Evaluating the Fuel Efficiency and Eco-Driving Potential of the EDSA Carousel using On-Board Diagnostics (OBD) and Mobile Crowdsourcing

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Abstract: This study examines how engine RPM, acceleration/deceleration, and pressing of the accelerator pad as the physical and skills-based eco-driving behavior that drivers can enhance contribute to fuel savings. For the EDSA Busway case, however, the impact of the operating system of the route that expects to move more than 500 buses per day to the overall bus operations and commuting efficiency were also explored in this study. It is found out that the drivers can save up to 8.12 liters when cruising and eco-driving behavior over an hour. Meanwhile, the determined end-to-end travel time of the busway, highly variable from 1.5 to 2.45 hours, serves as a note that travel speed for commuters is also bad for the operations of buses and for the environment. These findings are useful to encourage the stakeholders to use data to operate in an environment and commuter friendly way.

Keywords: Bus Operations, Fuel Efficiency, Eco-driving, On-board Diagnostics, Mobile Crowdsourcing

1. INTRODUCTION

1.1 Background

During the COVID-19 pandemic in 2020, one of the solutions implemented by the Philippine government in addressing the mobility restrictions and demand for safe and efficient public transport in Metro Manila was the introduction of the EDSA Carousel to complement the existing MRT3 operations which was operating on a limited capacity due the community quarantine restrictions. The bus operations on the EDSA Carousel was supplemented by the implementation of the Service Contracting Program, more commonly known to commuters as the *Libreng Sakay* Program. Implemented by the Department of Transportation (DOTr) and the Land Transportation Franchising and Regulatory Board (LTFRB), the program aimed to provide economic relief as well as raise and improve the level of service of road-based public transport services. As such, the Service Contracting Program allowed commuters to get to work and at the same time allowed operators to continue its operations with subsidy from the government.

Alternatively referred to as the EDSA Busway, bus units from the two consortia operated along the inner lanes on the stretch of EDSA and full operations started on July 1, 2020. The EDSA Busway initially had 15 bus stops but as of August 2023, it has a total of 21 bus stops. During the time of its inception, the EDSA Busway was regarded as "Light-Quick-Cheap transport solution that can be made available within 6 weeks" (Gaspay, et al., 2023). On the other hand, the outermost lanes of EDSA were designated as pop-up bike lanes as part of the the Bayanihan to Recover as One Act or Bayanihan 2, otherwise known as under Republic Act No. 11494 signed into law on September 11, 2020 which mandated the provision of a network of bicycle lanes nationwide to enable people to use the bicycle as an alternative mode.

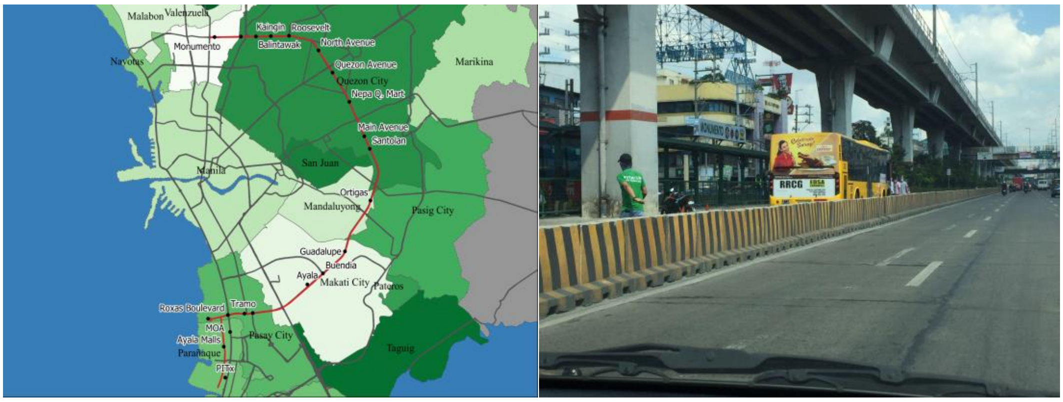

Figure 1: EDSA Busway Route and Busway Station Layout

Recently, a group of operators whose units operate on the EDSA Carousel expressed their concern regarding their loss in profit. Since the Service Contracting Program ended in December 2022, these bus operators have proposed the reclaiming of the two outermost lanes of EDSA in order to increase the number of buses they can deploy to which MMDA said that "bringing back passenger buses along EDSA under the old system would cause traffic congestion." (Ong, 2023).

With the price volatility of diesel fuel and worsening energy security situation in the country, the introduction of eco-driving concepts that improve fuel consumption, together with the overall improvement of tactical operations and bus driving behavior would go a long way in alleviating the challenging problems of bus operators.

1.2 Research Objectives

This study aims to evaluate the fuel efficiency of public transport bus operations on the EDSA Carousel and analyze the potential of eco-driving concepts in improving operational management. At the same time, the study explores the innovative use of on-board diagnostics and mobile crowdsourcing data to generate a database of different driving behavior and engine performance of bus models operating on the EDSA Carousel.

2. STUDY AREA

2.1 EDSA Carousel

Epifanio de los Santos Avenue, popularly known as EDSA, is a 24-kilometer road traversing through Metro Manila. It is the main corridor of Circumferential Road 4, which encircles the metropolis through the cities of Caloocan, Quezon City, San Juan Mandaluyong, Makati and Pasay. With an average annual daily traffic of 385 thousand vehicles in 2022 (MMDA, 2022), it is the busiest arterial road in Metro Manila. Traffic congestion is a main issue in the highway as the road only has daily capacity for 300,000 vehicles (Cos, 2022).

There have been multiple bus routes along different segments of the highway, with some of these routes overlapping each other and competing with each other for passengers. The Mega Manila Public Transport Planning Support System (DOTC/UP NCTS, 2012) states that there were 47 routes that go through EDSA before the EDSA Carousel was established. Aside from the buses, there is a railway based public transportation system called the MRT 3, which runs along the highway from North Avenue to Taft Avenue.

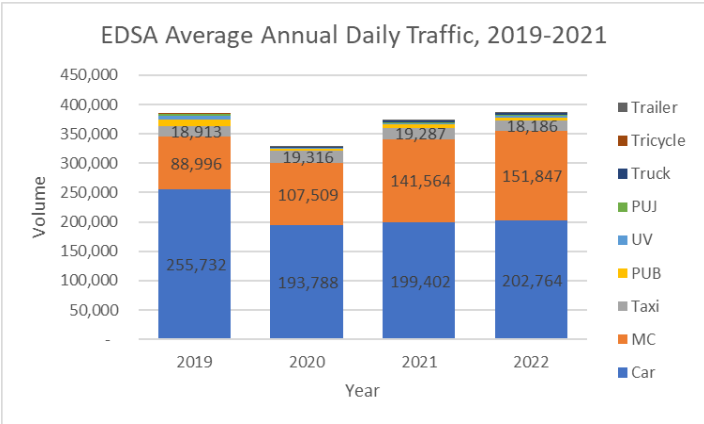

Figure 2: Average Annual Daily Traffic in EDSA (Source: MMDA)

When the COVID-19 pandemic hit, all public transportation was halted, save for some that served the healthcare workers to the hospitals during the strictest of the lockdowns from March 2020 to May 2020. Upon the resumption of public transportation services in June 2020, the Land Transport Franchising and Regulations Board (LTFRB) released the Memorandum 2020-19 which reorganized the bus routes in Metro Manila and adjacent provinces. This memorandum established the EDSA Busway or “Carousel” which is now the lone bus route that runs from the north terminus in Monumento to the south terminus in PITX throughout the length of EDSA and Macapagal Boulevard. The route also mostly runs along a separated bus lane in the innermost lane, making some segments separate from the general traffic. The route has an approved Number of Authorized Units (NAU) of 550 bus units, with the buses required to follow specifications on the bus units that were laid out in the Omnibus Franchising Guidelines. The NAU has now been increased to 565.

2.2 EDSA Carousel Operations

The EDSA Carousel is currently under the supervision of the Department of Transportation (DOTr) and the Metropolitan Manila Development Authority (MMDA). Through LTFRB Resolution No. 81 Series of 2020, two (2) transport groups composed of city bus operators, Mega Manila Consortium Corporation and Metro Mega Consortium Transport Corporation, formerly ES Transport and Partners Consortium, was granted the special permit to operate on Route E, otherwise known as the EDSA Carousel.

According to LTFRB, as of April 2023, their inventory records a total of 533 buses plying on the EDSA Carousel spread across 47 bus operators. Jell Transport Inc. has the most number of units plying on EDSA (98 units), followed by Earth Star Express Inc. (35 units), HM Transport (28 units), ES Transport (26 units) and Kellen Transport Inc. (25 units).

For July 2023, MMDA noted an average of 324 and 320 dispatched bus units from the Monumento and PITX stations respectively out of 565 authorized units in EDSA. In addition to this, a total of 28,118 trips were noted in Monumento station, while a total of 25,942 trips were recorded from the PITX station for the whole month of July.

Figure 2 illustrates the average travel time of 314 buses during a typical trip on July 11, 2023. The average travel time between end-to-end stations ranges from 1 hour and 35 minutes to 2 hours and 43 minutes. This differs from the travel time of 45 minutes to 1 hour asserted by transportation authorities. During peak times (5am - 8am and 4pm - 7pm), commuters experience shortest travel times while those traveling during off-peak times undergo relatively longer durations.

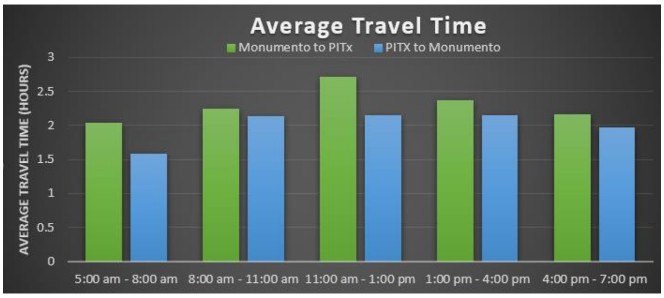

Figure 2: Average Travel Time from end-to-end Station (July 11, 2023)

The time gap between consecutive buses for each day of the week at the PITX station is illustrated in Figure 3. The shortest interval is on Monday, where buses have an average time gap of 62 seconds. Meanwhile, the longest average time gap was observed on Sunday, with buses arriving roughly every 82 seconds due to a lower passenger volume.

The time interval between successive buses for each day of the week at Monumento Station is depicted in Figure 4. The shortest headway is observed on Tuesday, with an average time gap between buses of 58 seconds. Conversely, the longest average time gap happened on Sunday, where buses arrived approximately every 76 seconds due to the lower number of passengers. This results in extended waiting times for passengers.

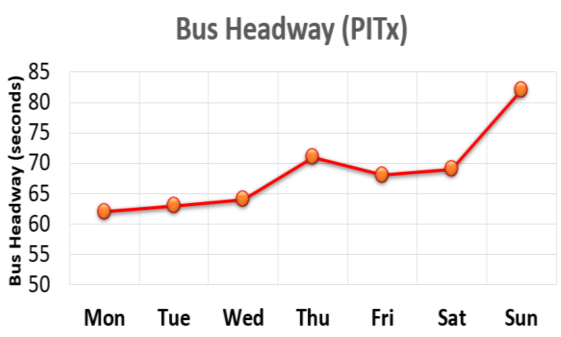

Figure 3: Bus Headway at PITX

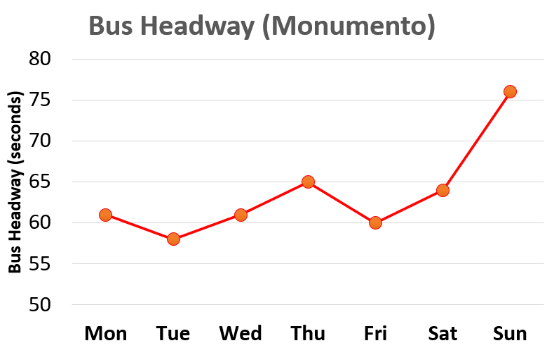

Figure 4: Bus Headway at Monumento

2.3 Need for Bus Operations Monitoring

Figure 3 shows the total number of buses plying on EDSA for the month of July 2023 based on the MMDA Bus Management Dispatch System (BMDS). It is shown that the maximum utilization rate for the month of July did not go over 65% and a low of 47.1% utilization of all authorized units. There is a low utilization of buses given the 565 authorized units wherein only a daily average of 330, and a total of 460 units were dispatched in July 2023. The BMDS also showed that there is a mismatch with the number of units dispatched from the Monumento and PITX stations. The disconnect may be caused by a malfunction of the units in between the two (2) stations, traffic violations, or drivers cutting trips.

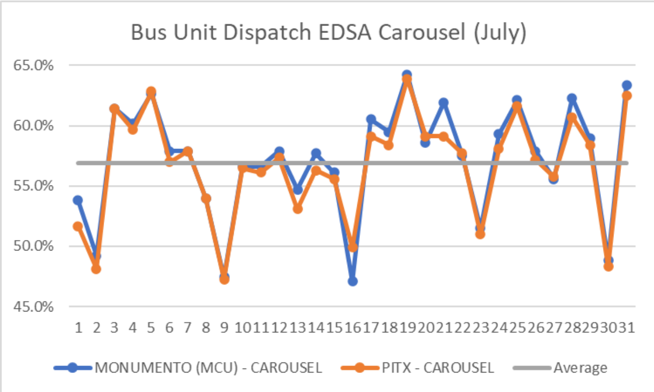

Figure 5: Bus Unit Dispatch EDSA Carousel, July 2023

Continuous analysis and monitoring of bus operations on EDSA is essential for enhancing the planning and control mechanisms of relevant authorities, the bus industry, and the general public using the services. The utilization of bus telematics has predominantly centered around Automatic Vehicle Location (AVL) and automatic passenger counting (APC) systems, which have the capacity to collect extensive amounts of diverse operational, spatial, and temporal information. When these data are effectively captured, stored, and examined, they offer significant potential for enhancing the efficiency of public transportation. This potential is manifested through the facilitation of improved management strategies in areas like service design, scheduling, and the monitoring of service quality.

3. LITERATURE REVIEW

3.1 Potential of Eco-Driving

According to the Department of Energy (DOE), the energy consumption for transport increased by 1.2 million tons of oil equivalent (MTOE) reaching a total of 11.0 MTOE in 2021 from 9.8 MTOE in 2020. Taking into consideration the easing of mobility restrictions brought about by the pandemic, the transport sector became the most energy-intensive sector in 2021, taking up 31.3% of the country's total final energy consumption. Out of the 11.0 MTOE of the transport sector, 9.9 MTOE (90.5%) is attributed to road transport, which increased from 8.9 in 2020 (Department of Energy, 2022).

Literature points out that through the practice of eco-driving, fuel consumption can be reduced by 25%. Eco-driving can be measured by determining that the vehicle would operate at optimal fuel efficiency, or within the *green area*, through the estimation of parameters including speed, speed variation, acceleration/deceleration, and the continuous improvement through the use of real time data. However, the main challenge of implementing this is that there is a lack of engine load gauge to inform the drivers regarding their position and for them to act accordingly and to stay within the optimal area thus making the concept of the *green area* reduced to RPM green band concept in traditional eco-driving techniques (Huertas, et al., 2017).

Sivak and Schoettle (2012), in their presentation of information about effects on driver behavior on the fuel economy of light vehicles, classified three (3) decision levels: Strategic decision; Tactical decision and Operational decisions. 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 when switching to compressed natural gas (CNG) powered vehicles, a popular energy conservation strategy. Sanguenitti et al. (2017) synthesized prior research on eco-driving behaviors that results in varying fuel consumption saving and outlined six typology of driver's (and shop's/operator's) behaviors that can be the basis of interventions for holistic fuel savings in fleet management. These six typologies were listed as 1) driving, 2) cabin comfort, 3) trip planning, 4) fueling, 5) load management, and 6) maintenance.

3.2 Fuel Consumption Savings and Parameters

Focusing on engine operations, eco-driving practices may be reinterpreted as techniques in reducing fuel consumption by restricting the engine to work within the recommended operational range, otherwise known as the *green area,* where the engine exhibits its highest energy efficiency, or attains minimum fuel consumption. This range has been expressed as a constant range for RPM, and it is referred to as the engine RPM green band (DFT, 2009).

In a field trial with 1156 trips in two cities, deceleration rate, engine RPM, speed, and external factors such as congestion and road slope directly influence fuel consumption (Lois et al., 2019). Likewise, differences in driving styles of drivers using the same vehicle 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 the fuel consumption of a city bus is consumed during acceleration (Ma et al., 2015).

Conversely, a decrease in fuel consumption in an urban area can be achieved through negative deceleration or when deceleration is minimized during smoother rides with less braking. However, fuel savings depend 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 studies showing that engine energy efficiency also depends on engine load therefore extends the engine RPM green band concept of eco-driving—RPM green area, which corresponds to the load vs. RPM area where engines exhibit the highest energy efficiency.

Multiple regression analysis is a straightforward way of correlating vehicle information as independent variables to fuel consumption as a dependent variable (Lee and Son, 2011). Results from previous studies can be used to create a model based on relationships of variables that are 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 the non-linearity of diesel engine dynamics and control system (Chiara et al., 2011).

In their study of the interaction of driving behavior and external factors, Lois et al. (2019) employed a sequential method in data analysis comprising factorial analysis, regression analysis, and path analysis for a dataset of 1,156 trips, and 128 variables. Factorial and regression analyses were done to determine empirically important variables. Path analysis models the relationships among internal and external factors and fuel consumption. At $p<0.001$, the multiple regression method has an r-squared of 0.702, which indicates a 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 algorithm called C4.5. The C4.5 algorithm is said to be better because of its ability to get good classification prediction with minimal computational resources, statistical significance and relative significance of factors can but output decision trees methods and could inform drivers and fleet managers to optimize their operations, and this decision tree method can process continuous input from the driver's telematics data.

4. METHODOLOGY

4.1 Public Transport Crowdsourcing Platform

This study utilized the crowdsourcing mobile application SafeTravelPH, an app that enables real-time vehicle location and occupancy data monitoring and provides a highly-customizable platform for public transport data analysis, visualization and reporting. The platform provides measurements of bus vehicle locations at most every second when cellular signal availability is best and the bus occupancy data which is generated from the surveyor's interaction with the SafeTravelPH app's passenger boarding and alighting buttons.

The SafeTravelPH app was developed at the height of the COVID-19 pandemic. The platform actively engages the government, transport industry providers, and passengers in sharing transformative information to improve public transport by collecting and analyzing real-time data on vehicle trajectory, boarding and alighting locations, occupancy and other public transport operational parameters (Tiglao, et al. ,2023). Figure 6 presents the Fleet Tracking module of the SafeTravelPH app.

The deployment of the mobile application and on-board diagnostics and telematics, through the partnership of bus operators along EDSA busway route, was conducted from July 11 to 28, 2023.A unique combination of Bus Driver-Day of the Week-Bus Unit was considered to be one sample. This is within the assumption that fuel consumption is dependent on the bus unit and the bus drivers' driving practices, and that the demand for public transport varies for each day of the week. A total of 33 unique samples were collected throughout the survey period, each assigned with a unique data code, anonymized in consideration of the data privacy act.

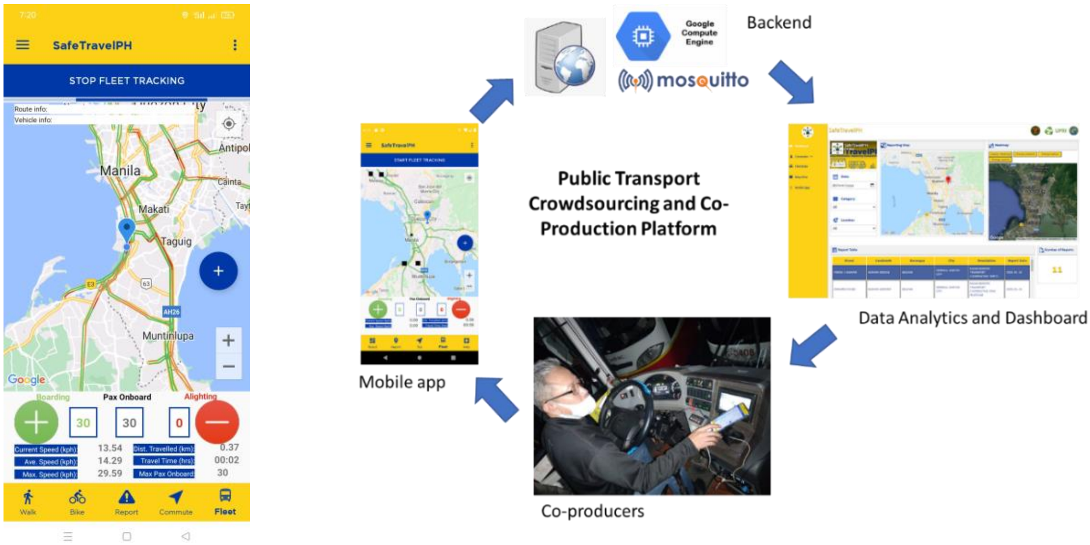

Figure 6: SafeTravelPH App and Information Exchange Platform

4.2 On-board Diagnostics (OBD)

With the modernization initiatives of the government and operators came the bus units that use modern on-board diagnostics (OBD), enabling real-time access to the vehicles' various subsystem conditions. The brand of bus vehicles from the sample are Volvo, Zhongtong, and Higer. The tracker used in the study is the Teltonika FMB003[1] Plug and Track device. FMB003 is a tracking terminal with GNSS and GSM connectivity, which is able to collect device coordinates and transfer them via GSM network to a server. The main feature of the FMB003 device is its ability to read OEM parameters (PIDs) via ODB port.

Among the data that has been collected during the survey period and through the unit's OBD are the following:

- Acceleration
- Ambient Air Temperature
- Calculated Engine Load
- Distance Traveled
- Distance Traveled Since Fault Codes Cleared
- Engine Coolant Temperature
- Engine Fuel Rate
- Engine Oil Temperature
- Engine RPM
- Fuel Injection Timing
- Fuel Pressure
- Fuel Rail Temperature
- Intake Manifold Absolute Pressure
- Mass Air Flow Rate
- Throttle Position
- Trip Odometer
- Vehicle Speed

Figure 7: Bus ODB-II port (left image) and Teltonika FMB Plug and Track Device (right images)

Figure 8 Presents the procedure of extracting OBD data through the utilization of a Teltonika OBD tracker data. The process involves reading data from the OBD port and subsequently transmitting it to the server using the TCP/IP protocol. Following this, the data is received from a cloud server and subjected to decoding via an open-source OBD parser. The deciphered data is then stored within a NOSQL database. In parallel, data is retrieved from the cloud server. This acquired data is further subjected to extraction and cleansing procedures, allowing for the alignment of OBD timestamps with the corresponding STPH data timestamps.

[1] https://teltonika-gps.com/products/trackers/fmb003

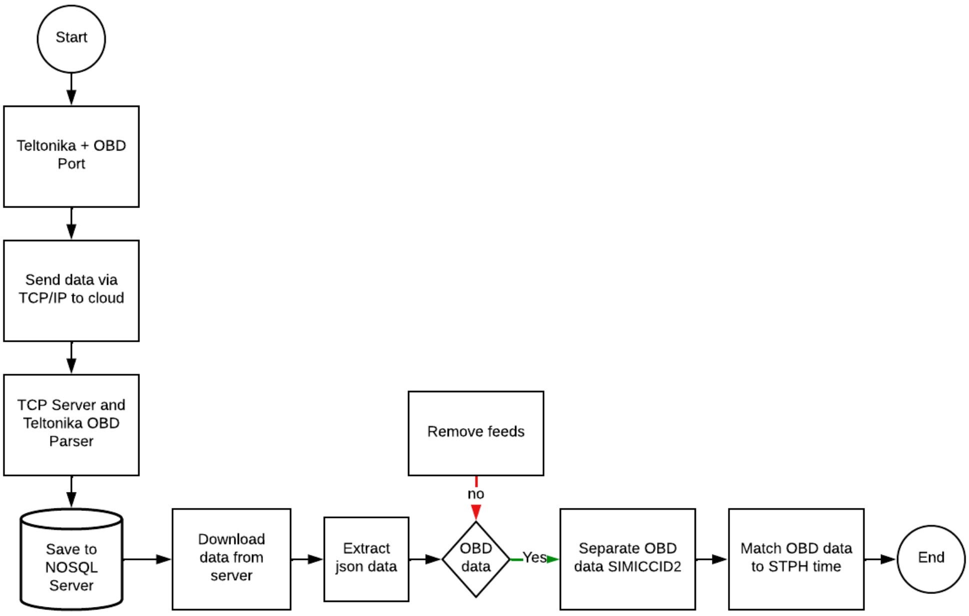

Figure 8: OBD Data Extraction Process

4.4 Bus Fuel Efficiency Indices

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 is also lower in eco mode. The preceding paper also concluded that there is a strong correlation between fuel consumption and various parameters such as sloping, RPM, and speed. This research examined how dashboard image processing can effectively monitor RPM readings and 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.

The work by Ayyildiz, et al. (2017) presents a practical method in evaluating the effectiveness of eco-driving on freight transport based on a micro-scale approach. Their approach involves real-world driving patterns of the single vehicles and the drivers' individual behaviors are considered in evaluating instantaneous fuel consumption. One specific Key Performance Indicator (KPI) highly suggested in their study is the Energy Performance Indicator EPI, expressed in cl/(t Ú km) which indicates the average quantity of fuel required to transport 1 ton of freight.

In a similar fashion, efficiency indicators to evaluate public utility bus operations on the EDSA Busway can be explored and tested. As such, three operational parameters are proposed to provide the basis for an evaluation of the most fuel-efficient bus driving operations (Tiglao, et al., 2021), namely:

- Total Distance Traveled, TD;
- Weighted Occupancy, WOcc, which is computed as the total of hourly values of the average number of passengers per hour multiplied by the distance traveled within the hour; and
- Weighted Speed, WSpd, which is computed as the total of hourly values of average speed per hour multiplied by the distance traveled 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 various operational parameters as denominators. Take note that the units of the indicators are similar to EPI as opposed to mileage indicators which are measured in distance traveled per liter of fuel. The following fuel efficiency indices are proposed to compare the driving behavior and fuel consumption of bus drivers.

- Distance Index, DI, measured in liters/km;
- Occupancy Index, OI, measured in liters/passenger; and
- Speed Index, SI, measured in liters/kph

5. INITIAL RESULTS AND DISCUSSION

5. 1 Route-level Performance

The data collection was conducted between the dates July 11-28, 2023 to determine ridership and travel time of the sampled bus units in the EDSA Carousel. Figure 9 represents the bus dwelling times for various stops along the Northbound direction. It can be observed that Roxas Boulevard, North Avenue and Roosevelt station have the highest dwelling times with 171, 167, and 153 seconds respectively. These stations are known for a substantial number of passengers. As a result, this increased passenger influx might lead to a longer dwelling time as passengers take their time to get on or off the bus. Consequently, DFA, Santolan, and Balintawak exhibit the lowest bus dwelling times, registering 3, 15, and 23 seconds, respectively. These stations experience lower passenger demand compared to other stops, resulting in expedited stops.

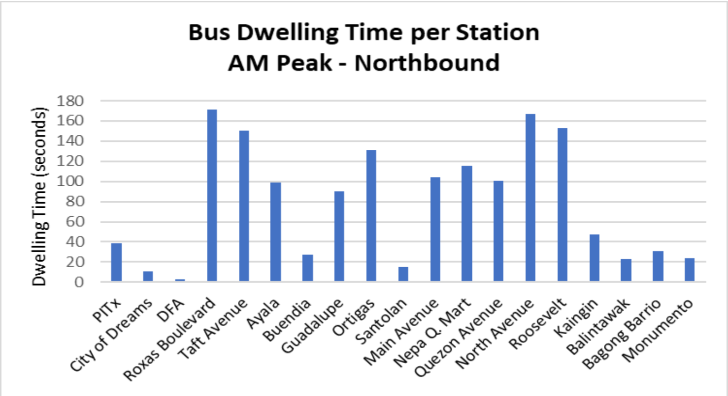

Figure 9: Bus Dwelling Time per Station (Northbound)

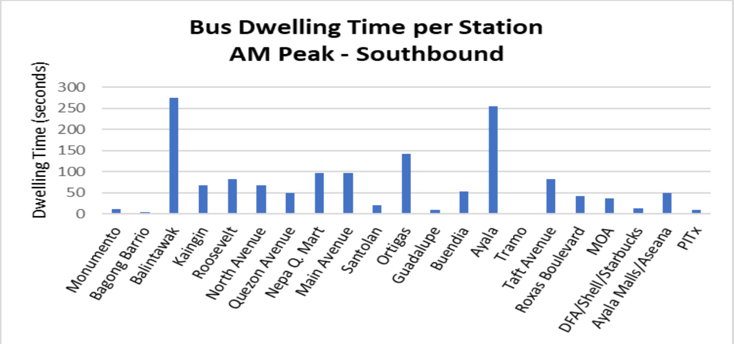

Figure 10: Bus Dwelling Time per Station (Southbound)

Figure 10 demonstrates the bus dwelling time at designated stations along the Southbound route. Notice that Balintawak, Ayala and Ortigas have the highest dwelling times with 275, 254, and 143 seconds respectively. Ayala bus station exhibits a high dwelling time primarily because it serves as a prominent transport hub. The station experiences substantial passenger activity as a major point of convergence for numerous bus routes, leading to longer periods of dwelling. On the other hand, Bagong Barrio, Guadalupe, and PITX have the lowest bus dwelling times with 5, 10 and 10 seconds respectively.

5.2 Bus-level Performance

Figure 11 compares the fuel rate in liters per hour for the typical bus travel behavior within the busway, grouped as "Idling" with zero to 5 kph vehicle speed usually when waiting or approaching the loading and unloading bay at the stops, or when stopped at traffic lights, and "Moving" wherein the speed is more than 5 kph.

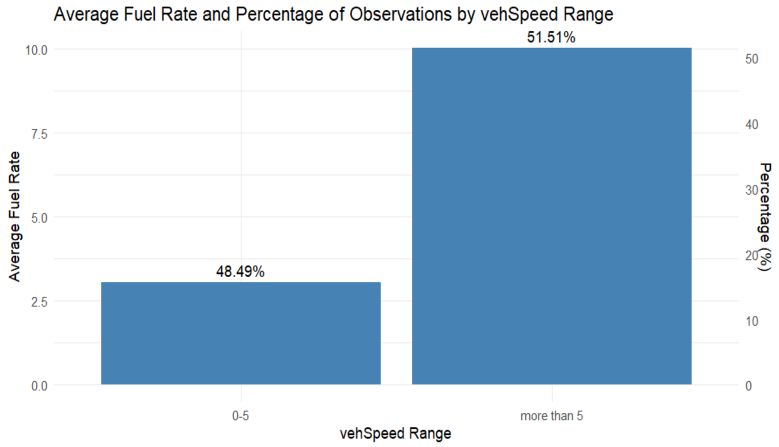

Figure 11: Graph of Fuel Rate and Vehicle Speed Range

Figure 12, meanwhile, provides evidence to the recommended RPM level of 1,000 to 1,500 for eco-driving based on vehicle manufacturers and displayed on vehicle cabin dashboards (marked or labeled with green color on the tachometer/RPM dial). For RPM classes below 1,800 RPM, the instantaneous fuel consumption will increase as the RPM increases. However, this engine fuel rate for a moving bus vehicle where the RPM is at least 1,000 RPM, according to the data collected per driver-vehicle pair, has significant upward inflection when it reaches and goes beyond 1,500 RPM.

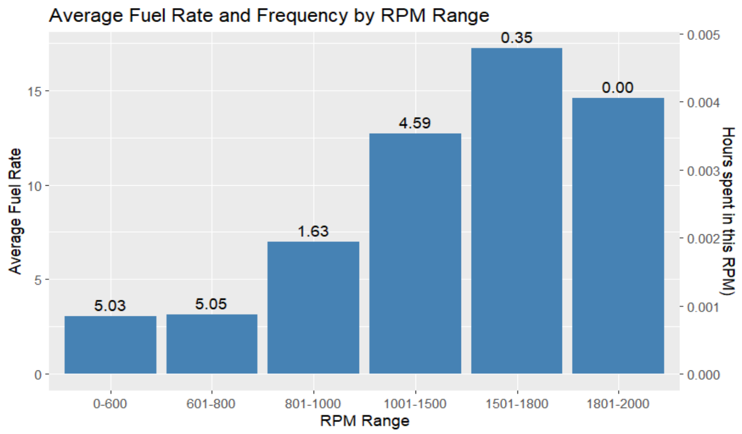

Figure 12: Histogram of Fuel Rate

Figure 13 also shows the average number of hours a driver spent each of the RPM classes on a typical daily work. Alarmingly, it shows there is about 5 hours wasted to idle running engine (RPM < 600), the is equivalent to a total of 13.13 liters of diesel fuel (5.03 hours x 2.61 liters/hour). Figure 14 presents the fuel rate and engine RPM by driver which clearly depicts the difference among driver performance.

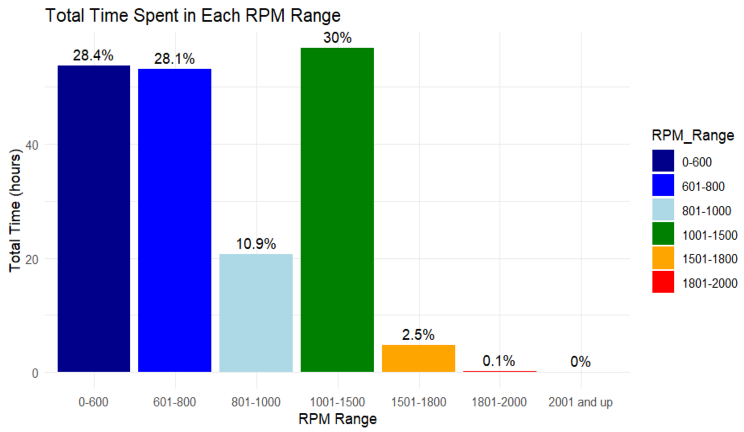

Figure 13: Histogram of Engine RPM

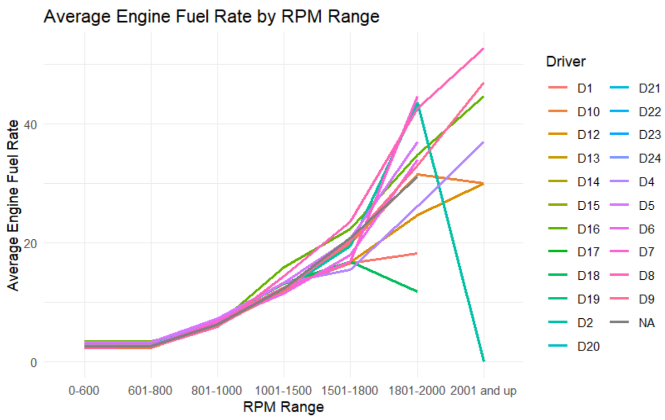

Figure 14. Histogram of Fuel Rate and Engine RPM (per Driver)

5.3 Engine-level Performance

The datasets from each driver-vehicle pair for on-board diagnostics data and SafeTravelPH passenger occupancy (*Numpass* variable in the model) and *gpsSpeed* data are combined to create a general linear model and inspect the significance of the relevant operational variables to the fuel consumption, as represented by the *engineFuelRate* dependent variable. Filtering out outliers in speed and vehicles that had no fuel in the OBD, there were a total of 681,801 data points in the model.

The subsequent modeling and data analytics to be presented in the section were completed using R statistical programming software and its packages. The coefficients of the independent variables represent the change in the response variable for a one-unit change in the predictor variable, holding other variables constant. For example, the *engineRPM* coefficient of 0.00391029 means that for each one-unit increase in *engineRPM*, the *engineFuelRate* increases by approximately 0.00391029, assuming other variables are constant.

```
Residuals:
    Min      1Q  Median      3Q     Max
-26.016  -0.994   0.289   0.925  22.526

Coefficients:
                       Estimate  Std. Error t value            Pr(>|t|)
(Intercept)         -6.98098980  0.08455493  -82.56 <0.0000000000000002 ***
Numpass              0.00056815  0.00019889    2.86              0.0043 **
vehSpeed            -0.03841535  0.00089235  -43.05 <0.0000000000000002 ***
gpsSpeed             0.01498135  0.00084037   17.83 <0.0000000000000002 ***
engineRPM            0.00391029  0.00003522  111.01 <0.0000000000000002 ***
calEngineLoad        0.15437690  0.00024840  621.48 <0.0000000000000002 ***
throttlePosition     0.13963870  0.00026427  528.40 <0.0000000000000002 ***
engineOilTemp       -0.01577504  0.00093183  -16.93 <0.0000000000000002 ***
abdFuelRailTemp      0.00050225  0.00000368  136.63 <0.0000000000000002 ***
fuelInjectionTiming  0.00401355  0.00003411  117.67 <0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.4 on 681798 degrees of freedom
Multiple R-squared:  0.922,      Adjusted R-squared:  0.922
F-statistic: 8.95e+05 on 9 and 681798 DF, p-value: <0.0000000000000002
```

Figure 15: Initial linear model of Engine Fuel Rate

To do the subsequent analyses, expert knowledge and EDSA Carousel operating characteristics are taken into account to identify outliers in the dataset. For example, data entries with speeds greater than 80 kph were removed in the dataset. Although the legal speed on the busway is 60 kph, it was observed during late-night trips that buses can speed up to 80 kph on a freer lane. Also, instantaneous passenger occupancy data recording, used to estimate engine load, from the SafeTravelPH boarding and alighting data that experience resetting due to disconnection of signals were corrected with the actual individual boarding and alighting event in the app based on the activity of the surveyor within the app. Extreme data that corresponds to beyond standing and overloaded capacity were eliminated.

The initial linear model provided suggests a highly significant model with a high R-squared value. This means that the model explains a significant amount of the variance in the *engineFuelRate*. On the other hand, the correlation among different factors for fuel consumption were computed and plotted on Figure 16.

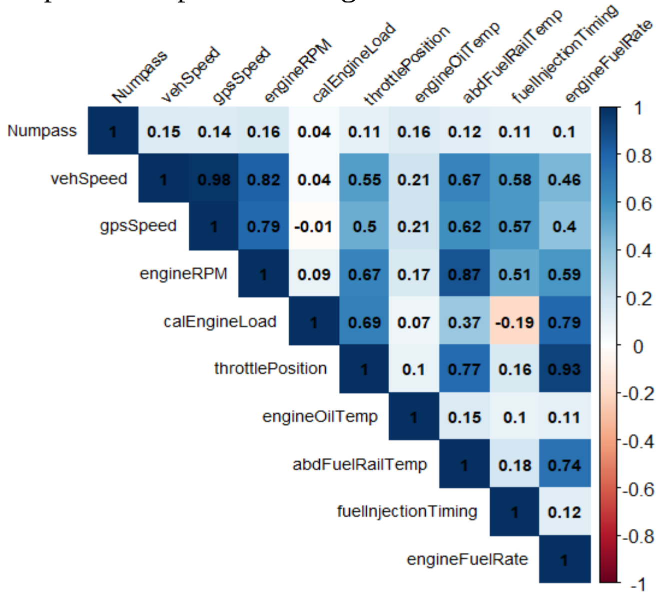

Figure 16: Linear Correlation Model Matrix

There is a high correlation among some variables which suggests multicollinearity, where these variables are interrelated and can potentially lead to inflated standard errors and less reliable coefficient estimates in the linear model. Excluding some of these highly correlated variables to improve the model's stability was considered in the subsequent analysis. The Variance Inflation Factor (VIF) values help identify potential multicollinearity among predictor variables. In general, a VIF value greater than 10 is considered high and suggests that multicollinearity might be an issue. The VIF values are presented in Figure 17.

```
Numpass: 1.1
vehSpeed: 28.5
gpsSpeed: 24.2
engineRPM: 13.1
calEngineLoad: 4.0
throttlePosition: 6.5
engineOilTemp: 1.1
abdFuelRailTemp: 9.0
fuelInjectionTiming: 2.3
```

Figure 17. Variance Inflation Factor (VIF) Values

As indicated above, *vehSpeed*, *gpsSpeed*, and *engineRPM* variables have high VIF values. This indicates that these variables might be correlated with each other, potentially leading to multicollinearity. High multicollinearity can make the interpretation of coefficients less reliable and might indicate a need to reconsider the inclusion of these variables in the model. As *vehSpeed* and *gpsSpeed* are both strongly correlated with *engineRPM* then *engineRPM* I retained.

On the other hand, while *engineOilTemp*, *abdFuelRailTemp* and *fuelInjectionTiming* have VIF values before the threshold of 10, these variables are highly correlated with each other. As such, *engineOilTemp* is chosen to be retained. Finally, since *throttlePosition* and *calEngineLoad* are highly correlated, *calEngineLoad* is chosen to be retained.

Figure 18 presents the final linear model of Engine Fuel Rate where the explanatory variables for *engineFuelRate* are *engineRPM*, *calEngineLoad* and *engineOilTemp*. The coefficients' t-values and associated p-values indicate the significance of each variable and interaction term. All the variables, including the interaction term, seem to be statistically significant. The adjusted R-squared value of 0.887 indicates that the model explains about 88.7% of the variance in the response variable, which suggests a good fit.

```
Residuals:
     Min       1Q   Median       3Q      Max
-29.1474  -1.4912   0.0277   1.1913  26.2680

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -8.707e+00  9.865e-02  -88.26   <2e-16 ***
engineRPM      1.516e-02  1.192e-05 1271.50   <2e-16 ***
calEngineLoad  2.703e-01  1.496e-04 1806.23   <2e-16 ***
engineOilTemp -8.524e-02  1.091e-03  -78.15   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.921 on 681799 degrees of freedom
Multiple R-squared:  0.887,       Adjusted R-squared:  0.887
F-statistic: 1.785e+06 on 3 and 681799 DF, p-value: < 2.2e-16
```

Figure 18: Final linear model of Engine Fuel Rate

We evaluate its performance using appropriate metrics such as R-squared, adjusted R-squared, and cross-validation techniques. Using the 'caret' package in R, the datasets for training and testing the model for cross validation are randomly set. The cross-validation results for the linear regression model using the final set of independent variables are shown in Figure 19.

```
Linear Regression

681803 samples
     3 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 613623, 613624, 613623, 613623, 613623, 613622, ...
Resampling results:

  RMSE      Rsquared   MAE
  2.920499  0.8870435  2.046939

Tuning parameter 'intercept' was held constant at a value of TRUE
```

Figure 19: Cross validation of final linear model

An RMSE of 2.92 suggests that, on average, the model's predictions are off by around 2.92 units of the target variable. An R-squared value of 0.887 indicates that the model is able to explain about 89% of the variance in the target variable, which is quite good. The MAE of 2.05 represents the average absolute difference between the predicted and actual values. An error of 1.6 to 2.5 liters per hour translates only to 0.00044 to 0.000.67 liters of fuel. Overall, these results suggest that the linear regression model with the recommended independent variables is performing well on this dataset.

5.4. Driver-based Performance

To gather more insights on how different driving behaviors affect overall fuel efficiency on the Busway, the driver-based trip level data were analyzed for the nine (9) drivers with validated and complete data for the following operating parameters: fuel rate, total fuel consumption record, total distance traveled, fuel economy, idling hours, moving/traveling hours, and hours spent under ideal or "eco" RPM levels. The summary on Table 1 anonymized the drivers (D1 to D9) and ranked them from highest average fuel rate. Meanwhile, Table 2 provides additional information on the trips made by each driver and their bus's workload in terms of average instantaneous occupancy and total ridership.

Table 1: Driver Driving Behavior Statistics

Driver	Average Fuel Rate	Total Fuel Consumption (Liter)	Total Distance (Km)	Fuel Economy (Km per Lit)	Total Idling Time (Hrs)	Total Moving Time (Hrs)	Total Eco-Driving Time (Hrs)	Total Non-Eco-Driving Time (Hrs)
D1	7.9	73	227.734	3.1	4.9	4.3	2.7	0.31
D2	7.3	33	84.433	2.6	2.1	2.4	1.4	0.08
D3	7.1	187	399.539	2.1	13.9	12.3	7.9	0.86
D4	6.9	96	293.415	3.1	6.9	7	4.4	0.35
D5	6.7	169	399.726	2.4	12.6	12.7	7.7	0.58
D6	6.6	92	229.716	2.5	7	7	4.2	0.34
D7	6.5	206	623.496	3.0	14.8	16.8	10	0.80

Driver	Average Fuel Rate	Total Fuel Consumption (Liter)	Total Distance (Km)	Fuel Economy (Km per Lit)	Total Idling Time (Hrs)	Total Moving Time (Hrs)	Total Eco-Driving Time (Hrs)	Total Non-Eco-Driving Time (Hrs)
D8	6.5	62	228.826	3.7	5.2	4.4	2.5	0.13
D9	6.2	133	466.683	3.5	11.1	10.4	6.2	0.76

Table 2: Driver Ridership Statistics

Driver	Total Distance (Km)	Average Occupancy	Total Ridership	Ridership per Km
D1	227.734	23	690	3.0
D2	84.433	27	185	2.2
D3	399.539	28	1062	2.7
D4	293.415	24	692	2.4
D5	399.726	25	1115	2.8
D6	229.716	21	431	1.9
D7	623.496	24	1507	2.4
D8	228.826	24	751	3.3
D9	466.683	28	1054	2.3

To compare the information above and determine operational patterns for each driver, the Distance Index, Occupancy Index, Speed Index, and RPM Index were calculated by dividing the total fuel consumption by each of the corresponding operating parameters. This was done for comparing the impact of each parameter in the overall fuel consumption of the bus. The data from Table 3 confirms that across all drivers, the low fuel consumption is expected for eco-driving behavior based on maintaining the RPM between 1,000 to 1,500 RPM.

Table 3. Driver Bus Fuel Efficiency Indices

Driver	Distance Index	Occupancy Index	Speed Index (Idling)	Speed Index (Moving)	RPM Index (Eco-Driving)	RPM Index (Aggressive)
D1	0.32	3.2	14.9	53.0	1.2	15.8
D2	0.30	1.2	15.7	35.2	1.8	25.9
D3	0.47	6.7	13.5	32.5	0.3	16.2
D4	0.42	4.0	13.9	41.9	0.7	19.7
D5	0.42	6.8	13.4	31.5	0.3	21.6
D6	0.41	4.4	13.1	32.8	0.6	20.6
D7	0.32	8.6	13.9	37.1	0.3	18.4
D8	0.27	2.6	11.9	52.0	1.5	40.0
D9	0.29	4.8	12.0	44.9	0.6	14.7

5.4 Cluster Analysis

Finally, to characterize eco-driving behavior based on the parameters and indices above, a clustering analysis was performed. Simplifying the association, the clustering explored only two (2) clusters, assumed to determine an "eco" driver and a non-eco-driver, who will be more likely to exhibit "aggressive" driving behavior. The aggressive driving factor is determined by examining the outliers in the acceleration data field and means of the traveling speeds on the busway from the collected datasets. Vehicles accelerating from zero to more than 30 kph or decelerating from more than 30 kph traveling speed into full stop in just one (1) second are considered aggressively accelerating or aggressively breaking. Those data points exhibiting this will be assigned with "1" in the *aggressiveness* variable, and "0" if otherwise.

Table 4. Clustering Analysis

Cluster	No. of Drivers	Fuel Rate (Liter/Hr)	RPM	Aggressiveness Factor	Acceleration (m/s^2)	Throttle Position (Max=100)
1	4	23.70	1258	0.003382	0.4922	71.15
2	5	3.60	1197	0.002211	-0.2466	15.99

Using K-Means Clustering and zooming in to driving data points that likely reflect traveling operation outside the stations and with 1,000 RPM and above, the drivers were assigned to each cluster based on their calculated "nearness" to each other, as characterized by the means or averages for each parameter as shown in Table 4 above.

Cluster 1 easily pointed to the group of aggressive drivers with significantly higher average fuel rate when driving on the highway and operating with at least 1,000 RPM. Generally, this group has higher RPM averages and more instances of aggressive driving, or 0.003382 to 0.002211 compared to "eco" drivers. Their average acceleration is also higher, around 3 times of Cluster 2's acceleration, which is negative–indicating a more braking or slowing down behavior for the non-aggressive driver. Finally, the more physically evident information of Throttle Position, which corresponds to how deep the driver "floors" the accelerator pad, shows that eco-drivers press the accelerator pad or throttles the bus to move at least 3 time "softer" or "easier" than non-eco-drivers from Cluster 1. In summary, eco-drivers when in motion and maintaining a cruising speed for an hour with at least 1,000 RPM can save up to 8.217 liters of fuel, compared to driving more aggressively.

Table 5. Aggressive and Eco-driving Difference

	Aggressive Driving	Eco-Driving	Difference
Engine Fuel Rate (Liter/Hr)	22.03	13.08	8.217

5.4 Key Informant Interviews

To further understand the results of the collected data, a series of interviews with the bus operators were conducted. Operators target at least a total of four (4) round trips to be completed by each driver along the EDSA Busway to be profitable. Some operators chose to set a quota wherein upon reaching a certain amount of gross income from their trips, the drivers are given incentives. Although operators do not encourage the drivers to take on trips on consecutive days, the drivers regularly choose to do so. But given the lack of a proper holding area for drivers in the main terminals, the drivers are prone to lack of proper rest or breaks during working hours.

With regards to the fuel consumption, it is noted that since the establishment of the EDSA Busway, a number of bus operators experience *dead run*, wherein those whose parking garages are located far from the EDSA Carousel route are not able to pick up passengers on their way to their assigned route. In addition, with most of the EDSA Carousel stations being located in the median lane and having similar stops to the MRT3, passengers would choose the cheaper and more convenient MRT3 than to take the EDSA Busway.

6. CONCLUSION

This study effectively showcased the utilization of on-board diagnostics and mobile crowdsourcing data, and enhanced it with trip and passenger flow and bus station dwelling from the open platform SafeTravelPH for big data analytics. In the context of the EDSA Busway operations, this paper built on previous work of the authors with more granular data and extensive data on route, bus and engine, and driver level datasets.

The study provided a local effort to characterize how fuel efficiency can be achieved through eco-driving behavior and quantified the potential fuel consumption savings that can be translated into financial benefits to the operators and drivers. However, the benefits to the environment can be more enhanced when systems related issues, starting from the route level, are addressed by the government to minimize dwelling and unproductive engine idling of buses on the terminals and stops, and providing better staging areas near the terminals to reduce dead runs of buses when coming from or going to their garages before or after their operations on the busway. Ultimately, efficiency on bus level will be more evident when system level adjustments are made to ensure less waiting times for buses and passengers at the stops, pointing to the need to provide improvements on the geometries of the bus lane and loading and unloading areas.

Further research and development efforts are required to automatically integrate the OBD telematics with route and passenger flow data that can be provided by SafeTavelPH. To better understand the level of driving behavior’s impact fuel consumption, the datasets can be analyzed on different highway conditions along the route such as downhill and uphill road sections, and the impact of mainstreaming eco-driving skills building through proper setting of incentives and penalties, coupled with skills coaching that may be included in skills training and development modules for bus drivers.

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