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Modeling Fuel Consumption of Heavy-duty Trucks Using Telematics Data

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Abstract

Fuel is the largest cost component in Vehicle Operating Costs (VOC) and a significant contributor to greenhouse gas (GHG) emissions in the trucking sector. This study developed a real-time telematics-based fuel consumption model for Euro-3 and Euro-4 trucks operating on toll roads in Indonesia, focusing on 5-axle heavy-duty trucks. The model utilizes telematics data, including average speed, gross vehicle weight, and road gradient under free-flow conditions, a novel aspect of this research. Two modeling approaches were applied: Model 1 employed multiple linear regression with Box-Cox transformation, while Model 2 utilized Generalized Linear Models (GLM) with a Gamma distribution and log link. Model 1 performed better, explaining 85.8% of the variability in fuel consumption (adjusted $R^2 = 0.858$) with a deviance of 0.947, RMSE of 0.033, and AIC of −3.246.625. Conversely, Model 2 recorded a deviance of 8.827, RMSE of 0.296, and AIC of −2.483. The Wilcoxon Signed Ranks Test indicated no significant differences between predicted and observed fuel consumption for both truck types, with a Z value of −1.700 ($p = 0.089$) for Euro-4 and −0.038 ($p = 0.970$) for Euro-3, supporting the model's reliability. Beyond optimizing fuel consumption, the model offers practical recommendations for truck operators considering conversion to Euro-4 and provides valuable insights for policymakers developing energy efficiency strategies in the transportation sector. Further research is recommended to expand the model's application to non-toll routes and integrate machine learning for more complex patterns.

Keywords

fuel consumption, emission, euro-4, telematics data, heavy-duty truck

1 Introduction

Logistics plays a significant role in economic growth. However, the high logistics costs remain a major challenge to Indonesia's economic competitiveness (Kanungo, 2014; Wirabrata and Silalahi, 2012). Transportation expenses contribute 46.4% of the total national logistics costs, with road transport dominating at 67.13% (Santoso et al., 2021). In Indonesia, trucking constitutes 80–90% of road transportation, making it a crucial sector within the national logistics system (Ministry of Transportation, 2021; Yang et al., 2021). Economically, fuel represents the largest component of truck Vehicle Operating Costs (VOC). In the United States, fuel accounts for approximately 21% of truck VOC (Leslie and Murray, 2022), while in Indonesia, this figure is higher, reaching 28% (Brasukra and Hergesell, 2008). In the regions of DKI Jakarta and West Java, fuel's share in truck VOC further increases to 32% (Burhanudzaky and Nariendra, 2022). An even more severe scenario occurs on non-toll roads in South Sumatra, where fuel costs constitute between 44.3% and 49.3% of total VOC (Kadarsa et al., 2019). On the Kanci-Pemalang route, fuel costs for 5-axle trucks range from 40.76% to 46.87% of the total trip cost, emphasizing the significant role of fuel in logistics costs (Nariendra, 2024). High fuel consumption affects not only transport expenses but also has broader implications for local and national economies (Posada-Henao et al., 2023).

Several studies indicate that vehicle fuel consumption is influenced by both vehicle and road conditions (Ahn et al., 2002; Zhou et al., 2016). Gross weight and road gradient have a more pronounced impact than speed, particularly under overloaded conditions (Wang et al., 2017a; Posada-Henao et al, 2023). In Indonesia, inclines significantly increase operational costs, while reducing gradients can decrease these costs by up to 13% (Sudjana, 2011). Flat routes can save between 5% and 20% in fuel consumption compared to hilly routes (Zaabar and Chatti, 2014; Zhou et al., 2016). Implementing eco-driving systems on hilly terrain can

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enhance efficiency by approximately 7% (Kamal et al., 2011), whereas low gradients can save up to 9% for fully loaded trucks (Carrese et al., 2013; Zaabar and Chatti, 2014). Mathematical models have demonstrated that road gradients significantly affect engine power, fuel consumption, and exhaust emissions (Gao et al., 2019; Posada-Henao et al., 2023). Within the VOC context, vehicle speed and gross weight are critical factors differentiating operational costs between normal and overloaded conditions (Setiawan and Tjahjono, 2020).

In addition to affecting operational costs, trucking significantly contributes to greenhouse gas (GHG) emissions. Each increase of 1 liter/100 km in fuel consumption corresponds to an increase of 26.4 g/km of CO_2 emissions (Yang et al., 2021; Department for Energy Security & Net Zero, 2023). Heavy-duty trucks are major emitters of CO_2 and NOx, emitting higher levels compared to other vehicles (Mahalana et al., 2022). To address rising emissions, the Indonesian government has implemented Euro-4 emission standards aligned with the Paris Agreement and Sustainable Development Goals (Ministry of Environment and Forestry, 2017). Euro-4 standards provide fuel efficiency improvements of 10–15% over Euro-3 trucks, reducing CO_2 and NOx emissions by up to 30% (Erkkilä and Nylund, 2007; Maulidya, 2019).

The HDM-4 model has been widely applied to predict fuel consumption through local calibration in various countries. However, its complexity due to the need for calibrating engine parameters, frontal area, and rolling resistance renders it less effective for rapid applications in the transport industry and less accurate for heavy-duty trucks (Jiao and Bienvenu, 2015; Perrotta et al., 2019; Nariendra and Lestiani, 2025).

The novelty of this research lies in the development of a new, practical, and simplified real-time telematics-based fuel consumption model for 5-axle Euro-4 and Euro-3 trucks, utilizing data on average operational speed, gross vehicle weight, and road gradient. This approach eliminates the need for complex parameter calibration as required in the HDM-4 model, thereby enhancing implementation efficiency and relevance to operational conditions on Indonesian toll roads. Additionally, the model aligns with Euro-4 GHG reduction policies (Ministry of Environment and Forestry, 2017) by developing a model more suited to modern heavy vehicles and road conditions in Indonesia.

The objective of this research is to develop a real-time telematics-based fuel consumption model for Euro-4 and Euro-3 trucks operating on toll roads in Indonesia and to compare predictive and observed fuel consumption to assess the model's effectiveness. Linear regression analysis was employed to construct the model, while the Wilcoxon Signed-Rank Test was applied to evaluate its accuracy in reflecting operational conditions.

The main advantage of this research lies in the use of real-time telematics data, which offers higher accuracy because it can collect large datasets. However, its current application is limited to toll roads and 5-axle trucks, indicating the need for further studies to expand its applicability. Additionally, the model's effectiveness heavily relies on the quality of the collected data, particularly under extreme operational conditions.

Overall, this research makes a significant contribution by replacing the Euro-1 parameter-based truck model in the Bina Marga method (Iskandar et al., 2000) with a telematics-based approach for Euro-3 and Euro-4 trucks. By integrating real-time data on speed, gross weight, and road gradient, the proposed model not only enhances accuracy but also increases its relevance to current operational conditions. This approach also provides a methodological framework for future studies related to the implementation of emission standards.

2 Methodology

This research focuses on 5-axle semi-trailer trucks transporting containers with Euro-3 and Euro-4 emission standards, operating along the primary logistics route between Tanjung Priok Port and Bandung. This route features varying road gradients and pavement conditions representative of toll roads in Indonesia. The research objects are the Hino FG 260 TH (Euro-4) and UD Quester GKE (Euro-3) trucks, selected due to their prevalent use by companies, similar comprehensive telematics systems, and nearly equivalent weight-power ratios of 5.6 kW/ton and 5.7 kW/ton, respectively, ensuring consistent truck performance

Data collection occurred over two months (February-March 2024) through manufacturer-integrated telematics systems linked with GPS, including Hino Connect, My UD Fleet, and Transport Management System (TMS), capturing average operational speed, gross vehicle weight, fuel consumption, and road gradient. Telematics data were obtained from vehicle sensors such as GPS, On-Board Diagnostics (OBD-II), and IoT networks, subsequently transmitted through the Electronic Control Unit (ECU) for analysis to evaluate heavy-duty vehicle operational efficiency under real-world conditions (Farzaneh et al., 2020; SAE International Technical Standard, 2022; Perrotta et al., 2019).

Road gradients were calculated using elevation data from Google Earth with an accuracy of MAE 1.32 meters and RMSE 2.27 meters, deemed adequate for transportation applications (Wang et al., 2017b). Road gradient categorization followed the Indonesian Geometric Road Design Guidelines, classifying gradients into flat, hilly, and mountainous categories (Directorate General of Highways, 2020). Data were specifically focused on uninterrupted operations with stable speeds and curve radii greater than 550 meters, as fuel consumption on such curves closely matches straight roads, minimizing impacts on fuel usage and CO_2 emissions (Zhang et al., 2019). The data pre-processing involved identifying and removing outliers using the Z-score method (threshold ±3 standard deviations) and linear interpolation to handle missing data, maintaining dataset consistency.

Two analytical models were employed. Model 1 used Ordinary Least Squares (OLS) to analyze the influence of speed, gross vehicle weight, and road gradient on fuel consumption. Before estimation, linear regression assumptions were validated through residual normality and homoscedasticity tests. Violations of these assumptions were addressed using robust standard errors and Box-Cox transformations to correct data distribution issues (King and Roberts, 2015; Malik et al., 2018). Alternatively, Model 2 utilized Generalized Linear Models (GLM) with Gamma distribution and log link function to effectively handle skewed fuel consumption data and manage heteroscedasticity. Model validation involved comparing Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), considered more effective than R^2 for optimal model selection (Dobson and Barnett, 2018).

To ensure model reliability, predicted results were compared with observed data. Hypothesis testing evaluated whether significant differences existed between predicted and observed fuel consumption. The Wilcoxon Signed-Rank Test, a non-parametric method not reliant on normal distribution assumptions, was employed to assess paired averages, especially when observed data failed normality assumptions. The null hypothesis (H0) proposed no significant differences between predictive and observed fuel consumption, implying zero difference between them (Deshpande et al., 2017). This test determined whether differences between predictions and observations were sufficiently significant to reject the null hypothesis or if predictive data could accurately reflect observed data.

3 Data and results

The results of data processing and analysis included segmentation, grouping, and outlier identification in truck fuel consumption modeling. This analysis continued with examining factors influencing fuel consumption and developing predictive models. Subsequently, the model's accuracy was evaluated by comparing the predictive data with observed data.

3.1 Data processing

Data management in this research began with segmenting road sections based on gradient and vehicle speed under free-flow conditions. This segmentation aimed to create more homogeneous and representative observation segments, enabling a more accurate analysis of gradient impacts on vehicle performance and fuel consumption. Three gradient categories were utilized: flat, hilly, and mountainous, covering 12 road segments on the Jakarta-Cikampek, Cipularang, and Purbaleunyi Toll Roads. Segment identification codes corresponded to kilometer markers on the toll roads, using Code A for truck movements from Tanjung Priok to Bandung and Code B for the opposite direction. The flat segments included segments 57-A and 57-B, with maximum gradients of 0.01% and 0.07%, respectively. Meanwhile, the hilly and mountainous segments included segment 108-B with a gradient of 4.72% and segment 92-A with a gradient of 6.13%. A total of 1,094 speed data points were collected, comprising 474 data points for Euro-4 trucks and 620 for Euro-3 trucks. These data were categorized based on vehicle speed, gross vehicle weight, and road gradient. Speed was classified into three levels: low (below 20 km/h), medium (20–40 km/h), and high (above 40 km/h). Gross vehicle weight (load factor) was grouped into three categories: low (below 30%), medium (30–75%), and high (above 75%). Road gradients were divided into flat (maximum 4%), hilly (maximum 5%), and mountainous (maximum 6%). The map of observation segments based on road gradient is presented in Fig. 1,

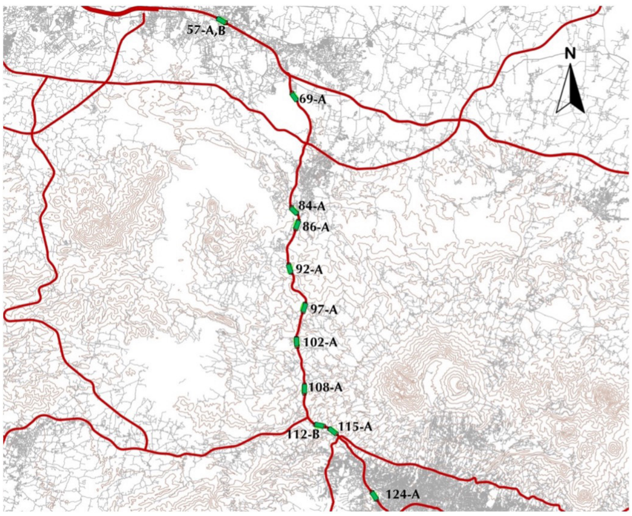

Fig. 1 The road sections classified based on road gradient

while detailed data on operational speed, gross vehicle weight, and fuel consumption according to road gradients are provided in Table 1.

Results in Table 1 indicate significant variations in speed, gross vehicle weight, and fuel consumption between Euro-4 and Euro-3 trucks across the observed segments. The highest speed for Euro-4 trucks was recorded on segment 57-A with an average of 47.16 km/h (standard deviation 8.73 km/h), while Euro-3 trucks recorded an average speed of 46.42 km/h (standard deviation 7.81 km/h). Conversely, the lowest speeds were observed on segment 108-B, with Euro-4 trucks averaging 28.63 km/h (standard deviation 9.26 km/h) and Euro-3 trucks averaging 26.43 km/h (standard deviation 7.53 km/h). Notable differences were also observed in gross vehicle weight. On segment 92-A, Euro-3 trucks had the highest average gross weight of 33.04 tons (standard deviation 10.35 tons), whereas Euro-4 trucks averaged 28.33 tons (standard deviation 9.01 tons). The lowest weight for Euro-4 trucks was on segment 124-A, averaging 23.87 tons (standard deviation 7.36 tons), while Euro-3 trucks averaged 30.78 tons (standard deviation 10.72 tons) on segment 57-A. Fuel consumption demonstrated a consistent pattern, with Euro-4 trucks generally showing greater efficiency than Euro-3. On segment 57-A, Euro-4 trucks had a fuel consumption of 6.98 km/l (standard deviation 2.86), significantly higher than Euro-3 trucks with 3.76 km/l (standard deviation 1.25). However, on segment 92-A, which features steep gradients, fuel consumption dropped for both truck types, although Euro-4 trucks remained more efficient with 0.69 km/l (standard deviation 0.27), compared to Euro-3 trucks at 0.61 km/l (standard deviation 0.29). Overall, these findings illustrate that Euro-4 trucks not only operated with lighter loads but were also more fuel-efficient, particularly on flat and hilly segments, compared to Euro-3 trucks.

3.2 Fuel consumption modeling

This research models fuel consumption (FC) as the dependent variable, with average vehicle operating speed (V),

Table 1 Summary of speed, gross weight, and fuel consumption data by road gradient

Segment	Road Gradient (%)	Truck Type	Data count	Average operation speed (V)		Gross vehicle Weight (W)		Fuel consumption (FC)	
				Mean V (km/h)	Standard Deviation	Mean W (ton)	Standard Deviation	Mean FC (km/l)	Standard Deviation
57-B	0.01	Euro-4	44	46.88	7.78	32.09	5.57	5.38	1.41
		Euro-3	54	42.92	6.36	32.67	7.48	3.16	0.77
57-A	0.07	Euro-4	37	47.16	8.73	28.42	8.72	6.98	2.86
		Euro-3	51	46.42	7.81	30.78	10.72	3.76	1.25
69-A	1.00	Euro-4	37	46.44	7.50	26.58	9.01	6.88	2.96
		Euro-3	52	46.05	6.26	30.04	10.67	3.58	1.14
84-A	4.32	Euro-4	44	41.07	9.97	27.62	9.79	3.12	1.32
		Euro-3	54	34.63	9.85	31.18	11.16	1.99	0.88
86-A	5.24	Euro-4	47	39.82	10.03	27.51	9.63	1.97	0.87
		Euro-3	53	31.36	11.22	31.23	11.33	1.36	0.63
92-A	6.13	Euro-4	39	31.01	8.85	28.33	9.01	0.69	0.27
		Euro-3	59	26.59	8.71	33.04	10.35	0.61	0.29
97-A	4.41	Euro-4	44	35.96	10.04	29.79	10.01	2.69	1.23
		Euro-3	51	33.29	9.84	31.12	10.82	1.84	0.85
102-A	2.76	Euro-4	39	38.54	10.68	26.81	8.84	4.32	1.71
		Euro-3	50	35.54	12.35	31.52	10.61	2.19	1.02
108-B	4.72	Euro-4	42	28.63	9.26	30.81	5.96	1.80	0.48
		Euro-3	52	26.43	7.53	33.02	7.12	1.21	0.43
112-A	2.85	Euro-4	38	41.79	9.48	30.02	9.08	3.59	1.47
		Euro-3	55	38.98	10.49	32.14	10.53	2.48	0.99
115-A	3.68	Euro-4	34	43.56	8.69	28.35	9.22	3.09	1.25
		Euro-3	50	39.65	9.65	31.88	10.20	2.01	0.74
124-A	3.37	Euro-4	31	45.53	6.82	23.87	7.36	3.93	1.14
		Euro-3	39	40.13	8.90	30.64	9.98	2.24	0.84

gross vehicle weight (*W*), road gradient (*S*), and truck type as a dummy variable (*T*) as independent variables. Meanwhile, gross vehicle weight (*W*) includes the total weight of the vehicle, cargo, truck crew, components, and vehicle equipment. For trucks carrying heavy loads, this total weight can reach 11.794 kg or more (Bennett, 2020).

Simple linear regression tests indicated that variable *V* has a significant non-linear relationship with fuel consumption, yielding an R^2 of 0.509 and an F-value of 856.769. Variable W displayed logistic and exponential non-linear relationship patterns with an R^2 of 0.349 and an F-value of 442.222. Additionally, variable *S* significantly influenced fuel consumption, with an R^2 of 0.356 and an F-value of 228.128. Given the significant effects of all variables, the analysis proceeded with multiple linear regression.

In the subsequent stage, multiple linear regression analysis (Model 1) applied the Box-Cox transformation ($\lambda = 0.25$) to address non-normal residual distributions. The Kolmogorov-Smirnov test after transformation yielded a p-value of 0.095, indicating that the residuals approximated a normal distribution. Multicollinearity tests produced Variance Inflation Factor (VIF) values ranging from 1.031 to 1.578, signifying no multicollinearity issues. The Durbin-Watson test provided a value of 1.953, close to the ideal value of 2, indicating the absence of significant autocorrelation. Although the Glejser test suggested heteroscedasticity in variables *W* and *T*, the Breusch-Pagan test, with a p-value of 0.165, indicated constant residual variance.

The multiple linear regression results from Model 1 indicated significant impacts of all independent variables on fuel consumption. Average operational speed (*V*) exhibited a positive influence, meaning an increase in speed tended to elevate fuel consumption. Conversely, gross vehicle weight (*W*) and road gradient (*S*) showed negative impacts, indicating that increased weight or gradient reduced fuel consumption. Additionally, Euro-4 trucks demonstrated higher fuel efficiency than Euro-3 trucks, with the dummy variable coefficient for truck type showing significant fuel savings for Euro-4 vehicles. Detailed coefficient values, t-values, and p-values for each variable are presented in Table 2, demonstrating significance at a 5% significance level with a critical t-value of 1.647.

As an alternative, Model 2 utilized Generalized Linear Models (GLM) with Gamma distribution and a log link function to model the relationships between the same variables. Goodness-of-fit tests indicated excellent model fit, demonstrated by a deviance of 8.827 with a deviance/df of 0.011, and a Pearson Chi-Square value of 8.755 with a Pearson Chi-Square/df of 0.011. Parameter estimation results from the GLM indicated that operational speed (*V*) and truck type (*T*) positively influenced fuel consumption, with coefficients of 0.018 and 0.316, respectively. Conversely, gross vehicle weight (*W*) and road gradient (*S*) showed negative impacts, with coefficients of −0.030 and −0.148. Detailed results of the GLM parameter estimation are provided in Table 3.

A comparison between Model 1 and Model 2 showed that Model 1 performed better. Model 1 recorded a lower deviance value of 0.947 compared to 8.827 in Model 2 and a smaller RMSE value of 0.033 compared to 0.296. Additionally, the adjusted R-squared value of 0.858 indicated that 85.8% of the variability in fuel consumption could be explained by the independent variables in this model. The AIC value for Model 1 was −3.246.625, superior to Model 2, suggesting lower prediction error levels. Based on performance indicators, multiple linear regression with the Box-Cox transformation (Model 1) is recommended as the optimal model for predicting fuel consumption in Euro-4 and Euro-3 trucks due to its higher accuracy and greater explanatory power, as shown in Table 4. The final regression equation derived from Model 1 is presented in Eq. (1):

$$FC^{0.25} = 1.539 + 0.000066V^2 - 0.009W - 0.048S + 0.098T \quad (1)$$

where:

- FC = fuel consumption (km/l),
- *V* = average operating speed (km/h),
- *W* = gross vehicle weight (ton),
- *G* = positive road gradient (%),
- *T* = truck type (Euro-4 = 1 and Euro-3 = 0).

Table 2 Model 1 parameter estimation

Parameter	Coefficient	Robust Standard Error	t-value	p-value
Intercept	1.539	0.009	178.989	<0.001
V^2	6.64 E-02	2.33 E-03	28.542	<0.001
W	−0.009	0.000	−66.986	<0.001
G	−0.048	0.001	−54.371	<0.001
T	0.098	0.003	35.953	<0.001

Table 3 Model 2 parameter estimation

Parameter	Coefficient	Robust Standard Error	Wald Chi-Square Value	p-value
Intercept	1.399	0.0360	1.507.653	<.0.001
V	0.018	0.0006	1.025.472	<.0.001
W	−0.030	0.0004	4.435.602	<.0.001
G	−0.148	0.0025	3.433.817	<.0.001
T	0.316	0.0082	1.465.779	<.0.001

Table 4 Comparison of model performance metrics

Indicator	Model 1	Model 2
Deviance	0.947	8.827
Pearson Chi-Square	0.947	8.755
Log Likelihood	1.629.313	7.241
AIC	−3.246.625	−2.483
AICC	−3.246.523	−2.380
BIC	−3.218.311	25.832
CAIC	−3.212.311	31.832
RMSE	0.033	0.296
MAE	0.027	0.217
RSS	0.947	72.810

3.3 Comparison of modeled predictions and observed outcomes

Based on the results of the Wilcoxon Signed Ranks Test, a comparison between observed and predicted fuel consumption was conducted for Euro-4 and Euro-3 trucks to evaluate the accuracy of the predictive model. For Euro-4 trucks, a Z value of −1.700 and an Asymp. Sig. (2-tailed) of 0.089 indicated a p-value greater than 0.05, suggesting no statistically significant difference between observed and predicted fuel consumption. However, slight differences may still hold operational relevance, such as variations in terrain or other external conditions. For Euro-3 trucks, a Z value of −0.038 and an Asymp. Sig. (2-tailed) of 0.970 revealed a minimal difference between observed and predicted results, with a p-value significantly greater than 0.05. These results suggest that the predictive model for Euro-3 trucks accurately reflects actual fuel consumption, providing greater confidence in its reliability for predicting real-world performance.

Overall, no significant differences between predicted and observed outcomes were identified for either Euro-4 or Euro-3 trucks, with the Euro-3 predictive model demonstrating higher accuracy. These findings support the validity of the telematics-based predictive model used in this research, particularly for real-world applications. The results align with previous studies indicating that predictive models based on telematics data can effectively reduce prediction errors for trucks with lower emission standards. Nevertheless, the minor discrepancies observed for Euro-4 trucks suggest potential areas for further refinement, including additional analysis of variables such as road surface conditions or variations in vehicle load.

4 Conclusion

This research successfully developed a novel, practical, and accurate real-time telematics-based predictive model for fuel consumption in Euro-4 and Euro-3 trucks operating on Indonesian highways. The contribution of this study lies in the development of a simplified predictive model that eliminates the need for complex parameter calibration as required in conventional models such as HDM-4. Model 1, utilizing multiple linear regression with Box-Cox transformation, demonstrated superior performance compared to the GLM-based Model 2, indicated by lower AIC, BIC, RMSE, and MAE values. The analysis revealed that operational speed, gross vehicle weight, road gradient, and truck type significantly influenced fuel consumption, with an adjusted R^2 of 0.858, meaning that 85.8% of the variability in fuel consumption could be explained by the model. The accuracy evaluation using the Wilcoxon Signed Ranks Test showed no significant differences between predicted and observed values for both Euro-4 and Euro-3 trucks, indicating that the predictive model is sufficiently accurate.

The findings suggest that telematics-based predictive models for fuel consumption can be optimized for truck operations on highways with similar travel characteristics, weather conditions, vehicles, road types, traffic patterns, and driver behavior. Furthermore, this model provides a useful basis for fleet conversion considerations towards Euro-4 trucks. Implementing this model enables truck operators to identify more efficient operational combinations for Euro-4 trucks, optimizing fuel consumption and effectively reducing greenhouse gas emissions. However, to broaden the model's application, testing on non-toll roads, mountainous terrain, and areas with extreme weather conditions is necessary to ensure the model's effectiveness under various operational scenarios.

Future research should focus on challenging terrains, higher load factors, and Euro-5/Euro-6 trucks to support global emission reduction targets. Although multiple linear regression and GLM were chosen for interpretability and data constraints, machine learning methods such as Artificial Neural Networks (ANN), or Decision Trees could be explored to capture more complex data patterns and strengthen the external validity of the model across different geographic settings. Testing on non-toll routes, urban roads, and regions with varying climatic conditions and infrastructure will also be essential to validate the model globally. Additionally, incorporating supplementary variables such as weather, traffic density, and driver behavior could enhance the predictive power of the model in more complex operational situations.

This research contributes to the development of a practical and accurate telematics-based predictive model for fuel consumption, outperforming manually calibrated models such as HDM-4. Thus, the model is not only relevant for truck operations in Indonesia but also has the potential to be applied in other regions with similar characteristics. It also opens opportunities for further research on the impact of additional variables such as weather, fuel type, and driver behavior on fuel consumption and greenhouse gas emissions. Additionally, the model offers a new methodological framework for fuel consumption prediction in 5-axle heavy trucks, integrating real-time telematics data, which is a significant advancement over traditional parameter-based models and aligns with Euro-4 emission reduction policies.

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