# A Comprehensive Review of Driving Cycles for Electrical Light Duty Vehicles


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***Abstract*— This paper provides a comprehensive review of driving cycles (DCs) for electrical light-duty vehicles, with a focus on their development. Early modal DCs, including the New European Driving Cycle (NEDC) and FTP-75, were originally designed for internal combustion engine vehicles and often fail to capture the complex dynamics of electric vehicles (EVs). In response, recent research has focused on developing transient and region-specific cycles that better reflect real-world driving conditions. The review comprises the methodologies of DCs development, including data collection, data processing techniques, and validation using key performance indicators. Overall, the study emphasises the necessity of revising traditional DCs to accommodate the unique operational characteristics of EVs, such as regenerative braking and instant torque, and highlights future directions for enhancing cycle representativeness and supporting sustainable transportation.**



***Keywords*— *Driving cycles, electric vehicles, lithium-ion batteries, transient cycles, real-world driving conditions.***


## I. Introduction

Typical driving cycles (DCs) not only play a significant part in designing electric vehicles (EVs), but they also serve as a standardized procedure for the certification and evaluation of new automotive vehicle performance, including economy, dynamics, energy consumption, emissions, and range. Designed to deliver velocity–time profiles, DCs aim to accurately replicate realistic operating conditions such as idle, acceleration, deceleration, and cruise. Then, it was deployed to imitate driving conditions on a laboratory vehicle dynamometer or on vehicle simulator software [1]. Common DCs include the World Light Vehicle Test Procedure (WLTP), New European Driving Cycle (NEDC), Urban Dynamometer Driving Schedule (UDDS), and Highway Fuel Economy Test Driving Schedule (HWFET) [2].

Nevertheless, research has shown that these standard DCs are not always suitable for regional energy evaluations of EVs, as traffic, road conditions, urban density, weather conditions, driver behaviour, and the rates of acceleration and deceleration change from area to area [3]. For instance, Berzi et al. [4] designed customized DC for Florence by using real driving data, revealing that electric vehicles (EVs) under this DC consume 10–30% more energy per mile than under the NEDC. Similarly, Wager et al. [5] found significant discrepancies in real energy consumption and range for vehicles in Perth compared to standard test conditions, with the tested vehicle's range being only 19% of the NEDC range at 110 km/h.

The main objective of this study is to provide a comprehensive overview of the development and analysis of driving cycles specifically for light-duty EVs. The approach followed starts by presenting the methodologies used to develop DCs, examining the factors influencing real-world EV energy consumption, and discussing the challenges and future directions in developing accurate and regionally relevant driving cycles. Through analysing the recent literature, this review aims to highlight the importance of using realistic DC conditions for light-duty EV assessment.

## II. Driving Cycle Classification

The existing DCs can be categorized along several aspects, reflecting their application and development methodology.

Based on the presentation of the velocity-time DCs, they can be distinguished by modal and transient categories. Linear acceleration and constant velocity segments characterize modal groups, but this makes them less accurate as a whole, as seen in DCs like the NEDC. Transient cycles, on the other hand, comprise velocity variations, reflecting the real driving road conditions extracted from. Modal drive cycles exhibit less variability, whereas transient cycles display greater randomness, exemplified by the WLTP. The velocity profile of WLTC and NEDC is depicted in Fig. 1 as graphical support to distinguish the two approaches. The two methods are different in how they prioritize simplicity versus a realistic representation of driving.

Additionally, DCs could also be classified as legislative or non-legislative. Legislative driving cycles are primarily used for vehicle certification and emissions testing as required by regulatory bodies. National DCs, like the United States (U.S.) FTP-75 or China CATC, aim to guarantee that vehicles adhere to specific regulations. At the international level, WLTP emerged as the standard DC, exhibiting more realistic features [6]. In contrast, non-legislative DCs are often developed for research purposes, focusing on specific driving conditions or geographical locations, such as Dublin and Florence DC [7], [8].

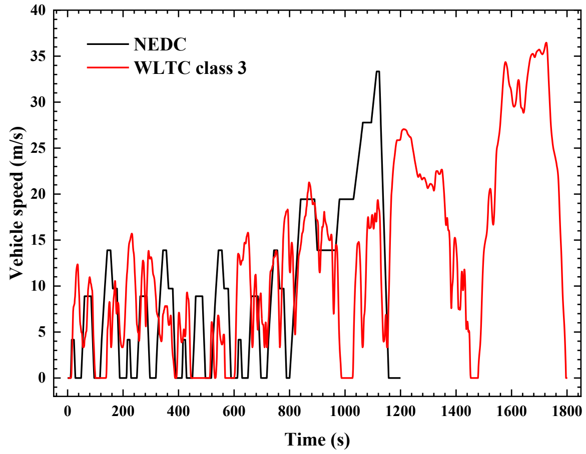


Fig. 1. NEDC (modal) and WLTC class 3 (transient) driving cycle.

The differences between national and regional DCs across the world reflect the unique traffic conditions, road designs, and cultural driving practices. For instance, in Europe, the first DCs, ECE-15 (1970) and NEDC (1980), were modal cycles simulating urban driving with constant speed cruising and linear accelerations [9]. The NEDC included the Extra Urban Driving Cycle (EUDC) to include highway speeds (120 km/h). Criticized for oversimplification, the NEDC was replaced in 2017 by the WLTP, a transient cycle segmented into low, medium, high, and extra-high phases to better represent real-world driving conditions. WLTP's profile is appropriate for EVs, by including deceleration phases (up to 1.5 m/s²) to quantify energy recovery during regenerative braking [10].

The U.S. pioneered transient DC with the release of FTP-72, also known as UDDS (1972), later extended to FTP-75 (1975) as defined by the Environmental Protection Agency (EPA). The Supplemental Federal Test Procedure (SFTP), released in 1996 and mandated in 2007, incorporated aggressive driving (US06) and climate-control usage (SC03) to address energy consumption in extreme conditions, i.e., 35°C and -7°C. The Highway Fuel Economy Test Cycle (HWFET) was the last DC added to the EPA test procedure in 2008, focusing on sustained speeds (97 km/h), reflecting America's highway-centric infrastructure [11].

Japan's 10-15 Mode Cycle (1991), combining urban (10-Mode) and highway (15-Mode) segments based on modal profile and unfeasible accelerations, was replaced by JC08 in 2005. The new transient DC has a high idling percentage time of 28.9%, which reflects the traffic jams in Tokyo [12].

China's rapid EV growth incites the development of the China Light-Duty Vehicle Test Cycle (CLTC) in 2021. Derived from 32 million km of real-world data across 41 cities, CLTC emphasizes low-speed urban operation (28.96 km/h average) and prolonged idling of 22% of duration [12].

The design of these DCs not only cover the environmental and energy regulations but also considers the traffic and driving patterns within each region. The JC08 has the lowest maximum speed and average speed, followed by China, reflecting their population's urban density [13]. In terms of the global standard test, WLTP incorporates real-world driving data from five contributing territories: the U.S., Europe, Japan, Korea, and India, increasing its correspondence with actual driving conditions worldwide [10]. However, these countries still use their national DC for legislative aspects due to significant differences, as shown in Fig. 2 and Fig. 3.

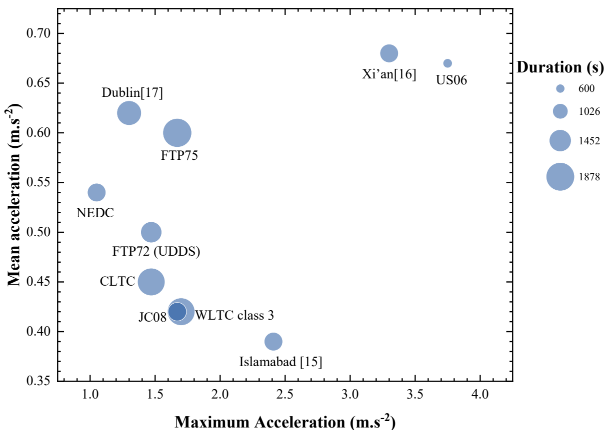


Fig. 2. Analysis of maximum and average acceleration with duration of DCs.

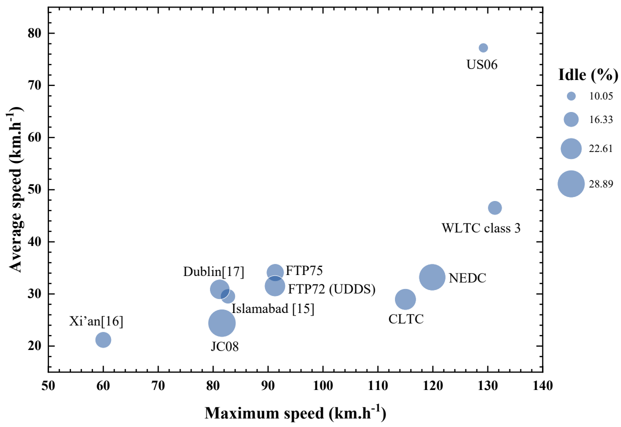


Fig. 3. Analysis of maximum and average vehicle speed with idle percentage for the different DCs.

## III. Driving Cycle Construction Methodology

The development of DCs is based on a conventional methodology to ensure accuracy in representing real-world driving behaviours. The standard methodology encompasses data collection, data processing, and validation stages. This approach can be applied to address the intrinsic dynamics of EVs, such as regenerative braking and rapid torque response [14].

### *A. Real-world Driving Data Collection*

The car chase method and the on-board diagnostics (OBD) method are both used for collecting driving data. In the car chase method, a Global Positioning System (GPS) sensor and data logger are used to follow the target vehicle and record its speed profile [9]. However, this approach has a limited accuracy range and is ineffective in capturing instances of aggressive acceleration [15]. While the OBD entails a system attached to the vehicle to collect speed-related data, it lacks positional coordinates. Recent studies have adopted a hybrid approach, combining OBD and GPS to capture real-time vehicle speed, acceleration, and geolocation [16].

### *B. Driving Cycle Construction*

DCs are synthesized using two primary methodologies: cutting real driving data and probabilistic methods such as

Markov chains. These approaches differ in their segmentation strategies, analytical frameworks, and applicability to regional driving behaviour [9].
The cut real driving data approach breaks down real-world driving records into smaller components, then reconstructs them into a representative DC. This method is further classified into two sub-methods [17], [18]. Firstly, the micro-trip approach involves breaking real-world driving data into multiple micro-trips, each bounded by two consecutive stops. These micro-trips are then selected and reassembled into a single driving cycle that statistically represents real-world driving behaviour [19]. Unlike the micro-trip method, the trip segment technique defines distinct driving conditions for segmenting a trip rather than relying solely on stoppages, refer to Fig. 4. The conditions that define a trip include time segmentation [20], one cycle of acceleration and deceleration phase [21], roadway type (congested, semi-urban, urban, and extra urban conditions [13], and driving modes (acceleration, deceleration, cruise, and idling) [9], [22]. The trip segmentation method provides a flexible and more realistic representation of real driving conditions [20], [23]. [20,23].

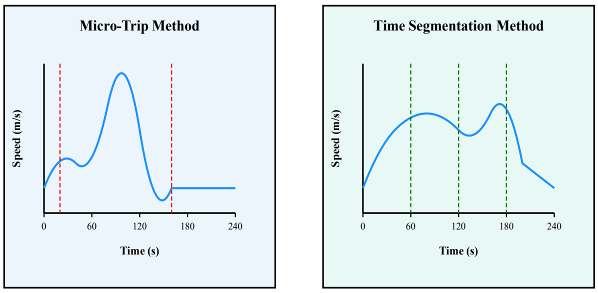


Fig. 4. Micro trip versus time segmentation approach for partitioning collected data.

Markov chain-based approaches model driving patterns through state transitions, offering flexibility in dimensionality and regional adaptability. The Markov Chain Monte Carlo (MCMC) method and transition probability matrices (TPMs) were first applied to driving cycle analysis by [24]. Markov chains are particularly effective because they can capture the stochastic nature of velocity transitions, making them a valuable tool for modelling real-world driving conditions. The complexity of Markov chain-based models varies based on the number of conditions included in the transition probability matrix [14]. In a one-dimensional Markov chain, only the velocity state is considered [25]. A two-dimensional approach is more common; it incorporates both velocity and acceleration as transition states, providing a more realistic representation of driving dynamics [18]. Higher dimensions are used to enhance the accuracy by including additional parameters in the transition probability matrix, such as road grade or traffic congestion [26]. A comparison between the different technique is established in Table 1.
Researchers have employed other numerical techniques, such as two-class Fisher's discriminant analysis and wavelet analysis, to construct comprehensive DCs [27], [28]. Although these advanced methods introduce additional complexity, they enhance the accuracy in reflecting urban driving conditions [29].

TABLE I. COMPARATIVE ANALYSIS BETWEEN DC CONSTRUCTION

| Method | Strengths | Limitations |
|---|---|---|
| **Micro-Trip** | Simple, ideal for urban stop-and-go | Over-reliance on traffic signals |
| **Trip Segment** | Flexible, condition-based segmentation | Requires large datasets for condition tuning |
| **Markov Chains** | Stochastic realism, multi-dimensional | Computationally intensive for high TPMs |
| **Wavelet/Fisher's** | High precision in transient events | Limited regional generalizability |

### C. DC Validation with Collected Data

The validation of newly developed DC involves comparisons with real-world driving data using quantitative error metrics and key performance indicators (KPIs) [25].
To quantify errors between generated DC and real-world data, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are employed. Where, the MAPE is used to evaluate relative differences in key parameters (idle time, acceleration frequency), RMSE measures absolute error magnitude in dynamic parameters (speed, acceleration, deceleration) [26].

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{1}$$

$$MAPE = \frac{100\%}{n}\sum_{1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2}$$

Where, n is the number of the observations, is the predicted value, and is the actual observed value.
The accuracy of the representations of DCs depends on the KPIs used; velocity-related KPIs are often used in the literature to quantify the DCs accuracy [30]. However, over 40 DC features can be deduced from the literature [21], [26], [31]; those features could be fitted into different categories linked to velocity, acceleration, energy, emission, terrain-linked features, and operation modes [13]. To develop realistic DC, the comparison should include the KPI from different categories; velocity-related KPI fail to capture the overall picture of real data [21,32].
Below is a detailed description of some DC features:
The average speed [km/h] (3) of a driving cycle is defined as the total distance travelled divided by the total time taken, considering all variations in speed throughout the cycle [32].

$$v_{dr} = \frac{1}{n} \times \sum_{i=1}^{n} v_i \tag{3}$$

where *n* is the total number of data points, and *vi* is the speed at the *i*-th observation.

The velocity variance [km/h]$^2$ (4) and the standard deviation of velocity [km/h] (5) quantify the dispersion of speed values relative to the mean speed. Higher values indicate greater fluctuations in velocity profile [8], [30].

$$\sigma_v = \frac{1}{n}\sum_{i=1}^{n}\left(v_i - v_{avg}\right)^2 \tag{4}$$

$$v_{std} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (v_i - v_{dr})^2} \quad (5)$$

The standard deviation of acceleration [m/s²] (6) represents the variability and aggressiveness of velocity during the cycle [32].

$$a_{std} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (a_i - a_{dr})^2} \quad (6)$$

The average acceleration [m/s²] (7) is computed as the mean of all positive acceleration. While the average deceleration [m/s²] (8) corresponds to the mean of all negative acceleration values [26], [30].

$$a_{acc} = \frac{1}{n} \times \sum_{i=1}^{n} a_i \quad (7)$$

$$a_{dec} = \frac{1}{n} \times \sum_{i=1}^{n} a_i \quad (8)$$

The acceleration variance [m/s²]² (9) is a statistical measure that determines the dispersion of acceleration values [8].

$$\sigma_a = \frac{1}{n} \sum_{i=1}^{n} \left(a_i - a_{avg}\right)^2 \quad (9)$$

The average elevation [m] (10) denotes the mean altitude recorded, reflecting the impact of terrain on energy consumption and vehicle efficiency [26].

$$H_{dr} = \frac{1}{n} \times \sum_{i=1}^{n} H_i \quad (10)$$

The standard deviation of elevation [m] (11) assesses the fluctuation in terrain altitude throughout the entire driving cycle [26].

$$H_{std} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (H_i - H_{dr})^2} \quad (11)$$

The average slope (12) is defined as the mean road gradient [30].

$$S_{dr} = \frac{1}{n} \times \sum_{i=1}^{n} S_i \quad (12)$$

The standard deviation of slope (13) captures the degree of fluctuation in road gradients. High deviations suggest a variable topography [26].

$$S_{std} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (S_i - S_{dr})^2} \quad (13)$$

The percentage of cruising (14) refers to the proportion of time the vehicle maintains a constant speed relative to the total driving time [26].

$$P_{cr} = \frac{t_{con}}{t_{tot}} \quad (14)$$

The acceleration time ratio (15) represents the proportion of time spent in acceleration phases [30].

$$P_{acc} = \frac{t_{acc}}{t_{tot}} \quad (15)$$

The idle time ratio (16) is the fraction of total driving time during which the vehicle remains stationary [30].

$$P_{idle} = \frac{t_{idle}}{t_{tot}} \quad (16)$$

The deceleration time ratio (17) denotes the proportion of time spent in deceleration phases [26].

$$P_{de} = \frac{t_{de}}{t_{tot}} \quad (17)$$

The vehicle specific power (18) [kW/ton] represents the instantaneous power demand per unit mass of a vehicle, considering both kinetic and potential energy changes, as well as the effects of aerodynamic drag and road grade. It's used to estimate energy consumption and emissions [26].

$$VSP = v\left(1.1a + 9.81\left(atan(sin\theta)\right) + 0.132\right) + 0.000302v^3 \quad (18)$$

## IV. Conversion to Power Cycles

To evaluate the energy consumption and environmental aspects of EVs, speed-time DC profiles are converted into power-time profiles, by applying vehicle dynamics principles. The theoretical foundations, applications, and computational tools central to this process are described in this section [8].

The total tractive force $F_{total}$ required to propel a vehicle is the sum of three primary components, air drag force $F_{drag}$, rolling resistance force $F_{roll}$ and acceleration force $F_{inertia}$. These forces are defined as follows [33]:

$$F_{drag} = \frac{1}{2} C_d A \rho v^2 \quad (19)$$

Where $C_d$ is the drag coefficient, A is the frontal area of the vehicle, ρ is air density, and v is the relative wind velocity in vehicle direction, which can be approximated as vehicle velocity. While the vehicle speed increases, the drag force increases to the square of its speed. The rolling resistance force is given by [33]:

$$F_{roll} = C_r mg \cos(\theta) \quad (20)$$

$C_r$ is the rolling resistance coefficient, m is vehicle mass, g is gravitational acceleration, and θ is road gradient [8]. The inertial force due to acceleration and deceleration is defined as [33]:

$$F_{inertia} = ma + I_{eff} \frac{d\omega}{dt} \quad (21)$$

Where, a is vehicle acceleration, $I_{eff}$ is the effective rotational inertia, and $\frac{d\omega}{dt}$ is angular acceleration. By adding these three forces, the time variation of the total power demand can be determined [34]:

$$P_{total} = \frac{\left(F_{drag} + F_{roll} + F_{inertia}\right)v}{\eta_{drivetrain}} \quad (22)$$

Where, $\eta_{drivetrain}$ accounts for efficiency losses in the motor, gearbox, and auxiliary systems. Regenerative braking is modelled by negative power values, scaled by a recovery efficiency factor $\eta_{regen}$ ranging from 60% to 80% depending on motor-inverter-battery system efficiency.

By converting DCs into power cycles, it allows for critical EV component evaluations. The peak power is often used to size the motor capacity. Also, battery capacity is also derived from the integral of $P_{total}$ over time [10].

To facilitate the conversion of DCs into power cycles, researchers employ tools such as Advanced Vehicle Simulator (ADVISOR) to estimate energy consumption, emissions, and powertrain performance in hybrid and electric vehicles. Also, MATLAB/Simulink environment is adaptable for modelling EV dynamics, optimizing power management strategies, and conducting sensitivity analyses to size different EV components.

## V. Future Directions

The evolution of DC must align with advancements in vehicle propulsion technology, data analytics tools, and sustainability goals. Therefore, some recommendations regard research and development directions to address emerging challenges in EV testing and regional adaptability:

- Dynamic Updating: The integration of real-world driving data obtained from connected vehicles, smartphones, and onboard sensors will facilitate the development of a more accurate and continuously updated DC data set.

- Generative AI Models: Training advanced algorithms such as deep learning, reinforcement learning, and unsupervised clustering on multi-regional driving datasets to generate micro-trip segmentation. These techniques could repeatedly identify complex driving patterns and regional variations [26].

- Integration of environmental and roadway data: Incorporating parameters such as road grade, pavement state, and weather into DC models will improve the accuracy of real-world operating conditions. It can improve energy consumption estimates for geographical regions or urban settings.

- Connected and autonomous vehicles (CAVs): With the growing popularity of vehicle automation and connectivity, DC development needs to consider various driver archetypes (aggressive, eco-conscious, smoother accelerations, and predictive braking) associated with autonomous and semi-autonomous vehicles [35].

- Sustainability and Policy Alignment: Formulate driving strategies that encourage energy-efficient behaviors in urban and highway environments by optimizing acceleration rates and prioritizing routes [36].

In conclusion, by investigating these possibilities, future research could propel the construction of DCs to reflect trendy driving behaviour while also enhancing the design, certification, and performance evaluation of the next generation of EVs.

## VI. Conclusion

The evolution of national and international DCs from traditional modal to transient approaches marks a crucial shift in the evaluation of EV performance. This review has shown that conventional DCs are inadequate for capturing the dynamics of EVs, unlike regional ones. Standard procedures to establish DC involve collecting real-world driving data, micro-trip segmentation, and probabilistic methods like Markov chains. Comparative analyses reveal that tailored, region-specific cycles provide precise estimations of energy consumption and vehicle range. Moreover, the conversion of DCs into power cycles is a necessary step for optimizing battery capacity and motor sizing. Despite the advancement in DCs, challenges remain in standardizing DC construction methodologies. Future investigation should prioritize the development of diverse driving datasets.

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