Development of a Representative Banjarmasin Drive Cycle Integrating Real-World Traffic for Robust Emission and Fuel-Economy Modeling

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Abstract. Urban driving conditions in developing cities are often inadequately represented by international standard driving cycles, leading to inaccurate estimation of vehicle energy consumption and emissions. This study presents the development and validation of a local driving cycle for the city of Banjarmasin, Indonesia, based on real-world vehicle speed data collected from representative urban routes. The recorded data were preprocessed and smoothed using a biweight kernel filtering approach to reduce high-frequency noise while preserving essential driving dynamics. The resulting Banjarmasin Drive Cycle (BDC) exhibits a mean speed of 25.34 km/h, a maximum speed of 57.77 km/h, a low idle ratio, and relatively high transient characteristics, reflecting typical rolling traffic conditions in the study area. To evaluate its applicability, the BDC was implemented in a series–parallel hybrid electric vehicle (HEV) simulation model developed in MATLAB/Simulink. Simulation results show that the BDC produces fuel consumption and emission levels that differ significantly from those obtained using standard cycles such as NEDC, FTP, and Manhattan, and more closely represent real urban driving behavior. The proposed BDC therefore provides a realistic and reliable input for vehicle performance evaluation, energy management strategy development, and emission analysis under urban traffic conditions in Banjarmasin.

1 Introduction

Urban air pollution and energy consumption, including in the City of Banjarmasin, are strongly influenced by the operational characteristics of vehicles circulating in daily traffic. Motor vehicles not only constitute a major source of exhaust emissions but also account for a significant share of energy consumption in the transportation sector [1]. Therefore, accurate evaluation of vehicle emissions and energy use requires simulation and testing approaches that realistically represent actual vehicle operating conditions. In

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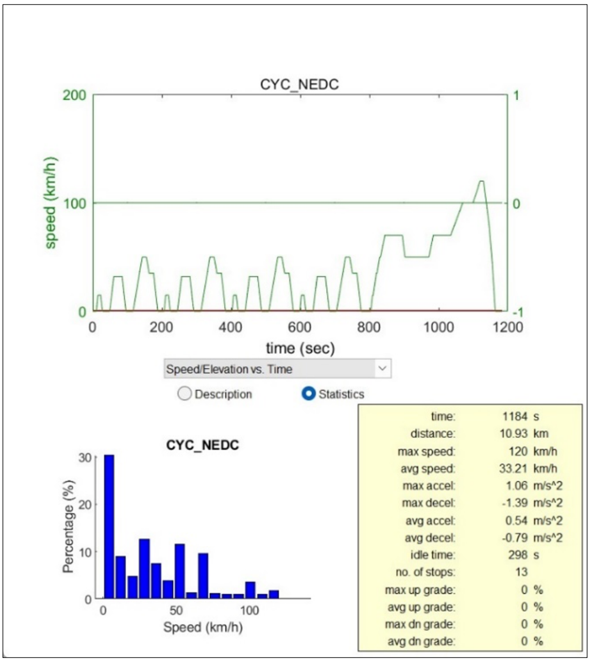
this context, drive-cycle-based simulations form the core of vehicle performance analysis, including the development and assessment of Energy Management Strategies (EMS) for hybrid and plug-in hybrid vehicles [2].

A drive cycle is a mathematical representation of a speed–time profile that reflects actual driving patterns within a specific operating environment. In simulation studies (**Fig. 1**), the drive cycle acts as the primary excitation signal that governs load distribution among the internal combustion engine (ICE), electric motor, and energy storage system. Consequently, key drive cycle characteristics—such as speed distribution, acceleration and deceleration intensity, stop-and-go frequency, and cruising duration—directly affect simulated fuel consumption, electrical energy usage, battery state-of-charge (SOC) dynamics, and exhaust emission levels [3].



```
           time:   1184  s
       distance:  10.93  km
      max speed:    120  km/h
      avg speed:  33.21  km/h
      max accel:   1.06  m/s^2
      max decel:  -1.39  m/s^2
      avg accel:   0.54  m/s^2
      avg decel:  -0.79  m/s^2
      idle time:    298  s
   no. of stops:     13
  max up grade:       0  %
  avg up grade:       0  %
  max dn grade:       0  %
  avg dn grade:       0  %
```

Fig. 1. Drive cycle setup in simulation program

Widely adopted global driving cycles, such as NEDC, FTP-75, and WLTC, are developed based on traffic conditions and driver behavior specific to their regions of origin. When applied to cities with substantially different traffic dynamics, these cycles may fail to represent actual vehicle operation accurately, leading to biased estimations of emissions and fuel economy [4]. In Banjarmasin, urban traffic is characterized by relatively low average speeds, frequent deceleration and idling, heterogeneous vehicle composition, and dense intersections—features that are not adequately captured by standard cycles. Consequently, reliance on global driving cycles may compromise the robustness of local emission and fuel-consumption modeling.

This study develops a representative Banjarmasin Drive Cycle derived from real-world traffic data collected under typical urban conditions. The proposed cycle serves as a robust input for vehicle simulation and powertrain analysis, enabling more reliable evaluation of emissions and fuel economy under local operating conditions [5]. Beyond its local relevance, the proposed data-driven methodology establishes a systematic and replicable framework for developing city-specific driving cycles in regions lacking localized standards. By integrating real-world measurements with statistical cycle construction, this work not only addresses the limitations of global cycles in local contexts but also provides a scalable reference for more accurate emission modeling and fuel-economy assessment in diverse urban environments.

2 Method

The driving cycle was developed based on real-world on-road measurements capturing vehicle speed–time data under actual operating conditions. The collected dataset was preprocessed and analyzed to extract representative driving characteristics. Considering the dependence of driving behavior on traffic conditions, the data were classified into multiple traffic states according to traffic intensity and operational patterns. For each state, statistical analyses were conducted to generate representative driving segments. The final driving cycle was constructed by concatenating these segments into a continuous speed–time profile while preserving the statistical characteristics of real-world driving.

2.1 Speed Measurement and Recording Method

The primary requirement of this study is the accurate measurement and recording of vehicle speed under real-world operating conditions. In principle, vehicle speed measurement can be performed either by utilizing onboard vehicle systems or by employing additional external devices. In this research, vehicle speed data are acquired using a second-generation On-Board Diagnostics (OBD-II) device in combination with a Global Positioning System (GPS) logger, without requiring any modification to the vehicle's original systems [6] as illustrated in **Fig. 2**.

Fig. 2. Vehicle speed measurement

The OBD-II device is used to obtain vehicle parameters, particularly vehicle speed recorded directly from the Electronic Control Unit (ECU), while the GPS logger provides supplementary data by recording geographical position and serving as an independent means of validating speed based on distance traveled over time. Data from both devices are recorded synchronously and stored as time-stamped datasets, enabling comprehensive analysis of the vehicle speed–time profile. The integration of OBD-II and GPS logging ensures sufficient temporal resolution and high measurement accuracy, thereby supporting the development of a representative driving cycle based on real-world driving data [7].

2.2 Analysis of the Recorded Data

The driving cycle was developed using a microtrip-based approach, where each microtrip is defined as the segment between two consecutive vehicle stops and consists of acceleration, cruising, deceleration, and an initial idling phase. The recorded speed–time data were processed using a cycle construction algorithm to identify and extract microtrips from the complete trip. For each microtrip, key parameters—including idle duration, phase durations, and characteristic speed and acceleration metrics—were calculated to capture its driving behavior. Representative microtrips were then selected based on these statistical characteristics and sequentially concatenated to construct the final driving cycle while preserving the principal statistical properties of the original dataset [8].

2.3 Driving Data Analysis Parameters

To construct the driving cycle, the recorded real-world driving data are systematically analyzed using a microtrip-based approach. Each microtrip is characterized through a set of representative parameters that capture essential driving behavior. In this study, the analysis focuses on key metrics, namely the average speed (km/h) and the idling time ratio (%), which are used to describe and classify microtrip characteristics for subsequent driving cycle construction.

2.4 Traffic State Classification

Since traffic characteristics vary across different urban areas, a systematic traffic state classification is required. In this study, traffic states are classified based on the average speed and the idling time ratio of each microtrip. Using these classification parameters [9], Four different traffic conditions are defined in **Table 1**.

Table 1. Traffic state classification

Route Segment	Characteristics
Congested Urban	Characteristics: Very slow traffic flow in central business areas with frequent stops. Average speed: Less than 10 km/h. Idle time: Highly variable, ranging from short to very long due to persistent congestion.

Route Segment	Characteristics
Urban	Characteristics: Traffic flow is not fully free-flowing but less congested than the first zone. Average speed: 10–25 km/h. Idle time: Moderate to low; vehicles occasionally stop (e.g., at traffic signals) but not frequently.
Extra-Urban	Characteristics: Roads in suburban or peripheral urban areas with relatively smooth traffic flow. Average speed: 25–40 km/h. Idle time: Low; only occasional stops (e.g., at intersections).
Highway	Characteristics: Limited-access roads with minimal traffic disturbances. Average speed: Greater than 40 km/h. Idle time: Very low or nearly zero; vehicles can operate continuously.

2.5 Traffic State Duration Allocation in the Final Driving Cycle

To preserve the statistical characteristics of real-world driving conditions, the duration of each traffic state in the final driving cycle was allocated proportionally based on its occurrence in the recorded driving dataset [10]. Specifically, the duration of traffic state category i in the constructed cycle, denoted as ti, was determined by scaling its cumulative duration in the original dataset to the predefined total duration of the final driving cycle, as expressed in (1).

$$t_i = \frac{t_{\text{drivecycle}}}{t_{overall}} \sum_{j=1}^{n_i} t_{i,j} \qquad (1)$$

Where: t_i is duration of traffic state category *i* (*i* = 1, 2, 3, 4) in the driving cycle, $t_{drivecycle}$ is total duration of the final driving cycle, $t_{overall}$ is total duration of all recorded driving data, $t_{i,j}$ is duration of the *j*-th *microtrip* in traffic state category *i, n_i* is total number of *microtrips* in traffic state category *i*.

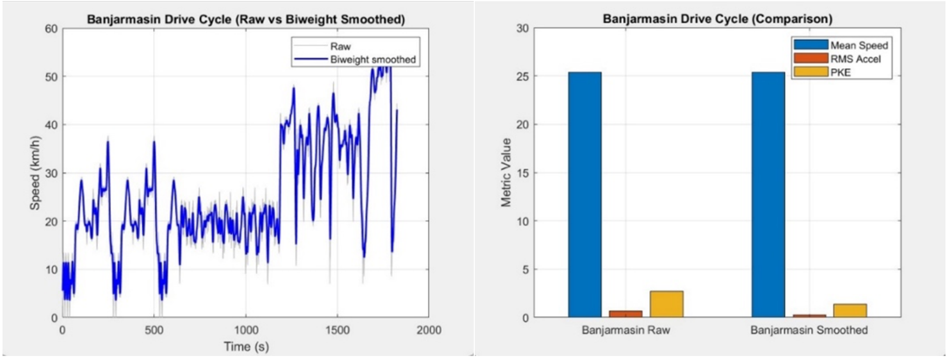
2.6 Data Processing and Cleaning

The raw driving data were preprocessed to eliminate noise, anomalies, and incomplete records to ensure data reliability. A biweight kernel–based weighted smoothing technique was then applied to the vehicle speed time series, assigning greater weights to observations closer to the target time instant [11], [12]. This method effectively attenuates high-frequency noise while preserving fundamental driving dynamics, resulting in a stable and representative speed profile suitable for driving cycle construction and subsequent energy and emission simulations [13].

3 Results and Discussion

3.1 Results

Based on driving data collected from vehicles operating in the City of Banjarmasin and the calculation methods described above, driving cycles for all traffic conditions were constructed. The non-smoothed and smoothed cycles, representing congested urban, urban, extra-urban, and highway conditions, are shown in **Fig. 3**.



(a) (b)

Fig. 3. (a) BDC construction results, (b) Quantitative validation

The key characteristics of the driving cycle are represented through validation indicators (**Table 2**), with the corresponding results summarized in **Table 3** [14]. The smoothed cycle is then adopted as the final driving cycle representing vehicle operating conditions in the city of Banjarmasin. This cycle, hereafter referred to as the Banjarmasin Drive Cycle (BDC), is subsequently used as the primary input for vehicle emission and energy consumption analyses under urban driving conditions in Banjarmasin.

Table 2. Validation indicators

No	Parameter	Symbol	Meaning
1	Mean speed	$\bar{v}$	Traffic characteristics
2	Maximum speed	v_{max}	Speed envelope
3	Idle ratio	IR	Traffic congestion level
4	RMS acceleration	RMSa	Driving aggressiveness
5	Positive Kinetic Energy	PKE	Powertrain transient load

The mathematical definitions of each indicator are as follows [15]:

Mean speed = $\bar{v} = \frac{1}{T}\int_0^T v(t)\; dt$ (1)

Idle ratio = $IR = \frac{t_{v<1\,km/h}}{T} IR$ (2)

RMS acceleration = $RMS_a = \sqrt{\frac{1}{T}\int a^2(t)\; dt}$ (3)

PKE = $PKE \;= \frac{1}{T}\sum \mathrm{ma\,x}(\Delta v^2, 0)$ (4)

Table 3. BDC validation results

Duration	1825.0 s
Mean speed	25.34 km/h
Maximum speed	57.77 km/h
Idle ratio	0.08
RMS acceleration	0.700 m/s2
Positive Kinetic Energy	2.735 1/s

3.2 Discussion

The construction and validation of the Banjarmasin Drive Cycle (BDC) provide a representative characterization of urban traffic conditions in Banjarmasin. The mean speed of 25.34 km/h indicates traffic dominated by low-to-moderate speeds, which is lower than that of standard cycles such as the mid-class WLTC, suggesting that conventional driving cycles may not adequately reflect local vehicle operating conditions.

The construction and validation results confirm that the Banjarmasin Drive Cycle (BDC) captures distinctive urban traffic dynamics that differ structurally from conventional standard cycles. The BDC exhibits a mean speed of 25.34 km/h and a maximum speed of 57.77 km/h, indicating predominantly low-to-moderate speed operation within a moderate speed envelope. Notably, the low idle ratio of 0.08 suggests that congestion in Banjarmasin is characterized more by slow-moving rolling traffic than by pronounced stop-and-go conditions. At the same time, the RMS acceleration of 0.700 m/s² and the Positive Kinetic Energy (PKE) of 2.735 1/s reveal considerable transient intensity and elevated powertrain loading. The applied smoothing procedure preserves these intrinsic characteristics while ensuring numerical stability for simulation. Collectively, these findings indicate that the BDC embodies a traffic structure that is not fully represented by widely adopted international driving cycles, thereby raising important questions regarding its quantitative differences from previously developed urban drive cycles.

Why does the BDC exhibit a mean speed of 25.34 km/h, a low idle ratio of 0.08, and a relatively high Positive Kinetic Energy (PKE) value of 2.735 1/s, whereas several previous urban driving cycle studies, such as the Malaysian Urban Drive Cycle developed by Abas et al. [9], report more stable average speed patterns with higher idle proportions? This quantitative difference can be attributed to variations in road network structure, traffic density, and dominant vehicle composition across cities. The study by Abas et al. indicates that Malaysian urban traffic characteristics are more strongly influenced by distinct stop-and-go patterns, leading to a higher idle ratio and lower transient intensity. In contrast, the BDC reflects a rolling traffic pattern characterized by a low idle ratio but more intensive acceleration fluctuations, as evidenced by the RMS acceleration value of 0.700 m/s² and the PKE value of 2.735 1/s. This condition suggests that traffic in Banjarmasin is dominated by dynamic vehicle interactions with slow yet continuous movement, thereby increasing transient loads on the powertrain system.

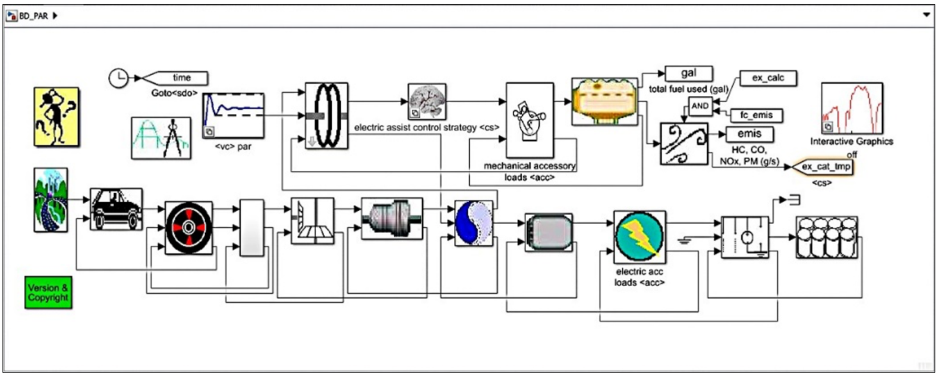


Fig. 4. Vehicle Simulation Modeling in Simulink

An important implication of these characteristics is that Energy Management Strategies (EMS) optimized using standard driving cycles may produce control parameters that are less adaptive to the actual transient conditions in Banjarmasin. Therefore, employing the BDC as the basis for EMS optimization enables more responsive power-split control and State-of-Charge (SOC) regulation in accordance with real acceleration dynamics, thereby improving the accuracy of fuel consumption estimation, emission prediction, and battery life assessment under local operating conditions.

The simulation results of the series–parallel hybrid electric vehicle (HEV), as presented in **Fig. 4** and **Table 4**, further validate the applicability of the developed BDC for powertrain performance assessment. The BDC produces fuel consumption and emission characteristics that closely reflect real urban driving conditions, driven by its moderate speed profile, low idle ratio, and pronounced transient dynamics. These results indicate that the BDC provides a realistic and reliable basis for evaluating energy management strategies and overall performance of series–parallel HEV systems under typical urban traffic conditions in Banjarmasin.

Table 4. Series–Parallel HEV Simulation Results under the BDC

Cycle	HC	CO	NOX	Fuel Consumption
BDC	0.708	0.794	0.155	4.9
NEDC	0.784	0.772	0.108	5.1
FTP	0.542	0.615	0.135	5
Manhattan	2.37	2.325	0.219	8.7

4 Conclusion

This study successfully developed and validated a local Banjarmasin Drive Cycle (BDC) that accurately represents urban traffic conditions in Banjarmasin. The validated BDC exhibits a total duration of 1825 s, a mean speed of 25.34 km/h, a maximum speed of 57.77 km/h, a low idle ratio of 0.08, an RMS acceleration of 0.700 m/s^2, and a Positive Kinetic Energy (PKE) of 2.735 1/s, collectively reflecting predominantly rolling traffic with relatively strong transient dynamics. These characteristics are not adequately captured by international standard driving cycles. The application of biweight kernel smoothing effectively reduced high-frequency noise without altering the fundamental driving properties, resulting in a numerically stable cycle suitable for simulation purposes.

Vehicle simulations using a series–parallel hybrid electric vehicle (HEV) configuration further demonstrate the practical relevance of the BDC. Under the BDC, the HEV model produced fuel consumption of 4.9 L/100 km and emission levels of 0.708 g/km HC, 0.794 g/km CO, and 0.155 g/km NOx, which differ notably from those obtained using standard cycles such as NEDC, FTP, and Manhattan. These results confirm that the developed BDC provides a more realistic and reliable basis for evaluating vehicle performance, emission behavior, and energy management strategies under typical urban traffic conditions in Banjarmasin.

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