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A TELEMATICS-BASED EVALUATION FRAMEWORK FOR HEAVY-DUTY TRUCK FUEL EFFICIENCY UNDER DIFFERENT EMISSION STANDARDS AND UPHILL OPERATING CONDITIONS: EVIDENCE FROM EURO 3 AND EURO 4 TRUCKS IN INDONESIA

Pradhana Wahyu NARIENDRA[1], Wimpy SANTOSA[2], Anastasia Caroline SUTANDI[3]

[1] *Transportation Management, Universitas Logistik dan Bisnis Internasional, Bandung, Indonesia*

[2, 3] *Civil Engineering, Universitas Katolik Parahyangan, Bandung, Indonesia*

***Abstract**:*

Fuel efficiency is a critical issue in road freight transportation because fuel costs represent a major component of truck operating expenses under increasingly stringent emission standards. Although Euro 4 technology is designed to reduce emissions compared with Euro 3, its real-world fuel-efficiency performance under uphill, load-varying, and speed-varying conditions remains insufficiently understood. This study evaluates the comparative fuel efficiency of Euro 3 and Euro 4 five-axle semi-trailer heavy-duty trucks using manufacturer-based telematics data from Indonesian uphill toll-road freight operations. Fuel efficiency was expressed in km/l, where higher values indicate better performance. A four-factor factorial structure was applied, consisting of emission standard, operating speed class, load factor class, and road gradient category, resulting in 54 operational combinations. After cleaning and outlier filtering, 828 valid records were analyzed. A four-way factorial ANOVA examined main and interaction effects, while matched comparisons between Euro 4 and Euro 3 trucks were conducted under identical speed, load, and gradient combinations, producing 27 scenarios. The results show that Euro 4 trucks generally achieve higher fuel efficiency on flat segments, particularly under medium and high load factors. However, the Euro 4 advantage becomes less consistent on hilly and mountainous terrain, especially at higher speeds and heavier loads. The fuel-efficiency benefit of Euro 4 decreases as road gradient and operating demand increase, indicating that newer emission-control technology does not provide uniform energy-efficiency advantages across operating conditions. The study concludes that fuel-efficiency performance is shaped by the interaction among emission standard, speed, load factor, and road gradient rather than by vehicle technology alone. The findings support terrain-sensitive fleet deployment, suggesting that Euro 4 trucks should be prioritized on relatively flat corridors and moderate operating regimes, while Euro 3 trucks may remain operationally comparable in selected high-gradient and high-load conditions, although Euro 4 remains preferable for emission control.

Keywords: *telematics data, heavy-duty trucks, fuel efficiency, road gradient, emission standards, fleet deployment strategy*

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Contact:
1) pradhana@ulbi.ac.id [https://orcid.org/0009-0000-7256-9800] - corresponding author; 2) wimpy@unpar.ac.id [https://orcid.org/0000-0002-6593-7932]; 3) caroline@unpar.ac.id [https://orcid.org/0000-0002-7514-264X]

1. Introduction

Global emissions from road transport, particularly from heavy-duty trucks, continue to increase, highlighting the urgent need for improved energy efficiency and more effective supporting policies (International Energy Agency 2022). At the same time, fuel efficiency in freight transport has become a critical concern as logistics demand expands, operating costs rise, and environmental regulations become more stringent. Despite ongoing development of alternative propulsion technologies, including fuel-cell and battery-electric trucks, conventional diesel-powered heavy-duty vehicles remain widely used in long-haul freight transport, while alternative technologies are still being evaluated in terms of ownership cost, energy consumption, infrastructure readiness, and operational feasibility (Sim et al. 2019; Torbatian et al. 2024). Consequently, road freight transport accounts for a substantial share of global energy consumption and carbon emissions, with heavy-duty trucks playing a central role in long-distance logistics systems (International Energy Agency 2022; Torbatian et al. 2024).

In Indonesia, dependence on road-based freight transport is even more pronounced. Trucks dominate intercity freight distribution, while high logistics costs remain a persistent challenge for Indonesia's economic competitiveness (Santoso et al. 2021). Within truck operations, fuel costs constitute one of the largest components of Vehicle Operating Costs (VOC), particularly along major Indonesian freight corridors and toll-road routes (Kadarsa et al. 2019; Nariendra 2024; Nariendra et al. 2026). These challenges are further intensified on Indonesian freight corridors that include hilly and mountainous toll-road segments, where road gradient increases fuel demand and operating costs for heavy-duty trucks (Nariendra 2024; Nariendra et al. 2026). As a result, trucks frequently operate under conditions that substantially increase energy demand and operating costs. Previous studies on Indonesian toll-road corridors have shown that fuel expenses can account for a very large share of total trip costs for five-axle trucks, particularly on segments with higher gradients (Kadarsa et al. 2019; Nariendra 2024; Nariendra et al. 2026). Moreover, improvements in road geometry, especially reductions in gradient, have been reported to potentially reduce transport or vehicle operating costs by up to approximately 13%, underscoring the sensitivity of truck operating costs to terrain characteristics (Sudjana 2011).

From an operational standpoint, truck fuel consumption is highly sensitive to real-world driving conditions, particularly road gradient, vehicle weight, and operating speed. These factors interact in complex ways to determine engine load and overall energy demand (Zhou et al. 2016; Wang and Rakha 2017; Gao et al. 2019; Posada-Henao et al. 2023). Numerous studies have consistently identified road gradient and vehicle weight as among the most influential determinants of fuel consumption, often exerting stronger effects than speed alone, especially under uphill conditions (Zhou et al. 2016; Wang and Rakha 2017; Posada-Henao et al. 2023). On steep segments, additional gravitational resistance substantially increases traction demand, leading to sharp increases in fuel consumption, particularly when trucks operate under heavy loading conditions (Hauenstein et al. 2021; Posada-Henao et al. 2023). Therefore, evaluating truck fuel efficiency based only on average operating conditions may not adequately represent actual freight performance, particularly on corridors where road gradient, vehicle load, and operating speed vary simultaneously.

At the same time, technological changes driven by increasingly stringent emission regulations have reshaped heavy-duty truck design. The progressive implementation of Euro emission standards has tightened limits on pollutants such as nitrogen oxides (NOx), hydrocarbons (HC), carbon monoxide (CO), particulate matter (PM), and particle numbers in road vehicles (Lindqvist 2012; Velders et al. 2013). Indonesia has adopted Euro 4 standards for diesel trucks as part of its efforts to align national emission policies with international practices (Ministry of Environment and Forestry of the Republic of Indonesia 2017). To meet these standards, diesel engines increasingly rely on emission-control technologies such as exhaust gas recirculation (EGR) and selective catalytic reduction (SCR), which are designed to reduce NOx emissions but may interact with engine performance under different operating conditions. While these regulations are expected to deliver substantial environmental benefits, emission-control systems can also influence CO_2 emissions, fuel use, or engine efficiency depending on vehicle speed, load, exhaust temperature, and operating regime (Boriboonsomsin et al. 2018; Suresh Kumar et al. 2020; Li et al. 2022). This may create an operational trade-off between emission reduction and energy-efficiency performance, making field-based evaluation increasingly important for fleet operators and policymakers (Boriboonsomsin et al. 2018; Li et al. 2022). Therefore, the transition from Euro 3 to Euro 4 should not only be assessed from the perspective of emission compliance, but also from real-world fuel-efficiency performance under terrain-sensitive and load-sensitive operating conditions.

From a research perspective, much of the existing analysis of heavy-duty truck fuel consumption still relies on mechanistic and simulation-based models, most notably the Highway Development and Management (HDM-4) model. HDM-4 has been widely used as an analytical framework for road planning, road management, and vehicle operating cost estimation, while its application requires calibration and adaptation to local conditions (Bennett and Paterson 2000; Odoki and Kerali 2006). However, several studies have demonstrated that HDM-4 fuel-consumption estimates may require refinement or recalibration when applied to specific operating conditions, including congestion effects, modern truck characteristics, vehicle weight, frontal area, pavement roughness, and road-condition-related resistance parameters (Greenwood et al. 2007; Zaabar and Chatti 2010; Perrotta et al. 2019). In Indonesia, recent studies have shown that incorporating operational and vehicle-specific parameters into HDM-4 calibration can improve prediction accuracy for five-axle trucks when telematics data are utilized (Nariendra and Lestiani 2025). Nevertheless, such calibration procedures remain relatively complex, data-intensive, and often route- or vehicle-specific, which limits their practicality for routine fleet management and large-scale operational decision-making. This limitation indicates the need for a more practical data-driven framework that can evaluate truck fuel efficiency directly from observed operating conditions while maintaining sufficient statistical rigor for operational interpretation.

Recent advances in vehicle telematics provide an alternative pathway by enabling continuous monitoring of vehicle operations through GPS, On-Board Diagnostics (OBD), and engine communication protocols (Perrotta et al. 2017; Farzaneh et al. 2020; SAE International Standard 2022). Telematics-based studies in Indonesia indicate that data-driven models derived directly from observed operational conditions can explain a substantial proportion of fuel-consumption variability without relying on complex mechanistic formulations (Nariendra et al. 2026). However, most previous data-driven and experimental studies have focused on fuel-consumption prediction, route-level modeling, road-slope and vehicle-weight effects, or general operational variability rather than matched technology comparisons under equivalent speed, load, and gradient conditions (Perrotta et al. 2017; Posada-Henao et al. 2023; Nariendra et al. 2026). Despite this progress, several gaps remain. Empirical comparisons of fuel efficiency between trucks with different emission standards, particularly Euro 3 and Euro 4, under sustained uphill operation are still limited. Few studies have examined the interaction among truck type, operating speed, vehicle load, and road gradient within a single analytical framework, especially on toll-road networks in developing countries with complex topography. Moreover, data-driven approaches that are statistically rigorous, operationally practical, and less dependent on extensive mechanistic calibration remain underexplored in freight energy analysis. Previous studies have also rarely translated empirical fuel-efficiency comparisons into practical fleet deployment strategies that specify which truck technology should be prioritized under specific terrain, speed, and load conditions. This creates a gap between fuel-efficiency analysis and operational decision-making in freight transport.

In response to these gaps, this study evaluates fuel-efficiency differences between Euro 4 and Euro 3 five-axle semi-trailer trucks using official manufacturer-based telematics data from real-world operations on uphill segments of Indonesian toll roads. A factorial experimental design is applied to examine the interaction among emission standard, operating speed, gross vehicle weight, and road gradient. Based on the research gaps identified above, this study is guided by three hypotheses: (1) fuel efficiency differs between Euro 3 and Euro 4 trucks under comparable operating conditions; (2) the fuel-efficiency difference between Euro 3 and Euro 4 trucks is moderated by road gradient, operating speed, and vehicle load; and (3) the fuel-efficiency advantage of Euro 4 trucks decreases under hilly or mountainous terrain, particularly when trucks operate with higher loads and higher speeds. These hypotheses provide the basis for evaluating whether Euro 4 technology offers a consistent fuel-efficiency

advantage or whether its performance depends on specific terrain-speed-load combinations.
The main contribution of this study is the integration of manufacturer-based telematics data, matched operational scenarios, and a multivariable factorial analysis framework to compare Euro 3 and Euro 4 fuel efficiency without relying on mechanistic calibration procedures such as HDM-4. The novelty lies in identifying how emission standard, speed, load factor, and road gradient interact under real freight operations, and in determining the conditions under which Euro 4 advantages are maintained, reduced, or statistically insignificant. Thus, the study moves beyond a simple technology comparison by providing empirical support for terrain-sensitive fleet deployment decisions.
Beyond Indonesia, the proposed framework may be relevant to developing regions with similar freight characteristics, including dependence on road-based logistics, diesel heavy-duty truck fleets, variable payloads, and hilly or mountainous corridors. However, the findings should be generalized carefully because they are based on specific vehicle types, selected uphill toll-road segments, and observed freight operations in Indonesia. Broader application requires validation using additional fleets, longer observation periods, and more diverse operating environments.

2. Literature review

2.1. Effect of road gradient on energy demand of heavy-duty trucks

Road gradient is widely recognized as one of the most influential factors affecting energy demand and fuel consumption of heavy-duty trucks. During uphill operation, vehicles must generate additional traction force to overcome the gravitational component along the roadway, which substantially increases engine load and fuel use (Gao et al. 2019). Numerous empirical studies have demonstrated that the impact of road gradient often exceeds that of operating speed, particularly when trucks operate under heavy payload conditions (Zhou et al. 2016; Wang and Rakha 2017; Posada-Henao et al. 2023).
Recent field-based and telematics-driven investigations further confirm that fuel consumption rises sharply on uphill segments, especially at gradients exceeding approximately 4%, where the additional fuel demand during climbing cannot be fully compensated by energy savings on downhill sections, resulting in a net increase in trip-level energy consumption (Jiang et al. 2025). Large-scale telematics analyses also reveal strong nonlinear interactions between road grade and vehicle mass, which significantly amplify engine load, power demand, and fuel consumption under high-load uphill conditions (Gao et al. 2019; Liu et al. 2024). These findings indicate that uphill segments represent critical operational environments that disproportionately influence overall freight energy efficiency.
To mitigate fuel penalties on grades, various vehicle control and operational strategies have been proposed, including gradient-adaptive gear shifting, torque management, and predictive speed control using road slope preview (Lei et al. 2024; Jiang et al. 2025; Skrúcaný et al. 2025). In addition, route optimization based on topographic information and eco-driving strategies have been shown to reduce fuel consumption on road networks with moderate gradient variations (Hauenstein et al. 2021). However, multiple studies report that the effectiveness of these approaches diminishes on long or steep uphill segments, particularly for heavily loaded trucks, where physical power demand cannot be sufficiently reduced through speed or gear control alone (Gonçalves da Silva and Lazar 2022).
Recent experimental and real-world operational studies consistently demonstrate that sustained uphill driving leads to prolonged high engine power demand, which can dominate total trip energy consumption even when average operating speeds remain relatively stable (Yoo et al. 2025). Complementary telematics-based evidence shows that accounting for road slope increases estimated fuel consumption by approximately 3-5% across different road classes, with parallel increases observed in CO_2 and NO_x emissions, reflecting intensified engine workload during uphill operation (Ghaffarpasand and Pope 2024). Together, these results reinforce that road gradient and vehicle loading are dominant determinants of energy efficiency in freight corridors characterized by complex topography and long climbing sections, and therefore must be explicitly considered in both operational analysis and policy-oriented energy efficiency assessments.

2.2. Euro emission regulations and their implications for fuel efficiency

Euro emission standards were introduced to reduce harmful pollutants from road vehicles, particularly nitrogen oxides (NOx) and particulate matter (PM), through progressively stricter limits, improved engine calibration, and exhaust aftertreatment technologies (Lindqvist 2012; Velders et al. 2013). For heavy-duty diesel vehicles, compliance with higher Euro standards increasingly requires integrated control strategies that combine in-cylinder measures with aftertreatment systems, making engine operation more dependent on emission-management requirements than earlier technologies (Lindqvist 2012).

In Indonesia, Euro 4 standards for new diesel vehicles were formalized through national regulation to improve air quality and align with international emission-control practices (Ministry of Environment and Forestry of the Republic of Indonesia 2017). This transition is highly relevant for freight transport because heavy-duty trucks dominate intercity logistics and frequently operate on toll-road corridors with long uphill sections. Although Euro 4 is expected to provide environmental benefits, its operational consequences may extend beyond emission reduction because the added complexity of control and aftertreatment systems can influence fuel consumption, particularly under sustained high load uphill operation.

Evidence from controlled and steady highway conditions indicates that trucks meeting higher Euro standards can achieve better fuel performance than earlier technologies when engine-efficiency improvements accompany emission reductions (Kimmo and Nils-Olof 2007; Matti et al. 2009). However, these benefits are context-dependent. In real-world operations, fuel efficiency and emission performance are strongly affected by speed, load, road gradient, and exhaust temperature because these factors determine whether aftertreatment systems operate within optimal conversion ranges and how intensively the engine must manage NOx control (Bishop et al. 2013; Boriboonsomsin et al. 2018).

A key limitation is that aftertreatment effectiveness depends on sufficient exhaust temperature and suitable control behavior, which may not always be achieved under low speed, congested, or transient driving. Under these conditions, SCR activity and emission-control effectiveness may deviate from ideal expectations, while system-related control strategies can impose additional energy demand (Boriboonsomsin et al. 2018; Tian et al. 2024). Therefore, fuel-efficiency advantages observed under controlled testing or favorable cruising conditions may decrease in real-world duty cycles, especially on prolonged uphill grades with heavy payloads and sustained traction demand.

At the regional level, Euro-equivalent implementation across ASEAN remains uneven because of differences in regulatory enforcement, fuel quality readiness, and fleet renewal rates (Nguyen Van et al. 2024). This reinforces the need for empirical field-based evaluation of Euro-technology performance under realistic freight operations. In developing-country contexts with complex topography and strong dependence on road freight, the transition from Euro 3 to Euro 4 should therefore be assessed not only from the perspective of emission compliance, but also from energy-efficiency outcomes across terrain- and load-sensitive conditions.

2.3. Role of SCR and EGR technologies in heavy-duty diesel engines

To meet Euro 4 and higher emission standards, heavy-duty diesel engines commonly use Selective Catalytic Reduction (SCR) and Exhaust Gas Recirculation (EGR) to reduce nitrogen oxide (NOx) emissions. SCR converts NOx into nitrogen and water using a urea-based reductant, while EGR lowers NOx formation by recirculating exhaust gas into the intake air, thereby reducing combustion temperature and oxygen concentration (Jeon et al. 2016).

However, these emission-control benefits may involve fuel-efficiency trade-offs. SCR requires sufficiently high exhaust-gas temperatures to maintain catalytic activity and prevent ammonia slip, which can increase thermal and pumping losses during prolonged uphill operation, especially under heavy payloads (Boriboonsomsin et al. 2018). EGR may also reduce combustion efficiency, increase pumping work, and increase particulate formation because it lowers oxygen availability in the combustion chamber (Suresh Kumar et al. 2020; Zhang et al. 2024a). Higher EGR rates have also been shown to increase brake-specific fuel consumption (BSFC) and reduce brake thermal efficiency, particularly under medium-to-high load conditions (Rimkus et al. 2025).

The combined use of SCR and EGR increases engine-control complexity because NOx reduction requires coordination between in-cylinder combustion management and exhaust aftertreatment performance (Liu et al. 2019). In long uphill sections,

where speed and gear selection often fluctuate, this coordination may increase energy demand. The effect can be more pronounced in mountainous terrain and tropical climates, where sustained high-load operation increases thermal stress, cooling demand, and the influence of EGR on combustion stability and particulate formation (Chaichan et al. 2022).
These mechanisms provide a technical basis for explaining why Euro 4 trucks may not always deliver superior fuel efficiency under severe uphill and heavy-load conditions, despite their emission-control advantages. Therefore, laboratory-based or flat-road evaluations may overestimate Euro 4 energy-efficiency benefits in real freight corridors with steep gradients and heavy loading. This reinforces the need for telematics-based field evaluation that captures the interaction between emission technology, road gradient, vehicle load, and operating speed under actual freight operations.

2.4. Telematics-based approaches for fuel consumption and efficiency analysis

Conventional analyses of heavy-duty truck fuel consumption have traditionally relied on mechanistic vehicle dynamics and pavement interaction models, particularly the Highway Development and Management (HDM-4) framework, which is widely used for infrastructure planning and vehicle operating cost estimation (Bennett and Paterson 2000; Odoki 2016). Although HDM-4 provides a standardized approach, its default parameters often do not fully represent modern truck technologies, especially engine performance, aerodynamic drag, and rolling resistance, which may cause bias in fuel consumption estimation on roads with varying gradients (Greenwood et al. 2007; Zaabar and Chatti 2010; Perrotta et al. 2019). In addition, accurate HDM-4 application requires extensive route- and vehicle-specific calibration, limiting its practicality for routine fleet-level operational analysis (Nariendra and Lestiani 2025).
Vehicle telematics offers an alternative data-driven approach by enabling continuous monitoring through Global Positioning System (GPS), On-Board Diagnostics (OBD-II), and standardized engine communication protocols such as SAE J1939 (SAE International Standard 2022). These systems provide high-resolution data on speed, fuel use, engine parameters, and vehicle position, allowing direct observation of real-world operating conditions rather than reliance on modeled assumptions (Perrotta et al. 2017; Farzaneh et al. 2020). Consequently, telematics datasets are increasingly used to capture operational variability in freight transport, including speed fluctuations, load effects, idling behavior, and route-specific driving patterns.
Recent studies show that telematics-derived variables, such as road grade, vehicle mass, speed, and acceleration, have strong nonlinear relationships with fuel consumption and emissions, which are difficult to represent using simplified physics-based formulations (Ghaffarpasand and Pope 2024; Fan et al. 2024). Second-by-second operational data also indicate that uphill operation combined with heavy payloads can produce disproportionate increases in energy demand, meaning that a small portion of road segments may dominate total trip fuel consumption (Fan et al. 2024). These findings support the use of spatially explicit and temporally dense datasets for evaluating truck performance on energy-intensive corridor segments.
Machine-learning approaches have also been applied to telematics datasets to predict fuel consumption and CO_2 emissions using artificial neural networks (ANN), long short-term memory (LSTM), and hybrid CNN-LSTM models (Haghshenas et al. 2025). However, most studies emphasize prediction accuracy rather than comparative evaluation of vehicle technologies under controlled operational classifications. As a result, they provide limited insight into how emission standards interact with operating speed, load factor, and road gradient in determining real-world fuel efficiency.
Furthermore, many telematics-based studies still focus on light-duty vehicles or specific truck fleets without systematically examining the combined effects of vehicle technology, payload, speed regime, and terrain within a unified analytical framework (Posada-Henao et al. 2023). Consequently, interaction effects among operational variables are often absorbed into prediction models rather than explicitly quantified and interpreted, limiting their usefulness for policy design and fleet deployment decisions.
Therefore, a methodological gap remains for empirical approaches that combine high-resolution telematics data with structured experimental designs capable of isolating and interpreting interaction effects among key operational factors. Factorial analysis offers a statistically rigorous framework to

evaluate how multiple variables jointly influence performance outcomes and to identify operating regimes in which technology advantages are strengthened or reduced (Ross and Willson 2017). However, such designs remain rarely applied to large-scale real-world telematics datasets in freight transport studies.

Building on the literature on road gradient, vehicle loading, Euro emission-control technologies, and telematics-based fuel analysis, this study identifies a synthesis gap between technical understanding and operational decision-making. Previous studies have explained how terrain, payload, vehicle speed, and emission-control systems affect fuel consumption, but these factors have rarely been integrated into a matched, data-driven framework for comparing Euro 3 and Euro 4 trucks under equivalent real-world operating conditions. Therefore, integrating manufacturer-based telematics data with factorial analysis and matched operational scenarios provides a practical and robust framework for identifying when Euro 4 fuel-efficiency advantages are maintained, reduced, or statistically insignificant. This synthesis supports terrain-sensitive fleet deployment decisions rather than a simple technology comparison.

3. Methodology

This methodology was developed as an empirical decision-support framework rather than a general technology comparison. By combining manufacturer-based telematics data, factorial experimental design, and matched operational scenarios, the study is designed to identify the speed, load factor, and road gradient conditions under which Euro 4 fuel-efficiency advantages are maintained, reduced, or statistically insignificant. Thus, the methodology links statistical analysis with practical terrain-sensitive fleet deployment decisions under real freight operating conditions.

3.1. Data collection and processing

This study uses secondary operational data from manufacturer-installed telematics systems to evaluate the fuel consumption and fuel efficiency of Euro 3 and Euro 4 heavy-duty trucks on Indonesian toll roads. The dataset includes time-stamped records of fuel use, vehicle speed, and GPS position collected through OBD systems integrated with each vehicle's ECU. Fuel use and speed were recorded at 60-second intervals, while road gradient was evaluated over fixed 1 km uphill observation segments to capture terrain variation while reducing GPS noise and short-term speed fluctuations. Fuel efficiency was calculated as distance travelled divided by fuel consumed within each segment and expressed in km/l, where higher values indicate better performance.

The telematics data were obtained from official Hino and UD Telematics platforms provided by participating fleet operators. Route selection and operating schedules were coordinated with trucking companies so that the dataset reflected typical freight operations along the Tanjung Priok Port–Bandung corridor, a major logistics route in western Indonesia with flat, hilly, and mountainous sections. The analysis focused only on uphill segments because these conditions place greater energy demand on heavy-duty trucks and strongly affect trip fuel consumption and operating costs.

Additional data were collected to improve technical accuracy, including vehicle specifications, trailer configuration, cargo characteristics, road geometry, and regulatory constraints. Vehicle specifications were obtained through structured interviews with fleet operators and authorized Hino and UD Trucks dealers. Gross vehicle weight was verified using official weighbridge records from ports and logistics facilities, allowing load factor to be calculated from measured operating weights rather than nominal payload assumptions. Road elevation and geometry were obtained from remote sensing sources, Google Earth elevation data, and official road inventory data from the Indonesian Ministry of Public Works and Housing. Road gradients were calculated from elevation differences between successive observation points and aggregated at the 1 km segment level to reduce short-distance elevation noise. This approach is supported by validation studies showing that Google Earth vertical data provide acceptable accuracy for transportation applications, with an MAE of approximately 1.32 m and an RMSE of about 2.27 m (Wang et al. 2017).

The analysis focused on five-axle semi-trailer trucks with a 1.2-222 axle configuration, consisting of a two-axle tractor and a three-axle open-bed trailer. Two vehicle models were evaluated: the Quester GKE (Euro 3) and the Hino FG 260 TH (Euro 4), both equipped with factory-installed telematics systems, as shown in Fig. 1.

(a) (b)

Fig. 1. Trucks used in the study (a) Quester GKE (Euro 3); (b) Hino FG 260 TH (Euro 4)

Each tractor has six tires, while the 40-foot open-bed trailer has three axles, twelve tires, an empty weight of approximately 8.8 tons, and a GVWR of 40 tons. The tractor units have comparable power-to-weight ratios of approximately 5.6 kW/ton for Euro 3 and 5.7 kW/ton for Euro 4. This similarity helps ensure that performance differences are mainly related to emission standard and powertrain configuration, rather than vehicle size, axle configuration, or payload capacity.

To minimize external traffic disturbances, telematics records were filtered to retain only free-flow conditions, where vehicles are minimally affected by congestion and can maintain relatively stable speeds (Zhang et al. 2019). In this study, free-flow conditions were operationally identified by excluding records with prolonged stop-and-go movement, zero-speed values on uphill segments, and abrupt acceleration or deceleration patterns inconsistent with stable truck operation, while moderate speed variations caused by roadway geometry were retained. This filtering rule is consistent with connected-vehicle and telematics-based analyses that control for congestion effects and use speed, acceleration, deceleration, idling, cruising, stop events, and driving volatility as relevant indicators of fuel consumption and emissions (Treiber and Kesting 2013; Xiang et al. 2024; Llopis-Castelló et al. 2026; Petraki et al. 2026). Only segments with horizontal curve radii greater than 550 m were included because, under free-flow conditions, truck operation on such curves is operationally comparable to straight sections, allowing curvature effects on fuel consumption to be reasonably neglected (Zhang et al. 2019; Dong et al. 2023). All preprocessing, filtering, and aggregation procedures were conducted using standard statistical computing software to ensure consistency, transparency, and reproducibility. The dataset was not fully balanced between Euro 3 and Euro 4 trucks, reflecting the availability of real-world telematics records from participating fleets; therefore, this imbalance was considered when interpreting the matched comparison results.

3.2. Experimental design and factorial structure

This study adopts a four-factor factorial experimental design to evaluate how operational variables jointly influence fuel efficiency. The factors include emission standard with two levels (Euro 3 and Euro 4), operating speed with three levels (low, medium, and high), load factor with three levels (low, medium, and high), and road gradient with three levels (flat, hill, and mountain). This structure enables the analysis of both main and interaction effects, because fuel-efficiency differences between Euro 3 and Euro 4 trucks are expected to depend not only on emission standard, but also on the combined effects of speed, payload, and terrain.

Operating speed and load factor classes were defined using data-driven clustering to capture natural operational patterns in the telematics dataset rather than relying on arbitrary thresholds. K-means clustering was selected because it is widely used in freight and logistics analytics to discretize continuous operational variables into representative behavioral states (Sarıgül et al. 2025). Three clusters were used to produce operationally meaningful low, medium, and high categories. Cluster centroids were

then used to define class boundaries, ensuring consistency between statistical grouping and practical interpretation.
In contrast, road gradient was classified using regulatory-based geometric thresholds to maintain engineering relevance and consistency with national design standards. Based on Indonesian freeway geometric design criteria, gradients were categorized as flat for slopes up to 4%, hill for slopes greater than 4% and up to 5%, and mountain for slopes greater than 5% and up to 6% (Directorate General of Highways 2020). This hybrid classification combines empirical grouping for vehicle-related variables with standardized geometric definitions for roadway characteristics, while ensuring that each observation belongs to a mutually exclusive terrain class.
Temporal consistency checks were applied to improve data reliability within each 1 km uphill segment. Each segment was required to contain at least two valid telematics records to support stable estimation of average speed and fuel efficiency. Records with zero-speed values on uphill segments, implausible fuel consumption rates, or abrupt spikes inconsistent with physical vehicle behavior were removed. Outliers were further detected using the interquartile range criterion, where observations below Q1 − 1.5×IQR or above Q3 + 1.5×IQR were flagged and excluded after data quality verification (Magar et al. 2024; Agathokleous et al. 2026).
After classification and filtering, the dataset was arranged into a full four-way factorial structure of 2 × 3 × 3 × 3, resulting in 54 operational combinations. Each combination represents a specific interaction among emission standard, speed class, load factor class, and road gradient category, as summarized in Table 1. This structure provides the basis for the ANOVA analysis used to evaluate interaction effects among all operational variables.
For technology-specific evaluation, Euro 4 and Euro 3 trucks were directly compared under identical combinations of speed, load factor, and road gradient. Since emission standard has two levels, the 3 × 3 × 3 operational structure produced 27 matched scenarios. This framework isolates the effect of emission standard while controlling for operating conditions, allowing fuel-efficiency differences to be interpreted more clearly. Combined with the full factorial interaction analysis, this matched comparison strengthens both the statistical rigor and operational relevance of the results by identifying where Euro 4 trucks outperform, perform similarly to, or lose their fuel-efficiency advantage over Euro 3 trucks. Thus, the factorial structure provides a practical basis for terrain-sensitive fleet deployment recommendations.

3.3. Statistical analysis and assumption testing

Prior to the factorial Analysis of Variance (ANOVA), diagnostic tests were conducted to ensure that the telematics dataset was suitable for linear modeling. Because factorial ANOVA can be treated within the general linear model framework, the diagnostics focused on residual normality, variance homogeneity, and independence of observations (O'Brien 2007; Montgomery 2017; Ross and Willson 2017; Kim 2019). Normality was assessed using the Kolmogorov-Smirnov test, while homogeneity of variance across factorial groups was evaluated using Levene's test (Ross and Willson 2017).

Table 1. The factorial design with operational combinations

Combination	Truck Type	Speed (km/h)	Load Factor	Road Gradient
1	Euro 4	Low	Low	Flat
2	Euro 4	Low	Low	Hill
3	Euro 4	Low	Low	Mountain
4	Euro 4	Low	Medium	Flat
…	…	…	…	…
52	Euro 3	High	High	Flat
53	Euro 3	High	High	Hill
54	Euro 3	High	High	Mountain

When normality deviations were detected, a Box-Cox transformation was applied to the fuel efficiency response variable to stabilize variance, reduce skewness, and improve distributional symmetry. The transformation was then verified using quantile-quantile plots and repeated normality testing, following standard recommendations for parametric inference in operational datasets (Malik et al. 2018). Since all explanatory variables were categorical, explicit linearity testing was not required; however, diagnostic plots were still examined to ensure consistent response patterns across factor levels.

Multicollinearity was assessed using Variance Inflation Factor (VIF) diagnostics after dummy coding the categorical variables. VIF values well below the commonly used threshold of 10 indicated that collinearity did not compromise model stability or the interpretation of interaction effects (O'Brien 2007; Kim 2019). Residual independence was examined using the Durbin-Watson statistic across consecutive 1 km observation segments, consistent with its application to ordered time or spatial residual series (Chen 2016).

Heteroskedasticity was identified through Levene's test and residual diagnostics. Because unequal variances are common in telematics data with heterogeneous loading and driving conditions, robust standard errors with Huber-White correction were applied to maintain reliable inference under unequal variance conditions (King and Roberts 2015).

After these checks and corrections, a four-way factorial ANOVA was conducted to evaluate the main and interaction effects of emission standard (T), operating speed class (V), load factor class (W), and road gradient category (G) on fuel efficiency. Model performance was assessed using R^2 and adjusted R^2, while Tukey's Honest Significant Difference (HSD) post hoc test was used to identify pairwise differences among operational combinations when significant effects were detected, while controlling the family-wise error rate (Gao 2024; Mirzaei et al. 2025). When variance homogeneity was not fully satisfied, pairwise results were interpreted alongside heteroskedasticity-consistent standard errors to avoid overinterpreting marginal differences.

All analyses were conducted using SPSS, with statistical significance evaluated at the 95% confidence level ($\alpha = 0.05$). This statistical strategy was designed not only to test whether fuel-efficiency differences exist between Euro 3 and Euro 4 trucks, but also to identify the speed, load factor, and road gradient conditions under which these differences are operationally meaningful for fleet assignment and energy-efficiency decision-making.

4. Results and discussion

4.1. Data structure, assumption testing, and overall factorial model performance

This study examines fuel-efficiency performance under actual freight operating conditions while minimizing the influence of unstable traffic situations. For this reason, the analysis was limited to uphill road segments under free-flow traffic, where vehicle speed is more likely to reflect truck performance, road geometry, and loading conditions rather than congestion effects. Twelve observation segments, each 1 km in length, were selected along the Jakarta-Cikampek, Cipularang, and Purbaleunyi toll roads. These roads form a major logistics corridor connecting Tanjung Priok Port and the Greater Bandung area. The selected segments represent sustained uphill grades, horizontal curve radii greater than 550 m, and relatively stable traffic flow. The steepest segment, coded as 92-A, has an average gradient of 6.13%, while the other segments range from approximately 0.01% to 5%. To capture elevation changes more accurately, road gradients were calculated at 50 m intervals within each segment.

The road segments were then classified based on the Indonesian Freeway Geometric Design Standards. Flat segments (≤4%) include 57-B, 57-A, 69-A, 102-A, 112-A, 115-A, and 124-A; hill segments (>4% to ≤5%) include 84-A, 97-A, and 108-B; and mountainous segments (>5%) consist of 86-A and 92-A. The segment codes refer to kilometer markers, with suffix "A" indicating eastbound travel toward Bandung and suffix "B" indicating westbound travel toward Jakarta and Tanjung Priok. This coding system helps ensure that operating conditions can be interpreted consistently across terrain categories and travel directions.

Fuel efficiency observations from Euro 3 and Euro 4 trucks were grouped by operating speed, load factor, and road gradient. Operating speed was classified using K-means clustering into three regimes: low (<20 km/h), medium (20-40 km/h), and high (>40 km/h). Load factor, defined as the ratio of actual gross vehicle weight to rated capacity, was also divided into three categories: low (<30%), medium (30-75%), and high (>75%). The initial dataset contained 1,094 telematics records, consisting of 620 Euro 3 observations and 474 Euro 4 observations. Most records were concentrated in medium-speed, medium-load, and hill-gradient conditions, while high-speed, high-load, and mountainous cases were less frequent. This pattern reflects the actual distribution of freight operations along the studied corridor.

To improve the reliability of the analysis, outliers were identified using the interquartile range (IQR) criterion and removed when they fell outside Q1 - 1.5×IQR or Q3 + 1.5×IQR. After filtering, 828 valid observations remained, consisting of 540 Euro 3 records and 288 Euro 4 records. This corresponds to the removal of 12.9% of Euro 3 data and 39.2% of Euro 4 data. The cleaned dataset was still dominated by flat to hilly gradients and medium load factors, while high-speed and high-load mountainous cases remained limited. Thus, the statistical analysis mainly represents typical freight operations rather than extreme or anomalous operating events.

Before conducting the four-way ANOVA, diagnostic checks were performed to assess whether the dataset was suitable for factorial analysis. The Kolmogorov-Smirnov test showed that the raw fuel efficiency data were not normally distributed ($p < 0.001$). After applying a Box-Cox transformation with $\lambda = 0.25$, the normality assumption was satisfied ($p = 0.068$). Multicollinearity was not an issue, as the Variance Inflation Factor (VIF) values ranged from 1.017 to 1.312, well below the commonly accepted threshold of 10. Residual independence was also supported by a Durbin-Watson statistic of 1.953. However, the Glejser and Breusch-Pagan tests indicated heteroskedasticity ($p < 0.05$). Therefore, robust Huber-White standard errors were applied to maintain reliable statistical inference under unequal variance conditions.

The four-way factorial ANOVA demonstrated strong explanatory performance, with $R^2 = 0.851$ and adjusted $R^2 = 0.840$. This means that approximately 85.1% of the variation in fuel efficiency can be explained by the combined effects of operating speed, load factor, road gradient, and emission standard. The model covered 54 operational combinations ($2 \times 3 \times 3 \times 3$), and the overall factorial model including factors ($V \times W \times G \times T$) was statistically significant ($F(53, 774) = 78.342$, $p < 0.001$). The Partial Eta Squared value of 0.851 indicates a very large effect size. These results show that fuel efficiency is not shaped by emission standard, speed, load factor, or road gradient separately, but by the way these factors interact under real freight operating conditions.

4.2. Interaction effects among emission standard, speed, load factor, and road gradient

The significant interaction among operating speed, load factor, road gradient, and emission standard shows that fuel-efficiency performance cannot be explained by a single factor alone. Instead, each factor changes in importance depending on the operating context. In practical terms, the difference between Euro 3 and Euro 4 trucks cannot be understood only from the emission standard, because road gradient, vehicle load, and speed regime also shape the final fuel-efficiency outcome. This supports the use of combined operational scenarios rather than average fuel-efficiency values or single-factor comparisons (Zhou et al. 2016; Wang and Rakha 2017; Posada-Henao et al. 2023).

This interaction becomes clearer when Euro 4 performance is observed across different terrain categories. Under favorable terrain, Euro 4 trucks generally show better fuel-efficiency performance. However, this advantage becomes less stable as road gradient increases. For example, at high speed and high load, Euro 4 achieves 3.167 km/l on flat terrain, but this value decreases to 1.798 km/l on hilly terrain and further declines to 1.202 km/l on mountainous terrain. This pattern indicates that steep gradients reduce the ability of Euro 4 trucks to maintain their fuel-efficiency advantage, especially when the truck operates under higher speed and heavier load conditions.

A similar pattern is observed under medium-speed and high-load conditions. As the road gradient changes from flat to hill and mountain, Euro 4 fuel efficiency also decreases. This indicates that road gradient amplifies the effect of load factor and operating speed on fuel efficiency. When the vehicle carries heavier loads on uphill segments, more engine power is required to overcome gravitational resistance (Wang and Rakha 2017; Hauenstein et al. 2021; Posada-Henao et al. 2023). As a result, the potential efficiency benefit of Euro 4 technology becomes smaller under more demanding terrain conditions.

These results also help explain why the fuel-efficiency gap between Euro 4 and Euro 3 trucks narrows in several hilly and mountainous scenarios. Under flat terrain, road resistance is relatively lower, allowing Euro 4 trucks to operate more efficiently. In contrast, under steeper terrain, the combined effects of gradient resistance, heavier load, and higher operating speed increase engine demand. Under these conditions, the fuel-efficiency advantage of Euro 4 becomes less consistent, and Euro 3 trucks may show comparable fuel-efficiency performance in selected operating scenarios.

A plausible technical explanation is that Euro 4 emission-control systems may increase energy demand under sustained uphill and high-load operation. SCR systems require sufficiently high exhaust-gas temperatures to maintain catalyst activity, while EGR systems can introduce thermodynamic and pumping losses under heavy-load conditions (Li et al. 2022). Experimental studies also show that higher EGR rates can increase brake-specific fuel consumption and reduce brake thermal efficiency due to oxygen dilution, poorer combustion quality, increased pumping work, and higher heat losses, indicating a trade-off between NOx reduction and engine efficiency (Zhang et al. 2024a; Rimkus et al. 2025). During prolonged high-load operation on mountainous roads, the simultaneous operation of EGR and SCR may impose additional thermal and mechanical demands, requiring extra fuel to satisfy both traction and emission-control requirements (Gopinath et al. 2023; Zhang et al. 2024b). Thus, although Euro 4 technology provides environmental benefits through lower NOx emissions, it may involve fuel penalties under demanding uphill conditions, making Euro 3 comparatively competitive in selected high-speed and steep-grade scenarios (Li et al. 2022).

Overall, the interaction results indicate that Euro 4 technology provides fuel-efficiency benefits mainly under more favorable operating conditions, particularly on flatter terrain and moderate operating regimes. However, under hilly and mountainous conditions, especially when combined with higher speed and heavier load, this advantage becomes smaller and less consistent. Therefore, the performance of Euro 4 trucks should be interpreted as condition-dependent rather than universally superior. This finding provides the basis for the matched comparison and terrain-sensitive deployment strategy discussed in the following sections.

4.3. Matched comparison between Euro 3 and Euro 4 trucks

To translate the ANOVA results into operationally meaningful insights, direct pairwise comparisons between Euro 4 and Euro 3 trucks were conducted under identical combinations of speed, load factor, and road gradient. Since each operating condition is shared by both truck types, this procedure produced 27 matched operational scenarios (3 × 3 × 3). This matched comparison allows technology-to-technology evaluation under equivalent driving environments and helps isolate the influence of emission standard from terrain, speed, and load effects.

The comparison results indicate that Euro 4 does not always exhibit statistically superior fuel efficiency across all operating conditions. On flat segments, differences are not statistically significant at low speed with low load factor ($\Delta = 1.193$ km/l, $p = 0.150$) and at medium speed with low load factor ($\Delta = 1.264$ km/l, $p = 0.070$). This means that under relatively light-duty conditions on flat terrain, Euro 3 and Euro 4 trucks may be operationally comparable from a fuel efficiency perspective.

On hilly terrain, the Euro 4 advantage becomes less consistent. No significant differences are observed at low speed with low load factor ($\Delta = 0.995$ km/l, $p = 0.100$), low speed with medium load factor ($\Delta = 0.602$ km/l, $p = 0.150$), medium speed with high load factor ($\Delta = 0.160$ km/l, $p = 0.150$), high speed with medium load factor ($\Delta = 0.373$ km/l, $p = 0.110$), and high speed with high load factor ($\Delta = 0.296$ km/l, $p = 0.580$). These findings suggest that under more demanding hilly conditions, the fuel-efficiency advantage of Euro 4 is not consistently significant, particularly when load and speed increase.

Under mountainous conditions, the convergence between Euro 3 and Euro 4 becomes more apparent. Fuel-efficiency differences are not statistically significant at low speed with medium load factor ($\Delta = 0.201$ km/l, $p = 0.480$), low speed with high load factor ($\Delta = 0.201$ km/l, $p = 0.480$), medium speed with low load factor ($\Delta = 0.814$ km/l, $p = 0.103$), medium speed with medium load factor ($\Delta = 0.067$ km/l, $p = 0.844$), medium speed with high load factor ($\Delta = 0.144$ km/l, $p = 0.582$), high speed with medium load factor ($\Delta = 0.100$ km/l, $p = 0.845$), and high speed with high load factor ($\Delta = 0.102$ km/l, $p = 0.807$). These results indicate that under steep terrain and moderate-to-heavy load conditions, the two emission technologies exhibit increasingly comparable fuel-efficiency performance.

To present these technology-specific comparisons more clearly, Table 2 summarizes the fuel-efficiency differences between Euro 4 and Euro 3 trucks under 27 matched operational scenarios. The differences were calculated as Euro 4 minus Euro 3 average fuel efficiency for each matched operating condition. The relative difference quantifies the Euro 4 advantage in percentage terms. This matched comparison allows the effect of emission standard to be interpreted under equivalent operating conditions.

As shown in Table 2, Euro 4 shows more consistent fuel-efficiency advantages on flat terrain, particularly under medium and high load factors. However, this advantage becomes less consistent on hilly and mountainous terrain. Under mountain conditions, most matched scenarios show statistically insignificant differences, especially when trucks operate with medium to high load factors. These results indicate that the fuel-efficiency advantage of Euro 4 is conditional rather than universal and depends strongly on the combined effects of road gradient, operating speed, and load factor.

Overall, Euro 4 advantages are most consistent under flatter terrain and moderate operating regimes. However, as road gradient, speed, and load factor increase, the fuel-efficiency gap between Euro 4 and Euro 3 becomes smaller and often statistically insignificant. Therefore, Euro 4 cannot be treated as universally superior in terms of fuel efficiency, although it remains preferable from an emission-control perspective.

Table 2. Fuel-efficiency difference between Euro 4 and Euro 3 trucks (Euro 4 − Euro 3)

Speed	Load Factor	Gradient	Fuel-Efficiency Difference (Δ, km/l)	Sensitivity (%)	p-value	Significance
Low	Low	Flat	1.193	33.2	0.150	NS
Low	Low	Hill	0.995	39.8	0.100	NS
Low	Low	Mountain	1.201	50.0	0.030	S
Low	Medium	Flat	1.095	47.6	0.048	S
Low	Medium	Hill	0.602	40.1	0.150	NS
Low	Medium	Mountain	0.201	25.1	0.480	NS
Low	High	Flat	0.701	46.7	0.020	S
Low	High	Hill	0.642	49.3	0.010	S
Low	High	Mountain	0.201	25.1	0.480	NS
Medium	Low	Flat	1.264	29.4	0.070	NS
Medium	Low	Hill	0.527	19.3	0.020	S
Medium	Low	Mountain	0.814	30.1	0.103	NS
Medium	Medium	Flat	1.319	39.4	<0.001	S
Medium	Medium	Hill	0.390	22.2	<0.001	S
Medium	Medium	Mountain	0.067	5.1	0.844	NS
Medium	High	Flat	0.632	29.1	<0.001	S
Medium	High	Hill	0.160	12.5	0.150	NS
Medium	High	Mountain	0.144	14.4	0.582	NS
High	Low	Flat	0.521	11.5	<0.001	S
High	Low	Hill	0.678	17.9	<0.001	S
High	Low	Mountain	0.689	23.3	0.011	S
High	Medium	Flat	1.832	39.4	<0.001	S
High	Medium	Hill	0.373	16.1	0.110	NS
High	Medium	Mountain	0.100	6.2	0.845	NS
High	High	Flat	1.016	32.1	<0.001	S
High	High	Hill	0.296	16.5	0.580	NS
High	High	Mountain	0.102	8.5	0.807	NS

Notes: Δ = Euro 4 − Euro 3. Positive Δ values indicate that Euro 4 has higher fuel efficiency than Euro 3 under the same speed, load factor, and road gradient condition. S = significant ($p < 0.05$), NS = not significant.

4.4. Terrain-sensitive fleet deployment implications

The matched comparison results provide a practical basis for terrain-sensitive fleet deployment. Rather than assigning trucks solely by emission standard, fleet operators should consider how terrain, speed, and load factor jointly affect fuel efficiency. This is particularly important under medium-to-high speed and medium-to-high load operations, where the fuel-efficiency gap between Euro 3 and Euro 4 trucks becomes more sensitive to road gradient.

Fig. 2 highlights four critical operating scenarios for fleet deployment decisions: medium speed–high load, high speed–high load, medium speed–medium load, and high speed–medium load. These scenarios represent demanding freight conditions in which the interaction between load, speed, and terrain is most relevant. The figure shows that Euro 4 generally maintains a clearer fuel-efficiency advantage on flat terrain, but its advantage narrows as gradient increases from flat to hill and mountain, especially under higher load and speed conditions. This pattern confirms that Euro 4 performance is not uniform across all operating environments, but depends strongly on the terrain-speed-load combination.

To translate these findings into operational guidance, Table 3 summarizes a terrain-sensitive fleet deployment strategy based on the selected scenarios in Fig. 2. The strategy focuses on medium-to-high speed and medium-to-high load operations because these conditions represent more demanding freight operations and show clearer changes in the Euro 4-Euro 3 fuel-efficiency gap across terrain categories.

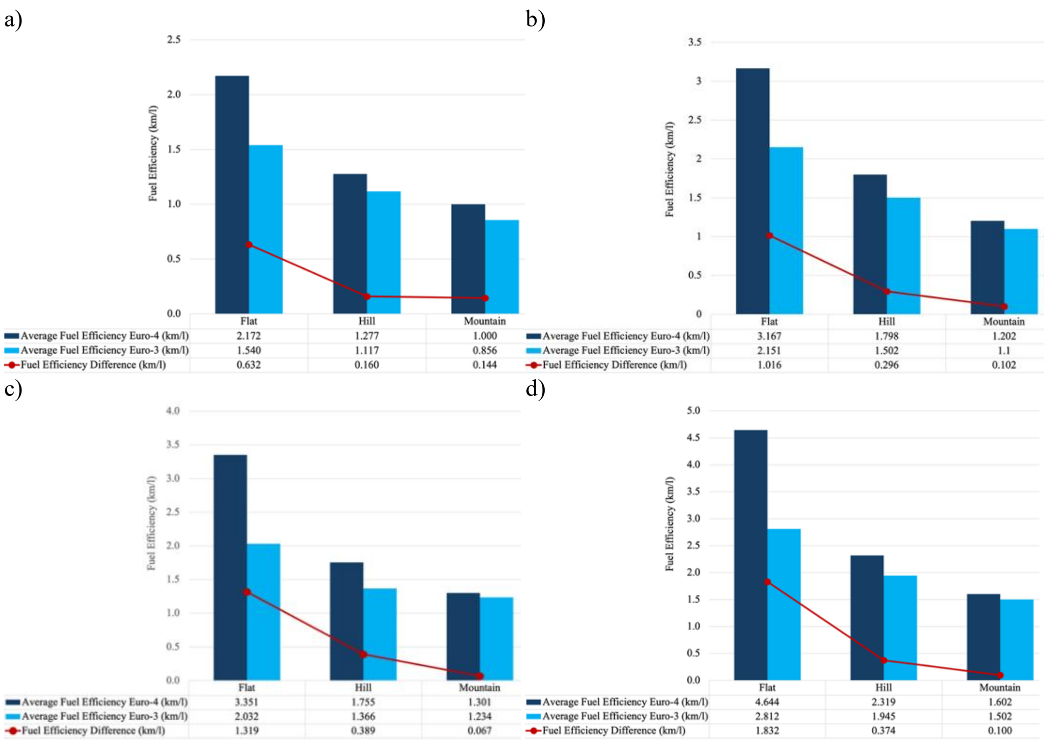

Fig. 2. Average fuel efficiency comparison of Euro 3 and Euro 4 trucks across road-gradient categories under selected critical speed-load scenarios: a) medium speed–high load; b) high speed–high load; c) medium speed–medium load; and d) high speed–medium load

Table 3. Terrain-sensitive fleet deployment strategy based on selected speed-load scenarios

Speed-load scenario	Flat terrain	Hilly terrain	Mountainous terrain
Medium speed - high load	Prioritize Euro 4	Use Euro 4 selectively with load control	Euro 3 and Euro 4 are operationally comparable; avoid relying on Euro 4 solely for fuel efficiency
High speed - high load	Euro 4 remains suitable, but monitor fuel use	Avoid prioritizing Euro 4 solely for fuel efficiency; reduce speed or load	Euro 3 and Euro 4 are operationally comparable; avoid high-speed heavy-load operation
Medium speed - medium load	Prioritize Euro 4	Euro 4 remains preferable, but monitor gradient effects	Euro 3 and Euro 4 may be comparable; validate with route-specific conditions
High speed - medium load	Prioritize Euro 4	Use Euro 4 selectively with speed control	Euro 3 and Euro 4 may be comparable; combine deployment with speed management

Notes: The strategy is based on the selected critical scenarios shown in Fig. 2 and applies mainly to medium-to-high speed and medium-to-high load operations. "Operationally comparable" indicates that the Euro 4 fuel-efficiency advantage is reduced or statistically insignificant. Euro 4 remains preferable from an emission-control perspective.

The strategy indicates that Euro 4 trucks should be prioritized on flat corridors, where their fuel-efficiency advantage is more consistent. On hilly terrain, Euro 4 can still be used, but deployment should be accompanied by speed and load control because its advantage decreases as operating demand increases. On mountainous terrain, the decision should not rely only on emission standard, as Euro 3 and Euro 4 trucks may become operationally comparable from a fuel-efficiency perspective under higher loads or speeds. These findings do not imply that Euro 3 trucks are environmentally preferable. Euro 4 trucks remain preferable from an emission-control perspective because the standard is designed to reduce regulated pollutants such as NOx and particulate matter. However, from an energy-efficiency perspective, Euro 4 deployment should be aligned with terrain, speed, and load conditions. By adopting terrain-, speed-, and load-specific deployment strategies, fleet operators can improve vehicle assignment, reduce unnecessary fuel consumption, lower operating costs, and support energy-efficiency planning on freight corridors with complex topography.

4.5. Limitations and generalizability of the findings

The findings should be interpreted with consideration of the structure and scope of the dataset. First, the final dataset was not fully balanced between Euro 3 and Euro 4 trucks, consisting of 540 Euro 3 observations and 288 Euro 4 observations after data cleaning. This imbalance reflects the availability of real-world telematics data from participating fleet operations and may affect the precision of comparisons in some matched operational scenarios. Second, several combinations involving high speed, high load, and mountainous terrain contained relatively few observations because such conditions occurred less frequently in actual freight operations along the studied corridor. Therefore, results for these specific combinations should be interpreted cautiously, particularly when drawing conclusions from matched scenarios with limited sample representation. Third, the analysis was limited to five-axle semi-trailer trucks operating on selected uphill segments of the Jakarta-Cikampek, Cipularang, and Purbaleunyi toll roads. Consequently, the findings are most applicable to freight corridors with similar vehicle configurations, payload characteristics, roadway geometry, and topographic conditions. Broader application to other truck classes, emission standards, road networks, or regional contexts requires further validation using additional fleets, longer observation periods, and more diverse operating environments.

These limitations do not invalidate the observed interaction patterns, but they indicate that the proposed deployment strategy should be interpreted as corridor- and vehicle-specific until further validation is conducted. Therefore, the results should be used as an empirical basis for terrain-sensitive fleet deployment in comparable freight corridors rather than as a universal rule for all heavy-duty truck operations. Despite these limitations, the study provides a practical framework for comparing Euro 3 and Euro 4 fuel-efficiency performance under matched real-world operating conditions and for identifying when Euro 4 advantages are maintained, reduced, or statistically insignificant.

5. Conclusion

This study provides empirical evidence on fuel-efficiency differences between Euro 4 and Euro 3 five-axle semi-trailer trucks operating on uphill toll-road segments in Indonesia using manufacturer-based telematics data and a multivariable factorial analysis framework. The findings show that fuel efficiency is shaped not by vehicle technology alone, but by the interaction among emission standard, operating speed, vehicle load, and road gradient. Euro 4 trucks generally achieve higher fuel efficiency on flat road segments, particularly at low to medium speeds with medium to high load factors. However, this advantage decreases on hilly and mountainous segments, especially under higher speeds and heavier loads, where the fuel-efficiency advantage of Euro 4 becomes less consistent and is often statistically insignificant.

The reduced Euro 4 advantage under steep and high-load conditions may be linked to the operating requirements of emission-control systems. SCR requires sufficiently high exhaust-gas temperatures to maintain catalyst activity, while EGR can reduce oxygen availability and increase pumping losses. During sustained uphill operation with heavy loads, these mechanisms may increase energy demand and narrow the fuel-efficiency gap between Euro 4 and Euro 3 trucks.

These findings indicate that Euro 4 fuel-efficiency benefits are condition-dependent. Therefore, fleet deployment should not rely solely on emission standard, but should also consider road gradient, speed, and payload. Euro 4 trucks should be prioritized on relatively flat corridors and moderate operating regimes, while Euro 3 trucks may remain operationally comparable from a fuel-efficiency perspective on selected steep corridors with heavier loads. Nevertheless, Euro 4 remains preferable from an emission-control standpoint.

Methodologically, this study demonstrates the value of integrating manufacturer-based telematics data, factorial experimental design, and matched operational scenarios to evaluate truck performance under real operating conditions. The proposed framework provides a practical alternative to fully mechanistic calibration-based methods such as HDM-4 and supports terrain-sensitive fleet deployment decisions.

The findings should be generalized carefully because the analysis is based on specific vehicle types, selected uphill toll-road segments, and observed freight operations in Indonesia. Future research should include longer observation periods, additional truck technologies, broader route types, and driving behavior indicators such as engine speed, gear selection, throttle position, and acceleration patterns. Integrating telematics data with machine-learning models may further support route- and load-specific fleet deployment strategies for more efficient and sustainable freight transportation systems.

Abbreviations

ANOVA - Analysis of Variance
BSFC - Brake-Specific Fuel Consumption
CNN - Convolutional Neural Network
CO_2 - Carbon Dioxide
DOE - Design of Experiments
DW - Durbin-Watson statistic
ECU - Electronic Control Unit
EGR - Exhaust Gas Recirculation
EU - European Union
FC - Fuel Consumption
FE - Fuel Efficiency
GPS - Global Positioning System
GVWR - Gross Vehicle Weight Rating
HSD - Honest Significant Difference
HDM-4 - Highway Development and Management Model (Version 4)
IQR - Interquartile Range
km/l - kilometers per liter
K-S - Kolmogorov-Smirnov test
LSTM - Long Short-Term Memory
MAE - Mean Absolute Error
ML - Machine Learning
NO_x - Nitrogen Oxides
OBD / OBD-II - On-Board Diagnostics
PCC - Predictive Cruise Control
PM - Particulate Matter
Q-Q plot - Quantile-Quantile plot
R^2 - Coefficient of Determination
RMSE - Root Mean Square Error
SCR - Selective Catalytic Reduction
SPSS - Statistical Package for the Social Sciences
VIF - Variance Inflation Factor
VOC - Vehicle Operating Costs

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