F2018-PTE-081

DATA MINING APPLICATIONS FOR VEHICLE TESTING AND DEVELOPMENT

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2018 FISITA World Automotive Congress, Chennai, India, October 2-5, 2018

ABSTRACT

Vehicle telematics systems are transmitting massive volumes of data that are underutilized during the test, development and production lifecycle. Analyzing all of this data is challenging, not only due to size but also because of the variability that is encountered during on-road driving. Vehicle performance is affected by drive route, road grade, traffic, weather, vocation and driver tendencies. This study explores the efficacy of using data mining techniques to predict vehicle fuel consumption and exhaust emissions from On Board Diagnostics (OBD) data that may be harvested from telematics data stores. These data mining concepts have potential applications for eco-drive vehicle control system development, real-world emissions factor development for source apportionment models, and the analysis of Intelligent Transportation System (ITS) technology impacts on vehicle energy efficiency and emissions.

INTRODUCTION

Modern day engines and vehicles are equipped with myriad engine sensors and microcontrollers, and typically employ over five types of networks including telematics connectivity to the internet. In this era of big data, there are unprecedented opportunities for data collection and deeper analysis. Vehicle manufacturers collect over a thousand channels of data per vehicle at high frequency in their test and development campaigns. Manufacturers also capture and transmit smaller frames of data from their customer vehicles, commonly triggered in the event of a powertrain fault. In the future, government agencies will also have increasing access to engine and vehicle sensor data. “Remote OBD” programs may require transmittal of On Board Diagnostics messages including the self-reporting of diagnostic trouble codes to enable more effective monitoring of in-use emission system performance. Connected vehicles may transmit emissions control information as vehicle-to-infrastructure (V2I) technologies advance.

With the increasing availability of large volumes of in-use vehicle data and the advancement of data mining technologies, there are new opportunities to explore vehicle utilization, energy efficiency, and exhaust emissions impacts. This study explores the viability of using engine sensor data to predict in-use vehicle fuel consumption and emissions.

A vast amount of research has been conducted to simulate vehicle fuel consumption and emissions, noting that many of the physics-based models require specification of engine component and vehicle attributes such as performance maps, mass, rolling resistance and aerodynamic drag. Since such vehicle design details are not readily obtained, transportation researchers have explored the prediction of vehicle fuel consumption and emissions using OBD data. Previous empirical modeling approaches have used multivariate linear regression and exponential solutions to fit in-use vehicle data [1,2,3,4]. Research by Frey et. al. [1,2] explored both internally and externally observable variable models, and the results quantified the difficulty in modeling emissions rates from ultra-low emissions vehicles.

This study expands upon the cited research by using the latest machine learning algorithms to establish the relationships between the engine sensors and the measured fuel consumption and exhaust emissions rates. A machine learning approach may uncover engine sensor and emissions interactions that are too subtle for human observation, and is unencumbered by the constraints of linear regression.

The objective of this study was to determine the efficacy of predicting vehicle fuel consumption and exhaust emissions using data mining techniques. Three light-duty vehicles were tested using an emissions certification-grade Portable Emissions Measurement System (PEMS). The study explored the general applicability of the data mining approach and included cross-validation using the PEMS measurements. The study included newly published real driving emissions data and microscopic vehicle analysis for a variety of different operating modes.

APPROACH

Vehicle Selection and Testing

Three light-duty vehicles equipped with gasoline engines and three-way catalysts were selected for study (Figure 1). Jeep #2 was intentionally chosen to have the same engine model and U.S. EPA emissions certification family as Jeep #1 to assess the general applicability of the predictive modeling approach. The Ford #1 truck was selected to evaluate predictive model performance for a much heavier class of vehicle equipped with a turbocharged engine.

The vehicles were fitted with an AVL M.O.V.E GAS PEMS 493 that included gas analyzers, exhaust gas flow measurement, and recording of engine sensor data via SAE J1979 Mode 01 OBD-II. The AVL PEMS is a laboratory-grade instrument that is calibrated with zero and span gases and uses partial flow exhaust sampling. This gas analyzer technology is used for U.S. EPA NTE and EU real driving emissions testing, and is considered more accurate than in situ exhaust gas sensor measurements. Emissions measurements included carbon monoxide (CO), carbon dioxide (CO_2), nitric oxide (NO), and total hydrocarbons (THC). Instantaneous fuel consumption was calculated using the carbon balance method.

Jeep #1	Jeep #2	Ford #1
2013 Jeep Wrangler 2-Door Manual	2013 Jeep Wrangler 4-Door Automatic	2016 Ford F-150 SuperCrew 6.5' Box, Automatic
Engine: 3.6L V6, Port Fuel Injection, Nat. Asp.	Engine: 3.6L V6, Port Fuel Injection, Nat. Asp.	Engine: 3.5L V6, Direct Fuel Injection, Turbo Asp.
Emissions Certification: EPA Tier 2 Bin 4	Emissions Certification: EPA Tier 2 Bin 4	Emissions Certification: EPA Tier 2 Bin 4 – LDT4
Odometer = 34,600 km (21,500 miles)		Odometer = 43,770 km (27,200 miles)
Dyno Testing: 3.7 hours, 122 microtrips	Dyno Testing: None	Dyno Testing: 5.6 hours, 127 microtrips
On-Road Testing: 4.3 hours, 93 microtrips	On-Road Testing: 6.0 hours, 109 microtrips	On-Road Testing: 8.9 hours, 204 microtrips

Figure 1. Test Vehicles with PEMS Installed

Jeep #1 and Ford #1 vehicles were tested on a chassis dynamometer (Figure 1, right) and on the road. Chassis dynamometer testing was conducted at the SGS Environmental Testing Center in Aurora, Colorado. Jeep #2 was tested on-road only. On-road testing was performed in the Aurora region. The test fuel was not precisely specified for Jeep #1 tests, and U.S. EPA Tier 3 certification gasoline (10% ethanol, ≤ 10ppm sulfur) was used for all Jeep #2 and Ford #1 tests.

An initial objective of the experiment was to use "machine learning" algorithms to learn vehicle performance in the chassis dynamometer laboratory, and then use the resulting model to predict on-road vehicle emissions. Therefore, the chassis dynamometer tests needed to include a range of vehicle driving styles and operating modes with enough explanatory information being collected to make on-road predictions possible. Chassis dynamometer tests used a variety of driving cycles, including city-highway (EPA Federal Test Procedure), highway only driving (EPA Highway Fuel Economy Test), high speed driving (EPA US06 and LA92), the Standard Road Cycle (SRC) and a real-world cycle created from on-road test results for each vehicle.

The vehicles were correspondingly tested on the road for different operating modes including cold start, city driving, highway driving, aggressive accelerations and high road grades. The dynamometer lab testing time, on-road testing time, and number of micro-trips are summarized in Figure 1. A micro-trip begins when the vehicle launches from rest and ends when it stops, thus providing a convenient means to aggregate in-motion vehicle data for analysis. The raw test results were time-series data logged at 1 Hz, equivalent to about 103,000 observations for each channel being recorded.

Data Mining

The dynamometer lab tests measured a similar range of fuel consumption and emission rates that were encountered during on-road testing. Typical results are shown in Figure 2, with each point representing an observation from the time-series data. The similar coverage within the testing space suggested there was no obvious bias between the on-dyno and on-road PEMS test results.

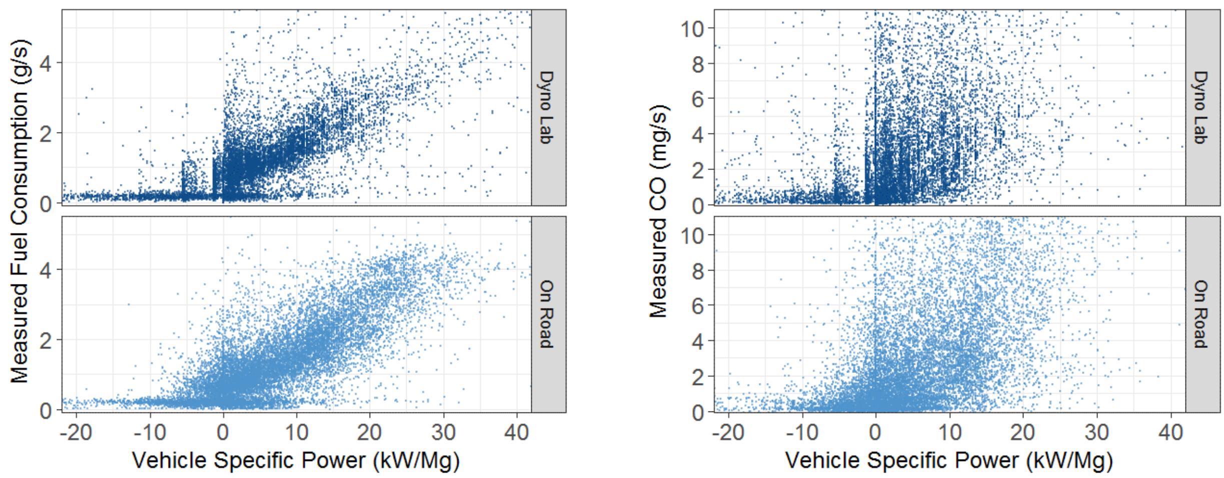

Figure 2. On-Dyno and On-Road Comparison of Fuel Consumption and CO Emissions, Jeep #1

Noting that time-series vehicle data are highly variable, the concept of Vehicle Specific Power (VSP, in kW/Mg [5]) was adopted to aggregate data into bins and promote better visualization. Whereas several different VSP binning schemes are in use, the authors chose a concise and visually interpretable scheme from Frey, et. al. [6]. The percent of vehicle operating time in each of the VSP modes during testing is summarized in Figure 3. Jeep #1 and Jeep #2 had very similar VSP distributions as expected, since they had the same engine model and were driven on similar routes. Ford #1 had very little operation in VSP modes 10 to 14 during testing and these modes were therefore excluded from predictive modeling and data analysis.

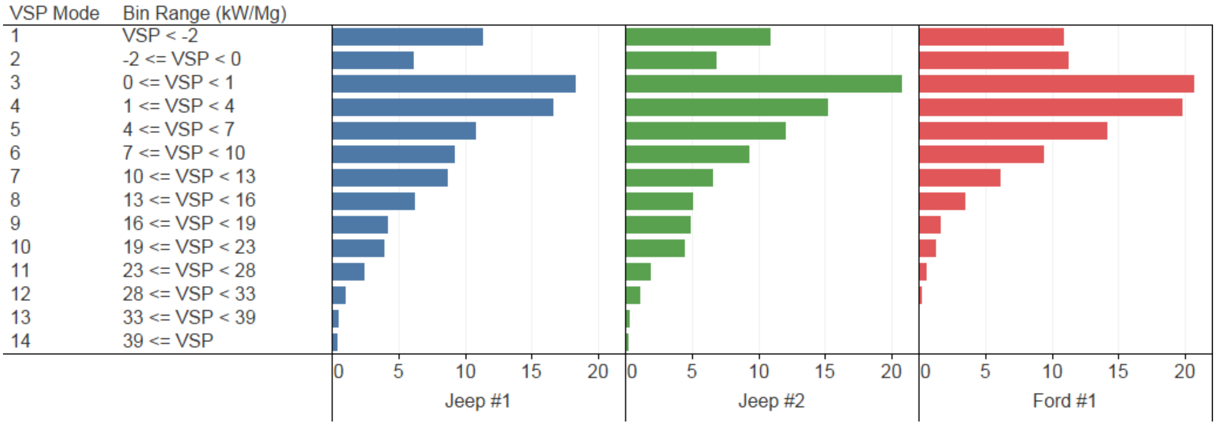

Figure 3. Percent of Vehicle Operating Time in each Vehicle Specific Power Mode

Machine learning, a sub-discipline within data mining, was used to establish the relationships between the engine sensors and the measured fuel consumption and exhaust emissions rates. The authors used random forest regression trees within the Apache Spark™ 2.0 machine learning library to develop predictive models. Best practices were used, including the partitioning of the vehicle data into "training sets" for supervised machine learning, and "testing sets" for cross-validation of the predictions. The "training set" initially included the dyno lab data only, and the resulting models were found to be adequate for fuel consumption but lacked accuracy for emissions prediction. The "training set" was subsequently expanded to include 50% of the on-road test data by randomly sampling complete micro-trips. The resulting models were then used to predict fuel and emissions rates for the remaining 50% of the on-road test data, and only those predictions are presented in this paper. The model fits to the "training set" are not presented for brevity.

Machine learning models were developed for Jeep #1 and Ford #1 vehicles, and cross-validated using distinct on-road "testing sets" from those same vehicles. The machine learning models developed for Jeep #1 were also used to predict the on-road performance for Jeep #2 to determine the applicability of the model to similar vehicles in the fleet. All of the Jeep #2 data were used for cross-validation purposes and designated as "different-vehicle" results.

The candidate machine learning features (independent variables) included engine and ambient sensor information available from the J1979 OBD-II protocol and summarized in Figure 4. Externally observable factors such as vehicle speed, acceleration and road grade were excluded from the machine learning training set, as their effects were already manifested in the engine sensor measurements. The dependent variables included fuel consumption and CO, NO and THC emissions rates in grams/second measured using PEMS.

Each record in the 1 Hz time-series data represented a sequence-independent observation that was used in the machine learning model (Figure 4). There are potential data acquisition system inaccuracies to be considered when using such fine granularity data in this manner, including time alignment of the acquired data channels, sensors with lagging update rates, and data drop-outs. Once properly accounted for, the time series data logs provided many thousands of observations for machine learning purposes from only a few hours of test data.
The prediction of exhaust emissions is challenging for modern vehicles that have very low emissions concentrations following catalyst light-off. For Jeep #1, NO and THC emissions were

below the detection limit 21% and 53% of the time, respectively. The analysis approach aimed to capture average behavior within these low emission regimes, noting that model fitting for this noisy and complex 1 Hz vehicle data was often not aesthetically pleasing following feature extraction. The analysis demonstrated that good estimates of central tendency were sufficient to provide credible predictions when data were aggregated by micro-trip or by VSP mode.

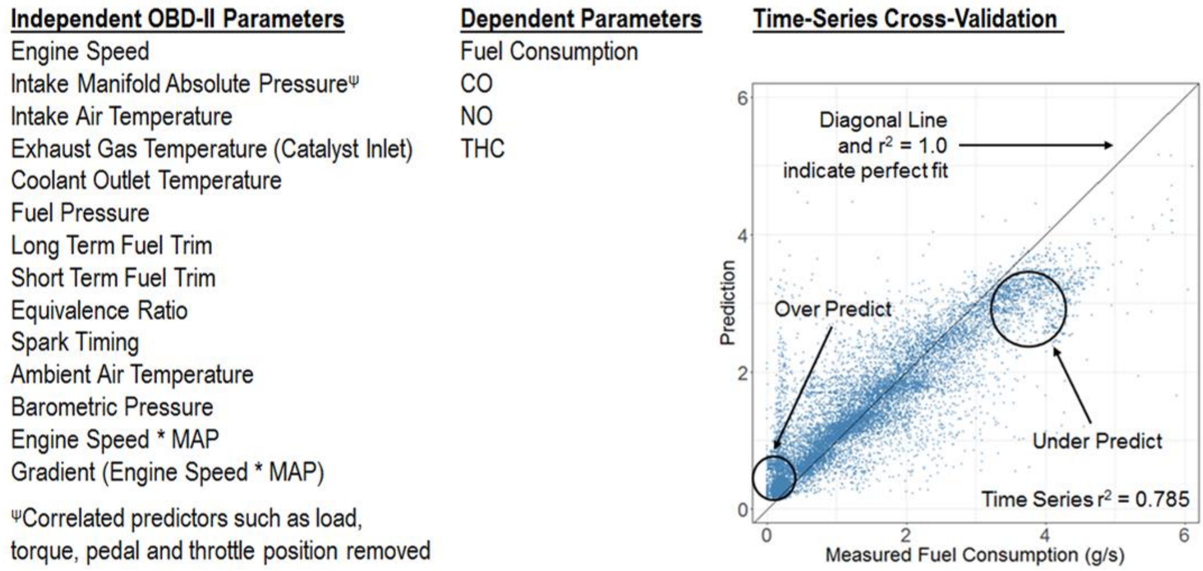

Figure 4. Machine Learning Variables and an Example of Time-Series Data Cross-Validation

RESULTS

Fuel Consumption Results

The machine learning models built using the “training set” data were used to make fuel consumption predictions for a distinct set of on-road test data. The average fuel rates were calculated for each micro-trip, and the measured and predicted values were compared using the parity plots in Figure 5. The fuel consumption model predictions were strongly correlated with PEMS measurements.

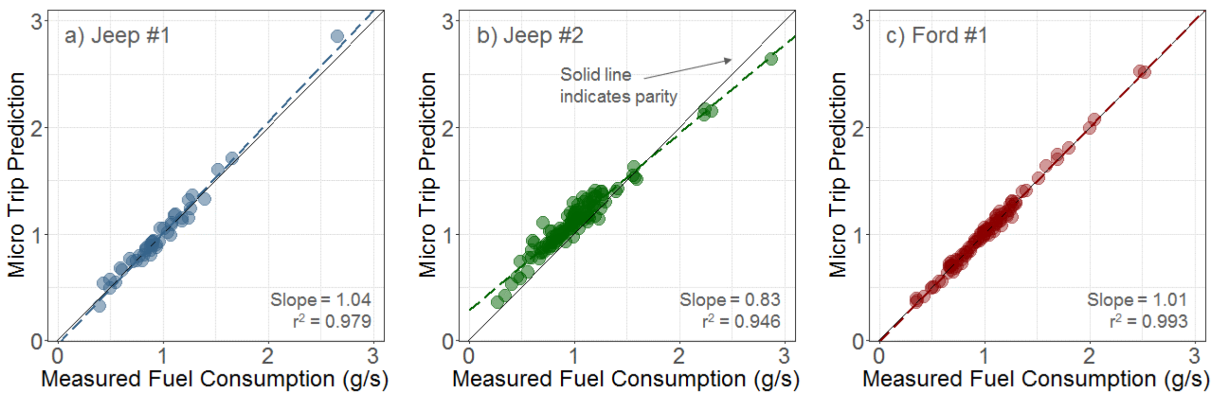

Figure 5. Fuel Consumption Predictions for On-Road Vehicle Operation

The average fuel rate prediction error for the Jeep #1 micro-trips was +0.97%. The prediction error exceeded 10% for 5 of the 45 micro-trips. The largest prediction errors occurred for short duration micro-trips, with 5 trips being under 20 seconds.

The machine learning model created for Jeep #1 was used, without any re-tuning, to predict Jeep #2 on-road fuel rates (Figure 5b). The model consistently over-predicted Jeep #2 micro-trip fuel rates, with the average prediction error of 14% being considered unacceptable for microscopic vehicle analysis. Further data research is required to prove the cause of this systematic error. Possible causes may be the overfitting of Jeep #1 training data making the model less applicable to other vehicles, or an insufficient volume of training data for making sufficiently accurate "different-vehicle" predictions. It is unlikely that the cause of the Jeep #2 fuel rate prediction error was due to lack of explanatory information provided by the OBD features (Figure 4), since the same feature set was used successfully for the development of the Jeep #1 and Ford #1 fuel consumption models.

The average fuel rate prediction error for Ford #1 micro-trips was only -0.02%. The prediction error exceeded 10% for 5 of the 100 micro-trips. These favorable results indicated that the relatively limited OBD feature set (Figure 4) was sufficient to predict the fuel consumption of vehicles equipped with turbocharged gasoline engines.

Jeep #1 Emissions Results

The prediction of vehicle emissions using empirical data is challenging in part due to the dichotomy between data quality and quantity. Whereas the vehicle operates at low power for a high percentage of time (Figure 3), the measured emissions concentrations may be near the threshold of detection for a large proportion of the recorded data. Conversely, higher emissions rates have a better "signal-to-noise" ratio, but often occur at high power where there is considerably less vehicle operation and fewer observations available for model training. The data were aggregated by micro-trip and by VSP modes to evaluate predictive performance in both operating regimes. The micro-trip data are presented as parity plots, and scaled to determine the model's capability for discerning trends at very low emissions levels. Average emissions rates were also aggregated by VSP modes in bar chart format and used for quantitative comparisons over the full emissions range.

The machine learning models built from the "training set" data were used to make emissions predictions for a distinct set of on-road test data. Predictions were compared to PEMS emissions measurements for Jeep #1 in Figure 6. A general correlation between the predicted and measured CO and THC emissions was apparent from the micro-trip data even at very low emissions levels. The CO, NO and THC models were all able to faithfully predict emission rate changes from mode-to-mode. For example, a step change between low and high emission regimes was successfully predicted for all species (VSP Mode 13 for CO and THC, Mode 10 for NO).

The percent difference between the modal averaged predictions and PEMS measurements (designated as "prediction error") are indicated for select modes in Figure 6. The models provided good emissions estimates overall. The prediction errors were typically within the bounds of dyno test measurement repeatability [7] when aggregated by VSP mode. Some average modal emission rates were overpredicted and others were underpredicted, indicating that the machine learning models did not produce systematic errors for Jeep #1. The large discrepancy for CO emissions in VSP Mode 14 was attributed to the lack of training data for this high-power condition (Figure 2).

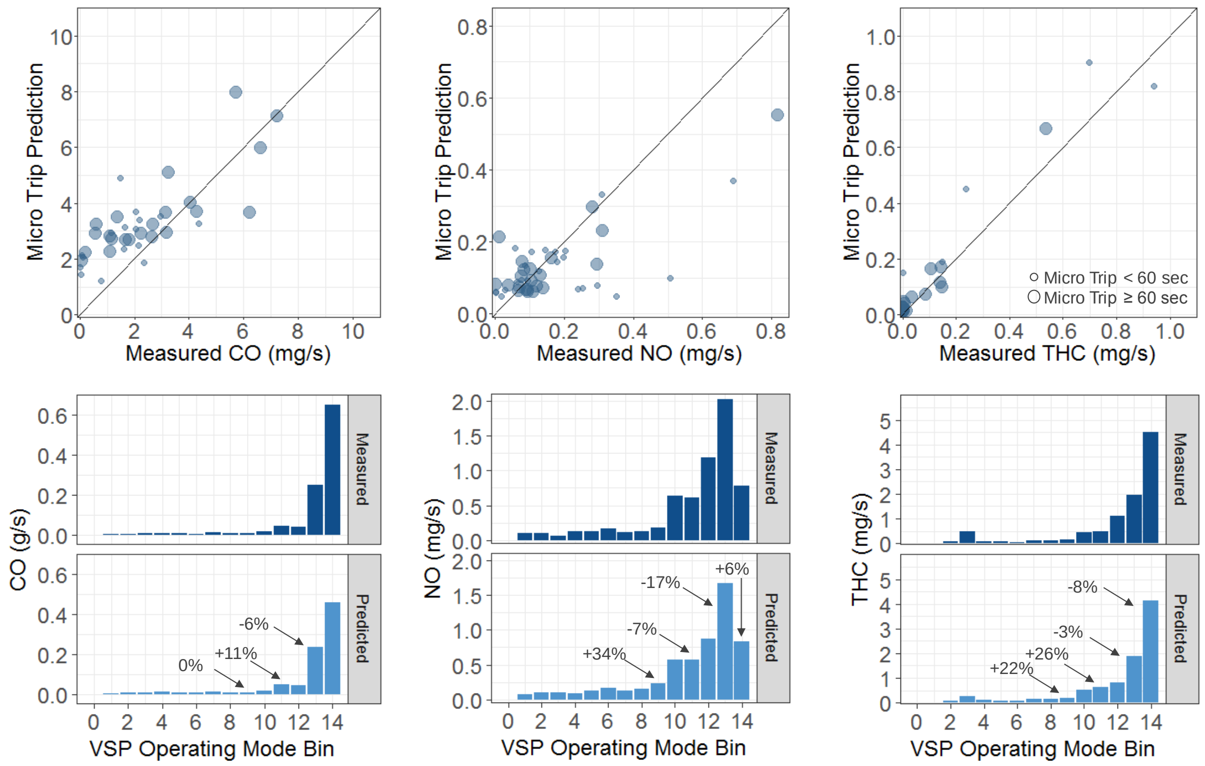

Figure 6. Average Micro-Trip and VSP Modal Emission Rates for On-Road Driving, Jeep #1

Jeep #2 Emissions Results

The same machine learning model created for Jeep #1 was used, without any re-tuning, to predict Jeep #2 on-road emissions rates (Figure 7). A general correlation between the predicted and measured CO and THC emissions was apparent from the micro-trip data at low emissions levels. The predicted CO rates were within ±25% of PEMS measurements for Modes 4 to 11. Large prediction errors were observed for the high power Modes 12 to 14. Jeep #1 and Jeep #2 vehicles had extremely different measured CO emissions behavior at these modes (as evident by comparing measured data in Figure 6 and Figure 7). The machine learning model was trained on Jeep #1 emissions data that were an order of magnitude higher and likely explained the overprediction for Jeep #2 at high power.

The model overpredicted NO emissions at every VSP operating mode for Jeep #2, and was especially apparent at low emissions levels and low power operating modes as indicated in Figure 7. NO predictions improved at higher power. The THC emissions were within ±20% of the PEMS measurement values for Modes 4 to 13.

The CO, NO and THC models were all able to match the relative emissions level variations seen from mode-to-mode. Absolute NO emissions rates were significantly overpredicted and considered erroneous for Modes 1 to 9. The NO and fuel consumption predictions for Jeep #2 appear to have similar systematic errors that may potentially be caused by model overfitting or insufficient data volume as previously discussed.

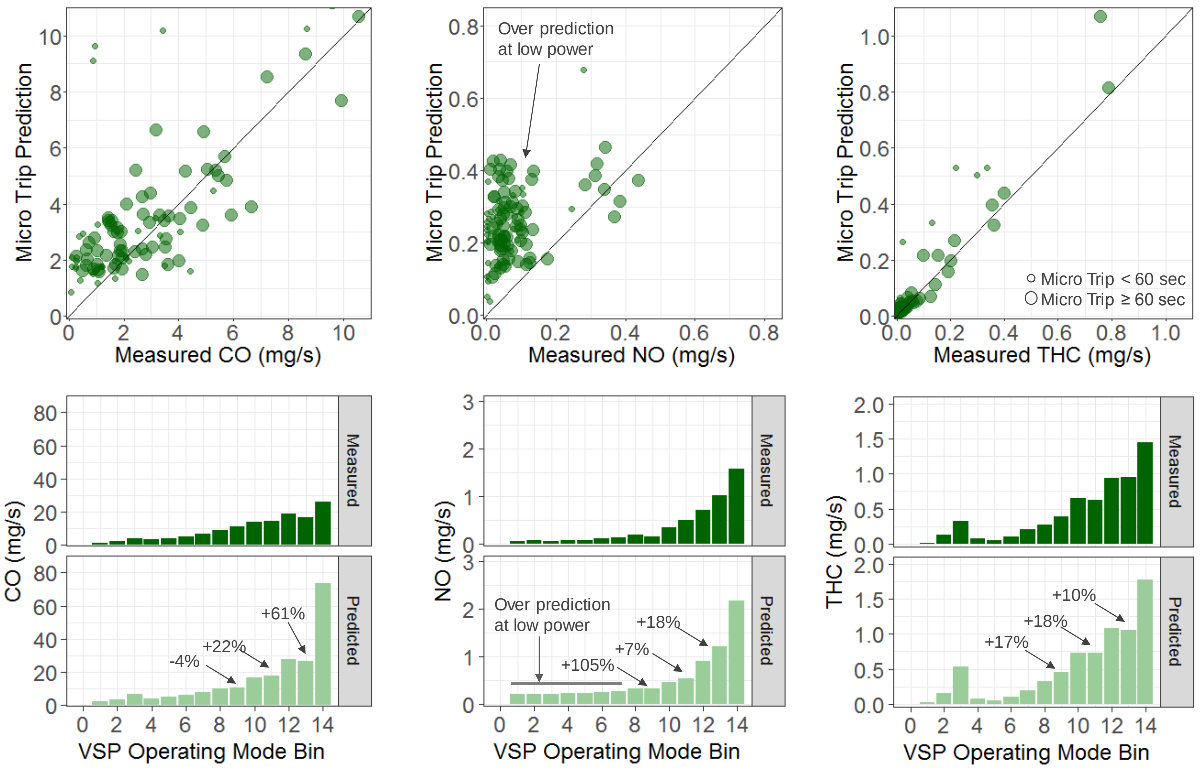

Figure 7. Average Micro-Trip and VSP Modal Emission Rates for On-Road Driving, Jeep #2

<u>Ford #1 Emissions Results</u>

The machine learning models created from the "training set" data were used to make emissions predictions for a distinct set of on-road test data. Emissions predictions were only made for Modes 1 to 9, due to insufficient test data at higher power modes. Akin to Jeep #1, the machine learning models were strongly correlated with measured PEMS data when aggregated by VSP mode (Figure 8), and provided good estimates for the emissions rates. The CO, NO and THC models were all able to predict the emissions rate variations seen from mode-to-mode.

The fuel and emission rate prediction errors were typically smaller for the Ford #1 vehicle than for the Jeep #1 vehicle. The Ford #1 vehicle had about 70% more training data available (4.2 hours more data) compared to Jeep #1. The Ford #1 analysis also excluded the sparse data from VSP Modes 10-14, potentially lessening the influence of extreme values during model training.

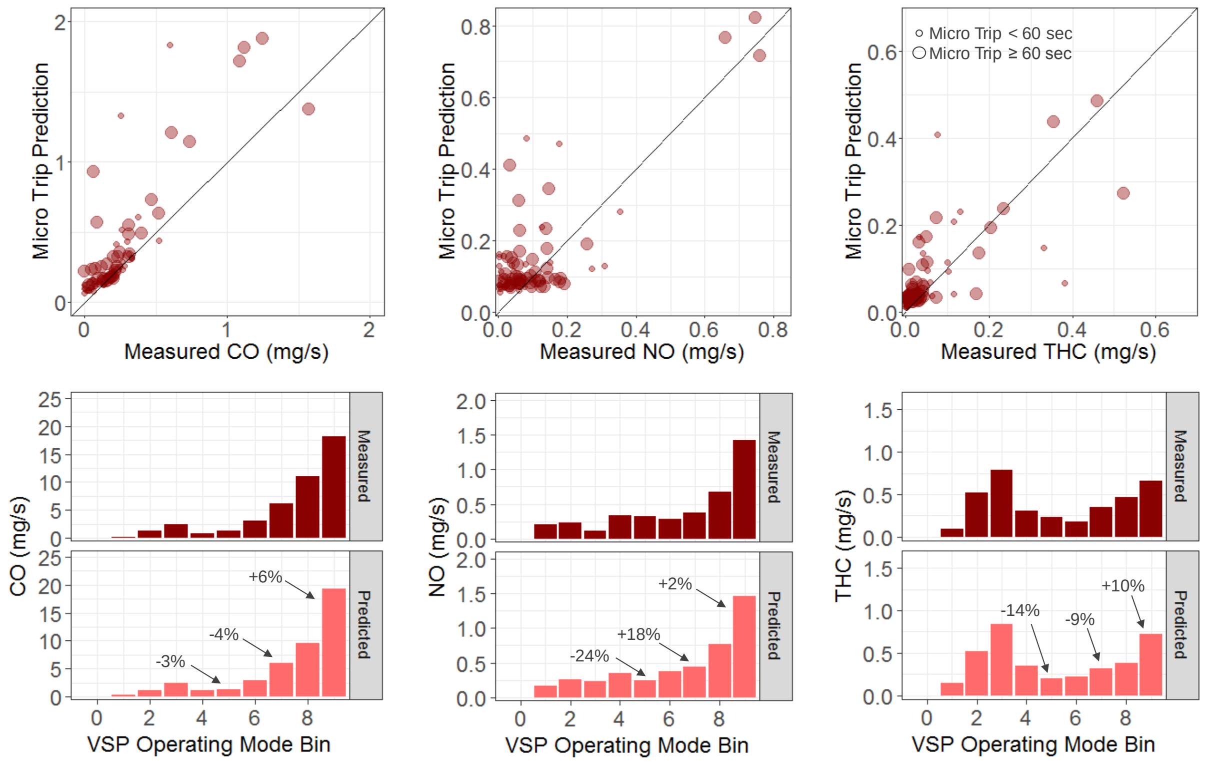

Figure 8. Average Micro-Trip and VSP Modal Emission Rates for On-Road Driving, Ford #1

SUMMARY AND CONCLUSIONS

This study explored the efficacy of predicting vehicle fuel consumption and exhaust emissions using data mining techniques. Machine learning algorithms were used to establish the relationships between the engine sensors and the measured fuel and emissions rates. The application of random forest regression tree algorithms in this manner is believed to be somewhat novel, in that time-series data collected from laboratory and on-road vehicle testing using PEMS were used for predictive model development and cross-validation. The study was conducted using three vehicles certified to U.S. EPA Tier 2 Bin 4 emissions standards.

Machine learning models were built from “training set” data collected for two of the vehicles, and were then used to make fuel rate and emissions predictions for distinct sets of on-road test data. The on-road test datasets were used to produce the cross-validation results presented in this paper. The model prediction errors for fuel consumption, CO, NO and THC emissions were typically within the bounds of dyno test measurement repeatability when aggregated by VSP mode. Moreover, the machine learning models were capable of predicting the progressive increase in emissions rates at higher VSP modes. The study demonstrated the successful application of data mining to learn and predict “same-vehicle” fuel consumption and emissions rates, for both naturally aspirated and turbocharged gasoline-powered vehicles.

The extension of the models to predict “different-vehicle” fuel consumption and emissions rates was explored by testing and analyzing a second Jeep Wrangler certified to the same EPA engine emissions family. The machine learning models produced credible estimations and adequately predicted trends, but systematic errors were observed for fuel consumption and NO predictions.

The machine learning results were achieved using a relatively small feature set that was limited to only the manufacturer-supported Parameter IDs (PIDs) available via SAE J1979 OBD-II. We expect that predictive capability would significantly improve if more of the existing J1979 PIDs were supported, or if new J1979 PIDs or proprietary CAN sensor data were made available for model training.

The present research suggests that it is feasible to apply these data mining concepts to the larger vehicle fleet on a big data scale. Large time-series vehicle data sets are being collected by the manufacturers' testing and remote monitoring programs, and from statutory programs such as the Euro6 Real Driving Emissions requirement for on-road testing of light-duty vehicles using PEMS. These rich data sources provide the means to develop machine learning models for individual makes/models of vehicles. Predictions may then be made for these makes/models operating in the fleet using OBD data collected from telematics data transmissions. The systematic errors for "different-vehicle" predictions would be reduced as the training dataset grows, because the mean emissions estimate for a given make/model will tend to converge as more samples are collected per the Central Limit Theorem. These data mining concepts may potentially be applied to provide real-time emissions feedback for eco-drive vehicle control systems, to support real-world emissions factor development for source apportionment models such as U.S. EPA MOVES, and to support the analysis of Intelligent Transportation System technology impacts on vehicle energy efficiency and emissions.

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