Fuel consumption evaluation for the testing of Advanced Driving Assistance Systems: first issues and solutions

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Abstract: - This paper presents some preliminary results toward the development of a microscopic fuel consumption model usable in real time. The aim of our research is the development of Advanced Driving Assistance System tools which are based on the fuel consumption model, and implement eco-driving strategies. The parameters of the model have been identified and validated with respect to a huge experiment carried out by using the Instrumented Vehicle owned by the University of Naples, and involved about 100 drivers (for a total amount of about 8000 km of driving data). We developed an instantaneous model, and showed that the estimation is very accurate when the model is used in order to evaluate the aggregate fuel consumption of a driving session. Results of this paper put the basis for the development of a powerful tool for Advanced Driving Assistance Systems development and testing.

Key-Words: - Fuel Consumption; Intelligent Transportation Systems; Advanced Driving Assistance Systems; Instrumented Vehicle; Microscopic Model; OBD Data.

1 Introduction
The research here presented takes place in the frame of traffic behaviour studies, and the design of Advanced Driving Assistance Systems (ADAS). ADAS are developed by using electronic control units (ECUs) that are aimed to supervise the safety, the comfort and/or the efficiency of the driving; their design is carried out in the framework using the so-called automotive V-Cycle, a process of analysis, development and prototyping that envisages a first phase of conception of the control logic characteristics and mechanisms, a second phase in which the software needed to manage such a logic is developed, and a third phase consisting on the implementation of the ECU and the evaluation of its interaction with the other components (hardware sensors, actuators and other devices, control units) of the vehicle. The first stage is called Model In the Loop (MIL), and in that case the model of the control logic interact with the models (already certified and tested) that represent the operation of the entire vehicle (as well as the environment and traffic). In the second phase, called Software In the Loop (SIL), the controller management software that implements the control logic interact with other software codes and other system component models in a simulated environment; however, the input and output of the tested software are of the same kind and type of real ones. In the third stage, known as Hardware In the Loop (HIL), a prototype controller is actually developed (by using embedded programming techniques), and the obtained hardware-component is plugged into a mixed testing environment composed by using both hardware and other software components (already developed and certified) are used to reconstruct the vehicle architecture; the actual hardware/software mix depends on the particular aim of the experiment. Research here described falls in the MIL context and is aimed at allowing existing ADAS testing platforms (e.g. the software PreScan) the possibility of including more sophisticated models that takes in account the interaction of the controlled vehicle with other vehicles (traffic), and with drivers’ behaviours; within these our particular focus is the development of a fuel consumption module.

The paper is organized as follows: section 2 resume the literature with respect to the various approaches used for the analysis of fuel consumption; in section 3 our experiment, tools and collected data are presented; in section 4 and 5, some models are presented and discussed; finally in section 6 some conclusions are drawn.
2 Problem Formulation
The impact of the transport sector is in the range of 20%-40% in terms of consumption of fossil fuels and emissions of greenhouse gases and particulate matter [1].

On 24 June 2013, the Environment Committee of the European Parliament approved an agreement on new rules to reduce the CO₂ emissions of light commercial vehicles. According to the text by 2021, for new vehicles sold in the EU, CO₂ emissions must be reduced by 28% (from the current 132 g/Km to 95 g/Km). The text was approved by the plenary in Strasbourg on 24-27 February 2014.

One possibility is to address the problem at a transportation network level, that is implementing proper instruments for the evaluation, and implementation of strategies for the reduction of traffic congestion [2],[3].

Another approach to the problem is to act at the vehicle level, understanding what mostly affects fuel consumption, and developing the design of Advanced Driver Assistance Systems (ADASs) that help the drivers in adopting an eco-driving style. A possible step necessary to achieve the latter objective is the characterization of a microscopic model able to predict fuel consumption. In the literature there are many approaches: macro models, meso models and finally micro models.

The first are able to predict fuel consumption for a relatively large region and for rather long periods of time; of course for the purposes of this research they will not be processed.

Meso models, are based on average parameters (e.g. the average speed of the vehicle), and can be divided into two major categories: models based on correction factors [4],[5]; models based on Vehicle Specific Power (VSP), or on instantaneous power per unit of mass of the vehicle [6],[7]. Consumption calculated using these approaches reflects the consumption "type" for a certain class of vehicles, presenting often some deviations in results when considering a specific vehicle [8].

Microscopic models can be classified according to different criteria. First and foremost, the fuel supply: gasoline, diesel and hybrid newly developed vehicles. Other models have as a basic principle the traction- law; in practice, several authors specified models based on the consideration that once the movement of a vehicle takes place, this one must overcome all the resistance forces, such as: the aerodynamic drag, the tyre rolling resistance and the resistance caused by the longitudinal road grade. Starting from that, fuel consumption can be estimated as a function of the mass of the vehicle, the aerodynamic drag coefficient, the vehicle frontal area, the vehicle acceleration and speed, the road gradient, etc. It is worth noting in this stream the model developed by [9], that was subsequently improved by [10], and finally incorporated into a software package able to predict fuel consumption as a function of speed and road geometry. In fact, for a given driving cycle, fuel consumptions are strongly correlated with the power required from the vehicle so that the motion occurs [11].

Finally, fuel consumption can be indirectly inferred from exhaust gas emissions, even in real time ( e.g. [12]).

Another category of models concerns those based on laboratory-tests, performed on a chassis dynamometer, that implements standard driving cycles such as the European NEDC (New European Driving Cycle), and/or the U.S. FTP (Federal Test Procedure). In the latter class of models it is worth mentioning the VT-CPFM (Virginia Tech – Comprehensive Power-Based Fuel consumption Model) which starts from the consumption model developed by [13], based on the computed instantaneous vehicle power. VT-CPFM ((14)) differentiates its parameters on the basis of several conditions such as driving environment (urban, suburban, etc.), simulated driving cycle (U.S. FTP or European NEDC), etc.

It is worth mentioning approaches that allows to compute instantaneous fuel consumption. [15] developed a nonlinear regression model, based on a polynomial combination of the instantaneous speed and acceleration, using different regression coefficients in deceleration or acceleration phase. This model was calibrated using data collected by ORNL (Oak Ridge National Laboratory) using a chassis dynamometer. It calculates the consumption/emissions through a logarithmic transformation to ensure that there are no negative estimates and to increase the accuracy of the model at low values of speed and acceleration. In the same period, the University of California [16] presented the Comprehensive Modal Emissions Model (CMEM) able to predict instantaneous fuel consumption and emissions in three different driving cycles for both light and heavy vehicles; the model uses as input variables both the vehicle kinematic and road’s characteristics (acceleration, velocity, and slope), and motor data (such as the coefficient of cold starting, and the coefficient of engine friction).

Finally, [17], using recorded data by the OBD (On Board Diagnostic) port, specified a nonlinear regression model for a gasoline vehicle with
automatic gearbox. In particular the variables used in the model are the RPM and Throttle. Micro-models have also been used for eco-driving purposes. The University of Twente (Netherlands) in collaboration with the School of Transportation and Society (Sweden) have developed a fuel-efficiency support tool capable of performing real-time control of consumption and provide both positive and negative video feedback while driving. Similarly, [18] have developed an Acceleration Advisor (AA) able to signal to the driver, causing a resistance on the gas pedal, if s/he is accelerating too quickly.

3 Experiment

Our analyses start from data collected in the experimental campaign of the National Research Project DriveIn2 (DRIVER monitoring: technologies, methodologies, and IN-vehicle INnovative systems; [19]). In this experiment a sample of 100 drivers drove on a large circular ring (Figure 1, first row, left side) of a total length about 80 Km composed by two tool-road segments with different posted speed-limits (100 and 130 Km/h) and a one-lane per direction road with 60 Km/h speed limit (and overtaking not allowed). The experiment also involved some test drivers from the FCA (Fiat Chrysler Automobiles) plant in Pomigliano d’Arco, near Naples, that were asked to drive the instrumented vehicle in a way that preserve fuel consumption; it is worth noting that the experimental site, although comparable, was not coincident for them (Figure 1, second row, left side).

Data were collected by means of an Instrumented Vehicle equipped at the University of Naples Federico II [20] and [21]. Among other measurements, the IV collects data from the on-board CAN via the OBD (on-Board Diagnostic) port system, and the vector of acceleration along the three axes of motion, provided by a X-Sense Inertial Measurement Unit (IMU). The speed obtained from the OBD has been validated versus the one obtained by a GPS Topcon, adopting the (filtered) GPS speed (sampled at 10Hz). All data were collected at a 10 Hz frequency, synchronized and recorded on-board. All kinematic data were subject to a Kalman filter procedure, as described in [22], in order to have consistent profiles of speed, and accelerations (and also relative speed and spacing with respect to a possible front vehicle). All data are complemented with the videos taken by four cameras.

In particular, the analyses of this paper refer to the subset of the collected variables mostly related to fuel consumption, and in particular we focus on the kinematic of the controlled vehicle, and on the driver’s interaction with it. In particular the data taken by using the OBD port are: speed (measured in km/h), Gas Pedal (ranging from 0 to 100 with relation to the opening of the EGR valve), the engine Revolution Per Minute (RPM), the Fuel metering and the Intake Air, which represent respectively the milligrams of fuel consumed and the milligrams of air flowing inside the combustion chamber for each injection cycle measured in that instant. On the other hand, the only information taken from the IMU is the acceleration along the axis of motion (measured in m/s²).

3.1 Data reduction

Our evaluation of fuel consumption has the objective to compare all the drivers involved, thus we will refer our analyses only to the common part of the experiment (evidenced in Figure 1, rows 1 and 2, right side, by using as a reference the GPS tracks of two experiments)

Despite data are recorded at a frequency of 10 Hz, the ones coming from the OBD port are actually read at a frequency of 1 Hz (e.g. with reference to this group of data, the same value is recorded 10 times from the IV data acquisition system); for this reason we proceeded sampling the entire dataset of measurements at the lower frequency of 1 Hz by approximating the value of acceleration with the average of the last ten values. It is worth noting that we consider a frequency of 1 Hz as fully adequate to the scope of this research.

Fuel consumption is commonly represented in terms of two variables: the instantaneous Fuel Consumption (FC_{inst}), that expresses the fuel consumption for every second, and the liter per kilometer fuel consumption (FC_{km}), that expresses...
the fuel consumption in one kilometer if the current motion conditions are maintained stationary.
It is straightforward to obtain \( FC_{\text{inst}} \) from Fuel metering by using the following formulation:

\[
FC_{\text{inst}} \left[ \frac{1}{S} \right] = \frac{2 \times \text{RPM} \times \text{Fuel Metering}}{1000 \times 60 \times 825}
\]

where:
- 2 is the number of injections during one engine revolution;
- 1000 let to switch from mg to l;
- 60 is the number of seconds in one minute;
- 825 is the density of diesel fuel expressed \( l/m^3 \).

Similarly, the \( FC_{\text{km}} \) can be obtained by using the current speed value:

\[
FC_{\text{km}} \left[ \frac{l}{km} \right] = \frac{FC_{\text{inst}}}{\text{Speed} \times 3600}
\]

In our experiment, collected OBD data were found to be biased by a large number of outliers, and for this reason, some filtering operations were carried out. Filtering operations can be grouped in two phases: a smoothing procedure, and a refinement for the scope of the paper of the whole dataset. In the smoothing phase, a moving average operator was applied to Fuel Metering; the moving window was fixed at 5 seconds. In the second phase some values were removed from the dataset according to the following criteria:
- fuel metering values lower than 8.62 mgi; indeed this value represents the minimum value of consumption observed in engine idling speed;
- instantaneous consumption values higher than 0.12 l/km, considering that this is the maximum value of fuel consumption furnished by the manufacturer;
- speed values lower than 10 km/h, to cut off stop and go phase.

Described operations caused the removal of 27% of our dataset. It is worth noting that when a value is removed from the dataset, all recorded values concerning the same time instant are removed. In this way the final dataset is composed by a full set of variables n-tuple.

4 Results
The cleaned data were used to identify a fuel-consumptions model. As you can see in Figure 2 the variables where there is an obvious correlation of the Fuel metering are the Gas Pedal and the Intake Air. The two variables were identified by using the stepwise algorithm implemented in the Matlab Statistical Toolbox.

In addition, considering that on the basis of the law of traction a dependency of motion from the square of speed and acceleration exist, these two variables have been included in our model. Then the linear regression model is calibrated as follows:

\[
FM_{\text{mg}} = \beta_0 + \beta_1 v^2 + \beta_2 a + \beta_3 \text{GasPedal} + \beta_4 \text{IntakeAir}
\]
\[
ERR_{\text{inst}}(t) = \left| \frac{\hat{x}_i - x_i}{x_i} \right|
\]

\(ERR_{\text{inst}}\) represents the percentage deviation between the predicted value by the model, \(\hat{x}_i\), and that observed, \(x_i\), at the instant \(i\) of \(FM_{mg}\).

4.2 Aggregate Analysis
Another interesting point of comparison of model performances concern the performance in terms of aggregate fuel consumption \(C(T)\). Aggregated data is intended here as the temporal integration of \(FC_{\text{inst}}\) in the total length of the driving session \(T\), namely:

\[
C(T) = \int_0^T FC_{\text{inst}}(t) \cdot dt
\]

Even in this case a discrepancy parameters is defined:

\[
ERR_{\text{agg}}(t) = \left| \frac{\hat{C}(T) - C(T)}{C(T)} \right|
\]

Figure 4 shows the probability mass function (pmf) and cumulative mass function (cmf) of the values assumed by \(ERR_{\text{agg}}\) variable.

5 Discussion
The evaluation of fuel consumption is an hot topic for the development and evaluation of Driving Assistance Systems, and the definition of a proper evaluation measure has a fundamental importance. Our results show that modelling instantaneous fuel consumption is quite difficult. Indeed in Figure 4 we showed that in about 35% of the cases the instantaneous fuel metering can be predicted with a discrepancy lower than 10% (in terms of \(ERR_{\text{inst}}\)), but on the other hand we showed that in about 10% of the cases this discrepancy is greater than 50%. It is worth noting that this is not a matter of our experimental conditions, rather a confirmation of the presence of a several secondary components which strongly affect previsions.

Results improve strongly once the same model is used to compute the total fuel consumption associated to a driving session \(\hat{C}(T)\). Figure 4 has showed that in this case differences are lower than 6% in more than 90% of the cases. Also this result confirm literature [23], where a
$ERR_{agr}$ value of 4\% is considered to represent an excellent estimation. However the $ERR_{agr}$ is computed on the whole trajectory duration $T$, while the $ERR_{inst}$ is computed in each instant, thus an interesting question to be addressed concerns the evaluation of a trade-off time interval able to compute an acceptable estimation of the fuel consumption; this would be fundamental in the development of real-time eco-driving strategies. Importantly, our results are based on fuel metering based on data recorded by using the OBD port. A joint experiment with the National Research Center Istituto Motori CNR has been carried out in order to validate this methodology indirectly; indeed the instrumented vehicle, was also equipped with a Portable Emissions Measurement System (PEMS), that allows an indirect estimation of fuel consumption by analyzing vehicle emissions. The experiment has been based on both road and on a chassis dynamometer tests. In particular, the road experiments have been carried out on four main sections: the first section, approximately 4 km, is the Municipal Expressway “Vomero-Soccavo”, the second stretch, around 10 km consists of several urban streets that cross different quarters of Naples, the third, approximately 6.5 km is represented by provincial road Melito-Scampia, and finally the last part of approximately 10 km, is a section of the motorway A56, more properly known as Tangenziale di Napoli. Unfortunately experimental results are not available at the moment, because PEMS data are not integrated/synchronized with the IV data acquisition system.

6 Conclusion

We carried out a huge experimental campaign which involved more than 100 drivers, and allowed the collection of more than 8000 km of IV data. We showed that an evaluation of the fuel consumption can be carried out on the basis of the data acquired using the OBD port, and an IMU that furnishes the vehicle acceleration. Our results show that the fuel consumption estimation is better when the values of fuel consumption are aggregated in quite high time windows; however a good estimation of the instantaneous fuel consumption can be reached with a very simple formulation. We put the basis for a useful tool for the ADAS evaluation/development and, more generally, for the estimation of the fuel consumption in simulated environments (driving simulations, model in the loop, etc.).

References:


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