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Pollutant emissions estimation framework for real-driving emissions at microscopic scale and environmental footprint calculation

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Abstract— **Nowadays, health related issues of local pollutant emissions due to transport is becoming a major concern in our modern society. Exhaust emissions level for various gases are strongly related to the driving behavior of the user. It is of public knowledge that vehicle approval regulation techniques do not reflect actual emissions on everyday trips due, for instance, to the very smooth velocity profile considered. Available means of measuring the actual environmental footprint of a vehicle exist and are called Portable Emissions Measurement Systems (PEMS). However these sensors are usually bulky and too expensive for large scale campaigns. We propose a novel solution to monitor users environmental footprint using only a smartphone device with no additional sensors. The proposed solution is able to provide individualized feedback depending on vehicle characteristics, driving style and trips topology. The comprehensive pollutant gas emission estimation algorithm is presented including vehicle, engine, aftertreatment models and environmental footprint calculation.**

I. INTRODUCTION

In 2013, the World Health Organization (WHO) classified outdoor air pollution as a carcinogen [1]. In Europe, air pollution is the first environmental health risk [2]. According to the WHO and the Organization for Economic Cooperation and Development (OEDC), air pollution outside and inside buildings has caused 663,000 premature deaths in the European region in 2010 [3]. Air pollution is also a major financial issue: a senatorial commission of inquiry estimates in an assessment rendered in July 2015 that the total cost of air pollution is between 68 and 97 billion euros per year for France [4], integrating both the health damage of pollution and its consequences on buildings, ecosystems and agriculture. Real-world Driving emissions sensitivity to the driver behavior may be significant, both for NO_x emissions of Diesel engines due to the cut of the Exhaust gas recirculation at high load [5] and for CO emissions of gasoline engines due to power enrichment [6]. For a long time, the environmental impact of vehicles has only been evaluated by the means of dynamometer emission tests. The data derived from such testing is not representative of real-world driving conditions [7]. To deal with this issue, Portable Emissions Measurement System have been developed since the 1990s [8]. These systems are suitable for measurements on a specific vehicle, but not for a large scale diffusion due to their cost and installation time. A way to measure indirectly real traffic emissions of vehicles is to use air quality sensors but large scale diffusion is limited as well and it is then difficult to relate the pollution to its cause.

The state of the art in terms of vehicle emissions models is made up of two large families, macroscopic and microscopic. It is important to precise that the models suitable for large scale emissions estimation must not present prohibitive computing time or large number of required parameters. Among the macroscopic models, the most widespread approach considers Emission Factors (EF). Emission factors are average values that relate the quantities of a pollutant released to the atmosphere to their sources, car driving in our case. These factors are usually expressed as the mass of pollutant per kilometer. Such factors facilitate estimation of emissions from various sources of air pollution. In most cases, these factors are simply averages of all available data of acceptable quality, and are generally assumed to be representative of long-term averages for all facilities in the source category. The EF can be coupled with real Global Positioning System (GPS) data to estimate vehicle emissions [9]. The EF approach only considers average vehicles and average driving style. They are suitable for average emissions on long trips but not for real traffic emissions which needs to take into account the local impact of the infrastructure and of the driving style. Their major cause of error comes from the impact of the driving style and slope [10]. To take into account these phenomena, it is necessary to use a thinner level of model, a microscopic model, whose input is generally a 1-Hz vehicle speed profile. Several microscopic models already exist and the most widespread ones are the Comprehensive Modal Emission Model (CMEM) from University of California [11], the Passenger car and Heavy duty Emission Model (PHEM) from Graz University of Technology [12] and the Virginia Tech Microscopic energy and emissions model (VT-Micro) from Virginia Tech [13]. CMEM is microscopic in the sense that it predicts second-by-second tailpipe emissions and fuel consumption based on different modal operations from in-use vehicle fleet. One of the most important features of CMEM is that it uses a physical, power-demand approach based on a parameterized physical approach that breaks down the entire emission process into components that correspond to the physical events associated with vehicle operation and emission production. The model consists of six modules that predict engine power, engine speed, air-to-fuel ratio, fuel use, engine-out emissions, and catalyst pass fraction. Vehicle and operation variables (e.g., speed, acceleration, and road grade) and model calibrated parameters (e.g., cold start coefficients and an engine friction factor) are model inputs. While the CMEM model was developed as a power-demand model, the

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VT-Micro model was developed as a regression model from experimentation with numerous polynomial combinations of speed and acceleration levels. A validation of CMEM and PHEM can be found in the literature [14] and [15], showing a good consistency with experimental results. These microscopic models are designed for offline studies. They are often coupled with a traffic simulator such as SUMO or AIMSUN which provide the 1 Hertz speed profile. Unfortunately there is an important gap between simulated and measured speed profiles and therefore pollutant emissions [15].

This contribution aims to improve exhaust emissions monitoring in real world conditions, by the development of physical microscopic models coupled with new information and communication technologies (NICT) for large scale deployment. It was not possible to use the existing microscopic models for an automated large scale deployment because the input parameters of these models are not available for all vehicles. The modeling approach should be chosen according to the vehicle data available for each car. This is the major reason why it was necessary to develop new microscopic models, suited for the real-world emissions estimation of a large vehicle fleet.

Beyond the development of new models, this approach allowed to implement a tool for monitoring and coaching the impact of a user's mobility on air quality in order to :

- Encourage drivers to improve their driving behavior by offering simple, practical, and personalized advice;
- Raise awareness of the highly polluting nature of some types of journey. For example, on a short journey, there is not enough time for the aftertreatment system to reach its activation temperature. In these instances, drivers are encouraged to use other transport modes.

One last claim to this contribution is to collect and aggregate large scale real word driving conditions and associated estimated emissions, so as to dynamically monitor exhaust emissions at city scale and characterize infrastructures and regulations efficiency.

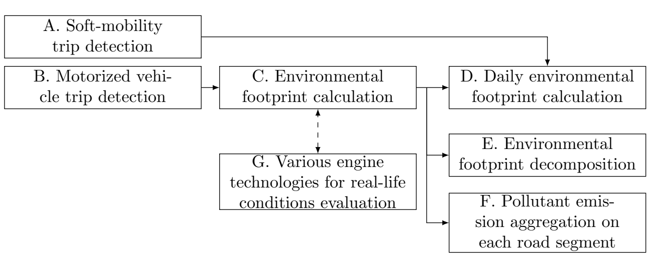

Fig. 1. Global algorithm architecture to estimate pollutants from real-world driving conditions

Figure 1 synthesis the framework deployed, whom each block is described in this paper:

- Soft mobility and motorized vehicle trip detection algorithms (Block A and B) are shortly presented in the section IV;
- The environmental footprint for each vehicle trip is then calculated (Block C) in several steps described in Section II :
  - Estimating exhaust pollutant emissions involving vehicle (Section II/B), engine (Section II/C) and aftertreatment modeling (Section II/D);
  - Aggregating the various emissions in a single environmental footprint accordingly to external cost literature (Section II/E);
- Based on each trip estimations, a daily environmental footprint is calculated (Block D) to help the user to monitor his/her environmental impact over several days (Section II/E);
- The environmental footprint being highly sensitive to the itinerary typology and driving style, and in order to sensitize drivers, algorithms has been developed (Block E) to quantify the respective parts that could be imputed to vehicle technologies, trip characteristics or driving style. They are described in the Section III.
- It is then possible to aggregate the emissions of different users and to project them on a cartography (Block F). It is even more interesting than smartphone deployment allowed the collection of a large amount of trips (several millions kilometers per year). This makes it possible to estimate statistical distributions and average levels of pollutant emissions on each road segment and, for example, to map the critical areas into pollutant emissions. The goal is to provide dynamic feedback on the environmental effectiveness of the road infrastructure and associated regulations. These works are not detailed in this paper and will be the subject of a dedicated future paper.

Finally, section V gives a brief review of experimental validation campaigns that were conducted.

II. Pollutant gas emissions estimation framework

A. Global approach presentation

In this section, we present the full pollutant estimation algorithm framework embedded in block C. described in Fig. 1. This algorithm is used firstly to estimate the different monitored exhaust gases from data measured via a single smartphone and secondly to aggregate these estimates into an intelligible metric for the users.

A model-based approach was designed to estimate instantaneous pollutant emissions, which are Nitrogen Oxides (NO_x), Particulate Matter (PM), Carbon Monoxide (CO) and Carbon Dioxide (CO_2) from the 1Hz GNSS (Global Navigation Satellite System) signal of smartphone device. Physical phenomena involved in pollutants formation are thus accurately modeled according to related literature. Vehicle specificities are taken into account by the way of a bank of 0D/1D sub-system models. Impact of control-unit strategies calibrations are taken into account as well, which are essential for real-world emissions modeling.

A trade-off between precision, number of input parameters, and computation complexity had to be made to design the most suitable modeling accuracy. The impact of real-world driving conditions and situations where pollutant

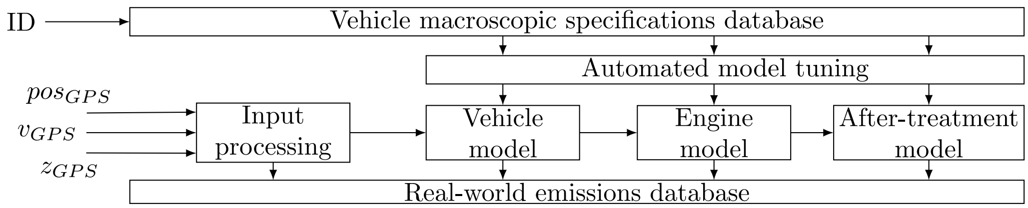

Fig. 2. Modeling architecture to compute the real-world emissions from solely GNSS data provided by a smartphone and vehicle characteristics

emissions are particularly high or low have to be caught by designed vehicle models. Moreover, available inputs are sampled 1Hz, as provided by GNSS on most smartphones which is quite a low sampling rate that models have to be suited for. This critical point has to be related to physics of pollutant formation which occurs during an engine cycle of only a few milliseconds.

Figure 2 presents the architecture to compute each exhaust gas components from GNSS measurement and vehicle parameters. Vehicle parameters can be easily assessed by online web-services thanks to vehicle registration number or simply based on the brand and vehicle model. This procedure was automated to be adapted to each driver's vehicle anonymously. Among the set of parameters χ defining vehicle k obtained via these online web-services, technological specifications used for model tuning are for instance:

- Engine type (gasoline, diesel, ...),
- European emission standard (Euro 6, Euro 5, ...),
- Engine displacement,
- Maximum torque and associated engine speed,
- Maximal power and associated engine speed,
- Vehicle mass,
- Gearbox type,
- Aftertreatment technology,
- Injection technology
- Hybridization level.

Interested reader can refer to [16] for more information about the modeling approach and parameters tunning including data collection procedures.

B. Vehicle Model

GNSS sensor provides only two inputs that can be used to model vehicle longitudinal dynamics : vehicle velocity and altitude. This first sub-model is used to compute engine speed and engine torque. The model can be written as follows:

$$m\frac{dv}{dt} = F_T - F_{res} - F_{slope} - F_{brk} \tag{1}$$

where m is the vehicle total weight, v the vehicle velocity, t the time, F_T the engine traction force, F_{res} the resistive force including the frictions, F_{slope} the gravity force and F_{brk} the braking force. F_{res} can be expressed as a function of the vehicle velocity : $F_{res} = a + bv + cv^2$, where a, b and c are the vehicle-dependent coast down coefficients. F_{slope} is a function of the vehicle mass and elevation angle α of the road: $F_{slope} = mg\sin(\alpha)$. α is computed from altitude measured from GNSS signal. These equations allow to compute the engine traction force and then the engine power P_e such that:

$$P_e = \frac{F_T v}{\rho_{trans}} = \left(m\frac{dv}{dt} + F_{res} + F_{slope} + F_{brk}\right)\frac{v}{\rho_{trans}} \tag{2}$$

where ρ_{trans} represents the transmission efficiency. At each time-step, the reduction ratio between the wheel and the engine crankshaft R_{e-w} (depending on v and P_e) is computed. It allows the conversion of velocity and power from wheel to engine torque T_e and engine speed N_e at the crankshaft : $N_e = R_{e-w}v$ and $T_e = P_e\frac{30}{\rho_{N_e\pi}}$.

In the case of hybrid vehicles, the engine power is not directly proportional to the actual power required to move the vehicle. Power split between the engine and the electric motor is set by a control strategy called energy management strategy (EMS). This strategy is implemented as well in the solution which thus takes into account hybridization functionalities: pure electric drive, regenerative braking, and engine operation optimization.

C. Engine Model

Internal physical quantities model

Internal physical quantities for the current engine operating point such as flows, temperatures or concentrations are the first parameters to be evaluated by this sub-model. Then these quantities are used to estimate the pollutant emissions, as well as fuel consumption. The following basic assumptions drive the estimation of those quantities:

- Maximum torque curve and air-path architecture are known for the engine;
- Friction mean effective pressure follow a generic law based on engine speed;
- Constant gross indicated efficiency;
- Fuel air equivalence ratio equal to 1 in SI engine (except at high load where it increases linearly with load), and varying between two values for CI engine;
- Exhaust gas rate (EGR) fraction is known for each point of the engine map.

The iterative algorithm to estimate exhaust mass flow rate was previously described in [17] and is based on an algorithm designed to determine fuel consumption, total intake mass flow rate, and pressure and temperature conditions in the air path are detailed in [18].

Engine-out emission models

Estimation of engine-out emissions is based on engine physical modeling using mostly equations from the literature adapted to the GNSS limited available data. Steady state assumptions (i.e. assuming stationary operations) are taken for most parameters but transient phenomena such as the air path settling time, thermal behaviors are included using dynamic models.

Detail of the models for all pollutant considered fell out of the scope of the paper and are not detailed here. However, an example is given for the NO_x emissions of a Diesel engine to help the reader to understand the considered model accuracy. A semi-empirical modeling coming from the literature [19] was implement with:

$$\log(NO_x) = a_0 + a_1 COC + a_2 m_{cyl} + a_3 m_{O2} \quad (3)$$

With NO_x the mass of NO_x per mass of fuel, COC the center of combustion (50% energy conversion, from TDC), m_{cyl} and m_{O2} the in-cylinder air and oxygen mass per stroke and displaced volume and a_0, a_1, a_2, a_3 model coefficients. This model was simplified such that:

$$log(NO_x) = a_4 + a_5 R_{BGR} \quad (4)$$

where R_{BGR} is the in-cylinder burnt gas ratio, estimated with the airpath model based on vehicle dynamics (velocity, engine speed, engine torque, ...) and takes into account engine calibration as well as the EGR loop dynamics as follows:

$$R_{BGR} = f(N_e, T_e, T) = f(v, z, T, \chi) \quad (5)$$

with N_e the engine speed and T_e the engine torque.

Thus engine out cumulative NO_x emission can be computed with the following model/

$$NO_x = f^{EO}_{NO_x}(R_{BGR}) = e^{a_4 + a_5 R_{BGR}} \quad (6)$$

where the superscript EO stands for Engine-Out.

Once engine out emissions are estimated, it is necessary to model the aftertreatment impact.

D. Aftertreatment Model

An aftertreatment model library was developed covering several submodels, each of which representing a widely used physical aftertreatment element of the exhaust line : Diesel Oxidation Catalyst (DOC), Diesel Particulate Filter (DPF), Selective Catalyst Reduction (SCR), Lean NO_x Trap (LNT), Three-Way-Catalyst (TWC) and PIPE (thermal model of a pipe connecting two elements). These elements can be arranged as required to fit most existing exhaust line architectures. Each variable represents the cross-section-averaged quantity at a given axial location. It is then possible to describe precisely the evolution of the gas temperature and composition through the different elements, and to estimate the tail-pipe pollutants. Going further into details, each element is in fact discretized spatially into several "slices" to account for the non-uniform axial distribution of the properties inside the element itself. This approach is fully consistent with classical models of packed-bed catalysts developed since the 1970s [20]. Several benefits of this approach make it necessary for our application: it leads to realistic dynamics of pollutants conversion efficiencies during heat-up phases (such as start-up and sudden accelerations) and during transient cool down phases as well (pedal release, slow driving), which would not be captured by a simple map-based model.

Once the pollutant emissions are estimated at tail-pipe, the cumulative emission $\phi^{[\frac{g}{km}]}_{i,j,k}$ for pollutant i on trip j with vehicle k is computed by integrating instantaneous emissions $\varphi^{[g/h]}_{i,j,k}(t)$ on the entire trip duration and normalizing it by the traveled distance. Instantaneous emissions are modeled using an emission model tuned to fit each vehicle emissions $f_k(v_j(t), z_j(t), T_j(t), \chi_k)$. $z_j(t)$ denotes the elevation profile as measured by GNSS device and $T_j(t)$ the ambient temperature for trip j. One can thus write:

$$\begin{cases} \phi^{[\frac{g}{km}]}_{i,j,k} = \frac{1}{D_j} \int\limits_{t_i}^{t_f} \varphi^{[\frac{g}{h}]}_{i,ref,k}(t)dt \\ \varphi^{[\frac{g}{h}]}_{i,j,k}(t) = f_k(v_j(t), z_j(t), T_j(t), \chi_k) \end{cases} \quad (7)$$

where D_j denotes the distance of the trip j and f_k correspond to the engine-out model combined with the aftertreatment model. In the following, this full pollutant estimation model is written in a compact form such that:

$$\phi^{[\frac{g}{km}]}_{i,j,k} = F_k(v_j(t), z_j(t), T_j(t), \chi_k) \quad (8)$$

where F_k represent the various engine and aftertreatment models for pollutant k.

Taking the same NO_x example, one can compute the tail-pipe emissions as follows:

$$\varphi^{[\frac{g}{h}]}_{NO_x,j,k}(t) = f^{TP}_{NO_x}(f^{EO}_{NO_x}(v_j(t), z_j(t), T_j(t), \chi_k)) \quad (9)$$

where the superscript TP stands for Tail-Pipe.

E. Environmental footprint calculation based on driving style

Once various pollutant gas emissions are estimated, a novel method to aggregate all pollutant into a single metric that is intelligible to the user called POP for pollutant points was designed. The main objective of POP metric being to help users to understand easily its own environmental footprint. POP are calculated such that:

$$POP_{j,k} = \sum_i \alpha_i \phi^{[\frac{g}{km}]}_{i,j,k} \quad (10)$$

where $POP_{j,k}$ indicates the aggregated pollutant points for trip j realized with vehicle k, α_i a weighting factor associated to ith considered cumulative emission $\phi^{[\frac{g}{km}]}_{i,j,k}$ (for pollutant i).

α_i weighting factors are tuned accordingly to external cost literature [21] that is based on health, congestion, climate estimated cost for each pollutant gas. Since the main objective of the POP metric is to highlight sensitivity of local air pollutant to the driving behavior, α_{CO_2} was deliberately diminished to avoid it to take the upper hand on other harmful gases.

A daily POP rating POP_{day} (Block D. on Fig. 1) is delivered to the user as well to help him/her monitor its environmental impact over several days. In order to do that, a weighted mean of all trips footprint is computed such that:

$$POP_{day} = \frac{\sum_j d_j^{[km]} POP_{j,k}}{\sum_j d_j^{[km]}} \quad (11)$$

where distance traveled in kilometer for trip j is denoted $d_j^{[km]}$.

III. Decomposition of footprint to provide end-users intelligible feedback

Engine control strategies calibration procedures as well as physical phenomenon involved have a strong impact on pollutant emissions. These emissions are thus much more sensitive than fuel consumption to usage cases. Indeed, for real-driving conditions, emissions on the same vehicle can vary significantly and the proposed approach tend to decompose the global footprint $POP_{j,k}$ into three parts related respectively to the vehicle, the driving style and the trip characteristics (Block E. on Fig. 1):

$$\begin{aligned} POP_{j,k} \quad = \quad & POP_{veh}(j,k) + POP_{drive}(j,k) \\ & + POP_{trip}(j,k) \end{aligned} \quad (12)$$

Figure 3 presents the end-to-end architecture of the solution presented above that computes environmental footprint decomposition and target velocity profile.

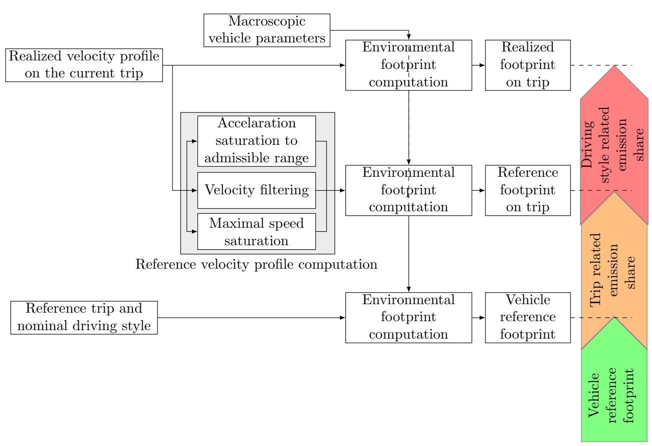

Fig. 3. Environmental footprint decomposition algorithm and target velocity profile computation.

A. Vehicle induced emissions

Environmental footprint relative to a specific vehicle is closely linked to its embedded technologies (engine type, pollution control system, ...) and by its emission standard defined on a reference trip (low emissions with a nominal driving style). It represents the minimal emissions of a vehicle for an optimal usage. To build up a driving style independent reference emission profile, each pollutant gas i is estimated by the vehicle model (block C of Fig. 1 and expressed in $\left[\frac{g}{km}\right]$) based on the reference cycle velocity v_{ref} and elevation z_{ref} known as NEDC standard driving cycle.

$$POP_{veh}(k) = \sum_i \alpha_i F_k(v_{ref}(t), z_{ref}(t), T_{ref}(t), \chi_k) \quad (13)$$

where D_{ref} denotes the distance of the NEDC cycle.

B. Driving style induced emissions

Basically, the driving style induced emissions can be seen as the part of exhaust emissions that could have been avoided if a more adapted driving style was adopted. This improvement capacity is determined by studying discrepancy to a target emission footprint in order to identify driving behavior responsible for high emissions and deliver adapted advice to the user. The considered approach is based on the instantaneous measured velocity v_j as well as the vehicle characteristics.

$$v_{target}(t) = f_{target}(v_j(t), \chi_k) \quad (14)$$

From the measured velocity profile and vehicle characteristics, target velocity v_{target} is obtained through the target vehicle model f_{target} which applies various empirical non-linear filters in order to:

- Ensure acceleration bounds imposed on such vehicle (these thresholds can be constants or velocity-dependent),
- Saturate maximum velocity allowed by road regulations,
- Improve speed stabilization and braking phases anticipation.

Each filtering steps are intelligible for the user in order to be transformed into driving advices that can be applied directly. Finally, the measured and targeted velocity profile are fed to the emission estimation model in order to compare both pollutant footprints:

1) Realized pollutant footprint for trip j on vehicle k

$$POP_{j,k} = \sum_i \alpha_i F_k(v_j(t), z_j(t), T_j(t), \chi_k) \quad (15)$$

2) Target pollutant footprint for trip j on vehicle k

$$\begin{aligned} POP_{target}(j,k) \quad = \quad & \sum_i \alpha_i F_k(v_{target}(t), z_j(t), \\ & T_j(t), \chi_k) \end{aligned} \quad (16)$$

Difference between realized and targeted footprint allows to estimate part of the footprint directly related to driving style and thus its improvement capacity.

$$POP_{drive}(j,k) = POP_{j,k} - POP_{target}(j,k) \quad (17)$$

Finally, a driving grade, comprised between 0 and 4, is calculated as a function of the ratio between POP_{drive} over POP_{veh}.

C. Trip induced emissions

The last part corresponding to the emission share relative to the type of trip is finally deduced by subtracting the vehicle footprint to the target footprint (substituting eq.(17) into eq.(12)) such that :

$$POP_{trip}(k) = POP_{target}(k) - POP_{veh}(k) \tag{18}$$

Indeed, the target footprint provide the lowest emissions that can be achieved with a nominal driving style. The rest of the subtraction is then due to trip specificities: short trips penalizing aftertreatment systems efficiency, congested traffic trips or trips with large elevation excursion. It has to be noted that the trip related share is also linked to the vehicle's embedded technology since it does not have the same sensibility to driving conditions. For example, vehicles equipped by stop-start system will be less impacted by congested traffic.

IV. Detection algorithm for soft-mobility and motorized vehicle trip

A short focus is presented here on the detection algorithm which is one of the main building blocks of the solution. Indeed it is mandatory to detect automatically each trips in order to provide a feedback on the full environmental footprint of the user (Block A. and B. on Fig. 1). Embedded solutions associated with low battery consumption are already provided by most smartphones to retrieve basic trip information such as mobility type (walking, cycling, running, car, ...) and duration. These features are thus used in block A (Fig. 1) to monitore soft-mobility. The solution could not be recording embedded sensors data (GNSS, accelerometers, magnetometer, ...) continuously due to battery consumption that have to be kept as low as possible.

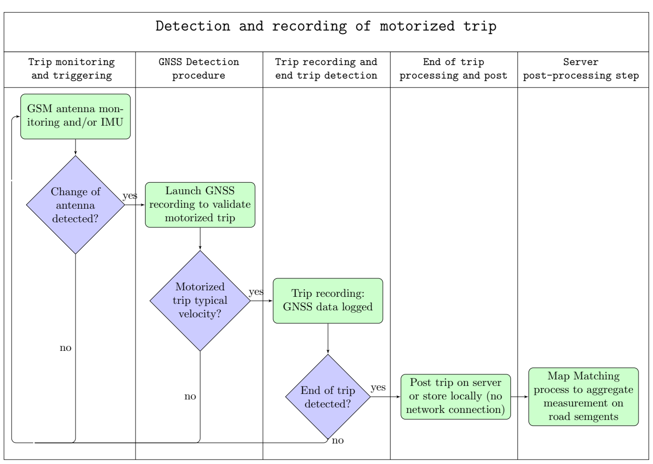

Fig. 4. Detection and recording architecture for motorized trips.

Regarding trips using motorized vehicles, a specific algorithm was designed based on GSM antenna activity. In terms of battery usage, it appears to be satisfactory to monitor event based changes of GSM antenna. Once a change of antenna triggers an event (or the embedded module that was explained above detect a car trip -less accurate-), the GNSS sensor is activated for a short period of time. If recorded velocity measurements indicates that a motorized vehicle trip is currently happening; a new trip is recorded and the GNSS is kept turned on. Otherwise, it is switched off and the algorithm goes back to the antenna monitoring state. The end of trip is detected by a condition on velocity that becomes close to zero for a certain duration. Finally, recorded data (latitude, longitude, velocity, elevation, time-stamp, GPS accuracy and vehicle parameters) are sent to the server or locally stored (in case of poor network connection). Map matching process consist in mapping latitude and longitude data on a map and if necessary correcting values to ensure that each measurement pin point to the closest road segment. This allows as well to get information on the road specification (road functional class, mean velocity on the segment, ...). Figure 4 presents the detection and recording algorithm presented above.

V. Experimental validation of the proposed solution

In this section, we show experimental results of those algorithms presented in the previous sections either from PEMS data for comparison of pollutant gas estimation validation or from users recorded trips. At the time of writing 10 000 users were registered and 15 millions kilometers were already recorded. The following figures presents some of the results

1) Comparison of cumulated NO_x and CO_2 versus PEMS recorded emissions,
2) Instantaneous 1Hz PEMS measurement versus estimated pollutant comparison on real life driving cycle,
3) Target cycle computation and pollutant emissions improvment
4) Environmental footprint decomposition exemples with the same vehicle and same trip to highlight approach sensitivity to driver's behavior.

Figure 5 presents a comparison between estimated and PEMS measurement for NO_x and CO_2 emissions for 8 different vehicles. It is interesting to focus on the case of the vehicle 24 and 25 which have equivalent technical main specifications and are compared on the same itinerary (87 km RDE test). By considering different levels of efficiency of the aftertreament systems due to different strategies, models successfully catch the specific behavior of each vehicle and the associated exhaust emissions, varying from 60 mg/km to around 400 mg/km for NO_x emissions. It shows that the models are able to represent the wide range of behaviors of recent Diesel vehicles in real-world situations.

In addition to being able to estimate cumulative emissions over the entire trip, the models are used to determine the instantaneous emissions at 1 Hz. Figure 6 shows an example of instantaneous performances of the fuel consumption and NO_x models for an Euro 6 Diesel car. The capture of these emissions peaks is essential for the study of the critical zones, which will be discussed later on. It is interesting to note that even strong NO_x peak that have a short duration are also well captured by the comprehensive vehicle model.

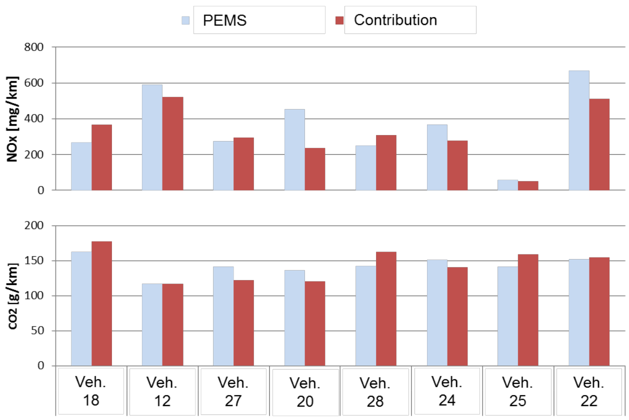

Fig. 5. Comparison between estimated and PEMS measurement for cumulative NO_x and CO_2 emissions for 8 different vehicles

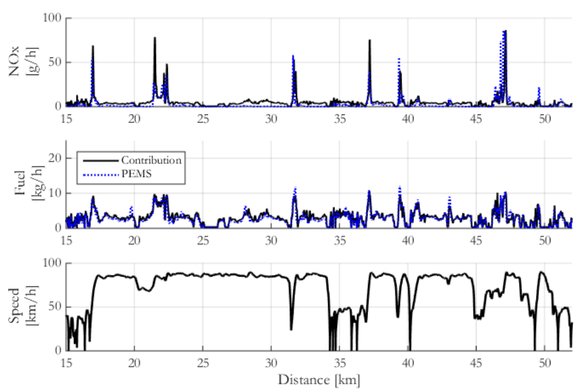

Fig. 6. Comparison between estimated and PEMS measurement for NO_x and CO_2 emissions for 1 trip at 1Hz sampling rate

One of the main contribution of the paper correspond to the design of a target reference velocity profile as shown by Fig. 7. One can see that the target profile provides smoother velocity profile with more constant segments and saturated maximal speed. This ends up in a significant reduction of the exhaust emission both in terms of cumulative NO_x (31.4% gain) and CO_2 (9.8% gain).

Finally, Fig. 8 shows an example of environmental footprint decomposition in the three different parts (vehicle, driving style and trip characteristics) for the same journey with the same vehicle but different drivers. One can see that the cumulative POP varies significantly from one trip to another. The objective of the solution is to identify the emission share that can be saved by an improved driving behavior. From Fig. 8 we note that the part related to the vehicle and trip conditions is nearly constant since the vehicle as well as the route are the same but the traffic conditions can not be kept constant (traffic sign, congestion, ...). Yet, the driving style share shows large deviation which validate the fact that the algorithm is able to identify the emission share that can be saved by a nominal driving behavior since all drivers studied have different driving style.

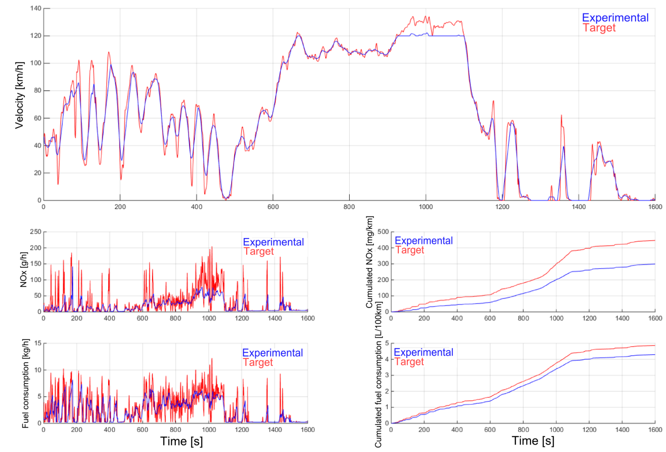

Fig. 7. Comparison between the realized velocity profile and the target velocity profile in terms of instantaneous and cumulative NO_x and CO_2 emissions

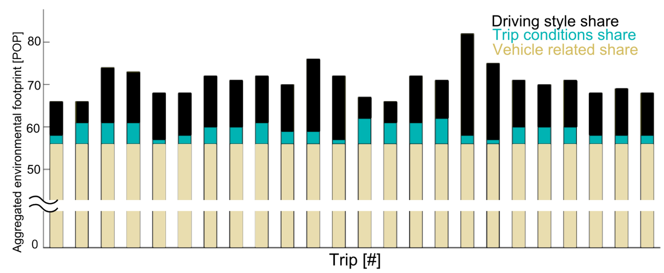

Fig. 8. Comparison of decomposition of the environmental footprint for 24 realizations of the same route with same vehicle but different drivers.

VI. CONCLUSIONS

In this paper, we presented an approach to estimate pollutant emissions for real-driving conditions at microscopic scale based only on GNSS data and vehicle parameters.

The solution was validated on a large scale manner via the design of a smartphone[1] application that counts more than 10,000 users in total. Thanks to the ability to decompose the environmental footprint into three main components related to the vehicle, the driving style and the trip characteristics, all three expressed in the same reference frame called POP for pollution point, we are able to provide the user intelligible feedback to understand its environmental and public health impact and improve its driving style.

On top of that, we showed the potential of the solution to quantify precisely the emission share that can be avoided with a nominal driving behavior and this approach was modeled to be adapted to each vehicle. It is important to note that models presented in this paper could be used independently from the smartphone application and its database.

Future steps will consist in developing tools to make map projections of emissions profile thanks to GNSS data (latitude and longitude). Various comparison are made possible, for example, one can compare multiple drivers behavior on the same road segment to see impact of driving style or

[1]Geco air application available for free on iOS and Android device

compare multiple trips of the same user to analyze traffic impact with the same vehicle. This will allow to estimate statistical distribution and mean emission level for each road segment and finally provide valuable and dynamic feedback to evaluate environmental road infrastructure efficiency and associated road regulations. Since each trip measurements are stored anonymously on a server, the emission estimation algorithm could be used as well to simulate once again each trip with different vehicles than the one used initially and thus simulate the impact of various situations such as limited access area or the evolution of the vehicle fleet.

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