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Comparison of driving cycles obtained by the Micro-trips, Markov-chains and MWD-CP methods

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ABSTRACT

Currently, there is an increasing interest for driving cycles (DCs) that truly represent the driving pattern of a given region aiming to evaluate the energy efficiency of electric vehicles and identify strategies of energy optimization. However, it has been observed increasing differences in the energy consumption reported using type-approval DCs and the observed in the vehicles under real conditions of use. This work compared the Micro-trips, Markov-chains and the MWD-CP methods in their ability of constructing DCs that represent local driving patterns. For this purpose, we used a database made of 138 time series of speed obtained monitoring during eight months a fleet of 15 transit buses operating on roads with different levels of service, traffic and road grades, under normal conditions of use. Then, we used 16 characteristic parameters, such as mean speed or positive kinetic energy, to describe the driving pattern of the buses' drivers monitored. Subsequently, we implemented three of the most widely used methods to construct DCs using this common database as input data. Finally, we evaluated the degree of representativeness of the local driving pattern contained in each of the obtained DCs. Toward that end, we defined that a DC represents a driving pattern when its characteristic parameters are equal to the characteristic parameters of the driving pattern. Therefore, we used as criteria of representativeness the relative differences between paired characteristic parameters and observed that the MWD-CP method produced the DC that best represents the driving pattern in the region where the buses were monitored, followed by the DC produced by the Micro-trips method.

Keywords:

Driving patterns;
Vehicle energy consumption;
Tailpipe emissions;
Optimization of vehicle energy systems;

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1. Introduction

It has been hypothesized that differences in the observed energy consumption from electric vehicles (and fuel consumption and tailpipe emissions from diesel or gasoline-fueled vehicles) with respect to the measured during the type-approval tests are mainly due to the lack of representativeness of the local driving pattern contained in the type-approval driving cycles used in these tests [1]. This situation affects the dimensioning of the vehicle power train and of the energy storage system [2].

A driving cycle (DC) is a synthesized representation of the driving patterns in a given road network. In most cases, the DCs are displayed as a velocity vs. time series [3]. As it represents the driving pattern of the region under consideration, the DCs are frequently used to evaluate the energy consumption and the tailpipe emissions of the vehicles [4–6]. Therefore, the DC representativeness should be understood as the DCs ability of representing the driving patterns of a region, and its capacity of reproducing the energy consumption

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List of symbols and acronyms

CP	Characteristic parameter
DC	Driving cycle
Mk	Markov-chains method
MT	Micro – trips method
MWD-CP	Minimum weighted difference - characteristics parameters method
QoF	Quality of fit
SAPD	Speed acceleration probability distribution
EC	Energy consumption

and the tailpipe emissions from the vehicles that follow that DC. In this context, DCs are independent of the vehicle technology. The DCs for electric vehicles are the same that the DCs for gasoline or diesel-fueled vehicles.

Besides the use of DC in the energy and environmental assessment of vehicles, they are also used for the design of vehicle components and systems, especially those related to the vehicle powertrain. This is due to the fact that DCs contain the instant loads and energy demanded by the road to the vehicle in the given region [7,8]. Consequently, DCs can be used to identify strategies to reduce energy consumption in vehicles. For example, they can be used to evaluate the potential reduction in GHG (Green House Gases) that can be attained by implementing public policies related to the use of electric vehicles or biofuels [9,10]. Furthermore, they can be used to optimize the power train design of electric and hybrid vehicles in terms of battery size [11] since they capture the characteristics of the routes, congestion level, driving behavior, which are factors that affect the way that the stored energy is delivered. Energy consumption models for powertrain optimization, like the VT-CPEM, require of representative DC data to compute the instantaneous power consumed and the state of charge of electric batteries [12].

Another important application of DCs is the study of variations in the driving behavior caused by the use of new vehicle motorization technology. Berzi et al. [13] concluded that when people drive an electric vehicle, the frequency of strong accelerations events increased due to the absence of the engine noise, especially at low-speed conditions. Finally, DCs contain the energy consumption patterns and therefore they can be used to design energy logistics strategies (charging points, energy demand, etc.) or energy consumption scenarios of a region, similar to the studies carried out by Setiartiti et al. [14] and Juul et al. [6].

DC representativeness is mainly affected by three factors: *i*) the quality and quantity of vehicle operation data used to construct the DC. *ii*) The method used to construct the DC. *iii*) The metrics used to evaluate the DC representativeness [15].

Currently, the Global Position System (GPS) allows obtaining reliable vehicles operation data with a sampling frequency higher than 1 Hz. Then, improvements in DC representativeness should be obtained through improvements in the methods used to construct the DCs and the metrics used to guarantee their representativeness.

The existing DC construction methods can be classified as stochastics and deterministic. Within the stochastics methods, the DCs are constructed splicing trips segments or states, which are quasi-randomly selected from trips segments or states database made from the trips sampled [16]. In the case of the deterministic method, one of the many monitored trips is selected as the representative DC.

In all methods, driving patterns and DCs are described by a set of metrics named characteristic parameters (CPs). They are variables based on speed and time such as average speed, average positive acceleration, positive kinetic energy, etc. [3]. A DC is said to be representative of a driving pattern when the CPs of the DC are similar to the CPs of the driving pattern. Therefore the DC representativeness is evaluated by the average relative differences of corresponding CPs.

No study has attempted to compare the existing methods in their ability of constructing DCs that truly represent the local driving patterns. We addressed this gap of knowledge and here we report the following contribution: using a common trips database, this study compares three common methods of constructing DCs: Micro-trips, Markov-chains and MWD-CP. The results obtained are useful for researchers who need to decide about the DC construction method to choose in order to obtain truly representative DCs. The use of representative DCs on the design and optimization of vehicle energy systems will lead to effective energy management strategies.

This paper is arranged as follows. Section 2 describes the approachr followed to evaluate the 3 DC construction methods. There, we describe: i) the monitoring campaign carried out to collect vehicle driving data in a region of general characteristics, ii) the three DCs construction methods, and iii) the methodology followed to compare the representativeness of DCs produced by each method. Section 3 shows the results of comparing DCs in terms of their representativeness of the local driving pattern. Finally, conclusions are summarized in section 4.

2. Materials and methods

We highlight that this research focuses on the comparison of the DCs obtained from three methods frequently used for constructing DCs, rather than obtaining a representative DC for a specific region. To do this, we used a common database of trips obtained monitoring the operation of a single vehicle fleet operating in a region with general characteristics and therefore it describes the driving pattern in that region. Then, we implemented the three methods and finally, we evaluated the ability of the obtained DCs of representing the driving pattern contained in the database. Next, we will describe how the database was built, the implementation of the methods for constructing DCs and the methodology used to assess the representatives of the DCs obtained.

2.1 Trips database

Reference [17] describes the work that led to the construction of the trip database. That work aimed to describe the driving patterns in regions with diverse topographies. It consisted in monitoring a vehicle fleet during its normal operation for a long period of time (~8 months). Next, we will summarize that work.

Authors in reference [17] looked for a region whose road network presents different types of topography, traffic, and level of service. These preferences were established in order to have vehicle operation data in regions of general characteristics. The MEX 15D road, that connects Toluca with México City, fulfills these requirements. The selected road has a length of 72.4 km. The first 17 km corresponds to urban driving conditions in Mexico City where traffic flow is low due to frequent traffic jams. The next 41 km correspond to an extra-urban road located in a mountainous region with altitudes between 2200 and 3100 meters above the sea level (m.a.s.l.). The last 14 km correspond to the extra-urban and urban area of Toluca city which is characterized by medium vehicular traffic flow over a flat region.

Fifteen buses were used during the monitoring campaign. They cover the Toluca-Mexico City route on a non-stop service. The buses were built between 2012 and 2014. They have CUMMINS ISM 425 diesel engines of 10.8 litters. Their passenger capacity is 49 people and their gross vehicle weight is 13850 kg [18]. The buses location (Altitude, Latitude, and Longitude) and speed were established using a global position system (GPS) [19]. Additionally, the operating variables of the vehicle's engine were extracted through the onboard diagnostic system (OBD II) vehicle port. Table 1 shows the technical characteristics of the instruments used in this work.

The variables listed in Table 1 were recorded during eight months of regular operation of the instrumented buses. The buses were operated by regular drivers in order to minimize any impact on the bus operation and passenger transport service. The trips sampled were performed in both directions of the route. Huertas et al. [8] concluded that a sample of 10 to 20 trips is sufficient to describe the driving patterns in flat regions. In this study we obtained 46 trips per region. Figure 2.a illustrates the speed vs. time plot obtained from an arbitrary chosen trip.

QA/QC analysis was conducted to eliminate atypical data and trip series with more than 5% of missing data. At the end of the measurement campaign, a database was constructed with 138 trips (54867 vehicle operation records)[19].

2.2 Implementation of the DCs construction methods

Stochastics methods: Micro-trips and Markov-chains

Micro-trips and Markov-chains methods are two of the most accepted approaches to construct DCs [16]. As stated before, in these two methods a synthetic DC is

Table 1: Technical characteristics of the instruments used in this study

Variable	Instrument	Technical characteristics
Position: • Latitude • Longitude • Altitude Speed and time	GPS	Position: 3-5 m, 95% typical Frequency: 1 Hz Speed: 0.05 m/s Root mean square (RMS) steady state Pulse per second (PPS) time: 1 microsecond at rising edge of PPS pulse
Engine operation variables	OBD II	Registered through engine sensors signal extracted by ECU through OBD2

made by splicing a quasi-random selection of trip segments [20] or states [21,22]. Figure 1 illustrates these methods.

In the Micro-trips method, the speed-time data, collected during the vehicle monitoring campaign, is partitioned in segments of trips bounded generally by vehicle speed equal to 0 km/h. These segments are named “micro-trips”. A clustering of Micro-trips according to their speed and acceleration is frequently used. Then, a set of Micro-trips are quasi-randomly selected based on their probability of occurrences [5,23]. The number of Micro-trips selected depends on the desired duration of the DC. Additional research work is required to determine the appropriate duration of the DC. Usually it is near to 20 – 30 min. Table 2 shows the time used in this work for each method. Finally, the selected set of Micro-trips are spliced together producing a candidate driving cycle.

In the case of the Markov-chains method, the speed-acceleration data is encoded into operational states. Following up the work of Shi et. al [22], we used 45 bins for speed and 9 for acceleration. Hence, the frequency of the occurrences of the operational states is registered in a states matrix. Then, from the same database, the probability for moving from state X_i to state X_i+$_1$ is computed. Results are recorded in a probability transition matrix [2]. Hereafter, this matrix is used to make a quasi-random selection of states that form a states vector. Finally, a candidate-DC is calculated decoding this states vector in terms of speed and time [22,24].

In these two methods, the representativeness of the driving pattern contained in the candidate-DCs is evaluated. Toward that end, the driving patterns monitored in the region under consideration and contained in the trip database was described by a set CPs. As described before, a CP is any variable formed starting from the speed and time variables, such as mean speed, positive kinetic energy, etc. Table 3 shows the most recurrent CPs used in the literature. Then, the candidate-DC was also described by its characteristic parameters (*CPs**). Finally, it was established that a DC represent a driving pattern when the characteristic parameters of the candidate-DC are similar to the characteristic parameters of the driving pattern. i.e., when $CP_i^* = CP_i$. Thus, the degree of representativeness of a candidate-DC is evaluated as the relative difference between paired CPs according to Eq. 1.

$$RD_i = \frac{\left|CP_i - CP_i^*\right|}{CP_i} \tag{1}$$

Most researchers use, during the construction process, a threshold between 5% and 15% as the maximum acceptable difference among the paired CPs [24,25] However, they use a reduced number of CPs (2 or 3). The CPs and the number of CPs used depend on the researcher´s criteria. The most commonly used CPs are average speed, average acceleration, average deceleration and percentage of idle time. Initially, we used these four CPs for both methods. However, the method based on Markov-chains did not converge and therefore, for that case, the CPs had to be limited to average speed and percentage of idle time. Table 2 specifies the CPs used in each method.

The process of obtaining a candidate-DC is repeated until the acceptable threshold is obtained. The first candidate-DC that fulfills this threshold becomes the representative DC. As these two methods are stochastic, the output DC change every time the method is applied, making the method repeatable but not reproducible. In this work, we carried out two iterations per method.

Deterministic method: Minimum Weighted Difference - Characteristics Parameters

The Minimum Weighted Difference of Characteristic Parameters (MWD-CP) is a deterministic approach to construct DC [17]. In this method, an estimated value of energy consumption (EC) is obtained for each trip, and the trip with the closest EC to the average EC of all trips is selected as the representative DC. Therefore, it uses EC as the assessment parameter to evaluate the representativeness of the DC. Currently, the simultaneous measurements of speed, time and energy consumption in vehicle fleets under real-world driving conditions could result in an expensive process with high uncertainties. As an alternative, the MWD-CP estimates the EC as a linear function of the CPs that most influence energy

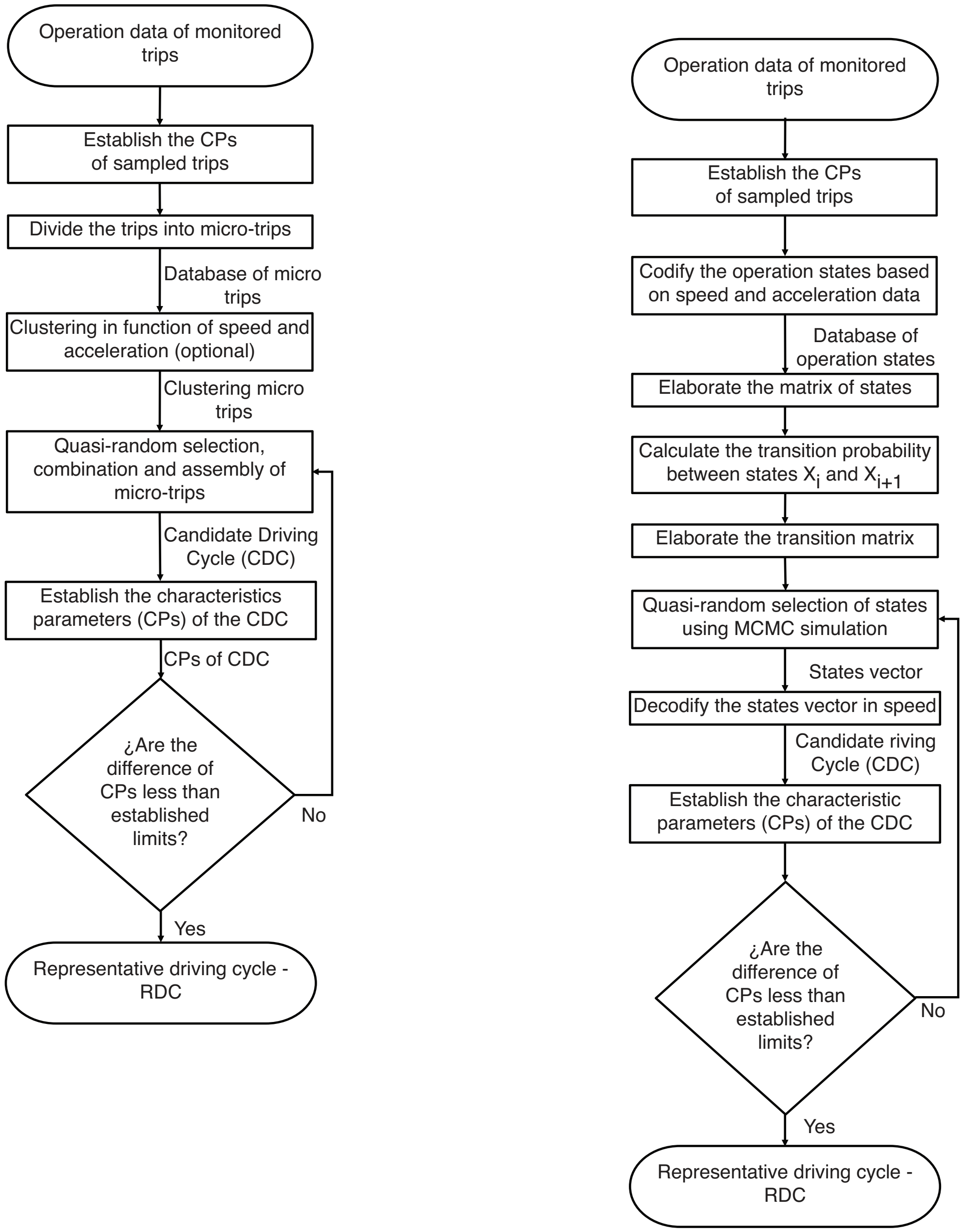

Figure 1: Illustration of the stochastics methods for constructing driving cycles: a) Micro-trips and b) Markov-chains method

consumption [17] such as mean speed and mean positive acceleration. The EC for each trip can be calculated using Eq. (2) and Eq. (3). Then, the average EC of all the monitored trips is calculated by Eq. (4).

$$\widehat{EC_J} = w_0 + \sum_i w_i CP_{ij} \tag{2}$$

$$EC_j = \widehat{EC_J} + \varepsilon_j \tag{3}$$

$$\overline{EC} = w_0 + \sum_i w_i \overline{CP_i} \tag{4}$$

In the previous equation, w_0 is a constant value, w_i is a weighting factor associated to the characteristic parameter i, $CP_{i,j}$ is the characteristic parameter i for the trip j. $\overline{CP_i}$ is the average value of the characteristic parameter i for all the trips sampled. ε_j corresponds to the difference between the real EC_j and the estimated $\widehat{EC}_j$. The representative DC is the trip j with EC a that minimizes the absolute difference respect to $\overline{EC}$. The

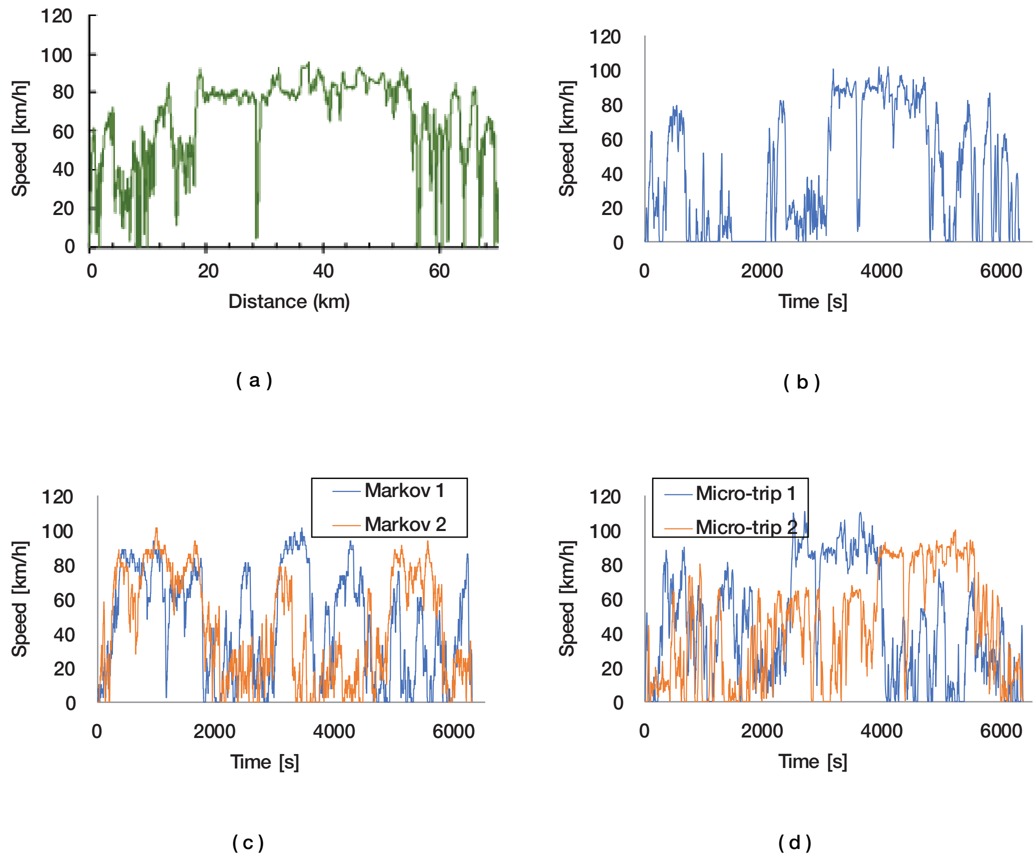

Figure 2: a) Speed vs. time obtained in an arbitrary chosen trip. Driving cycles obtained by the b) MWD-CP, c) Markov-chains and d) Micro-trips methods

Table 2. Characteristic parameters used in each method to construct driving cycles. *The expression used to calculate the SFC is shown in Eq. (7)

Input parameter	Micro-trips	Markov-chains	MWD-CP
Duration of cycle (minutes)	105 ± 2	105 ± 2	Depends on the selected driving cycle
Characteristic parameters selected to evaluate the driving cycle representativeness	Average speed Average acceleration Average deceleration Percentage of time in idling	Average speed Percentage of time in idling	SFC*
Relative difference among paired CPs	5%	5%	Not required
Other considerations	Clustering micro- trips	Speed discretization in 45 bins and 9 bins for acceleration	–

Table 3: Characteristic parameters that describe the driving pattern in the Tol-Mex road. MT: Micro-trips. Mk: Markov-chains

	Characteristic Parameters -CPs	Units	CPs of driving patterns	Mk 1	Mk 2	MT 1	MT 2	MWD-CP
Speed	Maximum speed	km/h	28.1	28.2	28.2	30.8	27.8	28.4
	Average speed	km/h	12.0	12.5	11.8	12.4	12.0	11.2
	Standard deviation of speed	km/h	8.9	8.7	8.6	9.0	8.7	9.7
Acceleration	Maximum acceleration	m/s^2	2.0	2.1	1.4	1.4	1.9	1.6
	Maximum deceleration	m/s^2	–2.5	–2.8	–2.1	–3.5	–1.9	–2.1
	Average acceleration	m/s^2	0.4	0.7	0.7	0.4	0.4	0.4
	Average deceleration	m/s^2	–0.5	–0.8	–0.8	–0.5	-0.5	-0.5
	Number of accelerations per km	1/km	7.3	8.8	9.2	6.5	7.2	7.4
	Standard deviation of acceleration	m/s^2	0.2	0.1	0.2	0.2	0.2	0.2
	Standard deviation of deceleration	m/s^2	0.4	0.3	0.3	0.3	0.4	0.4
Operation mode	Percentage of time in idling	%	9.9	9.7	9.8	9.5	9.9	19.3
	Percentage of time accelerating	%	29.5	18.9	18.7	31.3	28.2	27.2
	Percentage of time decelerating	%	25.6	16.8	16.9	27.3	23.9	23.7
	Percentage of time in cruise	%	34.9	54.6	54.6	31.9	38.0	29.7
Dynamics	Root men square of acceleration - RMS	m^2/s^2	0.4	0.5	0.5	0.4	0.4	0.4
	Positive Kinetic Energy - PKE	m/s^2	240.2	241.5	239.5	252.0	224.8	241.3

representative DC using the methodology MWD-CP can be identified through Eq. (5) and Eq. (6).

$$EC_j - \overline{EC} = \sum_i w_i (CP_{ij} - \overline{CP}_i) + \varepsilon_j \tag{5}$$

$$C = Arg_j = \left\{ \min \sum_i w_i \left| (CP_{ij} - \overline{CP}_i) \right| \right\} \tag{6}$$

Previous work on the same region found that $w_0 = 0.208$ and that the CPs that most influence energy consumption in this region are the average road grade (θ), the number of accelerations per kilometer (N_a), and the positive kinetic energy (*PKE*) [17]. Therefore, Eq. 2 becomes Eq. 7 and this last equation estimates the *EC* of the transit buses monitored in this region. Eq. 7 also defines the weighting factors (w_i) for Eq. 2.

$$EC = 0.208 + 4.149\overline{\theta} + 0.0041N_a + 0.423\ PKE \tag{7}$$

2.3 Evaluating the driving cycle representativeness

Once the three methods described above were implemented, we obtained their respective DC and evaluated how close the obtained DCs represent the monitored driving pattern.

We extended the process used to evaluate the representativeness of the candidate-DC to evaluate the representativeness of the DC but using all the CPs listed in Table 3. Additional work is required to define the set of CPs that fully describe a driving pattern and from there, the CPs that need to be included in this assessment of representativeness. For the time being, we used the CPs most frequently reported in the literature and listed in Table 3, without any particular prioritization.

The Speed Acceleration Probability Distribution (SAPD) is another alternative to describe driving patterns. As described before, it classifies the instant speed and acceleration of the vehicles into bins of speed-acceleration. Therefore, the similarity between the SAPD of the DCs and the SAPD of the driving pattern is an indicator of representativeness of the DC. The Quality of Fit (*QoF*), Eq. (8), has been used to evaluate the degree of similitude between SAPDs [26].

$$QoF = \sum_{i=1}^{n} \sum_{j=1}^{m} (P_{ij} - P^*_{i,j})^2 \tag{8}$$

In Eq. 8, P^*_{ij} is the probability that the vehicle travels within the bin i of speeds, and the bin j of accelerations, in the states matrix obtained for the DC, and P_{ij} is the same variable obtained for the driving pattern. This metric is independent of the number of bins used in the discretization of the speed and acceleration ranges. It ranges between 0 and 2 and values close to 0 indicate perfect math.

3. Results

As described before, the driving patterns monitored in the region under consideration and contained in the trip database was described by the CP_i listed in Table 3. The values obtained for those CP_i are also displayed in Table 3.

Figures 2 c-d show the speed versus time profiles of the five DCs obtained using the Micro-trips, Markov-chains and MWD-CP methods. Figure 2.d shows that the two DCs obtained with the Micro-trips method are different due to the quasi-random selection of the micro-segments. Although the global average value for the assessment CPs remains constant, variations at the local time scale could produce variations in the energy consumption and tailpipe pollutant emission that not necessarily balance at the global scale. For example, although the relative differences between the average speeds of the two driving cycles obtained is small (0.6 km/h), the speed and acceleration observed at any local intervals of time are drastically different causing variations in energy consumption and consequently on pollutant emissions. The previous observations are also valid for the two DCs obtained via the Markov-chains method (Figure 2.c).

When the CPs that describe the DC are calculated and compared to the CPs that describe the driving pattern (Figure 3), we observed that the two DCs constructed using the Markov-chains method represent accurately the CPs associated to speed, percentage of idling and PKE (RD_i <20%), but they do not for the CPs associated to acceleration, operational modes, and RMS. In the case of the Markov-chains method, we observed that the

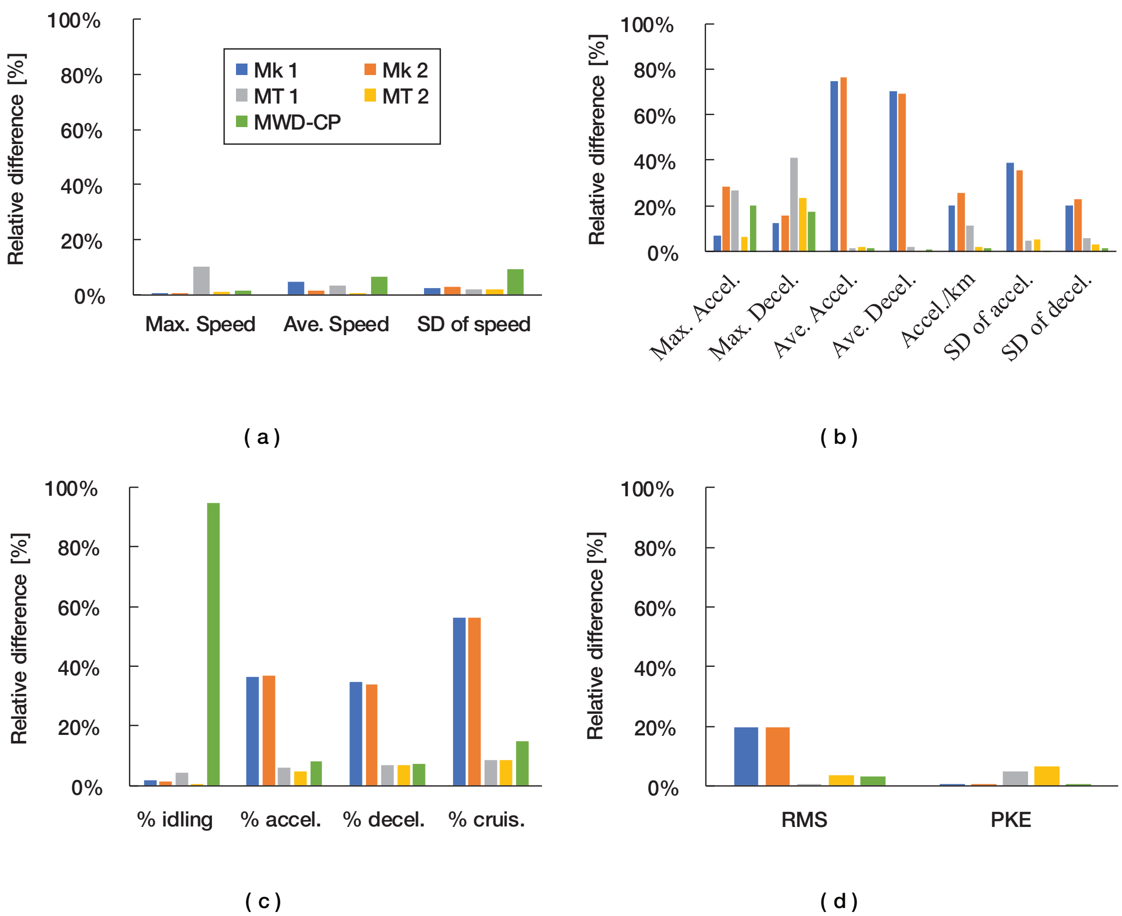

Figure 3: Evaluation of the representativeness of the driving patterns contained in the driving cycles obtained using the Micro-trips, Markov-chains and MWD-CP methods, expressed as relative differences of the characteristic parameters associated to: a) speed, b) acceleration, c) operational modes and d) vehicle dynamics

obtained DCs represent accurately the average speed, standard deviation of speed (Figure 3.a), average acceleration, operational modes (Figure 3.c), RMS and PKE (Figure 3.d), but they do not represent well the CPs associated to maximum acceleration and maximum deceleration (Figure 3.b). For the case of the MWD-CP method, the obtained DC represents accurately all the CPs that describe the driving pattern, except the CP associated to the percentage of idling time (Figure 3.c). This is due to the fact that the MWD-CP method does not include the percentage of idling time in the EC estimation function because this CP has a low contribution to energy consumption in the region considered in this study. In contrast, the Micro-trips and Markov-chains methods did consider idling time as an assessment parameter. Therefore, the DCs produced by the Micro-trips and the Markov-chains methods are forced to have relative differences in idling time below the defined threshold (5%).

Previous observations hold for the two DCs obtained by each method and reported in this manuscript. Since the DCs change each time the stochastic methods are applied, previous observations need to be re-confirmed for the case of many other DCs (>1000) obtained using these DCs construction methods, starting from the same trips database. We foresee that results on relative differences will show a tendency towards stable values and therefore the comparison should be based on average relative differences and the dispersion of those relative differences.

Figure 4.a shows the SAPDs of the driving pattern obtained for the Tol-Mex region. Figures 4.b-f shows the SAPDs of the five DCs obtained using the three DC construction methods. They show that all SAPDs look similar to the SAPD of the driving pattern.

Using the *QoF* metric (Eq. 8), we confirmed that all methods produced DC with a similar level of representativeness of the driving pattern ($QoF < 0.008$). The highest level of representativeness was obtained by the DC constructed by the Micro-trips method ($QoF_1 = 0.0039$ and $QoF_2 = 0.0054$), followed by the Markov-chains method ($QoF_1 = 0.0054$ and $QoF_2 = 0.0072$) and the MWD-CP method ($QoF = 0.0082$).

As mentioned above, DCs are used mainly to evaluate the energy consumption and tailpipe emissions from the vehicles. However, the assessment criteria currently used to construct DCs has no included those two metrics. Towards that end it is required the simultaneous measurements of speed, time, energy consumption and emissions from a large fleet of vehicles running under normal use, for extensive periods of time, which will be the focus of our future work.

4. Conclusions

We implemented three frequently used methods to construct driving cycles (Micro-trips, Markov-chains, and MWD-CP) and evaluated their capacity of producing driving cycles (DCs) that represent local driving patterns. Toward that end, we used a common trip database obtained from monitoring the operation of 15 transit buses under normal conditions of use on the road that connects Toluca City with Mexico City. From that database, we obtained the driving pattern of this region and described it by means of 16 characteristic parameters (CPs).

Then, we established that a DC represents a driving pattern when the CPs of the driving cycle are similar to the CPs of the driving pattern. Thus, we evaluated the degree of representativeness as the relative difference between paired CPs. We found that the MWD-CP method produced a DC that describes the driving pattern in that region with the highest level of representativeness. All of its CPs were similar to the CPs of the driving pattern (relative differences <20%), except for the case idling time.

The MWD-CP method is a deterministic, repeatable and reproducible method designed to construct DCs that reproduce real energy consumption. These important advantages over the other methods of constructing driving cycles are opaque by its major drawback which is the need of weighting factors that depend on the region under consideration.

Previous conclusions need to be re-confirmed with a database made of simultaneous measurements of speed, energy consumption and tailpipe emissions on a large vehicle fleet running under normal conditions of use during extended periods of time. Additionally, it is worthwhile to develop the present comparative analysis based on results of tendencies of the stochastics methods for constructing DCs (Micro-trips, Markov-chains) rather than on a single result, as it was done in the present study.

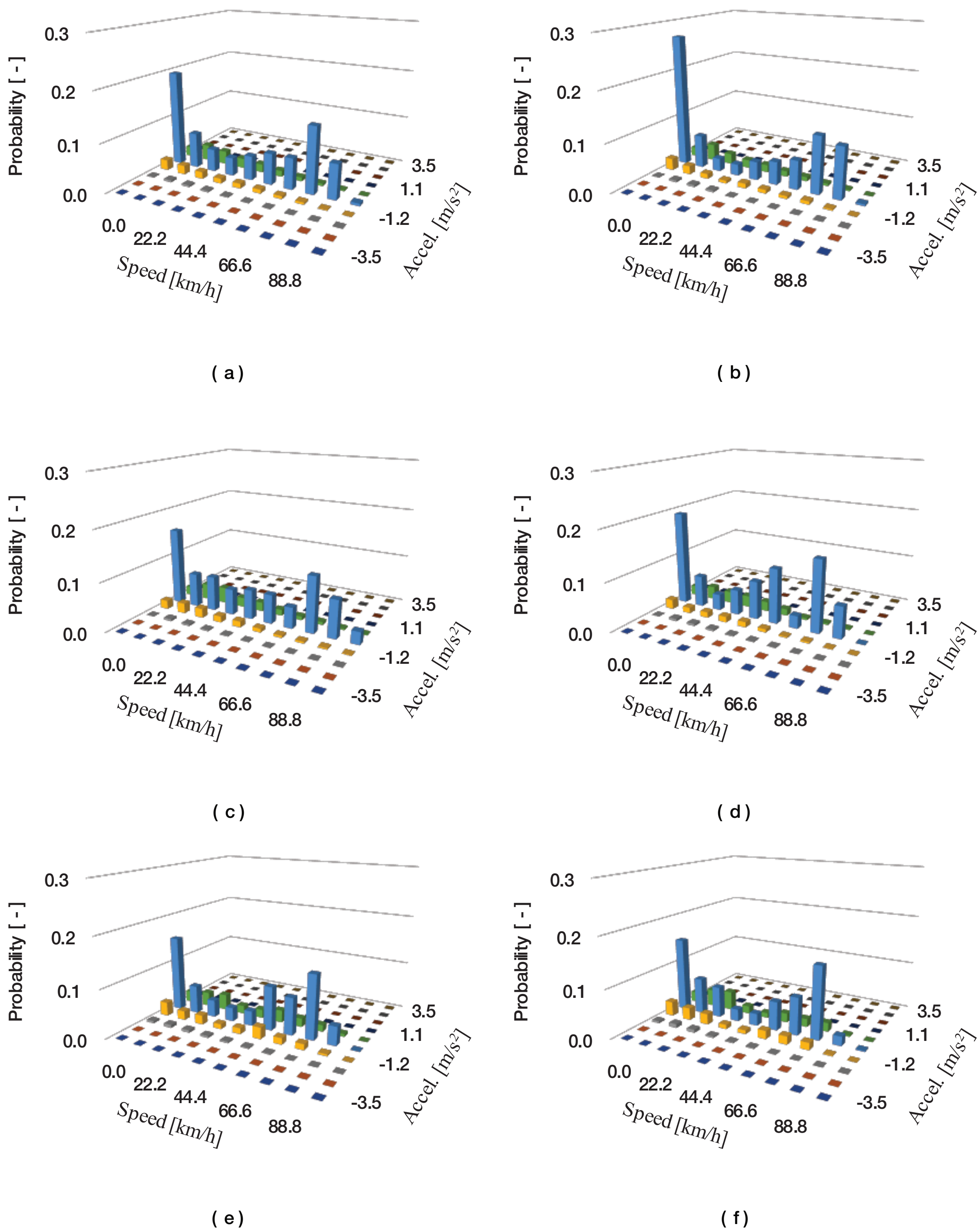

Figure 4: Assessment of the representativeness of the driving cycles obtained using the MWD-CP, Micro-trips and Markov-chains methods using as criteria the Speed Acceleration Probability Distribution (SAPD). a) SAPD for the driving pattern on the Tol-Mex road. SAPDs for the driving cycles obtained using the b) MWD-CP, c) Micro-trips first iteration, d) Micro-trips second iteration, e) Markov-chains first iteration, and f) Markov-chains second iteration

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