Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 15, No. 3, 2025

Influence of Driver Behavior on Fuel Efficiency in Intercity Buses: A Simulation-Based Study of the Yaoundé-Douala Corridor in Cameroon

Franck Landry Bayi Boumal, Ahmed E. Aboud, Sernin Banza Mwanabute, Josepha Fansi Nguietchuan and Jefferson T. Banquando

Department of Transportation Engineering, Huaiyin Institute of Technology, Huai'An, Jiangsu 223001, China

Abstract: This study examines the influence of driver behavior on fuel efficiency in intercity buses along Cameroon's Yaoundé-Douala corridor, a critical route in a fuel-import-dependent transportation sector. Using a combination of real-world driving cycle data and GT-SUITE simulations, we analyzed the fuel consumption of a 70-seater Mercedes Benz Actros 2031 bus under varied driving patterns. Findings indicate that aggressive driving behaviors, characterized by delayed shift timing, aggressive acceleration (0.476 m/s² in MD5 cycle) and abrupt braking, increased fuel consumption to 49.8 L/100 km, while smoother driving (0.396 m/s² in SD3 cycle) and proper shift timing achieved 40.6 L/100 km. Gear-shifting patterns and Brake Mean Effective Pressure (BMEP) analysis revealed that optimal engine operation and timely gear transitions significantly enhance efficiency. Despite the route's infrastructural challenges, such as variable road grades, eco-driving practices offer substantial fuel savings. However, the study's small driver sample and single-route focus limits generalizability. We recommend eco-driving training, real-time feedback systems, and multi-regional studies to develop tailored interventions for Cameroon's diverse driving conditions, contributing to economic and environmental sustainability in developing economies.

Keywords: Driver behavior, fuel economy, intercity buses, eco-driving, Cameroon.

1. Introductions

1.1. Background

In Cameroon, as in many other developing countries, the underdeveloped railway, inland waterway, and aviation systems have led to a heavy reliance on heavy-duty vehicles for intercity transportation of people and goods. In recent years, Cameroon has struggled to ensure adequate fuel supplies for its expanding transportation sector. Without domestic crude oil refining capabilities, the country depends on imported fuel, exposing its economy to supply chain disruptions and fluctuating global prices.

Improving fuel economy in heavy-duty vehicles (HDVs), particularly intercity buses, is crucial for reducing operational costs and environmental impacts in the transportation sector. While vehicle design, engine efficiency, and route characteristics contribute to fuel consumption, driver behavior has emerged as a significant determinant. The impact of driving style on fuel consumption is substantial, with aggressive driving patterns leading to increased fuel consumption compared to eco-friendly driving. Such aggressive driving includes behaviors such as speeding, harsh acceleration, and hard braking, all of which significantly reduce fuel efficiency. Studies have shown that driving style alone can affect fuel efficiency by 10–40% under varying operating conditions, leading to increased attention to behavioral interventions over the past decade [1,2].

1.2. Impact of Driving Style on Fuel Consumption

Driver behavior directly affects real-world fuel consumption through acceleration patterns, idling duration, gear-shifting strategies, and speed control. Aggressive driving—marked by harsh acceleration, hard braking, and excessive speeding—has been shown to increase fuel use by up to 30% in urban cycles [1]. For intercity buses, smoother driving practices, such as gradual acceleration and predictive braking, yield fuel savings of 5–15% on long-haul routes [2]. *Ma et al.* corroborate these findings, reporting that driving style variance accounts for over 10–20% of fuel consumption differences among experienced bus drivers, even under similar road conditions [3]. A notable study in Portugal quantified this impact, revealing that reducing acceleration rates from 1.5 m/s² to 0.5 m/s² saved 50 ml of fuel per acceleration event, cumulatively achieving 20–40% savings when transitioning from aggressive to eco-driving styles [4]. The impact of driver behavior varies across vehicle technologies. Hybrid and compressed natural gas (CNG) buses exhibit distinct fuel consumption patterns compared to conventional diesel models. A Serbian study found that terrain and speed were primary drivers of fuel use, with driver behavior amplifying or mitigating these effects. Hybrid buses achieved up to 41.14% fuel savings in urban settings, but aggressive driving diminished these gains significantly [5].

1.2.1. Specific Behaviors Influencing Fuel Economy

Several driver-controllable factors have been identified as critical to fuel efficiency including acceleration and deceleration, speed management, idling, and gear selection.

Harsh acceleration and braking strongly correlate with elevated fuel use, with a study on freight heavy-duty vehicles (HDVs) demonstrating that smoother driving can reduce consumption by up to 15% by minimizing abrupt maneuvers [6]; speed management also plays a key role, as fuel consumption follows a concave relationship with speed. Research dealing with an intercity bus showed that the bus achieved its optimal efficiency below 60 mph on flat terrain for intercity buses, though mountainous routes diminish these savings due to frequent elevation changes [7]. Prolonged idling, responsible for up to 19% of urban bus energy consumption, remains a significant inefficiency, prompting the adoption of anti-idling policies and auxiliary power units to mitigate waste [8], while timely gear selection in manual transmission HDVs—particularly in buses with fixed routes—reduces engine strain, with a study highlighting optimized gear-shifting strategies as a proven method to improve fuel efficiency [6].

1.2.2. Factors affecting drivers' behavior

Driver behavior is modulated by internal factors (e.g., fatigue, skill level, risk perception) and external factors (e.g., environmental conditions, road infrastructure, vehicle state, social interactions, technical interactions).

Environmental conditions significantly influence driver behavior and fuel efficiency in intercity buses, as adverse weather like rain and fog reduces visibility and road grip, prompting cautious driving with lower speeds and increased following distances, while poor night-time lighting challenges visibility and can cause driver fatigue and more frequent braking; additionally, extreme temperatures affect driver comfort and vehicle performance, potentially leading to suboptimal driving practices. *Yang et al.* highlighted the role of weather in shaping driving patterns and fuel consumption, and *Ma et al.* found that adverse weather conditions significantly alter driving behaviors and fuel efficiency [2,3]. *Rohani* provided evidence that temperature variations influence driver decision-making and vehicle operational efficiency, and *Yao et al.* noted that comprehensive external conditions, including weather and temperature, can impact both vehicle safety and fuel consumption [4,9].

Road infrastructure, including pavement quality, signage, and geometric design, significantly impacts driver behavior and vehicle fuel efficiency. Poor pavement quality can increase rolling resistance and vehicle vibrations, prompting drivers to reduce speeds for safety and comfort, potentially raising fuel consumption by 5% to 10% [10]. Route selection also plays a role, with drivers opting for low-gradient roads achieving better fuel economy [3].

Vehicle state, including maintenance status and onboard technology like Advanced driver assistance systems (ADAS) and tire pressure sensors, significantly impacts fuel efficiency in intercity buses. ADAS technologies such as adaptive cruise control help maintain optimal speeds and reduce unnecessary acceleration and braking; tire pressure monitoring systems (TPMS) provide real-time data on tire conditions, allowing drivers to address issues promptly, and studies have shown that TPMS can reduce fuel consumption by 2% to 3% by maintaining proper tire pressure [11].

Social interactions, including traffic density, pedestrian behavior, and cultural norms, significantly impact driver behavior and fuel efficiency in intercity buses. High traffic density increases frequent acceleration and braking, raising fuel consumption, while unpredictable pedestrian crossings can cause sudden braking or rapid acceleration. Cultural norms also shape road users' attitudes and behaviors; for instance, jaywalking or disregarding traffic signals in some cultures disrupts traffic flow, forcing drivers to adjust their patterns. A co-simulation study of Istanbul's Metrobus system demonstrated that aggressive driving in stop-and-go traffic increased fuel consumption by 20% compared to smoother driving in free-flow conditions [12]. *Pelé et al.* highlighted how social information use influences pedestrian road-crossing behaviors across cultures [13]. *Liu et al.* explored the relationship between attitudes, risk perceptions, and pedestrian behaviors in China [14]. These factors emphasize the need to consider social interactions when analyzing driver behavior and fuel economy in intercity bus operations.

1.3. Methodologies in Recent Studies

Recent studies employ diverse methodologies to analyse the relationship between driving behaviour and fuel consumption, combining real-world data, simulations, and advanced statistical techniques. Real-world data collection leverages tools such as on-board diagnostics (OBD), GPS, and portable emission measurement systems (PEMS) to capture real-time parameters like speed, acceleration, and fuel use. For example, a study on Istanbul's Metrobus system integrated IPG TruckMaker and AVL Cruise co-simulations to model fuel consumption, validating results with empirical data [12]. Simulation and modelling approaches, such as the VT-CPFM, incorporate instantaneous vehicle power and driving patterns to estimate fuel use. A study in Germany demonstrated this by applying the model alongside unsupervised clustering to classify driver behaviours and predict their economic impacts [15]. Statistical analyses further refine insights through machine learning algorithms such as random forests and general linear models. One study categorized highway driving into 12 manoeuvre states and used transition probabilities to link driving styles to fuel efficiency [3]. Together, these methodologies enable precise quantification of behavioural impacts and inform the development of targeted eco-driving interventions.

1.4. Implications for Intercity Buses

Intercity buses, with their fixed routes and schedules, present unique opportunities for fuel-saving strategies. Key implications include eco-driving training programs that emphasize smooth acceleration, optimal speed maintenance, and idle reduction, proven to achieve fuel savings of 6.8% in Chinese intercity fleets and 7.4% in European truck/bus fleets post-training [16, 17]. Complementary incentive programs enhance long-term adherence, as demonstrated in a study linking driver engagement to sustained behavioral changes [18]. Technology integration further boosts efficiency through real-time feedback systems like Dynafleet and G-BOS, which provide actionable insights on idling duration and speed control, improving fuel efficiency by guiding greener practices [8]. ADAS such as adaptive cruise control (ACC) and predictive energy management, optimize speed, gear shifts, and proactive adjustments using GPS and topographic data, yielding up to 7% highway fuel savings [19, 20]. Automated post-trip performance reports also foster continuous improvement, as exemplified by a Spanish waste-collection fleet achieving a 7.45% average fuel reduction over 14 months [21]. Additionally, idle reduction strategies, such as cutting idle time by 10 minutes per hour, saved 5% fuel in U.S. long-haul buses [22], and route optimization tools avoiding congestion or steep gradients improved efficiency by 3–5% [23], further supported by policy-infrastructure synergies, such as integrating eco-driving systems with traffic light communication to reduce fuel use by 10% [24,25], and enforcing anti-idling regulations or promoting low-gradient route selection to enhance operational efficiency [3].

2. Methodology

This study employs a comprehensive methodology to investigate the impact of driver behavior on fuel economy. The research begins with the collection of real-world driving cycle data obtained by having different drivers operate the bus under study along the route between Douala and Yaoundé in Cameroon. The real-world driving cycles capture driver behavior through the dynamic nature of bus operations under various conditions. Additionally, each driver's gear-shifting behavior was observed and recorded during the driving cycles to further document each driver's behavior. These data are then meticulously analyzed to understand the characteristics of different driving patterns. Subsequently, a detailed model of the vehicle powertrain is developed and simulated using this driving cycle data to predict fuel consumption. The simulation results are analyzed to quantify how different driving behaviours affect fuel efficiency. This methodical approach not only provides insights into the relationship between driving behavior and fuel economy but also offers a robust framework for developing strategies to optimize fuel consumption in intercity bus operations.

2.1. Driving Cycles

Driving cycles, which vary in type and purpose, are essential tools for analyzing driver behavior and vehicle performance. Standard driving cycles allow for the measurement of key metrics such as fuel efficiency, energy consumption, and performance in controlled environments. However, real driving cycles offer deeper insights by reflecting actual vehicle behavior under diverse real-world conditions, including fluctuating traffic, road gradients, and individual driving styles. These real-world cycles provide a more accurate depiction of road loads and driving behaviors, which are crucial for understanding driver behavior. They enhance the precision of fuel consumption predictions and overall vehicle performance assessments. When selecting driving cycles for heavy-duty vehicle simulations in software like GT-SUITE, it is crucial to choose cycles that mirror the unique operational characteristics of these vehicles. This ensures that simulation results closely match real-world performance metrics, thereby improving the reliability of predictions and supporting the development of optimized powertrain configurations tailored to specific operational environments.

2.1.1. Standard driving cycles

Standard driving cycles are used in this study as they offer a controlled and standardized reference for evaluating vehicle performance and driver behavior, even though they are not real driving cycles produced by actual drivers. These standardized cycles provide a consistent benchmark that reflects idealized driving conditions and more proper driver behavior, with results aligning closely with those of eco-driving practices. This makes them valuable for comparing and analyzing the fuel efficiency of heavy-duty vehicles in a standardized manner. In this study two standard driving cycles are used, Heavy-Duty Urban Dynamometer Driving Schedule (HUDDS) and Highway Fuel Economy Driving Schedule (HWY). The HUDDS cycle, with its frequent stops and accelerations, offers a realistic portrayal of urban driving conditions, while the HWY cycle effectively represents steady-state highway cruising. Their selection over alternatives like the FTP and WHVC was driven by their closer alignment with the specific operational characteristics of heavy-duty vehicles in Cameroon and to reflect the differences between typical urban and highway driving.

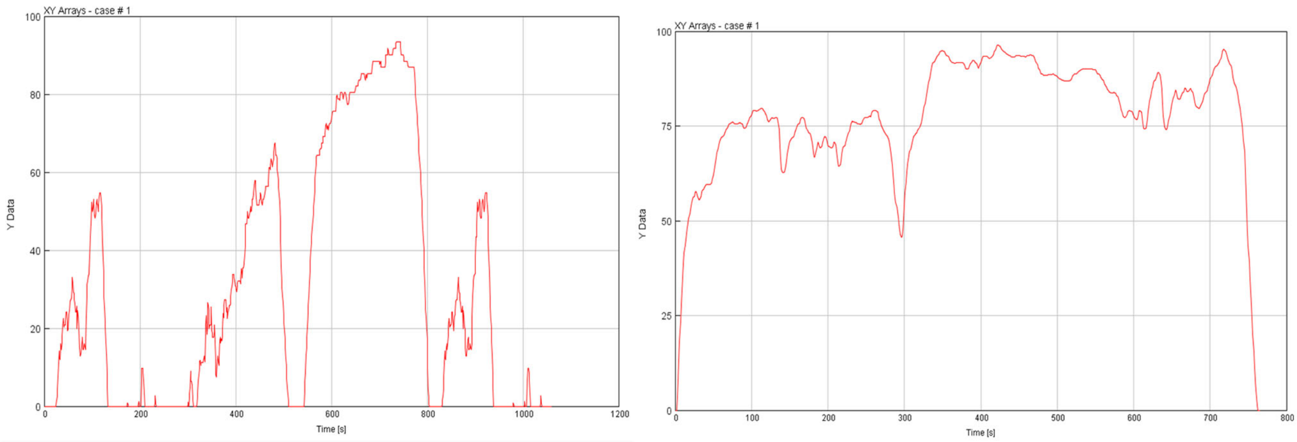
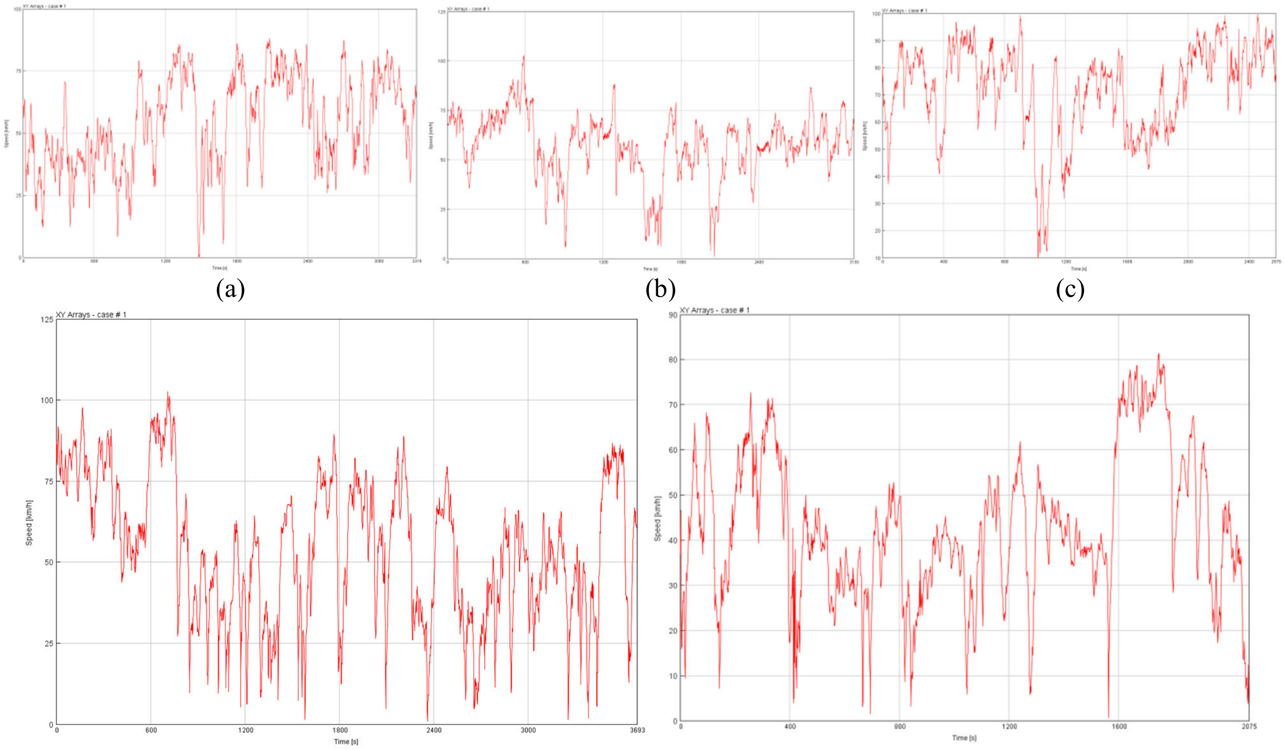


Figure 1. HUDDS & HWY Driving Cycles (From left to right)

2.1.2. Real driving cycles

Real-world driving cycles are crucial for enhancing the realism of powertrain simulations as they reflect actual operating conditions, including driver behavior, traffic, road types, and slopes. However, their application is limited by specificity to particular vehicle segments and susceptibility to variability from external factors. To address these challenges, this study employed real-world driving cycles measured from the specific vehicles under investigation: the 70-seater Mercedes Benz Actros 2031 model buses produced by the Cameroonian company SOTRABUS Mikel. Data was collected from the Douala-Yaoundé highway using the Bietian BM-610 GPS receiver, capturing position, altitude changes with time. The collected data is measured in seconds for time, and meter for the position and altitude, and the time interval for the data sampling was 1 second. Five driving cycles were measured for different road segments and with different drivers, to represent the route's topography, diverse driver behaviors, and varying traffic conditions. Another important data to capture the driver's behavior is the gear shift timing and gears shift duration. Each driver's behavior in gear shifting is observed (manually) and recorded for both engine speed for gear up and gear down shifting and for gear shift timing.



(a) (b) (c)

(d) (e)

Figure 2. Real driving cycles (a)YM3(b)MS1(c)SD3(d)DM1(e)MD5

From the driving cycles data (position “x[i]”, altitude “z[i]”, and time “t[i]”) collected the main driving cycle characteristics are calculated at each sampling point (i is the index of each data point).

First, the distance traveled at each sample point “D[i]” is calculated for i>0 using the formula:

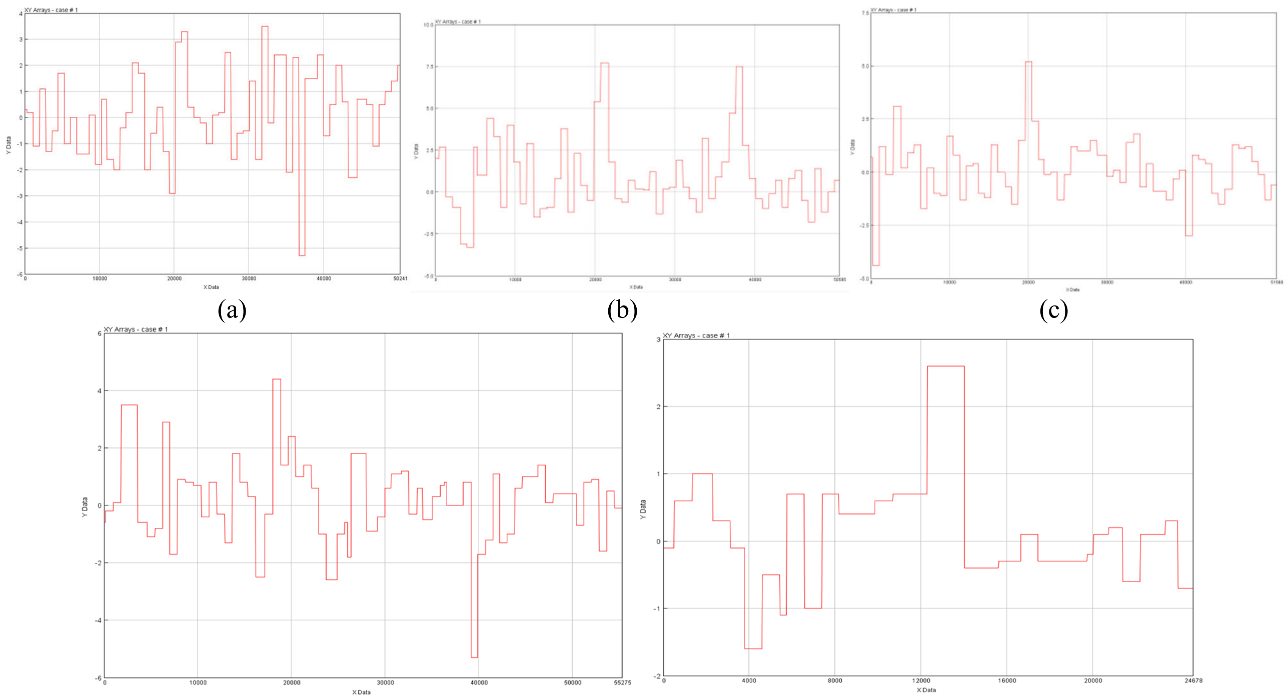
$$D[i] = x[i] - x[i-1] + D[i-1] \qquad (1)$$

Knowing that D[0] = 0

Then the grade of the road at each sample point “G[i]” was calculated for i>0 using the formula:

$$G[i] = \left(\frac{z[i] - z[i-1]}{x[i] - x[i-1]}\right) \times 100 \qquad (2)$$

The road grade calculation helped in understanding the topographical challenges posed by the route and was used in the driving cycle simulation to reflect the real load affecting the bus. The road grades of the five real droving cycles are shown in figure 3.



(a) (b) (c)

(e) (f)

Figure 1. Real Driving Cycle grades (a)YM3(b)MS1(c)SD3(d)DM1(e)MD5

The speed, acceleration and the other driving cycle characteristics related to them are calculated for the real and the standard driving cycles using the following formulas:

Instantaneous Speed

$$v[i] = \frac{x[i+1]-x[i]}{t[i+1]-t[i]} \tag{3}$$

Average Speed

$$\text{Average Speed} = \frac{1}{n-1}\sum_{i=1}^{n-1} v[i] \tag{4}$$

Instantaneous Acceleration:

$$\mathrm{a[i]} = \frac{\mathrm{v[i+1]-v[i]}}{\mathrm{t[i+1]-t[i]}} \tag{5}$$

Average Acceleration:

$$\text{Average Acceleration} = \frac{1}{m}\sum_{i:a[i]>0} a[i] \tag{6}$$

Average Deceleration

$$\text{Average Deceleration} = \frac{1}{k}\sum_{i:a[i]<0} a[i] \tag{7}$$

Where m is the number of positive acceleration values and k is the number of negative acceleration values.

These calculated parameters allowed for a detailed analysis of the speed and acceleration patterns, which were categorized into acceleration, deceleration, cruising, and idling phases. The comprehensive analysis integrated both standard cycles and real-world data, ensuring a detailed comparison of driving cycles and corresponding driver behavior.

Table 1 provides detailed results of the driving cycle analysis. This table presents the parameters of the two standard driving cycles and the five real driving cycles selected for the study. The data reveals that a significant portion of the real driving cycle is spent decelerating, implying substantial variation in driving conditions. This contrasts with driving cycles in most developed countries, where cruising dominates and deceleration is minimal. The comprehensive analysis enabled a detailed comparison of driving cycles and corresponding driver behaviour, supporting the development of influence of driver behaviour on fuel economy.

Table 1. Driving cycles

Driving Cycle Parameters	HUDDS	HWY	YM3	MS1	SD3	DM1	MD5
Time (S)	1060	765	3319	3130	2575	3693	2075
Distance (m)	8935	16507	49959	49559	51286	55084	24595
Maximum Speed (Km/h)	93.34	96.4	88.199	103.093	99.698	102.6	81.398
Average Speed (Km/h)	30.35	77.68	54.189	57	71.7	53.697	42.67
Maximum Acceleration (m/s^2)	1.96	1.43	2.082	1.943	1.998	2.277	2.291
Average Acceleration (m/s^2)	0.44	0.19	0.43	0.383	0.396	0.482	0.476
Maximum Deceleration (m/s^2)	-2.07	-1.48	-2.444	-2.36	-2.471	-2.665	-2.277
Average Deceleration (m/s^2)	-0.58	-0.22	-0.458	-0.424	-0.459	-0.552	-0.493
Percentage of time in idling	33.21%	0.65%	0.00%	0.00%	0.00%	0.00%	0.00%
Percentage of time in cruising	17.92%	16.3%	17.23%	18.05%	17.01%	17.8%	17.64%
Percentage of time in Acceleration	26.23%	44.2%	42.78%	43.10%	44.39%	43.7%	41.30%
Percentage of time in Deceleration	22.64%	38.8%	39.98%	38.85%	38.60%	38.5%	41.06%

The data of the driver's behavior in gear shifting are collected manually during the real driving cycle data measurements. For each driving cycle (each driver) the gear shifting up and down data collected from 25 to 30 time and the shift timing collected 15 time. From these data the average engine speed for gear up and gear down shifting and the average gear shift timing are calculated as shown in table 2.

Table 2. Driver's gear shifting behaviour

Driver Behaviour	YM3	MS1	SD3	DM1	MD5
Average gear up shifting engine speed (rpm)	1136	1462	1078	1155	1453
Average gear down shifting engine speed (rpm)	956	1053	934	951	1135
Average shift timing	2.3	2.5	2.5	2.9	2.8

2.2. Development of the Bus Powertrain Dynamic Model

The primary objective is to establish a baseline for evaluating the bus's performance, and fuel consumption under various driving behaviours. The bus, assembled by SOTRABUS Mikel, is equipped with a Mercedes OM 502LA diesel engine. Detailed data for the research was obtained through collaboration with SOTRABUS Mikel, their customers, and official Mercedes-Benz online resources. The "Dynamic Model" simulation is performed to estimate the bus's fuel consumption under operational conditions. This model incorporates key parameters such as engine torque-speed curves, transmission gear ratios, and vehicle properties (Table 2).

Table 2. Bus Attributes

Engine model	OM 502LA.II/3	Min Operating Speed	800rpm
Max Torque	2700Nm@1080rpm	Vehicle weight	19000kg
Max Power	420Kw@1800rpm	Type of engine	8Cylender 4Stroke diesel engine
Total Displacement	15928cm^3	Transmission model	G280-16
Type of tire	315/80 R22.5	Number of gears	16

Vehicle dynamics in real-world scenarios are analyzed through forward dynamic analysis, where the driver controls the accelerator pedal, clutch pedal, gear selection, and brakes. Real driving cycles are influenced by driving behaviour, vehicle characteristics, road conditions, and environmental factors, and are represented as vehicle speed and road grade profiles. To replicate real-life vehicle dynamics, dynamic powertrain modelling employs multibody dynamics to formulate longitudinal vehicle dynamics equations.

However, this approach requires comprehensive input data and lacks control over output performance parameters. In contrast, the quasi-static powertrain modelling approach used in this study employs vehicle speed and road grade profiles as inputs to calculate vehicle power demand. This method allows for precise adherence to predefined driving cycles, making it suitable for analyzing vehicle performance under specific conditions.

GT-SUITE was used to build the bus dynamic model (fig. 4.) based on the quasi-static approach with modifications to enhance its robustness and reduce simulation iterations. Key modifications included the implementation of a driver object to emulate human driving behaviour, optimization of the gear shift strategy based on real-world driving patterns, and integration of road grade data into the "Road" object to account for varying terrain effects. These enhancements ensure that the simulated vehicle behaviour closely aligns with real-world driving conditions.

2.3. Driving cycle simulations

The simulation model utilized the 'VehDriverAdvanced' controller to manage vehicle dynamics. For the Driver mode, speed targeting was employed, with the target speed profile derived from driving cycles. Similarly, launch control used speed targeting for engine speed, based on data from official Mercedes sources (fig. 5). The controller calculates the necessary engine load torque or wheel braking torque to achieve the desired vehicle speed or acceleration, utilizing a PI controller to adjust the engine or brake load and minimize the discrepancy between target and actual values.

For the driving cycle simulation setup in GT-Suite, it was essential to input both real and standard driving cycles as separate cases. Each simulation case instructed the driver model to follow the target speed specified in the driving cycles, and the specific shifting behavior related to each driver (for standard driving cycles gearshift strategy is chosen to favor fuel economy). A total of seven simulation cases were executed: five using real driving cycles and two using standard driving cycles. The simulations were run by configuring the driving cycle data into the GT-Suite environment, ensuring the driver model adhered to the desired speed profiles. The results were then analyzed to evaluate the vehicle's performance under various driving conditions.

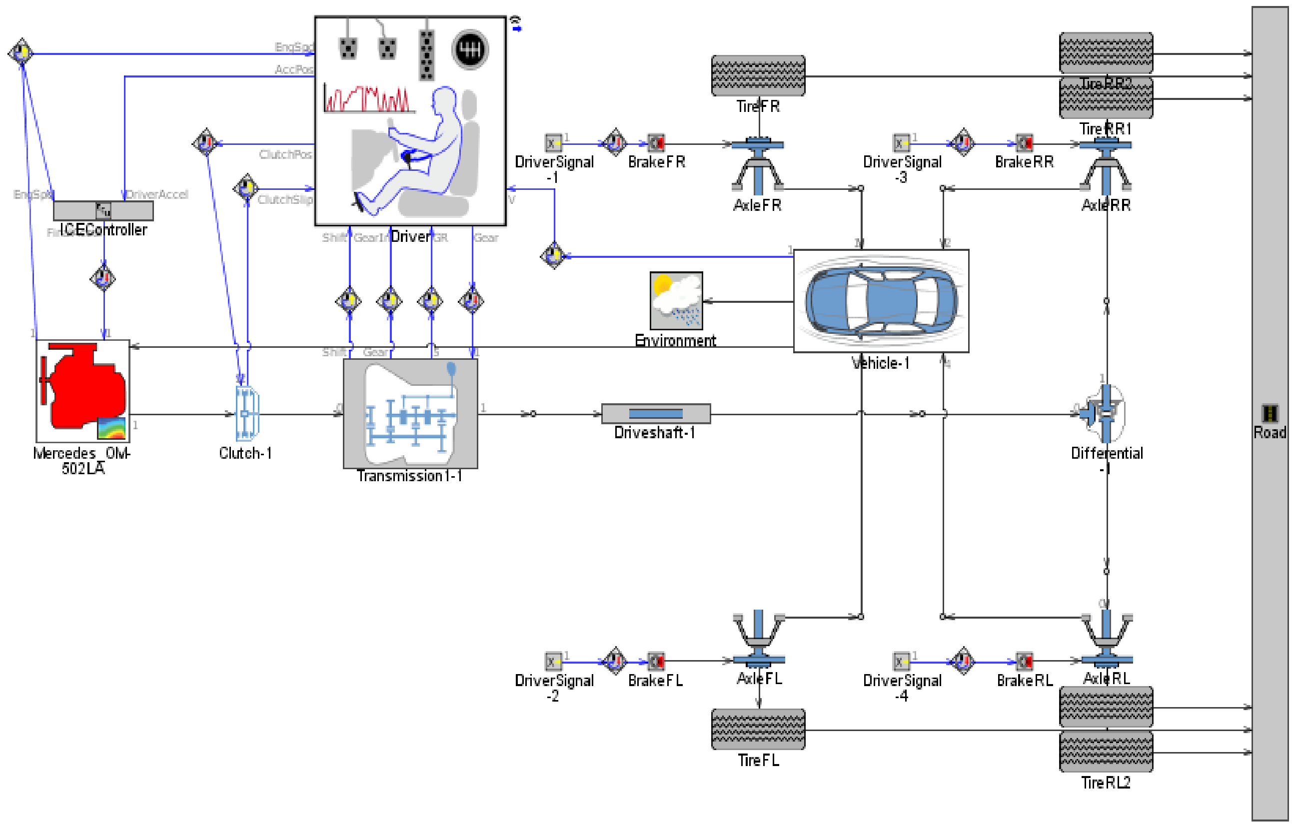


Figure 2. Bus dynamic model

2.4. Simulation results error analysis

The error analysis of the simulation results focuses primarily on how accurately the vehicle follows the target driving cycle, as this serves as the main reference for comparing the performance of the powertrain configuration to the actual powertrain. Fig. 6. shows the driving cycle simulation results against the targeted driving cycles.

To evaluate simulation accuracy, two criteria are used:

The percentage deviation of total distance travelled during the driving cycle.

The maximum speed deviation (km/h) during the driving cycle.

The simulation exhibits a slight underestimation of the total distance (-0.17% to -0.27%) across all segments. These minor discrepancies likely result from the suboptimal torque characteristics of the engine and power losses during gear shifting. Additionally, the maximum speed deviation during the driving cycle across the five real-world driving cycles on the Yaoundé-Douala route ranges from 2.4 to 3.3 (km/h).

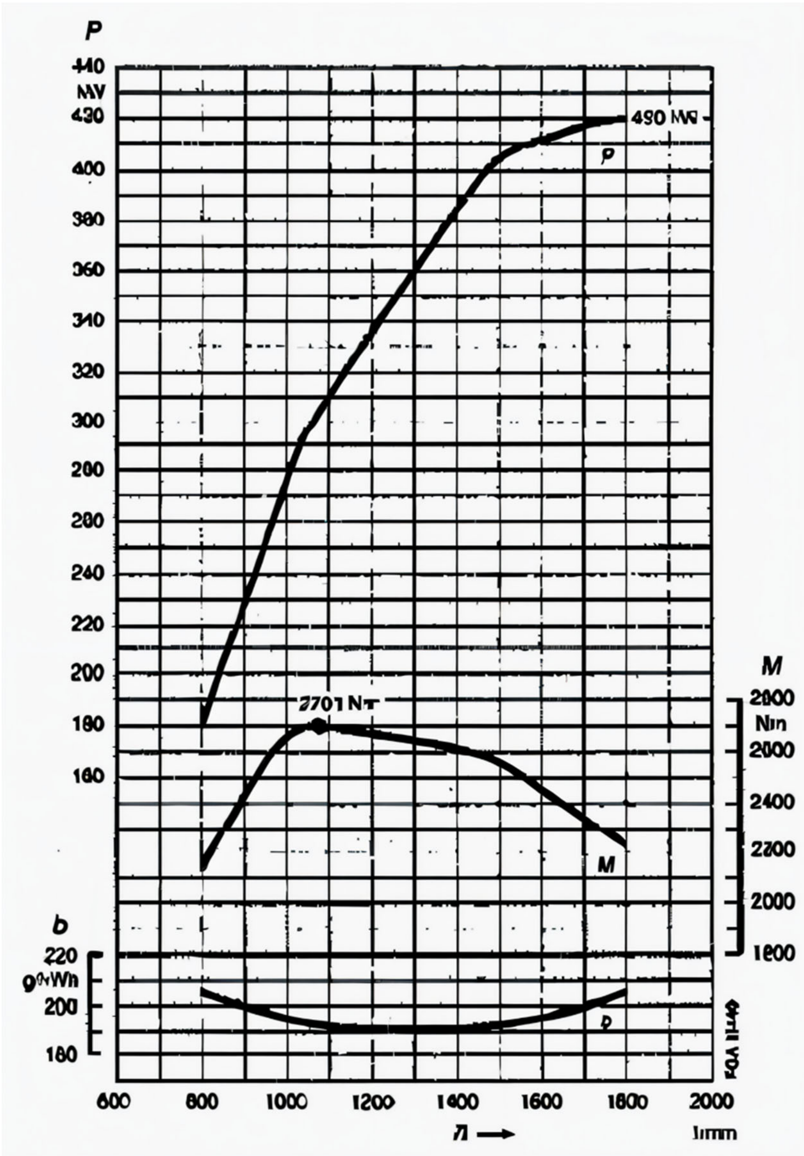


Figure 5. OM 502LA engine maps

The errors are consistently low, indicating high accuracy and reliability of the model. Despite these minor variations, all errors remain within acceptable limits, validating the simulation methodology. The results confirm that the simulations provide a robust basis for evaluating the performance of the powertrain under real-world driving conditions. The minimal errors observed do not compromise the key findings and underscore the model's effectiveness in predicting fuel efficiency. These reliable simulations offer valuable insights for determining the impact of driver behaviour on fuel economy in practical applications within Cameroon's intercity bus fleet.

3. Results

The simulation results, obtained through GT-POST, provide valuable insights into the relationship between driver behavior and fuel economy in intercity buses. The data encompasses the simulated driving cycles which is compared to the real driving cycle to validate the model, fuel economy metrics, energy consumption maps, and comprehensive statistics about the simulated driving cycles, which were crucial for model validation. The driving cycle simulations executed in GT-Suite yielded detailed data on the bus's performance under various driving conditions. The simulated driving cycles closely mirrored the target driving cycles (Fig. 6.), as evidenced by minimal deviations in key parameters.

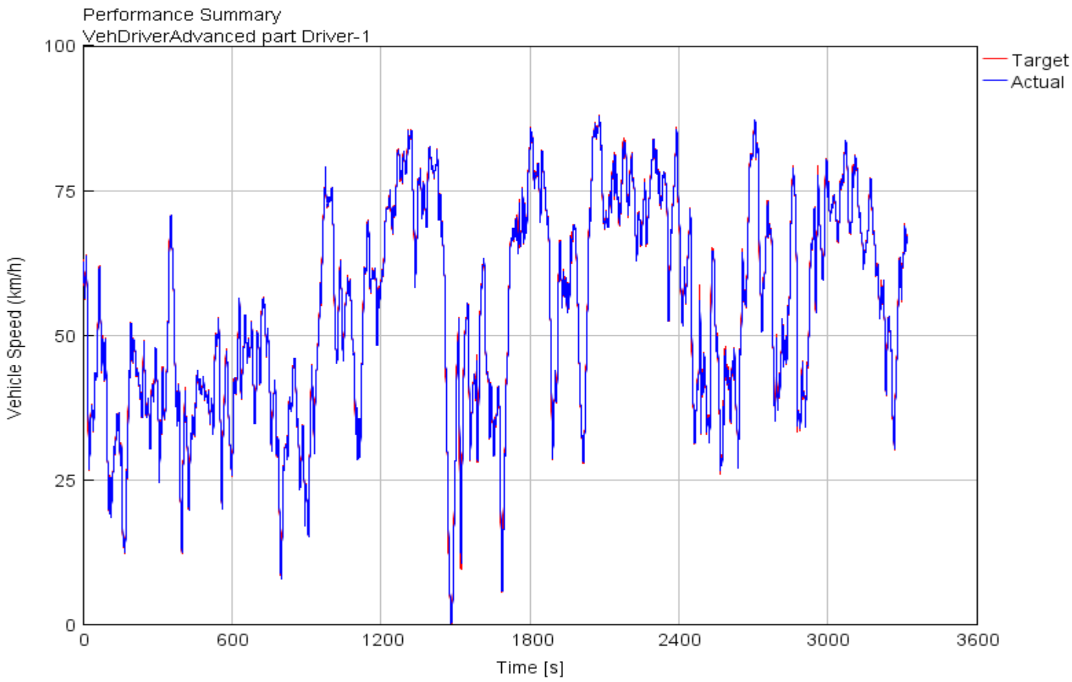


Figure 6. YM3 target driving cycle against simulated driving cycle result

To validate our model, we employed two criteria: the percentage deviation of total distance travelled during the driving cycle and the maximum speed deviation during the driving cycle. The simulation results demonstrated a slight underestimation of total distance travelled, ranging from -0.17% to -0.27% which was also reflected in the maximum speed deviations during the driving cycle ranging from 2.4 to 3.3 km/h across the five real-world driving cycles on the Yaoundé-Douala route. Despite these minor variations, all errors remained within acceptable limits. These consistently low errors indicate the high accuracy and reliability of the model. The minimal errors observed do not compromise the key findings and underscore the models' effectiveness in predicting fuel efficiency.

The fuel economy metrics revealed significant differences across the various driving cycles with the MD5 cycle showing a higher percentage of time in deceleration and acceleration phases compared to the SD3 cycle. The specific fuel consumption statistics for each driving cycle are presented in Table 3.

Table 3. Driving Cycle fuel consumptions

Driving cycle	Average Fuel Consumption [L/100km]
HUDDS	55.6
HWY	33.7
YM3	44.9
MS1	48.8
SD3	40.6
DM1	47.8
MD5	49.8

4. Discussion

4.1. Interpretation

The results of this study reveal that fuel consumption rates vary significantly across different driving cycles, influenced by factors such as shifting behavior, braking intensity, and acceleration frequency. The urban-oriented HUDDS cycle, characterized by frequent stops and starts and long idling time (33.21%), exhibits the highest average fuel consumption at 55.6 L/100km, while the HWY cycle, which represents steady-state highway cruising and has an average fuel consumption of 33.7 L/100km. The real driving cycles average fuel consumptions are between these two extremes.

Real driving cycles like YM3 (44.9 L/100kms) and MD5 (49.8 L/100km) also reflect variability tied to road conditions and driver behaviour. An analysis of Brake Mean Effective Pressure (BMEP) maps for all driving cycle was conducted. This analysis revealed that better fuel economy is primarily driven by the engine operating within its optimal efficiency zone, which is mainly affected by shifting time, acceleration aggressiveness, and choice of cruising speed. Improper cruising speed and poor gear matching can lead to higher fuel consumption. Fig. 7. further elucidates these differences. During the SD3 driving cycle, a higher proportion of engine operating points fell within the optimal efficiency zone compared to the MD5 cycle. This alignment with efficient torque-speed regimes directly contributed to SD3's superior fuel efficiency. Additionally, gear-shifting patterns recorded during simulations corroborated these findings. While parameters such as acceleration frequency and braking intensity are affected by both driver behavior and road conditions, shifting behavior is recognized as a factor solely controlled by the driver. Our analysis indicates that early or late gear shifting can significantly influence fuel efficiency. Prolonged or abrupt gear transitions in MD5—indicative of aggressive driving behaviors such as delayed upshifting or unnecessary downshifting—resulted in suboptimal engine load management, whereas smoother gear-shifting strategies in SD3 maintained the engine closer to its peak efficiency range.

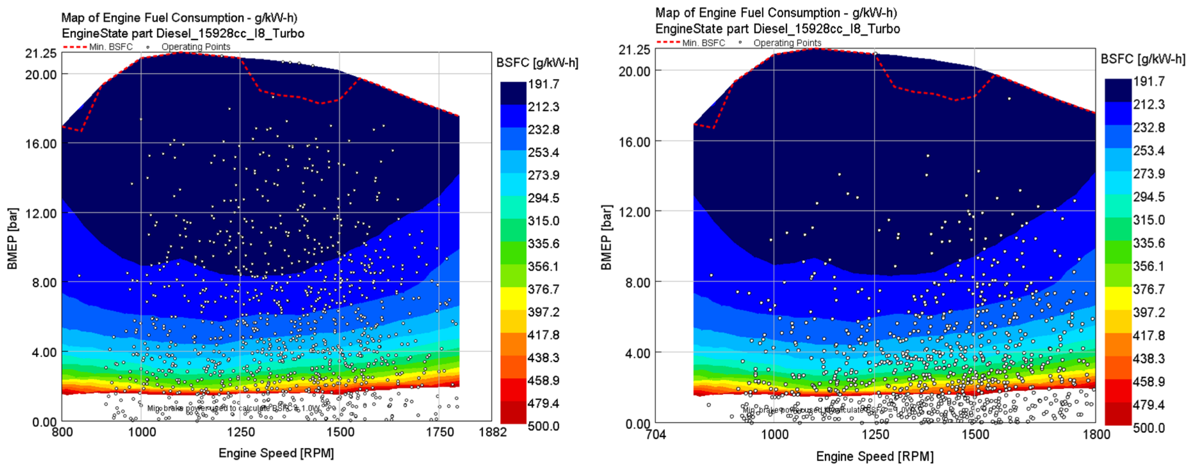


Figure 3. SD3 vs MD5 Engine fuel consumption maps

These differences arise because aggressive acceleration and hard braking – often linked to urban or reactive driving – force engines to work harder to overcome inertia and maintain speed, increasing fuel demand. Hard braking further reduces vehicle momentum, necessitating additional energy to regain speed, while aggressive acceleration spikes engine load and fuel injection rates. The contrast between the stop-and-go HUDDS and steady HWY cycles underscores how driving patterns directly affect efficiency. Notably, driving behavior is heavily influenced by external factors like road topography and weather, which exacerbate or mitigate the frequency and intensity of acceleration/braking events. These findings underscore how driver behavior affects fuel consumption on Cameroonian roads, particularly on the Yaoundé–Douala route. This mirrors challenges observed in Colombia, where steep terrain affecting driver behavior led to increased fuel demand in freight fleets, necessitating eco-driving adaptations to inefficiencies [26]. Both contexts highlight the critical role of region-specific training programs tailored to topographical and behavioral realities. Overall, the findings highlight that fuel efficiency hinges critically on moderating behaviors such as abrupt maneuvers, which disproportionately degrade energy efficiency in dynamic driving environments.

4.2. Validation

The results of this study align with existing literature. For example, prior studies have shown that driving behavior significantly impacts fuel consumption. *Ma et al.* found that driving characteristics during acceleration are decisive for 56.5% of total fuel consumption, while deceleration is only responsible for less than 5.7% of total fuel consumption [27]. Similarly, *Choi and Kim* found that acceleration of 2.60 m/s² during startup and 1.47 m/s² during driving causes abrupt increases in fuel consumption [28]. These findings are consistent with the results of this study, which also shows that fuel consumption rates are positively correlated with the frequency and intensity of acceleration and braking events.

4.3. Limitations

Despite the valuable insights provided by this study, there are several limitations that should be acknowledged. Firstly, the sample size of drivers is relatively small, limiting the generalizability of the findings to the broader population of drivers in Cameroon. Secondly, the study was conducted in a specific region of Cameroon, which may not fully capture the diversity of real-world driving conditions across the country. As stated above, driving behaviour is greatly influenced by external factors such as topography, weathers ect. Different regions in Cameroon have varying traffic densities, road topographies, and environmental factors, such as weather conditions and road quality, which could influence driver behavior and fuel consumption. Additionally, driver behavior can be affected by road conditions and environment, so the results might differ in other places within Cameroon or elsewhere in the world.

5. Conclusion & Recommendations

In conclusion, this study underscores the pivotal role of driver behavior in determining fuel economy within Cameroon's intercity bus operations. Through rigorous analysis of both standard and real-world driving cycles, aggressive behaviors—such as aggressive acceleration (averaging 0.396 m/s² in SD3 vs. 0.476 m/s² in MD5), delayed gear shifting, and harsh braking—were shown to elevate fuel consumption to 49.8 L/100km, compared to 40.6 L/100km under smoother driving practices. These findings align with global research but are particularly critical in Cameroon's context, where reliance on imported fuel and infrastructural constraints magnify the economic and environmental stakes.

5.1. Challenges and Future Directions

Despite the insights gained, challenges persist in sustaining eco-driving adoption due to behavioral inertia, modeling intricacies, and vehicle heterogeneity, compounded by the complex interplay of internal and external behavioral influences. To address current limitations, future research should prioritize expanding the sample size to include drivers from diverse backgrounds and experience levels, enhancing the representativeness and reliability of findings while capturing a broader spectrum of driving behaviors. Additionally, multi-regional studies across Cameroon's varied landscapes—from coastal plains to mountainous terrains—are critical to account for geographical disparities in road infrastructure, traffic dynamics, weather patterns, and cultural driving norms. Such efforts would yield context-specific insights, ensuring that eco-driving interventions are tailored to regional challenges, thereby fostering scalable, sustainable solutions for optimizing fuel economy in Cameroon's intercity bus sector.

Acknowledgements

This work was a collaborative effort among several students at Huaiyin Institute of Technology. Special thanks to the Transportation Engineering, and my supervisor, Dr. Ahmed Aboud, for his invaluable support and contributions throughout the process. I would also like to acknowledge the academic environment and resources provided by Huaiyin Institute of Technology, which facilitated the completion of this work.

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