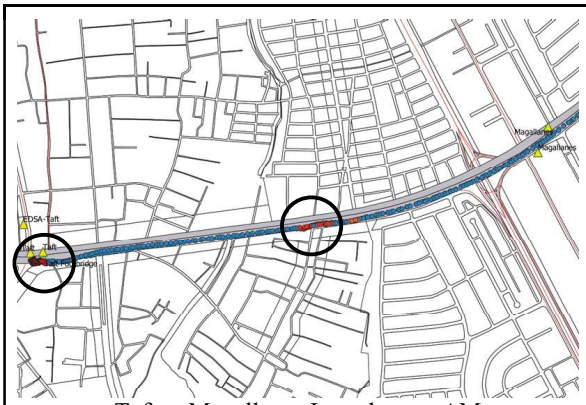
Figure 15. Hourly Occupancy by Driver

4.4 Cluster Analysis for Traffic Detection for Segments

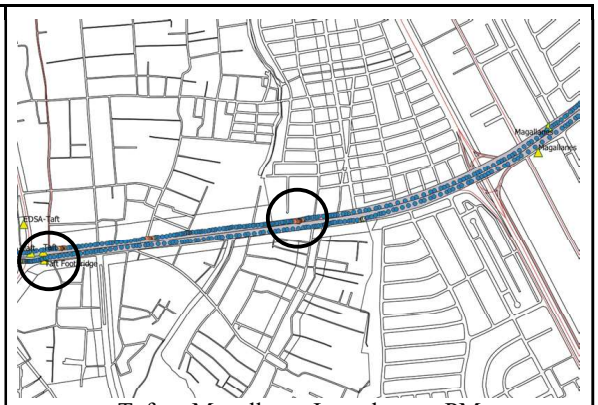
Based on the iterations of DBSCAN, it seems the best clustering parameters that minimizes noise without losing too much information on the vehicle tracks is using a minimum cluster size of 15 and a cluster radius epsilon of 17 meters. Setting the minimum cluster size at 20 results in clusters that highlight the traffic points along the EDSA busway but loses insights on sections that are relatively stop-and-go. The charts in Figure 16 below illustrate sections of EDSA busway. All figures on the left illustrate AM clustering, while those at the right illustrate PM clustering. The final cluster parameters are: Final Cluster Parameters: minPts = 15, epsilon = 17 meters, Final Clustering: 24 clusters (AM), 58 clusters (PM). Circled points in each figure indicate the areas where clustering are found.

The following observations arose from the chosen clustering:

1. As expected, clusters emerged from locations where vehicle location feeds are most frequent in a short period of time, indicative of either regular congestion areas or waiting areas.
2. The following segments have consistent clusters in the AM and PM: Ayala Station, Guadalupe Station, Ortigas Station (Megamall), Main Avenue Footbridge, Q Mart Footbridge, North Avenue Station, Roosevelt, Balintawak, and Monumento.
3. Taft Footbridge consistently has a long clustering in the morning from 5AM.



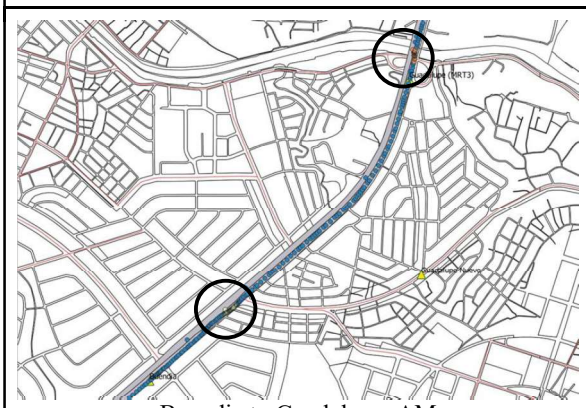
Taft to Magallanes Interchange, AM



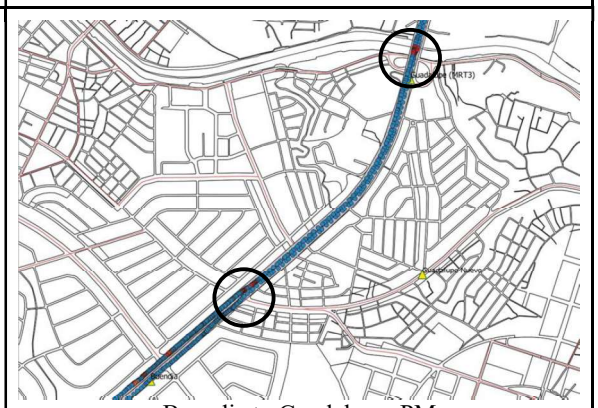
Taft to Magallanes Interchange, PM

Ayala to Buendia, AM

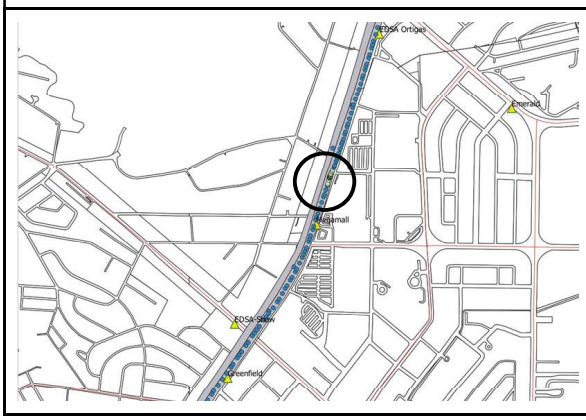
Ayala to Buendia, PM

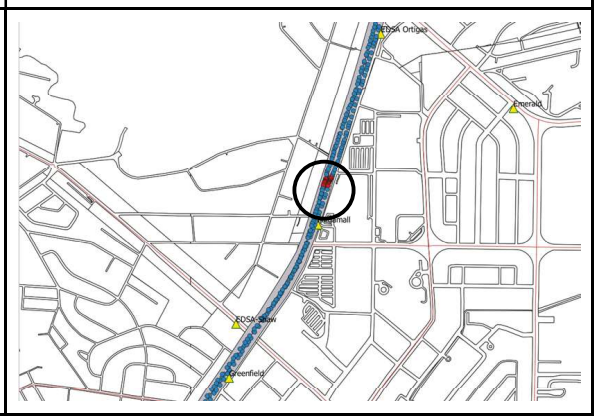


Buendia to Guadalupe, AM



Buendia to Guadalupe, PM





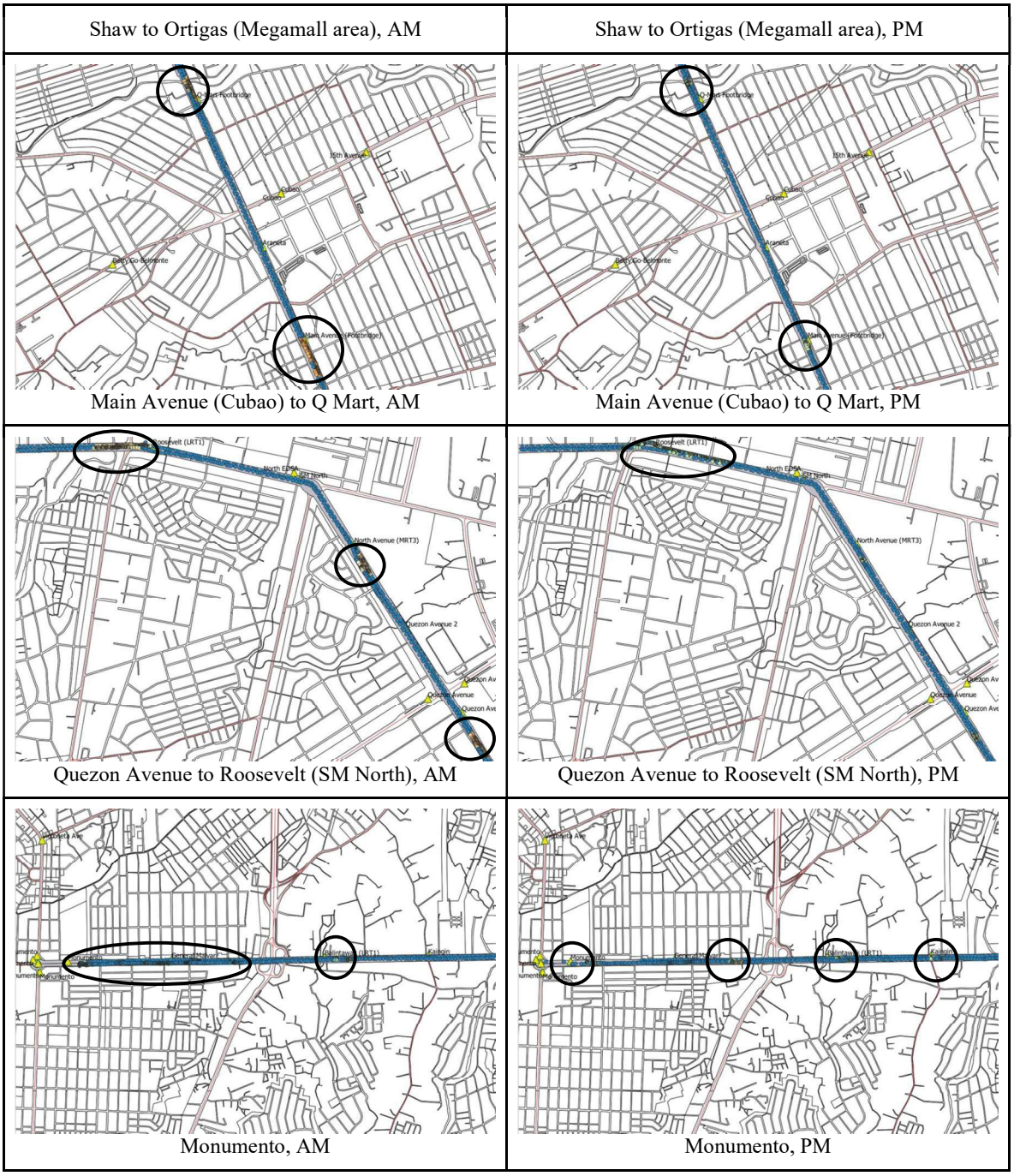


Figure 16. Segmentation of EDSA busway: results of DBSCAN

4.5 Real-time RPM Monitoring and Eco-Driving

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. In Figure 17, using Exponential Weighted Moving Average (EWMA) of RPM readings, the patterns of driver acceleration/deceleration within the monitoring period is presented, where there seems to be some erratic RPM levels between 5:40 AM when the driver is loading passengers, until 5:43AM when the driver begins to accelerate towards cruising to the next bus station.

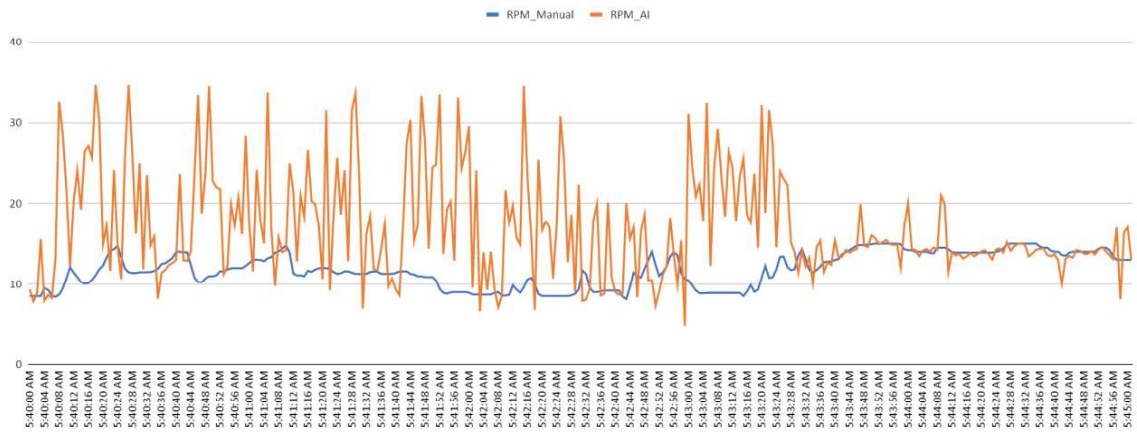


Figure 17. Image-derived and smoothed RPM Readings

The data suggests that there is value in applying the monitoring approach when coupled with smoothing methods to provide accurate monitoring data on RPM. Moving forward, there can be further processing where the readings can be matched with locational data (e.g. the GPS information also in this study) to also relate driving behavior variation at different points in the monitoring area. This will also be useful in relating topographic and infrastructural attributes to the readings.

5. DISCUSSION AND CONCLUSION

This study demonstrated the use of telematics and big data analytics through crowdsourcing and open platforms in analyzing road public transport performance. In the case of EDSA Carousel, this paper analyzed the performance of buses through one week of sample monitoring and crowdsourced data from November 23-29, 2020, highlighting the ramifications of the quarantine restrictions still prevailing around the monitoring period due to the COVID-19 pandemic. Through the monitoring exercise, the study found the following:

- During the monitoring period, buses seemed to comply with quarantine restrictions on bus loading, which was well within 35 passenger occupancy. Assuming that there is minimal human error in the passenger counting method, the passenger data collected from the app gives an accurate picture of the passenger occupancy of each buses throughout the revenue hours.
- The average speed of buses operated above bus lane design speed of 30 kph although within the EDSA speed limit of 60 kph. This indicates that the design speed is too slow for the bus service to efficiently move passenger from their respective origins and

destinations. Given the critical speed that was determined in the study, a review of the bus lane speed limits should be done.

- The DBSCAN effectively detects idling and traffic points along the corridor, as the results pointed to clustering at the bus stops along the EDSA bus. With some adjustment of the maximum radius and minimum cluster size, DBSCAN is also able to suggest idling points other than the stops, which is useful for recommending investigation towards traffic management at identified stretches of clustering. DBSCAN, however, cannot characterize the traffic in detail and should thus be used hand-in-hand with field verification and other performance metrics (e.g. speed, idling time at subsection).

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. DBSCAN, while useful in detecting noise and relating congestion to GPS readings, should better be framed within a decision framework for traffic management especially in the context of better bus service. Nonetheless, this research has shown promise in crowdsourced real time data processing for EDSA busway that can be replicated in other bus corridors.

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