Real-time air pollution exposure and vehicle emissions estimation using IoT, GNSS measurements and web-based simulation models

L. Thibault, P. Pognant-Gros, G. Sabiron and L. Voise
Control, Signal and Systems department, IFP New Energies, Solaize, 69360, France
name.surname@ifpen.fr

P. Dégeilh
Powertrain and Vehicle Technology department, IFP New Energies, Rueil-Malmaison, 92500, France
philippe.degeilh@ifpen.fr

K. Thanabalasingam
Infotem, 18-26 Rue Goubet, Paris, 75019, France
kusan.thanabalasingam@ifpen.fr

***Abstract*—Increasing urban air pollution level is one of the major concerns for citizens due to its impact on public health. In cities, vehicle emissions are one of the main contributors for nitrogen oxides (NO_x) and particulate matter (PM) emissions. These emissions are not only related to the vehicle technology but also to the driving behavior of the user. For most people air pollution is barely noticeable and the driver's impact is still unknown. The contribution of this paper consists in using new information and communication technology to create an in-vehicle-IoT device giving the driver a real-time feedback on his emissions and on his exposure during his trips. This is achieved by coupling complex simulation models deployed on distant servers and the existing smartphone GNSS sensor in order to get a low-cost solution, compliant with large-scale deployment. Air quality exposure is estimated using an atmospheric urban dispersion model based on the driver real-time location. Vehicle pollutant emissions are computed for each second of the trip from the measured GNSS speed, position and altitude using models simulating the physical phenomena involved in pollutant formation. Vehicle technical features are taken into account by the way of a data bank of sub-system models automatically selected and tuned based on technical parameters retrieved from the license plate number.**

***Index Terms*—Advanced driver assistance systems, Internet of Things, Systems modeling, Air quality, Urban pollution,**

I. INTRODUCTION

In 2018, the World Health Organization (WHO) estimated that 9 out of 10 people breathe air containing high levels of pollutant and that around 7 million people die every year from exposure to fine particles in polluted air [1]. Road transport is a major source of air pollution, mainly because of nitrogen oxides (NO_x) and particulate matter (PM) emissions. Tests with Portable Emissions Measurement Systems (PEMS) have demonstrated that most cars emit several times more pollutants on the road than during certifications driving cycles such as the New European Driving Cycle (NEDC) [2], [3] and that sensitivity to the driver behavior may be significant, both for NO_x emissions of diesel engines and for carbon monoxide (CO) emissions of gasoline engines [4]–[6]. However, for most people air pollution is barely noticeable and the driver's impact is still unknown. New information and communication technology offer the opportunity to develop new tools to create awareness and to give the driver a feedback on his environmental footprint as well as the local air pollution. The purpose of this contribution is to:

- Give the driver a direct feedback on the environmental air quality and on the pollutant emissions of his vehicle during his trip in order to encourage him to improve his driving behavior and raise awareness of the high polluting nature of some types of journey.
- Improve existing emissions-related traffic restrictions systems by taking into account the driver behavior and not only the emission standard level of the vehicle as currently used in multiple cities across Europe.

Previous works have described eco-driving solutions based on mobile applications and concluded that direct/real-time feedback provided during a driving episode was largely preferred by the drivers and allowed for a more efficient eco-driving in terms of energy consumption [7], [8]. A contribution of this paper is the use of a dedicated IoT device in addition to the mobile application. It allows to improve the real-time visual feedback given to the driver thanks to dedicated displays and the detection of the beginning of the trip using the sensors of the IoT. No action of the user needed and possibility to know which vehicle is used for which trip. Finally it improves the accuracy of the measurement of the vehicle acceleration, useful for vehicle emissions estimation (more accurate than the smartphone accelerometer which is not always fixed in the vehicle). To reduce the cost of the system for the user and allow large scale diffusion, existing features of the smartphone, such as GNSS sensor and Internet connection have been used through an application instead of embedding these components directly in the IoT device. Another contribution of this work is the taking into account of the air quality in addition to fuel consumption and carbon dioxide (CO_2) usually considered in

The authors would like to thank the Auvergne-Rhone-Alpes region air quality observatory that provide an high resolution air quality API

978-1-5386-6358-5/18/$31.00 ©2018 IEEE

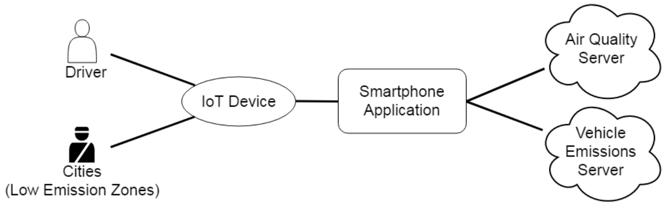

Fig. 1. Overview of the system

eco-driving systems. To avoid the use of expensive sensors, simulation models have been used to estimate the air pollution exposure and vehicle emissions. Among the existing vehicle emissions models, microscopic models are able to catch the driving behavior impact. Several microscopic models already exist and the most widespread ones are the Comprehensive Modal Emission Model (CMEM) [9], the Passenger car and Heavy duty Emission Model (PHEM) [10] and the Virginia Tech Microscopic energy and emissions model (VT-Micro) [11]. However 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 must be chosen according to the vehicle data available for each car.

Figure 1 gives an overview of the system, each of its block being described in this paper:

1) The IoT device is located behind the windscreen like a vignette sticker. The beginning of the trip is detected by the IoT device (described in Section II) which wakes up the smartphone application without needing any action from the user.
2) The smartphone application runs in the background and records the vehicle speed, acceleration, and road slope throughout the trip. This signal is then sent to the two servers which compute:
   - the vehicle pollutant emissions as described in section IV.
   - the air quality index at the vehicle location as described in section V.
3) The results are then sent back to the IoT device and displayed to the driver.

First experimental results are finally shown briefly in section V.

II. The IoT Device

The architecture of the in-vehicle IoT device is described in Fig. 2. It has been built using off-the-shelf components and its main features are detailed below:

- The embedded accelerometer allows the detection of a new trip and wakes up both the IoT device and the smartphone application. Battery consumption is a key issue and the Bluetooth module is turned on only when triggered by the embedded accelerometer. In future versions of the system, the accelerometer will also be used as an additional sensor for the computation of the pollutant emissions, since the device remains fixed in position inside the car which is not always the case for the smartphone.

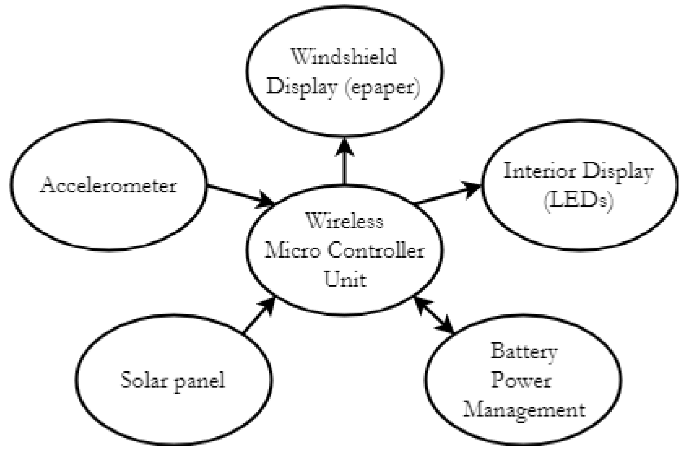

Fig. 2. IoT device main components

- The display toward the driver consists in two LEDs indicators which are turned on during a trip to illustrate with a simple color code the level of exhaust emissions and air quality during the trip. The two indicators are calculated using the algorithms described in section IV and V. These algorithms are deployed on distant servers for now. The indicators are not lightened permanently during the trip except during pollution peak. They are turned on only when some events appear such as: driving behavior especially good or bad and significant change in the air quality.
- The display toward the windscreen consists in an e-paper screen. This technology consumes energy only when refreshed allowing to give a permanent information outside of the car without power supply even when the vehicle is parked. This screen can be used as a dynamic vignette sticker for traffic restrictions (to grant access to Low Emissions Zones) or as a gamification screen to encourage the driver to reduce his pollutant footprint.
- Energetics self-sustainability : the battery is recharged using an inboard solar panel. In nominal conditions of sunshine (and assuming outdoor parking), it is not necessary to plug in the device.
- Communications with the smartphone and the outside world are made using Bluetooth Low Energy (BLE). Connected mode is used to receive the display commands from the smartphone. Advertising mode allows a short range (10 m) broadcast of the pollutant level of the vehicle.

III. Smartphone Application

The smartphone application has several functions:

- use the phones built-in sensor technologies, namely GNSS and accelerometer, to measure driving behavior such as acceleration, braking and cornering.

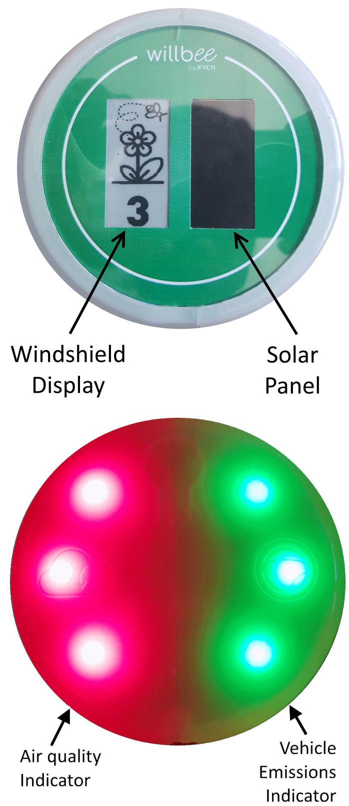

Fig. 3. Pictures of the windshield side (on the top) and the driver side (on the bottom) of the IoT device

- Communicate with the servers using 4G.
- Communicate with the IoT device using BLE.
- provide feedback and recommendations to the driver to reduce vehicle emissions.

It would have been possible to integrate all these functions directly in the IoT device without technical constraints but at the price of higher costs (device and data plan). Here, it is an extension of an existing application running on Apple or Android operating systems.

IV. Vehicle emissions simulation model

In this section, the vehicle pollutant simulation models are briefly described (more details can be found in [12]). These models have been developed in Matlab/Simulink and automated code generation has been used to embed them in a Java server which provides web services accessible from Internet (eg the smartphone). They estimate instantaneous pollutant emissions: (NO_x), exhaust Particulate Matter in mass (PM) and number (PN), non-exhaust Particulate Matter (from brakes and tires), CO and CO_2. Their outputs are used to give dynamic feedbacks to the driver with LEDs indicators and detailed post-trip analysis in the smartphone application.

The software modeling approach is described in Fig. 4. The main inputs are 1Hz vehicle speed, position and altitude of the GNSS sensor of the smartphone device. Physical phenomena involved in pollutants formation are modeled according to related literature. Vehicle technical features are taken into account by the way of a data bank of 0D/1D sub-system models automatically selected and tuned based on technical parameters retrieved from the license plate number. A trade-off between precision, number of input parameters, and computation complexity had to be made to get the most suitable modeling accuracy. The impact of real-world driving conditions and situations where pollutant emissions are particularly high or low have to be caught by the designed vehicle simulation models.

More in details, as a first step, GNSS sensor provides inputs for a longitudinal dynamic vehicle model: vehicle velocity and altitude allow to compute the power needed at the wheel to move the vehicle. A second sub-model is used to estimate, at each time-step, the reduction ratio between the wheel and the engine crankshaft, and so allows the conversion of velocity and power from wheel to engine speed and torque at the crankshaft.

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 or thermal behaviors are included using dynamic models.

To estimate tail-pipe emissions, an after-treatment model library was developed covering several sub-models, each of which representing a widely used physical after-treatment 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). These models allow to describe precisely the evolution of the temperature and composition through the different elements, and to estimate the tail-pipe pollutants. Going further into details, each element is in fact spatially discretized 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 [13]. Several benefits of this approach make it necessary for our application: it leads to realistic dynamics of pollutants conversion efficiency 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.

These models have been experimentally validated, both on engine and roller test benches (for 24 vehicles) and against PEMS measurements (for 12 vehicles). The estimations of fuel consumption and CO_2 emissions are the most precise with a typical modeling error from 5% to 10% depending on the vehicle and the trip. In this case, the main source of error is the estimation of the gearbox ratio. Among pollutant emissions, the estimation of NO_x emissions is the most effective with typical error from 5% to 20%. For NO_x emissions, the most critical situations are short trips with a modern Diesel engine fitted with an after-treatment system which are highly sensitive to the warm-up duration. CO emissions for gasoline engine and PM for Diesel are the most critical emissions to model with

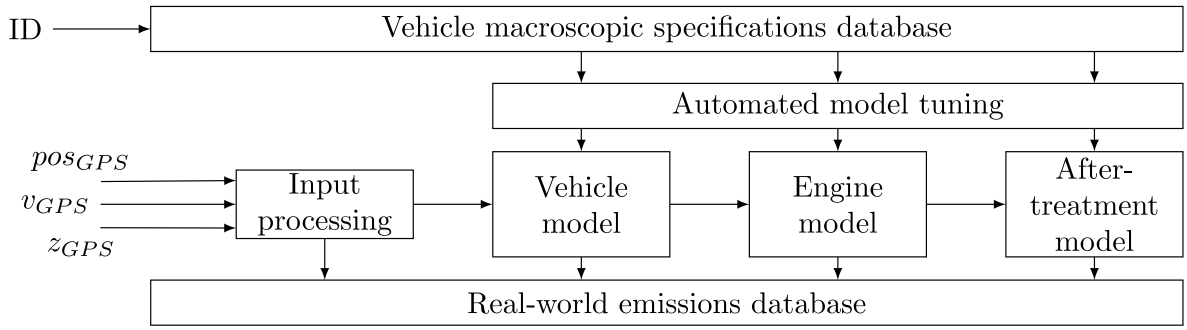

Fig. 4. Modeling architecture to compute the real-world emissions from solely GNSS data provided by a smartphone and vehicle characteristics

a typical error of 15% to 30%. Nevertheless, this accuracy is consistent with the level of complexity of the pollutant models and its objectives. Indeed, it allows to catch the influence of the vehicle, the trip and the driving behavior. A more extensive validation against PEMS measurements is currently in progress

Such a modeling approach allows to factor in:

- The impact of driving conditions including driving style since emissions are computed at each time step based on the GNSS measurements.
- Vehicle characteristics: mass and dimensions, engine injection and aspiration type, displacement, number of cylinders and valves, hybridization level, after-treatment type, engine rated power and torque and associated speeds, and gearbox type.
- The impact of ambient temperature, engine dynamics and after-treatment temperatures.
- The impact of control strategies calibrations. Typical control strategies are simulated and automatically adjustment of the calibration parameters of the models using an RDE emissions database.

For now these models do not take into account :

- the exact rules of control strategies used for each OEM and each model (see previous paragraph).
- the impact of aging, tampering and bad maintenance.

V. Air Quality Index

The air quality index consists of a color and a value between 1 and 100 as illustrated in 5. The green color corresponds to a very good to good air quality. The higher the index, the redder it is and the worse the air quality. A value greater than 90 corresponds to the exceeding of the information and recommendations threshold for one of the three pollutants concerned (NO_2, O_3, PM10) by the pollution episode management system. Currently in France, a value higher than 100 corresponds to the exceeding of the alert threshold and triggers the activation of traffic regulations forbidding the use of some vehicles depending on their fuel type and age. The air quality index is for now a daily estimate of the global pollution level updated every day around 14h. This is a multi-pollutant index which takes the value of the highest of the three sub-indexes. The hour-per-hour estimation of the air quality index is currently in progress. The index calculated at a scale of 10 meters for the major urban areas and on a kilometer scale for the rest of the region. The data come from the fine scale air quality forecasting models called SIRANE developed by the University of Lyon Ecole Centrale de Lyon and implemented by the Auvergne-Rhone-Alpes region air quality observatory. These models are reachable through web services giving the air quality index for any location defined by its GNSS coordinates. SIRANE is an operational urban dispersion model based on a simplified description of the urban geometry that adopts parametric relations for the pollutant transfer phenomena within and out of the urban canopy (interested readers could find more details in [14]).

		NO_2	O_3	PM10
	Index Value	max [µg/m3]	max [µg/m3]	mean [µg/m3]
	>0	>0	>0	>0
	>10	>40	>36	>10
	>20	>60	>54	>15
	>30	>80	>72	>20
	>40	>100	>90	>25
	>50	>120	>108	>30
	>60	>140	>126	>35
	>70	>160	>144	>40
	>80	>180	>162	>45
	>90	**>200**	**>180**	**>50**
	>100	**>400**	**>240**	**>80**

Fig. 5. Air Quality Index computation table

VI. Experimental Results

The purpose of this section is to show the preliminary results of the system in real-world conditions. Figure 6 shows an example of the direct feedback provided by the IoT device to the user during a trip. Left figure represents the evolution of the air quality index while the right figure represents the NO_x emissions. The main goal is to raise awareness among drivers by showing the pollution of the air they breathe and encouraging improved driving behaviors.

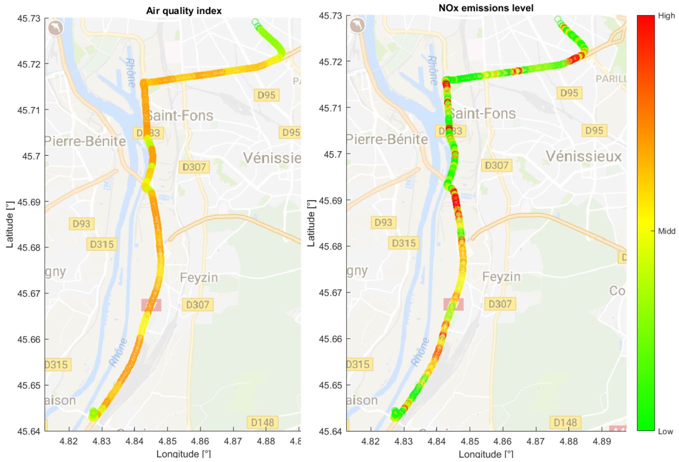

Fig. 6. Map projection of air quality index (left) and NO_x emissions (right) evolution during a real-life driving cycle.

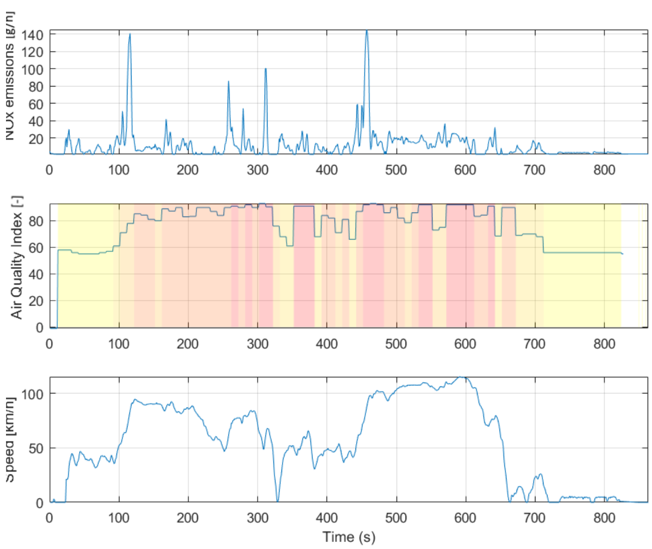

Fig. 7. Experimental results: comparison between estimated (NO_x) emissions and air quality index for a real-life driving cycle.

Figure 7 shows an example of emissions estimation and air quality monitoring during a trip. The first sub-figure presents the evolution of NO_x emissions estimated by the vehicle simulation models from the 1Hz GNSS data acquired from the smartphone. The second one corresponds to the air quality index (from 0 to 100) and a corresponding color (green for good air quality towards red for polluted environment). One can notice that main NO_x peaks appear during strong accelerations (third sub-figure presents the velocity profile) which usually correspond to areas with polluted / highly polluted environments (change of speed limit, highway entrance, etc.).

VII. CONCLUSIONS

In this paper, we presented an innovative solution to inform a driver in real-time of both his air quality exposure and pollutant emissions. It consists of an IoT device, a smartphone application and web-based simulation models. The software based approach allows large-scale deployment without needing expensive sensors. For cities it offers a new opportunity to improve the existing emissions-related traffic restrictions systems by taking into account real-world emissions and the driving behavior impact. The first prototypes of the IoT device are now being deployed. The next steps of the project consist in learning from the user feedback and measuring its efficiency with PEMS. A simplified adaptation of the vehicle emissions models is being developed to be embedded directly into the smartphone application, reduce the lag time of the eco-driving indicator and reduce data consumption. Another possible option consists in embedding the complete vehicle emissions models directly into the smartphone, thus providing the driver with even more accurate information.

REFERENCES

[1] World Health Organization and others, "WHO Global Urban Ambient Air Pollution Database," 2018.

[2] B. Daham, H. Li, G. E. Andrews, K. Ropkins, J. E. Tate, and M. C. Bell, "Comparison of real world emissions in urban driving for euro 1-4 vehicles using a PEMS," tech. rep., SAE Technical Paper, 2009.

[3] V. Franco, F. P. Sánchez, J. German, and P. Mock, "Real-world exhaust emissions from modern diesel cars," *communications*, vol. 49, no. 30, pp. 847102–847129, 2014.

[4] N. Fonseca, J. Casanova, and M. Valdes, "Influence of the stop/start system on CO 2 emissions of a diesel vehicle in urban traffic," *Transportation Research Part D: Transport and Environment*, vol. 16, no. 2, pp. 194–200, 2011.

[5] S. Samuel, L. Austin, and D. Morrey, "Automotive test drive cycles for emission measurement and real-world emission levels-a review," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, vol. 216, no. 7, pp. 555–564, 2002.

[6] B. A. Holmén and D. A. Niemeier, "Characterizing the effects of driver variability on real-world vehicle emissions," *Transportation Research Part D: Transport and Environment*, vol. 3, no. 2, pp. 117–128, 1998.

[7] W. Dib, A. Chasse, P. Moulin, A. Sciarretta, and G. Corde, "Optimal energy management for an electric vehicle in eco-driving applications," *Control Engineering Practice*, vol. 29, pp. 299–307, 2014.

[8] J. Tulusan, T. Staake, and E. Fleisch, "Direct or indirect sensor enabled eco-driving feedback: Which preference do corporate car drivers have?," in *Internet of Things (IOT), 2012 3rd International conference on the*, pp. 39–46, IEEE, 2012.

[9] 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.

[10] S. Hausberger, J. Rodler, P. Sturm, and M. Rexeis, "Emission factors for heavy-duty vehicles and validation by tunnel measurements," *Atmospheric Environment*, vol. 37, no. 37, pp. 5237–5245, 2003.

[11] H. Rakha, K. Ahn, and A. Trani, "Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions," *Transportation Research Part D: Transport and Environment*, vol. 9, no. 1, pp. 49–74, 2004.

[12] L. Thibault, P. Degeilh, O. Lepreux, L. Voise, G. Alix, and G. Corde, "A new GPS-based method to estimate real driving emissions," in *Intelligent Transportation Systems (ITSC), 2016 IEEE 19th International Conference on*, pp. 1628–1633, IEEE, 2016.

[13] C. Depcik and D. Assanis, "One-dimensional automotive catalyst modeling," *Progress in energy and combustion science*, vol. 31, no. 4, pp. 308–369, 2005.

[14] L. Soulhac, P. Salizzoni, F.-X. Cierco, and R. Perkins, "The model SIRANE for atmospheric urban pollutant dispersion; part I, presentation of the model," *Atmospheric Environment*, vol. 45, no. 39, pp. 7379–7395, 2011.