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

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ABSTRACT

Strong efforts are spent in automotive engineering for the creation of so called Driving Cycles (DCs). Vehicle DC 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 Electric Vehicles (EVs) and their diffusion on certain contexts (e.g. city centers), the demand for tailored cycles arises. A proposal for driving data analysis and synthesis has been developed through the review and the selection of known literature experiences, having as a goal the application on a EVs focused case study. The measurement campaign has been conducted in the city of Florence, which includes limited traffic areas accessible to EVs. A fleet of EVs has been monitored through a non-invasive data logging system. After data acquisition, time-speed data series have been processed for filtering and grouping. The main product of the activity is a set of DCs obtained by pseudo-randomized selection of original data. The similarity of synthetic DCs to acquired data has been verified through the validation of cycle parameters. Finally, the new DCs and a selection of existing ones are compared on the basis of relevant kinematic parameters and expected energy consumption. The method followed for the creation of DCs has been implemented in a software package. It can be used to generate cycles and, under certain boundary conditions, to get a filtered access to the measured data and provide integration within simulation environment.

Introduction

A DC can be considered as a part of a standardized procedure aimed to evaluate and compare vehicle performances in a reproducible way under controlled or laboratory conditions, such as simulation environment, power-adsorbing chassis dynamometer, testbed and sometimes road track. It has to include a time–vehicle speed signal as main input data, but a large set of boundary conditions can be also defined: dynamometer settings, gear shifting points, reference atmospherics conditions, vehicle conditions (tyre pressure, lighting, oil viscosity, transported mass...), cold start conditions (critical, for different reasons, both for ICE and EV vehicles) and any other parameter influencing the performances of the product under test. International standardized procedures are used to assess vehicle performances such as fuel/energy consumption and air emissions; the results are used to verify compliance with reference thresholds and to compare different vehicles.

According to the large variations in terms of driving habitudes, user needs, road characteristics and others it is known that the exact duty cycle to be satisfied during the life of a certain vehicle is not fully predictable. It is therefore probable that a

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Table 1
Summary of terminology used in the article.

Terminology	Definition
Use pattern	Characteristics of vehicle use including driving profile together with additional information related to charging, load, environment and/or any other factor influencing vehicle performance and durability
Driving cycle	Set of data points representing vehicle speed versus time. Adapted from (Schwarzer and Ghorbani, 2013)
Duty cycle	Set of data points representing power demand versus time. Adapted from (Schwarzer and Ghorbani, 2013)
Driving profile	Collectivity of all driving cycles in a lifetime of a vehicle. Adapted from (Schwarzer and Ghorbani, 2013)
Driving sequence	Time-speed vector consisting of all data points between two relevant events (e.g.: trip – driving sequence between vehicle key-on/key-off events; microtrip: driving sequence between two idle phases)

single DC cannot represent the real driving profile (see Table 1), that includes all the possible conditions on which the vehicle could be used during its life; a compromise is needed.

Despite of the fact that the research and the standardization process started in the early 1970s, the creation of DCs is still a topic under development in scientific and technical literature.

The aim of the activity presented in this paper is to propose a group of driving cycles addressed to EVs simulation and testing; the study includes the definition of a procedure for driving cycle definition and the description of its application on a case-study. The document is structured as follows: Section 'Introduction' introduces the topic, proposes a brief review of literature information and recalls state-of-the-art experiences; Section 'Development of driving cycles' deals with the definition of a procedure for data analysis and cycle synthesis; Section 'Case study: the city of Florence' describes the tailored approach developed and its application to a real case study, including data acquisition on the city of Florence (Italy). Finally results and conclusions are presented.

Driving cycles

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

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

Experiences in applied research show that customized cycles are used as input for virtual and testbed testing procedures during product development. A large number of parameters influence vehicle energy consumption and the related emissions, including driver capabilities, driving context, traffic conditions, ambient temperature, etc.: such a variability causes the need for extensive testing on the road of any kind of vehicle during its final development phase. One of the outcome of on-road driving is the definition of tailored DCs which are complementary to legislative ones and can be used to perform additional testing and simulation activities in a reproducible way. Such custom cycles are continuously developed; using appropriate parameters to evaluate the characteristics of driving cycles, in fact, the evidence explained in literature is that local or regional conditions can differentiate driving patterns depending on the area under examination (Lin and Niemeier, 2003; Wang et al., 2008).

The cycles can be defined depending on:

- Load (including continuous or transient speed phases).
- Context of applicability (urban, extra urban, motorway).
- Expected vehicle mission profile (e.g. private passenger use, freight delivery, bus service, etc.).

Car manufacturers usually perform activities on driver and cycle characterization in order to improve their own knowledge on representative test sequences, both using methods for driving cycle synthesis after acquisition on real-world use

Table 2
Full list of indicators to describe driving cycles (Barlow et al., 2009; Tong and Hung, 2010).

Group	Parameter	Units
Distance related	Total distance	m
Time related	Total time	s
	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: 75–25th percentile	km/h
	Maximum speed	km/h
Acceleration related	Average acceleration	m/s^2
	Average positive acceleration	m/s^2
	Average negative acceleration	m/s^2
	Standard deviation of acceleration	m/s^2
	Standard deviation of positive acceleration	m/s^2
	Acceleration: 75–25th percentile	m/s^2
	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^3
	Positive Kinetic Energy (PKE)	m/s^2
	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^2/s^2
	Relative real cubic speed (RRCS)	m^2/s^2
	Root mean square of acceleration (RMSA)	m^2/s^2

(Borgarello et al., 2010; Ma and Andreasson, 2007) and experimental test using professional drivers on controlled track conditions (Capitani et al., 2003). Tailored driving cycles have also been prepared to consider special applications for which general cycles are not suitable (Han et al., 2012) or to assess the behavior of a particular vehicle category on a known path, e.g. motorcycles on typical home-work routes (Saleh et al., 2009).

The need for driving cycles generated by EVs data within the EU FP7 project ASTERICs has been one of the factors that led to the development of the activity here presented (Pfluegl et al., 2015).

Use patterns and cycles for electric vehicles

In recent formulation of homologation procedure (see UNECE Regulation 101), the procedures to evaluate the performances of EVs have been introduced, e.g. through the use of weighting formulae for the assessment of electric energy and combined fuel consumption in case of HEVs. However, EVs introduce new parameters for the evaluation of their performances and are affected by specific criticalities in comparison to conventional vehicles. Such new factors act on range capabilities of the vehicle and on driving attitude by the users.

Two relevant factors related to range are:

- *Range limitation:* the range is usually below a value of about 150 km on optimal conditions for most EVs currently on the market; the limitation could induce drivers to particularly smooth, benign driving style under specific conditions (e.g. unavailability of charging points); such boundaries can also determine the so-called “range anxiety” phenomena (Neubauer and Wood, 2014).

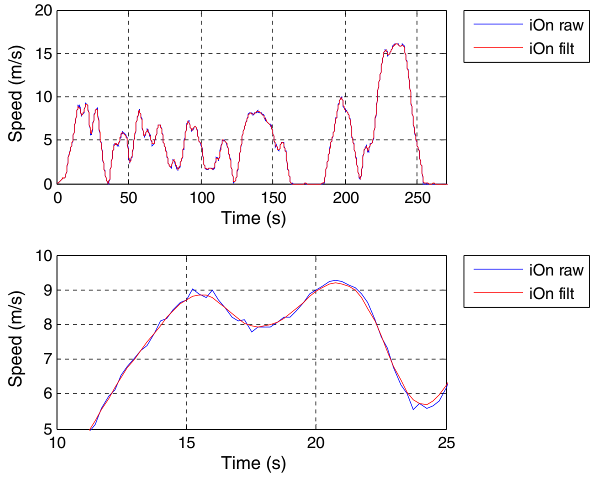

Fig. 1. Upper plot: a portion of speed measurement for iOn passenger vehicle, showing a comparison between raw and filtered data. Lower plot: a detail coming from the same measurement.

Table 3
Parameters used for cycle characterization and grouping.

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^2	Cruise %
Percentage of positive acceleration time	%	$a > 0.05$ m/s^2	Acc %
Percentage of negative acceleration time	%	$a < -0.05$ m/s^2	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^2	$a > 0.05$	Acc+
Mean negative acceleration (a < threshold)	m/s^2	$a < -0.05$	Acc−
Root Mean Square of speed	m/s^2		RMS
Positive Kinetic Energy	m/s^2		PKE
Relative Positive Acceleration	m/s^3		RPA
Stop rate	–		Stops/km
Additional parameters			
Mean positive acceleration (without using threshold)	m/s^2	$a > 0$	Acc+ noth
Mean negative acceleration (without using threshold)	m/s^2	$a < 0$	Acc− noth
SAPD edges			
Acceleration classes (51 classes)	m/s^2	From −2.5 to 2.5	
Speed classes (17 classes)	m/s	From 0 to 0.1 and from 0.1 to 30	

- *Relevance of auxiliaries:* a different sensitiveness of the vehicle to the use of auxiliary systems (in particular, HVAC system), which could reduce the range up to 50% (Geringer and Tober, 2012).

Recent works on EVs are aimed to characterize the users on the basis of their needs and habitudes in order to verify the suitability of EVs for general purpose use; in particular, the characterization of so-called "trip chains" (Primerano et al., 2008) has been studied both in Europe (Pasaoglu et al., 2014) and USA (Krumm, 2012; Van Haaren, 2011); trip-chaining is fundamental, in fact, in order to identify charging opportunities for EV users (Smith et al., 2011). Results on the use of electric vehicles by a panel of drivers have been published, and the data reported are useful to complete the duty cycle definition together with general use information such as charging habitudes (Adornato et al., 2009; Smart et al., 2013). Most proposed studies, however, are related to the identification of suitable mission profiles and of hypothetical applications of EVs both for private or business users; such studies are not focused on the description of driving characteristics of the vehicles. The proposal of EVs driving cycles is therefore complementary to existing literature.

Two relevant factors related to driver behaviour are:

- *Regenerative braking:* the availability of energy recovery braking systems can induce the drivers to modify their style in order to optimize energy consumption.

Table 4
Summary of main descriptor parameters for each microtrip group. The name of the class and the notes in relation to the speed are assigned after the grouping.

Number	Class	Stop notes	Speed notes	Avg mov speed m/s	Avg speed m/s	Stop duration %	Stops/km 1/km	Acc+ nth m/s^2	Acc− nth m/s^2
1	Urban	High stop duration	Unsteady	5.50	1.98	63.9	3.34	0.57	−0.58
2	Urban	Low stop duration	Very low speed	2.55	2.39	6.2	4.15	0.32	−0.30
3	Urban	Low stop duration	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 stop duration	Unsteady	6.14	5.47	10.6	2.04	0.65	−0.64
7	Urban	Low Stop duration	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 identification	Queue, maneuvers	High stop duration	Very low speed	1.20	0.50	57.4	318.00	0.43	−0.37

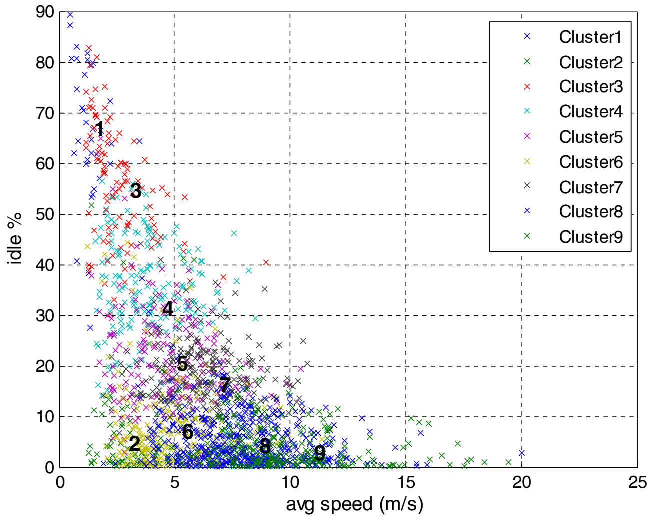

Fig. 2. Scatter plot representing average speed and idle percentage time for all cluster elements; centroids are indicated by numbers. The scatter plot has been used to describe group characteristics (see Table 4).

- *Performance and perception:* EVs can induce a different perception of vehicle performances in comparison with conventional ICEVs, due to different acoustic sensations, throttle feeling, and torque availability from the powertrain. For ICEVs, many studies have been proposed in the past (Capitani et al., 2001; Delogu and Pilo, 2002).

A clarification is needed about regenerative braking, that has been identified as a key element for the overall EV efficiency, especially in certain driving contexts (Travesset-Baro et al., 2015). It is worth to remind that for any car, in general, mechanical braking torque is usually an order of magnitude bigger than traction torque; for EVs, regenerative braking torque is comparable to traction torque, thus full braking performances can be obtained only using mechanical brakes. The integration of mechanical and regenerative braking capabilities is a vehicle control design issue; manufacturers currently adopted different implementation strategies (e.g. blending on brake pedal; light, moderate or strong regeneration on throttle release, and others). Technically, energy harvesting is maximized if the deceleration is not harsh; so that motor regeneration torque is sufficient and no torque from mechanical brakes is needed. Since dashboard instruments usually highlight that regenerative braking is active in case of smooth and intermediate deceleration, most users are aware of the conditions in which energy harvesting is taking place and can act consequently. Existing driving cycles have been obtained using driving data in which drivers and vehicles are not able to adopt regenerative braking. One of the aim of this study is to create driving cycles

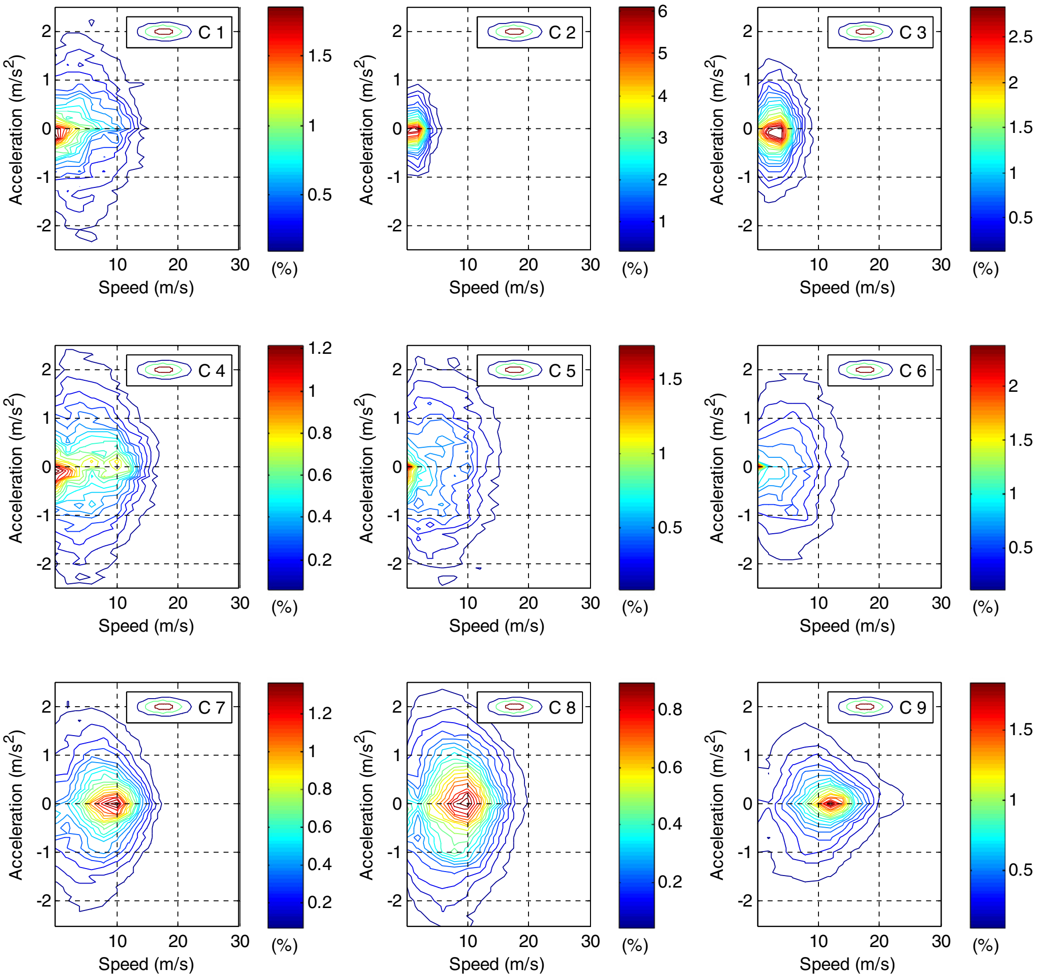

Fig. 3. SAPD contour plot for the microtrip groups described in Table 4; the plots do not include the point corresponding to idle phases (zero speed and acceleration) to avoid distortions due to its predominance.

obtained exclusively from electric vehicles, so that this feature, if significant for the users, is implicitly represented. A particular cycle developed for EVs in the city of Rome is available in literature (Alessandrini and Orecchini, 2003); the study highlighted that the characteristics of electric vehicles can induce a driving pattern somehow different from those adopted on conventional vehicles by the same users. Typical examples are:

- The frequent occurrence of moderately strong accelerations, especially at low speed, even for non-aggressive drivers; this can happen due to human perceptions in terms of reduced noise, that is typical of electric traction systems.
- The low peak power reduces aggressiveness on moderate or high speed; this occurrence could be related to the vehicle used in the cited study. For latest N1 or M1 class EVs maximum power is usually comparable with similar conventional vehicle; this observation, however, can still be appropriate for low powered vehicle such as electric quadricycles.

Starting from field operational tests, powertrain use patterns and efficiency have been identified and ranked on the basis of intensity and context identification (Liaw and Dubarry, 2007; Shankar et al., 2012); however, such studies did not propose a representative DC. As a consequence, the Rome EV cycle has been reported to be almost unique at least until 2011 (Chaudhari and Thring, 2011), while even recent works, which are aimed to assess the applicability of real world cycles on EVs, have been using time-series data acquired from conventional ones (Ozdemir et al., 2014).

Development of driving cycles

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

Table 5
Summary of the boundary conditions chosen for the cycles generation.

No.	Cycle name	Vehicles	Groups	Target distance (km)
1	All long	All	1–9	12
2	All mean	All	1–7	6
3	Passenger long	N1	1–9	15
4	Passenger mean	N1	1–7	6
5	LDV long	M1	1–9	15
6	LDV mean	M1	1–7	4.8
7	Quadricycle long	L7	1–9	15
8	Quadricycle mean	L7	1–7	6
9	Unsteady long	M1 and N1	3, 5, 6, 8, 9	12
10	Unsteady mean	M1 and N1	3, 5, 6	6

Table 6
Parameters of synthetized driving cycles.

No.	Cycle name	Duration (s)	Distance (m)	Idle %	Cruise %	Acc %	Dec %	Avg speed (m/s)	Avg mov speed (m/s)	Acc+ (m/s^2)	Acc− (m/s^2)	Stop/ km	PKE (m/s^2)	Acc+ noth (m/s^2)	Acc− noth (m/s^2)
1	All long	1536	11,566	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	15,675	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	14,017	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	15,480	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	12,854	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

Table 7
Percentage difference between the parameters describing the input measurements and the corresponding synthetized driving cycles.

No.	Cycle name	Idle %	Cruise %	Acc %	Dec %	Avg speed (m/s)	Avg mov speed (m/s)	Acc+ (m/s^2)	Acc− (m/s^2)	stop/km	PKE (m/s^2)	Acc+ noth (m/s^2)	Acc− noth (m/s^2)
1	All long	−3.9%	0.8%	1.0%	0.2%	−1.4%	−1.9%	−1.3%	−0.4%	1.0%	−2.6%	−2.5%	−0.7%
2	All mean	0.2%	−2.2%	0.8%	−0.5%	2.3%	2.5%	−0.7%	0.5%	0.9%	0.9%	0.8%	−6.2%
3	Passenger long	3.1%	0.0%	−0.6%	0.1%	−2.4%	−2.0%	2.6%	2.3%	0.4%	4.0%	4.0%	−5.2%
4	Passenger mean	−1.2%	3.4%	−2.2%	2.2%	1.2%	1.2%	2.1%	−2.2%	−0.2%	1.7%	1.5%	−0.8%
5	LDV long	−0.3%	−4.2%	2.1%	−1.3%	−2.9%	−2.8%	−3.1%	0.5%	−1.4%	1.2%	1.1%	−8.0%
6	LDV mean	−3.1%	1.9%	1.1%	1.5%	2.5%	1.4%	−1.4%	−1.8%	−3.3%	4.2%	3.7%	−1.6%
7	Quadricycle long	−0.1%	6.5%	−1.2%	−0.1%	−4.1%	−3.9%	−2.2%	−2.6%	−1.9%	−1.7%	−1.8%	2.2%
8	Quadricycle mean	−3.3%	0.5%	−1.8%	3.1%	−2.3%	−2.8%	0.7%	−4.0%	0.4%	3.2%	3.3%	−9.1%
9	Unsteady long	−2.0%	1.7%	−0.4%	0.4%	0.8%	0.8%	−0.4%	−0.9%	0.6%	2.1%	2.1%	−8.4%
10	Unsteady mean	1.5%	1.6%	−1.1%	0.3%	−1.0%	−0.5%	1.3%	−0.1%	0.5%	4.1%	4.0%	−1.1%

Driving sequences analysis

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

In this paragraph, numerical parameters will be reported using reference articles. It is possible to distinguish at least six main categories of driving segment/cycles parameters depending on their physical dimension: distance, time, speed, acceleration, stop data (e.g. % of time or event count), indicators of dynamics. Considering relevant experiences such as the ARTEMIS project, the full list of the parameters used includes 40 elements (André, 2004; Barlow et al., 2009); their list is provided in Table 2. In most research activities only a subset of such parameters has been considered; looking at literature works, the evaluation can be based on a reduced set of indicators, such as 22 parameters (Hung et al., 2007), 13 or 12 parameters (Kumar et al., 2012; Saleh et al., 2009).

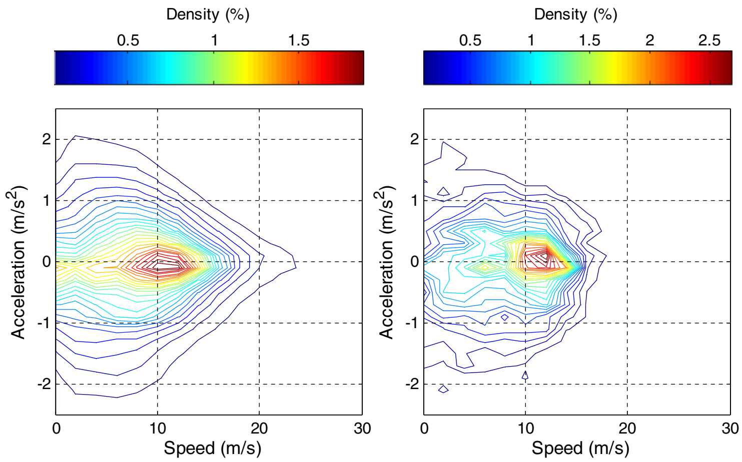

Fig. 4. All long cycle: comparison between source data SAPD (left) and cycle SAPD (right).

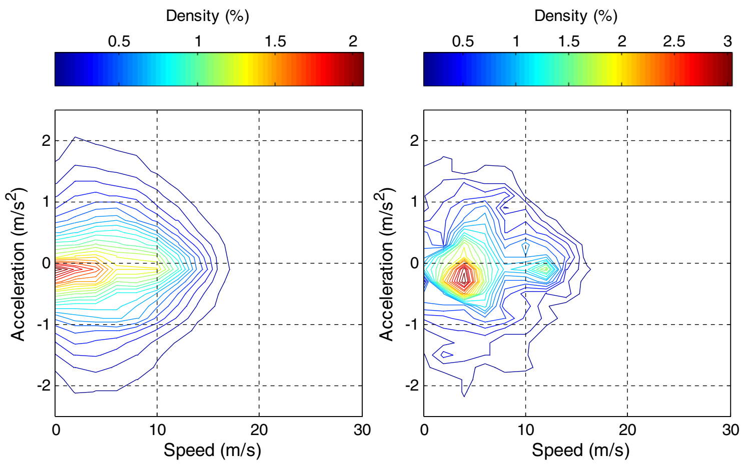

Fig. 5. All mean cycle: comparison between source data SAPD (left) and cycle SAPD (right).

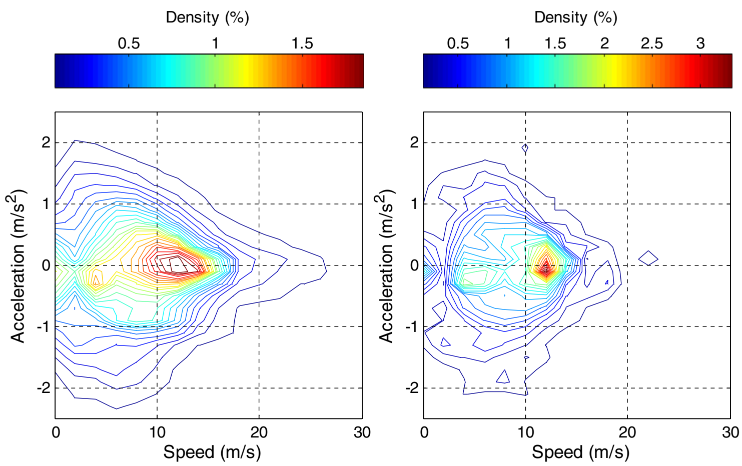

Fig. 6. Passenger long cycle: comparison between source data SAPD (left) and cycle SAPD (right).

During the analysis of the data, trip events (i.e. a driving sequence between key-on and key-off events) and microtrip ones (i.e. a sequence measured between two stops events) are identified; the numerical parameters described above can be calculated for such sequences to get their quantitative description. In addition to this, the analysis of cycles can take into

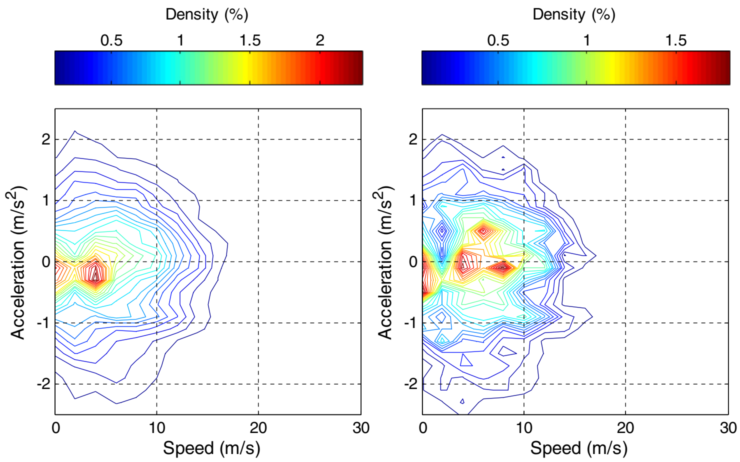

Fig. 7. Passenger mean cycle: comparison between source data SAPD (left) and cycle SAPD (right).

account a large set of data represented in the form of statistical distribution. Typical data can be calculated in terms of absolute indicators (e.g. distance driven or time spent over a certain condition) or in terms of relative frequencies (e.g. percentage of occurrence of a certain class of events). Regarding 2-variables distribution, a largely used method for cycle clustering and cycle build-up is based on the analysis of the distribution of events falling in a determined class of speed–acceleration couple, expressed as relative frequency of occurrence or as total time (De Haan and Keller, 2004). In case of the use of such information for the extrapolation of a new cycle, the relative frequency assumes the meaning of "probability" of a determined class; the definition used by some authors is therefore SAPD (Hung et al., 2007). The scope of distribution analysis is both related to data visual interpretation and to extended data processing; in particular, in case of creating of a new cycle using randomization methods, data distribution can be used for the selection of sequences through random walk approaches (Lee et al., 2011).

The ability to categorize the different segments of measured driving sequences is fundamental for cycle synthesis; clustering activities can be based on a vector of indicators such as those in Table 2 (Borgarello et al., 2001) or directly on SAPD. Significant differences have been found on typical SAPD depending on vehicle engine power (André et al., 2006). Other classification methods based on fuzzy logic are documented in literature (Liaw, 2004; Tong and Hung, 2010).

Signal acquisition and treatment

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

The minimum data acquisition frequency for vehicle speed should be at least 1 Hz, that is also the value used for the time-speed signals defining most existing driving cycle; decimation at 1 Hz has been suggested in defining driving cycle construction framework (Bishop et al., 2012). However, it has been demonstrated that vehicle energy consumption and efficiency can be evaluated with acceptable results using low sample rates (0.2–1 Hz) if a compensation technique is provided, but that higher sampling rate (from 2 Hz to 10 Hz) provide more accuracy and reliability for vehicle efficiency characterization due to the possibility to better describe vehicle dynamics (Corti et al., 2012). As explained in Section 'Data post processing and synthesis', the acquisition here presented and the cycle created are therefore based on a 4 Hz time-speed signal. During pre-processing of the data, the first need is to check the continuity of the information: data affected by strong cold-start uncertainties, that is typical of GPS devices, large signal lack or similar should be rejected. Also, if a fleet is monitored on naturalistic conditions, some events should be excluded from driving patterns analysis (e.g. parking phases). After that, the data signal should be appropriately filtered. Regarding GPS data, there are different suitable filtering methodologies, each one presenting advantages and disadvantages (Jun et al., 2006):

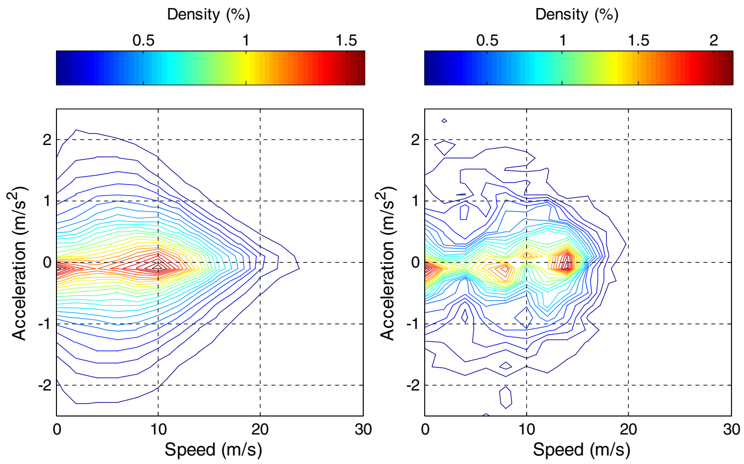

Fig. 8. LDV long cycle: comparison between source data SAPD (left) and cycle SAPD (right).

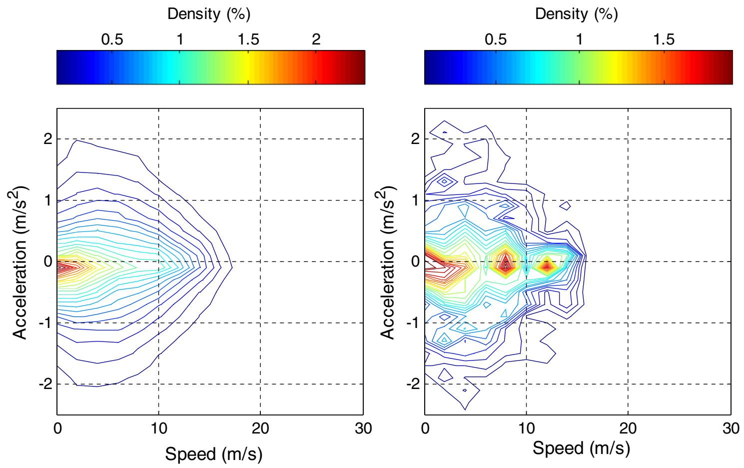

Fig. 9. LDV mean cycle: comparison between source data SAPD (left) and cycle SAPD (right).

- Piecewise polynomial regression model.
- Kernel-based smoothing methods.
- Discrete Kalman filter.
- Modified Kalman filter.

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

When studying the characteristics of typical driving patterns of a certain fleet, there are two main alternatives for the selection of drivers panel and of their route: on board measurement of vehicle/fleet monitoring and “chase” car approach. The reliability of the first method is related to the size and the characteristics of the monitored fleet itself. The more varied data are acquired (number of drivers, of vehicles, distance run), the more the acquired data are appropriate to fit the real characteristics of the fleet under study. A large data collection could be therefore necessary. The second method is widely used for the acquisition of data in order to represent the characteristics of the driving style on a specific area, e.g. to identify local driving patterns. Car chasing consists in following a “target” vehicle, initially randomly selected, with another vehicle; as soon as the chased vehicle stops or is loss, another vehicle is selected. A trained driver is therefore needed, while the measurement is performed on the chasing vehicle even if the characterization is related to the “target” vehicle. The main advantage of the method is the possibility to acquire a large amount of data related to a population within its operating area, while the main disadvantage is the risk of data deformation: chased and chasing vehicle transient speed difference could occur, or chasing vehicles could interfere with chased vehicle, thus influencing the driving style. For the present study, chasing has not been considered due to the need to measure the performances of the EVs under study.

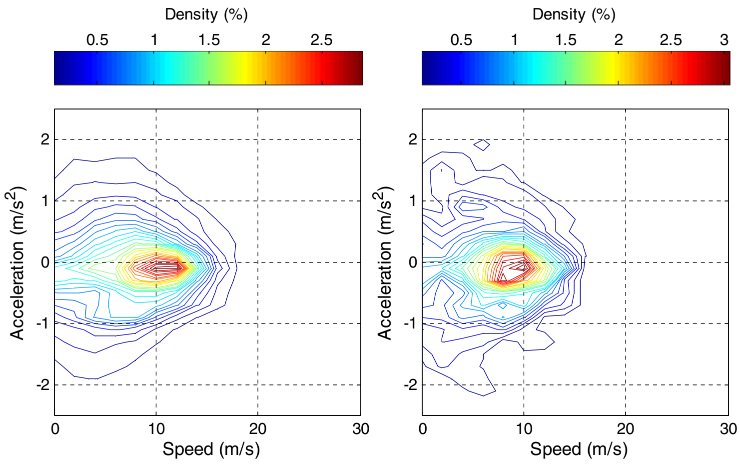

Fig. 10. Quadricycle long cycle: comparison betweensource data SAPD (left) and cycle SAPD (right).

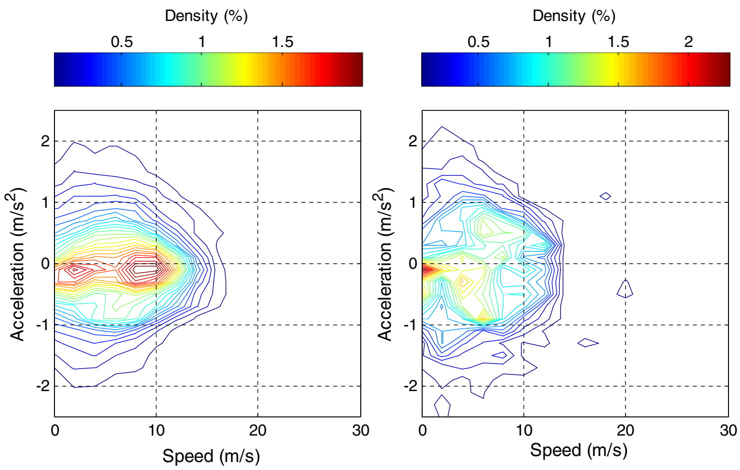

Fig. 11. Quadricycle mean cycle: comparison betweensource data SAPD (left) and cycle SAPD (right).

Synthesis of driving cycles

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

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

1. The processing of the data, through calculation of kinematic indicators and distribution data; when applicable, partial data (events) are grouped in different classes, each representative of a certain typical driving sequence such as urban, rural, smooth, aggressive.
   - Events can include ''modal events'', i.e. acceleration, deceleration, cruise and idle driving segments, or full microtrips segments, or partial microtrips segments.
2. Using the available database of driving sequences and of the associated kinematic parameters, a number of events is randomly selected according to the desired characteristics of the cycles; for general representativeness, a suitable method is to choose events from each group, maintaining the same proportion in terms of distance or duration that was identified between group data and total measured data.

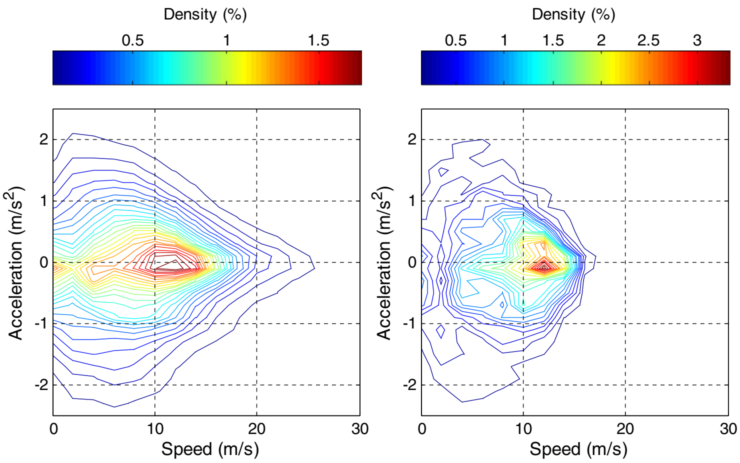

Fig. 12. Unsteady long cycle: comparison betweensource data SAPD (left) and cycle SAPD (right).

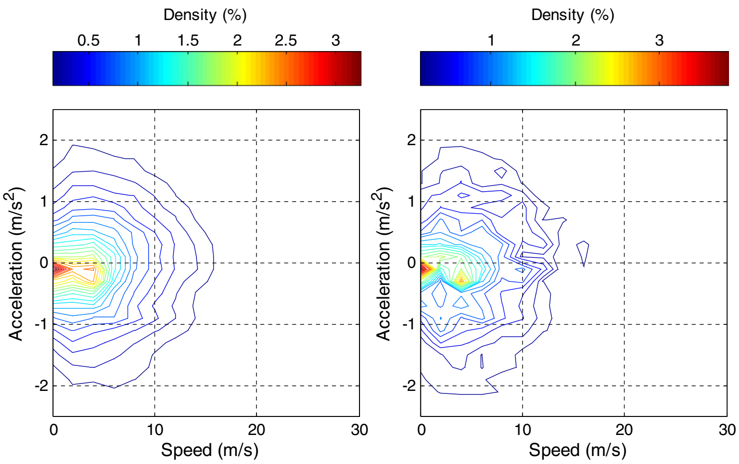

Fig. 13. Unsteady mean cycle: comparison betweensource data SAPD (left) and cycle SAPD (right).

3. The elements are randomly "glued" according to "matching" criteria.
   - o A criterion to order the transitions from a certain driving sequence to another, as well as for the transition from a recognizable driving context to another (e.g. from city to highway and then to city again, as typical), can be used; such random walk can be created on the basis of a transition probability matrix, so that typical methods for Markov chain creation are applied (Bishop et al., 2012).
   - o The coherence in terms of final speed of the preceding segment to the speed of its next segment has to be complied; as an example, in case of microtrips, both starting and ending speeds are zero; the juxtaposition of the events is simple, while the duration for stop phase and, in some cases, an acceleration value for the next event are randomly proposed.
4. As soon as the target duration or distance has been reached, a verification of the representativeness of the cycle is performed according to appropriate control parameters.

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

Control parameters

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

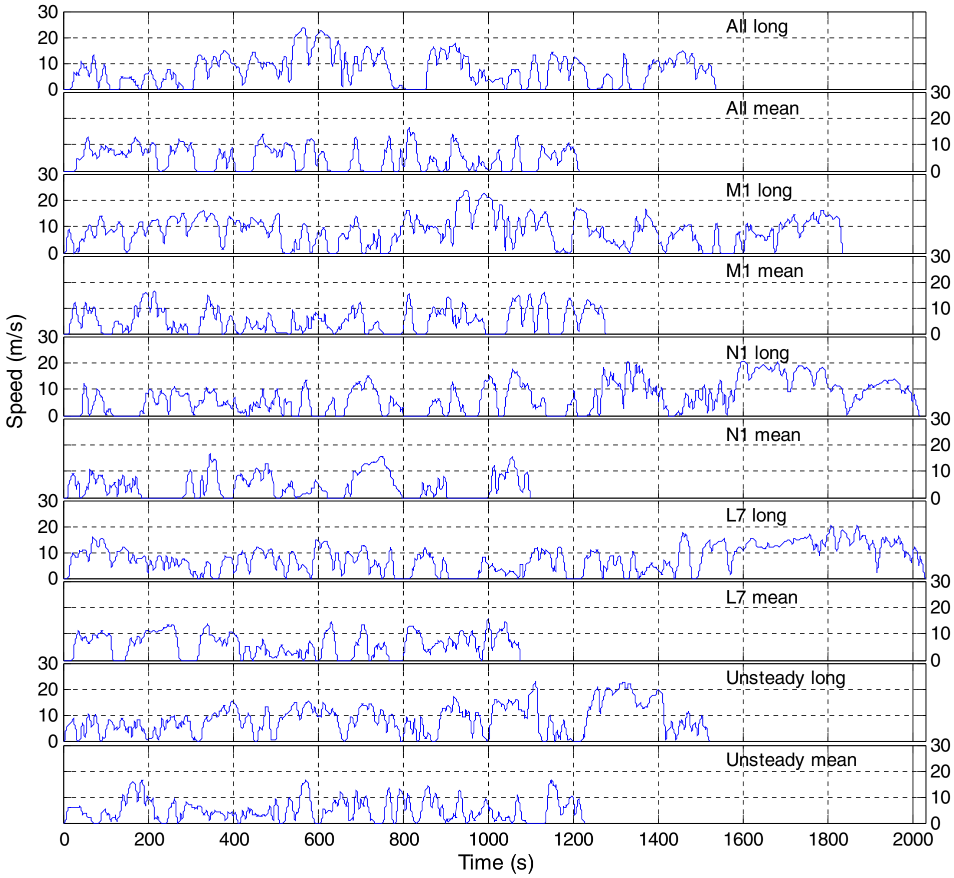

Fig. 14. Time-series plot of all the generated cycles.

$$\forall \vartheta_t \in \vec{\theta}_t, \left[\frac{\vartheta_t - \vartheta_i}{\vartheta_t}\right] < threshold \tag{1}$$

where $\vec{\theta}_t$ is the vector of the indicators (see Table 2) calculated for the main dataset and $\vec{\theta}_i$ is the same vector calculated for the synthetic cycle.

The parameters to be included in the vector $\vec{\theta}_t$ can vary (Tong and Hung, 2010); average speed, idling percentage, acceleration parameters and SAPD are the more frequently used. Such review does not identify a rigorous methodology for parameters selection, but highlights a tendency depending on cycle synthesis procedure; the "matching" approaches, aiming to provide statistical compliance between datasets and synthetic cycles, mainly use a larger set of parameters in comparison with other methods (e.g. vehicle driving simulation procedures generating second-by-second speed).

After that a number of possible candidate cycles are defined, additional confrontation parameters can be calculated, in order to let the user select the one having most favorable ones. Typical quantitative values are:

- Performance Value (*PV*), that is the scalar product of the difference between $\vec{\theta}$ vectors with a weighting vector:

$$PV = |\vec{\vartheta}_t - \vec{\vartheta}_i| \cdot \vec{W}^T \tag{2}$$

where $\vec{W}$ is the weighting vector ($\vec{W}^T$ being the transpose of the vector $\vec{W}$).

o An example of PV definition is (Lin and Niemeier, 2003):

$$PV = |\Delta\bar{v}| + |\Delta\bar{a}| + |\Delta v_{max}| \times 0.1 + |\Delta v_{min}| + |\Delta a_{max}| + |\Delta a_{min}| + |\Delta\%\_idle| + |\Delta\overline{P_d}| + |\Delta v_{95}| + |\Delta a_{95}| + |\Delta P_{95}| \tag{3}$$

where $\bar{v}$ is the average speed, $\bar{a}$ is the average acceleration/deceleration rate, v_{max} is the maximum speed, v_{min} is the minimum speed, v_{95} is the 95th percentile speed, a_{max}, a_{min}, and a_{95} are the maximum, minimum and 95th percentile acceleration rates, %_idle represents the percent idle time, $\overline{P_d}$ is the average road power, and P_{95} is the 95th percentile road power.

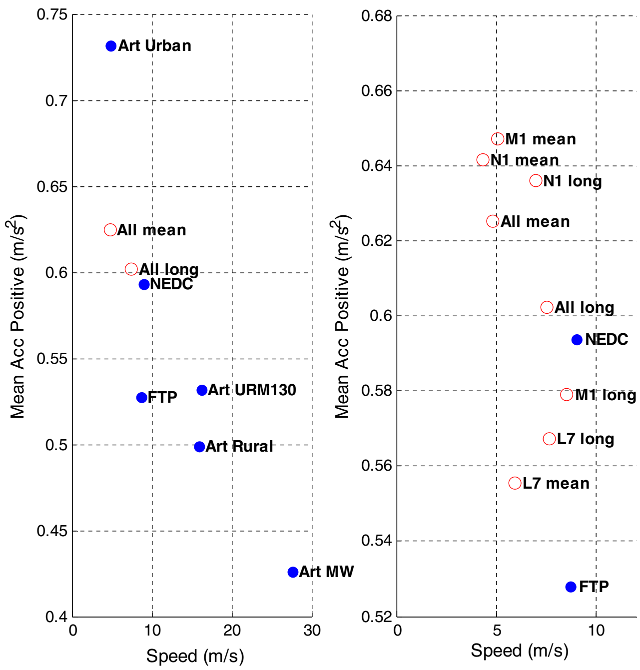

Fig. 15. Speed vs Mean Positive Acceleration for existing and generated cycles. Left side: only "All long" and "All mean" cycles are plot for readability. Right side: all generated cycles are included and the scale is modified to focus on those.

Table 8
List of abbreviations used to indicate the cycles.

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

- Sum Square Difference – SSD – of SAPDs, that is the summary of quadratic product of the error between corresponding speed–acceleration classes

$$SSD = \sum_{i=1}^{N_s}\sum_{j=1}^{N_a}(p_{ij} - q_{ij})^2 \tag{4}$$

where p_{ij} and q_{ij} are, respectively, the density of events for each class of speed (N_s) and acceleration (N_a).

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

From driving cycles to sequence generator

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

Methodology definition

Considering the brief literature review presented in Section 'Development of driving cycles', a methodology is here defined for the generation of new DCs. The method proposed is structured as follows:

- Context choice.
- Data acquisition.
- Data processing.
  - o Data filtering.
  - o Driving sequences identification and clustering.
- Customized DCs development.
  - o Driving sequence selection.
  - o Driving sequence editing and/or juxtaposition.
  - o DC validation through parameter analysis and comparison.

The application of the methodology is described in detail in Section 'Case study: the city of Florence'.

Case study: the city of Florence

This section describes the acquisition of data from EVs circulating in the city of Florence (Italy) and their use for generating of a new group of driving cycles. Florence is located in the central area of Italy, it is a Large city according to Eurobarometers criterion, its population being about 380,000 inhabitants for the municipality and about 1 million of inhabitants for its Metropolitan area (formerly defined as Province). The city applied in the last years a number of limitations for motor vehicles, including parking fares (on the whole city) and restricted access to central historical area. Large pedestrian zones have been created in the city center. EVs are not subjected to restricted access and can also be driven on some of the pedestrian areas; for these reason, the use of EVs in Florence has been one of the case studies considered within ASTERICs project activities (Pfluegl et al., 2015). A low power charging infrastructure is also available (about 110 points, for a total availability of about 450 plugs).

The first aim of the development of a group of driving cycles for the Florence case study is to generate an input for simulation and testing activities using only data coming from EVs. A second aim is to make the dataset of acquired data available for processing in other applications as a source of driving data, as explained in Section 'From driving cycles to sequence generator'.

Context description and data acquisition

The data acquisition took place on vehicles which were used during their normal service both for private and business use. The speed of the vehicles, together with other powertrain information, has been acquired from on-board diagnostics; GPS data have been used mainly for geo-referencing and identification of driving context when manually examining the data in post processing. The acquisition sessions took place for nine months on 2013 in the city of Florence. The usable acquired data comprehend about 2500 km. It is notably to say that all the users and the owners declared that one of the main reasons for the use of electric vehicles was determined by the necessity to drive within the restricted traffic area of the city. A small fleet of EVs used by both professional and private drivers has therefore been monitored within its normal use. The driving sequences obtained can be considered naturalistic, since no predefined itinerary was imposed and since the logging instrumentations were absolutely not invasive. It has been verified through GPS data that the acquisition took place on various areas of the city, including historical center, urban and suburban ways. Such areas are mainly flat and significant or prolonged slopes have not been registered. Slope has not been used to define the driving cycles presented in this activities.

Large part of the acquisition included data coming from vehicles used by a freight delivery company in the city context; the service is similar to post delivery. The fleet include light vans (Renault Kangoo ZE, N1 class vehicle, electric, curb mass about 1400 kg) and quadricycles (Renault Twizy, L7e class, curb mass about 470 kg). The company owns a fleet of 15 electric vehicles in total, but, in general, not all the vehicles of the fleet are used every day, since this depends on the workload and on the availability of the drivers. As a consequence, the same vehicle can be used by different drivers. The use of the fleet was quite intense and the required range in some days exceeded the capability of the vehicles, so that they were charged everyday: charging during night was always performed, while partial charge during the day was also done frequently (e.g. at lunch break). It is important to note that due to the availability of a charging infrastructure in Florence – even if suitable only for low power charging – some drivers use the vehicles to go home, then park and charge there. Such kind of trips can be longer than usual delivery trips (e.g. some systematic runs of about 10–15 km in morning and evening hours have been recognized); it was chosen not to exclude this data from analysis. The examination of GPS data, where available, showed that such systematic trips account for about 20% of the total distance measured for these vehicles. The monitored fleet include three N1 electric vans and seven L7e electric quadricycles.

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

Data post processing and synthesis

The first step of the analysis included speed data filtering for the elimination of “spikes” or of any irregular data. Data have been acquired at a rate of 4 Hz, than a Kernel filter – as described by (De Haan and Keller, 2001) – has been applied, considering a time interval of one second. The filter is in the form:

$$v_{smoothed}(t) = \frac{1}{h}\sum_{s=-h}^{h} K\left(\frac{s}{h}\right) v(t+s) \tag{5}$$

where h is the time interval considered for the filter, v is speed, t is time, s is the time shift in respect to t ($-h < s < h$).

K is defined as:

$$K(x) = \begin{cases} \frac{15}{16}(1-x^2)^2 & (x^2 < 1) \\ 0 & otherwise \end{cases} \tag{6}$$

where x is $\frac{s}{h}$ as defined in Eq. (5).

An example of speed signal smoothing through this method is shown in Fig. 1.

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

- A vector of indicators, that is a selection of those adopted in literature (see Table 3);
- A speed–acceleration density matrix.

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

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

- The first method calculates these values considering the same threshold used for cruise and acceleration time percentage calculation. In other words, each value is coherent with the related others (e.g. mean positive acceleration value is calculated for those phases which are considered effective acceleration phases).
- The second method does not consider any threshold for acceleration, thus the mean acceleration value is not perfectly coherent with acceleration time percentage; this criterion is applied only to perform a confrontation with some literature works.

Analysis and clustering of driving sequences

Before the application of a grouping algorithm on the data, a manual cleanup has been performed. Short distance microtrips have been identified, since they can include data which are not suitable for general driving cycle generation, such as incomplete microtrips (e.g. generated by a delay between vehicle key-on event and logging start), sequences including reverse gear maneuvers. The examination of total distance run at high speed (exceeding 25 m/s. which has been chosen as threshold) together with the comparison with GPS data (where available) confirms that no continuous motorway driving has been measured for the vehicles under study; however, short trips on interchange roads (similar to motorways) have been found. After preliminary selection, the microtrips have been subjected to grouping process. The selected algorithm is the k-means ones. The conditions used for partitioning are:

- Each sample is described by SAPD density elements and by RMS, RPA and PKE element, that 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 4, which includes a selection of main parameters describing the microtrips included in the group. According to the scatter plot shown in Fig. 2, a short note describing the most probable driving characteristics for each cluster is offered (e.g. high or low stop duration, steady/unsteady variation of speed). Such notes are offered as an interpretation of the results of the grouping algorithm, but are not influencing the DC generation sequence, which is only based on quantitative parameters. An 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.

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

Customized driving cycles development

After grouping the microtrips, the creation process of a representative cycle consists of a first phase of "generation":

- The selection of the microtrips to be considered for cycle creation; depending on the scope of the cycle to be created, two choices are possible.
  - o The vehicle or vehicles from which the acquired data are coming (e.g. only L7, or only N1).
  - o The microtrip groups to be used, e.g. for an intense traffic situation groups having low stop-per-km value can be excluded.
- The selection of a target distance for the whole cycle.
  - o For each cluster, a target distance is set in order to maintain the same proportion of the original data set
- Random microtrips from each group are selected, until the target distance for that cluster has been reached.
  - o If the addition of a certain microtrip causes the overcome of target distance, the microtrip is truncated on a random point and glued together with the final portion of another microtrip, maintaining coherence for speed, acceleration and jerk values (threshold being 0.1 m/s, m/s^2 and m/s^3 respectively); the junction between microtrips is repeated in an iterative process if necessary. New microtrips, different from those part of the database, are therefore generated.
- All the chosen or generated microtrips are put beside each other, thus generating a cycle.
- The process is repeated for a number of predetermined attempts.

After the generation of the attempt cycles, the final proposal cycle is selected within the created ones on the basis of a three-step selection. Three criteria are applied in sequence:

1. Considering the parameters of Table 3 (from number 3 to number 14), the differences between those of the original dataset and of the generated cycles have to be below a threshold (that is, 5%) for at least 11 over 12 values; about 0.5–1% cycles of the generated ones usually respect this condition for a distance of about 10–15 km.

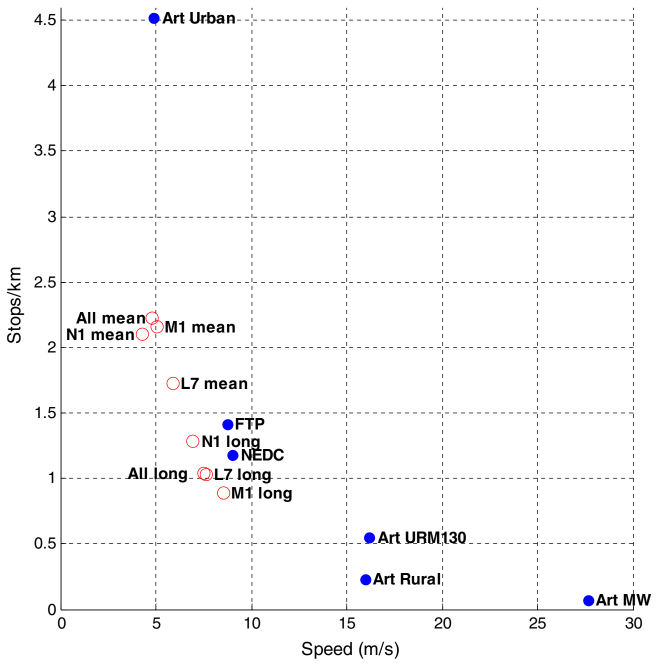

Fig. 16. Speed vs number of stops per km for existing and generated cycles.

2. For the reduced number of cycles chosen at step 1, those having similar PV are considered as candidate.
3. For the remaining candidate cycles, the final one is that having lower SSD between SAPD matrix.

If a satisfactory cycle cannot be found (e.g. it is not possible to find a cycle having both low PV and low SSD in comparison with other cycles), the whole process is repeated generating new cycles. The parameters to be included in $\underline{q}_t$ are numerous, in comparison with other literature studies, and have been decided through an internal consultation within EU FP7 ASTERICS project members.

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

- Depending on the source of the data, 5 vehicle categories are considered:
  - o All data from all vehicles are used, so that the cycle is representative of "average" electric vehicles; quadricycles data are included since, especially in urban driving, it is assumed that their performances are comparable with those of the other vehicles.
  - o Data from N1 passenger vehicles.
  - o Data from M1 light delivery vehicles.
  - o Data from quadricycles, so that the cycle is suitable for low powered vehicles.
  - o Data from N1 and M1 vehicles, using only "unsteady" sequences as identified during clustering phase.
- For each category, two different distances have been used:
  - o "long" cycles are based on the 95th percentile trip distance; all the microtrip clusters are considered (excluding clusters 1, 2, 4 and 7 for unsteady cycle) and, therefore, also high speed phases can be included.
  - o "mean" cycles are based on mean trip distance, but clusters 8 and 9 are not used since their data also include quite "long" microtrips, exceeding the whole target distance.

Table 5 summarizes the information and the assumptions used for the driving cycle generation. The characteristic of the synthetic cycles are shown in Tables 6 and 7. Figs. 4–13 show the comparison between the SAPD of original and synthetic data. The comparison between all vehicle SAPD and LDV vehicle SAPD highlights the more frequent occurrence of low-speed events for the latter one, as expected considering the typical needs of post services.

Finally, all the cycles are plot in Fig. 14.

The proposed cycles have been used within the ASTERICS project and, in particular, the unsteady long DC has been simulated to create a duty cycle for battery ageing test (Olofsson et al., 2014).

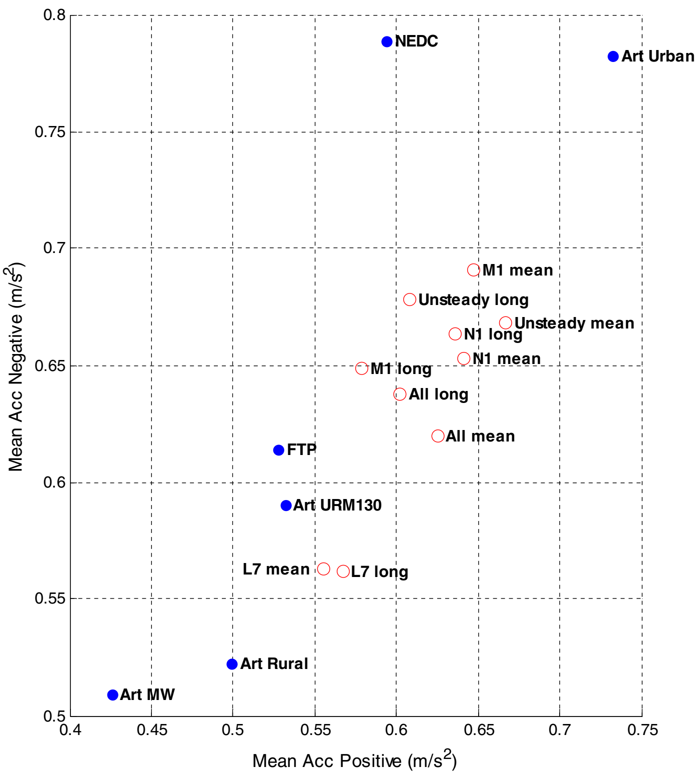

Fig. 17. Dot plots representing Mean Positive and Mean Negative accelerations for existing and generated cycles.

Comparison with existing cycles

As a final outcome, dot plots illustrating the characteristics of generated cycles in comparison with previously available ones are presented. In particular, Fig. 15 shows the average speed (including zero phases) in comparison with average positive acceleration, highlighting the proximity between typical urban cycles (NEDC and Artemis Urban) and generated ones (see "All mean" and "All long" dots), as expected due to the typical urban context in which the vehicles have been used (see Table 8 for DCs abbreviations).

The plot shown in Fig. 16 clearly shows that the mean speed and stops per km of the generated cycles fall in the same order of magnitude indicated for legislative cycles such as NEDC and FTP; however, a direct comparison between urban cycle ("All mean" generated cycles) and naturalistic urban driving cycles (Artemis Urban) highlights a lower stop per km number, even if the mean speed is absolutely similar. Similarly, Fig. 17 compares the cycles on the basis of Mean Positive and Negative accelerations. As known from previous studies, the trend shows that the values are generally higher for urban cycles in comparison with rural or motorway ones. Negative acceleration values are often slightly higher than positive ones. Regarding the generated cycles, mean negative values of acceleration are lower than those related to Artemis Urban naturalistic cycle.

At this stage, it is not possible to say if the shown differences are related to the peculiarities of EVs, to the characteristics of the traffic of Florence or to both. A qualitative observation is that EVs can be driven in a smooth way at very low speed, so that it is possible to reduce the number of start and stop phases even in intense traffic. In addition, such phases – sometimes described as "creeping" in literature – have been cut in former studies (Tong and Hung, 2010). Similarly, the attitude of the users to make the most of regenerative braking capabilities can explain the reduction of the mean negative acceleration value in comparison with other naturalistic cycles.

However, it is not possible, within this study, to completely separate the effect of the context (city of Florence), of the vehicle (Electric, various classes) and of its mission (passenger or freight transport). Therefore, future studies should verify the occurrence of different driving behavior due to EVs characteristics. A suitable method is to perform a direct comparison of driving parameters for EVs and ICEVs when used in the same context, in order to confirm or disprove the preliminary hypotheses here formulated.

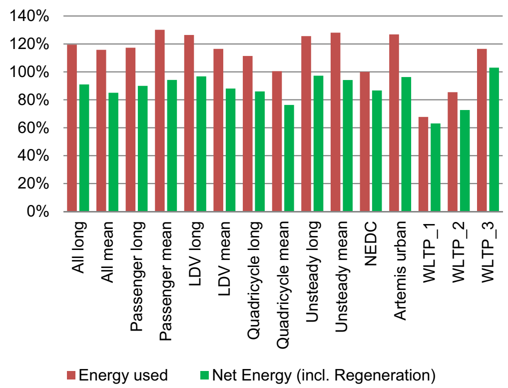

Fig. 18. Results of the estimation of EV energy consumption using different driving cycles as input. WLTP_1, WLP_2 and WLTP_3 refers to WLTP cycle class 1, class 2 and class 3 respectively. Base value: NEDC energy consumption, not including regeneration.

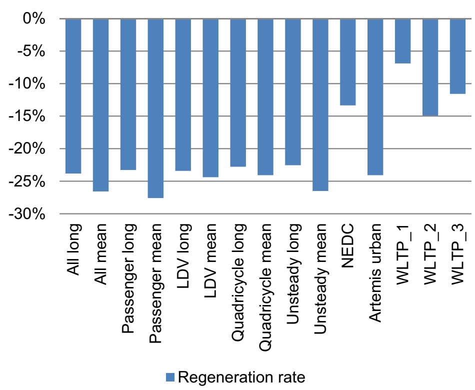

Fig. 19. Results of the estimation of EV energy regeneration rate using different driving cycles as input. Base value: energy used per cycle.

It can be noted also that L7 vehicle shows for both "long" and "mean" cycles lower values of mean accelerations, as expected due to its low power characteristics.

In addition to pure parametric comparison the generated DCs have been tested as input for a simulation model. The model is based on longitudinal dynamics and is suitable for energy consumption assessments; it has been prepared in Matlab/Simulink environment using the typical data representative of a small size M1 car (about 1100 kg curb weight, 50 kW power), comparable with Peugeot iOn vehicle; the model parameters have been set on the basis of measured data and using suitable benchmark studies (Eckstein et al., 2013; Geringer and Tober, 2012). The results of the assessment show that the Florence DCs are quite demanding in comparison with NEDC cycle, the energy consumption per km being higher from a minimum of 10% (Quadricycle long cycle) to a maximum of about 30% (Passenger mean and Unsteady cycles; see Fig. 18). Only the Quadricycle mean cycle shows an energy consumption comparable with NEDC. If regenerative braking capabilities are considered, the discrepancies between the cycles is significantly reduced, thus highlighting the relevance of such feature for EVs; the model, based on real regeneration map of iOn motor, highlights a reduction in the order of 20–25% for generated DCs, and about 14% for NEDC (see Fig. 19). Finally, it can be said that, according to a preliminary simulation model, the generated cycles are more energy demanding than the NEDC. The values obtained are comparable to the ones generated using ARTEMIS Urban cycle and WLTP class 3 cycles; this latter, however, shows a smaller potential for regeneration in comparison with generated DCs, probably due to the presence of a prolonged high-speed phase.

Extended use of measured driving data

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

The second main product of driving cycle analysis activity is therefore a package for data analysis and cycle synthesis. The package implements the same methodology applied for cycle generation (as described in the former paragraph) and is prepared as a Matlab-based product with Graphical Users Interface (GUI). The tool – "builder" – is an interpreter of data that can be used to generate new cycles and to verify their similarity with original data. The user can set a few parameters (the target distance, the vehicle data to be used, the data groups to be included, the acceptance thresholds), than a number of "attempts" cycles can be generated; if any of the created cycles fits with original dataset, the tools plots the generated "representative" cycle and saves it in a spreadsheet. Saved data include the speed signal, the acceptance results (number of similar parameters, Performance Values – PV – indicator, Sum Square Distance – SSD – of speed–acceleration density matrix – SAPD) and the general describing parameters.

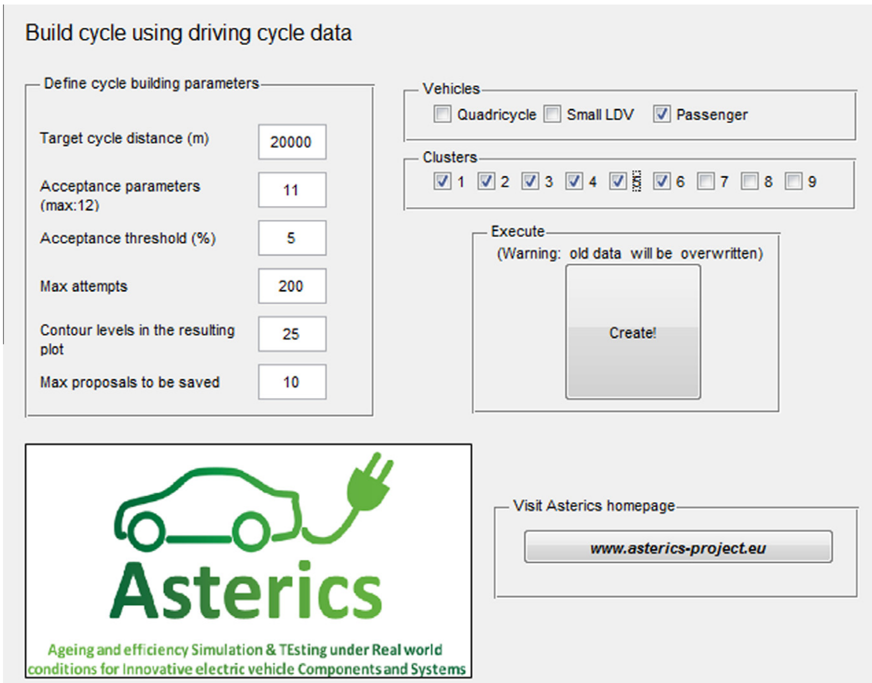

Fig. 20. Driving cycle "builder" tool: main GUI screenshot.

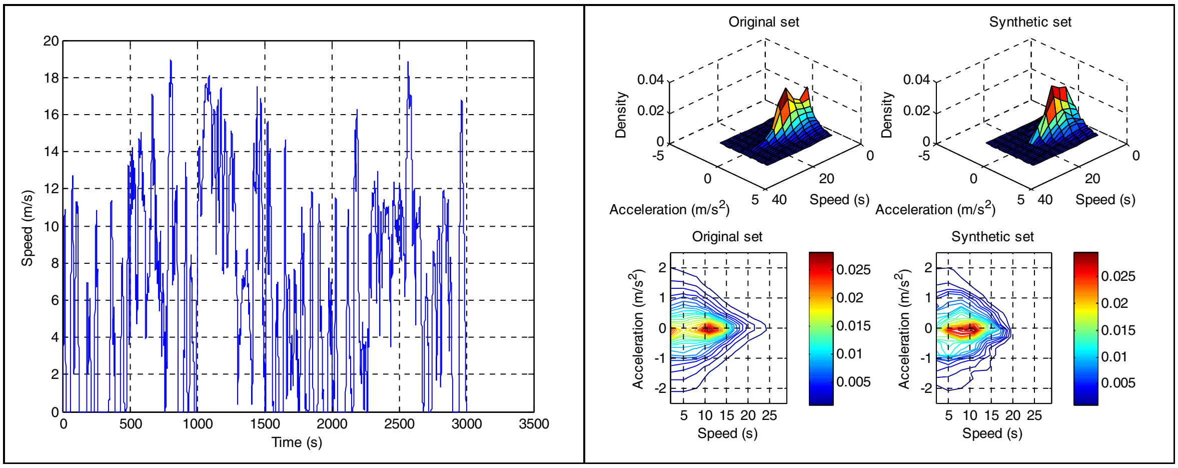

Fig. 21. Output from "builder" tool: cycle plot (left), cycle SAPD plot (right).

Generator tool can be used for two different applications:

1. If the purpose is to create a repeatable test, it can be used to create a customized cycle, selecting the groups to be used.
2. If the purpose is to overcome the limitations of existing or normalized test (e.g. to test vehicle control systems), the added value of the tool is to shuffle the data creating un-repeated sequences coming from the same database.

The interface of the tool is shown in Fig. 20; it is also part of the research products for the project ASTERICs. Its typical output is shown in Fig. 21. The tool can be used also through command line and is therefore suitable for the integration on simulation environment.

Conclusions

Driving cycles are a relevant input for the development of procedures for design, testing and homologation of any kind of vehicles; such topic is particularly relevant considering the high level of attention on vehicles both for pollutants emission and energy use. In the first part of the present work a summarization of current state of the art on the topic has been proposed. A few main findings emerged from the preliminary analysis of the topic. A large number of synthesis methods have been proposed, most of them being similar on their key points. Literature analysis also highlights a strong need for continuous improvement of the cycles in terms of detail and variety, in order to catch the peculiarities of the vehicle under study and of the area where it is used; such need is therefore the main motivation to propose a new case study. In addition, recent applied research activities show the emerging trend of tools able to generate "on demand" cycles; such data can be used during vehicle development and for simulation and testing activities, as improved input in comparison with synthetic cycles. However, a synthesis method has been prepared considering reference experiences.

In the second part of the work an application case study has been proposed through monitoring of a small fleet of EVs. Driving data within the city of Florence have been acquired, including restricted access areas open to EVs but not to ICEVs. Using the developed method, the data have been therefore processed in order to build up a set of ten synthetic cycles, differing for the type of vehicle used (from low powered quadricycles, to light vans and passenger cars) and for the distance proposed (from typical city route – build up using mainly urban sequences – to mixed route, including fluent driving on longer distances). The cycles represent main outcome of the activity, their peculiarity being the use of data coming exclusively from EVs. In addition, the time-speed vector for each cycle has been defined using four points per second, which is an improved level of detail in comparison with existing cycles; the aim is to offer the possibility to increase the precision of energy consumption and efficiency assessment in simulation activities. The activity is than concluded proposing a short comparison with existing cycles; considering naturalistic cycles, a few differences in typical kinematic indicators are noticeable; at the present stage it cannot be said if the spreading of the data is related to the characteristics of the city, to the relatively small number of drivers involved (a known limitation of the study) or to the peculiarities of electric vehicles, most evident being the regenerative braking capabilities and the fluent traction at very low speed. Both characteristics, in fact, can potentially let the drivers obtain smooth acceleration events even in intense traffic situations. The use of a simplified simulation model highlights that most generated cycles are expected to be more demanding than the well known NEDC.

A suggestion for future development is to investigate about the attitude of the users in driving EVs in comparison with ICEVs, in order to verify if different powertrain characteristics can induce remarkable modification on driving style. Finally, an interpreter tool for further valorization of the whole dataset has been developed and implemented both as GUI and command-line function. Such activity has been prepared to overcome the limitations of "rigid" representative cycles and extend the representativeness of the data during vehicle development phases, coherently with recent literature experiences and applied research trends.

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http://cordis.europa.eu/fp7/cooperation/home_en.html.

http://ec.europa.eu.

http://www.asterics.eu.

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References

Adornato, B., Patil, R., Filipi, Z., Baraket, Z., Gordon, T., 2009. Characterizing naturalistic driving patterns for plug-in hybrid electric vehicle analysis. In: IEEE Vehicle Power and Propulsion Conference, 2009. VPPC '09. Presented at the IEEE Vehicle Power and Propulsion Conference, 2009, VPPC '09, pp. 655–660. http://dx.doi.org/10.1109/VPPC.2009.5289786.

Alessandrini, A., Filippi, F., Orecchini, F., Ortenzi, F., 2006. A new method for collecting vehicle behaviour in daily use for energy and environmental analysis. Proc. Inst. Mech. Eng. Part J. Automob. Eng. 220, 1527–1537. http://dx.doi.org/10.1243/09544070JAUTO165.

Alessandrini, A., Orecchini, F., 2003. A driving cycle for electrically-driven vehicles in Rome. Proc. Inst. Mech. Eng. Part J. Automob. Eng. 217, 781–789. http://dx.doi.org/10.1177/095440700321700903.

Alessandrini, A., Orecchini, F., Ortenzi, F., Campbell, F.V., 2009. Drive-style emissions testing on the latest two Honda hybrid technologies. Eur. Transp. Res. Rev. 1, 57–66. http://dx.doi.org/10.1007/s12544-009-0008-3.

André, M., 2004. The ARTEMIS European driving cycles for measuring car pollutant emissions. Sci. Total Environ. 334–335, 73–84. http://dx.doi.org/10.1016/j.scitotenv.2004.04.070.

André, M., Joumard, R., Vidon, R., Tassel, P., Perret, P., 2006. Real-world European driving cycles, for measuring pollutant emissions from high- and low-powered cars. Atmos. Environ. 40, 5944–5953. http://dx.doi.org/10.1016/j.atmosenv.2005.12.057.

Barlow, T.J., Latham, S., McCrae, I.S., Boulter, P.G., 2009. A reference book of driving cycles for use in the measurement of road vehicle emissions. Ref. Book Driv. Cycles Use Meas. Road Veh. Emiss. 1, 1–280.

Beusen, B., Broekx, S., Denys, T., Beckx, C., Degraeuwe, B., Gijsbers, M., Scheepers, K., Govaerts, L., Torfs, R., Panis, L.I., 2009. Using on-board logging devices to study the longer-term impact of an eco-driving course. Transp. Res. Part Transp. Environ. 14, 514–520. http://dx.doi.org/10.1016/j.trd.2009.05.009.

Bishop, J.D.K., Axon, C.J., McCulloch, M.D., 2012. A robust, data-driven methodology for real-world driving cycle development. Transp. Res. Part Transp. Environ. 17, 389–397. http://dx.doi.org/10.1016/j.trd.2012.03.003.

Borgarello, L., Fortunato, A., Gortan, L., Mina, L., Ragione, L.D., Meccariello, G., Prati, M.V., Rapone, M., 2001. Preliminary results on emissions and driving behavior of ATENA fleet test project in Naples (SAE Technical Paper No. 2001-24-0083). SAE International, Warrendale, PA.

Borgarello, L., Galliera, E., Avanzo, A., Fagiano, A., 2010. Roller bench urban cycles identification for light commercial vehicles fuel consumption. Ital. J. Appl. Stat. 22, 353–362.

Capitani, R., Delogu, M., Orofino, L., 2003. Vehicle consumption evaluation using simulation models reproducing gear management. Strategies 25–32. http://dx.doi.org/10.1115/IMECE2003-41937.

Capitani, R., Delogu, M., Pilo, L., 2001. Analysis of the Influence of a Vehicle's Driveline Dynamic Behaviour Regarding the Performance Perception at Low Frequencies (SAE Technical Paper No. 2001-01-3333). SAE International, Warrendale, PA.

Chaudhari, A.R., Thring, R.H., 2011. Energy economy analysis of the G-Wiz: a two-year case study based on two vehicles. Proc. Inst. Mech. Eng. Part J. Automob. Eng. 225, 1505–1517. http://dx.doi.org/10.1177/0954407011408369.

Corcoba Magana, V., Munoz-Organero, M., 2011. Artemisa: an eco-driving assistant for Android Os. In: 2011 IEEE International Conference on Consumer Electronics – Berlin (ICCE-Berlin). Presented at the 2011 IEEE International Conference on Consumer Electronics – Berlin (ICCE-Berlin), pp. 211–215. http://dx.doi.org/10.1109/ICCE-Berlin.6031794.

Corti, A., Manzoni, V., Savaresi, S.M., 2012. Vehicle's energy estimation using low frequency speed signal. In: 2012 15th International IEEE Conference on Intelligent Transportation Systems (ITSC). Presented at the 2012 15th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 626–631. http://dx.doi.org/10.1109/ITSC.2012.6338758.

De Haan, P., Keller, M., 2004. Modelling fuel consumption and pollutant emissions based on real-world driving patterns: the HBEFA approach. Int. J. Environ. Pollut. 22, 240–258.

De Haan, P., Keller, M., 2001. Real-world Driving Cycles for Emission Measurements: ARTEMIS and Swiss Cycles – Final Report.

Delogu, M., Pilo, L., 2002. Influence of Throttle Control System in Vehicle-Driveline Dynamic and in Car Performance Perception (SAE Technical Paper No. 2002-01-2157). SAE International, Warrendale, PA.

Demuynck, J., Bosteels, D., De Paepe, M., Favre, C., May, J., Verhelst, S., 2012. Recommendations for the new WLTP cycle based on an analysis of vehicle emission measurements on NEDC and CADC. Energy Policy, Special Section: Fuel Poverty Comes of Age: Commemorating 21 Years of Research and Policy 49, 234–242. http://dx.doi.org/10.1016/j.enpol.2012.05.081.

Eckstein, U.-P.D.-I.L., Göbbels, D.-I.R., Wohlecker, D.-I.D.-W.I.R., 2013. Benchmarking des Elektrofahrzeugs Mitsubishi i-MiEV. In: Siebenpfeiffer, W. (Ed.), Energieeffiziente Antriebstechnologien. Springer Fachmedien Wiesbaden, ATZ/MTZ-Fachbuch, pp. 22–29.

Esteves-Booth, A., Muneer, T., Kubie, J., Kirby, H., 2002. A review of vehicular emission models and driving cycles. Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci. 216, 777–797. http://dx.doi.org/10.1243/09544060260171429.

Gerardo, B.D., Lee, J., 2009. A framework for discovering relevant patterns using aggregation and intelligent data mining agents in telematics systems. Telemat. Inform. 26, 343–352. http://dx.doi.org/10.1016/j.tele.2008.05.003.

Geringer, B., Tober, W.E., 2012. Battery Electric Vehicles in Practice, Costs, Range, Environment, Convenience – 2nd Extended and Corrected Edition. Vienna University of Technology.

Gong, Q., Midlam-Mohler, S., Marano, V., Rizzoni, G., 2012. Virtual PHEV fleet study based on Monte Carlo simulation. Int. J. Veh. Des. 58, 266–290. http://dx.doi.org/10.1504/IJVD.2012.047388.

Han, D.S., Choi, N.W., Cho, S.L., Yang, J.S., Kim, K.S., Yoo, W.S., Jeon, C.H., 2012. Characterization of driving patterns and development of a driving cycle in a military area. Transp. Res. Part Transp. Environ. 17, 519–524. http://dx.doi.org/10.1016/j.trd.2012.06.004.

Hung, W.T., Tong, H.Y., Lee, C.P., Ha, K., Pao, L.Y., 2007. Development of a practical driving cycle construction methodology: a case study in Hong Kong. Transp. Res. Part Transp. Environ. 12, 115–128. http://dx.doi.org/10.1016/j.trd.2007.01.002.

Jun, J., Guensler, R., Ogle, J., 2006. Smoothing methods to minimize impact of global positioning system random error on travel distance, speed, and acceleration profile estimates. Transp. Res. Rec. J. Transp. Res. Board 1972, 141–150. http://dx.doi.org/10.3141/1972-19.

Kenworthy, J.R., Newman, P.W.G., Lyons, T.J., 1992. The ecology of urban driving I—methodology. Transp. Res. Part Policy Pract. 26, 263–272. http://dx.doi.org/10.1016/0965-8564(92)90036-7.

Krumm, J., 2012. How People Use Their Vehicles: Statistics from the 2009 National Household Travel Survey (SAE Technical Paper No. 2012-01-0489). SAE International, Warrendale, PA.

Kumar, R., Parida, P., Saleh, W., Gupta, K., Durai, B.K., 2012. Driving cycle for motorcycle using micro-simulation model. J. Environ. Prot. 03, 1268–1273. http://dx.doi.org/10.4236/jep.2012.329144.

Lee, T.-K., Adornato, B., Filipi, Z.S., 2011. Synthesis of real-world driving cycles and their use for estimating PHEV energy consumption and charging opportunities: case study for Midwest/U.S. IEEE Trans. Veh. Technol. 60, 4153–4163. http://dx.doi.org/10.1109/TVT.2011.2168251.

Liaw, B.Y., 2004. Fuzzy logic based driving pattern recognition for driving cycle analysis. J. Asian Electr. Veh. 2, 551–556. http://dx.doi.org/10.4130/jaev.2.551.

Liaw, B.Y., Dubarry, M., 2007. From driving cycle analysis to understanding battery performance in real-life electric hybrid vehicle operation. J. Power Sources 174, 76–88. http://dx.doi.org/10.1016/j.jpowsour.2007.06.010.

Lin, J., Niemeier, D.A., 2003. Regional driving characteristics, regional driving cycles. Transp. Res. Part Transp. Environ. 8, 361–381. http://dx.doi.org/10.1016/S1361-9209(03)00022-1.

Lyons, T.J., Kenworthy, J.R., Austin, P.I., Newman, P.W.G., 1986. The development of a driving cycle for fuel consumption and emissions evaluation. Transp. Res. Part Gen. 20, 447–462. http://dx.doi.org/10.1016/0191-2607(86)90081-6.

Manzoni, V., Corti, A., De Luca, P., Savaresi, S.M., 2010. Driving style estimation via inertial measurements. In: 2010 13th International IEEE Conference on Intelligent Transportation Systems (ITSC). Presented at the 2010 13th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 777–782. http://dx.doi.org/10.1109/ITSC.2010.5625113.

Ma, X., Andreasson, I., 2007. Behavior measurement, analysis, and regime classification in car following. IEEE Trans. Intell. Transp. Syst. 8, 144–156. http://dx.doi.org/10.1109/TITS.2006.883111.

Montazeri, M., Fotouhi, A., Naderpour, A., 2012. Driving segment simulation for determination of the most effective driving features for HEV intelligent control. Veh. Syst. Dyn. 50, 229–246. http://dx.doi.org/10.1080/00423114.2011.577898.

Moura, S.J., Fathy, H.K., Callaway, D.S., Stein, J.L., 2011. A stochastic optimal control approach for power management in plug-in hybrid electric vehicles. IEEE Trans. Control Syst. Technol. 19, 545–555.

Neubauer, J., Wood, E., 2014. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. J. Power Sources 257, 12–20. http://dx.doi.org/10.1016/j.jpowsour.2014.01.075.

Newman, P.W.G., Kenworthy, J.R., Lyons, T.J., 1992. The ecology of urban driving II—driving cycles across a city: their validation and implications. Transp. Res. Part Policy Pract. 26, 273–290. http://dx.doi.org/10.1016/0965-8564(92)90037-8.

Olofsson, Y., Groot, J., Katrašnik, T., Tavčar, G., 2014. Impedance spectroscopy characterisation of automotive NMC/graphite Li-ion cells aged with realistic PHEV load profile. In: Electric Vehicle Conference (IEVC), 2014 IEEE International. Presented at the Electric Vehicle Conference (IEVC), 2014 IEEE International, pp. 1–6. http://dx.doi.org/10.1109/IEVC.2014.7056095.

Ozdemir, S., Elma, O., Acar, F., Selamogullari, U.S., 2014. Analyzing the capacity utilization rate of traction motor drives in electric vehicles with real world driving cycles. In: 2014 IEEE Vehicle Power and Propulsion Conference (VPPC). Presented at the 2014 IEEE Vehicle Power and Propulsion Conference (VPPC), pp. 1–6. http://dx.doi.org/10.1109/VPPC.2014.7007022.

Pasaoglu, G., Fiorello, D., Martino, A., Zani, L., Zubaryeva, A., Thiel, C., 2014. Travel patterns and the potential use of electric cars – results from a direct survey in six European countries. Technol. Forecast. Soc. Change 87, 51–59. http://dx.doi.org/10.1016/j.techfore.2013.10.018.

Pfluegl, H., Ricci, C., Borgarello, L., Magnin, P., Sellier, F., Berzi, L., Pierini, M., Mazal, C., Benzaoui, H., 2015. A framework for electric vehicle development: from modelling to engineering through real-world data analysis. In: Müller, B., Meyer, G. (Eds.), Electric Vehicle Systems Architecture and Standardization Needs. Springer International Publishing, Lecture Notes in Mobility, pp. 55–73.

Primerano, F., Taylor, M.A.P., Pitaksringkarn, L., Tisato, P., 2008. Defining and understanding trip chaining behaviour. Transportation 35, 55–72. http://dx.doi.org/10.1007/s11116-007-9134-8.

Saleh, W., Kumar, R., Kirby, H., Kumar, P., 2009. Real world driving cycle for motorcycles in Edinburgh. Transp. Res. Part Transp. Environ. 14, 326–333. http://dx.doi.org/10.1016/j.trd.2009.03.003.

Schwarzer, V., Ghorbani, R., 2013. Drive cycle generation for design optimization of electric vehicles. IEEE Trans. Veh. Technol. 62, 89–97. http://dx.doi.org/10.1109/TVT.2012.2219889.

Shankar, R., Marco, J., Assadian, F., 2012. A methodology to determine drivetrain efficiency based on external environment. In: Electric Vehicle Conference (IEVC), 2012 IEEE International. Presented at the Electric Vehicle Conference (IEVC), 2012 IEEE International, pp. 1–6. http://dx.doi.org/10.1109/IEVC.2012.6183192.

Sileghem, L., Bosteels, D., May, J., Favre, C., Verhelst, S., 2014. Analysis of vehicle emission measurements on the new WLTC, the NEDC and the CADC. Transp. Res. Part Transp. Environ. 32, 70–85. http://dx.doi.org/10.1016/j.trd.2014.07.008.

Smart, J., Powell, W., Schey, S., 2013. Extended Range Electric Vehicle Driving and Charging Behavior Observed Early in the EV Project (SAE Technical Paper No. 2013-01-1441). SAE International, Warrendale, PA.

Smith, R., Shahidinejad, S., Blair, D., Bibeau, E.L., 2011. Characterization of urban commuter driving profiles to optimize battery size in light-duty plug-in electric vehicles. Transp. Res. Part Transp. Environ. 16, 218–224. http://dx.doi.org/10.1016/j.trd.2010.09.001.

Souffran, G., Miegeville, L., Guerin, P., 2012. Simulation of real-world vehicle missions using a stochastic markov model for optimal powertrain sizing. IEEE Trans. Veh. Technol. 61, 3454–3465. http://dx.doi.org/10.1109/TVT.2012.2206618.

Tong, H.Y., Hung, W.T., 2010. A framework for developing driving cycles with on-road driving data. Transp. Rev. 30, 589–615. http://dx.doi.org/10.1080/01441640903286134.

Travesset-Baro, O., Rosas-Casals, M., Jover, E., 2015. Transport energy consumption in mountainous roads. A comparative case study for internal combustion engines and electric vehicles in Andorra. Transp. Res. Part Transp. Environ. 34, 16–26. http://dx.doi.org/10.1016/j.trd.2014.09.006.

UNECE, 2015. Worldwide Harmonized Light Vehicles Test Procedure (WLTP) – Transport – Vehicle Regulations – UNECE Wiki [WWW Document]. <https://www2.unece.org/wiki/pages/viewpage.action?pageId=2523179> (accessed 4.8.15).

Valero-Mora, P.M., Tontsch, A., Welsh, R., Morris, A., Reed, S., Touliou, K., Margaritis, D., 2013. Is naturalistic driving research possible with highly instrumented cars? Lessons learnt in three research centres. Accid. Anal. Prev. 58, 187–194. http://dx.doi.org/10.1016/j.aap.2012.12.025.

Van Haaren, R., 2011. Assessment of electric cars' range requirements and usage patterns based on driving behavior recorded in the National Household Travel Survey of 2009. Sol. Journey USA, 1–56.

Waldowski, P., Marker, S., Schulz, A., Schindler, V., Rippel, B., 2011. BEV, REEV or PHEV? – Deciding Between Different Alternative Drives Based on Measured Individual Operational Profiles. In: Les Rencontres Scientifiques d'IFP Energies Nouvelles. Presented at the International Scientific Conference on Hybrid and Electric Vehicles (RHEVE).

Wang, Q., Huo, H., He, K., Yao, Z., Zhang, Q., 2008. Characterization of vehicle driving patterns and development of driving cycles in Chinese cities. Transp. Res. Part Transp. Environ. 13, 289–297. http://dx.doi.org/10.1016/j.trd.2008.03.003.

Weiss, M., Bonnel, P., Kühlwein, J., Provenza, A., Lambrecht, U., Alessandrini, S., Carriero, M., Colombo, R., Forni, F., Lanappe, G., Le Lijour, P., Manfredi, U., Montigny, F., Sculati, M., 2012. Will Euro 6 reduce the NOx emissions of new diesel cars? Insights from on-road tests with Portable Emissions Measurement Systems (PEMS). Atmos. Environ. 62, 657–665. http://dx.doi.org/10.1016/j.atmosenv.2012.08.056.

Glossary

BEV: Battery Electric Vehicle
DC: Driving Cycle
EV: Electric Vehicle; the acronym can be used to indicate BEV, HEV and other vehicle categories
GHG: Greenhouse Gases
HEV: Hybrid Electric Vehicle
HVAC: Heating, Ventilation and Air Conditioning
ICEV: Internal Combustion Engine Vehicle
LDV: Light Delivery Vehicle
NEDC: New European Driving Cycle
PV: Performance Value
SAPD: Speed Acceleration Probability Distribution
SIL/HIL/MIL: Respectively: Software, Hardware, and Model-In-the-Loop environment
SSD: Sum Square Distance
WLTC: Worldwide harmonized Light vehicles Test Cycles
-: For driving cycle related indicators, please refer to the abbreviations provided in Table 2