# A smartphone based platform for personalized estimation of GHG in everyday driving using On Board Diagnostics

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***Abstract*— Road traffic is responsible for a significant share of pollution. Intelligent Transportation Systems are expected to contribute to reduce these emissions. Solutions thus far include design of greener vehicles, urban traffic management and control and behavior changes. Behavior changes may include vehicle sharing programs and driving habits changes. In order to change their habits, drivers need personalized feedback about the emissions of their own vehicles in the different routes they complete. Measuring emissions require special equipment, so emissions are often estimated depending on a number of parameters. In this work, we have developed a Android application for a smartphone that extracts all required parameters and return a geopositioned emission estimation on the fly. Our estimator is based on the ARTEMIS project results. In order to validate estimations, the smartphone taps into the vehicle OBD to obtain a number of parameters related to high emissions. The system has been successfully tested in different routes in Malaga (Spain), including different environments (highway, rural and urban areas).**

## I. Introduction

Recent studies have stated that transport related emissions are responsible for a significant share of environmental pollution and greenhouse gas (GHG) [12]. Furthermore, half of all road transport emissions are the result of traffic in urban areas. More specifically, motorized private transport accounts for 40% of the GHG emissions of the total road transport sector and up to 70% of other pollutants stemming from transport. The ill effects of pollution on health are also well reported[1]: up to 1,3 millions deaths each year, specially involving children and elderly people.

While a large number of studies contemplate the impact of Intelligent Transportation Systems (ITS) on areas like road safety, traffic management or intelligent vehicles, only a small number address the potential of ITS for reducing GHG emissions in qualitative or quantitative terms, so there is still lack of consolidated empirical evidence on the subject [5].

Since developed countries and regions should reduce their emissions by 60-80% over the period 1990-2050, reducing transport and logistics-related GHG emissions is of key importance to promote environmental sustainability. ITS are meant to help to this respect. Indeed, the Climate Group in its SMART 2020 study estimates that ITS based logistics optimization could result in a 16% reduction in transport emissions and a 27% reduction in storage emissions [7]. Improved logistics (eFreight) -including in-cab communication systems, vehicle tracking systems, sat-nav, warehouse and fleet management ...- could result in a 16% reduction in transport emissions and a 27% reduction in storage emissions. It has been reported that ITS-driven applications across logistics could achieve a reduction in total global emissions of 1.52 GtCO2e[2]. However, private transport is harder to address.

Most existing studies on the subject either focus on technical changes -e.g. cleaner cars or smart traffic management- or behavioral changes -e.g. increased use of public transportation or car sharing programs- to cope with the problem, although it has been suggested that the best choice would be a combination of both approaches [7]: although major reductions in GHG emissions will obviously depend on cleaner cars and fuels, it has been noted that without behavioral change, the increase in CO2 emissions from expected travel growth would outweigh the possible savings from changes in technology[3].

Urban traffic management and control (UTMC) approaches rely on cameras and sensors to control access to jammed areas and track flows of vehicles. UTMC is typically enforced by law, but there are personalized approaches to the problem. These approaches typically rely on advising the driver on which routes to use in order to avoid traffic jams[16][20], e.g. ASSIST-V (BMV). Much research on this area focuses on communication protocols, like DAB (Digital Audio Broadcasting) or TPEG (Transport Protocol Experts Group), and also on city-wide mesh sensor networks (e.g. Crossbow). However, pollution is not limited to traffic jams. It would be interesting to detect and correct driving habits that result in higher gas emissions under far more frequent, non-excepcional situations.

Car and bike sharing programs and Demand Management Systems (DMS) conform a well known approach to behavioral change [13][17]. However, these approaches only provide information on traffic as a whole, not personalized feedback for users to quantitatively estimate potential benefit for society and for themselves, e,g. fuel saving, pollution reduction, etc. Information on the impact of these approaches is only available after a significant time period and typically gathered by means of (potentially subjective) questionnaires [18].

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[1]Review of evidence on health aspects of air pollution. REVIHAAP Project. World Health Organization (WHO) Regional Office for Europe. 2013

[2]The Climate Group and the Global eSustainability Initiative (GeSI): SMART 2020: Enabling the Low Carbon Economy in the Information Age, 2008

[3]VIBAT (http://www.vibat.org), Visioning and Backcasting for UK Transport Policy, Bartlett School of Planning, University College London

In order to obtain immediate feedback on how a given user is driving, cars need to include on board sensors, processing unit(s) and some kind of human computer interface (HCI). Thus, fuel consumption and/or emissions can be monitored and feedback can be used to optimize driving style and vehicle behavior. There are severak approaches to acquire instant driving information from users -e.g. pressure on breaks or face gestures- in order to provide assistance to the driver when help is needed [15], but they are mostly focused on safety issues.

The main goals of the present work are: i) to study the dynamic impact of driver behavior and chosen routes on emissions; and ii) to provide feedback for behavior correction. This goal can be decomposed into the following ones:

- To experimentally validate theoretical data provided by official reports using vehicle on board sensors
- To develop a methodology to automatically detect highly pollutant driving behaviors and routes
- To provide personal feedback to drivers so that they can change their driving habits if necessary

We propose to use a smartphone to support the whole system, as it has been reported that smartphones will most likely be the most crucial tool in the next decade to motivate behavior changes [8]. It needs to be noted that no common framework architecture for ITS systems exists, so maximizing the potential of ITS for reducing emissions will depend significantly on interoperability. Current cars are equipped with OBD (On Board Diagnosis) systems that provide information about a number of vehicle parameters. Originally, it was not easy to access a car OBD, specially on the fly. However, nowadays there are electronic systems that tap into the OBD and return information via standard communication protocols. Furthermore, these devices have become progressively cheaper. Specifically, we will use a ELM327 V1.4 B g, which extracts the OBD information via Bluetooth (BT) and, hence, easy to capture using any existing smartphone. Additionally, the smartphone GPS will be used to extract the vehicle location and geoposition all data. The mobile phone will analyze the sensor information, plot it using a GIS -in our case, Google Map- and offer feedback to users. All these data will be used to validate a general existing emission model and obtain all estimations for the user behavior and route on the go. It can be noted that this approach follows the four main trajectories defined for the next generation of ICT:

- Networked, mobile, seamless and scalable, offering the capability to be always best connected any time, anywhere and to anything.
- Embedded into the things of everyday life in a way that is either invisible to the user or brings new form-fitting solutions
- Intelligent and personalised, and therefore more centred on the user and their needs;
- Rich in content and experiences and in visual and multimodal interaction.

## II. Estimation of emissions: the ARTEMIS project

There are two main approaches to estimate how much a vehicle pollutes: i) to carry on-board Portable Emissions Measurement Systems (PEMS) [4][9]; or ii) to estimate the emissions from related parameters via system modeling[6][10]. PEMS based analysis is usually more reliable, but it requires a very specialized hardware that limits its practicality for general application. Modeling techniques can be either statistically-based[1][21] or model-based [10][14][19]. Statistical approaches require fitting of an analytical model, so they may be affected by errors derived from ill data fit. Modal based approaches are not affected by these errors, but they involve a significant amount of data averaging and, hence, they might not be adequate for micro scale applications or individual vehicles analysis (e.g. [6]). This problem is (partially) solved by introducing simplified physical models that extrapolate required data from additional parameters. For example, vehicle-specific power (VSP) -a function of speed, acceleration, and road grade- is usually a good predictor of vehicle fuel use. Some of these simple models can be derived from large scale experiments and used later at smaller scale tests. In this work, we rely on this third approach, based on the results of project ARTEMIS.

Project ARTEMIS [3] gathered a data base of 2800 cars and 27000 emission calculations to derive models on emissions in Europe roads depending on different driving environment. There have been previous efforts in the field, like CORIANAI, COPERT (I-IV), EMET, MODEM, COST and MEET. ARTEMIS has worked with real traffic conditions in Europe (MODEM-Hyzen database) and, hence, offers representative results for a diversity of scenarios. ARTEMIS is based on driving cycles, which correspond to distinct driving behavior.

### A. Defining a driving cycle

A (new) driving cycle is defined each time a vehicle changes from a specific driving environment to another, e.g. urban to rural areas. Specifically, ARTEMIS considers 3 kind of cycles: urban driving, rural driving and motorway driving, as proposed in [2]. Cycles can be labelled according to road ”official status”, but it was reported in [3] that this status often did not fit the results of their tests. Instead, ARTEMIS proposed to define cycles according to *vehicle speed* and *stop durations*. For example, it can be loosely expected that speed in highway cycles is higher and the number of stops is lower than in urban cycles. Although somewhat arbitrary, this definition returned quite homogeneous cycle groups in ARTEMIS tests, where urban trips, rural trips and motorway trips reportedly had average stop durations of 28, 10 and 5 % of total trip time and driving speeds of 30, 55 and 98 km/h respectively.

Cycles can be further divided into sub cycles depending on traffic conditions (e.g. jamming). Specifically, ARTEMIS detected 12 subcycles (table I). Given this classification, driving cycles in a running experiment can be automatically labelled.

| | Cycle of driving conditions | | % of total mileage | running speed (km/h) | average speed (km/h) | stop duration (%) | stop rate (stop/km) | aver. positive accel. (m/$s^2$) |
|---|---|---|---|---|---|---|---|---|
| 1 | Congested urban | High stop duration | 3.7 | 25.9 | 10.2 | 60.8 | 3.9 | 0.87 |
| 2 | | | 5.9 | 23.6 | 15.9 | 32.7 | 3 | 0.81 |
| 3 | | Low steady speeds | 2.4 | 16.5 | 13.2 | 19.5 | 3.4 | 0.67 |
| 4 | Free-flow urban | | 5.1 | 28 | 26.1 | 6.7 | 0.97 | 0.65 |
| 5 | | Unsteady speeds | 12.2 | 35.6 | 32.3 | 9.1 | 0.98 | 0.81 |
| 6 | Secondary roads | Unsteady speeds | 10.8 | 52.2 | 48.8 | 6.6 | 0.41 | 0.75 |
| 7 | | | 8.8 | 45.5 | 43.8 | 3.7 | 0.39 | 0.63 |
| 8 | | Steady speeds | 7.2 | 65 | 64 | 1.5 | 0.15 | 0.55 |
| 9 | Main roads | Unsteady speeds | 11.8 | 75 | 72.5 | 3.3 | 0.15 | 0.67 |
| 10 | | | 6.2 | 86.1 | 85.7 | 0.4 | 0.04 | 0.48 |
| 11 | Motorways | Unsteady speeds | 10.4 | 115.6 | 114.9 | 0.7 | 0.03 | 0.53 |
| 12 | | | 15.6 | 123.8 | 123.7 | 0.1 | 0.01 | 0.4 |

TABLE I

CLASSIFICATION OF DRIVING CYCLES (ARTEMIS PROJECT)

Depending on the driving cycle and whether the vehicle is a diesel or a petrol model, emissions are affected by a different set of parameters. ARTEMIS general conclusions are briefed below:.

DIESEL VEHICLE

- Urban cycle: i) all pollutes increase with strong acceleration -average, frequency and acceleration time-; ii) HC and CO increase at high speeds (60-100 km/h) and strong accelerations; iii) HC grows with the number of stops and CO2 decreases at higher speeds.
- Rural cycle: ii) all pollutes grow with acceleration -average, frequency and acceleration time-; CO2, HC and NOx grow with the frequency and duration of stops; CO2 and NOx decrease when speed grows.
- Highway cycle: i) all pollutes grow with accelerations at high speeds (120-140 km/h).

PETROL VEHICLE

- Urban cycle: i) all pollutes increase with stop frequency and duration; ii) all pollutes but CO decrease when speed grows; CO increases at high speed (60-100km/h); iii) NOx and CO2 grow with stop frequency and sharp acceleration.
- Rural cycle: ii) all pollutes increase with stop frequency and duration; ii) all pollutes decrease when speed grows and increase for low speeds (20-40 km/h) and positive accelerations; CO is sensitive to large accelerations/decelerations.
- Highway cycle: i) NOx and CO2 grow at high speeds (120-140 km/h) and acceleration and decrease at medium speed (60-100 km/h); ii) CO grows at medium/low speeds and also with stop frequency and acceleration; it decreases at low speeds.

In brief, pollutes depend on the following parameters: speed, acceleration, number and duration of stops. It can also be observed that CO follows a pattern different from the rest of the pollutants, that loosely depend on the same factors and behave similarly. The estimators for each pollutant, cycle and vehicle type are fully reported in [3]. It must be observed that these parameters depend on user driving behavior, so it is not possible to predetermine how green a given route can be unless the driving conditions and driver behavior are analyzed. One of the novelties of this work is to extract these parameters on the fly for any given user using a smartphone. This approach has a number of benefits, e.g. resulting data could be used to proactively suggest greener routes to a destination depending on how a person drives. In this work, we will use gathered data to obtain emissions in different routes in a city on the go based on ARTEMIS estimators and to validate the estimators using OBD information.

### *B. Parameter acquisition*

The ARTEMIS project has been chosen for this study because all required input parameters can that can be directly obtained on the fly using a smartphone in a vehicle. Specifically, we need to obtain the following parameters for each detected driving cycle:

- **Number_Elements_Cycle**: Number of data frames in the current driving cycle
- **Distance_Cycle**: Total distance in the cycle
- **Number_Stops_Cycle** and **Stop_Km_Cycle**: Total number of stops and stop frequency (per km) in the cycle
- **Accelerations_Km_Cycle**: Number of (sharp) accelerations per km in the cycle

All these parameters can be obtained from location and speed, provided by the GPS of an onboard smartphone. Vehicle acceleration can be approximated as:

$$acceleration = \frac{\Delta speed}{\Delta t} \quad (1)$$

Distance ($D$) is obtained as the sum of distances between consecutive readings $d(lat_i, long_i lat_{i-1}, long_{i-1})$, $lat_i$ and $long_i$ being the longitude and latitude at reading $i$.

$$D = \sigma d(lat_i, long_i lat_{i-1}, long_{i-1}) \quad (2)$$

These parameters can be combined with the ones obtained from the OBD in the smartphone to validate ARTEMIS estimations. Next section covers the OBD parameters that will be used in our study.

## III. The OBD system: integration with a smartphone

It has been consistently reported both by major car manufacturers and by government agencies that simple changes in driving habits -the so-called Ecodriving- could lead to significant reductions in emissions and fuel saving[4]. Recommendations include actions like Maintaining a Steady Speed Using Highest Gear Possible, Decelerating Smoothly, Shifting to a Higher Gear as Soon as Possible, etc. Many drivers are not aware that they do not drive efficiently. Furthermore, efficient driving might be impossible due to traffic conditions -specially in urban environments-. Hence, it might be interesting to provide feedback to users on their bad habits and also on greener alternatives to their everyday routes. This requires instant access to the OBD and an ubiquitous processing/visualization device with geolocalization capabilities (a smartphone in our case). In our case, we can use these recommendations to check the ARTEMIS emission estimations for a vehicle on the go.

A vehicle OBD includes a set of sensors, actuators and diagnosis software attached to its onboard computer. The OBD system is expected to operate standalone: it generates a trouble code (DTC) whenever the system performance degrades. DTC can be type A, B or C. Both A and B types are related to emissions. The OBD handles up to 11 systems for emission control, although not all of them can be performed while driving. Typically, the OBD communicates with the user via a Malfunction Indicator Lamp (MIL). MILs inform on the existence of a problem, but provide no information about its origin. Hence, this system is not appropriate for proactive, emission-preventing driving.

Traditionally, OBDs could be accessed via an appropriate bus connector, usually by specialized staff. There are 5 established communication protocols with the system: ISO 9141-2, SAE J1850, SAE J1850, ISO14230-KWP 2000 and ISO 15765 Controller Area Network (CAN). Although smartphones can not access the OBD directly, some devices may work as interface. There are already Android Apps for instant visualization of OBD parameters, like Ian Hawkins's Torque[5], but they do not offer any processing or (proactive) advice on driving.

All tests in this work have been performed using a basic Android smartphone (with GPS and Bluetooth) and a ELM327 Bluetooth Versin 1.4 to abstract the low-level protocol via a UART. ELM327 i) fully supports every OBDII protocol; ii) presents a low power consumption mode; ii) it is widely available; and iv) it is very affordable. The smartphone exchanges information with the device using AT and OBD commands: if a string does not start with the characters AT, it is assumed that it is a OBD command. OBD commands start with a mode identifier. In our case, we work in mode 1, which returns the OBD parameters on the go. Fig. 1 shows some OBD frame examples in mode 1. The frames in the examples may include one (A) or two bytes (A,B) which are used to obtain the desired parameter.

| Mode (hex) | PID (hex) | Data (bytes) | Description | Units | Formula |
|---|---|---|---|---|---|
| 01 | 06 | 1 | Short term fuel trim—Bank 1 | % | (A-128)*100/128 |
| 01 | 07 | 1 | Long term fuel trim—Bank 1 | % | (A-128)*100/128 |
| 01 | 08 | 1 | Short term fuel trim—Bank 2 | % | (A-128)*100/128 |
| 01 | 09 | 1 | Long term fuel trim—Bank 2 | % | (A-128)*100/128 |
| 01 | 0B | 1 | Intake manifold pressure | kPa | A |
| 01 | 0C | 2 | Engine RPM | rpm | ((A*256)+B)/4 |
| 01 | 0D | 1 | Vehicle speed | km/h | A |
| 01 | 0F | 1 | Intake air temperature | °C | A-40 |
| 01 | 10 | 2 | MAF air flow rate | g/s | ((A*256)+B)/4 |
| 01 | 11 | 1 | Throttle position | % | A*100/255 |

Fig. 1. OBD frame structure

A typical OBD delivers:

- Engine load (%).
- Engine Temperature ($^o$C).
- Fuel Pressure (KPa).
- Engine RPM (rpm).
- Vehicle speed (km/h).
- Air Intake Temperature ($^o$C)
- Mass Air Flow (MAF).
- Ambient Temperature ($^o$C)

Unfortunately, there are several parameters of interest that are often not provided by OBD, including Air/Fuel ratio (A/F) (%), Fuel Level Intake or Fuel Consumption (Km/l). At the very least, an estimation of vehicle fuel consumption is required. Fortunately, we can estimate this parameter using vehicle speed and MAF. We need the A/F as well for our calculation. However, since this parameter is not provided by most OBD, we have to assume that in modern vehicles the proportion is close to ideal, i.e. the ratio is close to 1 (multiply AF by 14.7). Finally, we need the fuel density (FD), which is approximately 680 g/l and 850 g/l for petrol and diesel motors respectively. Then, fuel consumption can be approximated as:

$$Fuel_{cons} = \frac{A/F \cdot 14.7 \cdot FD \cdot speed}{MAF \cdot 3600} \qquad (3)$$

## IV. Experiments and results

In this section, we are going to use our system to compare emissions for different routes joining the same starting and destination point in the city of Malaga (Spain). To acquire and process data, we have developed and deployed the application in Fig. 2 in the drivers' smartphones. Its main activity is $ObdActivity.java$. It provides access to:

- $ConfigureActivity$: Parameters to configure before connection to OBD, e.g. which OBD parameters to request, enabling GPS, vehicle and route identification, etc. These parameters are stored in class $SharedPreferences$.

[4]Ecodriving: Smart, efficient driving techniques: Treatise training in environmental transport: Energy Saving Trust, London, 2005

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

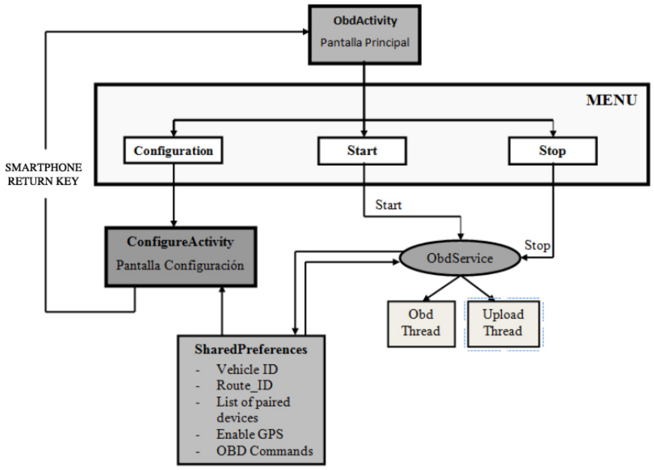


Fig. 2. Android application

- $ObdService$: acquisition of all specified parameters from the ELM327 device. These parameters are geolocated using the GPS and the $android.location$ service in the $android.locationpackage$.
- The $upload$ thread is in charge of presenting processed data on screen.

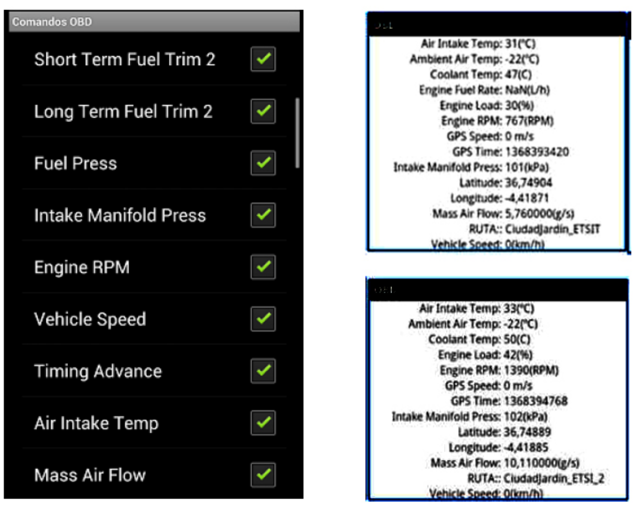


Fig. 3. Android application OBD configuration and examples during a stop

Fig. 3 shows the parameters that could be obtained in the test vehicles, plus two screen captures their values. All data in trajectories in this section has been gathered by different drivers from real routes in Malaga, using the aforementioned ELM327 and standard Android phones.

Every route may include different driving cycles. Traffic conditions, i.e. subcycles, depend on the hour and date, e.g. Fig. reffig:subcycles shows speed for the same route in dense and fluid traffic conditions, respectively. For fairness, in this section we have chosen three routes across the city that include all 3 types of cycles Fig. 5. All presented results correspond to the same user, i.e. same driving habits, and

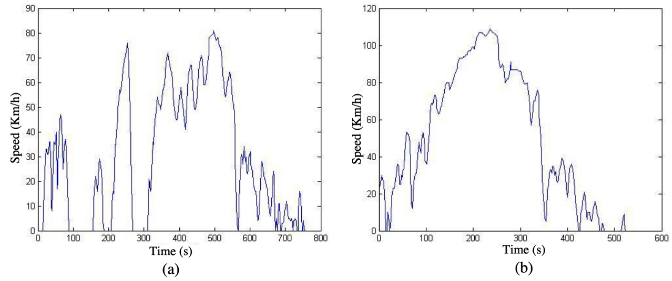


Fig. 4. Speed captured in the same route: a) dense traffic; b) fluid traffic

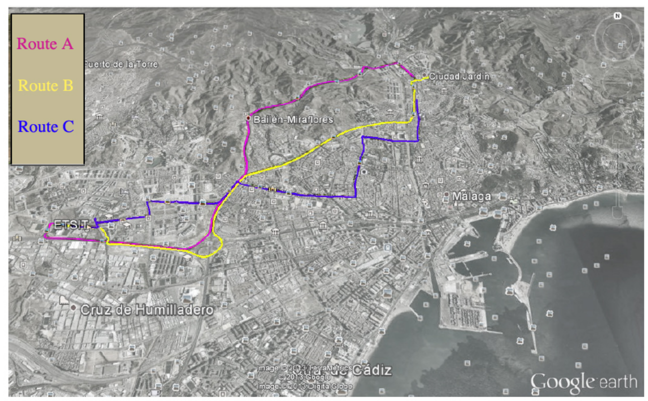


Fig. 5. Test routes from origin to destination

routes selected presented similar traffic conditions.

Fig. 6 shows the different cycles detected in all three routes. As commented, these routes were completed by same driver under similar traffic conditions, so that driving behavior related to habits are the same in all three cases and, hence, differences mostly depend on routes. It can be observed that every cycle defined in ARTEMIS is included at least in one route. As expected, speed is higher in highway routes and there are less stops, that are more frequent in urban cycles. Routes A, B and C in these tests took 12.3, 15.8 minutes and 21.6 minutes and they yield a 58.3%, 69.6% and 100% of urban cycles, respectively

Fig. 7 shows the acceleration in routes A, B and C. Routes B and C present more variations and these variations have larger magnitude than route A. Furthermore, it can be observed that these plots are correlated with the RPM changes in Fig. 8, i.e. larger accelerations match large rpm changes. This was to be expected: in urban cycles, drivers need to change gears more frequently, whereas in highway cycles, speed is consistently larger. In these areas -mostly in urban and rural cycles- the motor load grows and, consequently, fuel consumption is larger. This expectation can be checked by estimating fuel consumption for each route using the OBD and Eq. III. Results are presented in Fig. 9. It can be observed that plots for urban and rural cycles present larger variations, which reportedly lead to higher emissions. Indeed, according to Ecodriving advice (section III), route A should be the least pollutant. This expectation is going to be checked using the

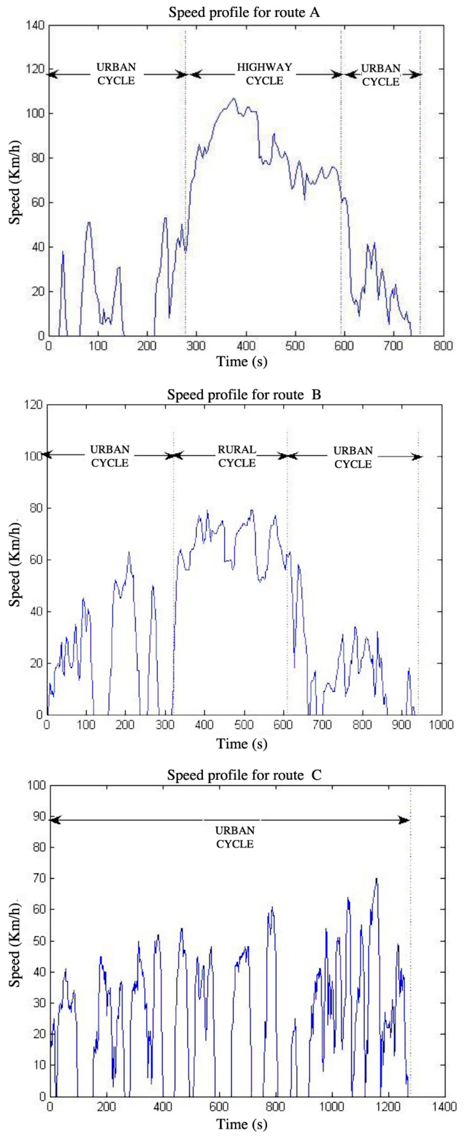


Fig. 6. Cycles detected during a run in routes A,B and C

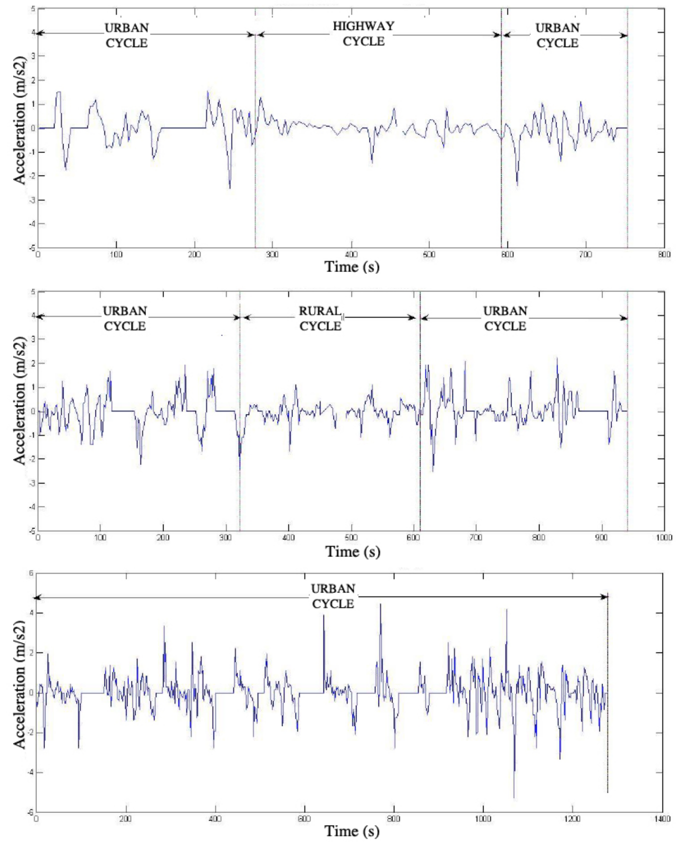


Fig. 7. Acceleration for routes A,B and C

TABLE II

STOPS PER KM IN ROUTES A, B AND C

| | Urban cycle 1 | Urban cycle 2 |
|---|---|---|
| Route A | 5.2 stops/km | 2.07 stops/km |
| Route B | 4.63 stops/km | 1.64 stops/km |
| Route C | 2.72 stops/km | — |

ARTEMIS estimators.

As commented, ARTEMIS estimators require the number of stops and accelerations per cycle. Tables II and III show the number of stops per km and accelerations per km in routes A, B and C. No stops were detected in the highway and rural cycles and it can be noted that urban cycle 1 has the larger number of stops in routes A and B. This probably happened because urban cycle 1 in both cases is close to the city center. Route B has the highest number of accelerations per km in both urban cycles, probably because it follows the main city road from east to west and it presents dense traffic and many traffic lights.

Emissions in our test routes can be stored in KML for intuitive visualization on Google Earth. The height of each location corresponds to the vehicle speed at that position and the color represents pollutes, ranging from green (low emissions) to red (high emissions). As commented, all emissions except CO present similar behavior. Hence, we are going to present results for CO in Fig. 10 and for other pollutants in Fig.11. It can be easily appreciated that, in both cases, route C is consistently the most polluting one, as expected. Results on routes A and B depend on the type of emission: route A is the least pollutant for CO -specially in the highway cycle-, whereas route B is greener for the other pollutants. These results are coherent with the previous data analysis, that validates our ARTEMIS-based estimation. In this particular example, behavior analysis would point out that the driver most dominant factor regarding emissions is a tendency to accelerate/decelerate sharply and, hence, it would be advisable to use highway cycles as much as

TABLE III

ACCELERATIONS PER KM IN ROUTES A, B AND C

| | Urban cycle 1 | Highway cycle | Rural cycle | Urban cycle 2 |
|---|---|---|---|---|
| Route A | 7.2 acc/km | 0.41 acc/km | — | 4.1 acc/km |
| Route B | 14.41 acc/km | — | 1.5 acc/km | 13.5 acc/km |
| Route C | 12.55 acc/km | — | — | — |

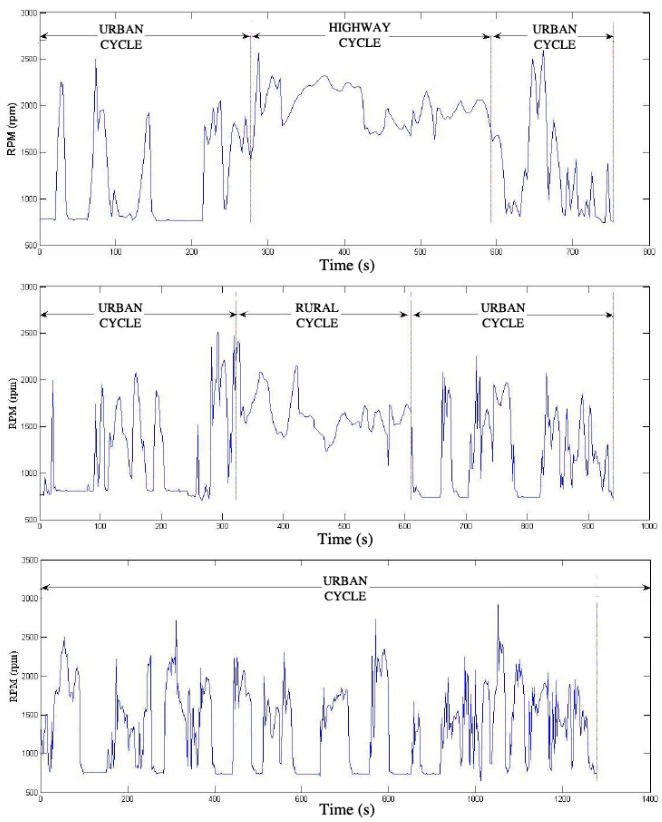


Fig. 8. RPM for routes A,B and C

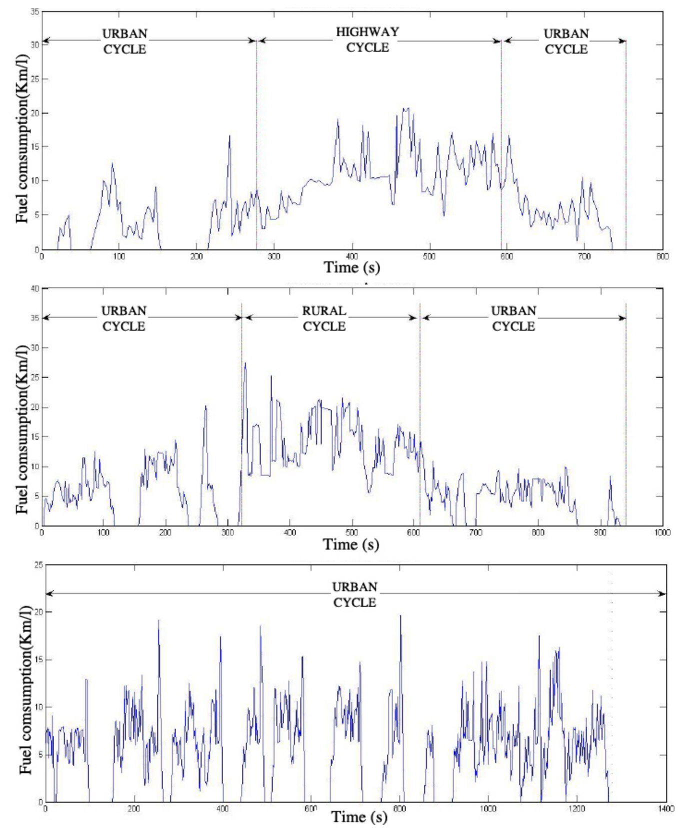


Fig. 9. Fuel Consumption for routes A,B and C

possible.

## V. Conclusions and future work

This work has presented a smartphone application to estimate emissions on the fly based on the ARTEMIS methodology [3]. The application visually offers personalized advice on pollutant driving behaviors are routes so users may change their driving habits if necessary. The system was tested in Malaga routes under different traffic conditions. In order to validate our ARTEMIS estimations, the application included BT connection to the vehicle OBD. It was checked that expected pollutant behaviors like frequent changes in acceleration, using low gears or a high number of stops in the route corresponded to the areas of largest emissions predicted by the application. It was also checked that urban cycles typically present the highest emissions in almost every test we ran.

Future work will focus on learning the most pollutant habits and visited city spots for each specific user to propose greener routes a priori rather than only analyzing results so users may adapt their future behaviors. To achieve this goal, we plan to produce personalized ”emission” maps, annotated with which kind of behavior can be expected from the user based on previous experience and what emission costs it would yield at different locations. Combination of maps from different users could lead to detection of red spots where most drivers yield high emissions. In these spots, government intervention might be needed to change regulations or physically change the road structure.

## VI. Acknowledgements

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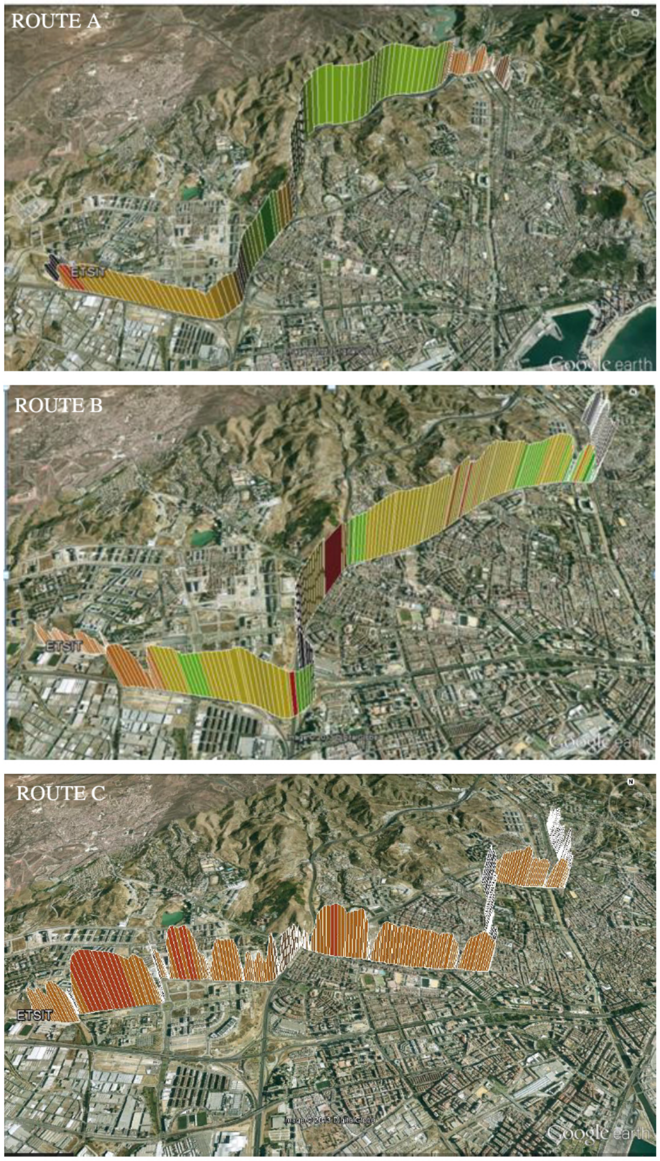


Fig. 10. CO emissions in routes A, B and C

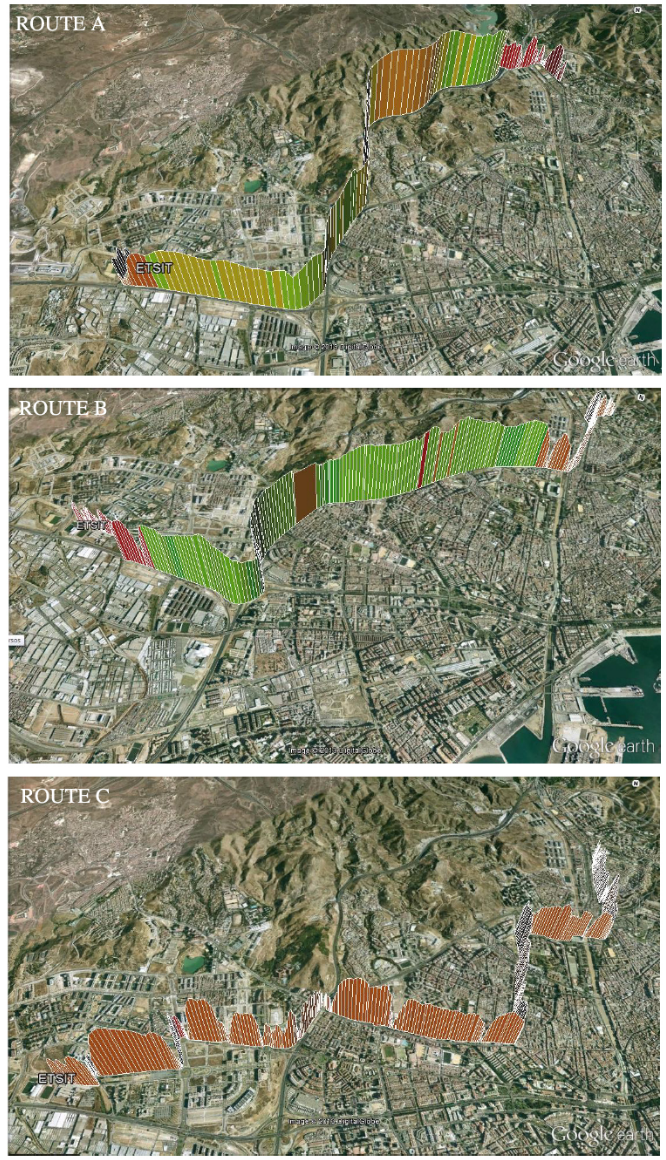


Fig. 11. Other emissions in routes A, B and C


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