Instantaneous Fuel Consumption Estimation Using Smartphones

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***Abstract*—This paper investigates how to estimate instantaneous fuel consumption using smartphones and OBD-II (On-board Diagnostics) adapters. Although most of the new cars have instant miles per gallon readout feature, the readings from those dashboard displays are usually proprietary and are difficult to record. Not to mention older cars do not have this feature. In this paper, we describe a system and associated algorithms to monitor fuel consumption of gasoline-powered vehicles in real time at second-level granularity. Specifically, we propose two algorithms: 1) Powertrain-based Model, which is derived from estimating an engine's fuel injection rate, and 2) Vehicle Dynamics-based Model, which considers fuel consumption in terms of the mechanical work applied to a vehicle. They are designed for vehicles with and without OBD-II adaptors respectively. The proposed system is compatible with most of the passenger vehicles and can be easily deployed. We evaluate our system in a field test and show that it can successfully estimate instantaneous fuel consumption, the average difference between estimation results and the ground truth is about 6%.**

Keywords*— *Fuel Consumption Estimation; Smartphone App for Cars; OBD-II; Green Driving;

I. Introduction

In recent years, green driving has attracted much attention. It refers to a driver's driving behavior and route selection that influence the energy consumption rate of a vehicle to reduce its environmental impact. We're getting the same message from all sides: everyone can reduce fuel usage by simply changing their driving behavior. Numerous studies have shown that a gradual, smooth acceleration and braking behavior lead to lower emission rates. This line of research is also known as Eco-Driving [1]. In light of these findings, most of the automobile manufacturers nowadays provide Instant MPG Readout (also known as Instant Fuel Consumption Display) on the dashboard to promote sustainable driving behavior.

While many older cars do not have a mpg (i.e., miles per gallon) readout, a major limitation of the dashboard mpg readout feature is that it is difficult to retrieve mpg readings from a vehicle. Third-party apps, such as those for navigation and eco-driving, cannot show instant mpg because the instant mpg feature from a vehicle is usually proprietary and the OBD-II (On-board Diagnostics II) command for accessing the related information varies by vehicles' make, model and year. On the other hand, estimating energy consumption at real-time is a non-trivial task, most of the energy/emission related evaluations rely on an off-line processing of vehicle trajectories. Energy consumption models usually provide a cumulative gas consumption or average mpg for a trip, rather than instantaneous ones at each moment. Additionally, simply monitoring fuel tank level of a vehicle does not work, because readings from the in-vehicle sensor are coarse and inaccurate for short travel distances (e.g., no fuel level change after a 2-mile trip). The nature of float sensors used in the fuel tank makes it incapable of measuring instantaneous gas consumption. Although there are a few smartphone apps in online app stores that claim to be able to estimate instantaneous fuel consumption, their methods are usually based on over-simplified assumptions (e.g., use the same set of parameters for all vehicles, does not consider noise, sensor error or communication delays) and lack of proper validation of their results.

To address the need of estimating instantaneous fuel consumption, we propose two algorithms: 1) Powertrain-based Model for vehicles equipped with an OBD-II adaptor, and 2) Vehicle Dynamics-based Model which only requires a smartphone in the vehicle. When sensor readings from the engine control unit are available (via an OBD-II adaptor to a smartphone), the Powertrain-based Model estimates how much fuel is being injected into the engine in real-time (i.e., fuel injection rate). Instead of taping into vehicles' proprietary information, the Powertrain-based Model uses standard OBD-II commands that are mandatory to all cars sold in the United States since 1996. Although OBD-II adaptors are cheap (about $20) and easy to set up, we propose Vehicle Dynamics-based Model that doesn't require OBD-II adaptors. Vehicle Dynamics-based Model uses smartphone's GPS (with speed and location) to estimate how much mechanical work is required to overcome resistance forces on a vehicle, and thus to infer gas consumption.

In order to minimize user effort in calibration and to support other applications, we describe the design, implementation and evaluation of a smartphone-based vehicular sensing system. The calibration process needs a vehicle's make, year and model to

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determine the powertrain of a vehicle, and requires additional road parameters (e.g., types of road, road grade) to calculate vehicle dynamics. Such information can be downloaded to the smartphone. We envision the system will continuously collect and update vehicle profile and road information in a crowd-sourced manner: as users use the system, their gas consumption related information will be recorded, and then can be used to calibrate other vehicles. In this paper, we focus on the fuel consumption estimation component of the system, we defer a discussion of our on-going project on a comprehensive crowdsourcing platform to future work.

This simple description hides various design challenges of the proposed system for instantaneous fuel consumption estimation, and we will elaborate our solutions in the following sections. The contributions of this work are:

1. We develop a smartphone-based, crowdsourcing system for instant fuel consumption estimation. It is easy to install and is compatible with most of the gasoline-powered passenger vehicles.
2. We develop two fuel consumption models for users with or without an OBD-II adaptor, i.e., Powertrain-based Model and Vehicle Dynamic-based model. Our field test shows that they are able to effectively estimate instantaneous fuel consumption.
3. The proposed system is extensible for other vehicular sensing applications. The source code of the sensing component (including the particulars of the OBD-II interface) of the system is available online [3]. It is capable of collecting OBD-II data at about 15 Hz (via Bluetooth with ELM 327 [2] integrated circuit).

II. RELATED WORK

Several methods have been proposed to estimate fuel consumption using data collected from the OBD-II interface. Authors of [4] show that engine's air intake rate is an effective indicator of fuel consumption. In [6], the authors find that fuel consumption can be estimated using a quadratic function of engine revolution per minute and the throttle position. Along with vehicle characteristics (such as engine torque and gear ratio), fuel system status (such as fuel trim, engine load, air fuel ratio, etc.) can be used to model fuel consumption [7, 8]. Most of the aforementioned studies use specialized equipment or aftermarket device to retrieve data. In comparison, in the proposed system data are collected by users' smartphone and optionally from universal OBD-II adapters. This makes it compatible with most of the vehicles and is easy to use.

Fuel consumption is usually evaluated in an aggregated manner. Simulation models such as EPA MOVES and NREL FASTSim [9] use driving profile (i.e., second-by-second vehicle speed from one full stop to another) to estimate fuel consumption during an entire trip. In the GreenGPS [10] project, each road segment is associated with a weight in terms of fuel economy, then the weighted map is used for selecting fuel-efficient routes. By contrast, the proposed system estimates the second-by-second fuel economy as the user driving the vehicle.

To the best of our knowledge, the proposed smartphone-based system is the first to estimate instantaneous fuel consumption in a systematic fashion. In app stores such as Apple Store and Google Play, popular fuel monitoring apps are designed to track long-term fuel usage, i.e., fuel economy is calculated during each refill of the gas tank. Ideally, we should be able to retrieve dashboard readings from the instant mpg readout, but we did not find such apps during the literature review. Vehicle manufacturers generally do not allow proprietary data to be accessed by the OBD-II connection, and different manufacturers are using different command sets. As to the proposed system, it is designed to be compatible with most, if not all, vehicle manufacturers.

III. SYSTEM DESIGN

A. Overview

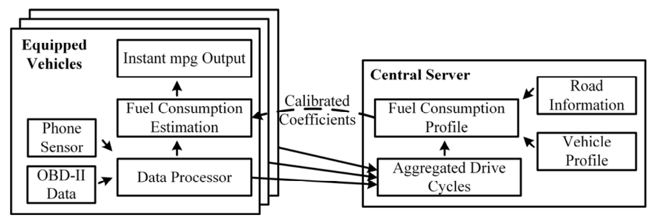

Figure 1. System overview

The proposed system consists of equipped vehicles and a central server, as illustrated in Fig. 1. In equipped vehicles, the proposed Fuel Consumption Estimation models rely on sensing data stream from the Data Processor and Fuel Consumption Profile to calculate instant mpg. The Data Processor module handles two tasks: 1) pre-processing raw sensor readings from smartphone and OBD-II interface to provide real-time inputs for estimation models, and 2) collecting typical drive cycles and then uploading them to the Central Server along with related information on fuel consumption. The aggregated information from multiple vehicles will be used to calibrate fuel consumption estimation models at the server side. The vehicles transmit collected sensor data to the backend server through various channels, e.g., Wi-Fi or cellular network. In our preliminary work, a vehicle-to-vehicle sharing mechanism is also implemented to let two nearby vehicles share their data, thus increasing the possibility that the data reaches the central server [11].

The main function of the Central Server is to provide calibrated coefficients for the proposed fuel consumption estimation models. These parameters, which we refer to as the Fuel Consumption Profile, depend on vehicles' make, model, year and traveling location. They can be trained by dashboard instant mpg readouts (retrieved via OBD-II interface in supported vehicles) or be calculated based on Aggregated Drive Cycles, Vehicle Profile and Road Information (refer to Section IV for details). Aggregated Drive Cycles includes vehicle speed trajectory, location, and various readings from the OBD-II interface. By continuously collecting drive cycles from participating vehicles, the Central Server will be able to support more types of vehicles and produce more accurate parameters for the proposed estimation models. The Vehicle Profile component identifies the type of vehicle, which can be collected by either asking user to put in manually or looking up from a third-party database using vehicles' VIN (Vehicle Identification Number). VIN can be retrieved through the OBD-II. As to the Road Information component, it uses smartphone's GPS location and altitude along with external maps, e.g., OpenStreetMap, to find road type and road grade.

In the ideal use case, users will be able to find its Fuel Consumption Profiles from the server, and then their fuel consumption at the moment can be estimated solely using a smartphone. If the exact Vehicle Profile is not available in the server, the system will choose a default Fuel Consumption Profile that is the most similar one to the new vehicle according to its build. We envision the system will work in a crowdsourced manner: participating vehicles get Fuel Consumption Profiles from the server while contribute data to improve those profiles.

B. Vehicle Testbed

Each vehicle collects the following raw information:

$$< time, GPS\ readings, acceleration,\\ vehicle\ speed, mass\ air\ flow, fuel\ tank\ level >$$

The first three parameters come from the sensors in a smartphone: GPS provides time and location data, and 3-axis accelerometer and gyroscope provide acceleration. For the purpose of fuel consumption estimation, this information is collected at 1 Hz. The next three parameters come from the OBD-II interface. Vehicle speed and mass air flow are collected at about 5 Hz and fuel tank level is collected at about 1 Hz. It is interesting to note that OBD-II adaptors work in a blocking manner, i.e., once the adaptor receives a command, it will not respond to new commands until the last command returns. So, there's no guarantee of a precise data collection rate.

In the simplest setting, the proposed system only requires a smartphone. Preferably, the hardware components for equipped vehicles also include an OBD-II adapter and a car charger. The fuel consumption estimation module is developed as an extension of our VehSense app. Previously, we developed VehSense as a vehicular sensing platform [11]. The latest version of VehSense runs on Android 7.0 Nougat and supports OBD-II adapters with ELM 327 integrated circuit (The ELM 327 integrated circuit from Elm Electronics is one of the most popular OBD-II-to-PC interpreters and supports the standard OBD-II protocols). The smartphone can be placed at any convenient locations for the driver, and the standard OBD-II connector is usually located under the steering wheel, above the brake pedal.

IV. Fuel Consumption Estimation Algorithms

In order to estimate the instantaneous fuel consumption of a vehicle, we propose two strategies: 1) Powertrain-based Model, and 2) Vehicle Dynamics-based Model. The powertrain-based model is derived from estimating an engine's fuel injection rate. Given that engines adjust fuel injection rate base on air flow rate and fuel trims, we use air flow rate as an indicator of instant fuel consumption. As to the vehicle dynamic-based model, we consider energy consumption in terms of the forces analysis. i.e., engine's power output depends on various forces (such as engine torque, rolling resistance, aerodynamic drag, etc.) applied to a vehicle. The input of the powertrain-based model is real-time engine status collected through the OBD-II interface, while in the vehicle dynamics-based model, the instant vehicle speed is the main input which can be collected solely from smartphone sensors. The output of both two models is the estimated instantaneous fuel consumption rate in mpg. We use a data-driven approach to determine coefficients in the proposed models. More specifically, the proposed algorithms work as follows.

A. Powertrain-based Model

Although SAE J1979 standard defined a Parameter ID for engine fuel rate (i.e., it refers to the fuel injection rate by liter/hour), car manufacturers usually implement fuel consumption rate as a proprietary command. In an effort to support the majority types of vehicles, in Powertrain-based Model, we use Mass Air Flow (MAF) Rate to estimate instantaneous fuel consumption. MAF measures the air intake rate of the engine, and it is commonly available through the OBD-II interface.

It is worth noting that the unit of MAF is grams of air per second, whereas people are used to measuring fuel economy in terms of miles traveled per gallon of gas (mpg). To calculate instant mpg, we need to collect vehicles' instant speed, which is also commonly supported in OBD-II. In the ideal case, we can calculate mpg by first converting MAF to Gallons of fuel per hour (GPH), then dividing vehicle speed (VS, in mile per hour) by GPH. The expression is:

$$mpg = VS \div \frac{MAF}{AFR \times \rho_{gas}} \times C$$

where AFR is the ideal air/fuel ratio, ρ_{gas} is the density of gasoline, and C is a constant for unit conversion (including g/pound, km/mile, sec/hour). The expression after the division symbol calculates GPH.

When directly applying the known values for AFR, ρ_{gas} and C, we find that results from the above equation are significantly different from the dashboard fuel consumption readings. We assume it is mainly caused by two reasons: 1) inaccurate values for AFR, ρ_{gas} and C, i.e., theoretical values of these parameters may be different from those of a testing vehicle, 2) measurement error, noise and delay from sensor readings.

Given these observations and inspired by previous research [4, 6, 7], we assume there is a linear relationship between the

MAF and fuel consumption rate, and propose the powertrain-based model f_1 as:

$$f_1 = a \times \left(\frac{VS}{MAF} + \beta\right) \qquad (1)$$

where VS is the vehicle speed in km/h (units in standard OBD-II output), MAF is the mass air flow ratio in grams/sec, and α and β are coefficients for air intake/fuel consumption conversion and time offsets to compensate for sensor delays respectively.

For different vehicles, α and β can be calibrated by fitting Eq. (1) to dashboard mpg reading during the same period. To get better results, we use the following data preprocessing steps:

First, align input timestamps and average input rate to 1 Hz. In our experience, OBD-II adopters can retrieve MAF and VS at about 10 Hz, and they do not report data in fixed time intervals, so we decide to take an average for the data within the same second. *Second*, smooth dashboard mpg readings and cap the maximum value. This step is applied to vehicles with an analogy mpg readout. Empirically, we use a Hanning convolution window of size 5, and cap the maximum mpg value to 50. *Third*, reduce noise in VS/MAF. We consider VS/MAF as one input and pass it through a low-pass filter (i.e., order 3 Butterworth filter) to remove their noise component.

B. Vehicle Dynamics-based Model

The Powertrain-based Model relies on real-time sensor readings from the engine control unit, so it is natural for us to look for a simpler approach to collect data. In the Vehicle Dynamics-based Model, once it's been calibrated, users only need second-by-second vehicle speed to estimate fuel consumption. Vehicle speed can be collected from smartphones' GPS for up to 1 Hz. As a power-saving alternative, vehicle speed can also be estimated using accelerometer and gyroscope.

Using vehicle speed profile (also known as speed trajectory) to evaluate vehicle emission and fuel consumption is a long-established research. We derive the proposed model by analyzing the vehicle dynamics in the lateral direction and the mechanical work applied to a vehicle. In order to build a general model that can characterize different types of vehicles, we calculate the engine load required to move the vehicle along a trip. Let f_2 be the gas consumption rate in terms of mpg, and P denote the instantaneous power demand of a vehicle. Assuming it takes time T to travel a distance of L, we have:

$$\frac{L}{f_2} \propto \int^{T} P dt$$

If we assume the thermal efficiency of an engine is fixed, then the total gas consumed during the trip should be proportional to the energy produced by the engine.

$$S \times \frac{L}{f_2} = \int^{T} P dt \qquad (2)$$

where S is a scaler for energy converted from gas to mechanical work generated by the engine.

Instantaneous power of a vehicle can be calculated by analyzing its aerodynamic drag, acceleration, rolling resistance and hill climbing. This leads to the research on Vehicle-Specific Power (VSP) as shown in numerous publications [9, 12]. VSP is derived by force analysis, and more details can be found in [12]. VSP is used as the primary metric for vehicle emission model developed by the United States Environmental Protection Agency (EPA). We derive our model using one of the most widely recognized VSP formula proposed by [13], and it is defined as:

$$VSP = VS \times (a + g \times sin\varphi + \psi) + \zeta \times VS^3$$

where VS is the vehicle speed, a is the vehicle acceleration, g is the acceleration due to gravity, $\varphi$is the road grade (slope), ψ is the rolling resistance coefficient, and ζ is the drag coefficient.

Note that VSP is defined in kilowatts per ton of vehicle weight, so $P = m \times VSP$, where m is the vehicle mess. Substituting P with VSP in Eq. (2), we have:

$$S \times \frac{L}{f_2} = m \times [VS \times (a + g \times sin\varphi + \psi) + \zeta \times VS^3] \times T$$

Because $L = VS \times T$, and after dividing T and VS on both sides of the equation above, we have:

$$f_2 = \frac{S}{m \times (a + g \times sin\varphi + \psi + \zeta \times VS^2)}$$

Finally, we combine constant parameters and define the Vehicle Dynamics-based Model f_2 as:

$$f_2 = \frac{k_1}{a + k_2 + k_3 \times VS^2} \qquad (3)$$

where k_1, k_2, k_3 are coefficients to be determined during calibration, a is the vehicle acceleration, and VS is the vehicle speed.

In this model, gas consumption depends on a set of vehicle parameters (i.e.,k_1, k_3), road grade (k_2), and driving behavior (i.e., VS and a). Conventionally, these coefficients can be determined from track coast-down tests (refers to S, m, ψ, ζ). The road grade information can be collected from GPS or public altitude data set such as OpenStreetMap and NASA SRTM. For a selection of vehicles, both of this information is available from the EPA certification database [13].

One common problem with looking up default coefficients is that a vehicle's profile may not be listed in the EPA database. Additionally, finding the road grade of urban road network can be challenging (urban roads may have many overpasses, ramps, tunnels, etc.). Moreover, while EPA database provides a good baseline for gas consumption estimation, we can achieve a better result if the model is calibrated by a specific vehicle on a specific road segment.

Given these observations, we use dashboard mpg readings to calibrate k_1, k_2, and k_3 in the Vehicle Dynamics-based Model. To reduce noise from the input data (i.e., the inputs during calibration are vehicle speed, road grade, and dashboard mpg reading), we use a similar data preprocessing algorithm as described in the previous section.

V. EVALUATION

The goal of this evaluation is to demonstrate that the proposed models are able to accurately estimate instantaneous fuel consumption. Two test vehicles, a 2010 Acura RDX and a 2012 Honda Civic, were equipped with a Google Nexus 5X smartphone and a Bluetooth OBD-II adapter. The proof-of-concept test consists of eight trials of driving, i.e., two eastbound trials and two westbound trials for each of the vehicles. The trials were performed on clear days on a relatively traffic-free road in Highland, California (Fig. 2). Each trial is 3-mile long with a generally steady road grade of 2.88%, and a speed limit of 55 mph.

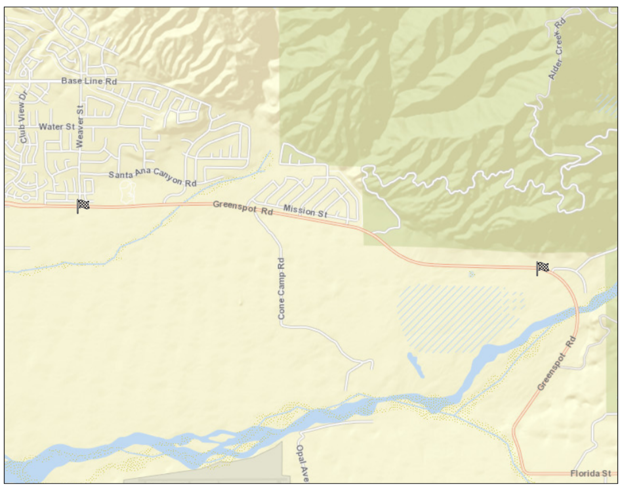

Figure 2. Map of the testing site.

In this evaluation, we use dashboard mpg readings as the ground truth of our tests. The dashboard mpg readout feature is available in both of these two test vehicles: the Acura RDX shows instant mpg in digital values, while the Honda Civic has an analog gauge. During the test, we used one additional

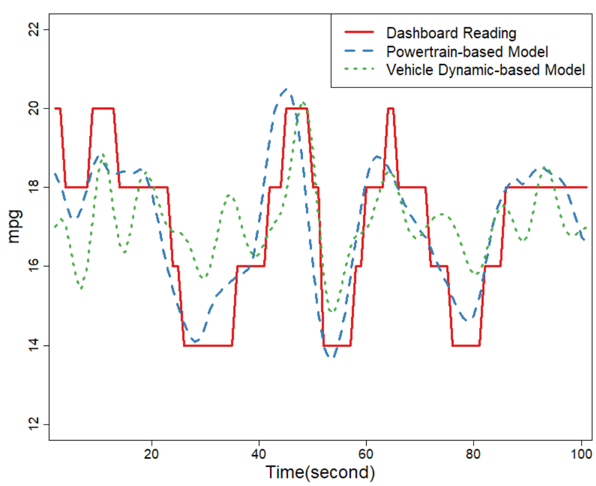

Figure 3. mpg comparison in different approaches.

smartphone to record dashboard mpg readings with its camera. Then, we manually extract the dashboard readings from these videos and use them to calibrate and evaluate the proposed models.

Fig. 3. shows the mpg output from the proposed models after calibration. It is a sample from an eastbound trials with Acura RDX when the vehicle was cruising. As we expected, there is a good match between the estimated mpg and the vehicle dashboard reading. The dashboard reading is in a "staircase-shape" because the Acura RDX reports mpg as integer values.

Since fuel tank level can be retrieved from the OBD-II interface, we tried to validate the fuel consumption with the fuel level readings. However, we find it is impractical due to the nature of float sensors used in both of the test vehicles. The height of the float does not provide enough accuracy and is subject to environmental influences (e.g., road grade, vehicle vibration). As shown in Fig. 4, we have two observations: 1) there is a large variance from the raw data in fuel level percentage. In the 2012 Honda Civic case, the variance is 23.5 with a mean fuel level percentage of 60.1. This might mainly result from vehicle vibrations. 2) road grade/slop has a significant impact on the raw data. For example, in Fig. 5 after time 150s, there's a bump in the readings for the 2010 Acura RDX. It is likely caused by a steeper slope of the road segment.

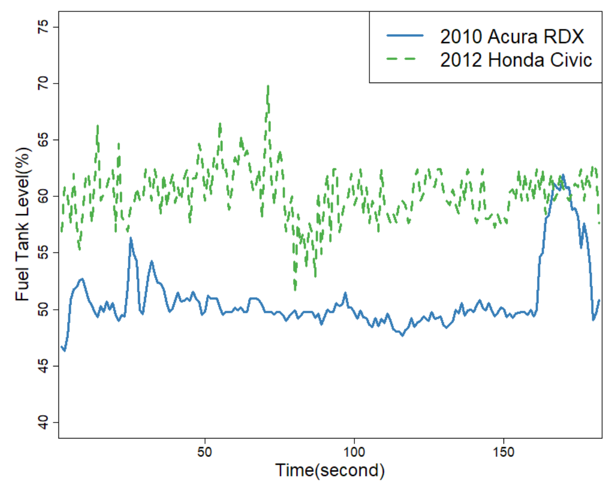

Fig. 4. Fuel tank level readings during two field tests (time and location of these two tests are not correlated).

In this test, we use the Future Automotive Systems Technology Simulator (FASTSim) to validate the cumulative fuel consumption. FASTSim is a powertrain model for comparing and estimating vehicle efficiency, performance and cost. It is developed by the National Renewable Energy Laboratory [9]. The inputs of FASTSim include vehicle model, speed trajectory and road parameters. In FASTSim, vehicle model refers to physical characteristics of a vehicle, such as weight, drag coefficient, frontal area size, etc. Unfortunately, our test vehicles are not included in the default models provided by FASTSim. We selected an SUV and a sedan model of similar build from the FASTSim database. For speed trajectory, we use second-by-second speed data retrieved from the in-vehicle smartphone. As to road parameters (which includes road type

TABLE I COMPARISON ON AVERAGE GAS CONSUMPTION

	Powertrain-based Model	Vehicle Dynamics-based Model	Dashboard Reading	FASTSim Result
RDX Average mpg	16.32	17.19	16.43	18.55
MAE*	1.74	1.64		
Civic Average mpg	34.4	34.5	32.78	30.9
MAE*	4.12	3.84		

* MAE refers to the mean absolute error between second-by-second models' estimation and the dashboard reading

and grade), we collect elevation data from the USGS TNM server.

Table I shows the results of cumulative fuel consumption in terms of the average mpg produced by different models. In general, both Powertrain-based Model and Vehicle Dynamics-based Model are effective for estimating fuel consumption. While there is no significant difference between these two models in the estimated average mpg, it is worth noting that these two models require different calibration efforts. Powertrain-based Model relies on vehicle's own characteristics (i.e., its powertrain), it only requires one set of constant coefficients describing a vehicle's characteristics. Whereas in Vehicle Dynamics-based Model, calibration also needs to be associated with the conditions of road segments. Different road type and road grade will lead to different coefficients for the same vehicle.

In Table I, the average mpg difference between FASTSim estimation, model estimation and dashboard reading are about 6%. In our opinion, this difference in average mpg is acceptable and has enough accuracy for green driving related applications. The largest difference is found between the dashboard readings and the FASTSim result. Additionally, we are also interested in whether the dashboard mpg readout is accurate when compares to the actual fuel usage. This will require specialized equipment to measure the exact fuel consumption, and we will explore this idea in future works.

VI. CONCLUSION AND FUTURE WORK

In this paper, we present the design, implementation, and evaluation of two instantaneous fuel consumption models that use smartphones and OBD-II adapters. The system utilizes standard OBD-II commands and smartphone sensor readings, and thus is compatible with most of the passenger vehicles. It requires minimum user configuration and can be readily integrated into apps for eco-driving, navigation and driving behavior analysis. Our pilot study at Highland, CA, shows that the proposed models can accurately estimate instantaneous fuel consumption.

In the future, we plan to explore using emission simulators to calibrate the proposed algorithms. This can be achieved by calibrating emission models with the cumulative gas usage of a vehicle. Ideally, we want to estimate instantaneous fuel consumption solely with a smartphone (i.e., using the Vehicle Dynamics-based Model) and retrieve vehicle speed using accelerometers instead of GPS. Additionally, we plan to develop models that support electric and hybrid vehicles. More rigorous and larger scale experiments are also necessary. It will be worth a while to validate the dashboard mpg readout with the actual fuel usage.

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