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Calibration of HDM-4 Model for Fuel Consumption in Heavy-Duty Trucks: Integration of Telematics, Engine Speed, and Aerodynamics

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Abstract

Fuel efficiency in heavy-duty trucks in Indonesia faces significant challenges, while the current HDM-4 fuel consumption model has limitations in reflecting local conditions. This study calibrates the HDM-4 model using telematics data, engine speed modeling, aerodynamic simulations, and calibration factors. The novelty lies in updating parameters such as engine speed, vehicle frontal area, and calibration factors for engine power efficiency (Kpea) and rolling resistance (Kcr2) to account for tire-road interaction in Indonesian conditions. Data were collected from 5-axle trucks on the Tanjung Priok–Bandung toll road, analyzed using regression, Computational Fluid Dynamics (CFD) simulations, and non-parametric paired tests. Results show updated engine speed parameters (RPM_a0 = 680.11, RPM_a1 = -4.9031, RPM_a2 = 0.3858, RPM_a3 = -0.0028), a drag coefficient of 1.0556, and a frontal area of 8.2 m². Calibrating Kpea and Kcr2 (both 0.6) improved prediction accuracy, with no significant difference between predicted and observed data ($p = 0.186$). The enhanced HDM-4 model supports operational decisions, infrastructure planning, and sustainable transport policies, improving energy efficiency, reducing emissions, and boosting national logistics competitiveness.

Keywords: Fuel consumption; HDM-4; Telematics; Heavy-duty trucks; Aerodynamics

1. Introduction

Fuel efficiency in heavy-duty trucks, particularly 5-axle vehicles, has become a critical issue due to their high contribution to greenhouse gas (GHG) emissions and increasing freight logistics costs. In Indonesia, these trucks account for a substantial portion of CO_2 and NO_x emissions, impacting environmental and economic sustainability [1]. A global analysis shows that the combustion of 1 liter of diesel per 100 km increase in fuel consumption adds 26.4 g/km of CO_2 emissions [2], [3]. In Indonesia, fuel consumption accounts for up to 49.3% of Vehicle Operational Costs (VOC) in South Sumatra and 32% in Jakarta and West Java [4], [5]. As the freight sector increasingly relies on road transport, improving fuel efficiency is both an environmental and economic necessity.

Various methods have been developed to improve fuel efficiency, and one of the most notable is the Highway Development and Management (HDM-4) model. Created by the World Bank, this model helps predict fuel consumption and assess how road infrastructure affects vehicle efficiency [6], [7]. Countries like the United States, the United Kingdom, and South Korea have successfully used HDM-4 to support eco-routing and eco-driving strategies, which have proven effective in reducing greenhouse gas emissions [8], [9]. Furthermore, research has shown that average operating speed plays a key role in determining the fuel efficiency of heavy trucks. This insight can serve as a foundation for developing more sustainable transportation strategies [8], [10], [11], [12].

Implementing HDM-4 in Indonesia comes with significant challenges due to differences in vehicle specifications, road conditions, and varying truck loads [8], [13]. Research has shown that calibrating key parameters like engine power, rolling resistance, frontal area, and engine speed can greatly improve the accuracy of fuel consumption predictions [14]. Several studies have explored HDM-4 calibration in different countries to enhance model accuracy. For example, in Michigan, when calibrating fuel consumption models for sedans, SUVs, light trucks, and heavy trucks, researchers considered factors like engine power, rolling resistance, frontal area, engine speed, weather, and road conditions. Studies have shown that fine-tuning these key parameters can greatly enhance the accuracy of fuel consumption predictions [14]. In Florida, similar calibrations were conducted for passenger cars and trailer trucks [15], while in South Korea, the focus was on passenger cars [16]. Meanwhile, in the UK, researchers verified the HDM-4 model for various types of trucks, also considering engine power, rolling resistance, and frontal area [17]. Therefore, more tailored calibrations are needed to ensure the model accurately represents the operational conditions of trucks in Indonesia.

A telematics-based approach offers a practical way to tackle these challenges. With telematics technology, we can gather real-time data on essential factors like operational speed, vehicle weight, and fuel consumption [18], [19], [20]. Studies show that calibrating HDM-4 fuel consumption models using telematics data works well for trucks with lighter loads, though improvements are needed for heavy-load trucks [17]. Moreover, accurately simulating aerodynamic drag is crucial for improving model accuracy, especially for trucks that travel through routes with challenging terrain [21], [22]. With this in mind, our study focuses on refining the HDM-4 Level II model by incorporating engine rotation parameters, aerodynamic resistance, calibration factors, and real-world operational conditions, such as speed, load weight, and road gradient. Specifically, we aim to develop a model that reflects the realities faced by 5-axle Euro-4 semi-trailer trucks operating in Indonesia, ensuring the results are relevant and applicable to local conditions.

This study enhances the HDM-4 Level II fuel consumption model to more accurately represent the real-world efficiency of 5-axle Euro-4 semi-trailer trucks in Indonesia [23]. By refining key calibration factors including engine rotation, aerodynamic resistance, frontal area, engine power efficiency, speed, load weight, and road gradient. The model is better aligned with actual trucking operations. These improvements enhance accuracy and practical relevance, making it a valuable tool for optimizing fuel consumption in Indonesia's trucking industry. The research focuses on the Tanjung Priok Port–Bandung route, one of the busiest logistics corridors in Indonesia [24]. This route includes toll roads with gradients of up to 6%, in line with the standards set by the Directorate General of Highways [25]. The trucks in this study use Pertamina's Bio Solar fuel for Euro-4 engines, ensuring a realistic setting for fuel consumption analysis. By combining real-time telematics data with aerodynamic simulations, this study aims to create a more accurate fuel consumption model. The end goal is to improve fuel efficiency, reduce greenhouse gas emissions, cut operational costs, and support more sustainable freight transportation in Indonesia.

A key breakthrough of this study is the empirical calibration of Kcr2 and Kpea parameters using real toll road data, something that has not been done before. Furthermore, the study uncovers a clear relationship between engine speed (RPM) and fuel consumption, offering critical insights for optimizing HDM-4's operational parameters. It also revises aerodynamic parameters, including the drag coefficient (Cd) and frontal area (AF), to more accurately represent the actual conditions of heavy-duty trucks in Indonesia. With these improvements, HDM-4 now delivers more accurate fuel consumption predictions, particularly by factoring in aerodynamic resistance. These refinements make the model more applicable and valuable for transportation planning, fleet management, and logistics operations in Indonesia.

2. Method

This study employs an integrated approach that leverages telematics data, engine speed parameter modeling, aerodynamic analysis, and the calibration of the Highway Development and Management Model (HDM-4) to analyze the fuel consumption of heavy-duty trucks in Indonesia. This systematic approach aims to produce accurate and replicable fuel consumption predictions. The research process begins with a preparation phase, which involves defining the research focus, identifying data collection routes, and coordinating with trucking companies to ensure smooth data collection [23], [26]. Following this, a literature review and methodology planning are conducted to understand fuel consumption models, the use of telematics data, and HDM-4 calibration techniques.

The data collection for this study incorporates both primary and secondary sources. Primary data include measurements of vehicle dimensions and wheel diameter, which were obtained using manual tools. The vehicle selected for this study is a 2022 Hino 5-axle truck, specifically a 2-axle head truck paired with a 3-axle semi-trailer. According to the Indonesian Trucking Association (APTRINDO), this configuration is the most common for heavy-duty trucks in Indonesia. Previous studies have highlighted that rolling resistance can vary significantly between vehicles, influenced by factors such as tire specifications, load distribution, and road conditions [27]. To enhance the model's accuracy, empirical calibration factors have been incorporated, including commonly used tire specifications, varying load conditions, and diverse road characteristics. While differences between individual trucks are inevitable, the methodology applied in this study ensures that the model accurately represents real-world trucking operations, offering a more precise reflection of actual conditions. Secondary data were collected alongside engine and vehicle speed data from the On-Board Diagnostics (OBD-II) system [28], [29], including actual fuel consumption, vehicle speed, position, and gross vehicle weight (GVW). While previous studies, have noted that CAN-bus vehicle weight data can often be unreliable, we took specific steps to ensure data accuracy. To address potential inaccuracies, GVW readings were validated against weighbridge records at the port, and necessary adjustments were made [30]. Furthermore, in 2022, Hino Motors re-certified their CAN-bus system, eliminating the need for calibration modifications and improving measurement reliability. As the vehicles in this study are 2022 Hino models, the collected data benefits from the latest, more accurate monitoring system. These efforts ensure that the CAN-bus data used in this study is reliable and accurately reflects real-world vehicle operations [31].

The data were gathered over a one-month period along the Tanjung Priok to Bandung route, a critical corridor for container semi-trailer truck operations in Indonesia. Road geometry and gradient data from Google Earth remote sensing provided sufficient accuracy for transportation analysis, with an MAE of 1.32 meters and an RMSE of 2.27 meters [32]. Other secondary data were sourced from government agencies such as the Ministry of Public Works and Housing and the Central Statistics Agency. These datasets provide information on International Roughness Index (IRI), and road surface texture depth [26], [28].

Using telematics data offers significant advantages because passive data collection methods provide high spatial and temporal resolution at a low cost [28]. Devices such as Photochemical Assessment Monitoring Stations (PAMS), Global Positioning Systems (GPS), and cellular networks facilitate real-time vehicle activity monitoring. Modern trucks equipped with sensors record operational parameters like fuel consumption, vehicle speed, and throttle position, which are then transmitted via the Electronic Control Unit (ECU) for analysis. Although manufacturer-provided telematics systems are not explicitly designed for HDM-4 calibration, the data they generate are reliable and reflect real-world driving conditions [17], [29].

The calibration is conducted at the whole-trip level to capture real-world operational variations, including travel distance, average speed, vehicle weight, and road gradient. To ensure balanced data representation, the data is split into 70% for calibration and 30% for validation using stratified random sampling. The model's accuracy is assessed using R^2, RMSE, and MAPE to evaluate its ability to explain the data, measure prediction errors, and assess percentage discrepancies. Outliers that reflect actual operational conditions are kept to ensure the model's relevance. This method ensures that the model is both accurate and applicable to real-world scenarios [33], [34].

The next step involves calibrating vehicle parameters by modeling the relationship between engine speed and vehicle speed. This relationship is critical because higher vehicle speeds require higher engine speeds, which directly impacts fuel efficiency [35]. To make the HDM-4 model more relevant to modern vehicle technology, calibration is essential, as the model's default values are based on older engine designs [14]. This process starts with gathering telematics data on vehicle speed and RPM, followed by filtering to remove any anomalies. Then, a third-degree polynomial regression is applied to capture the non-linear relationship between these two variables, as outlined in Eq. (7). The resulting calibrated parameters replace the default HDM-4 values, ensuring the model aligns better with modern engines, which feature common-rail fuel injection systems and advanced emission controls. To confirm the accuracy of the model, the coefficient of determination (R^2) is used, ensuring the model captures the true dynamics of speed and RPM, ultimately improving fuel consumption predictions.

Following this, aerodynamic analysis is conducted using Computational Fluid Dynamics (CFD) in SolidWorks Flow Simulation [36], [37]. This software applies the k-ε turbulence model, which is suitable for steady-state flow simulations but has limitations in capturing complex turbulent dynamics such as wake formation and vortex shedding. Since the focus of this research is on the macroscopic calibration of aerodynamic parameters in the HDM-4 model, this approach is considered sufficient [38], [39]. The process includes three main stages: pre-processing, processing, and post-processing. During pre-processing, a vehicle model based on actual dimensions is created, validated, and meshed. Boundry conditions such as flow type, gravity, fluid type, and test speed are defined. In the processing stage, numerical simulations are run to calculate frontal area (AF) and the drag coefficient (Cd). The calculation follows Eq. (1). In the post-processing stage, simulation results are interpreted to evaluate the vehicle's aerodynamic efficiency, where a lower drag coefficient indicates a more streamlined and fuel-efficient design [40], [41], [42].

$$Cd = \frac{2\,FA}{\rho\,V^2\,AF} \tag{1}$$

where Cd represents the drag coefficient (dimensionless), FA is the aerodynamic drag force (N), ρ denotes the air density (kg/m³), V corresponds to the relative velocity between the vehicle and air (m/s), and AF is the frontal area of the vehicle (m²). Once the calculation is completed, the post-processing stage is conducted to interpret the simulation results and evaluate the vehicle's aerodynamic efficiency. Consequently, the lower the Cd value, the more aerodynamic and fuel-efficient the vehicle design becomes [40], [41], [42].

In addition to the aerodynamic analysis, HDM-4 model calibration is performed by considering various factors such as vehicle weight, speed, and road gradient [26]. The fuel consumption estimation process begins by determining the total resistance force acting on the vehicle, which is calculated using Eq. (2).

$$\mathrm{FTR = FA + FG + FR + FCV} \tag{2}$$

where FA represents the aerodynamic drag force (N), FG is the gradient resistance force (N), FR is the rolling resistance force (N), and FCV refers to the curvature resistance force (N). After calculating the total resistance force, the traction power required to overcome this resistance is determined using Eq. (3).

$$\mathrm{PTR} = \frac{\mathrm{FTR \times V}}{1000} \tag{3}$$

where PTR denotes the traction power (kW) and V is the vehicle speed (m/s). Once the traction power is obtained, the total engine power is calculated using Eq. (4).

$$\mathrm{PTOT} = \left(\frac{\mathrm{PTR}}{\mathrm{EDT}} + \mathrm{PENGACCS}\right) \tag{4}$$

where PTOT represents the total engine power (kW), EDT corresponds to the drivetrain efficiency, and PENGACCS is the power required for engine accessories (kW). The total engine power is a crucial factor in determining the vehicle's fuel consumption under different operational conditions. Following this, the instantaneous fuel consumption is estimated using Eq. (5).

$$\mathrm{IFC} \quad = \max\left[\mathrm{ID\_FUEL}, \mathrm{ZETA} \times \mathrm{PTOT} \times (1 + \mathrm{dFUEL})\right] \tag{5}$$

where IFC represents the instantaneous fuel consumption (ml/s), ID_FUEL is the fuel consumption at idle, ZETA refers to the engine efficiency, and dFUEL is an additional fuel consumption factor due to speed variations. After determining the instantaneous fuel consumption, the specific fuel consumption is calculated using Eq. (6).

$$\mathrm{FC} = \frac{IFC}{V} \tag{6}$$

where FC refers to the specific fuel consumption (ml/km) and IFC is the instantaneous fuel consumption (ml/s). This calculation ensures that the model accurately reflects real-world fuel consumption behavior. To ensure that the fuel consumption predictions align with actual operational conditions, calibration is applied to several engine parameters. One of these parameters is the engine speed (RPM), which is determined using Eq. (7).

As shown in Eq. (7) RPM_a0, RPM_a1, RPM_a2, and RPM_a3 are engine speed model parameters obtained through calibration. Engine speed is a key variable affecting fuel consumption, as it influences both power output and mechanical efficiency.

Rolling resistance is a critical factor affecting vehicle fuel consumption, particularly for heavy-duty trucks operating on diverse road surfaces. To account for this, the rolling resistance factor is determined using Eq. (8).

As shown in Eq. (8) Kcr2 represents the rolling resistance factor, TD denotes the road texture depth (mm), and RI refers to the average road roughness value (m/km), while CR_CR2_a0, CR_CR2_a1, CR_CR2_a2 are rolling resistance coefficients calibrated based on field data. Rolling resistance plays a significant role in fuel efficiency, especially for heavy-duty vehicles operating under varying road conditions. Furthermore, the engine power factor is adjusted using Eq. (9).

As shown in Eq. (9), Kpea is the calibration factor, PRAT is the maximum engine power (kW), RPM_IDLE is the engine speed at idle (rev/min), RPM100 is the engine speed at 100 km/h (rev/min), RPM is the engine speed at operational speed (rev/min), PACCS_a0 is the ratio of engine and accessory resistance to the engine power at 100 km/h, and PACCS_a1 is a model parameter.

The comparison between the calibrated HDM-4 model predictions and the observed fuel consumption data is analyzed using the Wilcoxon Signed-Ranks Test. This non-parametric method is ideal for paired samples that do not meet normality assumptions [43]. The null hypothesis (H_0) states that the median difference is zero, while the alternative hypothesis (H_1) suggests a significant difference. The Z value is compared to the critical Z value of ±1.96 at a 0.05 significance level. The results are reported by comparing the number of negative ranks, positive ranks, and ties as indicators of the model's stability. In refining the model, we used an empirical trial and error calibration approach, where we adjusted Kcr2 (rolling resistance factor) and Kpea (engine efficiency factor) along with aerodynamic factors (Cd and AF). These adjustments ensured that the model effectively reflects real-world operational scenarios, enhancing its ability to predict fuel consumption with greater accuracy. The calibration was conducted in three scenarios: (1) scenario 1: Using the default HDM-4 parameters without adjustments, which showed a significant difference between predicted and actual fuel consumption, (2) scenario 2: Involving aerodynamic calibration with adjustments to the drag coefficient (Cd) and frontal area (AF), as well as engine RPM adjustments, and (3) scenario 3: Adding the calibration factors Kcr2 and Kpea through a trial and error process. With adjustments in all three scenarios, the model now represents real-world fuel consumption more accurately, with Scenario 3 providing the closest results.

$$\mathrm{RPM} = \mathrm{RPM\_a0} + \mathrm{RPM\_a1} \times \mathrm{V} + \mathrm{RPM\_a2} \times \mathrm{V}^2 + \mathrm{RPM\_a3} \times \mathrm{V}^3 \tag{7}$$

$$\mathrm{CR2} = \mathrm{Kcr2} \times (\mathrm{CR\_CR2\_a0} + \mathrm{CR\_CR2\_a1} \times \mathrm{TD} + \mathrm{CR\_CR2\_a2} \times \mathrm{RI}) \tag{8}$$

$$\mathrm{PENGACCS} \quad = \mathrm{Kpea} \times \mathrm{PRAT} \times \left[\mathrm{PACCS\_a1} + \frac{(\mathrm{PACS\_a0} - \mathrm{PACCS\_a1})(\mathrm{RPM} - \mathrm{RPM\_IDLE})}{(\mathrm{RPM100} - \mathrm{RPM\_IDLE})}\right] \tag{9}$$

3. Result and Discussion

The calibration was done at the whole-trip level instead of shorter road segments, as each data entry reflects key operational parameters such as travel distance, average speed, vehicle weight, and road gradient, with 94 trips included. To prevent ill-conditioning issues, we ensured that our dataset covered a wide range of operational conditions, including vehicle weights from 15.27 to 38.16 tons, operating speeds from 5.1 to 52.3 km/h, and road gradients between +4.9% and -6.7%. This diversity in input parameters means that the model is not restricted to a single type of trip but can adapt to various real-world scenarios, maintaining a high level of accuracy without being biased by overly similar data. The results showed strong predictive ability, with R^2 values of 0.83 for the training set and 0.79 for the test set. RMSE values of 0.39 km/l for the training set and 0.43 km/l for the test set, alongside a MAPE of 9.5%, confirm that the model remains reliable even with new data. Additionally, an outlier analysis using the Interquartile Range (IQR) method was performed, retaining extreme values as they accurately represent real-world operational conditions.

3.1. *Calibration of Engine Speed Model Parameters*

These differences can be attributed to advancements in engine technology, particularly in modern engines equipped with common-rail injection systems and advanced emission controls, which enable lower engine RPMs at the same speeds due to improved torque and fuel efficiency. Since the HDM-4 model was developed based on older engine characteristics, it tends to overestimate RPM at lower speeds and underestimate it at higher speeds. Although the Zaabar & Chatti model offers a more recent perspective, it still exhibits a sharp increase in RPM at higher speeds, which does not fully reflect the real-world conditions observed in Indonesia [14].

These differences reflect advancements in engine technology and how they impact truck performance and fuel consumption. The default engine RPM parameters in the HDM-4 model are RPM_a0 = 1900, RPM_a1 = -10.178, RPM_a2 = 0.1521, and RPM_a3 = 0.00004 [6]. These values represent the characteristics of conventional truck engines used during that period. As a result, the HDM-4 model tends to overestimate engine RPM at low to medium speeds, leading to higher predicted fuel consumption than what actually occurs. On the other hand, at higher speeds, the HDM-4 model underestimates engine RPM and does not fully account for the increased aerodynamic resistance and higher power demands. In comparison, the study by Zaabar & Chatti model presents more modern engine RPM parameters with values of RPM_a0 = 833.7, RPM_a1 = -17.717, RPM_a2 = 0.9671, and RPM_a3 = -0.0055. These parameters reflect improvements in combustion efficiency, fuel injection precision, and emission control. Although this model offers a more accurate prediction than HDM-4, it still falls short, especially at high speeds where the predicted engine RPM increases more sharply than observed in real-world conditions. This indicates that although the models used are based on more advanced technology, they still do not fully reflect the operational conditions of trucks in Indonesia. In line with previous research, differences in vehicle characteristics including rolling resistance and engine response are influenced by drivetrain configuration, control strategies, and local topography [27]. In this study, the 5-axle truck with a manual transmission showed that driving patterns, such as the use of engine braking on downhill slopes, significantly affect RPM behavior. Therefore, calibration based on local and up-to-date data is essential to improve the model's accuracy.

The current study provides parameters that are more tailored to the real-world conditions of Indonesian trucks. The parameters derived are RPM_a0 = 680.11, RPM_a1 = -4.9031, RPM_a2 = 0.3858, and RPM_a3 = -0.0028. These values align with Euro-4 engine technology, which incorporates common-rail injection systems and modern emission controls [44], [45]. This technology allows trucks to produce optimal power at lower RPMs, improving fuel efficiency and reducing emissions. These results highlight the efficiency of Euro-4 engines in maintaining stable RPMs across different speeds compared to older engine technologies. To better understand the relationship between speed and engine RPM, this study used a third-degree polynomial model. The equation derived from the data is: $y = -0.0028 x^3 + 0.3858 x^2 - 4.9031 x + 680.11$. With a coefficient of determination $R^2 = 0.9838$. This high R^2 value indicates that the model fits the observed data very well. The model developed in this study captures the gradual increase in RPM as vehicle speed rises, providing a more accurate representation of fuel consumption trends compared to the HDM-4 and Zaabar & Chatti models. By recalibrating key parameters, the model aligns with modern truck engine technology, incorporating common-rail injection and advanced emission controls. These refinements enhance the accuracy of fuel consumption predictions while supporting efforts to optimize vehicle performance and reduce emissions.

The differences between the HDM-4 model, the Zaabar & Chatti model, and actual observations are clearly illustrated in **Figure 1** and supported by **Table 1**. The blue dots represent observed telematics data, which show a gradual and consistent increase in engine RPM as vehicle speed rises. In contrast, the orange dots from the HDM-4 model tend to overestimate RPM at lower speeds and underestimate it at higher speeds. Meanwhile, the green dots from the Zaabar & Chatti model show a much sharper increase in RPM at higher speeds, diverging from actual operating conditions. The red dashed line derived from a third-degree polynomial regression developed in this study closely follows the observed trend, offering a more accurate reflection of modern engine performance. The curve shown in the graph represents the average engine RPM in relation to vehicle speed, calculated from full-trip telematics data. Average RPM values were obtained by aggregating all RPM data points and pairing them with the corresponding average speed for each trip. This approach provides a representative picture of typical vehicle operations. Furthermore, the average RPM values were validated against predictions from the HDM-4 model and prior studies, with the resulting polynomial regression achieving a coefficient of determination (R^2) of 0.9838. This indicates the model captures nearly all variation in the observed data. Despite inherent

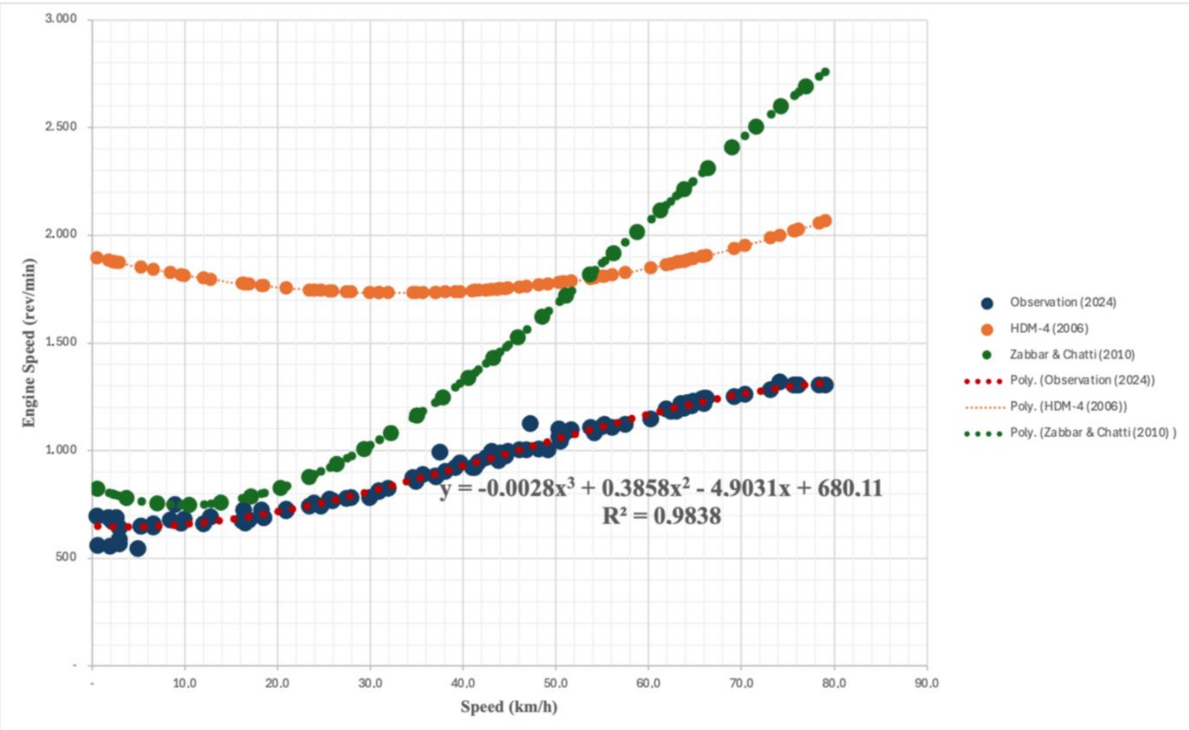


Figure 1. Calibration of engine speed model parameters

Table 1. Comparison of engine speed model parameters for heavy-duty trucks

Model	RPM_a0	RPM_a1	RPM_a2	RPM_a3
HDM-4	1900.0	-10.178	0.1521	0,00004
Zaabar & Chatti	833.7	-17.717	0.9671	-0.0055
Current Study	680.11	-4.9031	0.3858	-0.0028

fluctuations in engine speed due to shifting patterns and terrain, using averaged values proves to be a reliable method for modeling RPM and forms a solid basis for further analysis.

3.2. Calibration of Aerodynamic Parameters

The aerodynamic simulation results for heavy-duty vehicles offer a clear picture of how air flows around the vehicle, the drag force, and the drag coefficient. The airflow distribution, shown through streamlines with color gradients, reveals that air moves smoothly over the cabin and body of the vehicle. However, as the vehicle speed increases, significant turbulence forms behind the vehicle, known as the wake region. This turbulence creates a low-pressure zone, which in turn increases drag force [46]. From the simulation, the average drag force recorded is 1,455.792 N, with a minimum of 1,455.556 N and a maximum of 1,455.851 N. These values highlight that air resistance on heavy-duty vehicles is quite substantial, especially at higher speeds [46]. The simulation also indicates a drag coefficient (Cd) of 1.0556, with a range between 1.0551 and 1.0558, and a frontal area (AF) of 8.2 m². In contrast, the default values used in the HDM-4 model assume a drag coefficient (Cd) of 0.80 and a frontal area (FA) of 9.0 m² [26].

The differences between the simulation results and the HDM-4 defaults can be explained by the turbulence created in the wake region, which leads to increased pressure drag. This means the engine needs to work harder to maintain speed. Additionally, the turbulence behind the vehicle raises drag force and fuel consumption. Although the drag coefficient from the simulation is higher than the default HDM-4 value, aerodynamic drag still plays a major role in fuel efficiency, particularly because air resistance increases exponentially with speed [46].

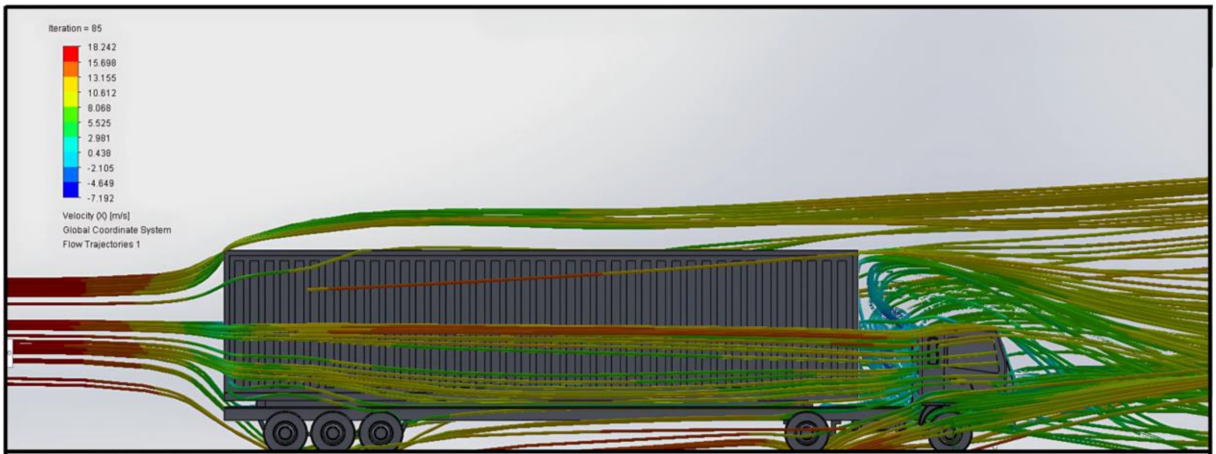
These findings align with earlier research, which shows that aerodynamic drag significantly affects the performance of heavy-duty vehicles, especially at high speeds [26]. Therefore, this simulation underscores the importance of calibrating the HDM-4 model to match the real aerodynamic conditions of modern heavy-duty vehicles. Such calibration is crucial to improve the accuracy of fuel consumption predictions, ensuring they reflect current vehicle technology and real-world operations [14], [17]. Given these significant differences between the simulation results and the default HDM-4 values, it is clear that modern vehicle designs have evolved aerodynamically. Therefore, adjusting parameters such as the drag coefficient (Cd) and frontal area (AF) is essential to improve the accuracy of fuel consumption predictions. As presented in **Table 2**, the differences between the default HDM-4 values and the calibrated model emphasize the significant role of aerodynamic resistance in influencing vehicle efficiency. The aerodynamic simulation shown in **Figure 2** illustrates the formation of intense wake turbulence behind the container, with airflow speeds reaching 31.324 m/s and a pressure drop to 67,568.17 Pa indicating flow separation behind the vehicle body. This turbulence generates a low-pressure zone at the rear, increasing aerodynamic drag, reducing energy efficiency, and ultimately raising fuel consumption [46], [47]. Although this wake effect is not visually prominent in **Figure 2**, the airflow behavior is consistent with previous studies on heavy-duty vehicles. Since this research primarily focuses on estimating Cd and AF for HDM-4 calibration purposes, detailed turbulence visualization falls outside the study's scope. However, future research is encouraged to apply advanced CFD tools for a more comprehensive analysis of wake dynamics.

3.3. Calibration of the HDM-4 Model

This analysis explores fuel consumption predictions using the HDM-4 model, comparing three different approaches. In Scenario 1, the model relies on default HDM-4 values without any adjustments. Moving to Scenario 2, the approach incorporates aerodynamic calibration by setting the drag coefficient (Cd) to 1.05 and the frontal area (AF) to 8.2 m², along with adjustments to the engine rotation model. In Scenario 3, the addition of correction factors Kpea and Kcr2 using a trial-and-error approach significantly improved the accuracy of fuel consumption predictions, resulting in differences that were no longer statistically significant compared to actual observations.

Table 2. Comparison of aerodynamic parameters for heavy-duty trucks

Model	Drag Coefficient (Cd)	Frontal Area (AF) [m²]
HDM-4	0.8	9.0
Current Study	1.05	8.2



Goal Name	Unit	Value	Averaged Value	Minimum Value	Maximum Value	Progress [%]	Use In Convergence	Delta	Criteria
Drag Force	[N]	1455.936	1455.792	1454.868	1456.853	100	Yes	1.985	124.813
CD	[ ]	1.0557363	1.0556319	1.0549621	1.0564018	100	Yes	0.0014397	0.0905049

Figure 2. Aerodynamic simulation results

In Scenario 1, the results show that 85 out of 91 cases fall into the negative ranks category, with an average rank of 48.51 and a total rank of 4,123.00. In contrast, only 6 cases fall into the positive ranks category, with an average rank of 10.50. The Wilcoxon test produces a Z-value of -8.035 and a significance level of $p < 0.001$, clearly indicating a significant gap between the model predictions and real-world observations [26]. This suggests that the default HDM-4 values underestimate fuel consumption, likely because they do not consider the vehicle's aerodynamic properties or the unique operational conditions on the ground. In Scenario 2, after calibrating the aerodynamic parameters and adjusting the engine rotation model, prediction accuracy improves. The number of negative ranks drops to 79 cases, with an average rank of 50.53, while the positive ranks increase to 12 cases, with an average rank of 16.21. Despite this improvement, the Wilcoxon test still yields a Z-value of -7.514 and $p < 0.001$, indicating that the differences between predicted and observed data remain significant. In Scenario 3, introducing the correction factors Kpea and Kcr2, both set at 0.6, further enhances prediction accuracy. The negative ranks drop significantly to 50 cases, with an average rank of 48.55, while the positive ranks rise to 41 cases, averaging 42.89. The Wilcoxon test returns a Z-value of -1.324 and a significance level of $p = 0.186$, indicating that the difference between the predictions and the observed data is no longer statistically significant. A summary of the calibration parameters and statistical results is presented in **Table 3**.

These results align with earlier research comparing HDM-4 fuel consumption predictions with telematics data from the UK. Significant discrepancies in fuel consumption estimates for heavy-duty trucks under the Base Case were found, although updates to vehicle weight and frontal area in the Update Case improved predictions. However, notable differences still persisted [17]. Overall, this study reinforces that default HDM-4 values often fall short in predicting fuel consumption for heavy-duty trucks because they do not reflect real-world operational weight and aerodynamic factors [23], [48]. While calibrating these parameters in Scenario 2 enhances prediction accuracy, it does not fully resolve the discrepancies. However, the adjustments introduced in Scenario 3 substantially minimized the discrepancies, as indicated by the statistically insignificant outcome.

Table 3. Calibration of HDM-4 fuel consumption model parameters for heavy-duty trucks

Scenario	Drag Coefficient (Cd)	Frontal Area (AF) [m²]	Kcr2	Kpea	p-value
1	0.8	9.0	Default = 1	Default = 1	< 0.001
2	1.05	8.2	Default = 1	Default = 1	< 0.001
3	1.05	8.2	0.6	0.6	0.186

Despite these improvements, some discrepancies remain even after updating vehicle weight and frontal area. These differences are likely due to recent technological advancements in heavy-duty truck design and performance [21], [49]. Therefore, further calibrations of the HDM-4 model at Level III are essential to accurately reflect the operational conditions of today's heavy-duty trucks [23].

4. Conclusion

This study aimed to enhance the accuracy of fuel consumption predictions for heavy-duty trucks by calibrating the HDM-4 model to better reflect modern engine technology and real-world operating conditions in Indonesia. The results clearly show that the default HDM-4 parameters no longer match the characteristics of today's trucks. Therefore, it is crucial to update these parameters by considering current engine technology and local operational factors. Firstly, calibrating the engine speed model revealed that the default HDM-4 parameters tend to overestimate fuel consumption at low to medium speeds, while underestimating it at higher speeds. The new parameters derived for Euro-4 engines capture the efficiency of modern engines, which deliver optimal power at lower RPMs, leading to more accurate fuel consumption predictions. Secondly, the calibration of aerodynamic parameters found that the default drag coefficient (Cd) and frontal area (AF) values in HDM-4 do not reflect real-world truck configurations. The simulation results thus provide a better representation of actual aerodynamic performance. In addition, calibrating the rolling resistance and engine efficiency factors further improved the model's accuracy across various road conditions and vehicle loads.

Moreover, calibrating the HDM-4 model through three different scenarios showed a steady improvement in prediction accuracy. In Scenario 1, the default HDM-4 parameters significantly underestimated fuel consumption. In Scenario 2, incorporating aerodynamic calibration and engine RPM adjustments improved accuracy, though some differences remained. Finally, in Scenario 3, adding technical correction factors (Kpea and Kcr2) resulted in predictions that closely matched real-world data, with no significant statistical difference. The most significant finding of this study is that Scenario 3 incorporating aerodynamic calibration and technical correction factors yielded fuel consumption predictions that were statistically consistent with observed values ($p = 0.186$), confirming the robustness and reliability of the calibrated HDM-4 model. By delivering updated HDM-4 parameters tailored to Euro-4 trucks and incorporating modern aerodynamic profiles, this study provides practical contributions to support data-driven decisions in logistics efficiency, cost management, and emission control. As a result, heavy-duty truck operations in Indonesia can become more efficient, economical, and environmentally sustainable.

Looking forward, future research should incorporate additional influencing factors such as detailed road surface conditions, short-gradient variability, ambient temperature, and driver behavior, which were beyond the scope of this study. Furthermore, as vehicle technology advances, continuous calibration using HDM-4 Level III will be necessary to preserve model accuracy over time. To enhance the quality of aerodynamic analysis, advanced Computational Fluid Dynamics (CFD) simulations using high-performance computing can deliver high-resolution insights into airflow separation, wake turbulence, and drag dynamics. Additionally, wind tunnel testing is recommended to validate CFD outputs and further refine aerodynamic coefficients. By adopting these approaches, future studies can develop a more robust, flexible, and adaptive HDM-4-based fuel consumption model, aligned with the latest truck technologies and diverse real-world operating environments.

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Author's Declaration

Authors' contributions and responsibilities

The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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The authors declare no competing interest.

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