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DRIVING CYCLE FOR PASSENGER CARS ON URBAN ROADS IN PRISTINA, KOSOVO

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Abstract. The driving cycle is a significant input for the micro-scale analysis of vehicle emission. Several cities around the world have developed driving cycles based on their driving behaviours, while Pristina still has a lack of studies on this issue. Thus, the first objective of this study was to represent the proper driver behaviour of passenger cars in Pristina by obtaining a driving cycle from real-time measurements on the road. The driving cycle was developed by extracting the micro-trips from 53 491 s of data using a "3-sequential points" algorithm, where 780 micro-trips were detected. Using the K-means method from 780 micro-trips, we selected only 25 to develop the final driving cycle. The second objective was to analyse the effects of different intersections on the final driving cycle parameters. We found that the final driving cycle had significant differences from driving cycle of other cities. Driving habits in Pristina are more aggressive compared to other European cities. Also, we found that the average speed of roundabouts and un-signalized intersections was statistically different from signalized intersections.

Keywords: bootstrapping, driving cycle, intersections driving characteristics, K-means method, micro-trips method, on-board diagnostic measurements.

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Introduction

Pristina is the capital of Kosovo, and passenger cars share significant traffic on the roads. Public transportation shares approximately 15% of total mobility, while other forms of transport are not as suitable for use. The rate use of passenger cars is more than 80% of the total of vehicles on the roads due to insufficient public transportation. While the authorities are trying to adopt different policies to reduce the use of passenger cars by investing in public transportation and infrastructure, people choose automobiles for their trips. Hence, it is urgent to develop a driving cycle in Pristina to estimate the real emission sourced from vehicles. Driving behaviour or driving pattern, represented by driving cycle, is a significant parameter for understanding how drivers behave in traffic along their trips and for predicting pollution sourced from vehicles. Selecting the speed with high and low amplitudes and vigorous or frequent acceleration and deceleration will lead to high emission and directly increase air pollution. Each driver has their own driving style, and countries have different driving styles depending on what types of policies have been settled to train a driver on how to use the car with low emission in the environment (Arun et al., 2017). An emission model based on a standard driving cycle (for example, New European Driving Cycle "NEDC", or any other standard cycle) for different countries is not sufficient to show a real driving behaviour because each city has its own driving cycle (Esteves-Booth et al., 2002). The NEDC based driving cycle has been developed to show the driver conditions of most European cities. However, many studies have shown that emission models in specific cities have given different results from the emission model derived by NEDC. Pelkmans & Debal (2006) found that vehicle emissions measured from NEDC and the real driving cycle were different, where CO and NOx for Euro 4 could be 10 times more than the emission model derived from NEDC. Standard cycle or data of driving behaviours from other countries cannot be used to create an emission model for a specific country because of driving behaviour differences (Van Mierlo et al., 2004). Therefore, it is crucial to create a driving cycle based on driving behaviour, city topography, vehicle type, traffic conditions, and transportation system control. A driving cycle can be synthesized or modal (NEDC, Japanese Cycle, etc.) and real-world (actual or transient driving cycle) (Amirjamshidi & Roorda, 2015; Kamble et al., 2009; Tong & Hung, 2010). The first type of driving cycle cannot represent driver behaviour for different cities, while the second must be developed from real data collected for a particular city under the study. Therefore, different studies have shown that the driving cycle is a significant input in creating a model for emission. A driving cycle must be developed for specific countries and it should be based on driver speed-time profiles (Amirjamshidi & Roorda, 2015; Yu et al., 2008). The speed-time profile includes all vehicle operations such as acceleration, deceleration, cruising mode (with constant speed) and idle (when the car is stopped because of traffic congestion or in a red light at a signalized intersection or in any situation where the car is stopped but the engine is running). Different methods have been used to develop driving cycles, while the micro-trips-based method has shown accurate results in assessing vehicle emission (Dai et al., 2008). The driving cycle is compounded from micro-trips, where the speed-time profile is divided into smaller parts between two idling periods (Lin & Niemeier, 2003), while the driving cycle should be 10–30 min long (Yu et al., 2010) to present a real-world driving behaviour. However, a driving cycle with a duration of 20 min is preferred to reflect real driving characteristics (Hung et al., 2007).

The proper driving cycle requires real measurements in traffic using the chase-car method or the on-board diagnostic (OBD) method to describe driving characteristics. Driving cycles acquired from the real traffic data are separated into micro sets of speed-time profiles called micro-trips.

A speed-time profile, which represents the time or position of a vehicle from start to rest mode (speed zero), should be defined to derive one micro-trip form. From this concept, it follows that one micro-trip should contain at least one acceleration and deceleration mode. However, when the idle mode is presented, it must be incorporated into a micro-trip (Figure 1). The measurements of driving data could

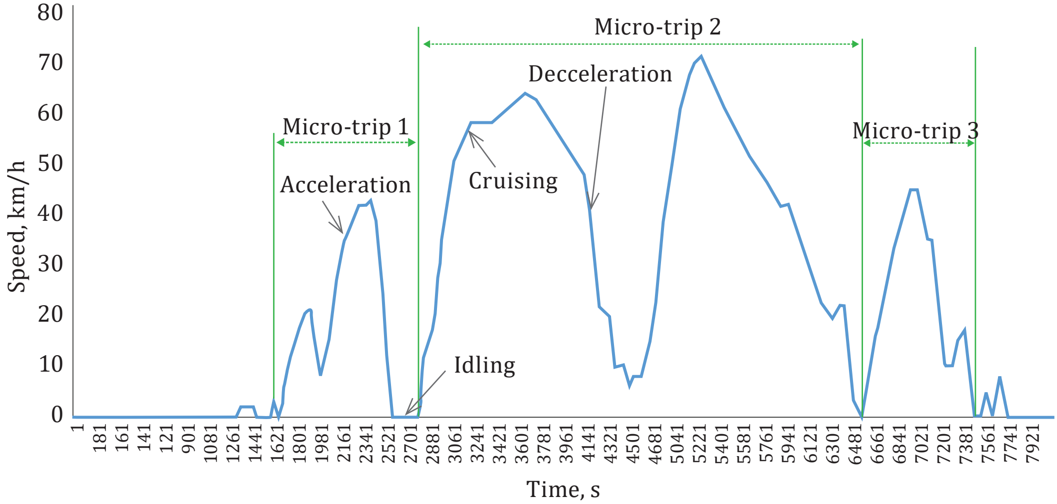

Figure 1. Speed-time profile

Table 1. Assessment measures to develop the driving cycle

	Parameters to describe driving characteristics (parameters from speed–time profile)	Nesamani & Subramanian, 2011	Amirjamshidi & Roorda, 2015	Arun et al., 2017	Kamble et al., 2009	Yang et al., 2019	Mahesh et al., 2018	Tong et al., 1999	Tsai et al., 2005	Hung et al., 2007	Wang et al., 2008	Saleh et al., 2009
1.	Average speed of the trips, km/h	V_1	V	V	$Vavg_{mt}$	V_m	P	v_1	v_1	v	V_1	V_1
2.	Average running speed of the trips (idling is excluded), km/h	V_2	V_r	V_r	–	V_{mr}	P	v_2	v_2	v_r	V_2	V_2
3.	Maximum speed of the trips, km/h	V_{max}	–	–	–	V_{max}	P	–	–	–	–	–
4.	Average acceleration of the trips, m/s^2	A_{cc}	A	a	–	A	–	a	a	a	A	A
5.	Average deceleration of the trips, m/s^2	D_{ec}	D	d	–	D	–	d	d	d	D	D
6.	Maximum acceleration of the trips, m/s^2	A_{ccmax}	–	–	–	A_{max}	P	–	–	–	–	–
7.	Maximum deceleration of the trips, m/s^2	D_{ecmax}	–	–	–	A_{min}	P	–	–	–	–	–
8.	Percentage of time spent in idle mode – Speed equals zero, %	P_i	P_i	P_i	Pi_b, Pi_{mt}	P_i >1 km/h	P	P_i	P_i	P_i	P_i	P_i
9.	Percentage of time spent in acceleration mode, %	P_a>5 km/h A_{cc}>0.1 m/s^2	P_a	P_a>5 km/h a>0.1 m/s^2	Pa_b, Pa_{mt}	P_a >0.14 m/s^2	P	P_a	P_a	P_a	P_a	P_a
10.	Percentage of time spent in deceleration mode, %	P_d>5 km/h D_{cc}>0.1 m/s^2	P_d	P_d>5 km/h d>0.1 m/s^2	Pd_b, Pd_{mt}	P_d <0.14 m/s^2	P	P_d	P_d	P_d	P_d	P_d
11.	Percentage of time spent in creeping mode, %	P_{cr}<5 km/h A_{cc}/D_{cc}<0.1 m/s^2	P_{crp} <4 km/h	P_{cr}<5 km/h a/d<0.1 m/s^2	–	–		–	–	P_{cr}	–	–
12.	Percentage of time spent in cruising mode, %	P_c>5 km/h A_{cc}/D_{cc}<0.1 m/s^2	P_{crs}	P_c>5 km/h a/d<0.1 m/s^2	Pc_b, Pc_{mt}	P_c>1 km/h a/d<0.14 m/s^2	P	P_c	P_c	P_c	P_c	P_c
13.	Positive kinetic energy $\sum\left(V_i^2 - V_{i-1}^2\right)/\text{Distance}$, m/s^2	PKE	–	PKE	–	–	–	PKE	PKE	PKE	PKE	PKE

	Parameters to describe driving characteristics (parameters from speed–time profile)	Nesamani & Subramanian, 2011	Amirjamshidi & Roorda, 2015	Arun et al., 2017	Kamble et al., 2009	Yang et al., 2019	Mahesh et al., 2018	Tong et al., 1999	Tsai et al., 2005	Hung et al., 2007	Wang et al., 2008	Saleh et al., 2009
14.	Number of stops per km, Stop/km	No.	–	–	–	–	–	–	–	–	–	–
15.	Average micro–trip duration, s		*D*	–	–	–	–	–	–	t_m	–	–
16.	Average percentage of acceleration – deceleration changes, %	–	Acc–dec	–	–	–	–	M	M	M	–	M
17.	Root mean square acceleration $a_{rms} = \sqrt{\left(\sum_{i-1}^{1} \text{acceleration}^2\right) / n}$, m/s^2	–	RMSA	RMSA	–	–	–	RMS	RMS	a_{rms}	–	RMS
18.	Root mean square of positive kinetic energy overweight, m/s	–	RMSPKE	–	–	–	–	–	–	–	–	
19.	Speed–acceleration frequency matrix Normalized speed–acceleration matrix	–	–	MF_b MN_b		–	–	–	–	–	–	
20.	Percentage of speed in different modes (0–20, 20–40, 40–60, 60–80, >80), %	–	–	–	–	V_0, V_{20}, V_{40}, V_{60}, V_{80}	–	–	–	–	–	
21.	Running distance of entire trip, km	–	–	–	–	*L*	–	–	*L*	–	–	–
22.	Running time of entire trip, s	–	–	–	–	*T*	–	*c*	*t*	–	–	C
23.	Frequency of the deceleration phase following right after the acceleration phase per 100 m driven	–	–	–	–	–	–	–	–	–	FDA	
24.	Relative positive acceleration	–	–	–	–	–	–	–	–		RPA	

be measurements of several trips or only one trip on the road. The measurement having several trips is the most representative of developing the driving cycle (Tong et al., 2011). Based on this approach, to create a driving cycle, a number of tests in different vehicle regimes on the road must be carried out by different drivers with different vehicles in different road conditions and types with different traffic control systems (Arun et al., 2017). During the analysis of speed and time profiles, it is crucial to select parameters that describe the driving behaviour of the corresponding city to achieve a consistent driving cycle, so different authors have used different parameters to develop the cycle. Some of the basic parameters are presented in Table 1 (Amirjamshidi & Roorda, 2015; Arun et al., 2017; Hung et al., 2007; Kamble et al., 2009; Mahesh et al., 2018; Nesamani & Subramanian, 2011; Saleh et al., 2009; Tong et al., 1999; Tsai et al., 2005; Wang et al., 2008; Yang et al., 2019).

Parameters of micro-trips are analysed with different methods to obtain the final appropriate driving cycle. Although these methods are a microscopic approach, they do not analyse the data partially in certain segments and sections of the road, but only as a part of the entire road trip. Therefore, the first objective of this study was to develop a driving cycle that will represent the real driving behaviour of the city of Pristina by proposing a detection algorithm of micro-trips extending the study for different location driving cycle analysis. The second objective was to analyse the micro-trip parameters in different parts of the road trip that mostly affect the parameters of the final driving cycle. The micro-trip parameters at the different types of intersection were selected as places where the conditions of traffic changed dramatically. This microscopic approach was done in order to analyse the parameters of micro-trips at roundabouts, signalized intersections, and un-signalised intersections having a greater impact on the final parameters of the driving cycle. During the analyses, it was observed that the parameters of micro-trips differed from one intersection to another and differed from the parameters in the road segment. We compared assessment parameters of micro-trips of the basic data, final driving cycle, roundabouts, signalised intersections and un-signalised intersections and then came up with the conclusion that the types of the intersection had great influence on the final driving cycle.

1. Methodology

1.1. Route selection

Route selection should reflect typical traffic conditions (Tong et al., 2011) in the study area. A route should have all the facilities, reflecting the actual driving behaviour of the city. Several studies have adopted different criteria to select the route for study. Tong et al. (2011) adopted criteria such as route type, route length, traffic volume, and land use criteria, while the 5 to 10 km route length resulted in proper driver characteristics. Knez et al. (2014) selected a route length of 12.9 km for the driver behaviour study. Yang et al. (2019) selected routes having a length of 77.1 km for the study to reflect different traffic conditions and types of roads. Mahesh et al. (2018) selected a 14 km route length for study. Given that driver behaviour characteristics vary according to city, route selection should be based on city characteristics, and different criteria for the different cities should be adopted. The roads in Pristina are mostly urban (no highway or other roads penetrate into the city centre). The selection of routes in Pristina is based on road type (main urban roads), traffic volume (roads with different traffic structures and significant volumes) and route length. The 23.40 km road segment in two directions on five roads in Pristina was selected for data acquisition (Figure 2). In total, there are 21 major intersections:13 of them are signalized intersections, 5 roundabouts, and 3 un-signalized intersections.

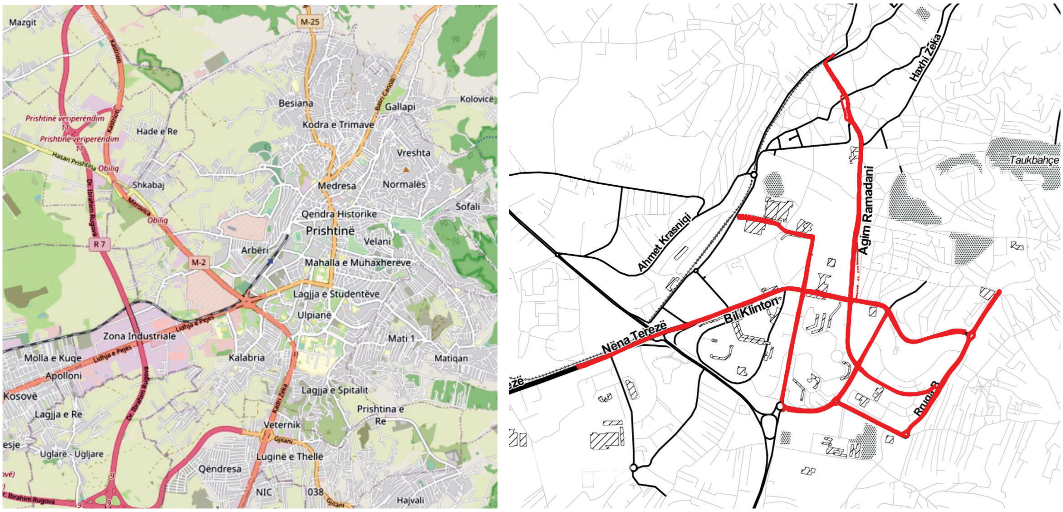

Figure 2. Urban zone of Pristina

1.2. Data collection

Recently, different methods and techniques have been used for data collection. For study purposes, on-board measurement techniques were adopted. On-road driving data were collected using CANegde1, which was connected to the vehicle with an on-board diagnostic (OBD2) adapter cable (Figure 3). The device CANegde1 records data with a 50-microsecond resolution or 26 data records such as speed, braking, rpm etc., per second. Due to the large data received from the device, the data were formatted in 1-second resolution by ASAMMDF (ASAM – Association for Standardization of Automation and Measuring Systems and MDF – Measurement Data Format). The speed-time profile obtained from CANegde1 was converted into an Excel file for future analyses.

Data collection period. Two different peak hour period tests (07:30–09:30 and 16:00–17:00) and peak-off period (14:00–15:00) test were carried out, but also tests in other periods were carried out to reflect different traffic conditions. Data were collected on workdays and weekends in June and July 2020. The ambient temperature ranged between 22 °C -30 °C and the humidity was 35%.

Vehicle and driver selection. In the study, different vehicles were included in data acquisition. Vehicles have different acceleration/deceleration and other features (manual/automatic, engine model, engine displacement, fuel, age, etc.). The Mercedes, Audi, and VW, being the most common brands used in Pristina, were selected as vehicles tests. For driver selection, the criteria of being familiar with the city was adopted to avoid the problem of finding routes and the objective was also to reflect the characteristics of diver behaviour of the city.

a) connector **b)** device

Figure 3. CANedge1 (2x CAN Bus Data Logger) setup and data collection process

Sample evaluation and population parameters. The mean, median and standard deviation statistics of the speed variable of the population were estimated by the bootstrapping method, and the mean, standard error and confidence intervals of each statistic were calculated. The statistics estimated by this method were used to measure the quality of the master sample. Bootstrapping is a statistical process that generates multiple simulation samples from a single set of data. This process allows calculating standard errors, building confidence intervals and conducting hypothesis tests for many types of sample statistics. Bootstrap methods are also alternative approaches to traditional hypothesis testing. The bootstrapping method is based on the repeated sampling from the main sample with replacement (Figure 4). Bootstrapping analysis enables you to investigate the sampling variability of a statistic without making any distributional assumptions about the population (Wiklin, 2018). For this purpose, 1000 subsamples (N) were randomly selected for sample sizes between 5 and 1000 from the main sample with replacement the mean, standard error, and confidence intervals were from subsample distribution of means, medians and standard deviations. When the sample size of the bootstrap increases, the bootstrap converges in most conditions on the correct sample distribution. When subsampling is chosen as N = 1000, the variation in the mean, median, and standard deviation statistics for the velocity decreases in sample sizes 400 and above (Figure 5). When the standard error of the statistics is greater than 400 for the sample size, it remains constant, as in the mean (Figure 6).

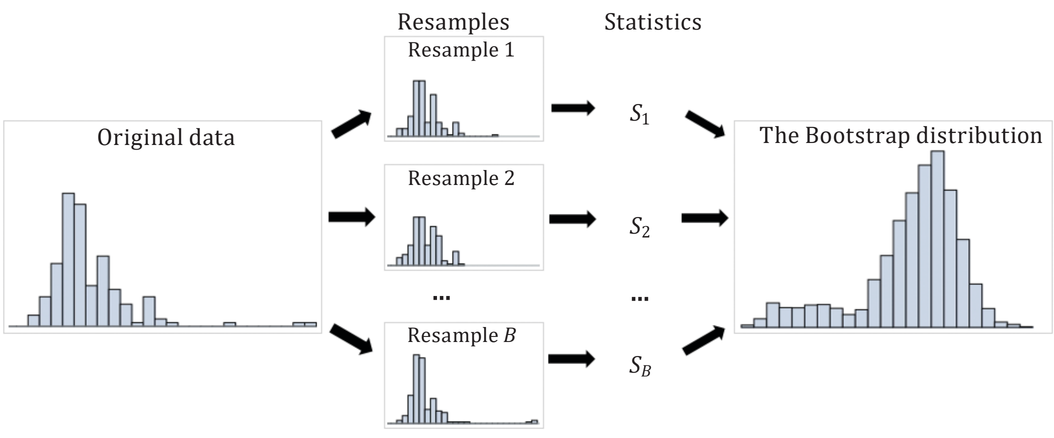

Figure 4. Bootstrapping method (Wiklin, 2018)

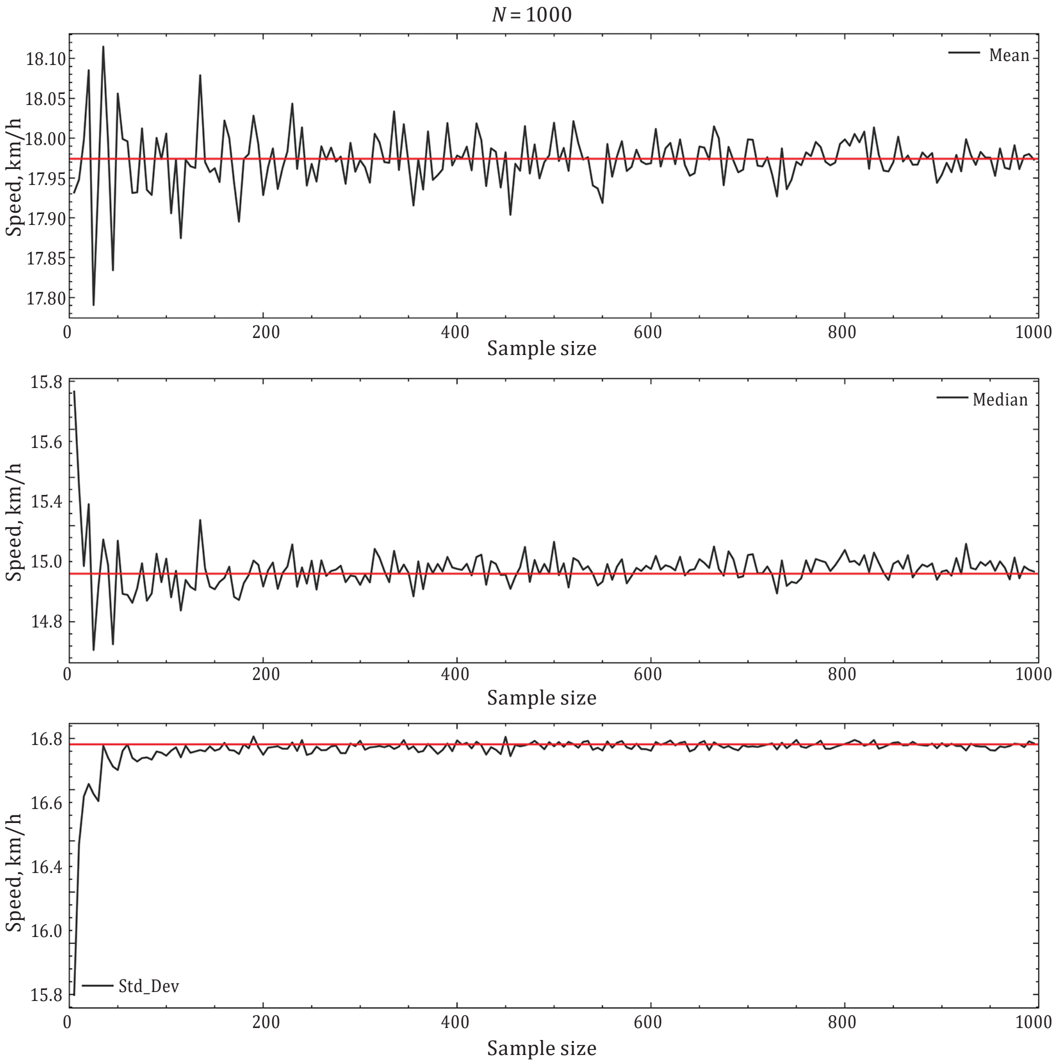

Figure 5. Change of the mean of the subsample relative to the sample size for speed, km/h

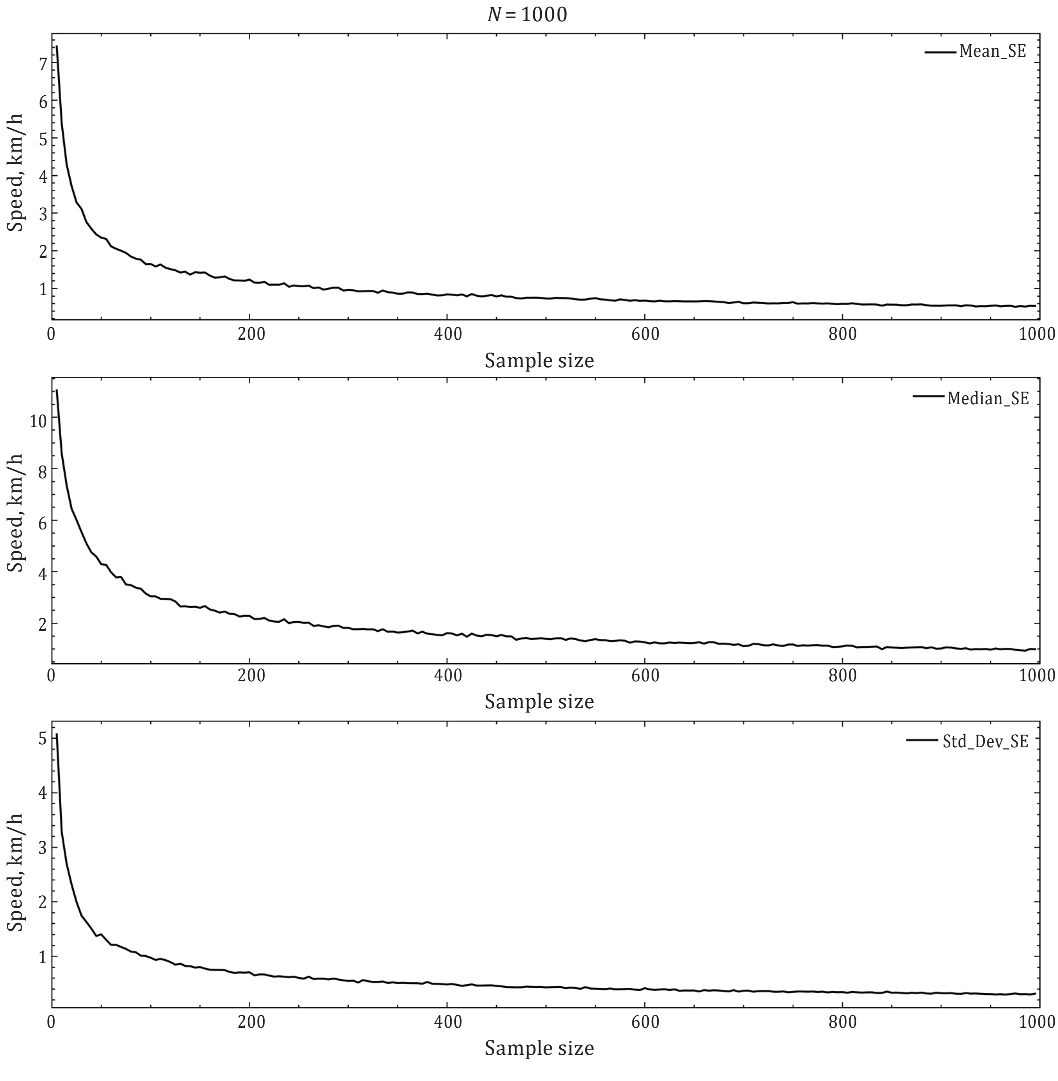

Figure 6. Change of the subsample standard error relative to the sample size speed, km/h

Two bootstrapping tests were conducted to find population statistics (mean, median, and standard deviation). Both runs generated statistics that were identical or very close to the main sample so the bias was about zero (Table 2). It means that parameters estimated from the main sample are reliable.

The distribution of the mean, median, and standard deviations of 1000 subsamples is shown in Figure 7.

Table 2. Bootstrapping results

	Main sample n = 56 491	Subsample n = 1000, N = 1000	Subsample n = 1000, N = 10 000
Mean	17.97	17.95	17.97
Mean Standard Error		0.51	0.53
Boundary of Mean (CI=%95)		(16.93, 18.97)	(16.91, 19.03)
Mean Bias		−0.02	0
Median	15	14.99	15.02
Median Standard Error		0.96	0.97
Boundary of Median (CI=%95)		(13.07, 16.91)	(13.08, 16.96)
Median Bias		−0.01	0.02
Standard Deviation	16.78	16.78	16.78
Standard Deviation Standard Error		0.31	0.31
Boundary of Standard Deviation (CI=%95)		(16.16, 17.4)	(16.16, 17.4)
Standard Deviation Bias		0	0

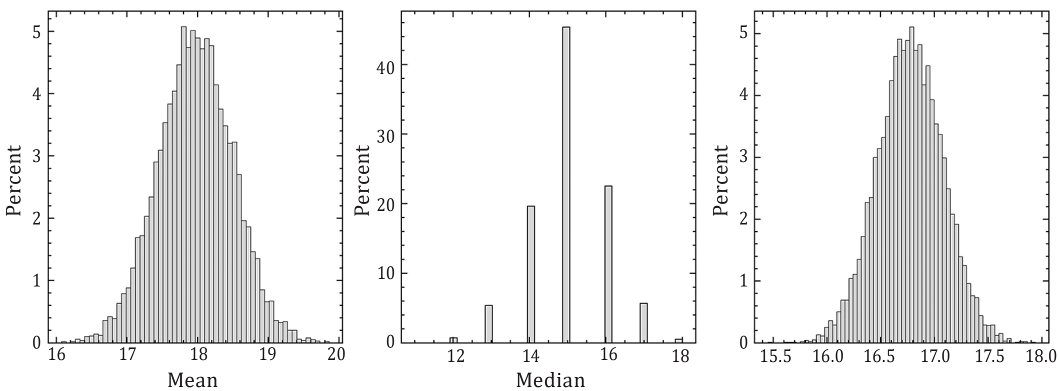

Figure 7. Mean distribution of subsample statistics (N=1000)

1.3. Development of driving cycle on urban roads

Different methods are used to obtain the driving cycle (Dai et al., 2008) and for particular purposes (Tong et al., 2011). The approach in this study is a micro-trips-based method for passenger cars. The process of driving cycle construction in Pristina is based on extracting micro-trips from speed-time profile data. From Table 1 the assessment parameters were adopted for basic data and micro-trips data:

1. Average speed of entire trips (V_m, km/h);
2. Average running speed of entire trips (idle time is excluded) (V_r, km/h);
3. Average acceleration of entire trips (A, m/s^2);
4. Average deceleration of entire trips (D, m/s^2);
5. Percentage of time in acceleration mode (P_a, %) (Speed > 5 km/h, $A_{cc} > 0.1$ m/s^2);
6. Percentage of time in deceleration mode (P_d, %) (Speed > 5 km/h, $D_{cc} > 0.1$ m/s^2);
7. Percentage of time in idle mode (P_i, %) (Speed equals zero);
8. Percentage of time in cruise mode (P_c, %) (Speed > 5 km/h, $A_{cc}/D_{cc} < 0.1$ m/s^2).

1.4. Micro-trip detection

The data collected from vehicles are 56 491 rows (seconds) in total. Each row contains trip data such as route, direction, travel time, acceleration, and gap. Additionally, GPS data were recorded simultaneously throughout the journeys. The size of the collected data turns the driver cycle work into a big data problem. Since it is not possible to manually make micro-trip patterns from the data frame, it becomes a necessity to do this with the help of an algorithm. For this reason, an algorithm called "3-sequential points" was developed to identify micro-trips within the data stack. The algorithm is based on three new columns named p1, p2, and p3, which represent the speed of the former vehicle, current speed, and the next speed, respectively. If the speed of a cell is greater than zero, it is converted to 1, otherwise it is converted to 0. The algorithm searches certain patterns formed by the values p1, p2 and p3 to detect the end and start of micro-trips. As seen in Figure 3, the start and end patterns of a micro-trip are 001 and 110, respectively (Figure 8).

Using the algorithm, a total of 780 micro-trips were detected and labelled. Figure 9 shows the detected start and end of two micro-trips in the data frame.

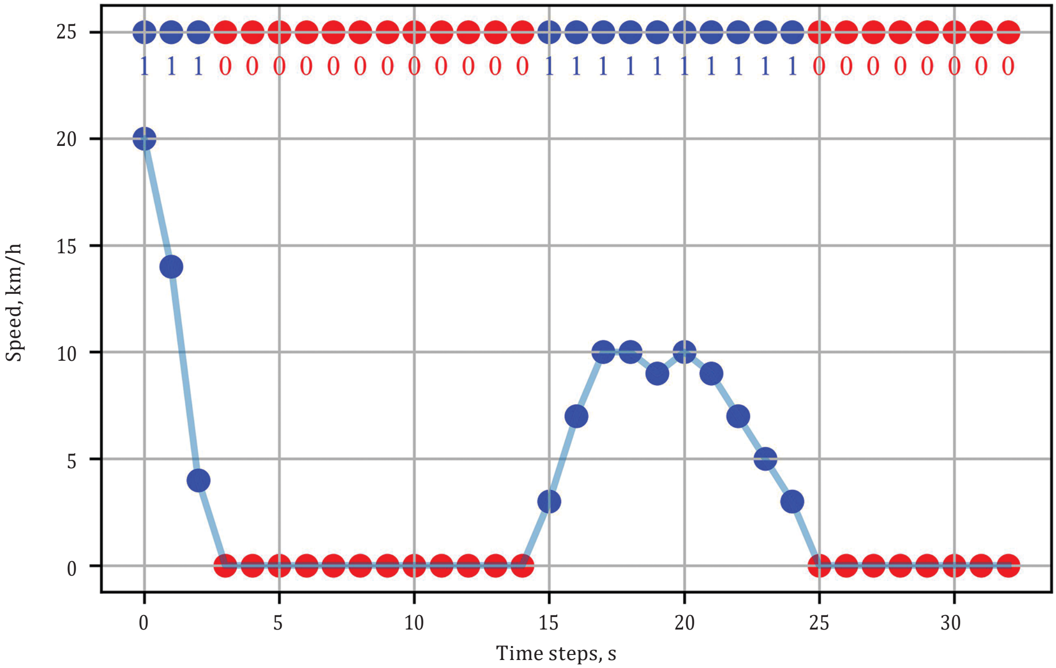

Figure 8. The start and end point of micro-trips

	Time	TimeSteps	Speed	AD	Gap	SpeedCategory	datetime	Hour	Minutes	Seconds	Day	Month	Day Section	Day Name	Month Name	Macro Trips	Micro Trips	p1	p2	p3	Trip State
118	09:30:14	118	20	0	12.05	15-20	2020-04-07 09:30:14	9	30	14	4	7	Morning	Sat	Jul	54	54-1	1	1	1	C
119	09:30:15	119	14	-6	6.91	10-15	2020-04-07 09:30:15	9	30	15	4	7	Morning	Sat	Jul	54	54-1	1	1	1	D
120	09:30:16	120	4	-10	3.7	1-5	2020-04-07 09:30:16	9	30	16	4	7	Morning	Sat	Jul	54	54-1	1	1	0	D
121	09:30:17	121	0	-4	2.88	0-1	2020-04-07 09:30:17	9	30	17	4	7	Morning	Sat	Jul	54	54-1	1	0	0	I
132	09:30:28	132	0	0	3.88	0-1	2020-04-07 09:30:28	9	30	28	4	7	Morning	Sat	Jul	54	54-1	0	0	1	I
133	09:30:29	133	3	3	5.62	1-5	2020-04-07 09:30:29	9	30	29	4	7	Morning	Sat	Jul	54	54-2	0	1	1	A
134	09:30:30	134	7	4	6.95	5-10	2020-04-07 09:30:30	9	30	30	4	7	Morning	Sat	Jul	54	54-2	1	1	1	A
135	09:30:31	135	10	3	2.63	5-10	2020-04-07 09:30:31	9	30	31	4	7	Morning	Sat	Jul	54	54-2	1	1	1	A
136	09:30:32	136	10	0	3.21	5-10	2020-04-07 09:30:32	9	30	32	4	7	Morning	Sat	Jul	54	54-2	1	1	1	C

Figure 9. The start and end of micro-trip within the data frame

1.5. Clustering of micro-trips

Each micro-trip ($x^{(1)}$,..., $x^{(m)}$) includes items with certain features such as A%, D%, I%, %C and V_{avg} and values for vector of these features ($x^{(i)} \in \mathbb{R}^n$). The task is to distribute the micro-trips into groups (k). For this purpose, the K-means algorithm was used. The K-means algorithm categorizes the micro-trips into k groups of similarity. Each group has similar items that do not belong to other groups. The numbers of groups (k) are selected for 25 for the study. To calculate this similarity, the Euclidean distance is used as a measurement.

The algorithm steps are the following:
Initialize k points randomly as the mean of the groups:

$$\mu_1, \mu_2, \&, \mu_k \in \mathrm{R}^n \tag{1}$$

Assign each item to its closest mean,

$$c^{(i)} := \arg\min_j x^{(i)} - \mu_j{}^2 \mathrm{R}^n \tag{2}$$

and update the means of groups considering new items in the groups.

$$\mu_j := \frac{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\} x^{(i)}}{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\}} \mathrm{R}^n. \tag{3}$$

The steps were repeated until there was no change in the mean of the groups.

All 780 micro-trips were grouped into 25 clusters. Figure 10 shows Group 5 and its micro-trips.

Trip State / Micro Trips	A	C	D	I	Sum	%Acceleration	%Deccaleration	%Cruise	%Idle	Average Speed	Duration	Groups
100-3	17.0	6.0	17.0	1.0	41	41.463415	41.46341463	14.634146	2.4390244	36.17	41.0	5.0
11-6	20.0	12.0	21.0	1.0	54	37.037037	38.88888889	22.222222	1.8518519	26.35	54.0	5.0
117-4	29.0	15.0	19.0	6.0	69	42.028986	27.53623188	21.739130	8.6956522	18.77	69.0	5.0
118-6	5.0	6.0	3.0		14	35.714286	21.42857143	42.857143	NaN	11.79	14.0	5.0
119-1	11.0	6.0	12.0	1.0	30	36.666667	40	20.000000	3.3333333	18.5	30.0	5.0
12-4	9.0	1.0	17.0	21.0	48	18.750000	35.41666667	2.083333	43.7500000	12.54	48.0	5.0
127-4	1.0	1.0		1.0	3	33.333333	NaN	33.333333	33.3333333	0.67	3.0	5.0
130-2	29.0	17.0	38.0	9.0	93	31.182796	40.86021505	18.279570	9.6774194	15.83	93.0	5.0
20-8	21.0	20.0	26.0	34.0	101	20.792079	25.74257426	19.801980	33.6633663	17.19	101.0	5.0
24-1	21.0	4.0	17.0	22.0	64	32.812500	26.5625	6.250000	34.3750000	14.8	64.0	5.0
30-2	90.0	53.0	97.0	2.0	242	37.190083	40.08264463	21.900826	0.8264463	35.4	242.0	5.0
49-4	6.0	7.0	8.0	3.0	24	25.000000	33.33333333	29.166667	12.5000000	5.75	24.0	5.0
57-1	19.0	4.0	11.0	1.0	35	54.285714	31.42857143	11.428571	2.8571429	22.29	35.0	5.0
61-1	47.0	15.0	41.0	6.0	109	43.119266	37.6146789	13.761468	5.5045872	40.73	109.0	5.0
62-2	6.0		6.0	1.0	13	46.153846	46.15384615	NaN	7.6923077	7.15	13.0	5.0
77-2	22.0	11.0	22.0	16.0	71	30.985915	30.98591549	15.492958	22.5352113	21.39	71.0	5.0
85-20	5.0	9.0	4.0	15.0	33	15.151515	12.12121212	27.272727	45.4545455	0.97	33.0	5.0
9-5	1.0	1.0	NaN	18.0	20	5.000000	NaN	5.000000	90.0000000	0.1	20.0	5.0

Figure 10. Grouped micro-trips

1.6. Analysis of micro-trip parameter of roundabout, signalized, and un-signalized intersections

Trip data and simultaneously collected location data were merged using timestamp data. The intersection coordinates on the routes were recorded as point data in a GIS file, including intersection types as a feature. The letters in Figure 6 indicate these points and the corresponding intersection types. R, S, and U represent roundabouts, signalized intersections, and un-signalized intersections, respectively. A buffer region around each intersection point was defined. During the definition of the region, intersecting with other regions was avoided as much as possible. To avoid bias due to the intersection of buffers, a distance of 200 meters, which is to prevent overflowing as much as possible, was chosen. The buffers are coloured according to the type of intersection and are depicted in Figure 11. The trip data within these regions was then extracted from the data set for each region using GIS tools. The black spots, which are inside the circles in Figure 11, represent the trip data belonging to the corresponding intersection.

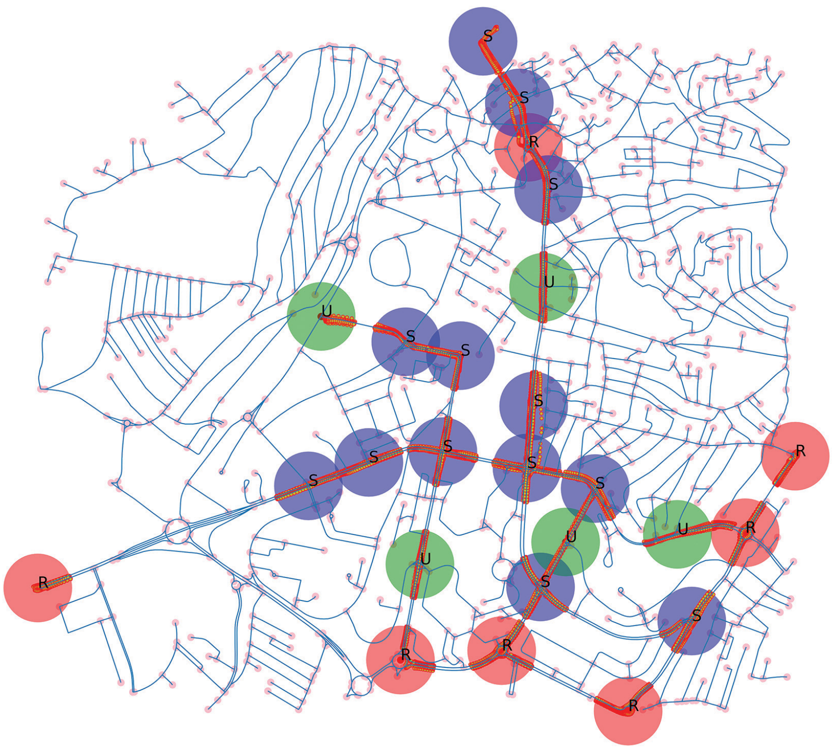

Figure 11. Selection of routes and intersections in Pristina

Finally, for each type of intersection, micro-trip parameters were calculated. The results are shown in Table 3. The idle time is lower in roundabouts, while acceleration and deceleration percentage are higher in roundabouts than at the other intersections.

The mean speed of roundabouts and un-signalized intersections are higher than those of signalized intersections. The differences are also seen in box plots in Figure 12.

Table 3. Micro-trip parameters of intersections

Type of Intersection	Acceleration, %	Cruise, %	Deceleration, %	Idle, %	V_{avg}, km/h
Roundabout (R)	34.1	19.4	32.3	143	20.197
Signalized intersections (S)	26.3	16.4	24.4	32.9	16.021
Un-signalized intersections (U)	27.9	20.9	28.5	22.7	19.96

Table 4. Pairwise Tukey

A	*B*	mean(*A*)	mean(*B*)	Difference	*se*	*t*	p-tukey	hedges
Roundabouts	Signalized	20.197	16.021	4.176	0.215	19.38	0.001	0.256
Roundabouts	Un-signalized	20.197	19.96	0.237	0.31	0.765	0.794	0.015
Signalized	Un-signalized	16.021	19.96	–3.939	0.273	–14.418	0.001	–0.241

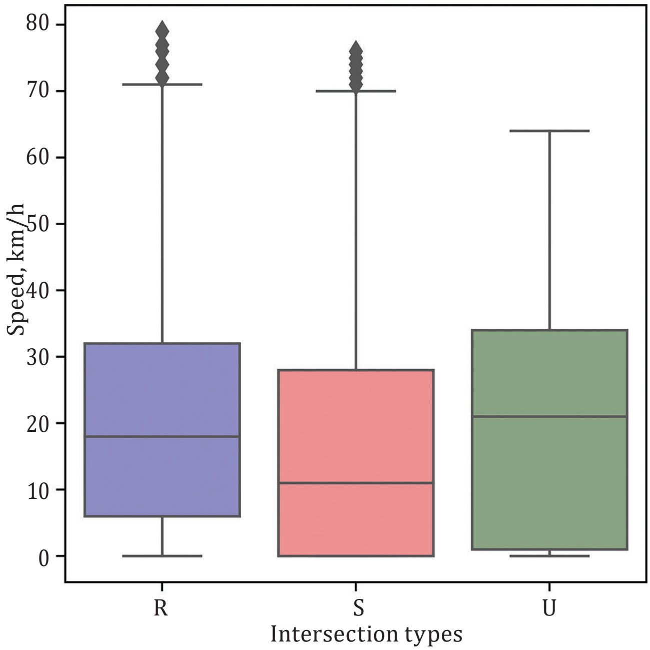

Figure 12. Mean speed at intersections

The speeds are tested for means with the pairwise Tukey test (Table 4). Average speed of roundabouts and un-signalized intersections is statistically different from signalized intersections.

1.7. Analysis of micro-trip parameters for all data

The assessment parameters from the basic data are shown in Figure 13. From the measured data, 53 491 groups of the speed-time profile are derived. For basic data, the percentage of time in acceleration mode is 27.83%, percentage of time in deceleration mode is 27.65%, percentage of time spent in idle mode is 25.06%, percentage of time spent in cruising mode is 19.45% and average speed for the entire trip

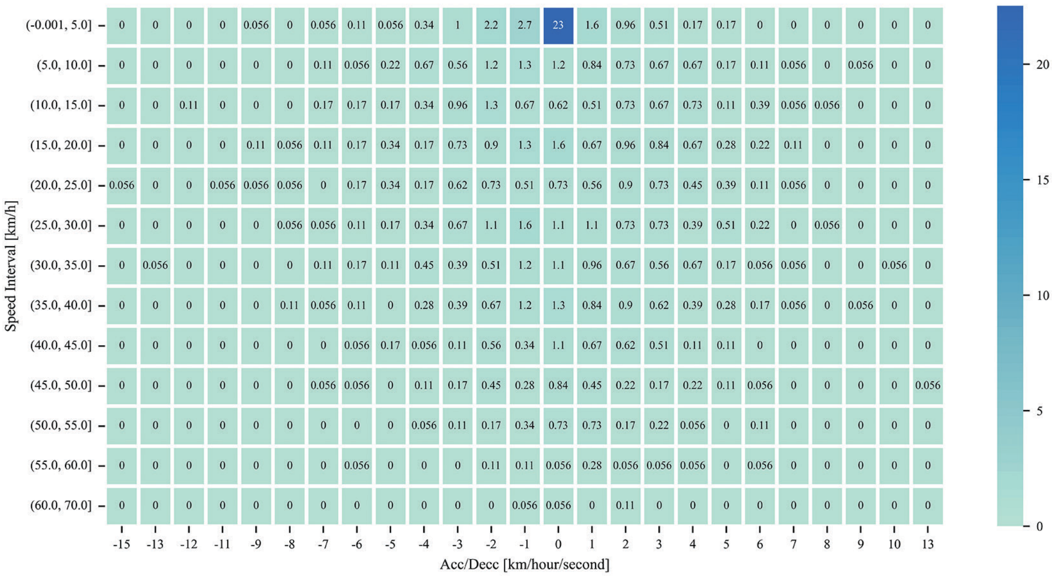

Figure 13. Assessment parameters from basic data

is 17.97 km/h. Micro-trips were extracted from basic data using the special algorithm in Python, and 780 micro-trips were obtained. Using the K-mean method, out of 780 micro-trips, only 25 were selected to develop the final driving cycle. These micro-trips are shown in Figure 15. The final driving cycle was obtained, and the duration was 1780 seconds (Figure 14). The assessment parameters of final Pristina driving cycle are: the percentage of time in acceleration mode is 32.47%, the percentage of time in deceleration mode is 32.98%, the percentage of time spent in idle mode is 22.42%, the percentage of time spent in cruising mode is 12.13% and the average speed for the entire trip is 18.42 km/h.

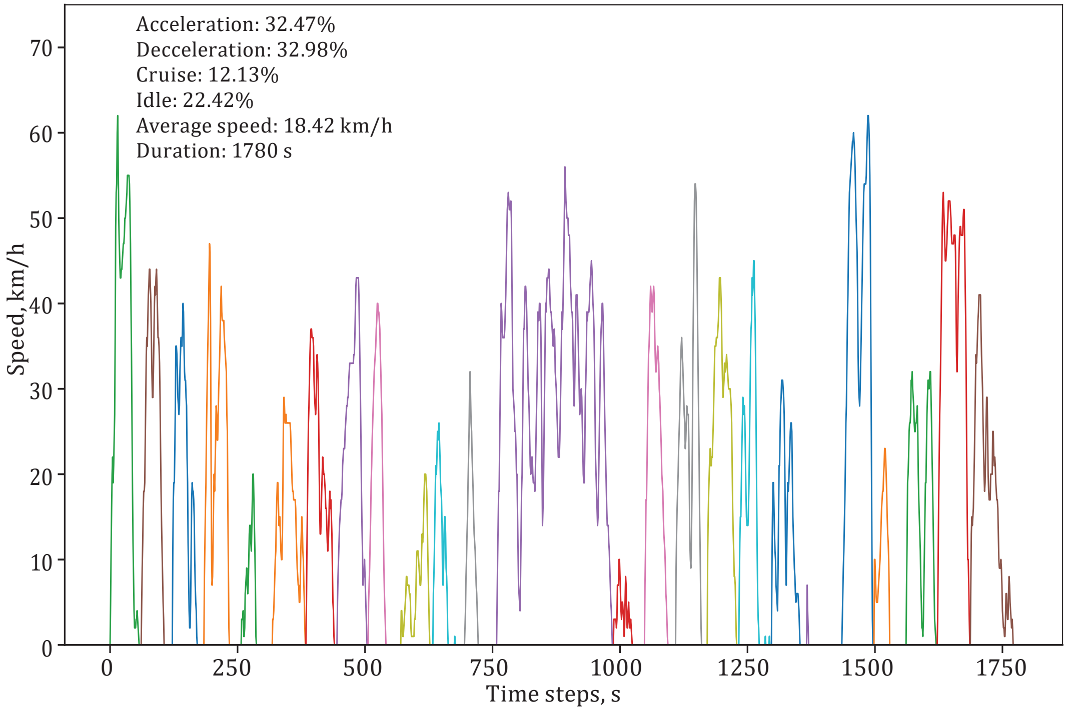

Figure 14. Pristina driving cycle

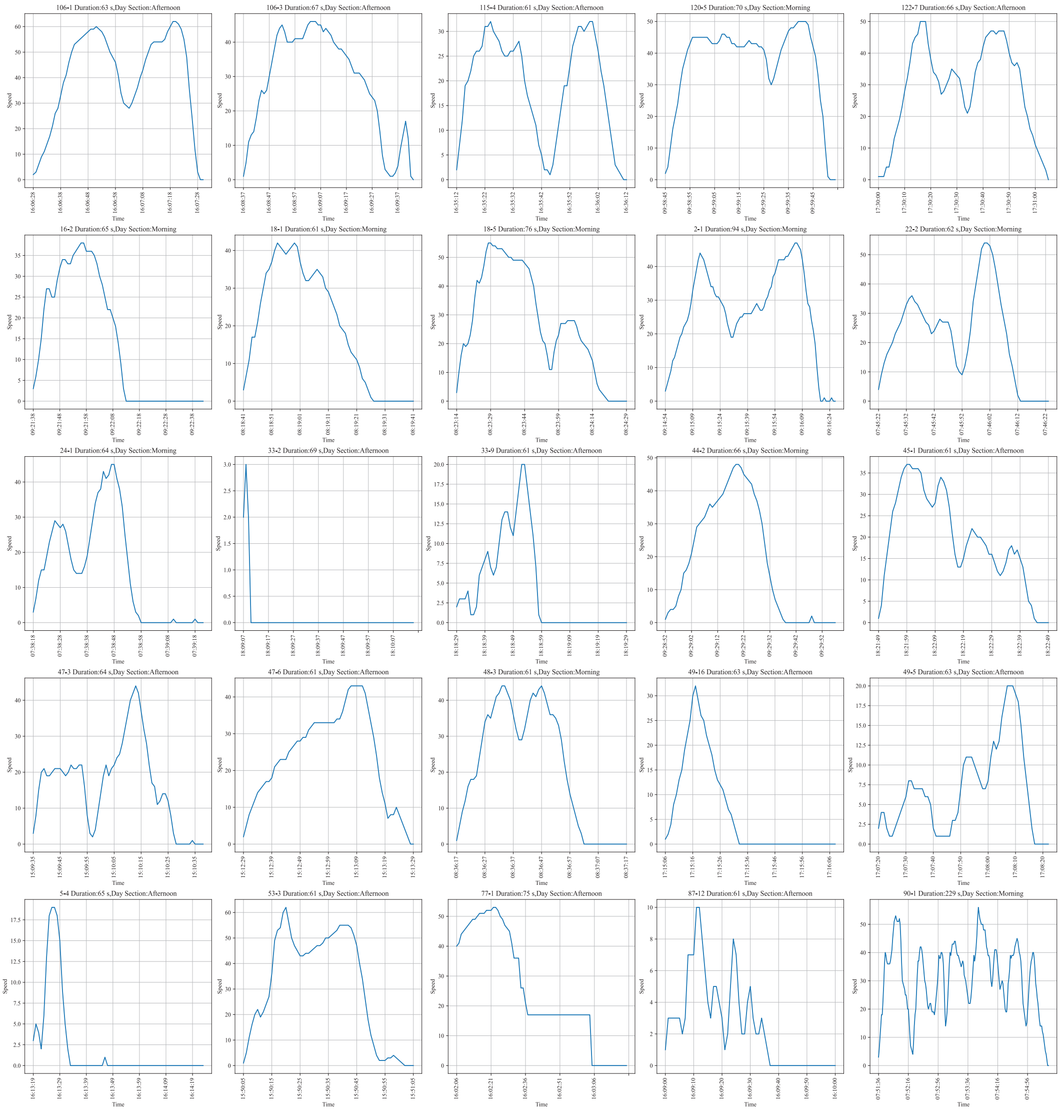

Figure 15. Micro-trips for the candidate driving cycle

1.8. Assessment parameters of Pristina and other existing international driving cycles

The driving cycle of Pristina for passenger cars was compared to other international driving cycles. The differences in the assessment parameters are significant (see Table 5).

Table 5. Comparison of the obtained Pristina driving cycle with the existing international driving cycles

Driving cycle	Assessment parameters						
	V, km/h	P_a, %	P_d, %	P_i, %	P_c, %	Duration, s	Distance covered, km
Pristina	18.42	32.47	32.98	22.42	12.13	1780	23.40
European	19	19	14	36	30	780	4.0
Celje	25.5	26	25	25	25	2453	12.9
Hong Kong	25.0	34.5	34.2	17.8	12.0	1548	10.33
Edinburg	18.7	34	34	28	4	975	5.8
Chennai	22.77	30	27	19	24	1448	9.09
Singapore	32.8	28.5	25.3	25.7	20.6	2344	21.5
Mashhad	20.41	37.34	37.69	21.75	3.22	1000	15.0
Nanjing	30.73	27	23	30	20	1172	77.1

2. Results

A driving cycle with duration of 1780 seconds (Figure 14) was developed for Pristina. The analyses were developed in two phases: In the first phase, the assessment parameters in the part of the routes that have mainly one type of the intersection were calculated (Figure 11). The type of the intersections are almost roundabouts, signalized, and un-signalized intersections. Then, in the second phase, the assessment parameters for the basic data and assessment parameters for final driving cycle were computed. The aim of this analysis was to see which type of intersection had the most impact on the final driving cycle of Pristina (Table 6).

From the results, the observations are as follows:

– Acceleration events for final driving cycle are approximately identical as in routes with roundabouts while have differences for routes with signalized and un-signalized intersections;
– Deceleration events for final driving cycle are approximately identical as in routes with roundabouts while have differences for routes with signalized and un-signalized intersections;

Table 6. Comparison of assessment parameters

	Assessment parameters				
	Acceleration, %	**Cruise, %**	**Deceleration, %**	**Idle, %**	**V_{avg}, km/h**
Roundabout (R)	34.1	19.4	32.3	14.3	20.197
Signalized intersections (S)	26.3	16.4	24.4	32.9	16.021
Un-signalized intersections (U)	27.9	20.9	28.5	22.7	19.96
Basic data	27.8	19.4	27.6	25.0	17.97
Final driving cycle	32.4	12.1	32.9	22.4	18.42

- The cruise events for the final driving cycle are different from any of the routes with the type of intersections;
- The idle events for the final driving cycle are approximately identical as in routes with un-signalized intersections and have differences for routes with roundabouts and signalized intersections;
- The mean speed is different; however, the mean speed for final driving cycle approaches with the mean speed for the routes with roundabouts and un-signalized intersections, while it has much differences with the routes with signalized intersections.

3. Conclusion and discussion

In Pristina, no study has been performed regarding the impact of vehicle emissions on the road; therefore, the development of the driving cycle as a significant input for microscopic analysis is an urgent need for the city's future policies. The driving cycle has been developed from actual driving data and can be used to create a vehicle emission model only for passenger cars in Pristina, but the methodology can be used to develop the driving cycle for other cities. The acceleration and deceleration parameters for the final driving cycle have been found to be identical to the micro-trip parameters on roundabout roads. Therefore, roundabout roads affected the acceleration and deceleration parameters of the final driving cycle. The drivers in Pristina during their total trips spent 65.30% in acceleration and deceleration mode, where 50% is acceleration and 50% is deceleration. On the other hand, idle events for the final driving cycle are approximately the same as the parameters at un-signalized intersections where this parameter for final driving cycle is affected by routes with un-signalised intersection. The percentage of idle time is shortest in roundabouts, while it is the highest at signalized intersections. Based on the approach above, it seems that driver behaviour at roundabouts and un-signalised intersections has been determined to develop parameters for final driving cycle. Driver behaviour at signalised intersections is unique and differs from the parameters of final driving cycle.

The parameters of Pristina's final driving cycle were compared with those of other international driving cycles, and the results revealed significant differences. All the parameters of the Pristina driving cycle in comparison with the European driving cycle and other standard cycles of different cities are totally different, showing the unique behaviour of the city driver. High acceleration and deceleration rates in the driving cycle indicate that drivers are aggressive in traffic. The mean speed of the vehicles changes dramatically during one trip if the route has combination of roundabouts and signalized intersections, while it has lower differences during a route trip with roundabouts and un-signalized intersections (Table 6). The findings may lead to the future policy of the city in two aspects. First, how to deal with driver aggressiveness in order to reduce acceleration and deceleration. The second is before changing the type of intersections and the combination of different type of intersection on the routes it is necessary to analyse the speed differences during the trip and not to make ad hoc decisions. The city of Pristina is under-development, and each year the infrastructure undergoes changes (type of intersections, addition or removal of lanes, the addition of new lanes, etc.). Any city whose infrastructure changes frequently may result in a different driving cycle for every infrastructure change. Consequently, it will be important in the future to develop new driving cycles and to compare and analyse the impact of these changes.

The study has certain limitations. First, the data have been collected only on the main urban routes and the final driving cycle has been developed only for them, while collectors and other local routes are beyond the scope of the study. Second, the type of vehicles and the age and gender of the drivers are limited. Drivers who are not familiar with the city are not considered, while the number of these drivers could be high because the city of Pristina is also the capital of Kosovo. Third, the variability of the type of vehicle and the age and sex of the driver have not been considered.

Further research can be conducted by collecting the data for other type of the vehicles, other types of the drivers (of different age and not familiar with the city), collectors and local roads. Furthermore, researchers should focus on the future effects of infrastructure intervention on the final driving cycle.

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