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### **Development of driving cycles for electric vehicles in the context of the city of Florence**

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Abstract: Use cycles represent one of the main input in any design activity; within automotive engineering strong efforts are spent for the creation of so called driving cycles. Vehicle driving cycle development has been a topic under research over the last thirty years, since it is a key activity both from an Authority and from an industrial research point of view. Considering the innovative characteristics of EVs and their diffusion on certain contexts (e.g. city centers), the demand for tailored cycles arises. A framework for driving data analysis has been developed through the review and the selection of known literature experiences, having as a goal the application on a case study. A measurements campaign in the city of Florence has been conducted; three different EVs categories have been monitored through a non-invasive data logging system. After data acquisition, time series have been processed for filtering and grouping. A method used for cycle synthesis based on general statistical competencies has been proposed and used for the generation of new cycles. The main product of the activity consists of a set of representative driving cycles for which only data coming from EVs are used. A comparison between existing cycles shows that typical driving pattern indicators are coherent with new cycle ones; a few differences are noticed. Another product of the activity is a software package which can be used to generate cycles within simulation environment, thus making accessible not only the synthesized cycles but, under certain boundary conditions, the whole measured data.

# Highlights

## Development of driving cycles for Electric Vehicles in the context of the city of Florence

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- The study deals with Driving Cycle development for Electric Vehicles
- A review of the driving cycle analysis, synthesis and use methods is presented
- The results from driving data acquisition under naturalistic conditions are presented
- A personalized method is developed and used to process the data
- A set of Electric Vehicle cycles is presented as final product
- A tool for “batch” cycle synthesis under tailored conditions is also presented.

# 1 Development of driving cycles for Electric 2 Vehicles in the context of the city of 3 Florence

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## 6 Abstract

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22 accessible not only the synthesized cycles but, under certain boundary conditions, the whole  
23 measured data.

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# 26 Glossary

- 27 BEV: Battery Electric Vehicle
- 28 EV: Electric Vehicle
- 29 FEV: Fully Electric Vehicle
- 30 GHG: Greenhouse Gases
- 31 HEV: Hybrid Electric Vehicle
- 32 ICE: Internal Combustion Engine
- 33 LDV: Light Delivery Vehicle
- 34 NEDC: New European Driving Cycle
- 35 SAPD: Speed Acceleration Probability Distribution
- 36 WLTC: Worldwide harmonized Light vehicles Test Cycles
- 37

## 38 1 - Introduction

39 A driving cycle can be considered as a part of a standardized procedure aimed to evaluate vehicle  
40 performance in a reproducible way under controlled or laboratory conditions, such as simulation  
41 environment, power-adsorbing chassis dynamometer, testbed and sometimes road track. It has to  
42 include a time-vehicle speed signal as main input data, but a large set of boundary conditions can be also  
43 defined: dynamometer settings, gear shifting points, reference atmospheric conditions, vehicle  
44 conditions (tyre pressure, lighting, oil viscosity, transported mass..), "cold start" conditions (critical, for  
45 different reasons, both for ICE and EV vehicles) and any other parameter influencing the performances of  
46 the product under test.

47 According to the large differences in terms of driving habitudes, user needs, road characteristics and  
48 others it is known that the exact duty cycle to be satisfied during the life of a certain vehicle is not fully  
49 predictable. It is therefore probable that a single "driving cycle" cannot represent all the possible  
50 conditions on which the vehicle could be used during its life, but that some kind of compromises are  
51 needed. Despite of the fact that the research and the standardization process started in the early '70s, the  
52 definition of driving cycles is still a topic under development in scientific and technical literature.

53 The aim of the activity presented in this paper is to propose a group of driving cycles which are suitable  
54 for EVs; the study includes the definition of a procedure for driving cycle definition and the description of  
55 its application on a case-study. The document is structured as follows: section 1 introduces the topic,  
56 proposes a brief review of literature information and recalls state-of-the-art experiences; section 2 deals  
57 with the definition of a procedure for data analysis and cycle synthesis; section 3 describes the tailored  
58 approach developed and its application to a real case study, including data acquisition on the city of  
59 Florence (Italy); results and conclusions are then presented.

## 60 1.1 - Driving cycles

61 In the legislative context, type approval procedures include scheduled tests over standardized driving  
62 cycles. The assessed parameters are mainly related to the evaluation of the environmental impact of the  
63 vehicle; in case of ICE ones, in fact, since the early 1970 years the attention has been focused on air  
64 pollutants and, recently, on GHG emissions, according to Regulation EC No 443/2009. Currently a very  
65 large number of driving cycles are used worldwide for homologation: e.g. EU cycles, US cycles, Japanese  
66 cycles and many others (Barlow et al., 2009). Legislative ones also differ on the basis of the class of the  
67 vehicle to be tested; main procedures have been defined for M-class passenger cars, light or heavy duty  
68 N-class vans or trucks, L-class vehicles such as quadricycles (distinguishing between low and full power  
69 ones) and motorcycles. These cycles often include more subphases which are aimed to represent low  
70 and high speed sequences, or, from another point of view, different driving areas such as urban, rural or  
71 motorway roads.

72 As explained since the presentation of early research articles on the topic, Driving Cycles are built on the  
73 basis of the processing of real-world measurements (Kenworthy et al., 1992; Lyons et al., 1986; Newman  
74 et al., 1992). Depending on the resolution used to describe the synthetic cycle, the driving sequences can  
75 include or not the irregularities in speed which are typical of real-world driving by the users; as an  
76 extreme, smoothing and decimation of the curves can result in driving sequences composed by straight  
77 lines on the time-speed charts, thus corresponding to constant or zero acceleration phases. The widely  
78 used NEDC cycle is one example of such approach, even if, according to recent trends, the newly defined  
79 WLTC cycle (UNECE, 2015) is going to be used for type approval on next years, improving the  
80 representativeness of tailpipe emissions and fuel consumption assessments. Recent literature papers on  
81 the topic agree on the opportunity of such introduction (Demuynck et al., 2012; Sileghem et al., 2014;  
82 Weiss et al., 2012).

83 In general, a large number of factors are acting on vehicle energy consumption and on the related  
84 emissions, including driver capabilities, driving context, traffic conditions, ambient temperature etc.: such  
85 variability is the reason determining the need for extensive testing on the road of any kind of vehicle  
86 during its final development phase. Using appropriate parameters to evaluate the characteristics of  
87 driving cycles, the evidence explained in literature is that local or regional conditions can differentiate  
88 driving patterns depending on the area under examination (Lin and Niemeier, 2003; Wang et al., 2008).

89 Therefore, in addition to the standardized cycles used for type approval, experiences in applied research  
90 show a wide variety of data which are aimed to improve the representativeness of emissions  
91 assessments and, in some cases, are directly used during product development. In order to reduce the  
92 cost of such critical phase, virtual and testbed testing procedures are performed, and in this controlled  
93 contexts a representative driving cycle is needed as input. The cycles can be defined depending on:

- 94 • load patterns (including continuous or transient speed phases)
- 95 • context of applicability (urban, extra urban, motorway)

- 96
- expected vehicle mission profile (e.g. private passenger use, freight delivery, bus service, etc.).

97 Car manufacturers usually perform activities on driver and cycle characterization in order to improve their  
98 own knowledge on representative test sequences, both using methods for driving cycle synthesis after  
99 acquisition on real-world use (Borgarello et al., 2010; Ma and Andreasson, 2007) and experimental test  
00 using professional drivers on controlled track conditions (Capitani et al., 2003). Tailored driving cycles  
01 have also been prepared to consider special applications for which general cycles are not suitable (Han  
02 et al., 2012) or to assess the behavior of a particular vehicle category on a known path, e.g. motorcycles  
03 on typical home-work routes (Saleh et al., 2009).

## 04 1.2 - Use patterns and cycles for Electric Vehicles

05 In most recent formulation of homologation procedure (see UNECE Regulation 101), the procedures to  
06 evaluate the performances of FEVs have been introduced, e.g. through the use of weighting formulae for  
07 the assessment of electric energy and combined fuel consumption in case of HEVs. However, FEVs  
08 introduce new parameters for the evaluation of their performances and are affected by specific criticalities  
09 in comparison to conventional vehicles. A brief list of such new factors includes:

- 10
- the possibility of energy recovery during braking, which could induce the drivers to modify their  
11 style in order to optimize the energy consumption according to this feature, e.g. reducing as much  
12 as possible the use of mechanical brakes on “smooth” deceleration; regenerative braking, in  
13 particular, has been identified as a key element for the overall EV efficiency, especially in certain  
14 driving contexts (Travesset-Baro et al., 2015)
  - the range is usually below a value of about 150km on optimal conditions for most EVs currently  
15 on the market; the limitation could induce drivers to particularly smooth, benign driving style  
16 under specific conditions as occasionally high daily distance driven or unavailability of charging  
17 points; such boundaries can also determine the so-called “range anxiety” phenomena (Neubauer  
18 and Wood, 2014)
  - a different perception of vehicle performances, due to different acoustic sensations, throttle  
21 feeling, and torque availability from the powertrain in comparison with conventional ICE vehicles
  - a different sensitiveness of the vehicle to the use of auxiliary systems, which could reduce the  
22 range up to 50% (Geringer and Tober, 2012) .
- 23

24 A particular cycle developed for Electric Vehicles is available in literature (Alessandrini and Orecchini,  
25 2003); the same study also highlighted that the characteristics of electric vehicles can induce a driving  
26 pattern somehow different from those adopted on conventional vehicles by the same users, such as:

- 27
- the frequent occurrence of moderately strong accelerations, especially at low speed, even for  
28 non-aggressive drivers; this can happen due to human perceptions in terms of reduced noise,  
29 that is typical of electric traction systems
  - the low peak power reduces aggressiveness on moderate or high speed; this occurrence could  
30 be related to the vehicle used in the cited study. For latest N1 or M1 class EVs maximum power  
31

132 is usually comparable with similar conventional vehicle; this observation, however, can still be  
133 appropriate for low powered vehicle such as electric quadricycles.

134 The cycle has been reported to be almost unique at least until 2011 (Chaudhari and Thring, 2011), while  
135 even recent works, which are aimed to assess the applicability of real world cycles on EVs, have been  
136 using time-series data acquired from conventional ones (Ozdemir et al., 2014).

137 Recent works on EVs are also aimed to characterize the users on the basis of their needs and habitudes  
138 in order to verify the suitability of EVs for general purpose use; in particular, the characterization of so-  
139 called “trip chains” (Primerano et al., 2008) has been studied both in Europe (Pasaoglu et al., 2014) and  
140 USA (Krumm, 2012; Van Haaren, 2011); trip-chaining is fundamental in, fact, in order to identify charging  
141 opportunities for EV users (Smith et al., 2011). Results on the use of electric vehicles by a panel of  
142 drivers have been published, and the data reported are useful to complete the duty cycle definition  
143 together with general use information such as charging habitudes (Adornato et al., 2009; Smart et al.,  
144 2013); field operational tests also offer the opportunity to rank powertrain use patterns on the basis of  
145 intensity and context identification (Liaw and Dubarry, 2007; Shankar et al., 2012).

## 146 2 - Development of driving cycles

147 A number of different methodologies can be used for data acquisition and for their synthesis in a  
148 representative cycle; main approaches are well described in literature, as highlighted in a recent review  
149 (Tong and Hung, 2010).

### 150 2.1 - Driving sequences analysis

151 Numerical parameters are needed for the comparison of signals coming from different measurements.  
152 Since driving cycle are coming from some kind of synthesis algorithm, the identification of numerical  
153 characteristics of input data permits the possibility to validate the representativeness of the compressed  
154 cycles. One important limitation that is often taken into account is that the duration and/or the total length  
155 (in terms of run distance) of some driving cycles is limited by practical needs (e.g. for test-bed execution);  
156 typical durations are in the range of 500–1500s.

157 In this paragraph, numerical parameters will be reported using a few reference articles. It is possible to  
158 distinguish at least six main categories of driving segment/cycles parameters depending on their physical  
159 dimension: distance, time, speed, acceleration, stop data (e.g. % of time or event count), indicators of  
160 dynamics. Considering relevant experiences such as the ARTEMIS project , the full list of the parameters  
161 used includes 40 elements (André, 2004; Barlow et al., 2009); their list is provided on Table 1. In most  
162 research activities only a subset of such parameters has been considered; looking at literature works, the  
163 evaluation can be based on a reduced set of indicators, such as 22 parameters (Hung et al., 2007), 13 or  
164 12 parameters (Kumar et al., 2012; Saleh et al., 2009).

Group	Parameter	Units
Distance related	Total distance	m
	Total time	s
Time related	Driving time	s
	Cruising time	s
	Drive time spent accelerating	s
	Drive time spent decelerating	s
	Time spent braking	s
	Standing time	s
	% of time driving	%
	% of cruising	%
	% of time accelerating	%
	% of time decelerating	%
	% of time braking	%
% of time standing	%	
Speed related	Average trip speed	km/h
	Average driving speed	km/h
	Standard deviation of speed	km/h
	Speed: 75th – 25th percentile	km/h
	Maximum speed	km/h
Acceleration related	Average acceleration	m/s <sup>2</sup>
	Average positive acceleration	m/s <sup>2</sup>
	Average negative acceleration	m/s <sup>2</sup>
	Standard deviation of acceleration	m/s <sup>2</sup>
	Standard deviation of positive acceleration	m/s <sup>2</sup>
	Acceleration: 75th – 25th percentile	m/s <sup>2</sup>
	Number of acceleration per km	[null]/km
Stop related	Number of stops	[null]
	Number of stops per km	[null]/km
	Average stop duration	s
	Average distance between stops	m
Dynamics related	Relative positive acceleration (RPA)	m/s <sup>3</sup>
	Positive kinetic energy (PKE)	m/s <sup>2</sup>
	Relative positive speed (RPS)	[null]
	Relative real speed (RRS)	[null]
	Relative square speed (RSS)	m/s
	Relative positive square speed (RRSS)	m/s
	Relative cubic speed (RCS)	m/s
	Relative positive cubic speed (RPCS)	m <sup>2</sup> /s <sup>2</sup>
	Relative real cubic speed (RRCS)	m <sup>2</sup> /s <sup>2</sup>
Root mean square of acceleration (RMSA)	m <sup>2</sup> /s <sup>2</sup>	

65 **Table 1 – Full list of indicators to describe driving cycles (Barlow et al., 2009; Tong and Hung, 2010).**

66 During the analysis of the data, trip events (i.e. a driving sequence between key-on and key-off events)  
67 and microtrip ones (i.e. a sequence measured between two stops events) are identified. The numerical  
68 parameters above described offer an aggregate information of the average results of cycle analysis. In  
69 addition to this, the analysis of cycles on the basis of quantitative information can take into account a  
70 large set of data represented in the form of statistical distribution. Typical data can be calculated in terms  
71 of absolute indicators (e.g. distance driven or time spent over a certain condition) or in terms of relative  
72 frequencies (e.g. percentage of occurrence of a certain class of events). Regarding 2-variables  
73 distribution, a largely used method for cycle clustering and cycle build-up is based on the analysis of the  
74 distribution of events falling in a determined class of speed-acceleration couple, expressed as relative  
75 frequency of occurrence or as total time (De Haan and Keller, 2004). In case of the use of such  
76 information for the extrapolation of a new cycle, the relative frequency assumes the meaning of  
77 “probability” of a determined class; the definition used by some authors is therefore SAPD (Hung et al.,  
78 2007). The scope of distribution analysis is both related to data visual interpretation and to extended data  
79 processing; in particular, in case of creation of a new cycle using randomization methods, data  
80 distribution can be used for the selection of sequences through random walk approaches, as described in  
81 next chapter (Lee et al., 2011).

182 The ability to group into categories the different segments of measured driving sequences is fundamental  
183 for cycle synthesis; clustering activities can be based on a vector of indicators such as those in Table 1  
184 (Borgarello et al., 2001) or directly on SAPD. In this latter case, it can be needed to introduce a correction  
185 criteria on the acceleration values. In fact, considering that the occurrence of certain speed–acceleration  
186 couples on the whole range of possible values is very low or even zero, acceleration values can be  
187 artificially enhanced to improve the resolution of the SAPD. A suitable option is to multiply it by a factor  
188 that increases linearly from 1 at low speed to 2 at typical motorway speed (André, 2004; André et al.,  
189 2006). Other classification methods based on fuzzy logic are documented in literature (Liaw, 2004; Tong  
190 and Hung, 2010).

## 191 **2.2 - Signal acquisition and treatment**

192 The acquisition of data from vehicles usually can comprehend a large number of parameters. Typically,  
193 values about dynamics can be obtained by accelerometers (e.g. inertial platforms used for multi-axial  
194 accelerations); together with GPS data such analysis can completely describe the kinematic of the vehicle  
195 and the context in which it is moving. However, logging of powertrain values can also be needed (e.g.  
196 rpm, speed, throttle position, engine parameters if ICE, battery/inverter/powertrain parameters if EV or  
197 HEV) especially in the case that the aim is to correlate emissions (directly measured at tailpipe) and  
198 driving style (Alessandrini et al., 2009) or to correlate traction power to probability of occurrence (Shankar  
199 et al., 2012). The availability of logging capabilities through cheap and wide diffusion devices such as car  
200 infotainment system and smartphones highlights new possibilities for the monitoring of driving attitudes  
201 (Gerardo and Lee, 2009); such data can be used for driver training through continuous learning (Beusen  
202 et al., 2009; Corcoba Magana and Muñoz-Organero, 2011; Manzoni et al., 2010), thus promoting safe or  
203 fuel-saving driving styles. When preparing a vehicle for data acquisition, the naturalistic behavior of the  
204 drivers can be influenced by the use of highly instrumented vehicles; the relation has been clarified in  
205 literature considering former research experiences (Valero-Mora et al., 2013).

206 The minimum data acquisition frequency for vehicle speed should be at least 1Hz, that is also the value  
207 used for the time-speed signals defining most existing driving cycle; decimation at 1Hz has been  
208 suggested in defining driving cycle construction framework (Bishop et al., 2012). However, it has been  
209 demonstrated that vehicle energy consumption and efficiency can be evaluated with acceptable results  
210 using low sample rates (0.2 – 1Hz) if a compensation technique is provided, but that higher sampling rate  
211 (from 2Hz to 10Hz) provide more accuracy and reliability for vehicle efficiency characterization due to the  
212 possibility to better describe vehicle dynamics (Corti et al., 2012). During pre-processing of the data, the  
213 first need is to check the continuity of the information: data affected by strong cold–start uncertainties, that  
214 is typical of GPS devices, large signal lack or similar should be rejected. Also, if a fleet is monitored on  
215 naturalistic conditions, some events should be excluded from driving patterns analysis (e.g. parking  
216 phases). After that, the data signal should be appropriately filtered. Regarding GPS data, there are  
217 different suitable filtering methodologies, each one presenting advantages and disadvantages (Jun et al.,  
218 2006):

- !19 • Piecewise polynomial regression model
- !20 • Kernel-based smoothing methods
- !21 • Discrete Kalman filter
- !22 • Modified Kalman filter

!23 In other experiences (Alessandrini et al., 2006) filtering techniques set at fixed cutting frequency are used;  
!24 0.5Hz is a typical value.

!25 When studying the characteristics of typical driving patterns of a certain fleet, there are two main  
!26 alternatives for the selection of drivers panel and of their route: on board measurement of vehicle/fleet  
!27 monitoring and “chase” car approach. The reliability of the first method is related to the size and the  
!28 characteristics of the monitored fleet itself. The more varied data are acquired (number of drivers, of  
!29 vehicles, distance run), the more the acquired data are appropriate to fit the real characteristics of the  
!30 fleet under study. A large data collection could be therefore necessary. The second method is widely  
!31 used for the acquisition of data in order to represent the characteristics of the driving style on a specific  
!32 area, e.g. to identify local driving patterns. Car chasing consists in following a “target” vehicle, initially  
!33 randomly selected, with another vehicle; as soon as the chased vehicle stops or is lost, another vehicle is  
!34 selected. A trained driver is therefore needed, while the measurement is performed on the chasing  
!35 vehicle even if the characterization is related to the “target” vehicle. The main advantage of the method is  
!36 the possibility to acquire a large amount of data related to a population within its operating area, while the  
!37 main disadvantage is the risk of data deformation: chased and chasing vehicle transient speed difference  
!38 could occur, or chasing vehicles could interfere with chased vehicle, thus influencing the driving style.

## !39 **2.3 - Synthesis of driving cycles**

!40 According to an early but still applicable definition (Lyons et al., 1986), during the synthesis of a new cycle  
!41 a “compression” algorithm has to be defined; in general a time-speed history of “real” driving data is  
!42 selected and assembled in such a way that it matches the overall characteristics of the data set.  
!43 Summarizing, the parts selected and processed to build the representative cycles can include sequences  
!44 or reduced trips along a particular route, or a number of randomly matched microtrips from the data.

!45 From early works, a large number of applications of similar or improved methods has been proposed. A  
!46 synthesis method, however, is usually composed by four main phases:

- !47 • the processing of the data, through calculation of kinematic indicators and distribution data; when  
!48 applicable, partial data (events) are grouped in different classes, each representative of a certain  
!49 typical driving sequence such as urban, rural, smooth, aggressive
  - !50 ○ events can include “modal events”, such as i.e. acceleration, deceleration, cruise and idle  
!51 driving segments, or full microtrips segments, or partial microtrips segments
- !52 • using the available database of driving sequences and of the associated kinematic parameters, a  
!53 number of events is randomly selected according to the desired characteristics of the cycles; for  
!54 general representativeness, a suitable method is to choose events from each group, maintaining

- 255 the same proportion in terms of distance or duration that was identified between group data and  
 256 total measured data
- 257 • the elements are randomly “glued” according to “matching” criteria
    - 258 ○ a criteria to order the transitions from a certain driving sequence to another, as well as for  
 259 the transition from a recognizable driving pattern to another (e.g. from city to highway and  
 260 then to city again, as typical), can be used; such random walk can be created on the  
 261 basis of a transition probability matrix, so that typical methods for Markov chain creation  
 262 are applied (Bishop et al., 2012)
    - 263 ○ the coherence in terms of final speed of the preceding segment to the speed of its next  
 264 segment has to be complied; as an example, in case of microtrips linking, speed is zero,  
 265 so that the juxtaposition of events requires only the proposal of a duration for stop phase  
 266 and, in some cases, an acceleration value for the next event
  - 267 • as soon as the target duration or distance has been reached, a verification of the  
 268 representativeness of the cycle is performed according to appropriate control parameters.

269 All the phases, depending on the goodness of fit of the compressed cycle in comparison with objective  
 270 parameters, can be repeated from the beginning in trial-and-error processes. Various randomization  
 271 methods have been used in literature, as summarized in previous works (Esteves-Booth et al., 2002;  
 272 Tong and Hung, 2010).

### 273 2.3.1 - Control parameters

274 In general, the synthesis procedure is iterated several times to obtain the satisfaction of basic matching  
 275 condition. A general indication to be respected is (Hung et al., 2007):

$$\forall \vartheta_t \in \bar{\vartheta}_t, \left[ \frac{\vartheta_t - \vartheta_i}{\vartheta_t} \right] < threshold$$

276  
 277 Where  $\underline{q}_t$  is the vector of the indicators (see Table 1) calculated for the main dataset and  $\underline{q}_i$  is the same  
 278 vector calculated for the synthetic cycle; the choice of the parameters to be included in the vector  $\underline{q}_t$  can  
 279 vary depending on the author. After that a number of possible candidate cycles are defined, additional  
 280 confrontation parameters can be calculated, in order to let the user select the one having most favorable  
 281 ones. Typical quantitative values are:

- 282 • Performance Value (PV), that is the scalar product of the difference between  $\underline{q}$  vectors with a  
 283 weighting vector:

$$PV = |\bar{\vartheta}_t - \bar{\vartheta}_i| \cdot W^T$$

284

- 285 ○ an example of PV definition is (Lin and Niemeier, 2003):

$$286 PV = |\Delta \bar{v}| + |\Delta \bar{a}| + |\Delta v_{max}| \times 0.1 + |\Delta v_{min}| + |\Delta a_{max}| + |\Delta a_{min}| + |\Delta \%idle| + |\Delta \bar{P}_d| + |\Delta v_{95}| +  
 287 |\Delta a_{95}| + |\Delta P_{95}|$$

- !88 • Sum Square Difference – SSD – of SAPDs, that is the summary of quadratic product of the  
!89 probability of each class of speed ( $N_s$ ) and acceleration ( $N_a$ ) for the source data ( $p_{ij}$ ) and the  
!90 candidate cycle ( $q_{ij}$ ):

$$SSD = \sum_{i=1}^{N_s} \sum_{j=1}^{N_a} (p_{ij} - q_{ij})^2$$

!91 As highlighted in literature, the longer the generated cycle, the smaller the distance between it and the  
!92 original data (Waldowski et al., 2011).

### !93 **2.3.2 - From driving cycles to sequence generator**

!94 According to those literature works related with development of vehicle management strategies (e.g. for  
!95 HEV or PHEV, or for automatic transmissions on ICE vehicles), the importance of the availability of a  
!96 large set of real world driving data is undoubted. The last trends in driving cycle definition methods show  
!97 an evolution from the construction of synthetic cycles – that, after that moment, are somehow “rigid” – to  
!98 the definition of a set of data which can be manipulated on the basis of probabilistic criteria (e.g. Markov  
!99 chain approaches). This methods can improve the value of vehicle performance simulation, thus being  
!00 suitable for the optimization of certain performances over non-repetitive cycles or for the build-up of  
!01 predictive control techniques (Gong et al., 2012; Montazeri et al., 2012; Moura et al., 2011; Schwarzer  
!02 and Ghorbani, 2013; Souffran et al., 2012). Data measured can therefore be used as a whole, as an  
!03 historical dataset of driving situations; in Montecarlo applications, such databases can be used for the  
!04 execution of a batch of simulations and/or experiments getting randomly extracted data from a suitable  
!05 space. If a database of driving sequences is available for consultation and processing, each simulation  
!06 can use a newly extracted driving cycle, exploring a large part of possible driving situations space. The  
!07 present work also includes a proposal for the extended use of all acquired data.

## !08 **3 - Case study: the city of Florence**

!09 This chapter describes the acquisition of data from EVs circulating in the city of Florence (Italy) and their  
!10 use for generation of a new group of driving cycles. Florence is located in the central area of Italy, it is a  
!11 Large city according to Eurobarometers criteria, its population being about 380.000 inhabitants for the  
!12 municipality and about 1 million of inhabitants for its Metropolitan area (formerly defined as Province).  
!13 The city applied in the last years a number of limitations for motor vehicles, including parking fares (on the  
!14 whole city) and restricted access to central historical area, including large pedestrian zones. EVs are not  
!15 subjected to restricted access and can also be driven on some of the pedestrian areas. A low power  
!16 charging infrastructure is also available (about 110 points, for a total availability of about 450 plugs).

!17 The first aim of the development of a driving cycle for the Florence case study is to include all the  
!18 peculiarities of driving in an historical city in a synthetic time–speed cycle (or a number of them) using  
!19 only data coming from EVs. A second aim is to make the dataset of acquired data available for  
!20 processing in other applications as a source of driving data, as explained in paragraph 2.3.2.

## 321 **3.1 - Description**

322 The data acquisition took place on vehicles which were used during their normal service both for private  
323 and business use. The speed of the vehicles, together with other powertrain information, have been  
324 acquired from on-board diagnostics; GPS data have been used mainly for geo-referencing and  
325 identification of suitable driving sequences when manually examining the data in post processing. The  
326 acquisition sessions took place for nine months on 2013 in the city of Florence (Pfluegl et al., 2015). The  
327 usable acquired data comprehend about 2500 km. It is notably to say that all the users and the owners  
328 declared that the one of the main reason for the use of electric vehicles was determined by the necessity  
329 to drive within the restricted traffic area of the city.

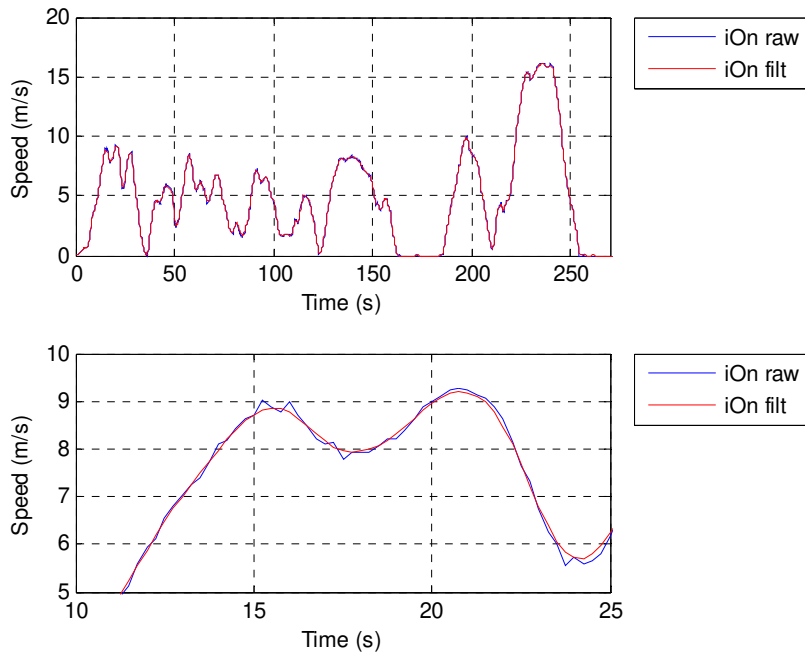
330 Large part of the acquisition included data coming from vehicles used by a freight delivery company in  
331 city context, a service similar to post delivery. The vehicles include light vans (Renault Kangoo ZE, M1  
332 class vehicle, electric, curb mass about 1400kg) and quadricycles (Renault Twizy, L7e class, curb mass  
333 about 470 kg). The company owns a fleet of 15 electric vehicles in total, but, in general, not all the  
334 vehicles of the fleet are used every day, since this depends on the workload and on the availability of the  
335 drivers. As a consequence, the same vehicle can be used by different drivers. The use of the fleet was  
336 quite intense and the required range in some days exceeded the capability of the vehicles, so that they  
337 were charged everyday: charging during night was always performed, while partial charge during the day  
338 was also done frequently (e.g. at lunch break). It is important to note that due to the availability of a  
339 charging infrastructure in Florence – even if suitable only for low power charging solution due to the  
340 presence of single phase plugs, comparable with home plugs – some drivers use the vehicles to go  
341 home, then park and charge there. Such kind of trips can be longer than usual delivery trips (e.g. some  
342 systematic runs of about 10-15km in morning and evening hours have been recognized); it was chosen  
343 not to exclude this data from analysis.

344 Another part of the data are related to passenger transport. Two types of vehicles have been used: the  
345 already cited Renault Twizy and the electric passenger vehicle of the PSA group (Peugeot iOn or Citroen  
346 C-zero). Three different cars of this type have been monitored, including one used by the members of a  
347 family for their daily needs (home – work trips, personal needs, weekend trips – but in this case, only if  
348 the expected distance is below about 100 km) and other two owned by a company and used by the  
349 workers for their movements within urban and suburban area. For this latter, most trips were systematic,  
350 being between two different sites of the Company (from city center -that is a pedestrian area accessible to  
351 EVs- to the peripheral area of Florence).

## 352 **3.2 - Data post processing and synthesis**

353 The first step of the analysis included speed data filtering for the elimination of “spikes” or of any irregular  
354 data. Data have been acquired at a rate of 4 Hz, than a kernel filter – as described in section 2.2 – has

i55 been applied, considering a time interval of one second. An example of speed signal smoothing through  
i56 this method is shown on Figure 1.



i57

i58 **Figure 1 – Upper plot: a portion of speed measurement for iOn passenger vehicle, showing a**  
i59 **comparison between raw and filtered data. Lower plot: a detail coming from the same**  
i60 **measurement.**

i61 The second step of the analysis included the grouping of the data in different categories. The main  
i62 strategy adopted is to identify in each mission (or trip) the sequences between two events of speed being  
i63 equal to zero (microtrips); after that, for each microtrip two different sets of parameters were calculated:

- i64 • a vector of indicators, that is a selection of those adopted in literature (see Table 2)
- i65 • a speed–acceleration density matrix.

i66 Regarding the vectors (edges) used for the calculation of SAPD matrix, the limit values have been  
i67 selected considering the maximum values measured (about 30 m/s for speed and 2.5 m/s<sup>2</sup> for  
i68 acceleration); the first speed class includes only very low speed (from 0 to 0.1 m/s<sup>2</sup>) to identify zero  
i69 speed phases.

i70 Two calculation methods have been adopted for mean positive and negative accelerations:

- i71 • the first method calculates these values considering the same threshold used for cruise and  
i72 acceleration time percentage calculation. In other words, each value of is coherent with the  
i73 related others (e.g. mean positive acceleration value is calculated for those phases which are  
i74 considered effective acceleration phases);

- 375 • the second method does not consider any threshold for acceleration, thus the mean acceleration  
 376 value is not perfectly coherent with acceleration time percentage; this criteria is applied only to  
 377 perform a confrontation with some literature works.

Parameter	Unit	Note	Abbreviation
Duration	s		duration (s)
Distance	m		distance (m)
Percentage of idle time	%	a=0; v=0;	idle %
Percentage of cruise time	%	a < 0.05 m/s <sup>2</sup>	cruise %
Percentage of positive acceleration time	%	a>0.05 m/s <sup>2</sup>	acc %
Percentage of negative acceleration time	%	a<-0.05 m/s <sup>2</sup>	dec %
Average speed	m/s		avg speed (m/s)
Average moving speed	m/s	v>0	avg mov speed (m/s)
Mean positive acceleration (a>threshold)	m/s <sup>2</sup>	a>0.05	acc+
Mean negative acceleration (a< threshold)	m/s <sup>2</sup>	a<-0.05	acc-
Root Mean Square of speed	m/s <sup>2</sup>		RMS
Positive Kinetic Energy	m/s <sup>2</sup>		PKE
Relative Positive Acceleration	m/s <sup>3</sup>		RPA
Stop rate	-		stops/km
<b>Additional parameters</b>			
Mean positive acceleration (without using threshold)	m/s <sup>2</sup>	a>0	acc+ noth
Mean negative acceleration (without using threshold)	m/s <sup>2</sup>	a<0	acc- noth
SAPD edges			
Acceleration classes (51 classes)	m/s <sup>2</sup>	from -2.5 to 2.5 from 0 to 0.1 and from	
Speed classes (17 classes)	m/s	0.1 to 30	

378 **Table 2 – Parameters used for cycle characterization and grouping.**

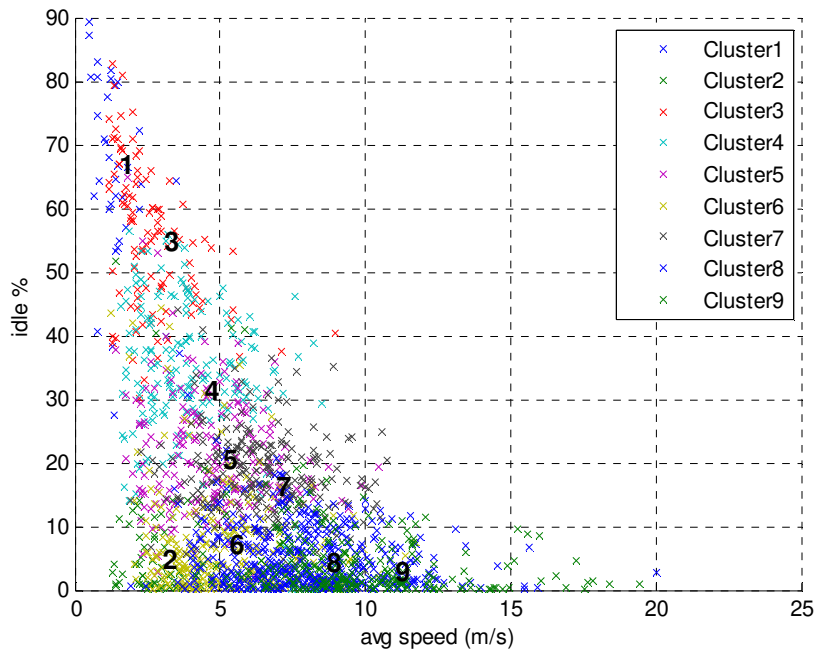
### 379 3.2.1 - Analysis and clustering of driving sequences

380 Before the application of a grouping algorithm on the data, a manual cleanup has been performed. Short  
 381 distance microtrips have been identified, since they can include data which are not suitable for general  
 382 driving cycle generation, such as incomplete microtrips (e.g. generated by a delay between vehicle key-  
 383 on event and logging start), sequences including reverse gear maneuvers, small vehicle displacement  
 384 (e.g. stop on traffic light without using brake pedal). The examination of total distance run at high speed  
 385 (exceeding 25 m/s. which has been chosen as threshold) together with the comparison with GPS data  
 386 (where available) confirms that no continuous motorway driving has been measured for the vehicles  
 387 under study; however, short trips on interchange roads (similar to motorways) have been found. After  
 388 preliminary selection, the microtrips have been subjected to grouping process. The selected algorithm is  
 389 the k-means ones. The conditions used for partitioning are:

- 390 • each sample is described by SAPD density elements and by RMS, RPA and PKE element, that  
 391 are all descriptors of microtrip speed and acceleration

- the k-means “distance” is calculated as correlation between points
- 9 different clusters have been determined.

The results of the grouping algorithms are shown in Table 3, which includes a selection of main parameters describing the microtrips included in the group and some notes describing the most probable driving situation for each cluster, which is coherent with the scatter plot shown on Figure 2. A priori classification (e.g. on vehicle type, since three different have been used) has not been performed, so that each cluster can contain microtrips coming from different vehicles and drivers.



:00

**Figure 2 – Scatter plot representing average positive and negative accelerations for all cluster elements; centroids are indicated by numbers.**

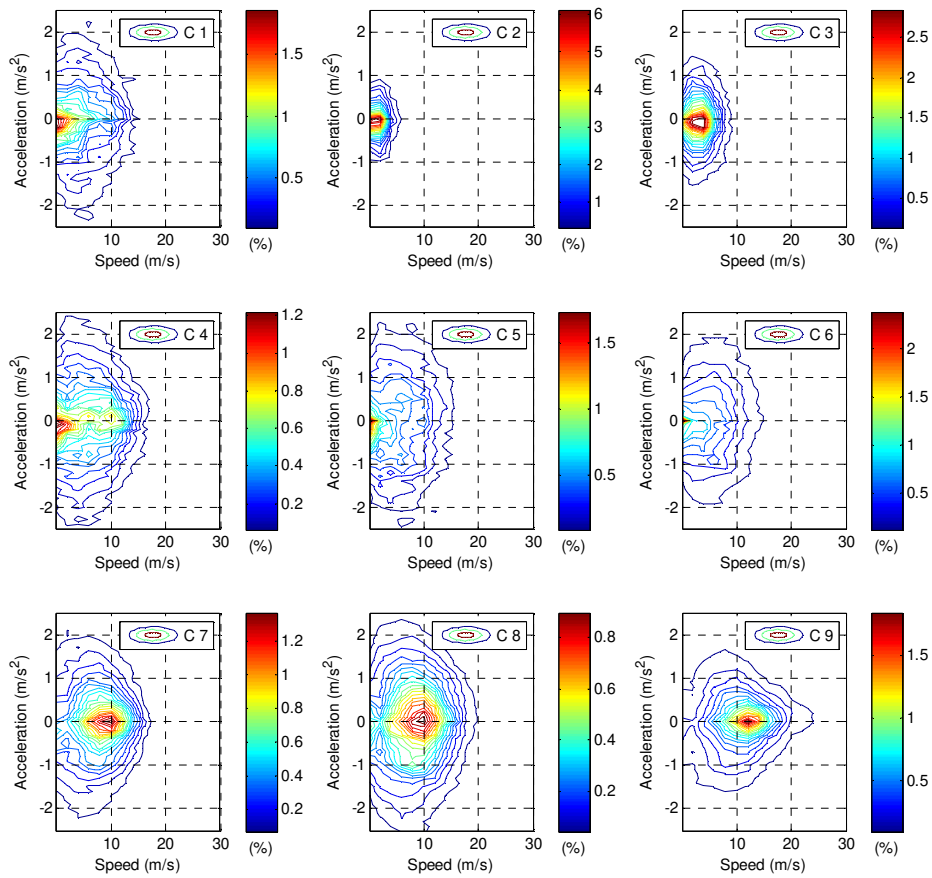
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Number	Class	Stop notes		Speed notes	Avg mov speed	Avg speed	Stop duration	Stops/k m	Acc+ nth	Acc- nth
					m/s	m/s	%	1/km	m/s <sup>2</sup>	m/s <sup>2</sup>
1	Urban	High duration	stop	Unsteady	5.50	1.98	63.9%	3.34	0.57	-0.58
2	Urban	Low duration	stop	Very low speed	2.55	2.39	6.2%	4.15	0.32	-0.30
3	Urban	Low duration	stop	Low speed	4.19	3.95	5.4%	2.09	0.43	-0.41
4	Urban	Intermediate stop duration		Steady	6.83	4.31	36.7%	2.35	0.58	-0.59
5	Urban	Intermediate stop duration		Unsteady	5.99	4.31	27.8%	3.23	0.65	-0.64
6	Urban	Low duration	stop	Unsteady	6.14	5.47	10.6%	2.04	0.65	-0.64
7	Urban	Low duration	Stop	Steady	8.26	6.83	17.2%	1.24	0.53	-0.55
8	Urban – Main roads	Flow		Intermediate speed	9.01	8.63	4.0%	0.79	0.60	-0.64
9	Urban – Main roads	Flow, steady		Intermediate speed, steady	11.30	10.92	3.3%	0.44	0.44	-0.52
Manual identified*	Queue, manouvers	high duration	stop	Very low speed	1.20	0.50	57.4%	318.00	0.43	-0.37

403 **Table 3 – Summary of main descriptor parameters for each microtrip group. The name of the class and**  
404 **the notes in relation to the speed are assigned after the grouping and are not relevant for**  
405 **analysis.**

406 Considering SAPD values that have been used for the definition of each group, it is possible to notice  
407 significant differences between the “patterns” of each cluster, as is shown in Figure 3.



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**Figure 3 – SAPD contour plot for the microtrip groups described in Table 3; the plots do not include the point corresponding to idle phases (zero speed and acceleration) to avoid distortions due to its predominance.**

### l12 3.2.2 - Customized driving cycles development

l13 After grouping the microtrips, the creation process of a representative cycle consists of a first phase of  
 l14 “generation”:

- l15 • the selection of the main group of microtrips to be used (e.g. only a certain vehicle or only a set  
 l16 of clusters)
- l17 • the selection of a target distance for the whole cycle
  - l18 ○ for each cluster, a target distance is set in order to maintain the same proportion of the  
 l19 original data set
- l20 • random microtrips from each group are selected, until the target distance for that cluster has  
 l21 been reached
  - l22 ○ if the addition of a certain microtrip causes the overcome of target distance, the microtrip  
 l23 is truncated on a random point and glued together with the final portion of another  
 l24 microtrip, maintaining coherence for speed, acceleration and jerk values (threshold being  
 l25 0.1 m/s, m/s<sup>2</sup> and m/s<sup>3</sup> respectively); the junction between microtrips is repeated in an

426 iterative process if necessary. New microtrips, different from those part of the database,  
427 are therefore generated.

- 428 • all the chosen or generated microtrips are put beside each other, thus generating a cycle
- 429 • the process is repeated for a number of predetermined attempts.

430 After the generation of the attempt cycles, the final proposal cycle is selected on the basis of three main  
431 criteria:

- 432 1. considering the parameters of Table 2 (from number 3 to number 14), the differences between those  
433 of the original dataset and of the generated cycles have to be below a threshold (that is, 5%) for at  
434 least 11 over 12 values; about 0.5–1% cycles of the generated ones usually respect this condition for  
435 a distance of about 10–15km
- 436 2. for the reduced number of cycle chosen at the former point, those having similar PV are considered  
437 as candidate
- 438 3. for the remaining candidate cycles, the final one is that having lower SSD between SAPD matrix.

439 If a satisfactory cycle cannot be found (e.g. it is not possible to find a cycle having both low PV and low  
440 SSD in comparison with other cycles), the whole process is repeated generating new cycles.

441 Using this procedure, 10 different cycles have been generated. A summary includes:

- 442 • depending on the source of the data, 5 vehicle categories are considered:
  - 443 ○ all data from all vehicles are used, so that the cycle is representative of “average” electric  
444 vehicles; quadricycles data are included since, especially in urban driving, it is assumed  
445 that their performances are comparable with those of the other vehicles;
  - 446 ○ data from N1 passenger vehicles
  - 447 ○ data from M1 light delivery vehicles
  - 448 ○ data from quadricycles, so that the cycle is suitable for low powered vehicles
  - 449 ○ data from N1 and M1 vehicles, using only “unsteady” sequences as identified during  
450 clustering phase
- 451 • for each category, two different distances have been used:
  - 452 ○ “long” cycles are based on the 95th percentile trip distance; all the microtrip clusters are  
453 considered (excluding clusters 1, 2, 4 and 7 for unsteady cycle) and, therefore, also high  
454 speed phases can be included
  - 455 ○ “mean” cycles are based on mean trip distance, but clusters 8 and 9 are not used since  
456 their data also include quite “long” microtrips, by far exceeding the whole target distance.

457 Table 4 summarizes the information and the assumptions used for the driving cycle generation. The  
458 characteristic of the synthetic cycles are shown in Table 5. Figure 4 and Figure 5 show two of the  
459 generated cycles, including a comparison between the SAPD of original and synthetic data. The  
460 comparison between All vehicle SAPD and LDV vehicle SAPD highlights the more frequent occurrence of  
461 low-speed events for the latter one, as expected considering the typical needs of post services.

62 Finally, all the cycles are plot in Figure 6.

63

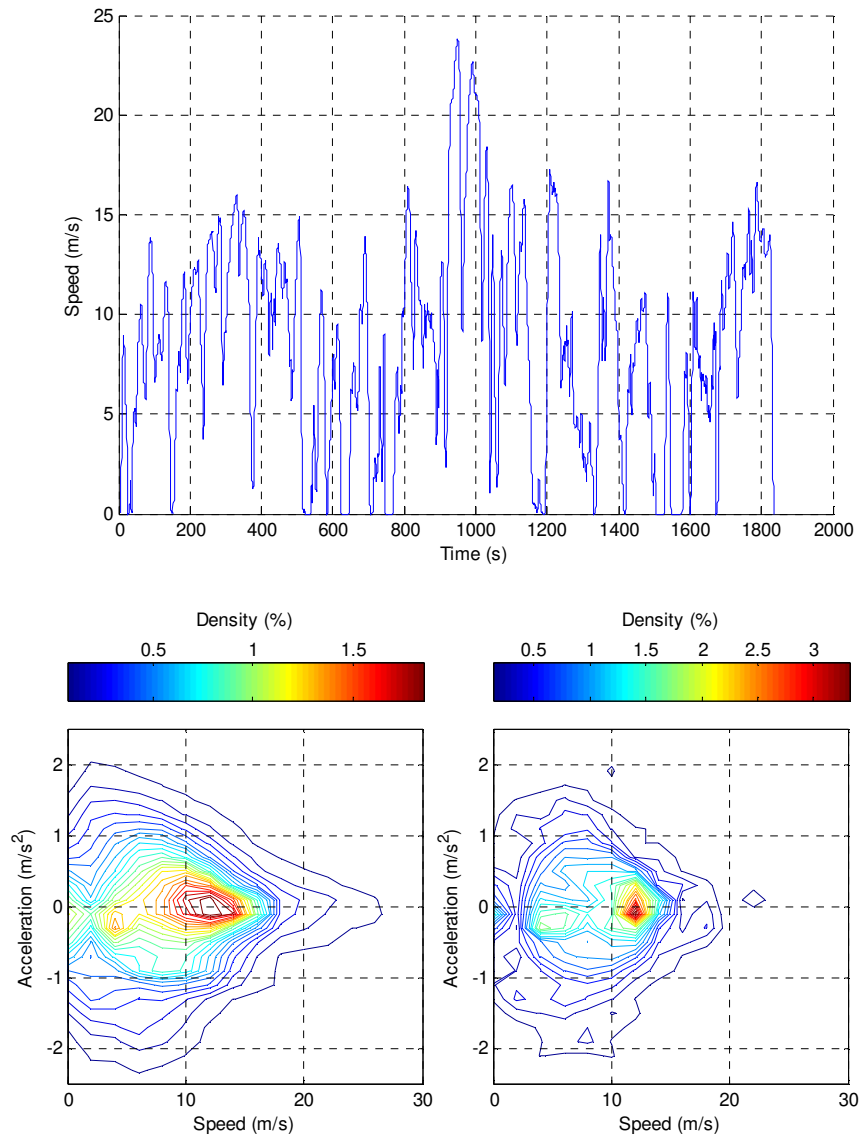
N.	Cycle name	Vehicles	Groups	Target Distance (km)
1	All long	All	1 to 9	12
2	All mean	All	1 to 7	6
3	Passenger long	N1	1 to 9	15
4	Passenger mean	N1	1 to 7	6
5	LDV long	M1	1 to 9	15
6	LDV mean	M1	1 to 7	4.8
7	Quadricycle long	L7	1 to 9	15
8	Quadricycle mean	L7	1 to 7	6
9	Unsteady long	M1 and N1	3, 5, 6, 8, 9	12
10	Unsteady mean	M1 and N1	3,5,6	6

64 **Table 4 - Summary of the boundary conditions chosen for the cycles generation.**

N.	Cycle name	duration (s)	distance (m)	idle %	cruise %	acc %	dec %	avg speed (m/s)	avg mov speed (m/s)	acc+ (m/s <sup>2</sup> )	acc- (m/s <sup>2</sup> )	stop/km	PKE (m/s <sup>2</sup> )	acc+noth (m/s <sup>2</sup> )	acc-noth (m/s <sup>2</sup> )
1	All long	1536	11566	13.7 %	7.4%	40.6 %	38.3 %	7.5	8.7	0.60	-0.64	1.0	0.53	0.55	-0.59
2	All mean	1214	5837	24.0 %	6.7%	34.6 %	34.8 %	4.8	6.3	0.63	-0.62	2.2	0.56	0.57	-0.57
3	M1 long	1835	15675	7.3%	7.6%	45.0 %	40.1 %	8.5	9.2	0.58	-0.65	0.9	0.51	0.54	-0.59
4	M1 mean	1277	6481	17.6 %	6.7%	39.2 %	36.6 %	5.1	6.2	0.65	-0.69	2.2	0.64	0.60	-0.63
5	N1 long	2015	14017	19.3 %	7.2%	37.6 %	35.9 %	7.0	8.6	0.64	-0.66	1.3	0.54	0.59	-0.62
6	N1 mean	1100	4755	31.3 %	6.1%	31.7 %	31.0 %	4.3	6.3	0.64	-0.65	2.1	0.55	0.59	-0.61
7	L7 long	2028	15480	10.4 %	7.8%	40.8 %	41.1 %	7.6	8.5	0.57	-0.56	1.0	0.46	0.52	-0.52
8	L7 mean	1076	6360	17.2 %	6.9%	38.3 %	37.7 %	5.9	7.1	0.56	-0.56	1.7	0.46	0.51	-0.52
9	Unsteady long	1521	12854	6.2%	7.7%	45.5 %	40.7 %	8.5	9.0	0.61	-0.68	1.0	0.53	0.57	-0.63
10	Unsteady mean	1227	6082	12.7 %	7.4%	40.0 %	39.8 %	5.0	5.7	0.67	-0.67	2.3	0.65	0.62	-0.61

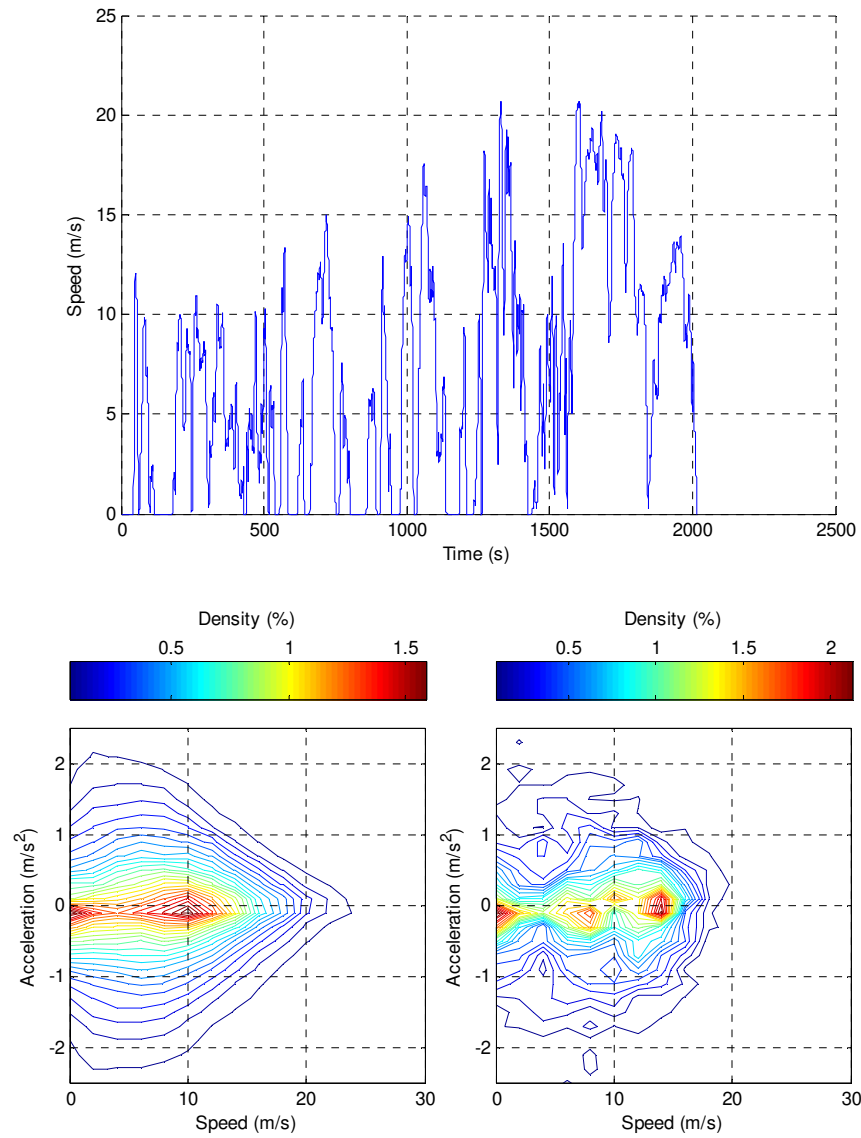
65 **Table 5 – Parameters of synthesized driving cycles**

66



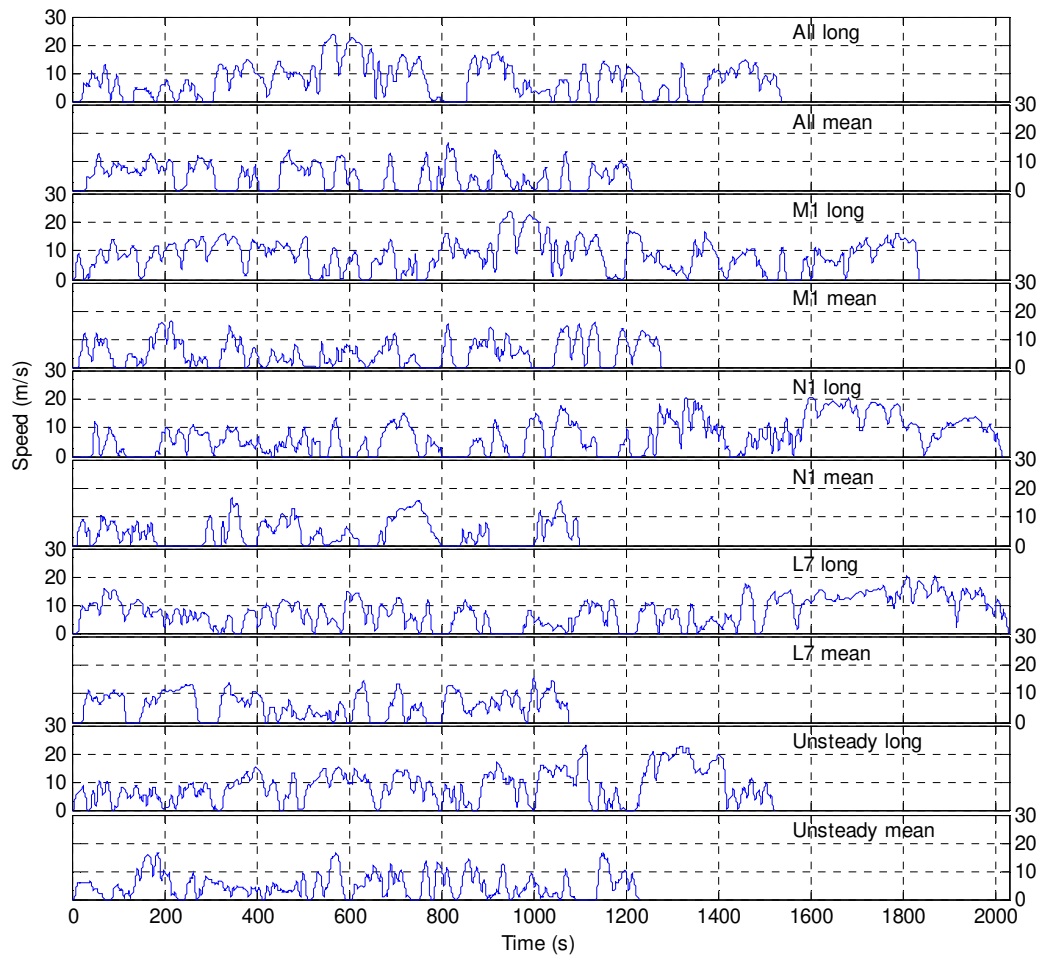
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**Figure 4 – Upper plot: “Passenger long” cycle. Lower plot: comparison between original SAPD (left) and cycle SAPD (right).**



:69  
:70

**Figure 5 – Upper plot: “LDV long” cycle. Lower plot: comparison between original SAPD (left) and cycle SAPD (right).**



471

472 **Figure 6 – Time-series plot of all the generated cycles.**

### 473 **3.2.3 - A comparison with existing cycles**

474 As a final outcome, dot plots illustrating the characteristics of generated cycles in comparison with  
 475 previously available ones are presented. In particular, Figure 7 shows the average speed (including zero  
 476 phases) in comparison with average positive acceleration, highlighting the proximity between typical  
 477 urban cycles (NEDC and Artemis Urban) and generated ones (see “All mean” and “All long” dots), as  
 478 expected due to the typical urban pattern in which the vehicles have been used.

479 The plot shown in Figure 8 clearly shows that the mean speed and stops per km of the generated cycles  
 480 fall in the same order of magnitude indicated for legislative cycles such as NEDC and FTP; however,  
 481 a direct comparison between urban patterns cycle (“All mean” generated cycles) and naturalistic urban  
 482 driving cycles (Artemis Urban) highlights a lower stop per km number, even if the mean speed is  
 483 absolutely similar. At this stage, it is not possible to say if this is related to the characteristics of the

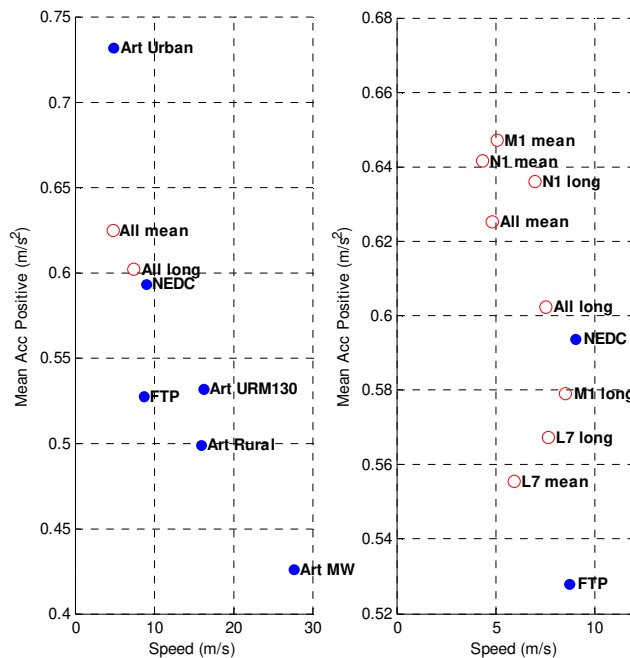
.84 electric vehicles (which can be driven in a smooth way in intense traffic, limiting start and stop phases) or  
 .85 not.

.86 Similarly, Figure 9 compares the cycles on the basis of Mean Positive and Negative accelerations. As  
 .87 known from previous studies, the trend shows that the values are generally higher for urban pattern  
 .88 cycles in comparison with rural or motorway ones. Negative acceleration values are often slightly higher  
 .89 than positive ones. Regarding the generated cycles, the mean negative values of acceleration are  
 .90 significantly lower than the value related to Artemis Urban naturalistic cycle; again, the difference could  
 .91 be related to the characteristics of the Electric Vehicle which could induce a particular driving behavior  
 .92 during deceleration. It can be noted also that L7 vehicle shows for both “long” and “mean” cycles lower  
 .93 values of mean accelerations, as expected due to its low power characteristics.

Cycle abbreviation	Cycle full name
NEDC	New European Driving Cycle
FTP	US FTP 75 Cycle
Art Urban	Artemis Urban
Art Rural	Artemis Rural
Art MW	Artemis Motorway
Art URM 130	Artemis Mixed cycle 130

.94 **Table 6 – List of abbreviations used to indicate the cycles.**

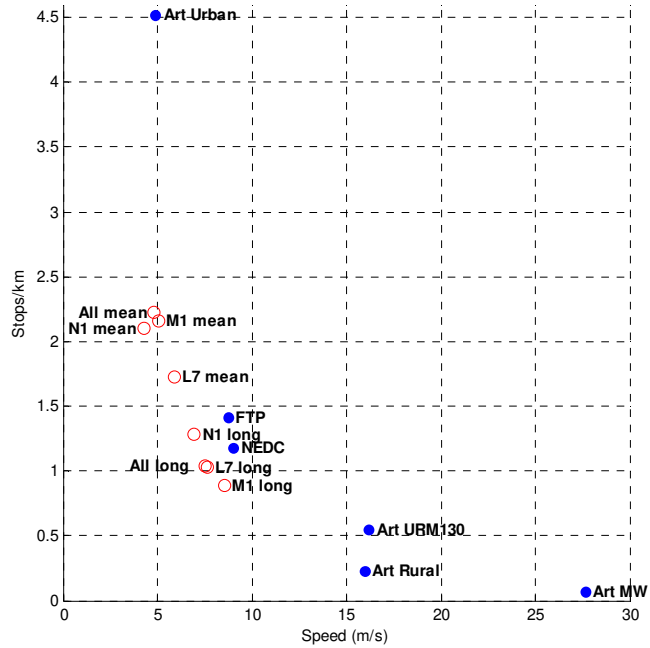
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.97 **Figure 7 – Speed vs Mean Positive Acceleration for existing and generated cycles. Left side: only “All**  
 .98 **long” and “All mean” cycles are plot for readability. Right side: all generated cycles are**  
 .99 **included and the scale is modified to focus on those.**

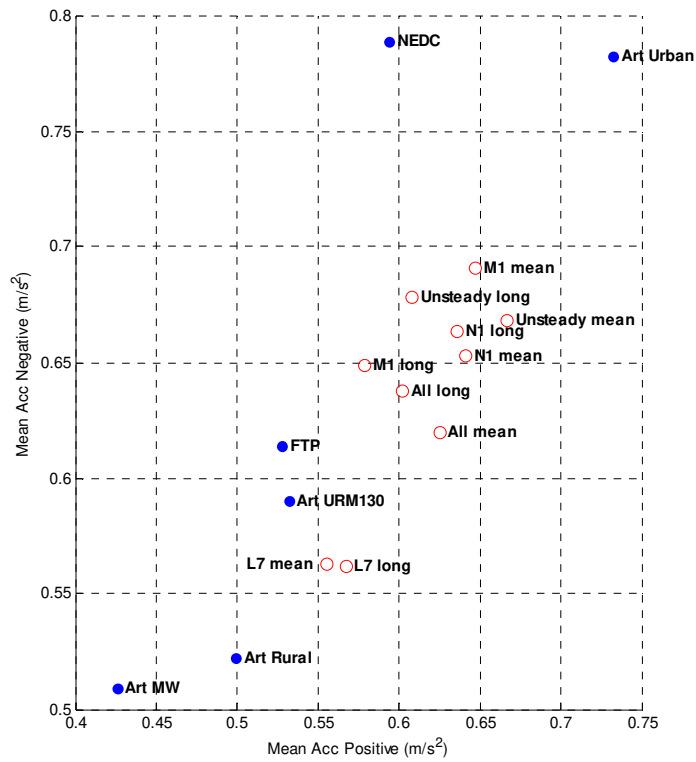
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Figure 8 – Speed vs number of stops per km for existing and generated cycles.



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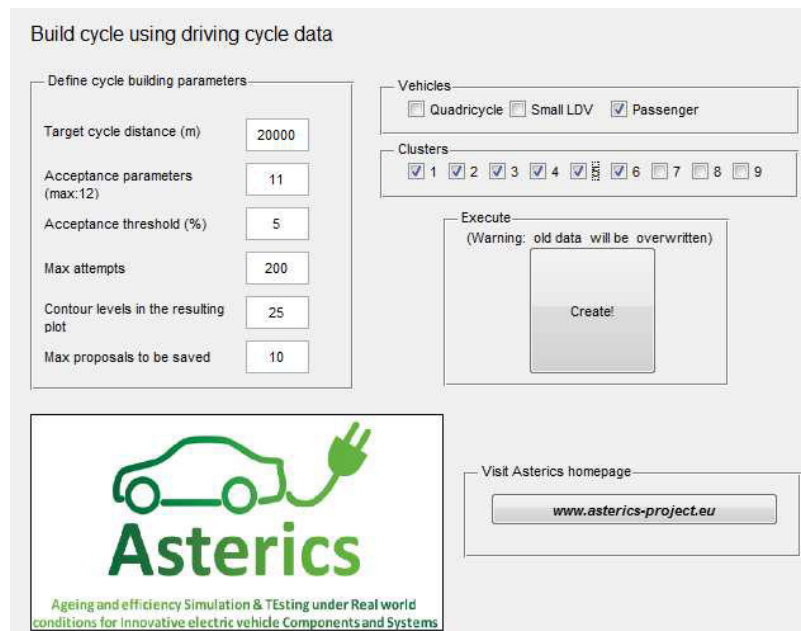
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Figure 9 – Dot plots representing Mean Positive and Mean Negative accelerations for existing and generated cycles.

### i06 **3.2.4 - Extended use of measured driving data**

i07 As described in paragraph 2.3.2, the randomization of driving cycles for vehicle development activities is  
i08 part of recent applied research trends. Such inputs are useful during testing (e.g. for control systems  
i09 robustness verification in SIL/MIL/HIL environment) or optimization of vehicle characteristics (e.g. for  
i10 energy management strategies, to be verified over a large number of use cases). A tool for the extraction  
i11 and the treatment of measured driving data has been developed; it is mainly conceived to be used during  
i12 batch simulation, extending the variability of the inputs in comparison with “fixed” generated data.

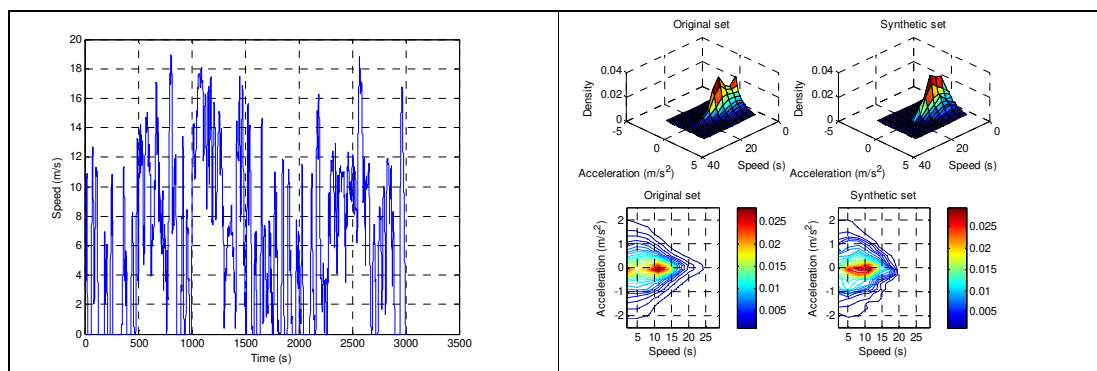
i13 The second main product of driving cycle analysis activity is therefore a “package” for data analysis and  
i14 cycle synthesis. The package implements the same methodology applied for cycle generation (as  
i15 described in the former paragraph) and is prepared as a Matlab-based product with Graphical Users  
i16 Interface (GUI). The tool – “builder” – is an interpreter of data that can be used to generate new cycles  
i17 and to verify their similarity with original data. The user can set a few parameters (the target distance, the  
i18 vehicle data to be used, the data “clusters” to be included, the acceptance thresholds), than a number of  
i19 “attempts” cycles can be generated; if any of the created cycles fits with original dataset, the tools plots  
i20 the generated “representative” cycle and saves it in a spreadsheet. Saved data include the speed signal,  
i21 the acceptance results (number of similar parameters, Performance Values – PV – indicator, Sum Square  
i22 Distance – SSD – of speed–acceleration density matrix – SAPD) and the general describing parameters.  
i23 The interface of the tool is shown in Figure 10; it is also part of the research products for the project  
i24 ASTERICS EU FP7. Its typical output is shown in Figure 11. The tool can be used also through command  
i25 line and is therefore suitable for the integration on simulation environment.



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527

Figure 10 – Driving cycle “builder” tool: main GUI screenshot.



528

Figure 11 – Output from “builder” tool: cycle plot (left), cycle SAPD plot (right).

## 529 4 - Conclusions

530 Driving cycles are a relevant input for the development of procedures for design, testing and  
 531 homologation of any kind of vehicles; such topic is particularly relevant considering the high level of  
 532 attention on vehicles both for pollutants emission and energy use. Considering precedent literature  
 533 products, in the first part of the present work a summarization of current state of the art on the topic has  
 534 been proposed. A few main findings emerged from the preliminary analysis of the topic. A large number  
 535 of synthesis methods have been proposed, most of them being similar on their key points. Literature  
 536 analysis also highlights a strong need for continuous improvement of the cycles in terms of detail and  
 537 variety, in order to catch the peculiarities of the vehicle under study and of the area where it is used; such  
 538 need is therefore the main motivation to propose a new case study. In addition, recent applied research  
 539 activities show the emerging trend of tools able to generate “on demand” cycles; such data can be used

i40 during vehicle development and for simulation and testing activities, as improved input in comparison with  
i41 synthetic cycles. However, a synthesis method has been prepared considering reference experiences.

i42 In the second part of the work an application case study has been proposed. The activity includes the  
i43 measurement of driving data within the city of Florence, which is characterized by the presence of  
i44 restricted traffic and pedestrian areas within its historical center; such areas can be accessed using EVs.  
i45 A small fleet of EVs used by both professional and private drivers has therefore been monitored within its  
i46 normal use; the driving sequences obtained can be considered naturalistic, since no predefined itinerary  
i47 was imposed and since the logging instrumentations was absolutely not invasive. Using the developed  
i48 method, the data have been therefore processed in order to build up a set of ten synthetic cycles,  
i49 differing for the type of vehicle used (from low powered quadricycles, to light vans and passenger cars)  
i50 and for the distance proposed (from typical city route – build up using mainly urban sequences – to mixed  
i51 route, including fluent driving on longer distances). The cycles represents main outcome of the activity,  
i52 their peculiarity being the use of data coming exclusively from EVs. In addition, the time-speed vector for  
i53 each cycle has been defined using four points per second, which is an improved level of detail in  
i54 comparison with existing cycles; the aim is to offer the possibility to increase the precision of energy  
i55 consumption and efficiency assessment in simulation activities. The activity is than concluded proposing  
i56 a short comparison with existing cycles; considering naturalistic cycles, a few differences in typical  
i57 kinematic indicators are noticeable. A few hypothesis have been proposed; however, at the present stage  
i58 it cannot be said if the spreading of the data is related to the characteristics of the city, to the relatively  
i59 small number of drivers involved (a known limitation of the study) or to the peculiarities of electric  
i60 vehicles, most evident being the regenerative braking capabilities and the fluent traction at very low  
i61 speed. Both characteristics, in fact, can potentially let the drivers obtain smooth acceleration events even  
i62 in intense traffic situations. A suggestion for future development, therefore, is to investigate about the  
i63 attitude of the users in driving EVs in comparison with ICEVs, in order to verify if different powertrain  
i64 characteristics can induce remarkable modification on driving style. Finally, an interpreter tool for further  
i65 valorization of the whole dataset has been developed and implemented both as GUI and command-line  
i66 function. Such activity has been prepared to overcome the limitations of “rigid” representative cycles and  
i67 extend the representativeness of the data during vehicle development phases, coherently with recent  
i68 literature experiences and applied research trends.

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i73 <http://ec.europa.eu>

i74 <http://www.asterics.eu>

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