CONSTRUCTION OF DRIVING CYCLES: CASE STUDY FOR MICROTRIP AND MARKOV CHAIN METHODS' USING REAL DATA

Maurício Pereira Magalhães de Novaes Santos
Fernando Wesley Cavalcanti de Araújo
Guilherme Medeiros Soares de Andrade
Fábio Santana Magnani
Universidade Federal de Pernambuco
Centro de Tecnologia e Geociências

ABSTRACT
Standard Driving Cycles are used by government, researchers, and industry to compare vehicles using a worldwide standard approach, while Local Driving Cycles (LDCs) are developed to realistically reproduce a vehicle behavior from a specific region. This study presents the two main methods regarding the construction of LDCs: Micro-trip and Markov Chain. We present a concise review and the main aspects of each method. In order to present a real example, we selected a 17.1 km route in the city of Recife (Brazil), collected speed-time data using cars and motorcycles, and constructed LDCs for both methods. As result, although the LDCs are visually different, both methods were capable of generating LDCs with error within the established threshold of 4%, when comparing the generated LDCs with the original data. We conclude that is recommended to choose the construction method prior to selecting the route and collecting the data.

RESUMO
Ciclos padrão de condução são usados por governos, pesquisadores e indústrias para comparar veículos utilizando uma abordagem padrão, enquanto os Ciclos de Condução Locais (CCLs) são desenvolvidos para reproduzir o comportamento dos veículos de uma determinada região de forma mais realística. Esse estudo apresenta os dois principais métodos utilizados para a construção de CCLs: Micro-trip e Cadeia de Markov. Nós presentamos uma revisão concisa e os principais aspectos de cada método. Como exemplo, selecionamos uma rota de 17.1 km em Recife, coletamos dados de velocidade para carros e motos, e desenvolvemos os CCLs para ambos os métodos. Como resultado, embora os CCLs sejam visualmente diferentes, ambos os métodos foram capazes de gerar CCLs com erros abaixo de 4%. Concluímos que é recomendado escolher o método de construção antes da seleção de rota e coleta de dados.

1. INTRODUCTION

Driving cycle (DC) is a speed-time profile that represents the driver behavior in a city, a region, or a country. Engineers and researchers use DCs to project and evaluate the performance, consumption, and emission of internal combustion, hybrid, and electric vehicles (Pouresmaeili *et al.,* 2018; Koossalapeerom *et al.*, 2019). Governments, on the other hand, use DCs with legislative purpose for emission and consumption. In this case, they are called Standard Driving Cycles (SDC). The most relevant SDCs employed in the world are the American FTP-75 and the Europeans WLTC and NEDC.

SDCs are developed to represent the real world. However, Huertas *et al.* (2017) and Ma *et al.* (2019) discuss that there is a considerable variation among the results obtained for emission and fuel consumption when a vehicle is submitted to the SDC test (in a chassis dynamometer) and when the vehicle is used in a real-world condition. This difference can be higher than 50%. The difference can be justified because SDCs do not consider the exact characteristics from the tested region, such as traffic condition, vehicle, driver behavior, road type, and topography (Hung *et al.*, 2007). In order to decrease the difference obtained between SDCs and real-world measurements, researchers develop a time-speed profile that represent the region analyzed after collecting data from field experiments. This developed cycle is called Local Driving Cycle (LDC).

Arun *et al*. (2017) and Yang *et al.* (2019) affirm that an LDC can be developed in three steps: route selection, data collection, and cycle construction. In the first step, the route selection, researchers should focus on selecting roads and schedules that reflect the reality experienced from a local citizen (Zhao *et al.*, 2020). In the second step, data collection, the data can be obtained "onboard", in which the measuring devices are installed in the tested vehicle. It is also possible to collect data from distance, using field sensors, video footage, or an equipped vehicle using sensors to follow others. Several papers employed recording frequency of 1 Hz, considered adequate to capture the vehicle dynamics (Ma *et al.*, 2019; Wang *et al.*, 2019). The third step, the cycle construction, is the stage in which the LDC is constructed from the data obtained and treated from the previous two steps. In the literature, the two most relevant and used methods for constructing driving cycles are the Micro-trip and the Markov chain methods. In the Micro-trip method, the speed-time profile from the vehicle is divided in "micro-trips", stretches of the vehicle's movement between two idling moments. Those stretches of trip are combined until obtaining a DC that is similar to the original data. The second method, Markov chain, is a mathematical approach to model a process that follow a specific property: the state in the actual moment only depends on the immediately previous state condition (Wang *et al.*, 2019). The Markov chain method evaluates all the state transitions (*i.e.*, the state evaluated can be the speed, acceleration, headway) in the original data creating a matrix containing all the possible state transitions with their probability of happening. The Monte Carlo method is usually applied following obtaining the matrix. Random values are generated and compared to the state transition matrix. From the conditions defined in the comparison stage, the next state for the vehicle is selected. This happens until generating a driving cycle considered similar to the original data.

To compare the different speed-time profiles and affirm that the cycles are similar, it is possible to characterize the data obtaining kinematic characteristic parameters (CPs). Examples of CPs are the average speed, average acceleration, and any other combination of the speed, time, stops, and data regarding the dynamic of the vehicle (*e.g.*, percentage of time that the vehicle spent accelerating, average speed excluding moment idling, and standard deviation of acceleration). There are more than 30 different CPs available in the literature (Barlow *et al.* (2009)). However, a comparison among CPs from different studies should not be performed directly, as every author decides which and how the CPs are defined in his/her paper. An example of how the same CP has different definitions between studies, Arun *et al.*, (2007) consider that the vehicle is accelerating when $a > 0$ m/s² while Koossalapeerom *et al.* (2019) define that the vehicle is accelerating only when $a > 0.27$ m/s².

In this study we provide a concise review of both methods for constructing LDCs (Micro-trip and Markov chain). In order to provide examples, we developed LDCs for both methods from real data collected from Recife, a large Brazilian city. The test was performed for two vehicle's categories: passenger car and motorcycle. The data collection was performed in weekdays and off-peak hours.

2. OBJECTIVES

The main objective of this study is to provide a concise review about the most used methods for constructing a driving cycle: Micro-trip and Markov chain. An additional objective of this paper is to use both methods to develop LDCs for cars and motorcycles from real-data collected using a smartphone GPS.

3. BIBLIOGRAPHY REVIEW

In this section we will provide a concise review regarding: a) Important aspects of SDCs and LDCs; b) the Micro-trip method; c) the Markov chain method; d) relevant aspects from the Micro-trip and the Markov chain method.

3.1. Important aspects of SDCs and LDCs

SDCs are used to represent an expected traffic behavior in a large region or country. The most known and used SDCs for passenger cars are the NEDC and WLTC (in Europe), the set of EPA cycles (in USA), and JC08 (in Japan) Giakoumis *et al.* (2017). These cycles are applied in official procedures to validate consumption and emission in their respective countries. Several countries use foreign cycles as their SDC in order to have an official pattern. In Brazil, two American cycles are used to evaluate the fuel economy of passenger cars: The EPA FTP-75 is used to represent the urban fuel consumption and the EPA HWFET is used to evaluate the highway fuel consumption. The procedure is detailed in the Brazilian legislation ABNT NBR 7024 (2017). Because of the differences obtained when comparing the results from official test procedure ABNT NBR 7024, to the ones obtained in real-world, the Brazilian National Institute of Metrology, Standardization and Industrial Quality (INMETRO) created Portaria nº10 (2012). In this ordinance, the fuel consumption obtained when the vehicle is submitted to the ABNT NBR 7024 procedure should be corrected to provide an adequate result to Brazilian conditions. After this correction, the official fuel economy and emission of the vehicle is publicly available to the consumers as requested by the Brazilian Vehicle Labeling Program (PBEV).

On the other hand, LDCs are developed to represent a specific region and to provide a result more adjusted to the local reality if compared to the result generated when employing a SDCs. LDCs have been developed in all over the world, including Brazil (Roso and Martins, 2015; Azevedo *et al.*, 2017). Roso and Martins (2015) found that FTP-75 cycle present kinematically and energy similarities to Santa Maria (RS) at 5 p.m., but the results were considerably different when compared to the same driving cycle at 12 p.m.. Other Brazilian LDC, developed by Azevedo et al. (2017) showed differences between the FTP-75 cycle and city of Fortaleza. For instance, FTP-75 has average speed of 34.1 km/h, compared to 23.8 km/h in Fortaleza. In a study performed in Chennai - India, Arun *et al.* (2017) obtained that the average speed for cars was 17.7 km/h, also contrasting to the average speed from several SDCs used around the world. Additionally, LDCs were developed for several classes of vehicles beside cars and motorcycles, such as trucks (Amirjamshidi and Roorda, 2015) and buses (Lai *et al*, 2013).

3.2. Review of the Micro-trip method

Micro-trip is a stochastic method applied to construct a driving cycle. In this method, a vehicle is equipped with a GPS/OBD device and has its speed recorded. The entire collection of data is divided into intervals that starts and finishes when the vehicle is stopped (idling). This interval is defined as a “micro-trip” (Figure 1). The “micro-trips” obtained are then reorganized randomly until obtaining a DC which the CPs error between the generated cycle and the original data is within a defined threshold (4%, in our study). The cycle candidate to be the LDC should also follow other recommendations, for instance, as that the duration of the testing should be between 10 and 40 minutes (Arun *et al.*, 2017), being short enough to be easily reproductible and lasting for time sufficient to provide a trustworthy result.

The Micro-trip method provides a suitable approach to evaluate emission and fuel consumption in the “stop and go” driving pattern, experienced in urban regions due to traffic signals and congestions, since its characteristic cover the vehicle activity between two adjacent stops (Chen *et al.*, 2007). The first important DC constructed using micro-trips was the LA-92 (California Unified Cycle 1992), developed in 1992 by the California Air Resources Board (CARB). Over the years, several other cycles were developed. Tsai *et al.*, (2005) developed an LDC for Kaohsiung (Taiwan) analyzing 316 micro-trips and 11 CPs, considering the average error of 5%. Their result indicated that the SDCs (*e.g.*, FTP-75, WMTC) presented different emission results when compared to the Kaohsiung Driving Cycle. Later, Kamble *et al.* (2009) focused in develop an LDC for Pune (India) considering their heterogeneous traffic condition. They concluded that their cycle was different from the NEDC and the Indian Driving Cycle after studying five CPs and defining an error between 5% and 15%. Seedam *et al.* (2015) developed an LDC for motorcycles in Khon Kaen (Thailand) after evaluating nine CPs, revealing that their cycle is different from other cities. Three recent Micro-trip LDCs for passenger cars and motorcycles were developed in Chennai (India) (Arun *et al.*, 2017). They also found significant differences between their cycles and SDCs after evaluating 11 CPs.

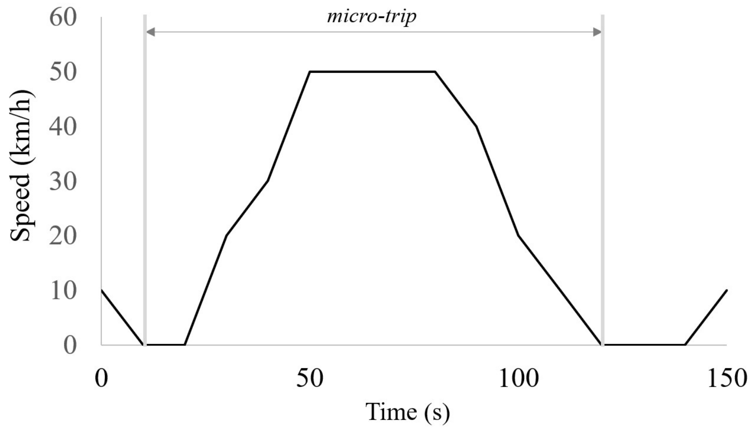

Figure 1: Definition of a micro-trip

Table 1: Collection of studies that used the Micro-trip method

Author	City
Tsai *et al.* (2005)	Kaohsiung, Taiwan
Hung *et al.* (2007)	Hong Kong
Kamble *et al.* (2009)	Pune, India
Tong *et al.* (2011)	Hanoi, Vietnam
Lai *et al.* (2013)	Beijing, China
Amirjamshidi and Roorda (2015)	Toronto, Canada
Seedam *et al.* (2015)	Khon Kaen, Thailand
Arun *et al.* (2017)	Chennai, India
Koossalapeerom *et al.* (2019)	Khon Kaen, Thailand
Yang *et al.* (2019)	Nanjing, China

3.3. Review of the Markov chain method

In the Markov chain method, one or more states can be analyzed. After choosing the state to be evaluated (*e.g.*, speed, headway, spacing), it is possible to create a matrix containing the number transitions (N_{ij}) of this state from ($i = t\text{-}1$) to ($j = t$). This matrix is called State Transition Matrix (STM). After the STM receives all the input data, the probability of transition from a state *i* to other is calculated as defined in Equation 1.

$$P_{ij} = N_{ij} / (\Sigma_j N_{ij}) \quad (1)$$

The Markov chain is usually combined with Monte Carlo method to construct driving cycles, and generates a different cycle each time it is used (Zhang *et al.*, 2019). After obtaining the STM, the Monte Carlo method compares a random number (r) generated in each time step and compare with the probability in the STM for $V(t)$. From this comparison, the vehicle status in the next step $V(t+1)$ is decided. In this study, we chose that $V(t+1) = j$ when r was immediately greater than the accumulated P_{ij}. This process is repeated for every time step until the error for the driving cycle created from this process is within a previously established threshold when compared to the original data (4%, in our study) or another limiting condition (Zhao *et al.*, 2020).

Lin and Niemeyer (2002) were the first to employ this method, but the Markov Chain was considerate reliable when Gong *et al.* (2011) applied the method using speed and acceleration obtaining a fit result for their data. Later, Shi *et al.* (2016) validated that Markov chain can be employed to construct driving cycles, evaluating the correlation of the actual speed to the speed in a previous t (in seconds). When evaluating the speed at the time t with the speed at a second before (t-1), the Pearson's correlation coefficient was 0.9918. From this analysis was possible to conclude that the method can be employed and that the time frequency in the data collection step is relevant for Markov chain method. The frequency should be short enough to be representative. If the data is sparse, it will provide data not correlated with the previous state. Using 1 Hz as frequency is considered adequate (Zhang *et al.*, 2019). At least eight more cycles were developed using this method from 2017 to 2020 (Table 2).

Table 2: Collection of articles that used the Markov chain method

Author	City
Dai *et al.* (2008)	California, USA
Brady and O'Mahony (2013)	Dublin, Ireland
Hereijgers *et al.* (2017)	Not informed
Yang *et al.* (2018)	Shenyang, China
Gong *et al.* (2018)	Beijing, China
Ma *et al.* (2019)	Beijing, China
Wang *et al.* (2019)	Beijing, China
Zhang *et al.* (2019)	Beijing, China
Rechkemmer *et al.* (2020)	Shanghai, China
Zhao *et al.* (2020)	Xi'na, China

3.4. Important aspects from Markov Chain and Micro-trip methods

The Micro-trip LDC will preserve and present real data, and it is a trajectory that a testing vehicle has travelled before. This happens because the "micro-trips" are shuffled and reorganized. Therefore, when obtaining the data, the researcher needs to organize it considering the vehicle type, such as the road conditions (*e.g.*, highway, urban), and testing hours (*e.g.*, weekday, peak conditions). When processing the data, several filters can be applied and are defined by the researcher (*e.g:* excluding micro-trips shorter than 10 seconds or containing maximum speed lower than 3.6 km/h). A case to be highlighted is when the Micro-trip method is used for highway condition, extra precaution should be taken, because the vehicle can travel for hours without the need for stopping. Relevant SDCs were developed based on the Micro-trip method (*e.g.*, WLTC for cars, WMTC for motorcycles) (Giakoumis *et al.*, 2017). A fluxogram of the construction step for Micro-trip and Markov chain methods are presented in Figure 2.

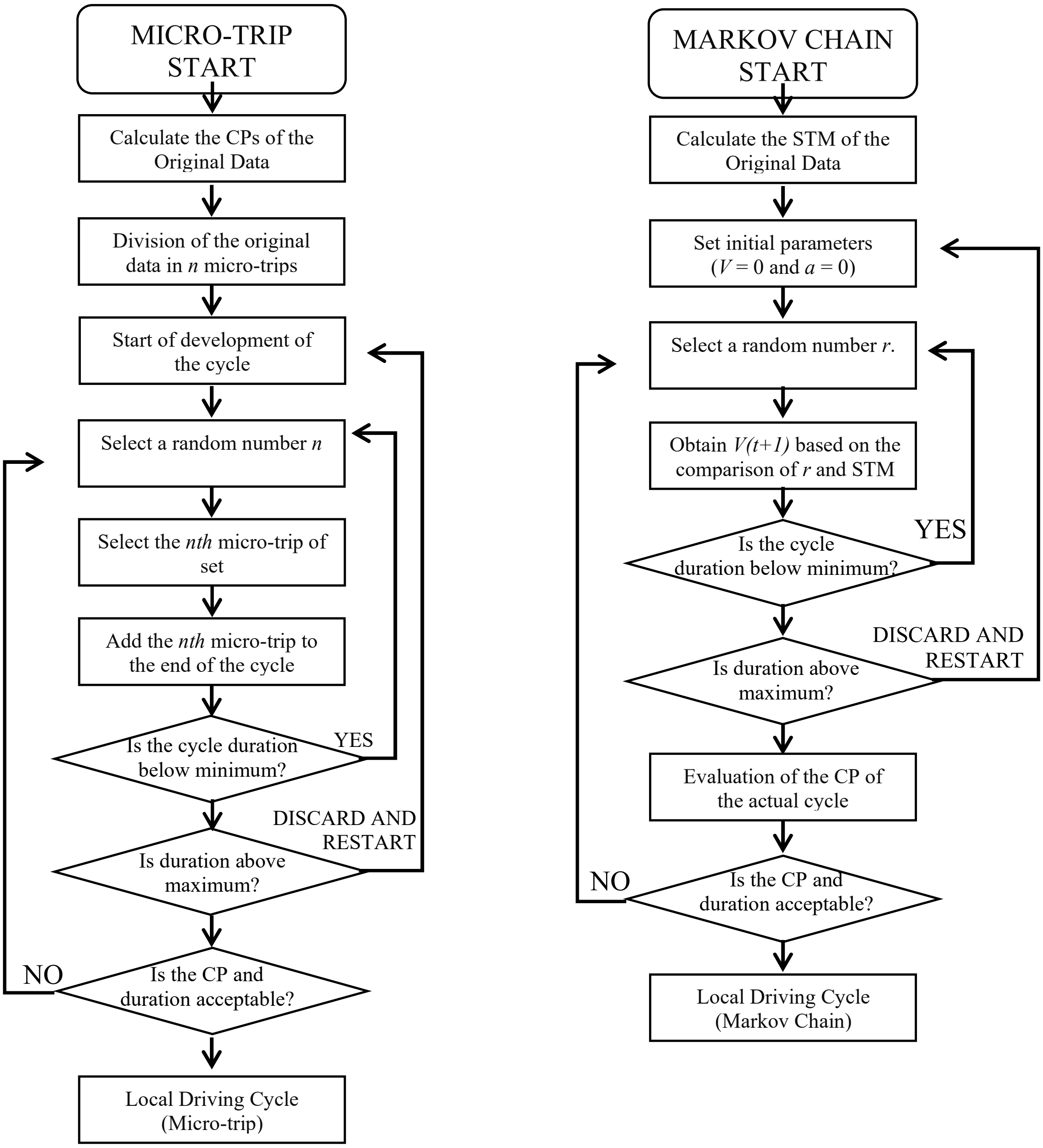

Figure 2: Fluxogram of construction of a) Microtrip and b) Markov chain LDCs

In the Markov method, the resultant LDC is created to statistically represent the data, based on the STM. The candidate cycle will replicate the global driving pattern preserving the micro-transient events (Giakoumis *et al.,* 2017). Thus, although will conserve the driving behavior, it will probably create a trajectory that no vehicle had actually travelled. It is important to remind that the STM is developed based on an arbitrary time and speed bin range decided by the researchers (*e.g.*, the speed bins (ΔV) for the analysis can be 5 km/h, 1 km/h, 0.1 km/h, or 0.01 km/h). Other relevant consideration is that the Markov method is recommended to be employed in possession of a large amount of data, although the exact minimum amount of data is not a clear number. Zhang *et al*., (2019) used data collected from

40 vehicles from 6 months. Zhao *et al*., (2020) monitored 2562 km of roads for 28 days in order to collect data. From the STM, several trips can be generated quickly, while for a large amount of data Micro-trip will need much more time to process (Chen *et al.*, 2019).

General recommendations apply for both methods. The data collected will not be representative if there is an external event (*e.g*., days before weekend, accidents, seasonal conditions as students' holiday, untypical weather, etc.).

4. METHODOLOGY

In this section, we describe: a) the selection of route and how the data was collected; b) the characterization of the driving cycles; c) the methodology used to develop an LDC using the Micro-trip method; and d) the methodology used to develop an LDC using the Markov method.

4.1. Selection of route and collection of speed-time data

The two steps were employed for both construction methods, for cars and motorcycles. First, in the route selection stage, we selected a 17.7 km trajectory in Recife, a large Brazilian city (Figure 3). In this route, three arterial avenues (Av. Abdias de Carvalho, Av. Mascarenhas de Moraes, and Av. Recife) were included.

Figure 3: a) Recife location in Brazilian map and b) route selected for data collection (Google Maps)

The data collection step was performed using different drivers and cars, riders and motorcycles, in several days. The drivers/riders were experienced with the Recife's traffic. Cars and motorcycles used in the data collection are representative of the Brazilian fleet (Cars: Hyundai HB20 1.0 L, Volkswagen Gol 1.0 L, and Fiat Argo 1.3 L; Motorcycles: Honda CG 150, and Honda CB 300). The data was collected only in off-peak hours, and we used a smartphone that was previously to obtain the vehicle speed profile in frequency of 1Hz (Rechkemmer *et al*., 2020).

4.2. Parametric characterization of driving cycles

The cycles need to be characterized in order to allow their comparison. In this paper, we use 9 CPs to evaluate the LDCs, as listed and defined in Table 3.

Table 3: Characteristic Parameters Evaluated

Parameters	Symbol	Definition
Average speed	V (km/h)	Average speed including zero speed
Average running speed	V_r (km/h)	Average speed excluding zero speed
Average acceleration	a (m/s²)	Average acceleration rate above 0.1 m/s²
Average deceleration	d (m/s²)	Average deceleration rate below -0.1 m/s²
Time ratio of idling	T_i (%)	Time fraction with the vehicle in 0 km/h and acceleration 0.1 m/s²
Time ratio of acceleration	T_a (%)	Time fraction in which the vehicle acceleration is above 0.1m/s²
Time ratio of constant speed	T_c (%)	Time fraction in which the speed is above 0 km/h and the acceleration is between a<0.1m/s², d>-0.1m/s²
Time ratio of deceleration	T_d (%)	Time fraction in which the vehicle deceleration is below -0.1 m/s²
Speed standard deviation	σ_v (m/s²)	Speed standard deviation for the entire driving cycle (m/s²)

To validate the cycles as LDCs, they need to be within a certain threshold. We apply the same condition as Pouresmaeili *et al.* (2018) in which the candidate cycle is accepted if the average error between the CPs of the candidate cycle and the CPs from the original data are below 4%. For the percentage timing related CPs (T_c, T_i, T_a and T_d) the error was the absolute difference between these CP in the candidate cycle and the original data. The reason is because those CP can present values near 0%, a division for the original value in this scenario can yield results that computationally will not generate DCs.

4.3. Micro-trip construction method

All the data collected, considering all drivers, vehicles, and days are considered (divided in cars and motorcycles, due to their distinct characteristics). The first step in this method is to divide all the data in micro-trips (Figure 1). A computational loop is defined for randomly selecting the micro-trips and ordering them sequentially. When the time is within the adequate range (between 10 and 40 minutes), for every micro-trip added to the candidate DC, the resultant CPs are calculated and compared to the original data CPs. If the error and time condition are satisfied, the candidate cycle is defined as the Micro-trip LDC trip. If the total time after adding a micro-trip to the candidate cycle is above the upper time limit, the cycle is discarded and the process is restarted (Figure 2).

4.4. Markov chain construction method

All the speed and time data collected is processed, creating a STM based on the transition of instantaneous speed between t and $t\text{-}1$. In this study, the transitions are aggregated in matrix bins of Δt = 1 s and ΔV = 0.01 km/h. As informed in section 3.2, the Monte Carlo process is used, in which a random number (r) is selected in every time step t and based on the comparison of the r and the probabilities in the STM values for the actual state, the speed for the $t+1$ is selected (Gong *et al.*, 2018). In this paper, after selecting the updated speed for each second, the CPs of the candidate cycle are compared to the original data CPs. If the average error between is within the threshold (< 4%), the candidate cycle is regarded as the Markov LDC. If the upper time limit is achieved and the cycle was not within the threshold, the cycle is discarded and the process restarted. Lastly, if the error and time condition are achieved with a vehicle speed different than zero, the vehicle breaks until stop, and the cycle is defined as the Markov chain LDC.

5. RESULTS AND DISCUSSION

In the data collection step, more than seven testing hours were performed for each vehicle class, totalizing more than 240 km travelled. The tests were performed from November/2018 to October/2019 in weekdays and in off-peak hours in the Recife selected route (Figure 3).

Considering all data, we obtained 405 micro-trips for passenger cars and 350 micro-trips for motorcycles. For comparison's sake, Arun *et al.* (2017) collected 236 micro-trips for cars and 269 for motorcycles for the off-peak condition. Pouresmaelli *et al.* (2018) obtained 273 micro-trips in their study for Mashhad (Iran), and Yang *et al.* (2019) have obtained 373 micro-trips for Nanjing (China) for peak and off-peak conditions

5.1. Micro-trip and Markov results for passenger cars

The LDCs constructed for passenger cars using both methods are displayed in Figure 4, and their CPs are shown in Table 4.

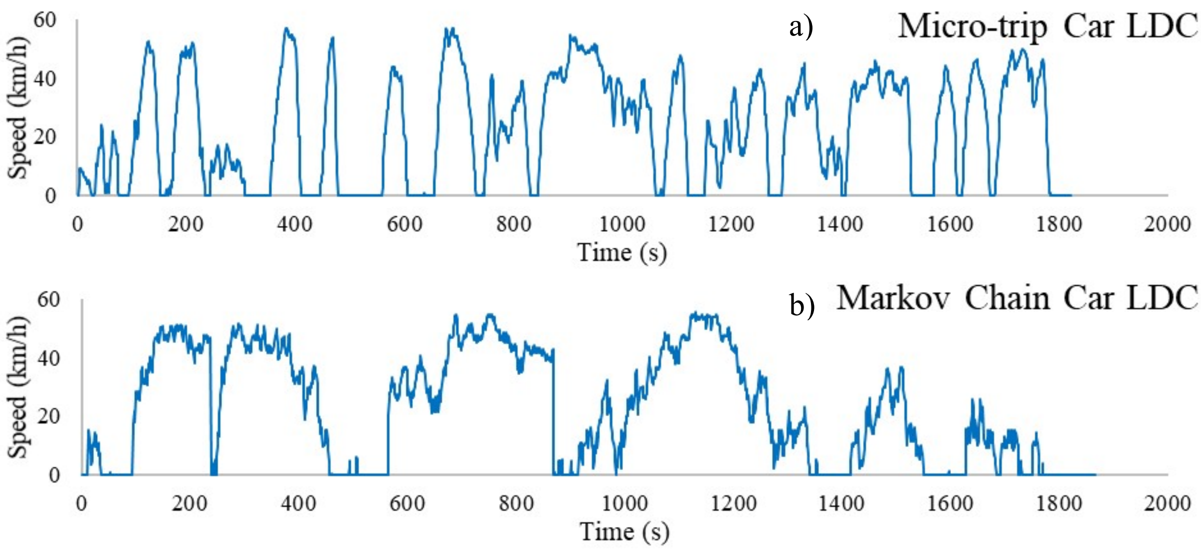

Figure 4: LDCs for passenger cars: a) Micro-trip and b) Markov chain

Table 4: CPs for the passenger cars original data and local driving cycles

Characteristic parameters	Time (s)	Dist. (km)	V (km/h)	Vr (km/h)	a (m/s²)	d (m/s²)	T_c (%)	T_i (%)	T_a (%)	T_d (%)	σ_v (km/h)
Original data for cars	33,352	222.7	24	31	0.53	-0.60	16	23	32	28	19
LDC Car Micro-trip	1,820	11.4	23	30	0.55	-0.63	15	24	33	29	18
LDC Car Markov	1,865	11.8	23	32	0.58	-0.66	11	25	34	30	19

For passenger cars (Figure 4), both cycles provide CPs average error and time limits within the threshold when compared to the original data. Nonetheless, even providing similar CPs, both cycles are visually different. For motorcycles, both LDC were also within the established average error, and they are shown in Figure 5 and the Table 5 exhibits their CPs.

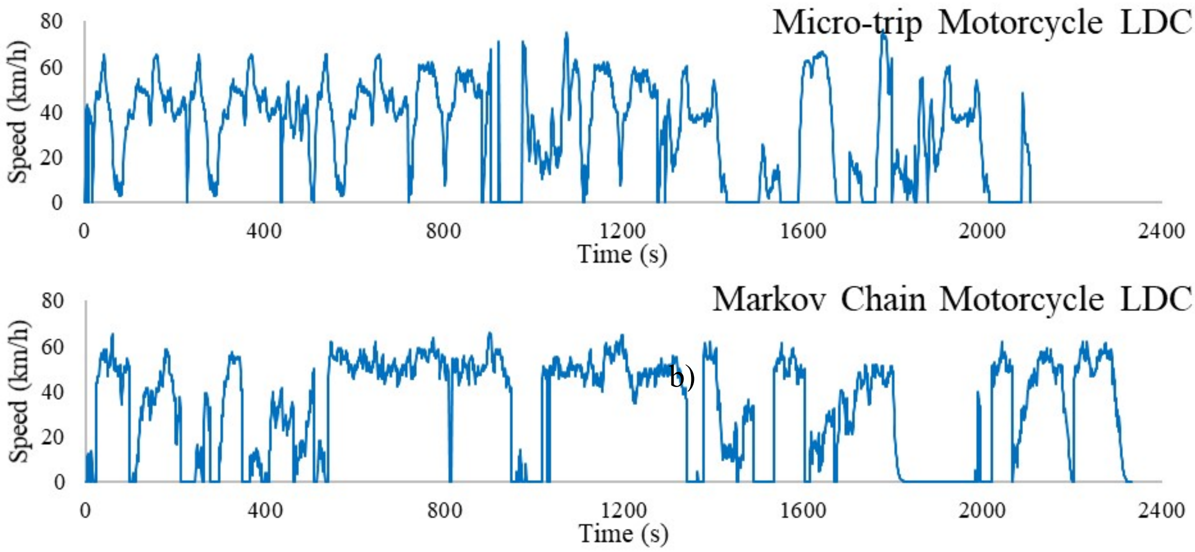

Figure 5: LDCs for motorcycles: a) Micro-trip and b) Markov chain

Table 5: CPs for the motorcycle original data and local driving cycles

Characteristic parameters	Time (s)	Dist. (km)	V (km/h)	Vr (km/h)	a (m/s²)	d (m/s²)	T_c (%)	T_i (%)	T_a (%)	T_d (%)	σ_v (km/h)
Original data for motorcycles	25,805	240.0	33	39	0.80	-0.92	12	23	32	28	19
LDC Motorcycle Micro-trip	2,016	19.0	33	38	0.84	-0.92	12	15	38	35	21
LDC Motorcycle Markov	2,202	19.8	33	39	0.85	-1.01	17	15	37	31	22

In Figure 4 and 5, it is possible to realize that the Micro-trip method presents micro-trips with average shorter time duration, what is expected of a urban traffic situation common in Brazilian urban areas. The number of micro-trips obtained (19 for passenger cars and motorcycles) is adequate when comparing to the number of crossroads and traffic lights in the selected route (28). The behavior of accelerating after a traffic light and stopping in the next one or to merge in other road, help to provide representative micro-trips for the region.

In Markov, the number of micro-trips was lower for cars (10), implying that the micro-trips generated have an average longer time duration when compared to Micro-trip method (*e.g.*, the longest micro-trip in Markov method has 357 s of duration, while the longest micro-trip in the Micro-trip method lasts for 210 s). To obtain a cycle with more micro-trips for cars, the authors considered inserting another CP (micro-trips per km) during the error evaluation stage, in order to verify if a DC with a greater number of micro-trips could be obtained. After inserting this new CP, we could not obtain an LDC within the established error. Also, is relevant to remind that every CP added increases the computational processing time to obtain the cycles, and that the 9 CPs used is considered an adequate amount of CPs (Zhao *et al*, 2020).

When comparing motorcycles to passenger cars, we verify that average acceleration, average speed, average speed in movement, and absolute average deceleration are higher. This is a reflex of an expected behavior for motorcycles in heterogeneous urban conditions. Motorcycles are faster and nimble vehicle, and they are able to filter the cars especially in lower speeds near traffic lights. In our results, the difference among the time duration of the motorcycle and cars is approximately 14%, but in relative distance the motorcycle travel 67%

more when compared to cars. Those results show how cars require a longer time to move in Recife when compared to motorcycles.

6. CONCLUSION

This study provides a concise review about the two main methods for construction of driving cycles: Micro-trip and Markov chain. We also present a case study of the LDC construction for both methods. In order to develop the cycles, we travelled more than 240 km with each vehicle (motorcycle and cars) in Recife, a Brazilian city. The tests were performed during off-peak conditions in weekdays, in different seasons, and the speed-time data was registered with a smartphone GPS of 1Hz frequency.

For our case, considering the obtained data, both methods were able to generate LDCs with the CPs within the expected threshold, although they were visually different. For passenger cars, the Micro-trip method generated an LDC with shorter micro-trips when compared to the Markov method. Most of the micro-trips obtained in the Markov method are longer than the original data obtained for Recife. We believe that the micro-trips from Markov would be more precise if there was more data (vehicles and testing time) collected to improve the STM. Considering the number of micro-trips obtained in this study, we understand the Micro-trip method provided a more realistic LDC than the generated by the Markov method for Recife. However, this result can't be generalized for all possible scenarios.

Based on the literature, we recommend using the Micro-trip method for a smaller amount of data and in urban conditions, since it has the ability to replicate the trajectory among traffic lights and cross roads. The Markov method is recommended to be used in possession of a considerably large amount of data and highway conditions. The main recommendation is for the researchers that desire to construct driving cycles to decide which the method that are going to be used prior to collecting the data, based on the number of vehicles available for testing, road conditions, and collection time.

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Maurício P. M. de Novaes Santos (mauricio.novaessantos@ufpe.br)
Fernando Wesley C. de Araújo (fernando.wesley@ufpe.br)
Guilherme Medeiros S. de Andrade (guilherme.soaresandrade@ufpe.br)
Fábio S. Magnani (fabio.magnani@ufpe.br)
Departamento de Engenharia Mecânica, Centro de Tecnologias e Geociências,
Universidade Federal de Pernambuco, Av. da Arquitetura, SN – Recife, PE, Brasil