Mining Geographic Data for Fuel Consumption Estimation

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***Abstract*— Mobility is one of the greatest contributors to the personal carbon footprint and to pollution and noise in urban areas. Still, these factors are not yet easily quantifiable in personal or urban scale, e.g. impact of each car trip or areas most exposed to CO_2 emissions. In this article, we propose an innovative solution for estimating fuel consumption and emissions leveraging the opportunities generated by the ubiquitous availability of mobile devices.**

We collect a large data set of GPS and fuel consumption data crowd-sourced by volunteer participants with an Android mobile application that logs the smartphone's embedded GPS data and gathers vehicle data using an external On-Board Diagnostics (OBD) device. This data is used to develop a model that estimates the instantaneous fuel consumption from the smartphone's GPS data alone, using the OBD data as ground truth. We use speed, acceleration and steepness as predictor variables to train polynomial models with and without cross-product terms. With the best general model (trained and tested on all participant vehicles), we obtain an average residual standard deviation of 1.58 l/100km for average consumption on 1min intervals. For individual models (trained and tested on each participant vehicle), we obtain an average residual standard deviation of 1.43 l/100km. The average fuel consumption for the used data set was 6.7 l/100km.

I. Introduction

Transportation was responsible for 31.7% of the total European final energy consumption of 2009 [1], and 71.7% of that energy was consumed in road transportation, causing 878.4 Million Tons of greenhouse gas emissions (GHG). According to the same source, households across Europe spent almost 500 billion Euro on the operation of personal transport equipment, i.e. in fuel costs in that year. These figures show that road mobility based on personal vehicles has high environmental and monetary costs.

Providing more accurate information in a more intuitive way and more related to the personal context increases user's awareness about the environmental impact of car transportation, and this awareness impacts the acceptance of transport policy measures [2]. Information like the per trip duration, fuel/emissions or monetary can raise awareness about energy consumption and mobility efficiency. Further, logging and comparing historical data for different people enables creative measures for more efficient resource usage, for example emission reduction games like who consumes less fuel in the same route and vehicle. From a business perspective, detailed information about fuel consumption can be used to improve processes and reduce costs.

However, information about individual mobility costs is still naive or experts-only to a great extent. Mobile applications that allow tracking average fuel consumption based on manual input about tank re-fills are an example of the first. Applications like Torque[1] resource to OBD and knowledge about motor functionality to enable logging and tracking fuel consumption are examples of the latter. Neither option is intuitive for the majority of the population.

Smartphones penetration in Europe has recently exceeded 50%[2], and they are widely distributed technology that is empowered with a large amount of sensors and provides intuitive interaction to the users. Hence, it has the potential to be a key enabler of behavioral change, as well as a much more accessible sensor than a specific technology, like OBD. However, the tools to enable this are not yet available, specifically, it is not yet clear how a smartphone alone can be used to estimate the fuel consumption, or how accurately.

In this article, we propose to use smartphones alone, specifically the embedded GPS sensor, to estimate the fuel consumption of a vehicle. The proposed methodology consists in using an OBD to obtain the ground truth of the actual fuel consumption in an initial data gathering phase. That data is later used to train a regression model that estimates the per second fuel consumption using the geographic position data measured by the GPS receiver alone. This model can be applied in applications that provide information to drivers or companies about the fuel consumption of their cars or fleets, in real-time or as historic data, as well as providing information about GHG emissions to urban planning when used in aggregate form.

The contributions of this article are: 1) a systematization of fuel consumption models based on different sets of OBD sensor information; and 2) a data-based fuel consumption model that uses as input the GPS location data, trained using OBD fuel consumption as the ground truth. The rest of the paper is organized as follows: the next section reviews related work and Section III describes how to calculate the fuel consumption from vehicle internal sensors; Section IV describes the data gathering process and Section V shows how we extract information from GPS data. Finally, Section VI shows the results of the regression and Section VII concludes the paper.

[1] http://torque-bhp.com/

[2] http://www.comscore.com/Insights/Presentations_and_Whitepapers/2013/2013_Europe_Digital_Future_in_Focus

II. Background and Related Work

A. On-Board Diagnostics

Concerns about GHG emissions from transportation prompted governmental agencies, like Environmental Protection Agency (EPA) and California Air Resources Board (CARB), to require improvements in the efficiency and cleanliness of new vehicles, and the deployment more-sophisticated emission sensors and better diagnostics systems. This lead to the On-Board Diagnostics (OBD) standard in 1996, and its subsequent OBD-II revision, which defines a connector and communication protocols between a controller and the vehicle. An OBD-II connector is mandatory on vehicles sold in the United States since 1996 and in Europe since 2001 for petrol/gasoline engines and 2004 for the diesel counterpart.

By connecting an OBD-II interface[3], it is possible to monitor a vehicle's emissions system and status of some of the vehicle's sensors, even in real-time. Even though the standard defines the access to hundreds of sensors, called Parameter IDs (PIDs), manufacturers can choose which to implement, with only a small set of them being mandatory. This, and the significant differences in speed between the allowed communication protocols and devices, creates a disparity of data availability across vehicles.

To compensate this fragmentation, in Section III we developed multiple formulas for fuel consumption estimation from various combinations of OBD variables (PIDs).

B. Fuel Consumption Models and Applications

Applications that provide fuel efficiency information exist, like Crew Chief[4], Garmin Mechanic with ecoRoute HD[5] or DashCommand[6], though they are not free and the first two use proprietary, undisclosed models. Moreover, the last two depend on the OBD technology, and not all users want to or know how to use OBD.

A few emission models have been compared in [3], such as CMEM [4] and MOVES[7]. The first model is vehicle oriented while the second is more suited for wide scale emission monitoring, and it is not the best for individual vehicle dynamics. Both models require user input that can be confusing and time consuming for users not familiar with vehicle specifications.

The solution that we propose can overcome these limitations by estimating fuel consumption from GPS data, using fuel consumption estimation from OBD data only as the ground truth for model fitting.The SAE J1979 [5], the DashCommand manual and the OBD-II Resource website[8] proved to be valuable guidelines in understanding the parameters needed for fuel consumption calculation and the expressions found in Section III.

[3]Many options are available to bridge between the OBD port and a computing platform, like USB, Bluetooth or WiFi.

[4]http://crewchief.telogis.com/

[5]https://buy.garmin.com/en-US/US/prod38354.html

[6]http://www.palmerperformance.com/products/dashcommand/

[7]http://www.epa.gov/otaq/models/moves/index.htm

[8]http://obdcon.sourceforge.net/

III. Fuel Consumption Calculation

In this section we give a brief overview of which sensors or parameters are available through the OBD protocol for gasoline and diesel engines, and how they can be used to estimate fuel consumption. A more in-depth explanation on OBD and its parameters is available in [5].

Our algorithm should work for both gasoline and diesel four-stroke engines, which compose the large majority of commercial vehicles. Both of these types of engine work in a similar fashion, putting fuel in a combustion chamber to generate kinetic energy from the expanding gas [6]. The Fuel Consumption is calculated as the ratio of Fuel Flow (FF), measured in liters per hour, to speed, in kilometers per hour, as shown in Equation 1. The Fuel Flow is a function of the Corrected Air to Fuel Ratio (CAFR), the Corrected Mass Air Flow (CMAF), and the Fuel Density (FD), which is a constant for each vehicle depending on the type of fuel, related as shown in Equation 2. Next, we explain how to calculate CAFR and CMAF for both types of engine.

$$Fuel\,Consumption_{(L/100Km)} = \frac{FF \times 100}{Speed} \tag{1}$$

$$FF = \frac{CMAF \times 3600}{CAFR \times FD} \tag{2}$$

In **gasoline engines** the fuel is mixed with air in a controllable ratio before being injected in the pistons, and is ignited by a spark plug at the right time. The Air to Fuel Ratio (AFR) in this mixture is tightly controlled in gasoline engines, in order to improve power and efficiency, and reduce emissions and engine wear. The optimum ratio is close to the ideal gasoline combustion stoichiometric ratio — 14.7 g of air to 1 g of fuel (14.7:1) — but is automatically compensated for additives and fuel impurities, or even engine defects, via feedback from exhaust systems. We call Corrected Air to Fuel Ratio (CAFR) to this compensated ratio. The correction to the base stoichiometric ratio (14.7) is sometimes available in the OBD as the Long Term Fuel Trim (LTFT) parameter, which is a positive or negative percentage for extra air or extra fuel in the ratio, respectively. The controlled ratio in gasoline engines makes it feasible to estimate fuel consumption from air sensors, and improving the results if the LTFT value is available, according to Equation 3.

$$CAFR = Stoichiometric\,Ratio \times (1 + LTFT) \tag{3}$$

In a **diesel engine** the air is first compressed in the cylinders, which causes it to heat up to the point that when fuel is injected it ignites. These engines needs a high volume of air and pressure in the cylinders to ensure combustion of the fuel, even under very low load, resulting in air to fuel ratios between +100:1 and 14.6:1. To obtain fuel flow we require either a fuel sensor, or air sensors together with an instantaneous indicator of the amount of air used in the combustion, such as Calculated Load[9] (explained below). The LTFT value in diesel engines is the correction to the optimum AFR when peak torque is requested, and can be used to increase the accuracy of fuel consumption calculation.

In both types of engines, LTFT is very close to 0% under normal operation, and an absolute value higher than 10% typically indicates a defect. Also common to both engine types is the estimation of the mass of air in the cylinders, which in some vehicles may not be directly available from the OBD sensors. In those cases, it is possible to estimate it using the Ideal Gas Law, taking into account the absolute or calculated load, ambient pressure, air temperature, engine displacement and its volumetric efficiency. Both diesel and gasoline engines can support Absolute and Calculated Engine Load PIDs. The Absolute Load is a percentage indicating the current air mass in the cylinders divided by the maximum air mass at standard temperature and atmospheric pressure[10]. This sensor takes into consideration the actual temperature and pressure, going up to 400% in a turbo charged engine, and is a good indicator of the amount of air in the cylinder. Calculated Load gives a similar measure, but does not take into account the current temperature, pressure, nor the engine volumetric efficiency, so the algorithm needs to compensate for those parameters. In diesel engines, both these values represent the ratio between applied torque and peak torque, instead of air mass to peak air mass, and so are essential to estimate the amount of air that was actually used in the combustion [7], which we call Corrected Mass Air Flow (CMAF). CMAF can be calculated in multiple manners, depending on the available sensors, and expressions are shown in Equation 4.

$$CMAF = \begin{cases} MAF, & \text{gasoline} \\ MAF \times LOAD_{CALC}, & \text{diesel} \\ LOAD_{ABS} \times \dfrac{RPM}{60 \times RIS} \times \\ \times ED \times \frac{P \times MM_{air}}{R \times (T + 273.15)}, & \text{any} \\ LOAD_{CALC} \times \dfrac{RPM}{60 \times RIS} \times \\ \times ED \times \frac{MAP \times VE \times MM_{air}}{R \times (IAT + 273.15)} & \text{any} \end{cases} \tag{4}$$

If necessary, the engine displacement, volumetric efficiency and fuel type should be obtained from the user. However, the MAF parameter is available in most vehicles, so the only needed variable is the fuel type, which can be predicted from the available OBD sensors: diesel vehicles are required to support Calculated Load and rarely provide the Absolute Load, and gasoline vehicles are required to provide Absolute Load. Regarding the Volumetric Efficiency, we use a predefined value of 80% if not provided.

[9]http://www.palmerperformance.com/products/dashcommand/

[10]http://obdcon.sourceforge.net/2010/06/about-pid-calculated-load-value/

TABLE I

CONSTANTS AND VARIABLES USED IN EQUATIONS 1 - 4.

Constants	
FD	Fuel density (g/l)
RIS	Revolutions per intake stroke, 2 in four-stroke engines
P	Standard atmospheric pressure (kPa)
MMair	Molar mass of air (g/mol)
R	Ideal gas constant (J/mol/K)
T	Standard air temperature (ºC)
Variables	
RPM	Engine revolutions per minute
FF	Fuel flow (l/h)
MAF	Mass air flow (g/s)
MAP	Manifold absolute air pressure (kPa)
IAT	Intake air temperature (ºC)
VE	Volumetric efficiency (%)
ED	Engine displacement (l)
CMAF	Corrected mass air flow (g/s)
CAFR	Corrected air to fuel ratio
LTFT	Long term correction value (%)
$LOAD_{CALC}$	Calculated Load (%)
$LOAD_{ABS}$	Absolute Load (%)

Using these equations, we are capable of estimating the fuel consumption of a wide range of vehicles. Of the vehicles we tested (see Table II), one vehicle can only use the 4th CMAF equation in the calculations, requiring 5 parameters (Speed, Load_Calc, RPM, MAP, IAT), whereas the rest provide the MAF parameter, allowing the use of the 2nd CMAF equation and requiring just 3 parameters (Speed, MAF, Load_Calc), with the optional LTFT for accuracy improvement.

IV. DATA GATHERING

We proposed an architecture for massive urban scanning in [8], which we extended to enable smartphones as data gathering units for this work. These devices are equipped with GPS receivers, as well as multiple other sensors, and have the capability to connect to external sensors, e.g. using Bluetooth. Furthermore, we integrated a module that collects vehicle data over Bluetooth from an OBD device plugged in the vehicle. The application has play and stop buttons to start and stop sensing sessions, and we also added the possibility to mark events through a button in the user interface. Data from GPS is collected at a frequency of 1 Hz.

The application runs in the background and was designed to have minimal energy consumption, avoiding hindering the normal operation of the smartphone. The data is temporarily stored in a local database on the smartphone until the user requests its synchronization with the back office server, to avoid using the mobile data plans of volunteers. All data-mining and processing operations are performed a posteriori in the back office.

The data gathering process involved eight volunteers with different smartphones and vehicles. Each driver signed an informed consent form acknowledging that their data was being collected and would later be processed for the purpose of this research.

V. Data Processing

Table II describes the population used in this study, along with engine displacement, fuel type, and amount of collected points for each participant vehicle. Although this was not intentional, all volunteers drove diesel vehicles, so the data collected only enables training a diesel fuel consumption model.

TABLE II
Characterization of collected data

Id	Model	Displacement	Fuel Type	Nr Points
V1	Audi A4	1896 cm^3	Diesel	32945
V14	Peugeot 207	1560 cm^3	Diesel	40132
V23	Volkswagen Golf 6	1598 cm^3	Diesel	24161
V42	Renault Clio	1461 cm^3	Diesel	131425
V45	Fiat Punto	1248 cm^3	Diesel	45454
V46	Renault Twingo	1461 cm^3	Diesel	3102
V47	BMW 525d	1995 cm^3	Diesel	6366
V48	BMW 320d	1995 cm^3	Diesel	3241

Our goal is to estimate a regression model that uses GPS information alone, but we do not use GPS positions directly. Instead, we use the GPS trace to estimate predictor variables, namely vehicle speed and acceleration, and road steepness. In the next sections, we describe how we estimate the predictor variables from the GPS data, and then we show calibration results for the fuel consumption estimation from OBD parameters. At the end of the section, we analyze the relationships between each predictor variable and the fuel consumption estimates.

A. *Estimating Acceleration And Steepness*

A GPS receiver provides time, latitude, longitude, altitude, speed and azimuth values for each second, and we use them to estimate vehicle acceleration and road steepness applying least square estimation in time and space. Since the speed provided by the GPS has a very low error, we estimate the acceleration for each GPS point as the slope of a least square estimation of three values consecutive in time.

We estimate steepness through least square estimation in space, using the altitude and distance traveled. However, to account for the low accuracy of the altitude information, we consider all GPS points that lie within a spatial neighborhood of the GPS point being considered. Specifically, we use all the points inside a radius that is gradually increased to include at least 5 neighbor GPS points. A maximum radius is also defined, in this case 80 m, to allow for highway speeds, where 3 points are sufficient since steepness variations are more easily captured with greater traveled distances.

The distance traveled is estimated for the spatial neighborhood thus defined. We use speed due to its higher precision [9], [10], [11], instead of using position to calculate the distance, like the Inverse formula used by Android [12]. Specifically, we sum the speeds at each instant, since the speed (in m/s) is obtained at a fixed sampling rate of 1 second.

B. *OBD Data Interpolation*

Every OBD parameter received is stored with millisecond time precision. However, different OBD devices and vehicles have different response times and sampling speeds, so there is no guarantee that a sample of all OBD parameters required to estimate fuel consumption (see Section III) are available every second. Moreover, the OBD and GPS data sets must be synchronized, since the OBD derived fuel consumption is used to train the regression model based solely on GPS data.

We use linear interpolations to re-sample the vehicle status — OBD parameters — at the precise GPS timestamps. Values are only interpolated between data points that are at most 2 seconds apart. Hence, large data gaps are not used, since interpolating these gaps would possibly result in noisy data and negatively impact the accuracy of the model.

C. *Validation*

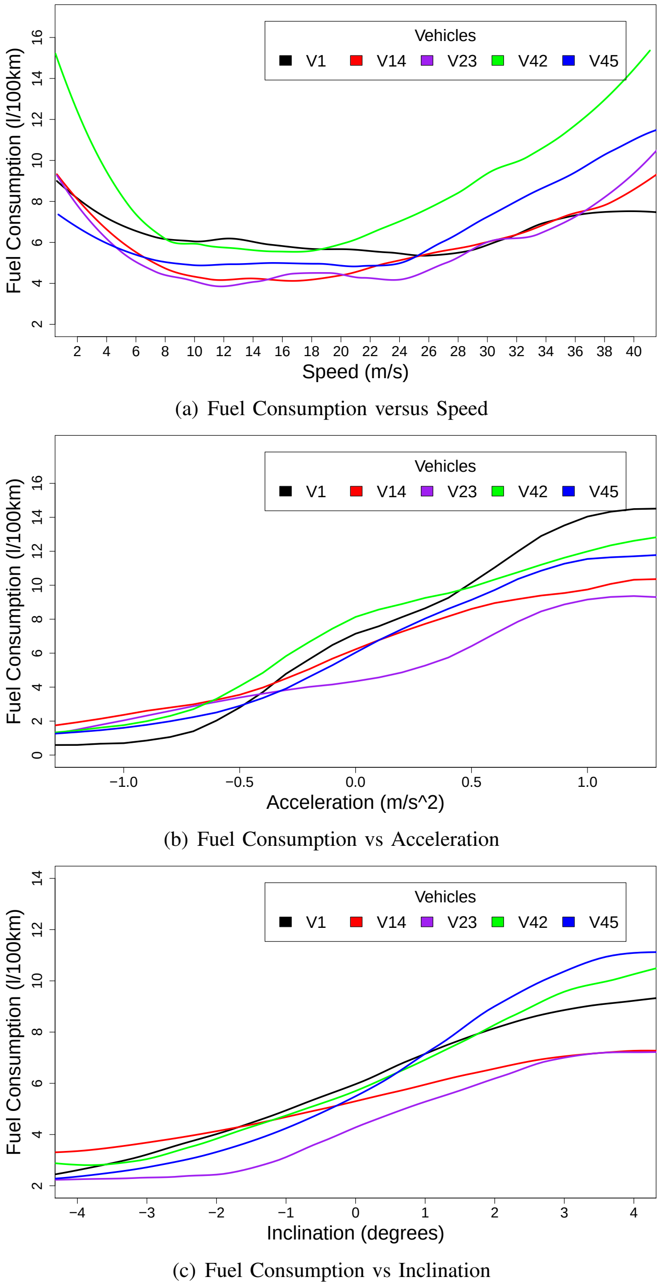
We validated the fuel consumption formulas shown in Section III with the trip-information available in the display panel of some vehicles, namely V1 and V14. These vehicles provide instantaneous and per trip average fuel consumption, and we used them to validate the accuracy of the fuel consumption values calculated from the OBD parameters. At the beginning of a trip, the user defined an event, such as 'Consumption at 6l/100km', in the mobile application used for collecting data. While driving, every time the vehicle's interface showed 6 liters per 100 kilometers the driver recorded the event by tapping the smartphone's screen. At the end, the vehicle's on-board computer values and values calculated using Equation 1 are compared using the timestamps from the event and the timestamps from the calculated value. Table III shows that the average of the calculated values match the values showed on the interface, validating the fuel consumption expressions shown in Section III.

TABLE III
Fuel Consumption Measurements

Vehicle display	Calculated average	Std. Dev.
8.9	8.9	0.4
7.5	7.4	0.0
6.0	5.6	0.5

D. *Data Filtering*

The data set used in the rest of the paper includes only data from vehicles V1, V14, V23, V42 and V45, because the others had less than 25% of the consumption points of these vehicles. Moreover, to reduce bias due to the very large differences in amount of data available for each vehicle, we decided to use only 20 000 points from each, resulting in a



(a) Fuel Consumption versus Speed

(b) Fuel Consumption vs Acceleration

(c) Fuel Consumption vs Inclination

Fig. 1. Fuel consumption versus predictor variables extracted from GPS data (LOESS smoothed with span = 0.45).

training data set of 100 000 measurements of instantaneous fuel consumption.

Finally, we only used position information with an accuracy higher than 50m, having an inclination between -15 and 15 degrees, and a maximum of 2 m/s of difference between GPS and OBD reported speeds. Overall, this corresponds to removing less than 10% of the data points.

E. Exploring Data Relations

In order to understand the relationship of fuel consumption with speed, acceleration and inclination, each was individually plotted and analyzed. The units used for the variables are liters per 100 kilometers for fuel consumption, meters per second for speed, meters per second squared for acceleration and degrees for inclination.

Figure 1 shows the mean fuel consumption versus the estimated predictor variables speed, acceleration, or inclination, respectively, for all data points. Observing these plots, we see that the dependence of fuel consumption on the predictor variables is not linear, in general. However, in the selected ranges, fuel consumption varies approximately linearly with acceleration and steepness, and non-linearly with speed.

VI. Regression and Performance

We experiment with multivariate regression models using two sets of predictor variables. In the first set, FC_1, we take the GPS derived predictor variables $Speed$, $Acceleration$, and $Inclination$, and also $Speed^2$ and $Speed^3$, since we observed that this relation is non-linear. The second set of predictor variables, FC_2, consists of FC_1 plus the cross-product terms of the linear variables: $Speed * Acceleration$, $Speed * Inclination$, and $Acceleration * Inclination$. We performed feature selection on each set using a greedy forward selection algorithm.

At each step, a multivariate regression was performed on the training data set using the previous set of predictor variables combined with each yet unused feature. The resulting coefficients were then used to estimate the instantaneous fuel consumption for every data point of the data set. The fitness metric used was the standard deviation of the residuals (std. dev.) of the instantaneous fuel consumption estimation.

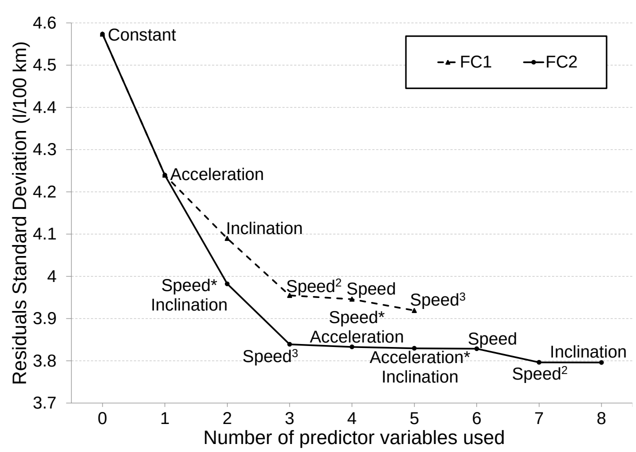


Fig. 2. Regression residuals for different number of features and the corresponding feature selected at each step.

The fitness metric for the instantaneous fuel consumption evolves as shown in Figure 2 with the number of features used. In both sets of predictor variables there is practically no improvement in the instantaneous residuals (0.3%) from increasing from 3 to the maximum number of features (5 or 8).

We performed the remaining regression analysis using the best 3 predictor variables from each set: $Acceleration$, $Inclination$ and $Speed^2$ for FC_1, and $Acceleration$,

TABLE IV

RESIDUALS' STD. DEV. FROM BOTH TRAINING METHODS AND MODELS

	Instantaneous				1 min Average			
	Global		Individually		Global		Individually	
	FC_1	FC_2	FC_1	FC_2	FC_1	FC_2	FC_1	FC_2
All	3.92	3.81			2.29	2.10		
V1	2.95	3.01	2.81	2.75	1.00	0.89	1.01	0.91
V14	3.90	3.79	3.87	3.75	2.04	1.56	2.09	1.72
V23	4.01	3.90	3.98	3.88	1.80	1.57	1.86	1.50
V42	3.36	3.16	3.17	2.95	2.13	1.84	1.67	1.30
V45	4.22	4.06	4.16	3.97	2.46	2.03	2.28	1.72
Avg	3.69	3.58	3.60	3.46	1.89	1.58	1.78	1.43

$Speed * Inclination$ and $Speed^3$ for FC_2. The global consumption models obtained from least squares fitting the above predictor variables to the data are given by:

$$\mathrm{FC}_1 \approx 5.31 + 3.99 * \mathrm{A} + 0.431 * \mathrm{I} + 0.00213 * \mathrm{S}^2$$

$$\mathrm{FC}_2 \approx 5.55 + 4.08 * \mathrm{A} + 0.0329 * \mathrm{S} * \mathrm{I} + 5.50E^{-5} * \mathrm{S}^3$$

where S is the vehicle speed, A is the acceleration, and I is the road steepness or inclination.

Table IV presents the residuals' standard deviation obtained by using the generic models above to calculate the fuel consumption of each vehicle, compared against the models trained individually for each vehicle with their own data. It also shows the 1 minute average fuel consumption, obtained from performing a moving average for every 60 s of sequential data points.For reference, the average fuel consumption of the whole data set is 6.7 l/100km.

We observe that by choosing the best predictor set (FC_2) we improve the residuals' std. dev. for the global model by 2.7% on average in the instantaneous case, and 15.7% in the 1 min average. For a specific vehicle, using FC_2 improves the 1 min average results up to 24%.

By individually training the models with each vehicle's data, we can improve the instantaneous accuracy by up to 9%, with an average of 4%. The 1 min average results can be improved on average 7%, though for one vehicle the improvement was 30% and for another one the accuracy decreased 10%, showing a large variability across vehicles.

The global model prediction using the best 3 predictor variables has an instantaneous accuracy with a standard deviation between 3.01 and 4.06 for the tested vehicles (average of 3.58), which can be considered high, resulting in a somewhat inaccurate instantaneous fuel consumption. However, the residuals' standard deviation for the 1 min average for the model are between 0.89 and 2.10 (average of 1.58), showing that our model is a more accurate estimator for the average fuel consumption, as the errors average out over short periods.

VII. CONCLUSIONS

We have analyzed and processed spread out information on OBD sensors and their usage for fuel consumption calculation, providing a systematized way to calculate fuel consumption from OBD sensor readings for a large variety of vehicles. Moreover, we validated the expressions presented on two vehicles. We used a smartphone application to simultaneously collect GPS and OBD data from 5 volunteers during daily trips, extracted speed, acceleration and road steepness from the GPS data, and used them as predictor variables to fit a fuel consumption model.

The proposed model shows a standard residual of about 3.6 liters per 100 kilometers when estimating instantaneous fuel consumption, and 1.6 liters per 100 kilometers when estimating the average fuel consumption of a 1 minute block. This and the normal distribution of the residuals indicate it is a good model to estimate average fuel consumption or produce fuel consumption maps aggregating a large number of vehicles.

Future work will focus on reducing the estimation errors for the predictor variables, by improving the methods used for their calculation from the GPS data. Further, we will search for other predictor variables that may improve the accuracy of the models. Finally, we will collect more data and experiment more advanced regression techniques, including well-known machine learning regression models, working towards a more accurate model.

ACKNOWLEDGMENTS

We thank Rui Meireles and João Barros for insightful discussions.

This work was supported by the Portuguese Foundation for Science and Technology (FCT) grant SFRH/BD/62537/2009 and Instituto de Telecomunicações strategic funds project PEst-OE/EEI/LA0008/2013, by the MIT|Portugal program under the MISC project MIT-PT/TS-ITS/0059/2008, by the QREN project NORTE-07-0124-FEDER-000064.

REFERENCES

[1] "EU Transportation in Figures," EC Statistical Pocketbook, 2012.

[2] L. Eriksson, J. Garvill, and A. M. Nordlund, "Acceptability of single and combined transport policy measures: The importance of environmental and policy specific beliefs," *Transportation Research Part A: Policy and Practice*, no. 8, pp. 1117–1128, Oct.

[3] H. Yue, "Mesoscopic fuel consumption and emission modeling," Ph.D. dissertation, Virginia Tech.

[4] G. Scora and M. Barth, "Comprehensive modal emissions model (cmem), version 3.01," *User guide. Centre for Environmental Research and Technology. University of California, Riverside*, 2006.

[5] "Sae j1979," Vehicle E E System Diagnostic, 02 2012.

[6] C. Hadfield, *Today's Technician: Automotive Engine Repair and Rebuilding*, 4th ed. Cengage Learning, 2010.

[7] A. Alessandrini, F. Filippi, and F. Ortenzi, "Consumption calculation of vehicles using OBD data," *epa.gov*.

[8] J. G. P. Rodrigues, A. Aguiar, F. Vieira, J. Barros, and J. P. S. Cunha, "A mobile sensing architecture for massive urban scanning," *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, pp. 1132–1137, Oct.

[9] T. Chalko, "Estimating Accuracy of GPS Doppler Speed Measurement using Speed Dilution of Precision (SDOP) parameter."

[10] E. Kaplan and C. Hegarty, "Understanding GPS," *Artech House*.

[11] J. ZHang, K. Zhang, R. GRenfell, and R. DEakin, "On the Relativistic Doppler Effect for Precise Velocity Determination using GPS," vol. 80, no. DoD 1996, pp. 104–110, 2006.

[12] T. Vincenty, "Direct and Inverse Solutions of Geodesics on the Ellipsoid with Application of Nested Equations," vol. XXIII, no. 176.