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# Development and analysis of eco-driving metrics for naturalistic instrumented vehicles

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**ABSTRACT**

This article is concerned with the development of eco-driving metrics for instrumented vehicles in a longitudinal study environment. Motivations for developing such metrics include an ability to distill driving style effects on fuel use from other confounding factors, to contrast and benchmark driving styles for a cohort of drivers and to ascertain the effects of information and/or incentives on fuel use both in the short and long term. High resolution (1 Hz) trip data were collected for a local sample of 35 drivers over a period of 2 years, yielding over 20 million second by second observations. To account for the difference in vehicle type choice, a standard vehicle was used to model fuel consumption based on instantaneous vehicle activity. Difference in route choice was accounted for using speed-bin dependent metrics. Two metrics were developed: a trip-based measure called the fuel efficiency score (FES), and a difference in fuel use metric that uses the second by second observations called the fuel use difference (FUD). FES varies from 20 to 100 while FUD covers positive and negative percentage differences from a speed-bin dependent mean value. Both measures passed the test of consistency so that, at the driver level, both revealed no temporal trend in the scores from month to month across a period of 2 years. Moreover, the FES metric passed the heterogeneity test. It was able to identify four distinct clusters of driving styles.

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Eco-driving; eco-driving evaluation; eco-driving metrics; driving behavior; energy; fuel efficiency; incentives

## Introduction

The transportation sector accounts for more than 25% of the total energy supply of the United States. In 2015, petroleum fuels provided about 92% of the total energy used by the transportation sector totaling about 25,000 trillion BTU (USEIA, 2016). Personal transportation contributed to 26% of total carbon dioxide ($CO_2$) emissions (USEPA, 2016). Any policy and operational improvement in reduction of personal transportation petroleum fuel consumption can significantly reduce emissions of greenhouse gases and save millions of dollars in energy import cost. Improvements of vehicle and fuel technologies have significantly increased fuel efficiencies of modern vehicles. Diversified energy sources such as bio-fuels and electric cars have provided means to reduce overall transportation fuel consumption. However, the penetration of improved technologies in the market is gradual due to prohibitive cost of new vehicles; only about 7% of vehicles replaced in a single year (ORNL, 2015). An alternative option is to reduce the vehicle miles traveled that involves either making fewer trips or reducing trip lengths. Unfortunately, any travel demand reduction policy suffers from low acceptance and attainment rates except in densely populated urban areas where commuters have more opportunities for transit and carpooling. Another promising approach is to alter the drivers' current driving style to improve fuel efficiency. This relatively newer approach, termed eco-driving, is more feasible now than ever before. High resolution driving style can be observed at real-time with the advancements in sensor and communication technologies and information can be provided to the driver through real time wireless communication or internet with advanced analytics at the back-end (Jariyasunant et al., 2015). As opposed to static eco-driving where instructions to improve driving style is given beforehand and instructions do

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not change depending on a driver's current driving style, dynamic eco-driving is changing instructions to better suit a particular driver at specific conditions (Xia, Boriboonsomsin, & Barth, 2013). This article will focus on dynamic eco-driving capabilities in naturalistic driving.

Effectiveness of an eco-driving scheme depends on how often a driver is following the instruction and to what extent the benefits from saving fuel consumption is important to the driver (Barkenbus, 2010). Advanced eco-driving control algorithms have shown energy consumption improvement up to 16.9% (Hu et al., 2016). Drivers may be too accustomed to their usual driving styles. Short-term fuel efficiency can be improved by 25% (Ford, 2015), however, without feedback can go down to 5% or no improvements at all. A solution to improve long-term fuel efficiency is to provide feedback and incentives (either monetary or non-monetary) to the drivers. Non-punitive financial controls such as coupons, tax relief, etc. can provide personal incentive to reduce fuel consumption. However, such personal incentive delivery requires a universal tracking method of driving style which is not impacted by the vehicle type and route chosen by the driver. Incentives can be provided when a driver's driving style has improved from a previous time period or when a driver is maintaining an optimal driving style. Therefore, there is a need to develop an unbiased metric of driving style which can be tracked over time and applied similarly to all the drivers participating in an eco-driving scheme.

The purpose of this article is to develop eco-driving metrics for naturalistic driving where there is no control over the drivers' choice of vehicle and route. An eco-driving metric needs to serve as a benchmark of driving styles. In addition to scoring, the metric needs to enable ranking and grading drivers. Previously, empirical fuel consumption was monitored to serve as an indicator of fuel efficiency and comparison of drivers' fuel efficiency was only possible if vehicle type and route characteristics were controlled. Such controlled experiments are suitable for understanding the effect of vehicle, route, or drivers separately. However, fuel consumption alone without any adjustments for other choices cannot serve as a metric for naturalistic eco-driving schemes.

In the next section, the related literature is reviewed to understand factors influencing actual fuel consumption. Later, data and methodology are described. Results and discussions followed by conclusions are described in the last two sections.

## Literature review

Actual fuel consumption of a vehicle is affected by multiple factors – vehicle type, roadway factors, meteorological conditions, traffic factors, and driving styles. Vehicle type has the highest impact among all others; EPA reported fuel economy can be as high as 107 miles per gallon for small electric vehicles and as low as 12 miles per gallon (USDOE, 2016). Roadway factors such as road grade and pavement condition have significant effect on fuel economy. Fuel economy of a flat route was found 15% to 20% higher than that of a hilly route (Boriboonsomsin & Barth, 2009). Meteorological conditions such as wind, barometric pressure, and ambient temperature has small impact on the fuel economy. For a specific vehicle type, traffic related factors such as speed and variability of speed due to facility conditions or traffic control devices have significantly greater effect on fuel economy than driving styles (Boriboonsomsin, Vu, & Barth, 2010). At urban conditions, average speed can explain more than 70% variability in fuel consumption (Evans, Herman, & Lam, 1976). Many later researches argued for the inclusion of acceleration and different functional forms of speed and acceleration to better estimate fuel consumption (Ahn, Rakha, Trani, & Van Aerde, 2002; Jimenez-Palacios, 1998). However, there are small differences between the factors to be considered as traffic stream related and driving style factors. Average speed can be considered as a traffic stream factor for a congested road as drivers need to follow preceding vehicle. In contrast, amount and frequency of acceleration and deceleration is a part of the driving style.

Most previous eco-driving experiments in the literature have, for the most part, included controls on vehicle type and route selection. In controlled experiments a small group of participants are instructed to drive along fixed routes using a pre-defined and similar vehicle (Ishiguro, 1997; Lenner, 1995); comparison among driving styles is made using actual fuel consumption. Barth and Boriboonsomsin used real-time information as speed advisories at different level of services (Barth & Boriboonsomsin, 2009). However, the study was limited to freeways and comparison was done for the same vehicle type and same route. A handful of previous studies explored naturalistic data for vehicle fuel consumption analysis (LeBlanc, Sivak, & Bogard, 2010, Berry, 2010, Bandeira, Almeida, Khattak, Rouphail, & Coelho, 2013). However, no previous study focused on the eco-driving aspect in terms of isolating the effect of driving style from other factors. Beusen et al. used on-board logging devices to track the long-term impact of a static eco-driving scheme using actual fuel savings (Beusen et al., 2009). Rolim et al. used similar devices to track the effectiveness of an eco-driving program; however, they used frequency and level of excessive acceleration and declaration to quantify the improvement (Rolim, Baptista, Duarte, & Farias, 2014). Song and Yu normalized average fuel consumption rates with the idling rate to eliminate the effects of engine size, fuel type, and vehicle mass (Song & Yu, 2009). The normalized fuel consumption rate was suitable for estimation of vehicle type independent fuel economy, however, lacked the quality to serve as a benchmark in comparing trips of different route choice by the same driver. There is a lack of generalizable and transferrable driving style metric in the literature which can control for both route and vehicle type choice.

Dynamic eco-driving metrics needs to allow not only delivery of information but also delivery of incentives. Information delivery as done by Barth and Boriboonsomsin (2009) is a two-stage process where driving style is observed and information is delivered. In contrast, incentive delivery requires an additional feedback stage where the driver performance is observed after information delivery and based on the performance incentive is provided. An eco-driving metric needs to serve as a performance indicator in that case. Performance indicators such as speed and braking are used by an insurance company, Progressive Casualty Insurance Co. (McQueen, 2008), to provide incentives for safety in naturalistic driving. However, there is no reported performance indicator for eco-driving applications that can be used for delivery of incentives.

Observation of long-term eco-driving behavior can provide better insight into driver consistency. af Wåhlberg (2007) monitored fuel consumption of buses during 12 months after an eco-driving training and found drivers returned to their previous habits within a small time period. Beusen et al. observed 10 drivers over the course of 10 months (Beusen et al., 2009) including before and after eco-driving training. They found scatter of average weekly fuel consumptions in both stages; making it difficult to measure any significant effect of driving styles. Therefore, it is important to understand usual randomness in driving styles of individual drivers through long-term studies.

On the basis of the review of literature presented above, three main limitations can be gleaned:

1. There is no agreed upon metric which can distinguish the effect of driving styles on fuel consumption from other confounding factors.
2. There is no comparative benchmark of driver behavior that can support the application of eco-driving incentives.
3. Few long-term longitudinal studies of individual driver's driving style were found that can assess the consistency of driving styles over an extended period of time.

Based on the identified gaps in literature, this study attempts at addressing the following research questions:

1. How to develop eco-driving metrics that consider heterogeneity among driving styles only?
2. Are the developed metrics consistent and reasonable as benchmarks?
3. Can the developed metrics be used to rank or grade drivers for incentive development purposes?

## Methodology

Methods of this study includes (a) a description of study data (b) method for benchmarking driving styles (c) method for development of eco-driving metrics (d) methods for characterization of heterogeneity and consistency in driving styles.

### *Data source*

Naturalistic driving data for this study are collected using an on-board logging system called "i2D." The system consists of an on-board unit (OBU), a mobile communications network (via M2M protocols), and a secure cloud database. The OBU connects to the vehicle's OBD-II interface, and includes a GPS sensor along with a 3D accelerometer and a barometric altimeter (Kim et al., 2016). Multiple engine and vehicle dynamics measures are acquired from the OBU at high resolution (1 Hz) and transmitted to the cloud database using mobile communications every 23 seconds. An illustration of the device is shown in Figure 1.

Participation in this study was completely voluntary and 35 drivers were recruited randomly in Raleigh NC. The study participants were anonymized and were not provided with any specific instructions during the study. All the vehicles used in this study were personal vehicles of the participants and participants were not required to disclose their vehicle specific information to maintain anonymity. Participants were mostly university staff and students with age ranging from 20 years to 68 years with mean age of 36 years.

Out of the 35 participants 25 were male and 10 were female. A total of 24 months of data were collected. Data collection started in April 2014 and ended in March 2016. A total of 34,425,572 seconds of data were collected. The total driving distance was 289,064 miles with the least active driver driving 315 miles and the most active driver driving 3,163 miles. Table 1 shows descriptive statistics of some key variables for the 41,217 trips collected for this study.

The system assigned a unique trip ID every time drivers started their vehicles. All second-by-second data for a particular trip was tagged with that trip ID. The second-by-second data included engine information such as revolution per minute, intake air temperature, manifold pressure and vehicle dynamics information such as vehicle speed. The drivers required to provide their vehicle information such as vehicle model, gross vehicle mass, fuel type at the time of recruitment. Integration of vehicle and engine information enabled the real-world instantaneous fuel consumption during a trip. Previous studies have reported that estimation of fuel consumption using internally observed variables can explain 99% of the variability in empirical measurements (Frey, Zhang, & Rouphail, 2008).


**Figure 1.** (Left) On-board data logging device connected to the vehicle. (Right) I. the device II. Antenna III. OBD-II connector cable.

In contrast to estimating fuel consumption using internally observed variables, instantaneous fuel consumption can be estimated using vehicle speed, acceleration, and road grade with previous knowledge of the vehicle specification. The latter approach is more suitable for observing driver behavior since the actual fuel consumption is governed by the type of vehicle driven. In the next section, the methodology for benchmarking driving style is discussed based on estimated fuel consumption using instantaneous vehicle speed.

## Benchmarking driving styles through standardized fuel use

Driving style of a driver can be observed through the driver's actions. Actions which can possibly affect fuel consumption are speed, acceleration, and braking of the vehicle. The effect of vehicle type on driving style was studied in a previous paper (Tanvir, Frey, & Rouphail, 2018). The paper concluded that the choice of vehicle does not significantly alter the natural driving style of a driver. Therefore, a benchmark of driving style and consequent fuel consumption needs to be standardized by the actions. Comparing two driver's empirical fuel consumption without standardization is only possible when they are driving the same vehicle type and driving in similar operating conditions.

Benchmarking of a driver's driving style requires standardization for choice of vehicle type and choice of route. This article deals with standardization for vehicle type choice by assuming all drivers are

**Table 1.** Descriptive statistics of key variables in the collected trip database ($n = 41{,}217$).

| Variable | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Trip Travel Time (minute) | 13.9 | 17.4 | 0.01 | 383.4 |
| Trip Distance (miles) | 8.55 | 17.86 | 0.11 | 397.05 |
| Maximum Acceleration (ft/s2) | 11.56 | 9.68 | 4.4 | 118.8 |
| Maximum Deceleration (ft/s2) | −12.23 | 5.31 | −2.2 | −107.07 |
| Start Delay (seconds)[1] | 27.3 | 72.9 | 0 | 2614 |
| End Delay (seconds)[1] | 26.9 | 80.7 | 0 | 7445 |
| Number of Stops[2] | 7.07 | 5.18 | 0 | 129 |
| Percent of Time in Freeway[3] | 5.3 | 14.7 | 0 | 100 |
| Percent of Time in Positive Jerk[4] | 24.1 | 5.8 | 0.02 | 45.5 |
| Percent of Time in Negative Jerk[4] | 22.2 | 5.5 | 0 | 44.7 |

[1]Both start and end delay time is calculated considering consecutive seconds of zero speeds at the beginning and end of a recorded trip, respectively.
[2]Stops are assumed when consecutive zero speeds are observed for at least 5 seconds.
[3]Freeway points are identified though map-matching of GPS locations.
[4]Jerk is rate of change of acceleration. Positive jerk represents acceleration build-up or deceleration ramp-down. Negative jerk represents acceleration ramp-down or deceleration build-up.

operating a standard car as their vehicle. The standard car in this study is a 2007 Honda Accord with 2.4 L 4-cylinder, 160 hp gasoline engine and a 3100 lb curb weight. Specifications of the standard car along with instantaneous speed, acceleration, and road grade can be combined to get estimate of vehicle specific power (VSP). VSP is a function of vehicle speed, acceleration, and road grade and expresses a vehicle's engine power demand. VSP has been found as an excellent predictor of vehicle fuel use (Jimenez-Palacios, 1998). VSP can be expressed by Equation 1. The coefficients in Equation 1 depend on the type of vehicle and for this article specifications of the standard vehicle ($A = 0.1565$ kW-sec/m, $B = 2.002 \times 10^{-3}$ kW-sec$^2$/m$^2$, $C = 4.926 \times 10^{-4}$ kW-sec$^3$/m$^3$, and $m = 1.479$ tonne) were used to estimate all second-by-second VSP values for all drivers. Instantaneous VSP values were mapped into 23 operating mode bins, which is a combination of VSP and speed. The mapping in to operating mode bins was done to better represent nonlinearities in the relationship between VSP and fuel consumption, especially, at higher speed ranges. There is one operating mode bin for braking, one for idling, 6 bins for speeds from 1 to 25 mph, 9 bins for speeds 25–50 mph, and 6 bins for speeds above 50 mph. Corresponding instantaneous fuel consumption values ($f_t$) were estimated from a previously established relationship between operating modes and fuel consumption for the standard car (Frey & Liu, 2014).

$$VSP = \left(A \times v_t + B \times v_t^2 + C \times v_t^3 + m \times v_t \times a_t\right)/m \quad (1)$$

where VSP is vehicle specific power, kW/tonne; $v_t$ is speed at time t, m/s; $a_t$ is acceleration at time t, m/s$^2$; $A$ is rolling resistance coefficient, kW-sec/m; $B$ is rotational resistance coefficient, kW-sec$^2$/m$^2$; $C$ is aerodynamic drag coefficient, kW-sec$^3$/m$^3$; m is vehicle mass, tonne.

This article used instantaneous or trip average vehicle speed as a surrogate to express route characteristics. The main route characteristics which change by driver's choice are sequence of facility type (freeway vs. arterial), departure time (pre-peak, peak, or off-peak), and operating conditions of the route (congested vs. uncongested or signalized vs. roundabout). In most cases, average speed for a given trip is controlled by the route characteristics, not by driver's driving style. Standardization of fuel consumption for route choice is possible through fitting multiple expected fuel consumption models at different speed levels. In the next section, two different eco-driving metrics are introduced which incorporates successive standardization of fuel consumption; first for vehicle type choice and then for route choice.

## Eco-driving metrics development

The purpose of an eco-driving metric is to compare driving styles across multiple drivers in a naturalistic driving study. The metric is required to reflect changes in driving styles only, not changes in vehicle type choice and route choice. The metric needs to be consistent over time for a given driver if no changes were made in the driver's driving style. Also, the metric needs to be sensitive to the heterogeneity in driving styles among drivers. Variation in the metric is required to be small enough for a given driver to identify significant changes in driving styles across reporting periods.

Another consideration for an eco-driving metric is to demonstrate improvement in driving style when a specific behavior is targeted. In the case of overall driving style improvement, a trip perspective of fuel usage is appropriate to track overall driver behavior change. However, studies exploring trip-level fuel consumption differences when only targeting behavior during parts of the trip (such as braking events), may lack the power to identify change when all driving events are aggregated into trips. A metric based on trajectory level analysis provides for the ability to segment trips into unique events in order to perform paired comparisons solely on the events of interest.

Standardized fuel consumption cannot be used as eco-driving metrics for several reasons – (a) it has no practical meaning to the driver; therefore, it is prone to misinterpretation, (b) it does not consider factors such as congestion and route type which is out of driver's control, and (c) it has a very low variability within the corresponding trip average speed bin (Figure 2b). Therefore, there is a need to adjust the standardized fuel consumption.

Aggregation of instantaneous standard fuel consumption at different resolutions leads to multiple approaches for adjustments by speeds. In each reporting interval (week or month) for an individual driver, adjustments can either be applied to each trip according to trip average speed or at trajectory level according to driver's behavior for each instantaneous speed level across all the trips made by that driver. In this article two different eco-driving metrics for naturalistic driving are introduced: one based on summary trip characteristics and another based on overall trajectory characteristics.

## Fuel efficiency score (FES)

For this study, information from about 42,000 trips was collected. Only trips over 1 mile in length and 1 minute in duration are selected for computing the metric. Trip average speed ($\overline{v_{ik}}$) can be calculated as average of OBD based instantaneous speeds for all the seconds of a trip. Miles per gallon of standard fuel consumption ($F_{ik}$) was chosen as the indicator of fuel efficiency for the trip.

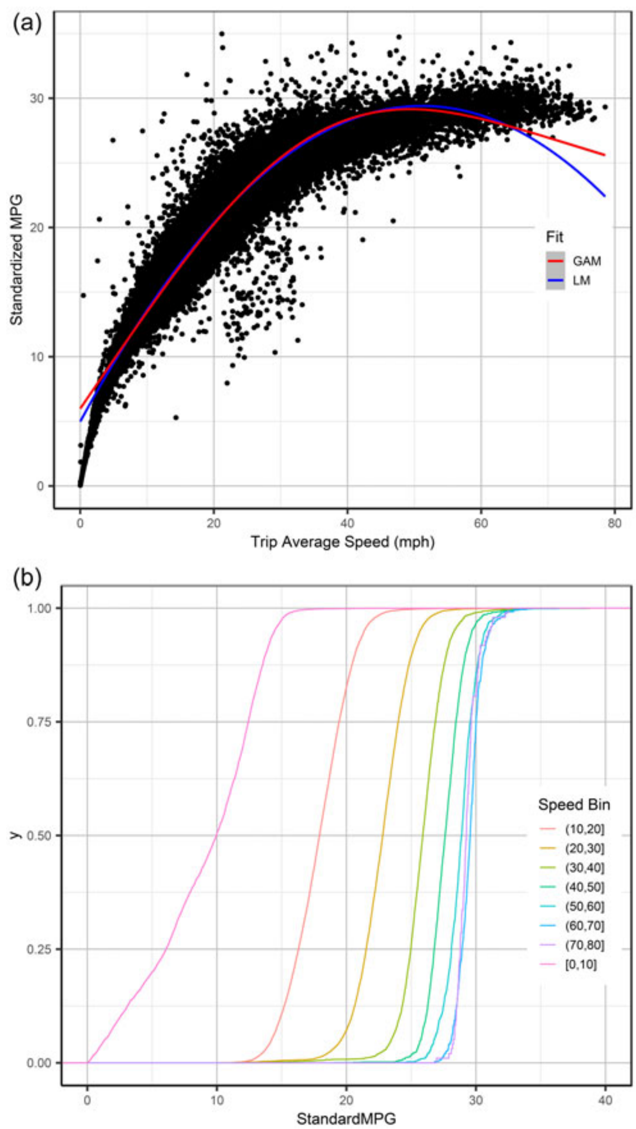



**Figure 2.** (a) Standardized MPG vs trip average speed (b) Cumulative distribution for standardized MPG at 10 mph trip average speed bins.

$$\overline{v_{ik}} = \frac{\sum_t^T v_{tik}}{N} \tag{2}$$

$$F_{ik} = \frac{2800}{3600} \frac{T \sum_t^T v_{tik}}{\sum_t^T f_{tik}} \tag{3}$$

where $\overline{v_{ik}}$ is average speed for trip $i$ for driver $k$, miles/hour; $v_{tik}$ is instantaneous speed for trip $i$ at time $t$ by driver $k$, miles/hour; $F_{ik}$ is standard vehicle fuel economy for trip $i$ by driver $k$, miles per gallon (MPG); $f_{tik}$ is instantaneous standard vehicle fuel consumption for trip $i$ at time $t$, grams/sec; $T$ is duration of trip $i$ in seconds.

The relationship between trip average speed ($\overline{v_i}$) and standard MPG ($F_i$) is shown in Figure 2a. The blue line is a quadratic function (LM) fit to the plot which shows a dip down in MPG at higher trip average speed. However, when a generalized additive model (GAM) was fit with a smooth on average speed as a predictor (considering dimension of basis function as 3), the fit stayed close to an optimal value of standard MPG. Summary statistics for the two different fits are shown in Table 2. Although both models were significant overall, the LM had slightly better adjusted-$R^2$ compared to the GAM. The shape of the fit suggests that there are separate distributions for standard MPG values at different speed levels. Cumulative distributions for standard MPG at 10 mph speed bins are shown in Figure 2b. The shape of all the distributions followed similar pattern with long tails on both sides. The median MPG values increased with increase in trip average speed. However, for the last (highest) two speed bins the distributions overlap.

The trip based eco-driving metric FES is developed from the insight gained from Figure 2b. Since the distributions shown in Figure 2b are Gaussian and non-skewed it is safe to assume FES changing linearly

**Table 2.** Summary statistics for fits between average trip speed ($\bar{v}$) and standardized MPG ($F$).

| Models | Model Parameters | Estimate | $p$ value | Adjusted- $R^2$ | Overall $p$ value |
|---|---|---|---|---|---|
| Linear Model (LM): $F = \beta_0 + \beta_1 * \bar{v} + \beta_2 * (\bar{v})^2 + \varepsilon$ | $\beta_0$<br>$\beta_1$<br>$\beta_{2,}$ | −1535<br>107.4<br>−1.477 | <0.0005<br><0.0005<br><0.0005 | 0.140 | <0.0005 |
| Generalized Additive Model (GAM): $F = \beta_0' + \sum_{i=1}^{2} f_i(\bar{v}) * \beta_i' + \varepsilon$ Where, $f$ is splines in Gaussian family with "identity" link function | $\beta_0$<br>$f_i(\bar{v})$ | −147.1 ,<br>$\beta_1'$ =1811.7, $\beta_2'$ =71.3 | <0.0005<br><0.0005 | 0.118 | <0.0005 |

between two extreme values. The relative fuel efficiency of the trip with respect to all other trips can be assessed if the trip average speed and trip standardized MPG are known. FES for an individual trip ($FES_i$) is scaled to vary from 20 to 100, with the minimum value occurring when trip standardized MPG ($F_{ik}$) is lower than the 10 percentile MPG value ($l_j$) for the speed bin and maximum value occurring when $F_i$ is greater than 90 percentile MPG value ($u_j$) for the corresponding speed bin. Minimum FES of 20 is chosen because displayed score under 20 may discourage drivers from following the e. Combined FES for all the trips (1, 2, 3,… …., I) made during a reporting period ($\tau$) is the trip length weighted summation of $FES_{ik}$.

$$FES_{ik} = 100 \ ; if \quad F_{ik} > u_j$$
$$FES_{ik} = 20 \ ; if \ \ F_{ik} < l_j$$
$$FES_{ik} = 20 + \frac{F_{ik} - l_j}{u_j - l_j} * (100 - 20) \ ; else \ u_j \ \geq F_{ik} \ \geq \ l_j \tag{4}$$

$$FES_k = \frac{\sum_i^I FES_{ik} * L_{ik}}{\sum L_{ik}} \tag{5}$$

where $FES_{ik}$ is fuel efficiency score for trip $i$ for driver $k$; $F_{ik}$ is standard vehicle fuel economy for trip $i$ for driver $k$, miles per gallon (MPG); $l_j$ is 10th percentile standardized MPG at speed bin $j$, interval 10 mph; $u_j$ is 90th percentile standardized MPG at speed bin $j$, interval 10 mph; $L_{ik}$ is trip length for trip $i$ for driver $k$, miles; $FES_k$ is fuel efficiency score for $I$ trips made during reporting period $\tau$ by driver $k$

### *Fuel use difference (FUD)*

The same trips used in calculating FES were also analyzed at the trajectory level. Observations of speed, acceleration, and instantaneous fuel consumption along with other information on vehicle performance are collected in 1 second intervals. A total of 20,947,617 observations were used in the following analysis after removing all trips shorter than one mile in distance or one minute in travel time. The trajectory level analysis aims to identify trends in standardized fuel consumption among drivers that can be aggregated at the trip or event level in order to track improvements in driver behavior.

The proposed metric for trajectory level analysis is the FUD, which is calculated as the percentage of instantaneous standard vehicle fuel consumption above or below the estimated fuel consumption at a given instantaneous speed. Fuel consumption was modeled using a segmented quadratic regression on driver average fuel consumption for a given speed range (fit in 2 mph speed bins). Figure 3a shows the observations of driver average fuel usage (in g/s) for each 2 mph speed bin, meaning that the maximum number of observations in each speed bin is equal to the number of drivers in the sample. Model fitting was performed using a weighted least squares regression on a segmented quadratic model that provides for equal value and slope at the breakpoint. Each driver average fuel usage observation was weighted by the number of seconds of data included in the averaging. The best fit model is described in Equation 6, resulting in a standard error of 0.035 g/s.

$$y = \ -0.000802v^2 + 0.0498v + 0.266 \ ; if \ \ v < 30 \ \ mph$$
$$y = \ -0.000432v^2 + 0.0243v + 1.377 \ ; else \tag{6}$$

where $y$ is Estimated standardized instantaneous fuel consumption in grams per second; $v$ is Speed bin median (mph)

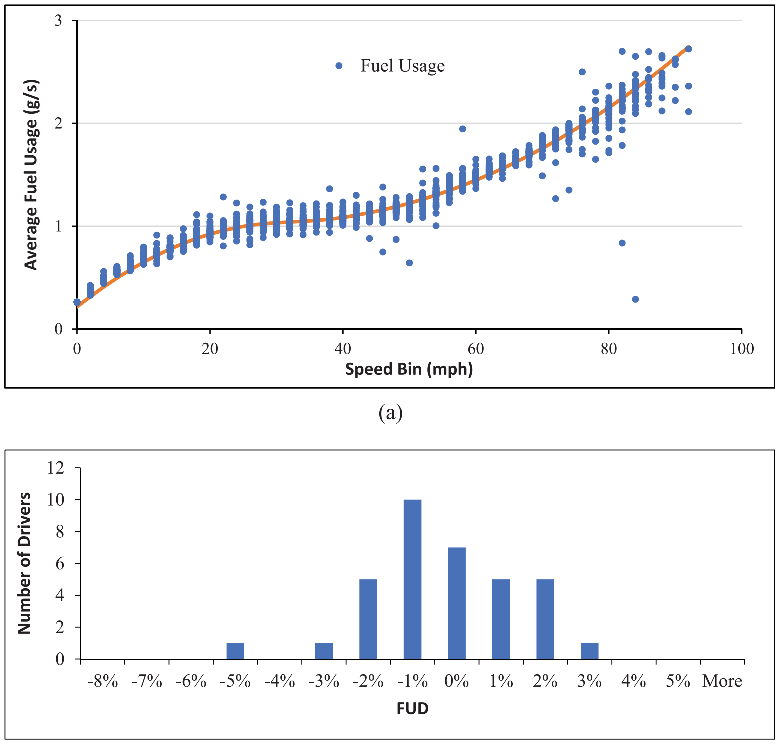
While the non-linear regression method used does not lend itself to direct measurement of individual parameter significance, reduced model forms were compared using the standard error of the regression; and the model shown in Equation (6) performed best. The individual co-efficient estimates meet the expectations of lower speeds as it shows a concave down shape while approaching the most fuel-efficient speed. In contrast, fuel use at higher speeds shows a concave up shape.

Using the model fit to driver average fuel usage, FUD is then calculated for each observation of speed according to Equation 7. This value can be averaged for a driver's individual trips or across any subset of a trip depending on the comparison of interest.

$$y_t = \ -0.000802{v_{tk}}^2 + 0.0498v_{tk} + 0.266 \ ; if \ \ v < 30 \ \ mph$$
$$y = \ -0.000432{v_{tk}}^2 + 0.0243v_{tk} + 1.377 \ ; else \tag{7}$$
$$FUD_{tk} = \frac{f_{tk} - y_t}{y_t} * 100 \tag{8}$$

where $FUD_{tk}$ is Fuel use difference at time $t$ for driver $k$; $y_t$ is Estimated standardized instantaneous fuel consumption in grams per second at time $t$; $f_{tk}$ is Actual standardized instantaneous fuel consumption in grams per second at time, $t$ for driver $k$; $v_{tk}$ is Instantaneous speed in mph at time $t$ for driver $k$.

Figure 3b shows the distribution of overall driver average FUD across the entire study period. It is important to note that as FUD is aggregated across larger time spans, the values will tend towards the mean according to the law of large numbers, so these




(b)

**Figure 3.** (a) Speed binned average fuel usage by driver vs. segmented model (b) Histogram of overall FUD by driver.

values do not necessarily explain the full range of fuel use differences between drivers.

## *Characterizing heterogeneity and consistency in driving style*

The essence of eco-driving lies in the ability for improving a driver's driving style to reduce fuel use. This infers that at least some drivers in the population are following an optimal style and some drivers are significantly lacking in fuel economy due to their inefficient style. Therefore, an eco-driving metric needs to identify this significant heterogeneity among drivers' styles. This article uses the Tukey's honest significant difference (HSD) to test whether the monthly scores of a pair of drivers are significantly different. The choice of month as reporting interval as opposed to week may cause a metric to be more centered on the driver mean.

Consistency of a metric requires it remain unchanged for an individual driver if no significant changes have been observed to his/her style. It also infers robustness of a measure. In this study, it is assumed that no changes have been made in drivers' driving styles as no instructions or incentives were given to them. Therefore, consistency of a metric means that its value across the reporting period should not be significantly different across reporting periods for all drivers. Thus, the presence of any time trend such as continuously increasing or decreasing value of the metric would violate the consistency requirement.

## Results and discussion

FUD is plotted against FES scores at monthly reporting period levels in Figure 4a. Each point is colored by the number of trips used to generate the metrics. The linear fit suggests an inverse relation between the two metrics; meaning the higher the FES, the lower is the FUD (negative FUD implies improved driving style). Such relation is expected as more fuel-efficient drivers are; less fuel will be consumed relative to the average fuel consumption. The statistics of fit between FES and FUD are reported in Table 3.

Even though the overall trend in the relation between FES and FUD matches expectations, the scatter is very high; suggesting that calculating one metric and converting them to the other may not provide reliable estimate of the other.

Scatterplots of the two developed metrics against averages of trip average speed and average trip length at monthly reporting period level is shown in Figure 4c and d. Since FES was developed using adjustments for trip average speed, there is no systematic pattern in monthly aggregated FES with average trip speed observed in Figure 4a. However, there appears to be a positive correlation of FUD with average of trip average speeds (Figure 4b). This suggests a collection of higher average speed trips during a month will cause FUD to increase; where in reality the same driver could be using different facilities or the operating conditions have changed. There is no significant effect of average trip length on both metrics.

Table 3. Fit statistics of relationship between FES and FUD.

| Model | Model Parameters | Estimate | $p$ value | Adjusted-$R^2$ | Overall $p$ value |
|---|---|---|---|---|---|
| $FES = \beta_0 + \beta_1 * FUD$ | $\beta_0$ | 7.41 | <0.0005 | 0.328 | <0.0005 |
| | $\beta_1$ | −0.132 | <0.0005 | | |

Monthly FES boxplots for each driver across the study period is shown in Figure 5. In addition to the 1-minute trip duration and 1-mile trip length filter, only driver-month combinations containing more than 30 trips were selected to remove bias in sample. Simple one-way analysis of variance (ANOVA) test was done with driver as a factor to test if FES varied significantly across drivers. Driver was found to be a significant factor from ANOVA.

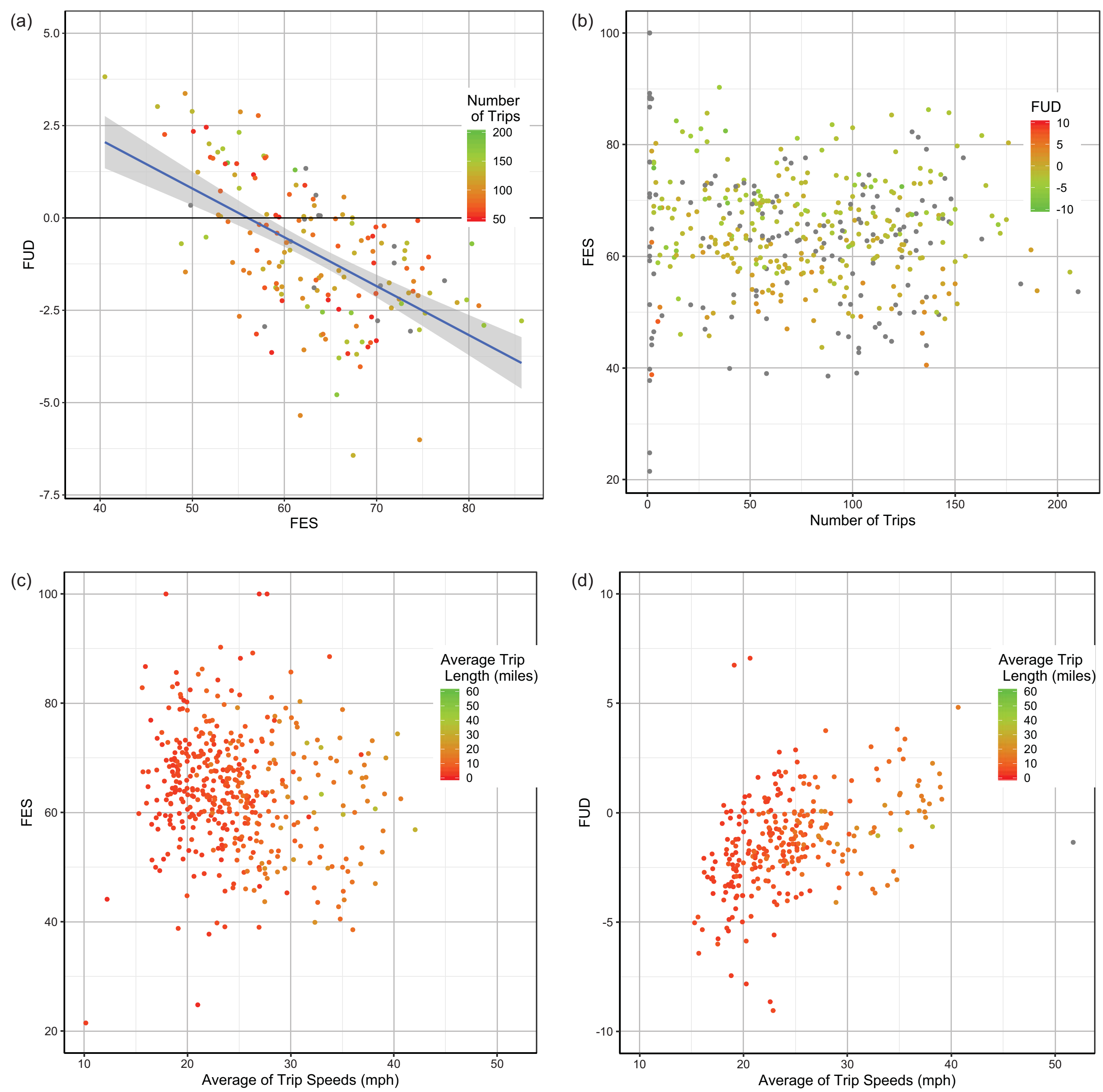



Figure 4. (a) Relation between driver FES and FUD at monthly aggregation level (b) Relation of FES and FUD with number of trips. (c) Monthly aggregated FES VS. average of trip average speeds (d) Monthly aggregated FUD VS. average of trip average speeds.

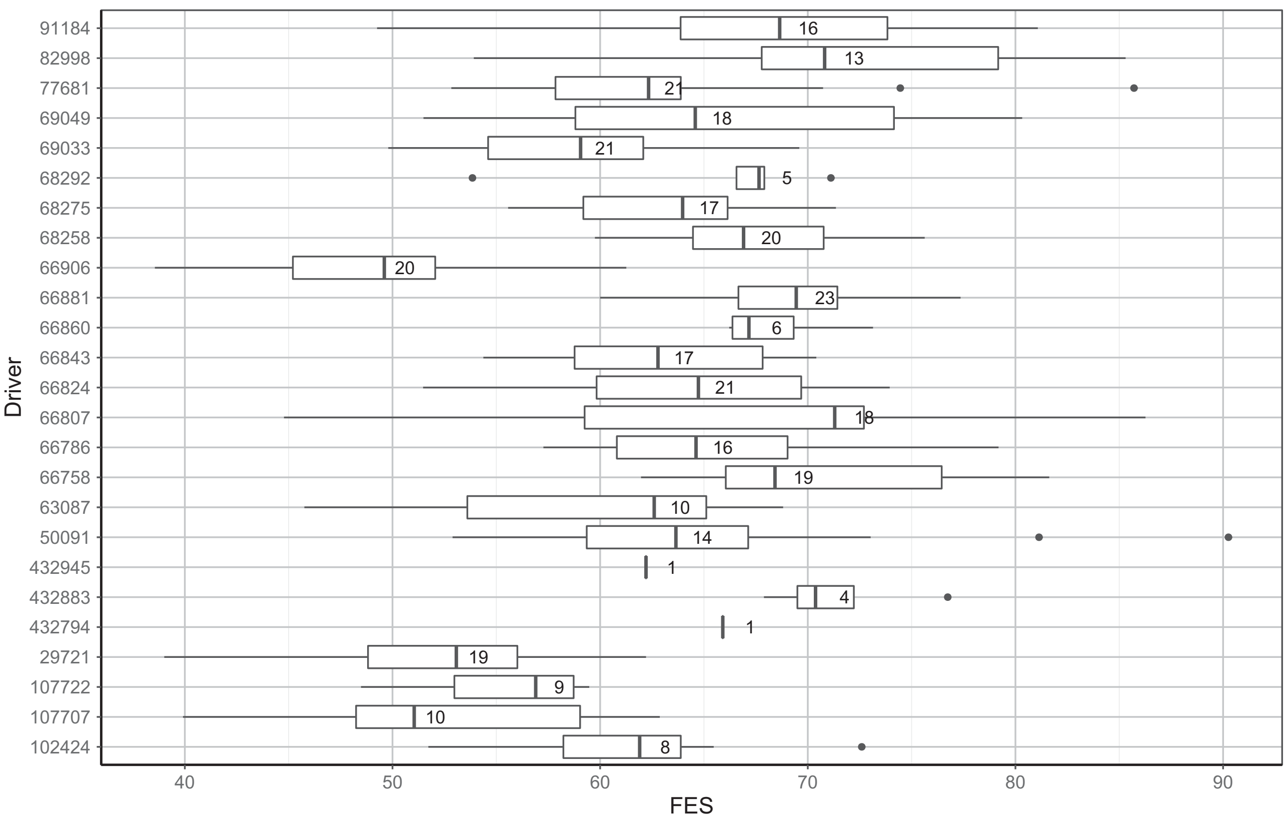



**Figure 5.** Boxplots of monthly FES for each driver across the study period. Number inside the box indicates total number of months of data used to generate that boxplot.

**Table 4.** Grouping of drivers according to monthly FES.

| Tukey's HSD Groups | | | | | | | Treatments (Driver ID) | Means (FES) |
|---|---|---|---|---|---|---|---|---|
| A | | | | | | | 82998 | 73 |
| A | B | | | | | | 66758 | 71 |
| A | B | C | | | | | 66881 | 69 |
| A | B | C | D | | | | 91184 | 68 |
| A | B | C | D | | | | 66807 | 68 |
| A | B | C | D | | | | 68258 | 68 |
| A | B | C | D | E | | | 66786 | 66 |
| A | B | C | D | E | | | 69049 | 66 |
| A | B | C | D | E | | | 50091 | 66 |
| A | B | C | D | E | | | 66824 | 65 |
| | B | C | D | E | | | 68275 | 63 |
| | | C | D | E | | | 77681 | 63 |
| | | C | D | E | | | 66843 | 63 |
| | | | D | E | F | | 63087 | 59 |
| | | | | E | F | | 69033 | 59 |
| | | | | | F | G | 107707 | 52 |
| | | | | | F | G | 29721 | 52 |
| | | | | | | G | 66906 | 49 |

The result from ANOVA was used to compute Tukey's HSD for pairwise comparison. Tukey's HSD of 8.6 was computed for the monthly FES. Based on this, Table 4 was generated to group drivers into similar clusters. Only drivers having at least 10 months of FES score were included in this grouping. Drivers with the same letter group are not significantly different. The mean FES value for the drivers ranged from 73 to 49. Four categories of drivers can be found in the data – 2 drivers with FES above 70, 8 drivers having FES in 65–70 range, 5 drivers in FES 55–65 range, and 3 drivers with FES below 55. In summary, this analysis has confirmed the hypothesis of the presence of heterogeneity across drivers based on their driving style.

Consistency of the developed metrics was tested in three steps – first the temporal progression of the metric was modeled with month as a predictor using one-way ANOVA. Second, individual driver time series were tested for stationarity. Finally, the coefficient of variation or standard deviation of a metric for an individual driver was calculated as a measure of dispersion.

FES progression for the selected group of drivers is shown in Figure 6. In most cases driver FES scores are scattered around the mean with a few outlier months where their driving style deviated significantly. FES modeled with one-way ANOVA resulted in month as an insignificant predictor. The probability that all monthly mean FESs are equal is 0.985.

A stationary time series is one whose statistical properties such as mean, variance, autocorrelation are all constant over time. Individual driver time series are tested for stationarity using autocorrelation plots and Dickey Fuller test (Dickey & Fuller, 1981) for a unit root with drift and deterministic time trend. Both

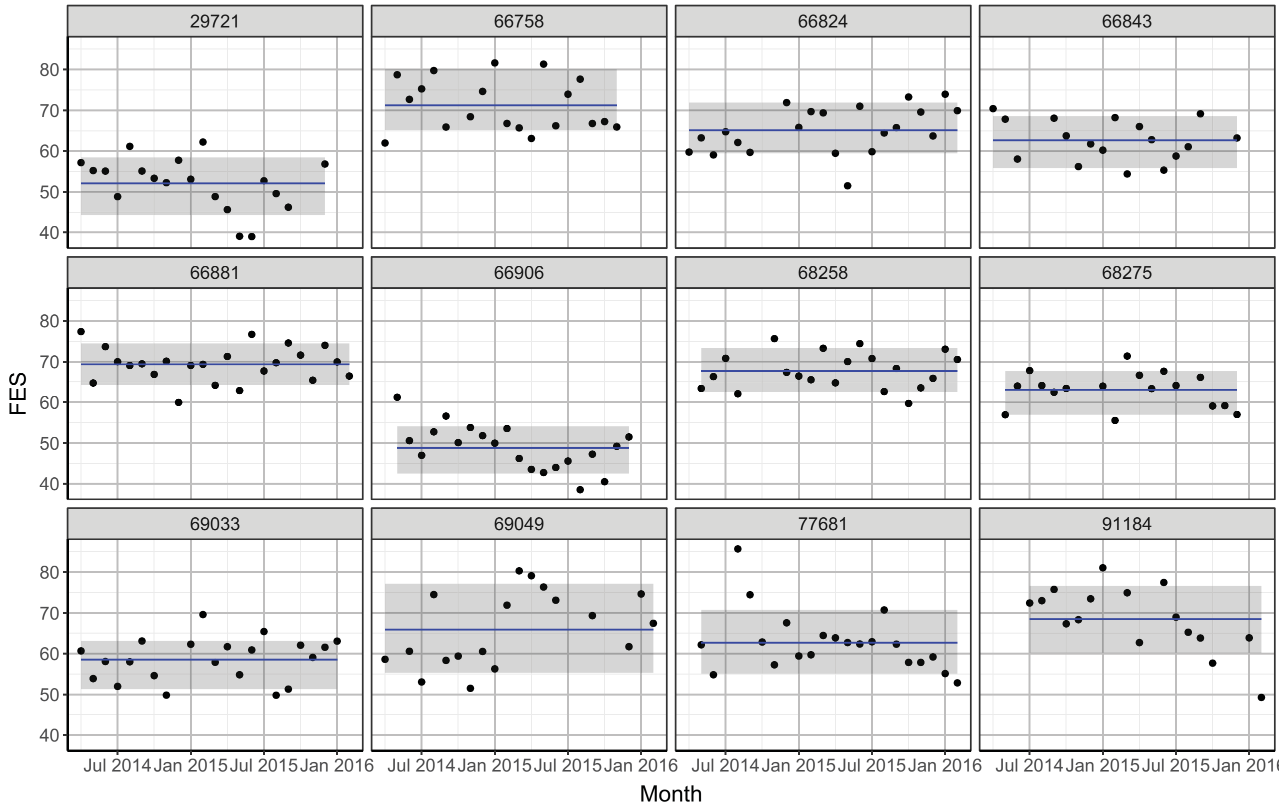



**Figure 6.** Progression of FES for individual drivers. Blue line indicates the mean FES and the gray ribbon shows 80% confidence interval.

test results indicated that the times series for FES and FUD are stationary across the months.

The coefficient of variation (standard deviation/mean *100) for monthly FES values for the selected drivers were calculated across the 2-year study. Coefficient of variation for FES varied from 6.2 to 13.9 with the mean value around 9.6. Since the mean value of FUD lies around 0 (due to presence of both positive and negative values), using the coefficient of variation for FUD is misleading to judge dispersion. Instead the standard deviation of FUD was calculated. Standard deviation of FUD varied from 0.50 to 1.84 with the median value at 0.98. In sum, considering all three consistency tests for both eco-driving metrics, it is reasonable to assume that they both are consistent individually. However, internal consistency of the two metrics is required to be tested. All drivers at a particular reporting period were ranked according to the values of their monthly metrics. Ranking of two drivers is shown in Figure 7. Driver ID 66758 had the second highest overall mean FES value and driver 66906 has the lowest overall mean FES. Even though both were consistently making the same number of trips across the months, their scores fluctuated and so did their ranking. However, their ranking fluctuated within a certain range. Ranking of the intermediate drivers fluctuated more frequently and their relative position changed. This infers that slight fluctuations in FES for intermediate drivers could result in large shifts in their ranking. This finding is consistent with the results in Table 4; intermediate drivers have overall FES that is not significantly different from each other.

## Conclusions and future work

The purpose of an eco-driving metric that benchmarks driving style is to remove the impacts of vehicle and route choice from fuel use while still identifying heterogeneity among drivers. Effects of vehicle type choice are standardized using instantaneous driving activity for a standard car. Average speed is used to standardize the differences in fuel consumption from route choice.

Studies of eco-driving may alternatively focus on complete trips or discrete events, and an eco-driving metric must be tailored to the study need. Based on the two perspectives of eco-driving analysis this study developed two metrics: a trip-based metric (FES) designed to analyze overall trip fuel efficiency while accounting for trip average speed; the second based

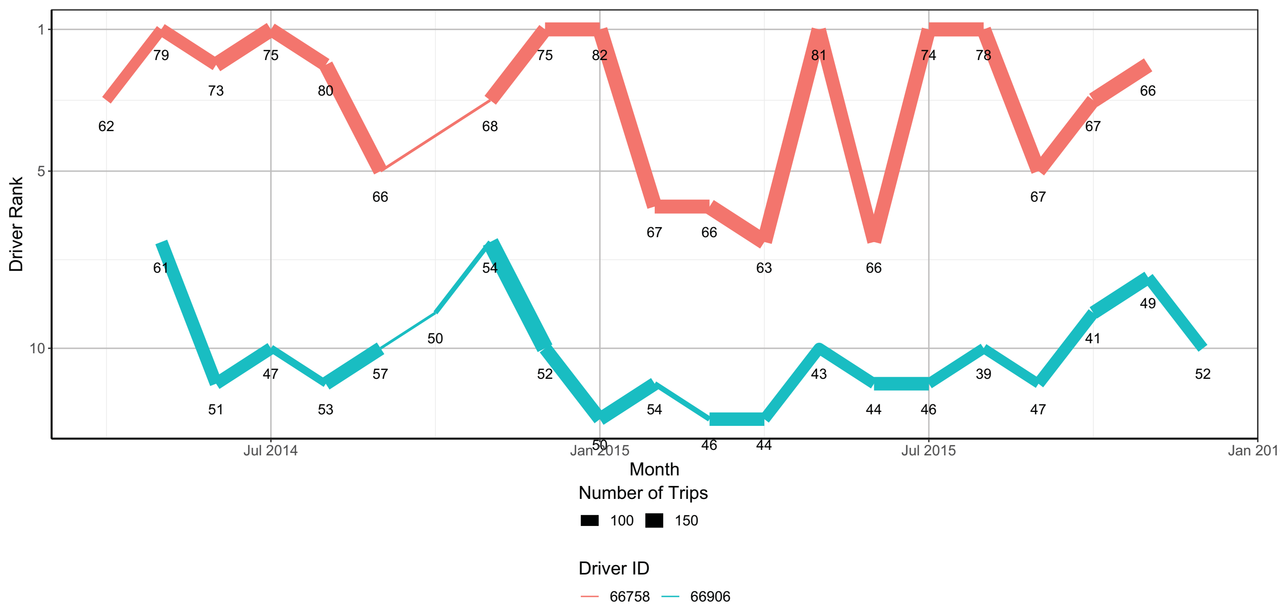



**Figure 7.** Ranking of two drivers across months according to monthly FES for two drivers. Numbers adjacent to the lines show actual FES.

on trajectory level FUD from estimated usage accounting for instantaneous speed.

Both FES and FUD were found to be capable of distinguishing heterogeneous driving styles. Individual drivers' scores on both metrics are consistent over time – there is no trend or level shifts in their behavior without any intervention. However, dispersion of metrics around the mean may cause confusions in judging effectiveness on an intervention. In that case, Tukey's HSD for pairwise comparison between before and after eco-driving interventions can be used to detect significance of differences. Incentive tracking and delivery can be done by grading the drivers according to eco-driving metrics.

FES can be implemented by eco-driving schemes where aggregate trip-based measures are available. In contrast, FUD can be implemented at sub-trip level where improvements during certain behaviors such as braking, accelerating-from-rest, cruising, etc. can be tracked separately. FES is more geared to post hoc delivery of eco-driving advisory and performance tracking; whereas FUD is suitable at microscopic level even when the trip is not yet completed. Calculation of FES is less data intensive compared to FUD.

FES and FUD have a significant inverse relationship with a lot of scatter. Conversion between two metrics is possible at an aggregate level, however, will not be reliable at a trip level. Since FES is already standardized by average trip speed, it does not show a trend against trip average speed. However, FUD was standardized by instantaneous speed and has slight positive slope with trip speed. FES and FUD are very different from one trip to another and aggregation at weekly or monthly level causes it to center. According to law of large numbers variability in either metric is reduced at higher aggregation levels. Reduced variability at higher aggregation level causes heterogeneity among drivers less distinguishable. However, the statistical analysis shows presence of groups of drivers with different fuel efficiency levels. Therefore, grading the drivers at discrete groups can be significant in order to communicate improvements immediately to the driver.

This research has provided a footing to benchmark the driving styles for a vehicle fleet. The researchers are currently acquiring additional naturalistic driving data in the DC-Baltimore region to verify robustness of the model parameters. Future research will be directed towards finding out the specific associations between trip level driving behaviors such as braking, accelerating, speeding, and the developed eco-driving metrics. Personalized recommendations thus developed along with personalized incentives will serve as a basis for "nudging" drivers to choose optimized driving styles.

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