Passenger Car Energy Demand Assessment: a New Approach Based on Road Traffic Data

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Abstract. Nowadays the automotive market is oriented to the production of hybrid or electric propulsion vehicle equipped with Energy Management System that aims to minimize the consumption of fossil fuel. The EMS, generally, performs a local and not global optimization of energy management due to the impossibility of predicting the user's energy demand and driving conditions. The aim of this research is to define a driving cycle (speed - time) knowing only the starting and the arrival point defined by the driver, considering satellite data and previous experiences. To achieve this goal, the data relating to the energy expenditure of a car (e.g. speed, acceleration, road inclination) will be acquired, using on-board acquisition system, during road sections in the city of Messina. At the same time, the traffic level counterplot and others information provided, for these specific sections, from GPS acquisition software will be collected. On-board and GPS data will be compared and, after considering an adequate number of acquisitions, each value of the traffic level will be associated with a driving cycle obtained by processing the acquired data. After that, the numerical model of a car will be created which will be used to compare the energy demand of two driving cycles. The first one acquired on a section with a random starting and destination point inside the historic city centre of Messina. The second is the one assigned, for that same section, considering only the value of the traffic level counterplot.

1 Introduction

Road transport is one of the main sources of air pollution in Europe, particularly if referring to particulate matter, nitrogen dioxide and tropospheric ozone [1]. For this reason, European governing bodies have enacted laws and regulations limiting harmful emissions into the atmosphere from cars. The major manufacturers have undertaken to market cars with non-conventional propulsion capable of emitting a level of pollutants accepted by the regulations. The market for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) has been particularly successful and, in Italy, it is showing a strongly growing trend especially from 2017 onwards [2]. This is another reason why the problem of optimizing energy management of this type of vehicles is particularly felt. Many methods of energy management have been proposed in literature, based on principles ranging from Dynamic

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Programming to the use of fuzzy logic or artificial neural networks [3-6]. Regardless of the type of management, it is agreed that in order to achieve optimal management of the powertrain, it is necessary to have the entire driving cycle that the car has to drive through [7-8] along with a forecast of energy expenditure. Several methods have been proposed for the prediction of the driving cycle considering sometimes a higher number and sometimes a lower number of characteristic parameters of a driving cycle [9], data then processed through the use of neural networks, Markov Chain, Exponentially Decreasing Model (EDM) and others [10-12]. This study proposes to assign a "speed-time" curve not to a specific route but to a specific traffic condition that is generally shown by Global Positioning System (GPS) and Intelligent Transportation System (ITS) software.

The work will be organized as follows: section 1 will explain the realization of the dynamic model of a car using the potential of the AVL Cruise-M™ software, a model that will be built by analyzing data in the literature and through previous experiences [13]. In section 2 will be treated the processing of data acquired during the execution of road sections within the city of Messina. For the collection of data the application Track Addict and the mobile interface of Google Maps were used. The typical traffic values shown by ITS systems, i.e. high, medium and low Traffic Level (TL), will be considered and each data collected will be included in the corresponding TL. For each of these, after analysis and reworking of the data, "speed-time" curves will be assigned, classified according to the analysis method carried out (for example arithmetic or weighted average).

In the third section of the article a cycle acquired within the city of Messina will be analyzed, the space travelled in the different traffic conditions will be evaluated and compared with the cycles carried out in section 2 and with the standard WLTC.

2 Conventional powertrain of passenger car model construction and validation

To proceed in the study of driving cycles it is necessary to have a mathematical model able to give information about fuel, power and energy consumption of the vehicle during the route. For this purpose, a dynamic model of a vehicle was made in AVL Cruise-M™ software using literature data for validation. The reference is a quasi-static model of a Saturn SL1 (1994) vehicle with a conventional front wheels drive powertrain, equipped with a gasoline ICE and a five-speed gearbox. The National Renewable Energy Laboratory (NREL) has collected the vehicle data. The main components of the realized model, shown in Fig. 1, are the following:

- Auxiliaries: they dissipate a constant power of 700 W at ICE speed higher than the idle one.
- ICE: 1000 cm³ spark injection engine with a maximum torque of 81 Nm at 3500 rpm and a maximum power of 41 kW at 5700 rpm. In addition to the characteristic curve under full load conditions, maps of fuel consumption and emissions of hydrocarbons, nitrogen oxides and carbon monoxide are available.
- Gearbox and differential: it consists of 5 gear ratio speeds (3.56, 2.00, 1.32, 1, 0.75) and a differential ratio of 3.77.
- Wheels: modeled considering an effective rolling radius of 0.282 m and a constant rolling resistance factor of 1.12%.
- Vehicle: it collects information about the inertia and aerodynamic forces of the car that has a frontal area of 2 m², drag coefficient of 0.335 and a total mass of 984 kg.
- Driver: simulated as a PI controller where the proportional value is equal to 1 while the integral parameter is equal to 0.5 1/s, reflecting the default settings of AVL Cruise-M™.

Fig. 1. Car model built in AVL Cruise-M™.

Model validation was carried out on a standard extra-urban cycle (EUDC) under the same boundary conditions (external ambient temperature, gear profile, road inclination). Two considerations led to this choice:

- The limited number of accelerations of the cycle reduce the influence of the PI control.
- The presence of long time intervals at constant and high speed highlights the goodness of the modelling due to the absence of the inertial force contribution.

Moreover, an external controller was used to manage the gear shifting by upshifting at 3500 rpm and downshifting at 1500 rpm. Figure 2(A) shows the comparison between car speed as well as engine torque over time during the driving cycle simulation. Figure 2(B) shows the cumulative fuel consumption and the pollutant emissions in both models.

Fig. 2. A) Comparison between velocity and ICE torque during time in both two models. B) Comparison between fuel consumption and pollutant emission in both two models

The absolute error between the reference instantaneous speed and the Cruise-M™ model instantaneous speed was then evaluated using equations (1).

$$\varepsilon_{abs} = v_{ir} - v_{im} \quad (1)$$

Being ε_{abs} the absolute error between the instantaneous reference speed, v_{ir} , and the speed executed at the same time by the car, v_{im} . During the simulation, the maximum absolute error value was 0.43 m/s and the minimum one was -0.70 m/s with an Average value of 8.71E-06 m/s. Other parameters taken into account were fuel consumption and pollutants emissions, to

evaluate thermal engine operating points. The amount of fuel mass and/or the mass of pollutants emitted from both the reference model and the Cruise-M™ one was evaluated using equation (2).

$$Fc = \int_0^{T_{end}} fcdt \quad (2)$$

In equation (2), the term fc represents the instantaneous consumption curve of fuel or the Nox, HC and CO emission curve. Table 1 presents the results the results show that the absolute error between the two models remains small.

Table 1. Assessment of emissions and fuel consumption in both models.

	Fuel [g]	HC [g]	Nox [g]	CO [g]
Reference	245.90	3.37	9.49	41.64
Cruise-m	249.74	3.34	9.53	48.63
ϵ_{abs}	3.84	-0.03	0.04	6.99

The CO production is more different than the other pollutants. However, this difference was considered acceptable since the CO emission map is extremely influenced by the engine's operating points.

3 Data collection and processing

3.1 Data collection

Figure 3 shows the diagram of data collection and processing operations. First step was to execute road sections within the city of Messina at different times of the day. During the execution of the routes, the TrackAddict application was used to record the information about speed profile, number and duration of the stops and time duration of the trip. In the meantime it has also been used Google Maps application to record the traffic conditions during the ride. This information were then synchronized and catalogued according to traffic level: it was then obtained "n" speed-time curves acquired in sections with high traffic level, "m" curves acquired in medium traffic level conditions and "l" curves acquired in low traffic level conditions. For each traffic condition, the profiles have different time duration, so a time normalization has been performed to obtain profiles of the same duration. Two kind of time normalization has been performed for each TL: minimum time normalization and maximum time normalization.

- Minimum time normalization: taking as reference the minimum time duration of the cycles for each traffic level, it was calculated how many times each cycle of the same TL was greater in terms of time than the reference one (only the whole number was considered). From the starting cycles, a number of cycles expressed by equation (3) was obtained

$$n_{cycle_{TL}} = \sum_{i=1}^k \left\lfloor \frac{t_{i_{TL}}}{t_{ref(min)_{TL}}} \right\rfloor \quad (3)$$

being $n_{cycle_{TL}}$ the number of cycle (speed profile) for each traffic level, k equal to n, m or l depending on the TL considered, t_i the time duration of the i-th cycle and $t_{ref(min)_{TL}}$ the reference time duration for the normalization in each traffic level.

Fig. 3. Diagram of data collection and processing operations.

- Maximum duration normalization: for each TL, the maximum duration between the duration of the cycles has been identified as the reference duration, so each cycle with lower time duration was repeated a number of times identified by equation (4).

$$n_{i_{TL}} = \frac{t_{ref(max)_{TL}}}{t_{i_{TL}}} \quad (4)$$

representing in this case $n_{i_{TL}}$ the repetition number of the “ i ” cycle belonging to the “TL” traffic level, $t_{i_{TL}}$ represent the time duration of i_{TL} -th cycle and $t_{ref(max)_{TL}}$ is the maximum duration of the cycles (so, in this case, the reference duration) belonging to the “TL” traffic level.

At the end of the normalization operations, two groups of cycles are available for each traffic level: the first group (group 1) considers all cycles with a time duration equal to the minimum duration evaluated in the same TL, while the second group (group 2) considers all cycles with a time duration equal to the maximum duration. For each of these groups of cycles the following operations have been carried out.

3.2 Application of Arithmetic average

For each group of cycles (minimum and maximum duration normalization) and for each TL, the equation (5) has been applied to calculate the representative speed profile as arithmetic average instantaneous velocity of each cycle group.

The equation gives a driving cycle representative of the individual group and so two driving cycles representative of each traffic level were obtained. To maintain the information about the number of downtimes and their duration, the average number of stops per kilometer, using equation (6), and the average stop time, using equation (7), has been calculated for each traffic level. This information have been included into the representative cycles of each traffic

level, taking care to assign accelerations from $v=0$ to $v \neq 0$ and decelerations from $v \neq 0$ to $v=0$ with a maximum value of $\pm 1.5 \text{ m/s}^2$.

$$\bar{v}_{i_{g_{TL}}} = \frac{\sum_{j=1}^{n_{cycle_{g_{TL}}} v_{i_{g_{TL}}.j_{g_{TL}}}}{n_{cycle_{g_{TL}}}} \quad (5)$$

$$Avg \text{ Stop time } TL = \frac{\sum_{j_{TL}=1}^k \left(\frac{\Sigma \text{ Stop time } j_{TL}}{\text{number of stop } j_{TL}} \right)}{k} \quad (6)$$

$$Avg \text{ Stop/km } TL = \frac{\sum_{j_{TL}=1}^k \left(\frac{\Sigma \text{ Stop number } j_{TL}}{\text{kilometers traveled } j_{TL}} \right)}{k} \quad (7)$$

representing the subscript $i_{g_{TL}}$ the instant of time considered within each group of each traffic level and subscript $j_{g_{TL}}$ the driving cycle considered within each group of each Traffic Level. $\Sigma \text{ Stop time } j_{TL}$ is the sum of downtimes of the cycle J_{TL} , meanwhile $\text{number of stop } j_{TL}$ is its number of downtimes. K is equal to “m”, “n” or “l” depending on the TL considered and $n_{cycle_{g_{TL}}}$ is the number of cycle that form the groups for each traffic level.

At the end of this procedure, two representative cycles for each Traffic Level were obtained, one of them identified as Arithmetic 1 obtained from the first group of cycles, and the other one identified as Arithmetic 2 obtained from the second group of cycles.

3.3 Application of Weighted Average

At the group cycles the weighted average was then performed, in which the weight is represented by the distance travelled between the instant of time t_i and t_{i-1} , in accordance with equation (8). The equation (9) indicates the calculation of the weighted average of the velocities performed instant by instant.

$$\Delta d_{i_{g_{TL}}.j_{g_{TL}}} = d_{i_{g_{TL}}.j_{g_{TL}}} - d_{i-1_{g_{TL}}.j_{g_{TL}}} \quad (8)$$

$$W. Avg. V_{i_{g_{TL}}} = \frac{\sum_{j=1}^{n_{cycle_{g_{TL}}} \left(v_{i_{g_{TL}}.j_{g_{TL}}} * \Delta d_{i_{g_{TL}}.j_{g_{TL}}} \right)}{\Sigma \Delta d_{ji}} \quad (9)$$

the subscript i and j have the same meaning of equation (5), $W. Avg. V_{i_{g_{TL}}}$ is the weighted average velocity at the i -th time instant of the “g” group belonging to “TL” traffic level. As before, the number and duration of downtimes have been inserted in accordance with the results obtained in the equations (6) and (7). The result of the application of equations (8) and (9) is to get six representative cycles, two for each Traffic Level: one achieved considering the cycles deriving from minimum time normalization (identified as Weighted Average 1) and one resulting from maximum time (identified as Weighted Average 2).

3.4 Application of Inverse Fast Fourier Transform

As already mentioned in the data collection section, the cycles belonging to the same TL have different time durations so, to avoid this problem, it was decided to approach the problem by focusing no longer on the time duration but on the speed profiles signals. Through the Fast Fourier Transform algorithm the frequency (f_j), amplitude (a_j) and phase (ϕ_j) of each sinusoid component of the single speed profile has been obtained. Each profile is characterized by this three vectors of length n_j , being n the number of sinusoids that make up the j -th original signal of the profile. For each traffic level, it was decided to join the vector

that characterized the signal. For the frequencies vector the result is the $\mathbf{F}_{x_{TL}}$ vector, with a length " x_{TL} " expressed by equation (10) that contains all the sinusoid frequencies in descending order without any repetition. Moreover $\mathbf{a}_j$ and $\mathbf{\phi}_j$ vectors were joined in the $\mathbf{A}_{xk}$ and $\mathbf{\Phi}_{xk}$ matrix respectively and so the arithmetic average value of the rows was calculated for each matrix using the equation (11) and (12).

$$n_j \leq x_{TL} \leq \sum_{j=1}^k n_j \quad (10)$$

$$A_{x_{TL}} = \frac{\sum_{n=1}^k A_{xk}}{k} \quad (11)$$

$$\Phi_{x_{TL}} = \frac{\sum_{n=1}^{x_{TL}} \Phi_{xk}}{k} \quad (12)$$

being k equal to "n", "m" or "l" according to the traffic level considerate.

With this data, it is possible to create a velocity- time curve using the Inverse Fast Fourier Transform (IFFT) algorithm, i.e. equation (13). The equation (13) returns a signal over time considered as a speed profile representative of the traffic level considered.

$$Speed\ Profile_{TL} = \sum_{i=1}^{x_{TL}} A_{x_{TL}} \cdot \cos(2 \cdot \pi \cdot F_{x_{TL}} \cdot dt + \Phi_{x_{TL}}) \quad (13)$$

being $A_{x_{TL}}$ the amplitudes of the x_{TL} sinusoids, $F_{x_{TL}}$ their frequencies expressed in Hz, $\Phi_{x_{TL}}$ their phases expressed in radians and dt the sampling step time of 1s.

To the cycles thus obtained were applied the conditions regarding the number and duration of downtimes, as well as the accelerations, already discussed by arithmetic and weighted average.

3.5 Data analysis

In order to evaluate the goodness of the cycles obtained, a comparison was made with a real driving travelled within the city of Messina. The cycle considered is represented in Fig.4. The starting point is 3 meters above sea level and the altitude of the road section increases linearly to the arrival point, which is at an altitude of 13 meters above sea level. Therefore, the effect of the forces caused by the road inclination on vehicle dynamics was considered negligible.

Fig. 4. Main data provided by track Addict and Google Maps on the reference cycle.

Figure 4 shows the distances travelled by the car in different traffic conditions. The route is 5.857 km long and has been travelled in 891s. Considering the distance travelled in different traffic conditions, five speed profiles were created to be compared with the real cycle. Each of them covers the same distance as the real cycle in the same traffic conditions. The representative cycles are:

- Arithmetic Average 1 and 2 resulting from the arithmetic average operation carried out respectively on groups 1 and 2 of the various traffic levels;
- Weighted average 1 and 2 resulting from the weighted average operation carried out respectively on groups 1 and 2 of the various traffic levels;
- IFFT resulting from the application of IFFT algorithms in the various traffic levels.

A comparison was also made with the standard WLTC cycle. Given the characteristics of the passenger car under examination and the type of study, the "low" section of the WLTC 3a (contained in the time interval 0-590s) was repeated up to reach the reference distance. In this case, it is not possible to evaluate emissions and fuel consumption in the different traffic condition but only at the end of the travel, as the WLTC does not consider traffic conditions.

TABLE 2: Fuel consumption and pollutant emissions comparison during the reference driving cycles

Traffic level	Reference	Arit. Avg 1	Arit. Avg. 2	Weig. Avg 1	Weig. Avg 2	IFFT	WLTC
Fuel Consumption [g]							
Low	141.73	158.04	152.82	164.89	154.19	136.74	/
Medium	99.58	79.96	97.18	70.46	69.6	98.48	/
High	13.12	4	8.56	15.33	15.59	8.59	/
Total	254.43	242	258.56	250.68	239.38	243.81	262.64
NOx [g]							
Low	2.38	1.59	1.67	1.61	1.53	1.53	/
Medium	1.77	1.15	0.99	1.14	1.33	1.03	/
High	0.29	0.36	0.28	0.33	0.32	0.29	/
Total	4.44	3.1	2.94	3.08	3.18	2.85	5.50
HC [g]							
Low	1.62	1.7	1.64	1.72	1.61	1.5	/
Medium	1.23	0.97	1.07	0.91	0.89	1.1	/
High	0.27	0.26	0.32	0.32	0.35	0.31	/
Total	3.12	2.93	3.03	2.95	2.85	2.91	3.26
CO [g]							
Low	18.88	23.86	22.38	25.99	23.11	19.96	/
Medium	14	11.27	14.03	12.3	12.5	14.47	/
High	2.11	0.1	0.45	1.89	1.66	0.48	/
Total	34.99	35.23	36.86	40.18	37.27	34.91	41.90

The Fig.5 shows the various cycles obtained. The cycles cover the same distance at different times due to the different average speed. The WLTC is the cycle with shorter time duration among the obtained cycles, but still higher than the reference one. Table 2 shows fuel consumption and pollutant emission results obtained from the simulations during the execution of different Traffic Level route and at the end of the trip.

Starting from this data it is possible make a comparison between the different speed profiles. Table 3 collects the performance data of the cycles: in the "best" section, there are the cycles that have the minimum absolute error in the prediction of the parameters taking into account, in the "worst" section there are the cycles that have the maximum absolute error.

Fig. 5. (a) Arithmetic Average 1 and 2 cycles derived from equation (5), (b) Weighted Average 1 and 2 cycles derived from equation (9), (c) IFFT a cycles derived from equation (13) and WLTC cycle.

TABLE 3: Cycles that, in emissions and fuel quantity, are more or less close to the reference cycle

	High Traffic Level	Medium Traffic Level	Low traffic Level	Total
Best				
Fuel	Weight Avg. 1	Ifft	Ifft	Weight Avg. 1
NOx	Ifft	Weight Avg. 2	Arithm. Avg. 2	WLTC
HC	Arithmetic Avg. 1	Ifft	Weight Avg. 2	Arithmetic Avg. 2
CO	Weight Avg. 1	Arithmetic Avg. 2	Ifft	Ifft
Worst				
Fuel	Arithmetic Avg. 1	Weight Avg. 2	Weight Avg. 1	Weight Avg. 2
NOx	Arithmetic Avg. 1	Arithmetic Avg. 2	Weig. Avg. 2/ Ifft	Ifft
HC	Weight Avg. 2	Weight Avg. 2	Ifft	Weight Avg. 2
CO	Arithmetic Avg. 1	Arithmetic Avg. 1	Arithm. Avg. 1	WLTC

In order to have an objective reference, a *Cycle Quality Index (CQI)* has been hypothesized, expressed in the equation (14), defined as the ratio between the number of times each cycle was better than the others in the evaluation of the different parameters and the number of times it was worse.

$$CQI = \frac{\text{number of times in best}}{\text{number of times in worse}}$$

(14)

As the value of the *CQI* increases, the confidence in the description of the reference cycle increases. Table 4 shows the *CQI* value calculated for the cycles treated so far: Arithmetic cycle 2 and Weighted cycle 2 are the most suitable to hypothesize the behavior of the car performing the reference cycle.

TABLE 4: CQI value for each cycle

	Arit. Avg 1	Arit. Avg. 2	Weig. Avg 1	Weig. Avg 2	IFFT	WLTC
CQI	0.25	3	3	0.36	2.4	1

4 Conclusions

The purpose of the present article was to identify driving cycles corresponding to specific traffic conditions represented with colors, according to traffic intensity, in the commonly used traffic information platforms. In order to identify the driving cycle that correspond to specific colors for traffic intensity, a methodology was implemented and tested in the municipality of Messina, using Google Maps application. In more details, some driving urban

routes in terms of speed, stop time, vehicle parameters, etc. were registered in the city of Messina using TrackAddict software connected to the vehicle OBD port. At the same time, traffic intensity information were registered using Goggle Maps software. Starting from the recorded data, opportunely processed and normalized, reference cycles were obtained for each traffic intensity. In particular, speed profiles were classified in three different traffic intensity categories (high, medium and low). For each traffic intensity, two different time normalizations were carried out: with reference to the minimum duration; with reference to the maximum duration. Representative profiles for each group and each traffic level were obtained using arithmetic average and/or weighted average methods to the instantaneous speeds. Moreover, an FFT algorithm was applied to the speed profiles recorded in the different traffic conditions obtaining the frequency, amplitude and phase of the sinusoids that made up each speed profile, avoiding time normalization. These quantities have been mediated and three driving profiles representative of the traffic levels have been created by means of IFFT algorithm applied to the averaged data.

The proposed methodology was tested using a new driving route and a vehicle mathematical model implemented within AVL Cruise-M™ software environment. Using the implemented vehicle model fuel consumption and pollutant emissions were calculated for both actual and representative profiles. The same evaluation was carried out using the low portion of WLTC 3a, repeated until obtaining a distance equal to that of the reference cycle. All obtained results were compared.

In order to compare different driving cycles obtained with different methods an overall quality index was defined. Based on the results reported in the paper, the reference cycle that best approximate actual conditions are the “average 2” and the “weighted average 1” equally for all traffic intensity evaluated. These two reference cycles can be used as driving cycles to calculate vehicle fuel consumption and pollutant emissions to find the best route and vehicle management strategy in urban areas.

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