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

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Penulis: Pradhana Wahyu Nariendra (Penulis Pertama & Korespondensi), Melia Eka Lestiani

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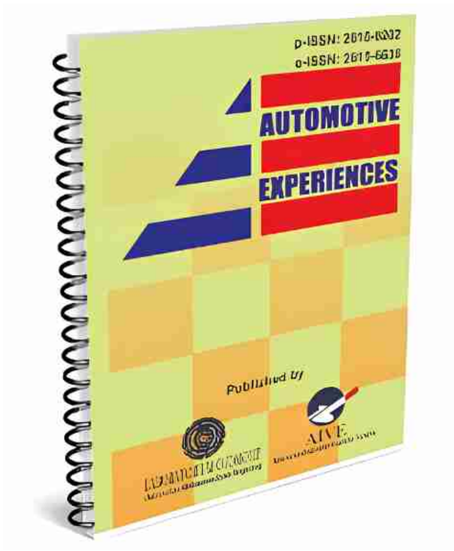

1. IDENTITAS ARTIKEL DAN PROFIL JURNAL
1.1. Profil Jurnal

Artikel berjudul **“Calibration of HDM-4 Model for Fuel Consumption in Heavy-Duty Trucks: Integration of Telematics, Engine Speed, and Aerodynamics”** telah diterbitkan pada jurnal **Automotive Experiences**, Vol. 8 No. 1 Tahun 2025, hlm. 109–121. Artikel ini ditulis oleh **Pradhana Wahyu Nariendra** sebagai **penulis pertama** sekaligus **penulis korespondensi** dengan afiliasi utama **Department of Transportation Management**, **Universitas Logistik dan Bisnis Internasional**. Artikel ini relevan dengan bidang **Teknik/Rekayasa Transportasi** karena membahas kalibrasi model HDM-4 untuk konsumsi bahan bakar truk berat melalui integrasi data telematika, kecepatan mesin, dan parameter aerodinamika. Substansinya berkaitan dengan kinerja angkutan barang, efisiensi energi, biaya operasi kendaraan, dan keberlanjutan transportasi.

Jurnal **Automotive Experiences** merupakan jurnal peer-reviewed terbitan **Universitas Muhammadiyah Magelang**, terbit tiga kali setahun, dan terindeks **Scopus Q2**. Bukti visual berikut menunjukkan identitas artikel, posisi penulis, afiliasi, serta profil jurnal dan proses publikasinya.

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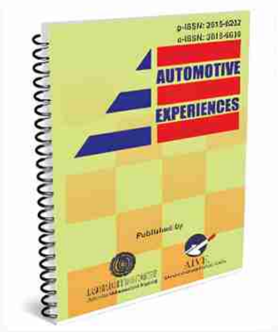

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Research Paper

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

Penulis pertama dan Korespondensi

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1.2. Relevansi Karya Ilmiah dengan Bidang Ilmu

Bagian **Aim** jurnal **Automotive Experiences** menunjukkan bahwa cakupan jurnal mencakup e**ngineering, environment, informatics, transportation, logistics, serta vehicle applications**, sehingga relevan dengan artikel yang membahas kalibrasi model **HDM-4** untuk pemodelan konsumsi bahan bakar truk berat melalui integrasi data telematika, kecepatan mesin, dan parameter aerodinamika. Kesesuaian ini diperkuat oleh objek kajian artikel, yaitu **heavy-duty trucks/freight vehicles**, serta keterkaitannya dengan pemodelan teknis kendaraan, pemanfaatan data telematika, hubungan konsumsi bahan bakar dengan emisi, dan analisis kinerja kendaraan angkutan barang. Dengan demikian, artikel ini berada dalam lingkup **Aim and Scope** jurnal **Automotive Experiences** dan mendukung kesesuaian bidang ilmu **Teknik/Rekayasa Transportasi**.

Aim

When the vehicle was manufactured, it involved scientists in chemistry, physics, energy, materials, design, engineering, environment, informatics, economics, ergonomics, standardization, health sciences, and even science related to regulation and policy. Then, when it is implemented, it will relate to the fields of transportation, logistics, economics, and social science. Therefore, this journal is open to researchers working in the design, production, and vehicle applications as previously stated.

All reports correspond to development, engineering, and implementation of vehicle types are facilitated in this journal, including private vehicles, all types of passenger vehicles, all types of freight vehicles, heavy-duty vehicles, ambulances, military vehicles, fire engines, indoor vehicles, motorcycle, race cars, sports cars, rail vehicles, multipurpose vehicles, aircraft, and boats. Only articles that have a contribution will be published, while articles that are only illustrative of established principles and procedures, even though they may contain numerical data, will generally not be published.

Scope

Automotive experiences invite researchers to contribute ideas on the main scope of Emerging automotive technology and environmental issues; Efficiency (fuel, thermal and mechanical); Vehicle safety and driving comfort; Automotive industry and supporting materials; Vehicle maintenance and technical skills; and Transportation policies, systems, and road users behavior.

Emerging automotive technology and environmental issues

Scopes related to this topic include:
Fuel and Energy: Alternative fuel (LPG, Natural gas, Bio-diesel, Ethanol, Methanol, DME, Hydrogen, and the combination, both of which function as fully dedicated, bi-fuel, or dual fuel). This also includes coverage on the wind, solar, hydro, geothermal, and other renewable energy for automotive applications through Vehicle-to-Grid (V2G) Technology. Recycled fuels from the pyrolysis process of biomass, plastics, and rubber are also included in this scope.
Material: Semiconductor; Environmentally friendly material for moving parts (tires, brake shoes, refrigerant, engine oil, coolants, rubber, glass, electrical parts, and other moving parts); Sustainable materials for advance vehicle technology (sensor, fuel cells, batteries, and other energy storage equipment).
Technology: Emission control strategy; Electric-based vehicle; Fuel cell vehicle; Hypercar; Hybrid technology; and After combustion technology (catalytic converter, diesel particulate filter, EGR).

Efficiency (fuel, thermal, and mechanical)

Scopes related to this topic include:
Thermal management: Supercharging; Turbocharging; Combustion engineering; Fuel spray technology; Modern engine supporting system (cooling, lubricating, charging, and HVAC); Energy harvesting; and Regenerative braking.
Material: Lightweight materials, Low-friction material, Nanofluids for cooling and lubricating, High-temperature resistant material, and High-pressure resistant material.
Design: Aerodynamics body; Traction control, and Tire rolling optimization.
Technology: On-board engine and emission monitoring technology; HCCI; Engine Management System (sensor, actuator, module); Common rail technology; Low/zero friction engine technology; Continuously Variable Transmission; and Modern drive train technology.

Vehicle safety and driving comfort

Scopes related to this topic include:
Safety system and technology: Low noise and vibration technology; Preventive technologies for driver drowsiness; Electronic stability control (ESC); Automatic and emergency braking; Blind-spot monitoring; Lane departure warnings; Speed monitoring and warning systems; Integrated vehicle technology; Vehicle-to-vehicle communication; Vehicle cybersecurity; and IoT support for safe driving and mobility.
Comfort system and technology: Hill Start Assist; Parking aid; Electronic gas pedal; On-board monitoring technology; Smart Air Conditioning system; Health monitoring; Modern Audio Visual; Mini cooler; and Electronic device supporting.

Automotive industry and supporting materials

Scopes related to this topic include:
Automobile production: Lean automobile production technology; Product design based on market signals; and Product quality control.
Material and Process: Alloy, Composite and bio-composite, Biodegradable plastics, Lightweight metal; Welding technology; Sustainable interior materials; Paint technology; Anti-corrosion technology; Forming and finishing technology; and Material treatment technology.

Vehicle maintenance and technical skills

Scopes related to this topic include:
Vehicle maintenance: Environmental-oriented workshop management; Service scheduling; Working time efficiency; Reuse and recycle material; and ECM/ECU Remapping.
Technical skill: New diagnosis and screening methods; New repair method; Development of equipment and special service tools; Technician skills development; and Occupational health and safety in the workshop.

Transportation policy, systems, and road users behavior

Scopes related to this topic include:
Regulation, policy, and practice: Reports on the regulation and policy associate the land transportation system that impacts on Economics, Engineering, Psychology, Sociology, Urbanism, and Driving behavior.
Management: Traffic management; Telemetric congestion monitoring; Eco-routing system; Smart transportation; and Feasibility studies on new transportation equipment and systems.
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1.3. Bukti Indeksasi Scopus Q2 & Scimagojr

Berdasarkan **Scopus Preview**, jurnal Automotive Experiences tercakup dalam indeks Scopus sejak tahun 2018–2025, dengan bidang **Engineering: Automotive Engineering, Social Sciences: Transportation, dan Energy: Fuel Technology**. Metrik Scopus tahun 2024 menunjukkan **CiteScore 5,0, SJR 0,410, dan SNIP 1,028**. Selain itu, berdasarkan **SCImago Journal & Country Rank**, jurnal ini berada pada **kategori Q2** dengan subject area **Fuel Technology, Automotive Engineering, dan Transportation**. Informasi ini menunjukkan bahwa jurnal tersebut relevan dengan bidang Teknik/Rekayasa Transportasi dan memenuhi kualifikasi sebagai jurnal internasional bereputasi terindeks Scopus.

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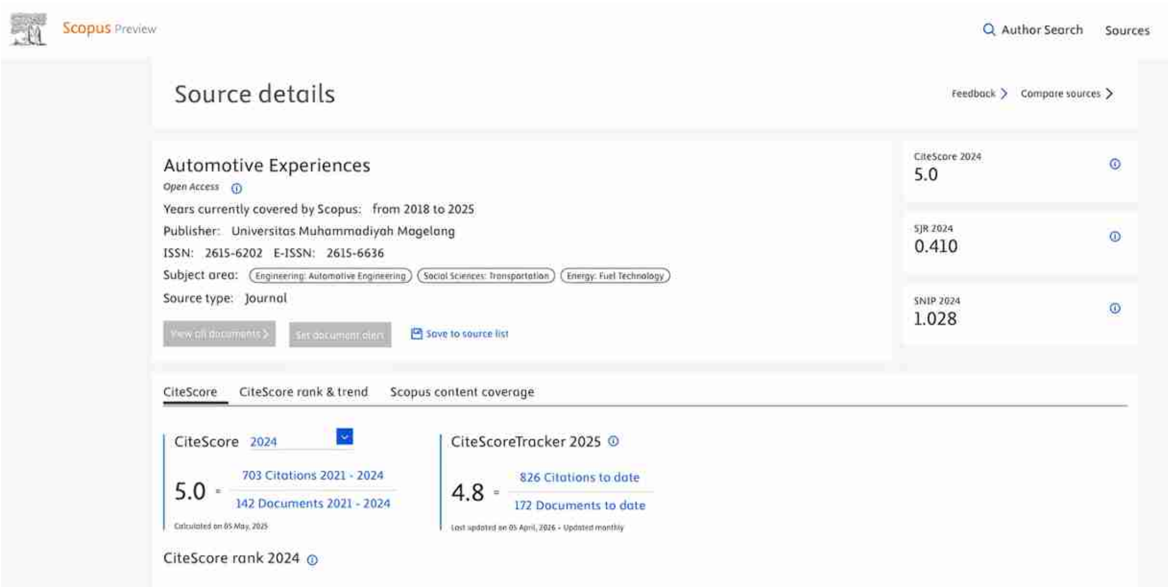

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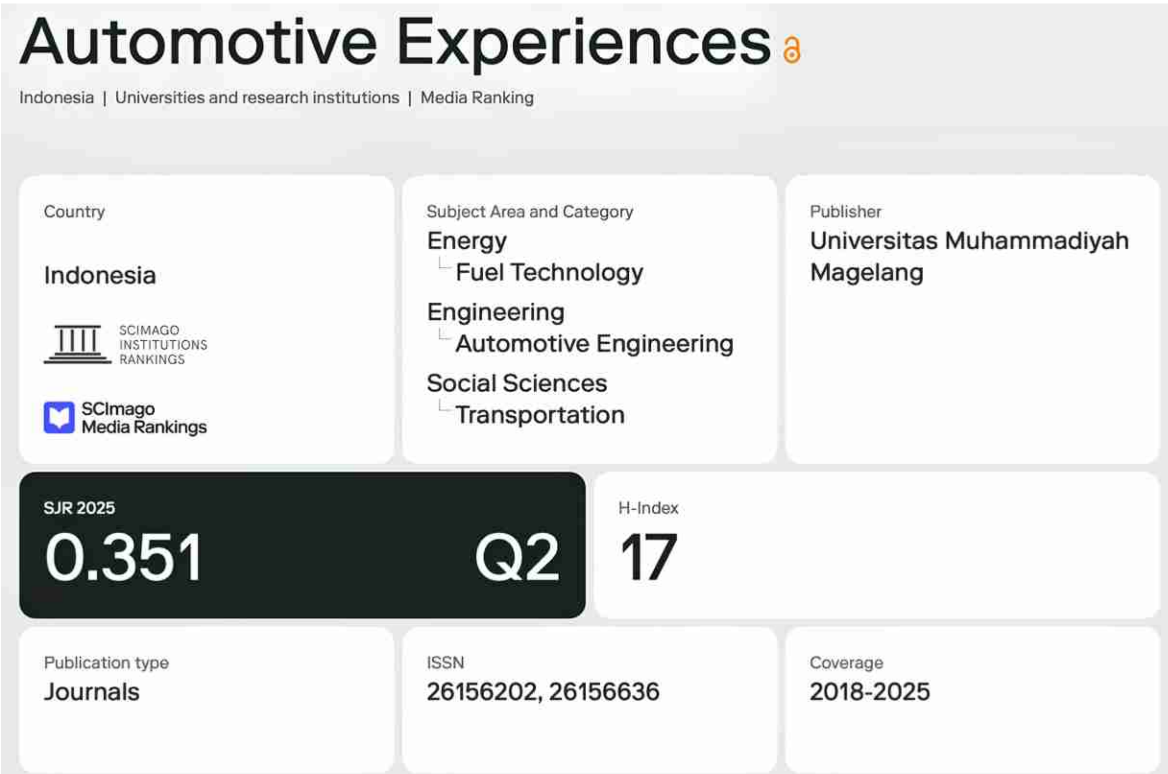

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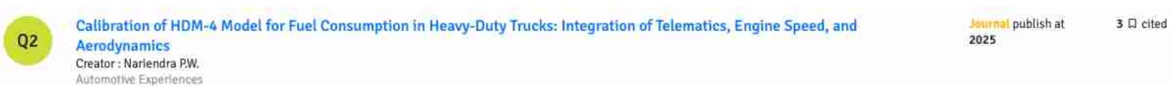


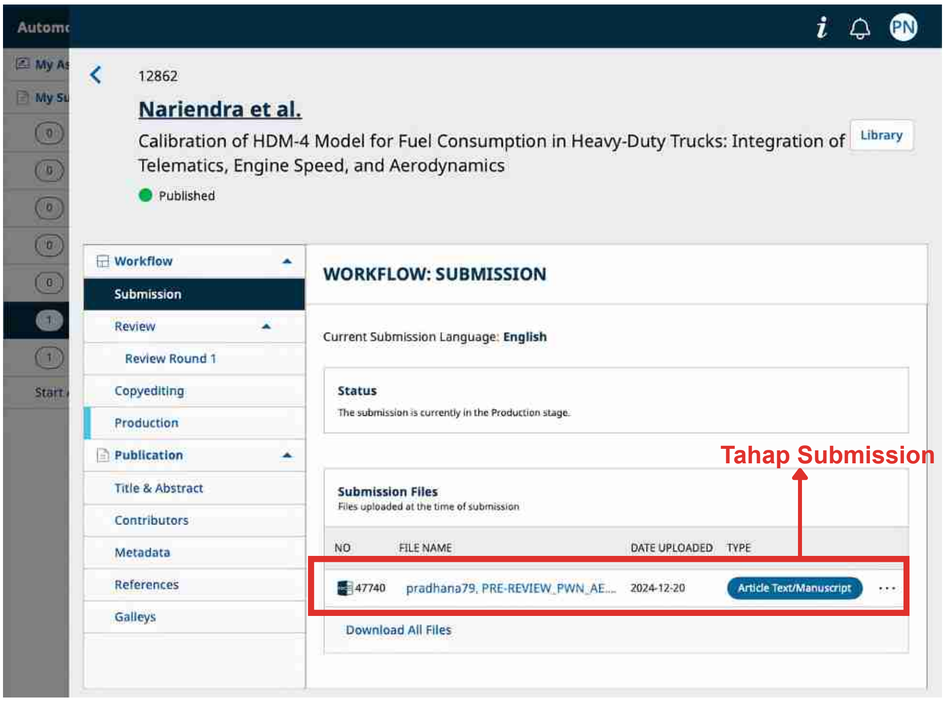
2. KRONOLOGIS KORESPONDENSI (LOG SUMMARY)

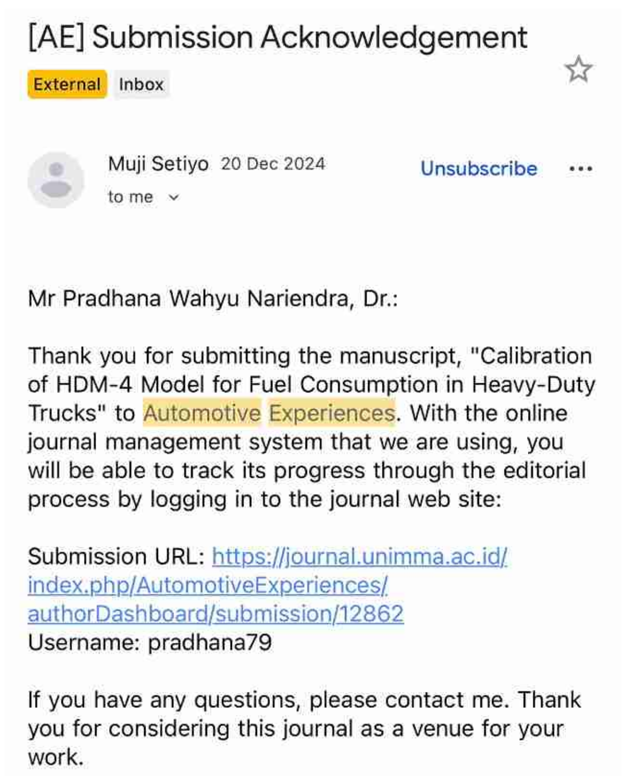
No.	Tahapan Korespondensi	Tanggal	Keterangan
1	**Submission**	20 Desember 2024	Naskah awal diunggah ke sistem OJS jurnal Automotive Experiences dengan nomor submission 12862.
2	**Tahap Review / Review Round 1**	Setelah submission	Artikel masuk ke tahap review dan Review Round 1, yang menunjukkan bahwa naskah telah melalui proses telaah editorial dan penilaian reviewer.
3	**Decision: Revisions Required**	8 Maret 2025	Editor menyampaikan keputusan Revisions Required berdasarkan hasil review dan meminta penulis melakukan perbaikan naskah.
4	**Substansi Masukan Reviewer**	8 Maret 2025	Reviewer memberikan masukan terkait metodologi, pengolahan data, validasi hasil, parameter teknis kendaraan, penyajian tabel dan gambar, serta kejelasan argumentasi ilmiah.
5	**Revised Manuscript dan Response Letter Submitted**	21 Maret 2025	Penulis mengunggah Revised Manuscript dan Response Letter sebagai bukti perbaikan naskah serta tanggapan formal terhadap masukan reviewer.
6	**Editor Decision: Accept Submission**	22 Maret 2025	Editor menyampaikan keputusan Accept Submission, yang menunjukkan bahwa artikel telah diterima dan dilanjutkan ke tahap pasca-acceptance.
7	**Editing Completed / Sent to Production**	13 April 2025	Editor menyampaikan bahwa proses editing telah selesai dan artikel dikirim ke tahap produksi.
8	**Copyediting File Uploaded**	13 April 2025	File hasil copyediting diunggah ke sistem dan digunakan dalam proses produksi artikel.
9	**Galley Proof**	4 Mei 2025	Editor menyampaikan bahwa proses typesetting dan layout telah selesai serta meminta penulis memeriksa format akhir artikel.
10	**Approval for Publication**	7 Mei 2025	Penulis memberikan konfirmasi bahwa dokumen telah diperiksa, sudah benar, dan siap untuk diterbitkan.
11	**Tampilan OJS / Bukti Artikel Published**	Metadata OJS: 13 April 2025	Laman OJS menampilkan artikel dengan status published pada jurnal Automotive Experiences, Vol. 8 No. 1 Tahun 2025.

3. TAHAP SUBMISSION

3.1. Bukti Submission Confirmation

Artikel diajukan melalui sistem OJS jurnal Automotive Experiences dengan nomor submission 12862. Pada tahap awal, naskah utama diunggah sebagai Article Text/Manuscript pada tanggal 20 Desember 2024.





[AE] Submission Acknowledgement

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to me

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Thank you for submitting the manuscript, "Calibration of HDM-4 Model for Fuel Consumption in Heavy-Duty Trucks" to Automotive Experiences. With the online journal management system that we are using, you will be able to track its progress through the editorial process by logging in to the journal web site:

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If you have any questions, please contact me. Thank you for considering this journal as a venue for your work.

3.2. Naskah Awal (Pre Review)

Bagian ini menyajikan bukti naskah awal artikel yang diajukan pada tahap submission ke jurnal Automotive Experiences. Naskah awal ini menjadi dokumen pertama yang masuk ke sistem OJS jurnal sebelum melalui proses pemeriksaan editor, review, revisi, dan publikasi akhir.

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 m^2. 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.

Calibration of HDM-4 Model for Fuel Consumption in Heavy-Duty Trucks: Integration of Telematics, Engine Speed, and 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], [2]. A global analysis shows that a 1 liter/100 km increase in fuel consumption adds 24.17 g/km of CO_2 emissions [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]–[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]–[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 aims to develop an HDM-4 Level II fuel consumption model tailored for 5-axle trucks in Indonesia. The calibration process focuses on factors such as engine rotation, aerodynamic drag, frontal area, engine power efficiency, and operational conditions like average speed, load weight, and road gradient to better capture the realities of daily truck operations. The research is centered on the Tanjung Priok Port–Bandung route, one of the busiest logistics corridors in Indonesia [23]. This route includes toll roads with gradients of up to 6%, in line with the standards set by the Directorate General of Highways [24]. The trucks in this study use Pertamina's Bio Solar fuel for Euro-4 engines [1], 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.

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 [25], [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.

Data collection incorporates both primary and secondary sources. Primary data consist of measurements of vehicle dimensions and wheel diameter obtained using manual tools. These measurements were conducted on a 2021 Hino 5-axle truck, a model commonly used for heavy-duty transportation in Indonesia. Secondary data were collected alongside engine and vehicle speed data from the On-Board Diagnostics (OBD-II) system [27], [28]. These datasets include actual fuel consumption, vehicle speed, vehicle position, and gross vehicle weight. 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 [29] . 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], [27].

Using telematics data offers significant advantages because passive data collection methods provide high spatial and temporal resolution at a low cost [27]. 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], [28].

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 [30]. The telematics data for vehicle speed and engine speed are processed using regression analysis, and the results are evaluated using the coefficient of determination (R^2) to assess the strength of the relationship.

Following this, aerodynamic analysis is conducted using Computational Fluid Dynamics (CFD) in SolidWorks Flow Simulation [31], [32]. 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. Boundary 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 (FA) and the drag coefficient (C_d). 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 [33]–[35].

$$Cd = \frac{2\,FA}{\rho\,V^2\,AF} \quad (1)$$

where, Cd is the drag coefficient, FA is the aerodynamic drag force (N), ρ is the fluid density (kg/m^3), V is the relative velocity between the vehicle and air (m/s), and AF is the frontal area (m^2).

During the HDM-4 model calibration, fuel consumption is estimated by taking into account factors like vehicle weight, speed, and road gradient [26]. This process relies on several key equations: (1) Total Resistance to Motion (FTR), which is calculated using Eq. 2; (2) Tractive Power (PTR), defined in Eq. 3; (3) Total Engine Power (PTOT), outlined in Eq. 4; (4) Instantaneous Fuel Consumption (IFC), described in Eq. 5; and (5) Specific Fuel Consumption (FC), determined in Eq. 6.

$$FTR = FA + FG + FR + FCV \quad (2)$$

where, FTR is the total resistance force (N), FA is the aerodynamic drag force (N), FG is the gradient resistance force (N), FR is the rolling resistance force (N), and FCV is the curvature or cornering resistance force (N).

$$PTR = \frac{FTR \times V}{1000} \quad (3)$$

where, FTR is the total resistance force (N), and V is the vehicle speed (m/s).

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

where, PTOT is the total engine power (kW), PTR is the traction power (kW), EDT is the driving efficiency, and PENGACCS is the engine and accessory power (kW).

$$IFC = \max\ [ID\_FUEL, ZETA \times PTOT \times (1 + dFUEL)] \quad (5)$$

where, IFC is the instantaneous fuel consumption (ml/s), and dFUEL is the additional fuel consumption factor due to changes in vehicle speed.

$$FC = \frac{IFC}{V} \quad (6)$$

where, FC is the fuel consumption (ml/km), and IFC is the instantaneous fuel consumption (ml/s).

In simpler terms, engine calibration parameters are fine-tuned to match local driving conditions [26]. These parameters include: (1) Engine Speed (RPM), explained in Eq. 7; (2) Rolling Resistance Factor (Kcr2), illustrated in Eq. 8; and (3) Engine Power Factor (Kpea), detailed in Eq. 9.

$$RPM = RPM\_a0 + RPM\_a1 \text{ x } V + RPM\_a2 \text{ x } V^2 + RPM\_a3 \text{ x } V^3 \quad (7)$$

where, RPM_a0, RPM_a1, and RPM_a3 are engine speed model parameters.

$$CR2 = Kcr2 \times (CR\_CR2\_a0 + CR\_CR2\_a1 \times TD + CR\_CR2\_a2 \times RI) \quad (8)$$

where, Kcr2 is the rolling resistance factor, TD is the texture depth (mm), RI is the average road roughness value (m/km), and CR_CR2_a0 to CR_CR2_a2 are rolling resistance coefficients.

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

where, 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 [36]. 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.

3. Result and Discussion

3.1. Calibration of Engine Speed Model Parameters

The findings of this study reveal significant differences in engine RPM parameters when comparing the HDM-4 model, the study by Zaabar & Chatti model [14], and the actual observations collected. 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 suggests that while the technology used in this model is more advanced, it still does not perfectly match the operating conditions of trucks in Indonesia.

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 [37], [38]. 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 polynomial model captures the gradual increase in engine RPM as speed rises, reflecting a more realistic trend in fuel consumption compared to the HDM-4 and Zaabar & Chatti models.

These differences are clearly illustrated in Figure 4. The blue dots represent actual observations, showing a steady increase in engine RPM with speed. In contrast, the orange dots from the HDM-4 model overestimate RPM at lower speeds and underestimate it at higher speeds. Meanwhile, the green dots from the Zaabar & Chatti model show a sharp increase in RPM at higher speeds, deviating from real-world observations. The red dashed line, representing the third-degree polynomial model, aligns closely with the observed data, offering a more accurate depiction of modern engine performance. In conclusion, this study emphasizes the need to calibrate fuel consumption models to reflect current engine technology and local operating conditions. By doing so, we can achieve more accurate fuel consumption predictions and develop efficient, sustainable operational strategies for heavy-duty trucks in Indonesia.

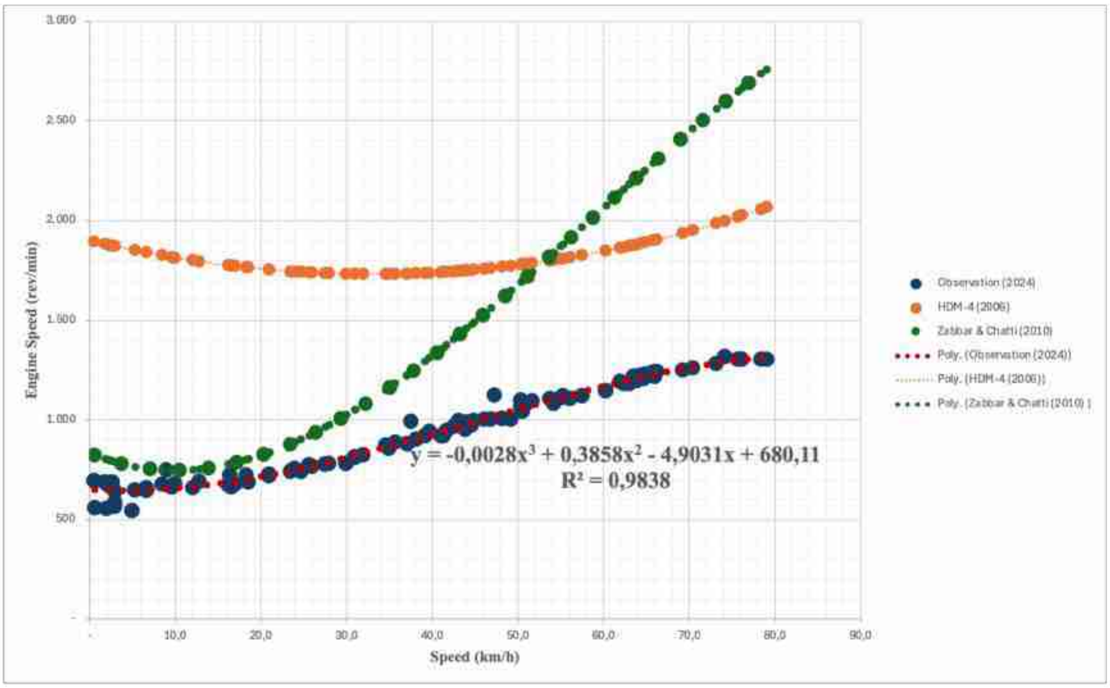

Figure 1. Calibration of Engine Speed Model Parameters

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 [39]. 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 [39]. The simulation also indicates a drag coefficient (Cd) of 1.0556, with a range between 1.0551 and 1.0558, and a frontal area (FA) of 8.2 m^2. 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 m^2 [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 [39].

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 like the drag coefficient and frontal area is essential for making accurate fuel consumption predictions. The aerodynamic simulation results are shown in Figure 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

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 (FA) to 8.2 m^2, along with adjustments to the engine rotation model. Finally, in Scenario 3, additional calibration factors, Kpea and Kcr2, are introduced through a trial-and-error process until the differences between predictions and actual data become statistically insignificant. 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.

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 [25], [40]. While calibrating these parameters in Scenario 2 enhances prediction accuracy, it does not fully resolve the discrepancies. However, the adjustments made in Scenario 3 reduce these differences significantly, as evidenced by the statistically insignificant result of p = 0.186 [25].

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], [41]. 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 [25].

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. In contrast, at higher speeds, the model underestimates fuel consumption. As a solution, the new parameters derived for Euro-4 engines capture the efficiency of modern engines, which deliver optimal power at lower RPMs. This leads to more accurate fuel consumption predictions. Secondly, the calibration of aerodynamic parameters found that the default drag coefficient (Cd) and frontal area (FA) values in HDM-4 do not align with real-world truck conditions. Consequently, the simulation results provide a better representation of the actual aerodynamic performance of modern trucks.

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. These findings highlight the importance of updating the HDM-4 model to reflect the realities of modern truck technology and local operating conditions. By providing more accurate parameters for Euro-4 engines and current aerodynamic profiles, this study helps planners and policymakers make better fuel consumption predictions. As a result, heavy-duty truck operations in Indonesia can become more efficient and sustainable. Looking ahead, future research should consider additional factors such as detailed road surface conditions, variations in shorter gradient lengths, ambient temperature, and driver behavior. Furthermore, ongoing calibration of the HDM-4 model at Level III will be necessary to keep up with the continuous advancements in truck design and performance.

5. Author's declaration

Authors' contributions and responsibilities

Write the contribution of each author here, or mark the following column.

- √ 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.

Availability of data and materials

- √ All data are available from the authors.

Competing interests

☑ The authors declare no competing interest.

Additional information

Write additional information related to this research, if any.

6. Acknowledgement

This research was funded by the Institute for Research and Community Service, International University of Logistics and Business. We also extend our gratitude to the students who assisted with field surveys. Appreciation is given to the trucking companies for providing access to telematics data and to the relevant institutions for supplying essential secondary data.

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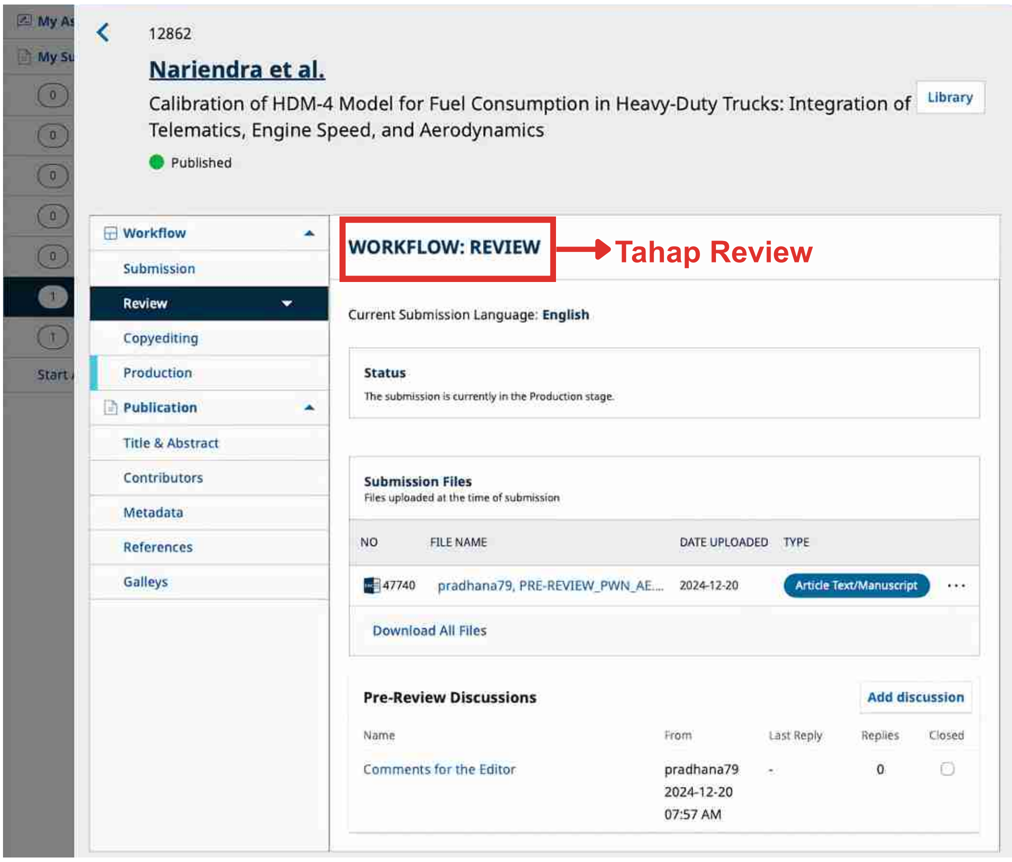
4. TAHAP REVIEW & REVISI

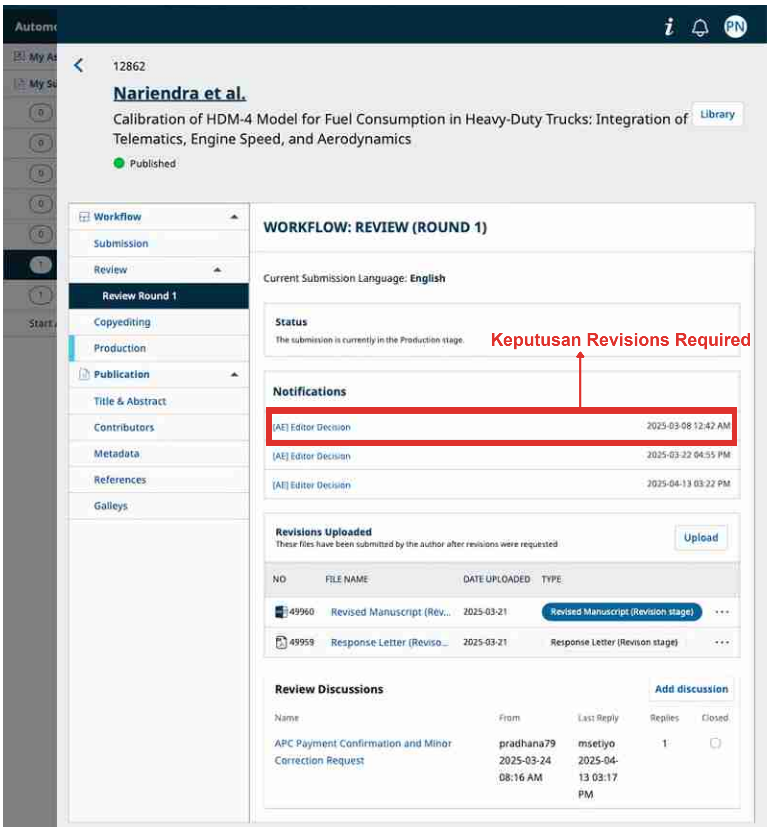
4.1. Tahap Review

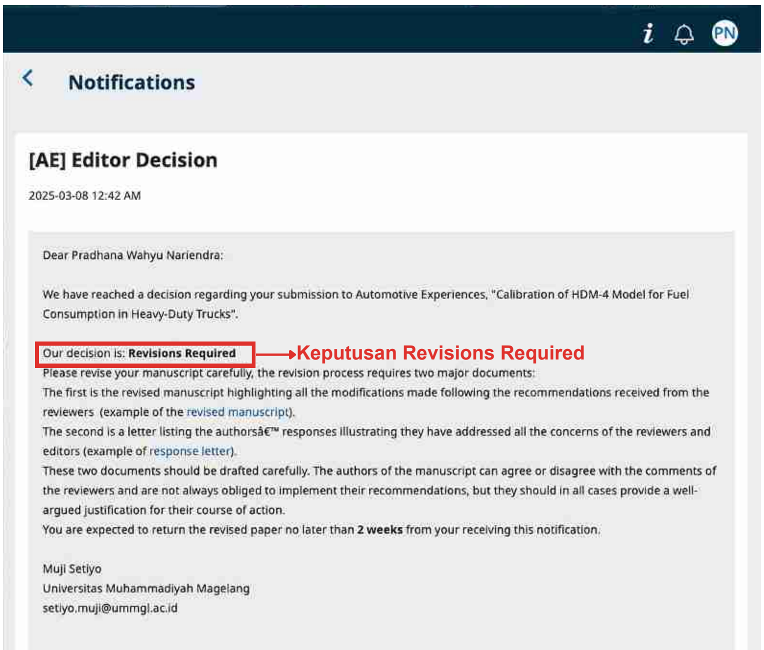
Setelah proses pengecekan awal, artikel masuk ke tahap Review dan Review Round 1. Tahap ini menunjukkan bahwa naskah tidak langsung diterima, tetapi melalui proses telaah ilmiah oleh editor dan reviewer.



4.2. Keputusan Editor: Revisions Required

Pada tanggal 8 Maret 2025, editor memberikan keputusan Revisions Required.





4.2. Komentar Reviewer

Masukan reviewer mencakup aspek metodologi, pengolahan data, validasi hasil, penggunaan parameter teknis kendaraan, penyajian tabel dan gambar, serta kejelasan argumentasi ilmiah.

Komentar Reviewer B

Reviewer B:

General remarks

The paper is consisely written in good English and follows a clear structure. Although not developing a novel method, the authors presents results that are important for the application of the HDM-4 model. Two major questions need to be addressed however:

1. When calibrating the fuel consumption model, it is not clear on what aggregate level this is done. Is it for whole trips or for shorter sections? Also, was the calibration done using the whole recorded dataset? At any rate it is essential that the training set and the test set be different for the predictive power to be validated.

2. Assuming the model is statistically validated, how does it perform on a different trip than the Tanjung Priokâ€"Bandung toll road? Fuel consumption is very sensitive to the values of the rolling resistance and engine efficiency Kcr2 and Kpea. Note that the problem of finding Kcr2 and Kpea is ill-conditioned if there is too little variation in input parameters like weight etc. If the driving conditions are similar for the calibration cases, it is easy to get a good fit between the model and the measurements. However, if later weight, speed and road grade differ considerably the predictive power of the model is lost unless physically accurate values of rolling resistance engine efficiency and air drag were found in the parameter calibration step.

In conclusion, it remains unclear what accuracy the presented values of Kpea and KCr2 can be expected to have. The comments above need to be addressed in a revised version of the manuscript.

Detailed comments

p 1, l 9: Please check this figure. Most current sources state around 26 g/km, but local/national addition of renewable fuel affects the value.

p 3, l 14-23: Please check these lines for possible condensation of repeated content.

p 4, l 13: Can we be certain that this vehicle specimen is representative of the whole fleet? Earlier studies have found considerable differences between different vehicle, mainly regarding rolling resistance (Noreland, 2024).

p 4, l 13: Does the truck really have 5 axles? It seems rather to be a 2 axle truck with a 3 axle semi-trailer.

p 4, l 15-17: Was any calibration routine carried out for the CAN-bus signals used? It is known that fuel flow can have an error of several percent, see e.g. Wang (2017). Also, the weight information from the CAN-bus is notoriously unreliable in many vehicles.

p 5, l 10: How accurate is SolidWorks Flow Simulation for simulating the presumably turbulent flow around a truck? This is a demanding task, normally warranting the use of dedicated CFD packages (including turbulence mocels) and supercomputers.

p 5, l 14: Please check for consistency in the use of subscripts throughout the paper. Although I understand the wish to stick to the naming convention from the HDM-4 model, I find it somewhat difficult to read Eq. (1).

p 7, sec 3.1: Is it possible that modern automatic gear shifting strategies in combination with local conditions are responsible for the large differences between different publications? When coasting or driving downhill not too steep slopes, automatic gearboxes of heavy trucks routinely put in the neutral gear. This allows the engine to idle, which saves fuel as a consequence of lowering the engine speed compared to if the vehicle were to coast in gear.

p 8, l 11: Do the curves present average RPM:s for different speeds? If so, how is this average calculated? Depending on momentary power demand and the gearbox, the engine speed can vary considerably (by a factor of 2) for a given vehicle speed.

p 10, l 12: As noted on p. 9, a heavily turbulent wake is developed behind the container but this is not obvious from Figure 2. Please comment.

p 10, l 21: What is the statistical significance of the results obtained from this procedure?

p 13: l 25: This reference seems to be unavailable from the presented URL.

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Recommendation: Resubmit for Review

4.2. Komentar Reviewer (Lanjutan)

Komentar Reviewer C

Reviewer C:

Relevance: why the authors do this research and what is its importance and application.

The paper is about the calibration of one existing model to estimate fuel consumption by heavy trucks. This topic is relevant at this time due the model used (HDM-4) is from some years ago and it is not for a particular region. In the other hand, the actual migration to another source of energy to trucks as gas, electricity and hydrogen.

The results can be applied to improve trucks operations, to value projects on highways, and to know the real vehicle operation costs due the fuel is 30 â€" 35% of this total value.

Novelty: paper gives new ideas, derivations, applications that have been not studied before or little- or not in depth-studied.

Not really. The research compares real data with model data and proposes to change some parameters or coefficients in the model HDM-4

Literature review: identify research gaps with the most recent primary references (last 10 years).

Not. The literature review explores some previous researches done some year ago and in another places.

Methods: appropriateness of methods, the accuracy of assumptions and/or estimates used, description of equipment and limitations, experimental steps, etc.

The method used is appropriate to the research.

The authors have to explain why did not use the method to calibrate the model HDM-4 that this model has in its manuals, specifically in the volume 5 â€œA guide to calibration and adaptationâ€.

The method to obtain the real-world data is not clear, and how these data are studied, cleaned and other revision made is not in the paper.

Results and discussion: quality of results, depth, and logic of discussion.

Please review page 7 (lines 12 to 14) and include an explanation for this.

Figure 4 (page 8, line 11) does not exist in the paper. Review and make corrections.

How was done the aerodynamic simulation? What method was used and why not another?

The results are interesting but their presentation is confused. The reviewer suggests include tables with values from the original model and those obtaining in the research.

The authors have to show the model obtained in a proper way showing the variables to be used in the future (equation in page 8 line 6 is not clear).

At the end of the research what are the models suggested including all variables, parameters, coefficients and others.

The authors have to give what are (and values) low, medium and high speeds.

Conclusion: Insight conveyed and recommendations that might be used by others for future work.

Conclusions have to be expanded. And include the mayor results obtained in the research.

English (or Bahasa Indonesia): used effectively to communicate the ideas and easy to understand with least or no grammatical errors or typos.

Good

Recommendation: Resubmit for Review

4.2. Komentar Reviewer (Lanjutan)

Calibration of HDM-4 Model for Fuel Consumption in Heavy-Duty Trucks: Integration of Telematics, Engine Speed, and 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 susta[...]ability [1], [2]. A global analysis shows that a 1 liter/100 km increase in fuel consumption adds 24.17 g/km of CO [...] In Indonesia, fuel consumption accounts for up to 49.3% of Vehicle Operationa [...] in South Sumatra and 32% in Jakarta and West Java [4], [5]. As the freight secto [...] relies on road transport, improving fuel efficiency is both an environmental [...] necessity.

DANO 29 Dec

Please check this figure. Most current sources state around 26 g/km, but local/national addition of renewable fuel affects the value.

Add a reply

Various methods have been developed to improve fuel efficiency, and o [...] notable is the Highway Development and Management (HDM-4) model. C [...] World Bank, this model helps predict fuel consumption and assess how road [...] 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]–[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

4.2. Komentar Reviewer (Lanjutan)

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]–[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, aero resistance, calibration factors, and real-world operational conditions, such as spe weight, and road gradient. Specifically, we aim to develop a model that reflects the faced by 5-axle Euro-4 semi-trailer trucks operating in Indonesia, ensuring the re relevant and applicable to local conditions.

This study aims to develop an HDM-4 Level II fuel consumption model tailo axle trucks in Indonesia. The calibration process focuses on factors such as engine aerodynamic drag, frontal area, engine power efficiency, and operational conditions like average speed, load weight, and road gradient to better capture the realities of daily truck operations. The research is centered on the Tanjung Priok Port–Bandung route, one of the busiest logistics corridors in Indonesia [23]. This route includes toll roads with gradients of up to 6%, in line with the standards set by the Directorate General of Highways [24]. The trucks in this study use Pertamina's Bio Solar fuel for Euro-4 engines [1], 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.

DANO 29 Dec

Please check these lines for possible condensation of repeated content.

Add a reply

4.2. Komentar Reviewer (Lanjutan)

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 [25], [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.

Data collection incorporates both primary and secondary sources. Primary data consist of measurements of vehicle dimensions and wheel diameter obtained using manual tools. These measurements were conducted on a 2021 Hino 5-a ... nly used for heavy-duty transportation in Indonesia. Secondary da ... engine and vehicle speed data from the On-Board Diagnostics (OBD-II) system [27], [2 ... datasets include actual fuel consumption, vehicle speed, vehicle position, and gros ... weight. The data were gathered over a one-month period along the Tanjung Priok to ... route, a critical corridor for container semi-trailer truck operations in Indones ... geometry and gradient data from Google Earth remote sensing provided sufficient ... for transportation analysis, with an MAE of 1.32 meters and an RMSE of 2.27 met ... Other secondary data were sourced from government agencies such as the Ministry ... Works and Housing and the Central Statistics Agency. These datasets provide inforn ... International Roughness Index (IRI), and road surface texture depth [26], [27].

Using telematics data offers significant advantages because passive data ... methods provide high spatial and temporal resolution at a low cost [27]. Device ... Photochemical Assessment Monitoring Stations (PAMS), Global Positioning Systen ... and cellular networks facilitate real-time vehicle activity monitoring. Modern trucks ... with sensors record operational parameters like fuel consumption, vehicle speed, an ... position, which are then transmitted via the Electronic Control Unit (ECU) for ... Although manufacturer-provided telematics systems are not explicitly designed fo ...

DANO 3 Jan

Was any calibration routine carried out for the signals at hand? It is known that fuel flow can have an error of several percent, see e.g.

Wang, L., Gonder, J.D., Wood, E.W. and Ragatz, A.C., 2017. The accuracy and correction of fuel consumption from controller area network broadcast.

Also, the weight information from the CAN-bus is notoriously unreliable in many vehicles.

Add a reply

4.2. Komentar Reviewer (Lanjutan)

calibration, the data they generate are reliable and reflect real-world driving conditions [17], [28].

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 [30]. The telematics data for vehicle speed and engine speed are processed using regression analysis, and the results are evaluated using the coefficient of determination (R^2) to assess the strength of the relationship.

Following [illegible]is, aerod[illegible]ducted using Computational Fluid Dynamics (CFD) in SolidWorks Flow Simulation [31], [32]. The process includes th[illegible] stages: pre-processing, processing, and post-processing. During pre-processing, [illegible] model based on actual dimensions is created, validated, and meshed. Boundary c[illegible] such as flow type, gravity, fluid type, and test speed are defined. In the processi[illegible] numerical simulations are run to calculate frontal area (FA) and the drag coefficient [illegible] calculation follows Eq.1. In the post-processing stage, simulation results are inter[illegible] evaluate the vehicle's aerodynamic efficiency, where a lower drag coefficient indicat[illegible] streamlined and fuel-efficient design [33]–[35].

$$Cd = \frac{2\,FA}{\rho\,V^2\,AF} \quad (1)$$

where, Cd is the drag coefficient, FA is the aerodynamic drag force (N), ρ is the flui[illegible] (kg/m^3), V is the relative velocity between the vehicle and air (m/s), and AF is the fro[illegible] (m^2).

DANO 29 Dec

How accurate is SolidWorks Flow Simulation for simulating the presumably turbulent flow around a truck? This is a demanding task, normally warranting the use of dedicated CFD packages (including turbulence mocels) and supercomputers.

Add a reply

During the HDM-4 model calibration, fuel consumption is estimated by taking into account factors like vehicle weight, speed, and road gradient [26]. This process relies on several key equations: (1) Total Resistance to Motion (FTR), which is calculated using Eq. 2; (2) Tractive Power (PTR), defined in Eq. 3; (3) Total Engine Power (PTOT), outlined in Eq. 4; (4) Instantaneous Fuel Consumption (IFC), described in Eq. 5; and (5) Specific Fuel Consumption (FC), determined in Eq. 6.

$$FTR = FA + FG + FR + FCV \quad (2)$$

4.2. Komentar Reviewer (Lanjutan)

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 [36]. 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.

3. Result and Discussion

3.1. Calibration of Engine Speed Model Parameters

The findings of this study reveal significant differences in engine RPM parameters when comparing the HDM-4 model, the study by Zaabar & Chatti model [14], and the actual observations collected. 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 fully account for the increased aerodynamic resistance and higher power dem comparison, the study by Zaabar & Chatti model presents more modern engi parameters with values of RPM_a0 = 833.7, RPM_a1 = -17.717, RPM_a2 = 0.9671, and = -0.0055. These parameters reflect improvements in combustion efficiency, fuel precision, and emission control. Although this model offers a more accurate predic HDM-4, it still falls short, especially at high speeds where the predicted engine RPM more sharply than obser ns. This suggests that while the te used in this model is mo ot perfectly match the operating c of trucks in Indonesia.

The current study provides parameters that are more tailored to the re conditions of Indonesian trucks. The parameters derived are RPM_a0 = 680.11, RP 4.9031, RPM_a2 = 0.3858, and RPM_a3 = -0.0028. These values align with Euro-

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Is it possible that modern automatic gear shifting strategies in combination with local conditions are responsible for the large differences between different publications? When coasting or driving downhill not too steep slopes, automatic gearboxes of heavy trucks routinely put in the neutral gear. This allows the engine to idle, which saves fuel as a consequence of lowering the engine speed compared to if the vehicle were to coast in gear.

Add a reply

4.2. Komentar Reviewer (Lanjutan)

technology, which incorporates common-rail injection systems and modern emission controls [37], [38]. 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 polynomial model captures the gradual increase in engine RPM as speed rises, reflecting a more realistic trend in fuel consumption compared to the HDM-4 and Zaabar & Chatti models.

These differences are clearly illustrated in Figure 4. The blue dots represe
observations, showing a steady increase in engine RPM with speed. In contrast, th
dots from the HDM-4 model overestimate RPM at lower speeds and underestimate it
speeds. Meanwhile, the green dots from the Zaabar & Chatti model show a sharp in
RPM at higher speeds, deviating from real-world observations. The red dasl
representing the third-degree polynomial model, aligns closely with the observ
offering a more accurate depiction of modern engine performance. In conclusion, t
emphasizes the need to calibrate fuel consumption models to reflect current engine te
and local operating conditions. By doing so, we can achieve more accurate fuel cons
predictions and develop efficient, sustainable operational strategies for heavy-duty
Indonesia.

DANO 29 Dec

Do the curves present average RPM:s for different speeds? If so, how is this average calculated? Depending on momentary power demand and the gearbox, the engine speed can vary considerably (by a factor of 2) for a given vehicle speed.

Add a reply

4.2. Komentar Reviewer (Lanjutan)

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 [39].

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 like the drag coefficient and frontal area is essential for making accurate fuel consumption predictions. The aerodynamic simulation results are shown in Figure 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

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 aero calibration by setting the drag coefficient (Cd) to 1.05 and t with adjustments to the engine rotation model. Finally, ir factors, Kpea and Kcr2 are introduced through a trial-and-error process until the di

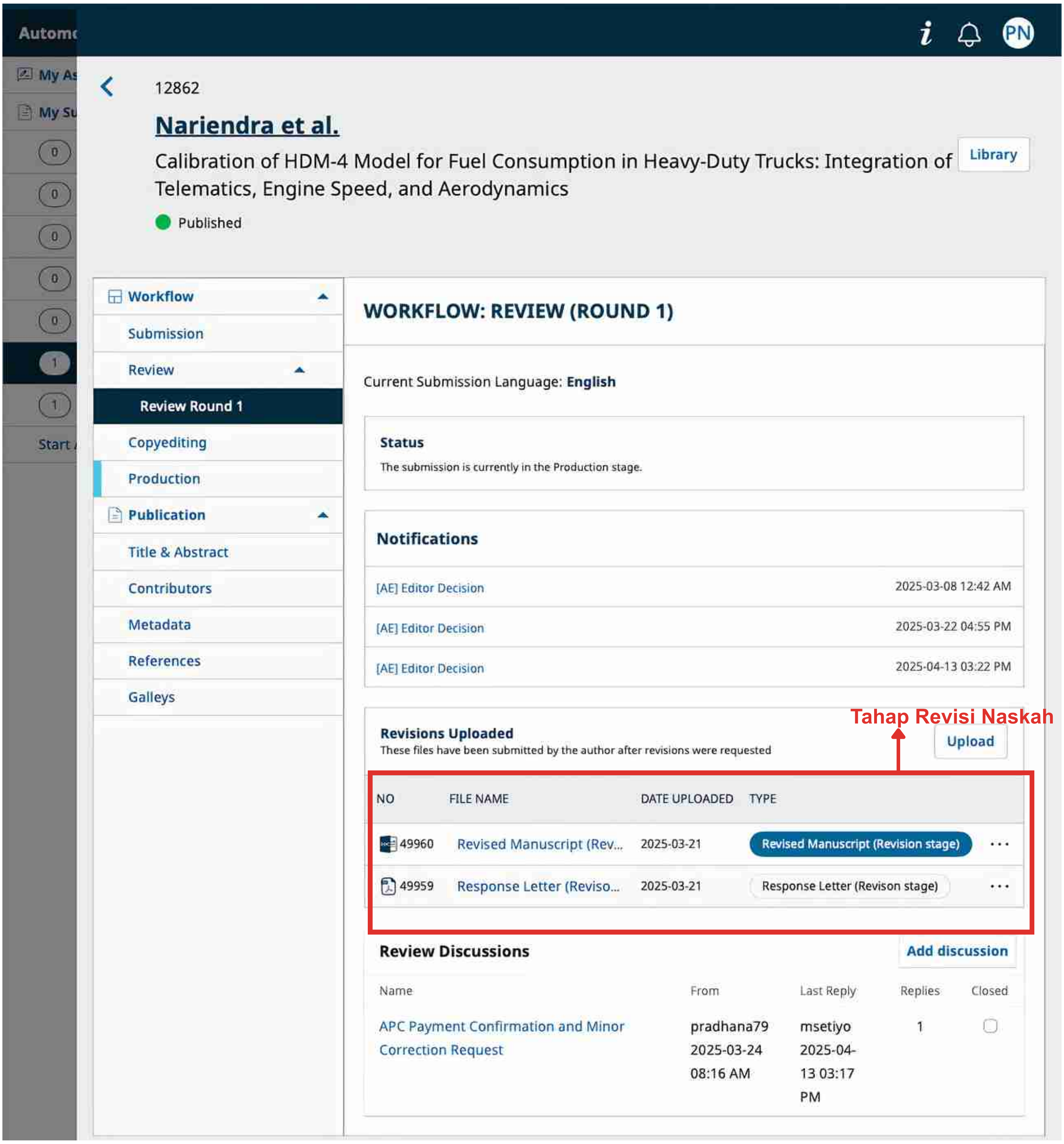
DANO 3 Jan

What is the statistical significance of the results obtained from this procedure?

Add a reply

4.3. Response to Reviewer

Penulis menindaklanjuti komentar reviewer dengan mengunggah Revised Manuscript dan Response Letter pada tanggal 21 Maret 2025. Revised Manuscript menjadi bukti bahwa naskah telah diperbaiki sesuai masukan reviewer dan editor, sedangkan Response Letter menjadi bukti bahwa penulis memberikan respons formal, sistematis, dan terdokumentasi terhadap setiap komentar reviewer. Dengan demikian, kedua dokumen tersebut menunjukkan bahwa artikel telah melalui tahapan revisi akademik sebelum diproses lebih lanjut menuju keputusan editorial.



4.3. Response to Reviewer (Lanjutan)

Dear Editors and Reviewers,

We truly appreciate your thoughtful and constructive feedback on our manuscript. Your insights have been invaluable in helping us refine and improve our work. We have carefully addressed all the comments and incorporated the necessary revisions. The updated manuscript has been uploaded through the journal's submission system, with changes highlighted in yellow for Reviewer #B and blue for Reviewer #C to make it easier to review.

If there are any additional clarifications needed, please don't hesitate to let us know. Thank you once again for your time and effort in reviewing our manuscript. We greatly appreciate your support and guidance throughout this process.

Best regards,

Author

Reviewer #B:

The paper is consisely written in good English and follows a clear structure. Although not developing a novel method, the authors presents results that are important for the application of the HDM-4 model. **Two major questions need to be addressed however:**

1. When calibrating the fuel consumption model, it is not clear on what aggregate level this is done. Is it for whole trips or for shorter sections? Also, was the calibration done using the whole recorded dataset? At any rate it is essential that the training set and the test set be different for the predictive power to be validated.
2. Assuming the model is statistically validated, how does it perform on a different trip than the Tanjung Priok–Bandung toll road? Fuel consumption is very sensitive to the values of the rolling resistance and engine efficiency Kcr2 and Kpea. Note that the problem of finding Kcr2 and Kpea is ill-conditioned if there is too little variation in input parameters like weight etc. If the driving conditions are similar for the calibration cases, it is easy to get a good fit between the model and the measurements. However, if later weight, speed and road grade differ considerably the predictive power of the model is lost unless physically accurate values of rolling resistance engine efficiency and air drag were found in the parameter calibration step.

Detailed comments:

4.3. Response to Reviewer (Lanjutan)

3. p 1, l 9: Please check this figure. Most current sources state around 26 g/km, but local/national addition of renewable fuel affects the value.
4. p 3, l 14-23: Please check these lines for possible condensation of repeated content.
5. p 4, l 13: Can we be certain that this vehicle specimen is representative of the whole fleet? Earlier studies have found considerable differences between different vehicle, mainly regarding rolling resistance (Noreland, 2024).
6. p 4, l 13: Does the truck really have 5 axles? It seems rather to be a 2 axle truck with a 3 axle semi-trailer.
7. p 4, l 15-17: Was any calibration routine carried out for the CAN-bus signals used? It is known that fuel flow can have an error of several percent, see e.g. Wang (2017). Also, the weight information from the CAN-bus is notoriously unreliable in many vehicles.
8. p 5, l 10: How accurate is SolidWorks Flow Simulation for simulating the presumably turbulent flow around a truck? This is a demanding task, normally warranting the use of dedicated CFD packages (including turbulence mocels) and supercomputers.
9. p 5, l 14: Please check for consistency in the use of subscripts throughout the paper. Although I understand the wish to stick to the naming convention from the HDM-4 model, I find it somewhat difficult to read Eq. (1).
10. p 7, sec 3.1: Is it possible that modern automatic gear shifting strategies in combination with local conditions are responsible for the large differences between different publications? When coasting or driving downhill not too steep slopes, automatic gearboxes of heavy trucks routinely put in the neutral gear. This allows the engine to idle, which saves fuel as a consequence of lowering the engine speed compared to if the vehicle were to coast in gear.
11. p 8, l 11: Do the curves present average RPM:s for different speeds? If so, how is this average calculated? Depending on momentary power demand and the gearbox, the engine speed can vary considerably (by a factor of 2) for a given vehicle speed.
12. p 10, l 12: As noted on p. 9, a heavily turbulent wake is developed behind the container but this is not obvious from Figure 2. Please comment.
13. p 10, l 21: What is the statistical significance of the results obtained from this procedure?
14. p 13: l 25: This reference seems to be unavailable from the presented URL.

4.3. Response to Reviewer (Lanjutan)

Our response:

Thank you for your feedback. While this study does not introduce a new method, it makes a significant contribution to improving the application of the HDM-4 model in Indonesia. One of the key contributions is the empirical calibration of Kcr2 and Kpea parameters using real toll road data, something that had not been done before. Additionally, the study identifies a clear relationship between engine speed (RPM) and fuel consumption, providing valuable insights for refining operational parameters in HDM-4. The research also updates aerodynamic parameters (Cd and AF) to better reflect the actual conditions of heavy-duty trucks in Indonesia. With these improvements, HDM-4 can now offer more accurate fuel consumption analysis, particularly by incorporating the effects of aerodynamic resistance at high speeds. These enhancements make the model more practical and relevant for real-world transportation planning and operations in Indonesia. **Below are our responses to the two key questions raised:**

1. **First**, the model calibration was conducted at the whole-trip level, rather than on shorter road segments. This approach was chosen because each data entry represents a complete trip, including key operational parameters such as travel distance, average operating speed, gross vehicle weight, and road gradient, with a total of 94 trips. In this study, travel distances ranged from 3.30 km to 199.44 km, operating speeds varied between 5.1 km/h and 52.3 km/h, and gross vehicle weight ranged from 15.27 tons to 38.16 tons, with road gradients between +4.9% and -6.7%. We opted for this whole-trip-based approach because it aligns with the HDM-4 framework, which is specifically designed for macro-scale fuel consumption analysis. This method also allows the model to capture real-world operational variations, especially since the dataset includes extreme conditions such as steep gradients and fluctuating vehicle loads. By incorporating these variations, the model becomes not only more accurate in representing fuel consumption, but also more practical for logistics transportation planning. **Second**, to prevent overfitting and ensure the model's predictive reliability, we did not use the entire dataset for calibration. Instead, we systematically split the data into 70% (66 trips) for calibration (training set) and 30% (28 trips) for independent validation (test set). This division was done using stratified random sampling (seed = 42) to maintain a balanced distribution of key variables like gross vehicle weight and road gradient across both sets. The validation results demonstrate that the model has strong predictive capability, with R^2 values of 0.83 for the training set and 0.79

4.3. Response to Reviewer (Lanjutan)

for the test set. Additionally, the RMSE values of 0.39 km/l (training set) and 0.43 km/l (test set) indicate that the predicted and actual fuel consumption values remain within an acceptable range. The Mean Absolute Percentage Error (MAPE) of 9.5% further confirms that the model remains stable, even when tested with new, unseen data. For example, in Trip 3 of the test set, the model predicted fuel consumption of 1.42 km/l, which closely matched the actual value of 1.36 km/l, resulting in an error of just 4.4%. Similarly, for Trip 43, the model predicted 5.51 km/l, which was only 8.0% off from the actual 5.99 km/l. **Third**, we conducted an outlier analysis to ensure that extreme values did not distort the model's accuracy. Using the Interquartile Range (IQR) method), we identified outliers with a lower bound of 0.67 km/l and an upper bound of 7.36 km/l. Some notable outliers included Trip 3 (1.36 km/l), which resulted from a combination of steep gradients (+4.9%/-6.7%) and low speeds (<15 km/h), and Trip 43 (5.99 km/l), which was caused by high speeds (>40 km/h) and a steep negative gradient (-4.0%). Although these trips were classified as outliers, we chose to retain them in the dataset since they represent real-world operational scenarios, ensuring the model remains applicable to actual trucking conditions.

2. We appreciate the question and fully understand that validating the model beyond the Tanjung Priok–Bandung route is crucial to ensuring reliable fuel consumption predictions. Our model was developed using toll road data, where the International Roughness Index (IRI) is around 4, the road gradient is moderate (0% to ±6%), and the vehicles analyzed range from 15 to 38 tons. Given these characteristics, the model can be applied to other toll roads with similar conditions, such as the Trans-Java and Cipali Toll Roads, since both have relatively smooth and consistent pavement surfaces, aligning well with the calibrated parameters in this study. However, because our research specifically focuses on toll roads, the model does not account for non-toll roads, which typically have rougher pavement surfaces (higher IRI values) and steeper gradients. If this model were to be applied to toll roads with significantly different conditions, additional calibration would be necessary to ensure accurate fuel consumption predictions. To prevent ill-conditioning issues, we ensured that our dataset included a wide range of operational conditions, covering 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. 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). The HDM-4 model provides Kcr2 as the rolling resistance factor and Kpea as the calibration factor, which can be adjusted according to local conditions (default value = 1) in addition to other parameters such as aerodynamics and engine speed. This ensured that the calibrated parameters were not just statistically optimized but also physically representative of actual vehicle conditions. The final calibration values of Kcr2 = 0.6 and Kpea = 0.6 were validated using independent test data, achieving strong predictive accuracy ($R^2 = 0.79$, RMSE = 0.43 km/l, and $p = 0.186$). This confirms that the calibrated parameters generalize well beyond the original dataset. To assess its reliability, the model was tested under three different calibration scenarios. In Scenario 1, we used default HDM-4 values, which ignored key operational factors like aerodynamics and local driving conditions. As a result, the model underestimated fuel consumption, with negative ranks ($Z = -8.035$, $p < 0.001$). Moving to Scenario 2, we introduced aerodynamic calibration (Cd = 1.05, AF = 8.2 m^2) and refined the engine speed model, which improved prediction accuracy, though negative ranks persisted, and the Wilcoxon test still indicated significant differences ($Z = -7.514$, $p < 0.001$) between predicted and actual values. In Scenario 3, incorporating full calibration (Kcr2 and Kpea = 0.6) resulted in a closer alignment between predictions and actual fuel consumption. The Wilcoxon test produced $Z = -1.324$ and $p = 0.186$, confirming that the differences were no longer statistically significant, indicating that the model had reached a reliable level of accuracy. These findings highlight that default HDM-4 values alone are insufficient for accurately predicting fuel consumption in heavy-duty trucks, as they do not account for aerodynamics or real-world operating conditions. While aerodynamic calibration in Scenario 2 improved accuracy, it still left noticeable discrepancies. Only Scenario 3, which included full calibration (Kcr2 and Kpea), successfully eliminated these differences, making it the most reliable approach for real-world logistics and transportation planning. Looking ahead, we recognize that changing vehicle technologies and evolving road conditions may impact fuel consumption patterns. To ensure long-term adaptability, future improvements should explore real-time telematics-based dynamic calibration, allowing the model to continuously adjust to new operational conditions as heavy-duty truck technologies advance.

Response to Detailed Comments:

4.3. Response to Reviewer (Lanjutan)

3. We would like to correct the statement that an increase in fuel consumption by 1 liter per 100 km results in only 24.17 g/km CO_2, as this figure does not align with global standards. According to credible sources, the combustion of 1 liter of diesel produces 2.64 kg of CO_2, meaning that an increase of 1 L/100 km should raise emissions by 26.4 g/km, not 24.17 g/km (Department for Energy Security & Net Zero, 2023; European Environment Agency, 2019).
4. **Revised version:** 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, specifically a 2-axle head truck paired with a 3-axle semi-trailer. 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.
5. We fully acknowledge that rolling resistance can vary significantly between vehicles, as noted in previous studies (Noreland, 2024). The vehicle selected in this study was based on data from the Indonesian Trucking Association (APTRINDO) and represents the most common 5-axle semi-trailer configuration in Indonesia. However, we recognize that variations in rolling resistance may still occur, influenced by factors such as tire specifications, axle alignment, and braking conditions.To address these differences, we incorporated empirical calibration factors into the model, including tire specifications, load distribution, and road conditions, in order to improve its accuracy. Importantly, this study utilized a dataset with a wide range of vehicle speeds (from 5.1 to 52.3 km/h) and gross vehicle weights (from 15.27 to 38.16 tons), ensuring that the model captures diverse real-world operating conditions and avoids calibration bias due to limited variability. While variations between vehicles are inevitable, we believe that the methodology employed combined with the inclusion of varied speed and load conditions ensures that the model accurately reflects the real-world operational characteristics of trucks in Indonesia. Furthermore, we acknowledge that expanding the range of vehicle samples in future studies will enhance the model's adaptability and generalizability across different configurations and operating environments.
6. The truck in this study consists of a 2-axle tractor paired with a 3-axle semi-trailer, commonly classified as a 5-axle articulated truck in both HDM-4 modeling and Indonesian regulations. According to APTRINDO and the Directorate General of Land Transportation (2008), this 1.2-

222 axle configuration determines road class suitability, maximum axle load, and allowable gross weight. To ensure clarity, we will specify this classification in the manuscript while keeping it aligned with both industry standards and regulatory frameworks.

7. According to Wang (2017), vehicle weight data from the CAN-bus is often unreliable in many vehicles. However, in this study, we took specific steps to ensure data accuracy. Our dataset includes actual fuel consumption, vehicle speed, position, and gross vehicle weight (GVW), with calibration and validation procedures applied to enhance reliability. To address potential inaccuracies in CAN-bus data, we validated GVW readings against weighbridge records at the port and made necessary adjustments to minimize measurement errors. Additionally, in 2022, Hino Motors re-certified their CAN-bus system, eliminating calibration modifications and improving measurement reliability. Since the tested vehicles in this study are 2022 Hino models, the collected data benefits from the latest, more accurate monitoring system. With these measures in place, the CAN-bus data used in this study is reliable and accurately represents real-world vehicle operations (Hino Motors, 2022).
8. In this study, SolidWorks Flow Simulation was primarily used for a preliminary aerodynamic assessment, focusing on general airflow patterns rather than detailed turbulence analysis. The software utilizes the k-ε turbulence model, which provides steady-state flow estimates but has limitations in capturing wake dynamics, vortex shedding, and transient turbulent structures, all of which are critical in truck aerodynamics (Ramlan & Darlis, 2020). Since our main objective was to evaluate overall aerodynamic behavior, this study did not generate turbulence-related outputs. As noted in previous research, SolidWorks Flow Simulation has limitations in handling complex turbulence parameters compared to ANSYS CFX, which offers more advanced turbulence modeling options (Ramlan & Darlis, 2020). We recognize that more specialized CFD software, such as ANSYS Fluent or OpenFOAM, which support LES (Large Eddy Simulation) and DES (Detached Eddy Simulation) models, would be better suited for high-precision turbulence analysis. Future studies could explore these tools to improve accuracy and gain deeper insights into truck aerodynamics.
9. We have carefully reviewed and ensured consistency in the use of subscripts throughout the manuscript. While we aimed to maintain alignment with the HDM-4 model's naming conventions, we acknowledge that readability is crucial. To address this, we have revised Equation (1) and all other equations in the manuscript to ensure clear and uniform notation.

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We have also standardized the formatting of subscripts across the text, figures, and tables to enhance clarity and coherence. We appreciate your suggestion and believe that these adjustments make the equations more accessible and easier to interpret, without compromising accuracy or adherence to the HDM-4 framework.

10. In this study, we used 2022 Hino trucks with manual transmissions, so automatic gear-shifting strategies like freewheeling mode or idle coasting weren't applicable. The drivers had full control over gear selection, meaning that fuel consumption was more influenced by driving patterns, vehicle load, and road conditions than by any automated gear-shifting algorithms. Additionally, on moderate downhill slopes, manual transmission drivers typically use engine braking by staying in a lower gear to maintain control and reduce the use of brakes. This differs from automatic transmission vehicles, which often switch to neutral coasting a strategy that can boost fuel efficiency but may reduce vehicle control. Therefore, any differences in the results of this study compared to others are more likely due to road topography, vehicle load, and driving behavior, rather than the absence of automatic gear-shifting strategies, which were not part of this research.
11. The curve shown in the graph represents the average engine speed (RPM) in relation to vehicle speed, based on telematics data collected during the trip. The average RPM and speed were calculated from the telematics data recorded during vehicle operation, so the results reflect the general trend of the relationship between vehicle speed and engine RPM. We recognize that RPM can vary significantly at the same speed due to factors like gear selection, vehicle load, and road conditions. However, since the vehicles used in this study are equipped with manual transmissions, RPM fluctuations are more controlled compared to those with automatic transmissions, which have dynamic shifting strategies. Even with these variations, the average values still provide a good representation of the relationship between vehicle speed and engine RPM. To ensure accuracy, the average RPM values were validated by comparing them against HDM-4 model estimates and previous studies. The polynomial regression results show that the relationship between speed and RPM has an R^2 of 0.9838, indicating that the model accounts for almost all of the data variability. So, despite some variations in RPM at specific speeds, the average approach remains a reliable way to represent the vehicle's operational pattern and can serve as a solid reference for further analysis.

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12. Based on the simulation results on page 9, significant wake turbulence forms behind the container, supported by the Global Min-Max-Table, with flow velocities ranging from 0 to 31.324 m/s and a minimum pressure of 67,568.17 Pa. This behavior aligns with flow separation and turbulence behind a bluff body. The wake turbulence behind the vehicle is primarily driven by longitudinal vortices due to the side flow from the test model. The pressure drop behind the vehicle creates a negative pressure zone, which increases aerodynamic drag, reduces efficiency, and raises fuel consumption. Rajamani (2012) points out that a larger wake results in higher drag forces, which negatively impact vehicle efficiency. Additionally, the study shows that the wake region leads to a significant pressure difference between the front and rear of the vehicle, further increasing the drag force. Other research also notes that flow separation at the rear of the vehicle is closely related to the formation of vortex structures and recirculation zones, which further support the existence of wake turbulence in these conditions (Tarakka, 2012). However, as you noted, this phenomenon isn't clearly visible in Figure 2. After reviewing the document, we'd like to clarify that turbulence analysis isn't deeply explored in this report. The report primarily focuses on analyzing the drag coefficient (Cd) and frontal area (AF), which are essential in assessing vehicle aerodynamic efficiency. While wake turbulence is indeed an important factor, the main focus here is on how Cd and AF influence the aerodynamic performance of the vehicle. As a result, turbulence and wake visualization aren't covered in detail. For future studies, we suggest incorporating visual analysis and model refinement to validate the numerical findings and gain a more thorough understanding of the effects of drag and overall vehicle aerodynamics.
13. The statistical significance of the results was analyzed using the Wilcoxon signed-rank test, which helps determine if there's a meaningful difference between the predicted fuel consumption and the observed data. In Scenario 1, which used the default HDM-4 values without calibration, the results of the Wilcoxon test showed $Z = -8.035$ with $p < 0.001$, indicating a highly significant difference between the predicted values and actual fuel consumption. This suggests that the default HDM-4 values tend to underestimate fuel consumption, likely because they don't account for the vehicle's aerodynamic effects and real-world operational conditions. In Scenario 2, where we applied aerodynamic calibration and engine adjustments, the prediction accuracy improved, but the Wilcoxon test still showed $Z = -7.514$ with $p < 0.001$, meaning the difference between the predictions and the observed data

remained statistically significant. In Scenario 3, after adding the correction factors Kpea and Kcr2 set to 0.6, the prediction accuracy improved significantly. The Wilcoxon test results showed $Z = -1.324$ with $p = 0.186$, indicating that the difference between the predictions and the observed data was no longer statistically significant. This means that the adjustments with the correction factors reduced prediction errors, making the calibrated HDM-4 model much more in line with the actual fuel consumption measured in the field. Overall, these results confirm that the default HDM-4 values significantly underestimate fuel consumption, as shown by $p < 0.001$ in Scenarios 1 and 2. However, after further calibration in Scenario 3, the p value increased to 0.186, meaning the corrected model now provides predictions that are statistically consistent with the actual data. Therefore, calibrating aerodynamic parameters, engine characteristics, and correction factors like Kpea and Kcr2 is crucial for improving the accuracy of fuel consumption predictions in the HDM-4 model for heavy-duty trucks.

14. The reference in question is correctly cited and can be accessed via the following link: https://iopscience.iop.org/article/10.1088/1755-1315/396/1/012034, with the DOI: 10.1088/1755-1315/396/1/012034. This article, titled "Comparison Analysis Operational Cost of Vehicle (VOC) Between Kayu Agung-Palembang-Betung Toll Road Plan with Existing Road", was published in the IOP Conference Series: Earth and Environmental Science, Vol. 396, No. 1, in December 2019.

Reviewer #C:

1. Relevance: why the authors do this research and what is its importance and application. The paper is about the calibration of one existing model to estimate fuel consumption by heavy trucks. This topic is relevant at this time due the model used (HDM-4) is from some years ago and it is not for a particular region. In the other hand, the actual migration to another source of energy to trucks as gas, electricity and hydrogen. The results can be applied to improve trucks operations, to value projects on highways, and to know the real vehicle operation costs due the fuel is 30 – 35% of this total value.
2. Novelty: paper gives new ideas, derivations, applications that have been not studied before or little- or not in depth-studied. Not really. The research compares real data with model data and proposes to change some parameters or coefficients in the model HDM-4

4.3. Response to Reviewer (Lanjutan)

3. Literature review: identify research gaps with the most recent primary references (last 10 years). Not. The literature review explores some previous researches done some year ago and in another places.
4. Methods: appropriateness of methods, the accuracy of assumptions and/or estimates used, description of equipment and limitations, experimental steps, etc. The method used is appropriate to the research. The authors have to explain why did not use the method to calibrate the model HDM-4 that this model has in its manuals, specifically in the volume 5 "A guide to calibration and adaptation". The method to obtain the real-world data is not clear, and how these data are studied, cleaned and other revision made is not in the paper.
5. Results and discussion: quality of results, depth, and logic of discussion. Please review page 7 (lines 12 to 14) and include an explanation for this.
6. Figure 4 (page 8, line 11) does not exist in the paper. Review and make corrections.
7. How was done the aerodynamic simulation? What method was used and why not another?
8. The results are interesting but their presentation is confused. The reviewer suggests include tables with values from the original model and those obtaining in the research.
9. The authors have to show the model obtained in a proper way showing the variables to be used in the future (equation in page 8 line 6 is not clear).
10. At the end of the research what are the models suggested including all variables, parameters, coefficients and others.
11. Conclusion: Insight conveyed and recommendations that might be used by others for future work. Conclusions have to be expanded. And include the mayor results obtained in the research.

Our response:

1. Thank you for your insightful observation. We fully recognize the importance of calibrating the HDM-4 model for heavy-duty trucks, especially to ensure its applicability to specific regional conditions like those in Indonesia. While the transition to alternative energy sources such as gas, electricity, and hydrogen is an important future consideration, this study focuses on optimizing the fuel efficiency of conventional trucks, which still dominate current operations. As a result, the findings remain highly relevant and practical for improving truck fuel consumption management today.

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2. We recognize that this study focuses on calibrating the HDM-4 model, but its key contribution lies in refining crucial parameters such as the drag coefficient (Cd), frontal area (AF), engine efficiency factor (Kpea), and rolling resistance coefficient (Kcr2) to better reflect the real-world operating conditions of heavy-duty trucks in Indonesia. These adjustments transform the HDM-4 model from a generalized framework into a more region-specific tool, addressing the unique challenges of Indonesian roads, vehicle loads, and aerodynamic conditions. Furthermore, this research introduces a novel approach by leveraging real-world telematics data for calibration, an aspect that has been largely overlooked in previous applications of HDM-4. By incorporating these refinements, the study significantly enhances the model's predictive accuracy for fuel consumption, making it a more practical and reliable tool for optimizing truck operations in Indonesia.
3. Thank you for your comment regarding the literature review. We understand that the most recent literature on HDM-4 model calibration is limited. However, we have tried to include relevant and recent references that discuss the calibration aspects of the model in a broader context, as well as research that aims to improve model accuracy for specific conditions. We acknowledge that the research gap on HDM-4 model calibration in Indonesia has not been extensively explored, which serves as the primary motivation for this study. We also suggest that the existing research gap mainly focuses on the importance of adjusting model parameters to better align with local operational conditions, especially for heavy trucks and road conditions in Indonesia, which has not been widely discussed in the current literature.
4. We understand that HDM-4 offers three calibration levels: Level 1, Level 2, and Level 3. We chose to use Level 2 calibration because it is more suitable for the objectives of this study, which focuses on adjusting the HDM-4 model for specific vehicles (Euro-4 heavy trucks) and operational conditions in Indonesia. Level 2 calibration allows us to make more practical adjustments to specific parameters that are relevant to the vehicles we are studying, without requiring the complex, large-scale data needed for Level 3. Level 1 calibration is simpler and lacks the detail needed for the specific conditions we aim to study, while Level 3 is more appropriate for macro-scale analysis and large infrastructure, which is not the focus of this research. Therefore, Level 2 calibration was chosen as the most appropriate approach to optimize the HDM-4 model with real-world data focused on Euro-4 trucks in Indonesia. We also acknowledge that the description of how the real-world data was obtained and processed

needs further clarification. The data used in this study were collected from telematics of trucks operating on Indonesian toll roads, including variables such as operational speed, gross vehicle weight, and road gradient. After the data were collected, we performed data cleaning to identify and remove outliers and ensure that only relevant and accurate data were used in the analysis. This cleaning process involved cross-referencing with field records and adjusting any inconsistent data. These steps have been more clearly explained in the updated methodology section of the revised manuscript. With this explanation, we hope to provide a clearer picture of why Level 2 calibration was chosen and how we processed and verified the real-world data used in this study.

5. Thank you for your comment. We have reviewed page 7, lines 12–14. 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
6. Thank you for your observation. We have reviewed the figure references in the manuscript and found that Figure 4 does not exist in the document. In this revision, we have corrected the error by replacing it with Figure 1, which aligns with the discussion on the corresponding page. We have ensured that all figure references in the manuscript are now updated and correctly matched to the research content.
7. The aerodynamic simulation in this study was conducted using SolidWorks Flow Simulation, which implements the k-ε turbulence model to evaluate airflow patterns around the vehicle. This method was chosen for its efficiency in modeling fluid flow for macroscopic scenarios, such as analyzing aerodynamic drag in heavy-duty vehicles, and its capability to capture pressure distribution and airflow patterns accurately while requiring shorter computation time than more advanced CFD software. We acknowledge that methods such as ANSYS Fluent or OpenFOAM could provide a more detailed turbulence analysis, particularly using LES (Large Eddy Simulation) or DES (Detached Eddy Simulation) approaches. However, this study focuses on evaluating macroscopic aerodynamic drag, rather than advanced turbulence

analysis. Therefore, SolidWorks Flow Simulation was selected as the most suitable method for this study, balancing accuracy and computational efficiency. We have added this explanation to the revised manuscript to clarify the methodology used.

8. We recognize that the presentation of results can be improved for better clarity. Therefore, in this revision, we have added comparison tables between the original HDM-4 model values and the results of this study. These tables help readers visualize the differences between the original and calibrated models, highlighting the impact of parameter adjustments such as Cd, AF, Kpea, and Kcr2 on fuel consumption. We hope this revision enhances readability and understanding of the research findings.
9. To address this, we have refined the model by clearly defining its variables and calibration parameters. These adjustments replace the default values from the HDM-4 and Zaabar & Chatti models, ensuring that it better reflects modern engine technologies, including common-rail injection and advanced emission control systems. By incorporating real-world telematics data, the updated model provides a more accurate representation of fuel consumption trends. Additionally, this calibration enhances its practical application in optimizing vehicle performance and supporting emission reduction efforts. We have revised the manuscript to improve clarity and ensure the model's usability for future research and applications.
10. Thank you for your question. To ensure clarity regarding the obtained model, we have summarized all calibrated parameters, including aerodynamic coefficients, frontal area, rolling resistance factor (Kcr2), and engine power efficiency factor (Kpea). All these parameters are presented in Table 3, which illustrates how the model has been adjusted in each scenario to improve fuel consumption prediction accuracy.
11. We have expanded the conclusion to emphasize key findings and future research directions. The revised section highlights the necessity of calibrating HDM-4 parameters to align with modern truck technologies, particularly in engine speed modeling and aerodynamic adjustments (Cd and AF). The study demonstrates progressive accuracy improvements across three calibration scenarios, with Scenario 3 achieving the closest match to real-world data ($p = 0.186$). For future research, we propose Level III Calibration of HDM-4, consideration of road surface conditions, gradient variations, ambient temperature, and driver behavior, as well as advanced CFD simulations using supercomputers for high-resolution aerodynamic assessments. Additionally, wind tunnel testing is recommended for refining aerodynamic

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coefficients and validating CFD results. These efforts will further enhance fuel consumption modeling accuracy and support more efficient heavy-duty truck operations.

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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 m^2. 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.

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

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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].

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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 Equation (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

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follows Equation (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].

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

where Cd represents the drag coefficient (dimensionless), FA is the aerodynamic drag force (N), ρ denotes the air density (kg/m^3), V corresponds to the relative velocity between the vehicle and air (m/s), and AF is the frontal area of the vehicle (m^2). 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 Equation (2).

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

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 Equation (3).

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

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 Equation (4).

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

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 Equation (5).

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

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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 Equation (6).

$$FC = \frac{IFC}{V} \quad (6)$$

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 Equation (7).

$$\text{RPM} = \text{RPM\_a0} + \text{RPM\_a1 x V} + \text{RPM\_a2 x V}^2 + \text{RPM\_a3 x V}^3 \quad (7)$$

where 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 Equation (8).

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

where 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 Equation (9).

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

where, 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

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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.

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.

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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.

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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

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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 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.

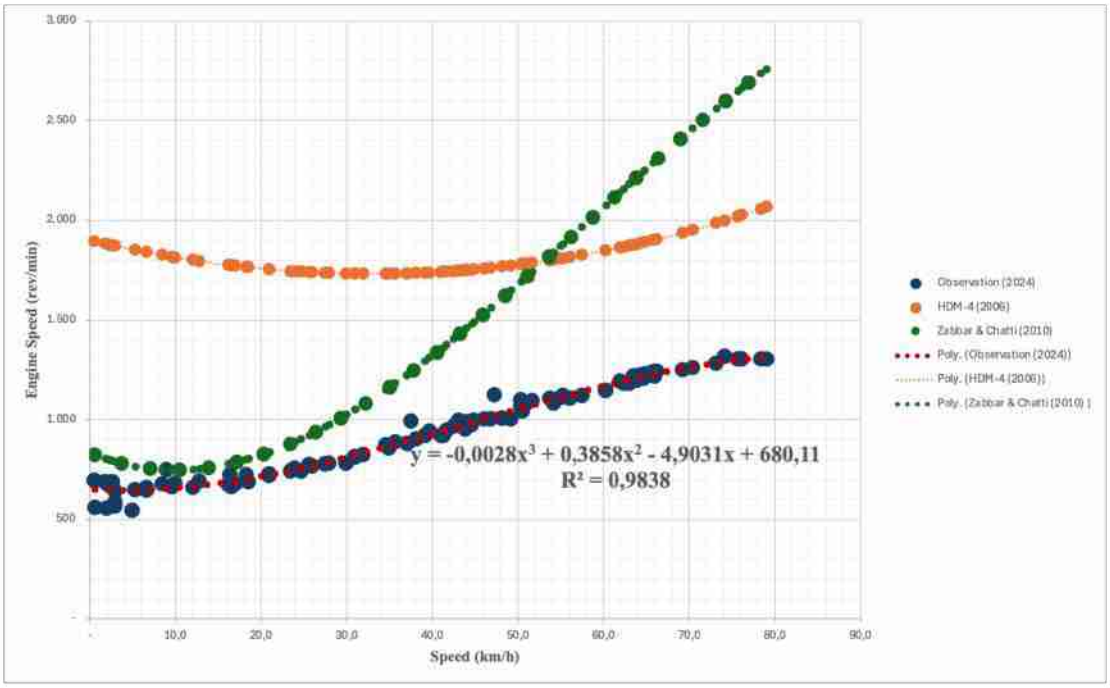

Figure 1. Calibration of Engine Speed Model Parameters

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

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

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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 m^2. 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 m^2 [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.

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However, future research is encouraged to apply advanced CFD tools for a more comprehensive analysis of wake dynamics.

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

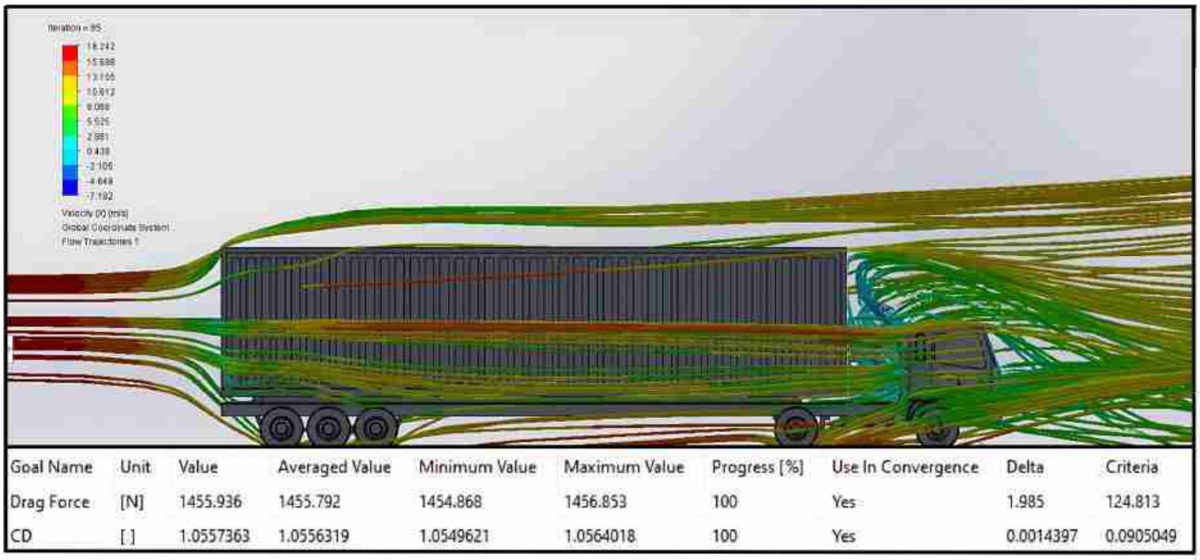

Figure 2. Aerodynamic Simulation Results

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.

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.

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].

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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

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.

5. Author's declaration

Authors' contributions and responsibilities

Write the contribution of each author here, or mark the following column.

- [√] 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.

Availability of data and materials

- [√] All data are available from the authors.

Competing interests

- [√] The authors declare no competing interest.

Additional information

Write additional information related to this research, if any.

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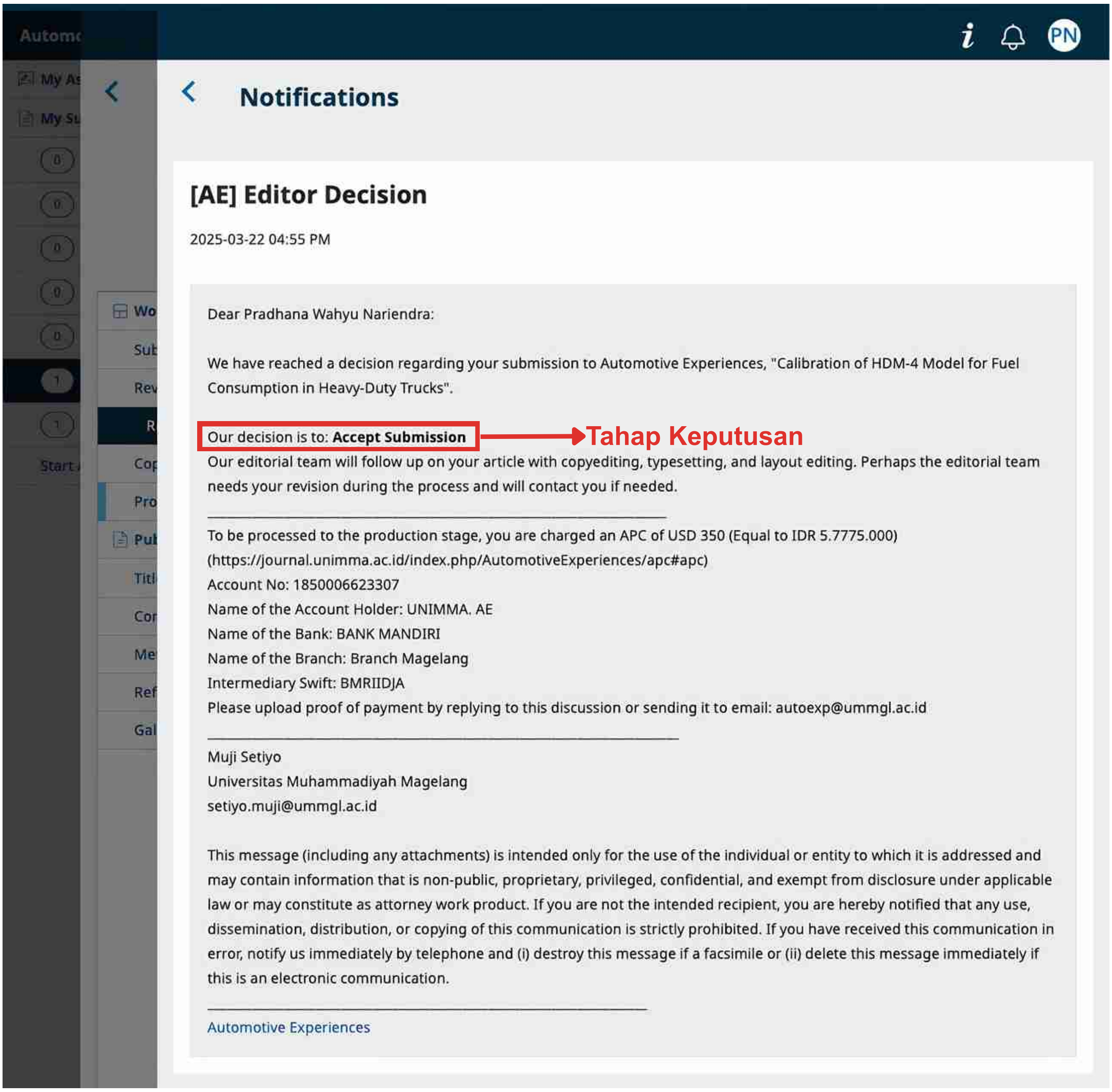
5. TAHAP ACCEPTANCE
5.1. Letter of Acceptance (LoA) Resmi

Bagian ini menyajikan bukti keputusan editor terhadap artikel yang diajukan pada jurnal Automotive Experiences. Pada tanggal 22 Maret 2025, editor menyampaikan keputusan Accept Submission, yang menunjukkan bahwa artikel telah diterima untuk diproses ke tahap berikutnya, yaitu copyediting, typesetting, dan layout editing. Bukti ini memperkuat bahwa artikel telah melalui proses editorial resmi sebelum masuk ke tahap produksi dan publikasi.


Notifications

[AE] Editor Decision

2025-03-22 04:55 PM

Dear Pradhana Wahyu Nariendra:

We have reached a decision regarding your submission to Automotive Experiences, "Calibration of HDM-4 Model for Fuel Consumption in Heavy-Duty Trucks".

Our decision is to: **Accept Submission**

Our editorial team will follow up on your article with copyediting, typesetting, and layout editing. Perhaps the editorial team needs your revision during the process and will contact you if needed.

____

To be processed to the production stage, you are charged an APC of USD 350 (Equal to IDR 5.7775.000)
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Automotive Experiences

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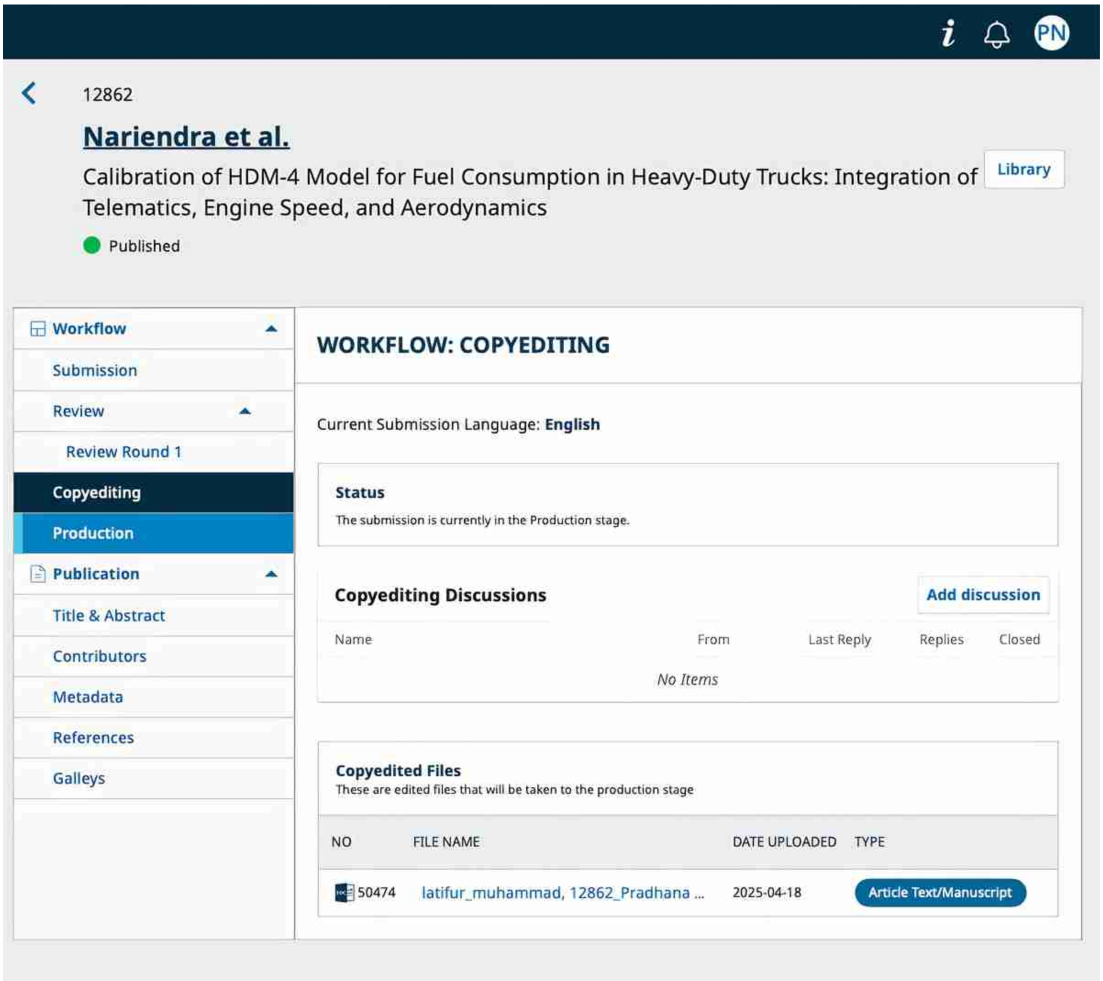

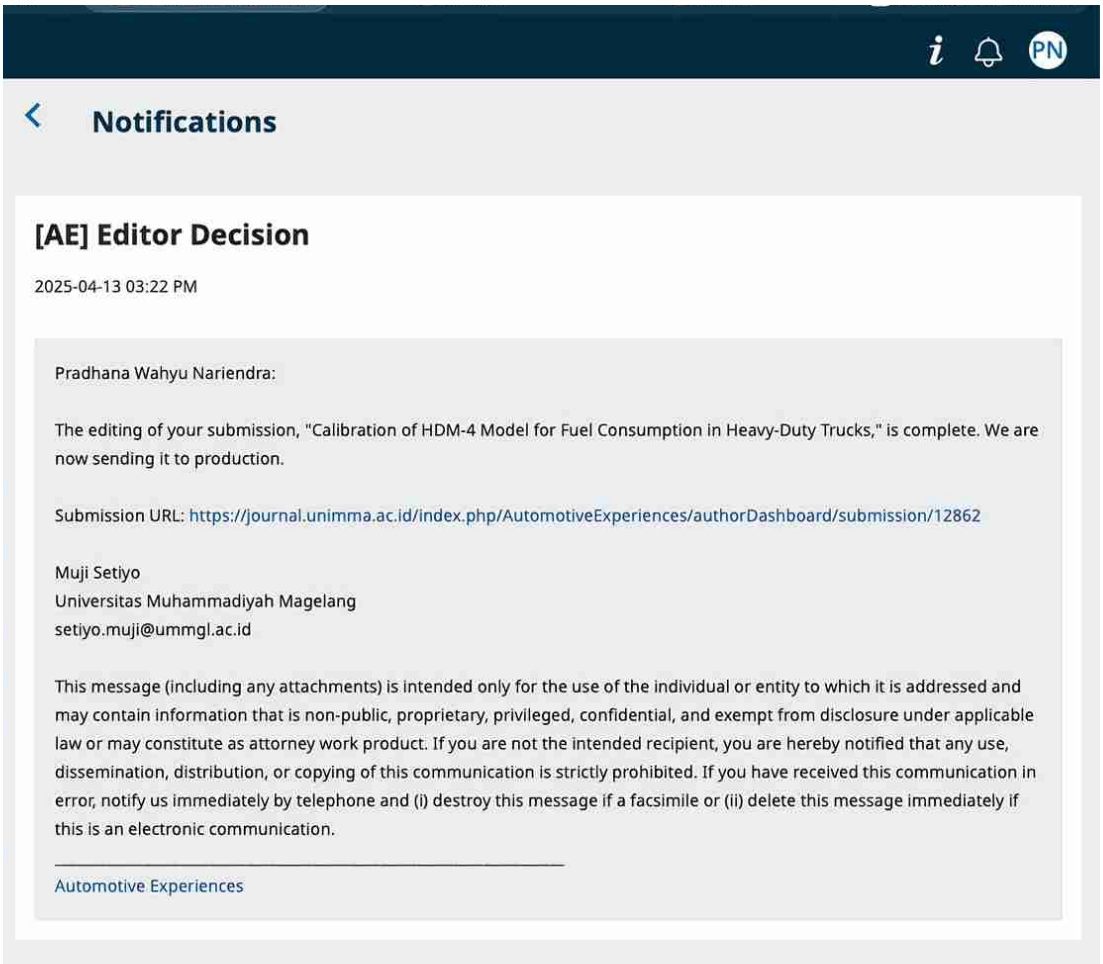

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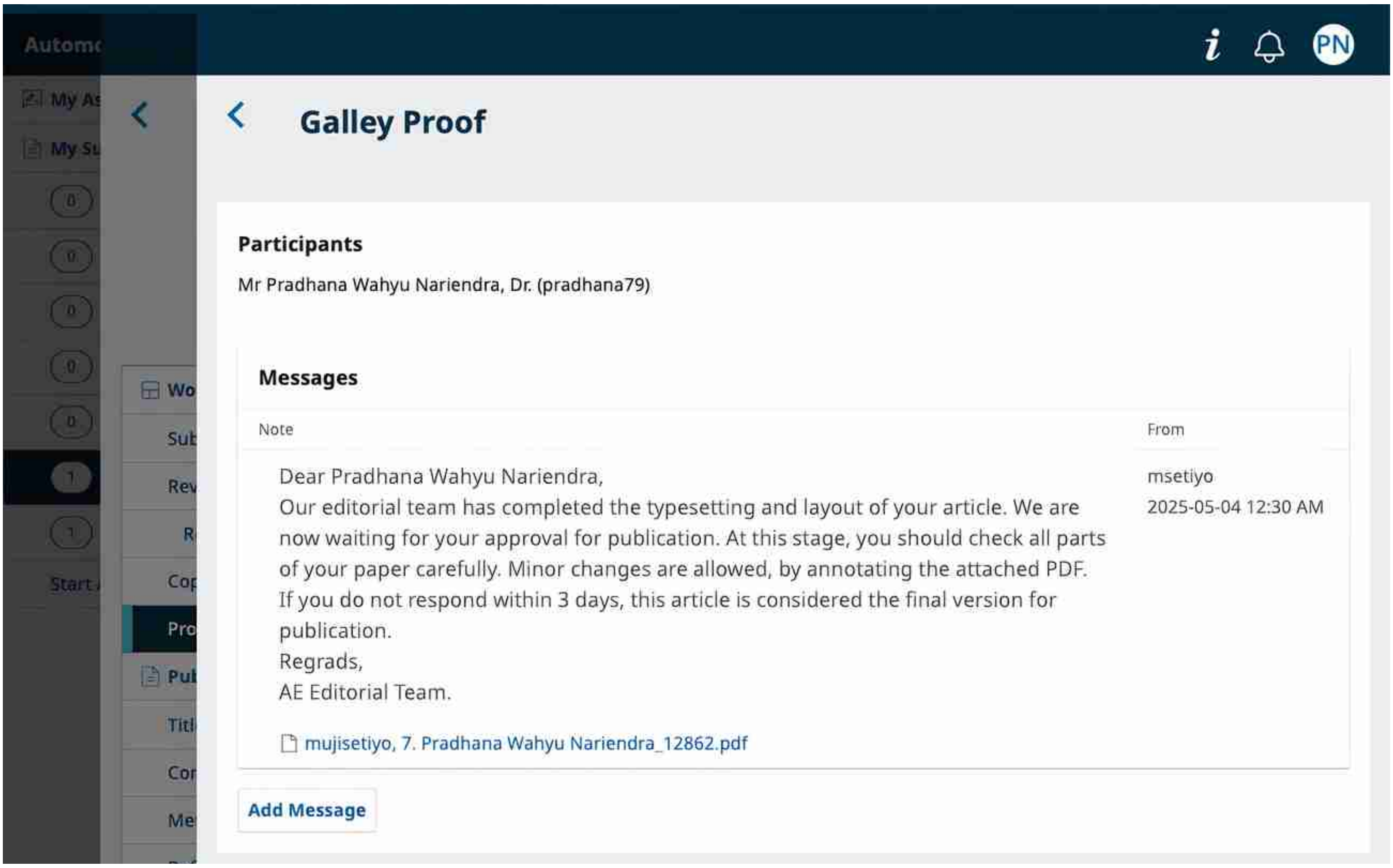

6. TAHAP PRODUCTION

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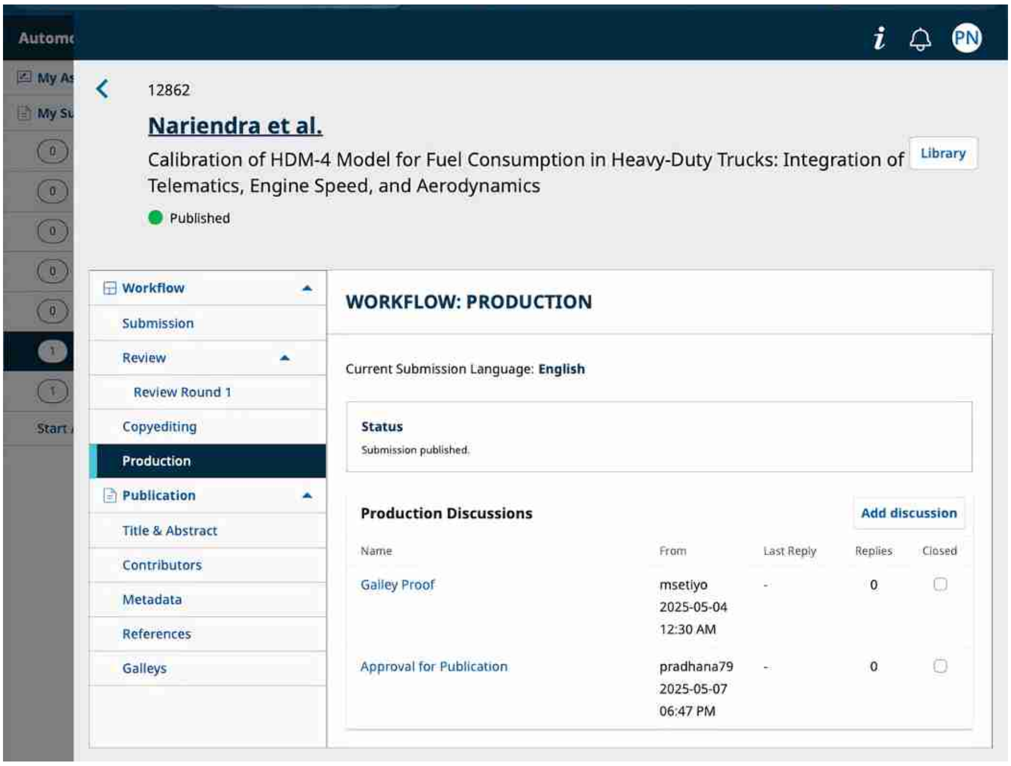
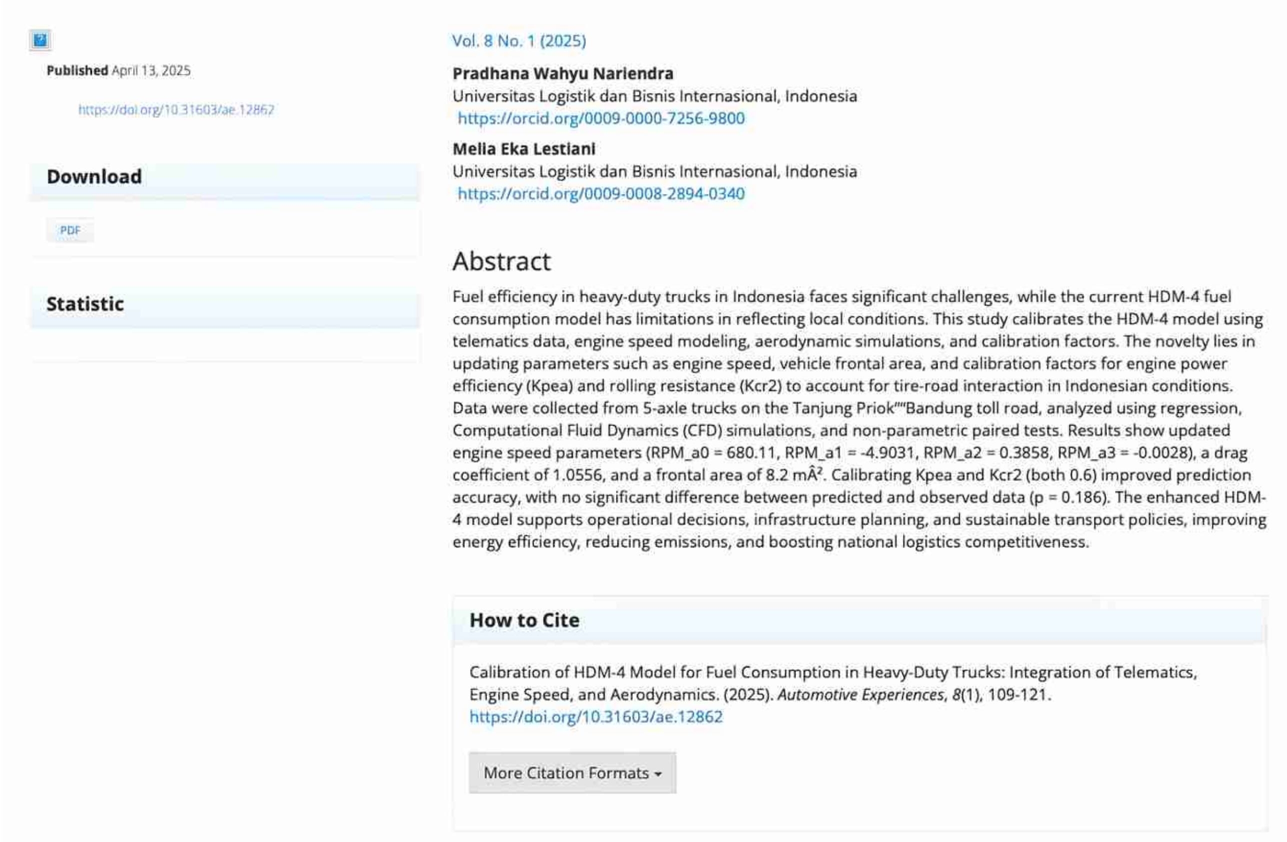


6.2. Bukti Artikel yang Telah Published

Bagian ini menyajikan bukti bahwa artikel telah terbit secara resmi pada laman OJS jurnal Automotive Experiences. Tampilan OJS menunjukkan bahwa artikel tercantum pada Vol. 8 No. 1 Tahun 2025, memiliki status published (online first) pada 13 April 2025 sesuai metadata laman jurnal, memiliki tautan DOI, serta tersedia dalam format PDF. Pada halaman tersebut juga tercantum judul artikel, nama penulis, afiliasi, abstrak, dan informasi sitasi artikel pada Automotive Experiences, Volume 8 Nomor 1, halaman 109–121.



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Research Paper

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 m^2. 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.

6.2. Bukti Artikel yang Telah Published

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/m^3), V corresponds to the relative velocity between the vehicle and air (m/s), and AF is the frontal area of the vehicle (m^2). 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).

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

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).

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

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).

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

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).

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

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.

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

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

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

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

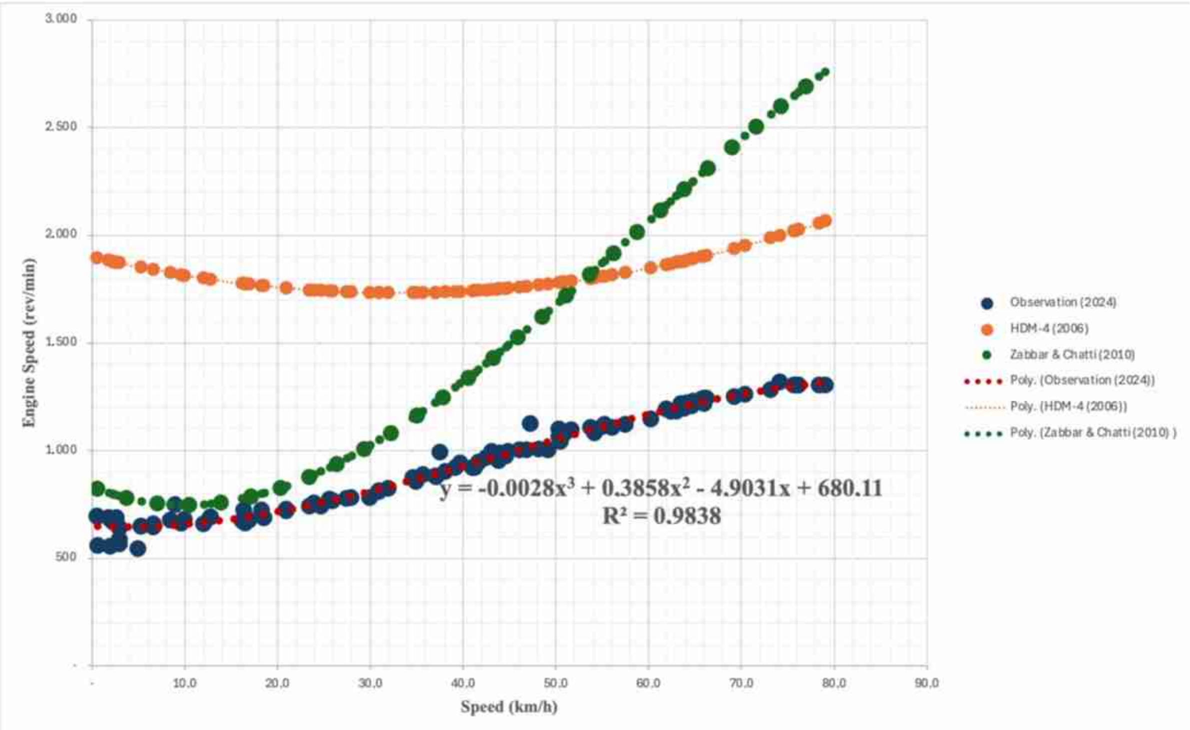


Figure 1. Calibration of engine speed model parameters

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].

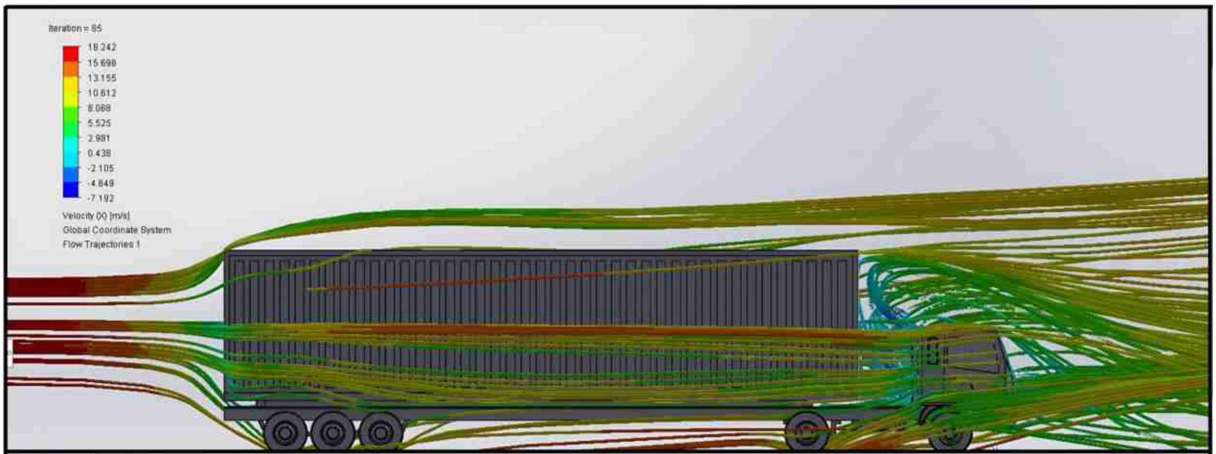
These findings align with earlier research, which shows that aerodynamic drag significantly affects the performance of heavy-duty vehicles, especially at high speeds [26]. Therefore, this simulation underscores the importance of calibrating the HDM-4 model to match the real aerodynamic conditions of 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

6.2. Bukti Artikel yang Telah Published

responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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Competing interests

The authors declare no competing interest.

Additional information

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