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APPLICATION OF DATA ANALYSIS IN ASSESSING FUEL CONSUMPTION EFFICIENCY IN A LOGISTICS ENTERPRISE

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Abstract:
Fuel consumption efficiency is one of the key areas for evaluating the operational performance of vehicle fleets in transport enterprises. Rising operating costs and the need for rational resource management are making the analysis of data recorded during real-world vehicle use increasingly important. This article aims to comprehensively assess the operational efficiency of a vehicle fleet based on a case study of a selected transport enterprise. The analysis also includes the identification of vehicles characterised by unfavourable fuel consumption parameters. As part of the study, the consistency of input data on fuel consumption obtained from the CAN bus, invoices and fuel level sensor readings was assessed against reference data from the telematics system. On this basis, the data source demonstrating the highest level of consistency was identified and used in further analysis. Efficiency was assessed based on total and unit fuel consumption, CO_2 emissions and the costs of excess fuel consumption. The applied criteria made it possible to identify vehicles with elevated fuel demand and suboptimal operational parameters. In addition, a scenario analysis was conducted to estimate potential savings and CO_2 emission reductions achievable by improving the efficiency of the vehicle identified as requiring further inspection. This approach supports fleet management by facilitating the assessment of potential reductions in operating costs and CO_2 emissions. The results indicate that targeted efficiency improvements may reduce fuel consumption and environmental impact without the need for immediate vehicle replacement.

Key words: fuel consumption, fuel efficiency, fleet management, operational data, CO_2 emissions, transport enterprise, telematics

INTRODUCTION

In the daily operations of logistics enterprises, fuel consumption represents a permanent and significant component of operating costs. In aggregated terms, fuel expenditure is estimated to account for approximately half of the total operating costs of road transport [1]. Transport fleets perform similar tasks under comparable operating conditions; nevertheless, the level of fuel consumption and the amount of CO_2 emissions generated may vary significantly between individual vehicles or drivers [2]. Although these differences may be unnoticeable at the level of a single trip, over a period of months or years they can lead to significant financial and environmental consequences. In the face of changes in the fuel market [3], as well as increasing regulatory requirements aimed at reducing greenhouse gas emissions [4], the issue of fuel efficiency is becoming particularly important for logistics enterprises.

Road transport is an integral element of the supply chain, and its operation requires significant energy expenditure in logistics activities [5, 6]. Effective fuel consumption management directly affects the level of operating costs incurred by enterprises, their competitive position, and the achievement of sustainable development goals [3]. The development of telematics tools has enabled the collection of detailed data on vehicle operation. Despite the increasing availability of such information, its analytical potential is not always fully exploited, which may limit the effectiveness of fleet management. From the perspective of a transport enterprise, it is therefore important to determine which vehicles in the analysed fleet account for the largest share of total fuel consumption and CO_2 emissions under real-world operating conditions.

Recent literature indicates a growing number of studies focused on fuel consumption calculation and CO_2 emissions estimation [7, 8, 9]. In parallel, telematics data are increasingly used to analyse driving behaviour, vehicle operational parameters and their impact on fuel consumption [1, 10]. At the same time, there remains a need for studies based on operational data from transport enterprises. Such studies should combine the analysis of real-world fuel consumption and CO_2 emissions with the identification of areas and vehicles generating the greatest operational and environmental burdens.

In response to the identified research gap, this article aims to conduct a comprehensive assessment of the fuel efficiency of an enterprise fleet based on real-world operational data. The scope of the study includes the identification of areas and vehicles generating the highest fuel demand, as well as the assessment of fuel consumption measurement methods in order to select the data source with the highest level of consistency with telematics data. This study uses operational data on fuel consumption and vehicle mileage obtained from invoices, fuel cards and real-world refuelling records. The research was conducted as a case study of a logistics enterprise. The analysis covered heavy-duty vehicles (HDVs) with a gross vehicle weight of 40 tonnes, as well as delivery trucks (DTs) with a gross vehicle weight of up to 3.5 tonnes. The analysed period covered November 2025 to January 2026. The results obtained are application-oriented and support decision-making processes in fleet management. In particular, they enable the identification of units generating above-average fuel consumption, the determination of priorities for corrective and diagnostic actions and the planning of the future fuel demand of the fleet.

LITERATURE REVIEW

Fuel efficiency in road transport is an important research issue, as it directly affects the operating costs of logistics enterprises and the level of CO_2 emissions. Based on previous studies, fuel expenditure may account for a significant share of transport operating costs, reaching approximately 37-48%. In the analysed enterprise, fuel costs are assumed to account for around 30% of transport operating costs; however, in practice, this share may be significantly higher, reaching values close to the upper limit of the indicated range [11]. Even a slight improvement in fuel efficiency at the operational level may lead to noticeable financial savings and a reduction in CO_2 emissions [12]. As a result, reducing fuel consumption not only contributes to lowering the operating costs of the enterprise but is also associated with a decrease in carbon dioxide emissions and other harmful substances generated in road transport.

The complexity of transport processes determines the multifactorial nature of fuel consumption in road transport, resulting from the interaction of technical, operational and driver-related factors. In the literature, it is emphasised that fuel consumption is associated, among other factors, with driver behaviour, particularly driving speed and driving dynamics. Traffic intensity and the technical condition of the vehicle also influence fuel consumption under real-world operating conditions. [1, 7]. In practice, this means that even with similar transport orders and comparable routes within a single fleet, clear differences in fuel consumption may occur between vehicles. At the same time, from an operational perspective, a significant challenge remains the translation of this knowledge into the analysis of data from real-world fleet operation. Such an approach makes it possible to identify units generating the highest fuel consumption and CO_2 emissions, as well as to determine priorities for improvement measures. To systematise the determinants of fuel consumption, a classification was adopted that includes four main groups of factors: the driver's eco-driving behaviour, the technical condition of the vehicle, transport infrastructure and environmental conditions. Factors related to the driver's driving behaviour include vehicle-handling skills, driving experience and the ability to respond appropriately to traffic situations. The group of factors related to the technical condition of vehicles includes, among others, vehicle design, year of manufacture, engine performance and payload capacity. Factors associated with transport infrastructure include route geometry, pavement condition and lane layout. Environmental conditions, in turn, comprise, among others, weather conditions, temperature, precipitation, wind and terrain relief [13]. The application of this approach makes it possible to systematise the factors influencing fuel consumption and provides a starting point for analysing variations in fuel consumption under operational conditions. Studies based on real-world data indicate that even when comparable transport orders are carried out, clear discrepancies in fuel consumption may occur between vehicles from the same fleet. Based on real-world fleet data, the percentage change in fuel consumption observed at the level of individual vehicles when comparing two periods may range from approximately -8.8% to +3.1%, despite a homogeneous technical configuration [14]. Infrastructural factors, particularly road gradient, may also significantly determine the level of fuel consumption [15]. Furthermore, driving style has been shown to shape fuel consumption, substantially differentiating fuel consumption results between trips [16]. When comparing these approaches, it should be noted that the determinants of fuel consumption rarely act independently but interact with one another under real-world conditions, justifying the need for approaches that integrate technical, infrastructural and behavioural aspects. Although the analysed literature emphasises different aspects of the problem, a common conclusion is that fuel consumption is shaped by many interacting factors.

The selection of a method for measuring real-world fuel consumption is the basis for a reliable assessment of fuel efficiency in road transport. The relevant literature indicates that fuel consumption values obtained under research conditions may differ significantly from those recorded under actual vehicle operating conditions**.** Type-approval procedures are carried out in a controlled environment and are based on standardised driving cycles, which do not fully reflect the variability of road conditions and operational factors [17]. In response to these limitations, methods based on the analysis of data from real-world refuelling records are increasingly being used. The use of the full-to-full approach, based on real-world fuel measurements before and after transport operations, makes it possible to determine actual fuel consumption more accurately under operating conditions [18]. In addition, the analysis of telematics data requires consideration of their hierarchical structure and careful preparation of the dataset [19]. It should be noted that the possibility of applying a specific measurement approach is in practice determined by the way refuelling is carried out and by the availability of complete observations. Although the full-to-full approach is methodologically justified, it cannot always be implemented, as refuelling decisions are often driven by the optimisation of fuel purchase costs and involve frequent partial refuelling during routes. In practice, drivers refuel in countries with more favourable prices, limiting refuelling in relatively more expensive countries. The variability of refuelling locations means that transport enterprises increasingly implement tools supporting the ongoing control of fuel transactions and the analysis of fuel purchase costs on international routes. One of the solutions used for this purpose is fuel cards, which enable cashless fuel purchases and the recording of data on the time, location, quantity and value of refuelling. An analysis of geographical coverage indicates significant differences between individual fuel card operators. Broad European coverage is offered by DKV Mobility and UTA Edenred. DKV Mobility enables the use of services in more than 50 countries, covering most European countries, including European Union countries, the Balkans, the United Kingdom and selected countries of Eastern Europe and Central Asia. It also provides the possibility of settling road tolls for expressways, motorways, tunnels and bridges [24]. A similar system is offered by UTA Edenred, which operates in 40 European countries and provides solutions for settling fuel costs and road tolls [25]. In turn, Eurowag and E100 operate in Europe, offering their services in around 30 countries. Eurowag focuses primarily on the European market, whereas the E100 network also covers selected Central Asian countries [26, 27]. AS24 covers 29 countries and stands out due to solutions adapted to the specific requirements of heavy-duty transport [28]. Tankpool24 has a smaller geographical scale and operates in 16 European Union countries [29]. In the case of Diesel24, operations are based on a network of partners operating in more than 30 countries, supplemented by eight stations of its own located in Austria [30]. Orlen presents a different operating model, basing its position in Central Europe on a much more extensive own station network and partner cooperation enabling wider use of fleet cards [31]. The presented systems differ in terms of coverage and operating model, which affects the nature of the data used in refuelling analysis. This means that fuel consumption analysis should take into account the consistency of the data used with the adopted measurement method. Consequently, the choice of measurement method should be treated as a key element from the perspective of the reliability and interpretability of results, determining the possibility of formulating reliable conclusions.

An important consequence of selecting a fuel consumption measurement method is the reliability of CO_2 emission estimation, which is particularly important in the heavy-duty vehicle segment, whose emission significance is disproportionately high in relation to their share in the total vehicle population. In the European context, HDVs are responsible for approximately 27% of CO_2 emissions from road transport, while their share in total greenhouse gas emissions in the European Union is close to 5%. National examples also confirm the importance of the transport sector, which in Ireland accounted for approximately 40% of energy-related emissions in 2018 [10]. Transport generates approximately 14% of global greenhouse gas emissions, of which 94.6% come from road transport, while HDVs account for approximately 25.1% of greenhouse gas emissions in Europe [20]. CO_2 emissions in road transport are directly determined on the basis of fuel consumed; therefore, the accuracy of its measurement becomes crucial in emission analyses. The results of the cited studies indicate that, in heavy-duty transport, the accuracy of fuel consumption measurement is essential for the reliability of estimated CO_2 emissions and the comparability of results between vehicles. The accuracy of emission estimation largely depends on the quality of input data, which is determined by the telematics systems used. Many of these systems provide generalised information, which may limit the possibility of reliable emission calculation and hinder the comparability of the obtained results [23]. Consequently, the assessment of fuel efficiency in HDV fleets requires not only the selection of a data source but also a structured analytical approach ensuring the comparability of results over time. Against this background, the importance of data analysis as a tool enabling the systematic processing of operational information is increasing.

From the perspective of fleet practice, analytical methods that integrate operational data from various sources are becoming increasingly important. Anomaly detection in fuel consumption is a key element in assessing fleet fuel efficiency, as it enables the detection of cases deviating from operational patterns. At the same time, detecting outliers is insufficient without interpreting their causes [21]. In practice, this means linking anomaly detection with the analysis of operational conditions, which makes it possible to identify factors responsible for excessive fuel consumption. In parallel, predictive approaches based on trip data are being developed, in which fuel consumption is estimated on the basis of relevant vehicle and engine operating parameters. This enables the assessment of fuel efficiency from an operational perspective and supports the identification of potential irregularities in vehicle operation [22]. From an analytical perspective, reliable estimation of fuel consumption over short road sections requires more than information on average speed, as road gradient, vehicle mass and acceleration also have a significant influence [15]. The application of data analysis in the assessment of fuel efficiency involves the use of integrated operational data to estimate fuel consumption from a fleet perspective.

The literature review indicates the dynamic development of methods for assessing fuel consumption and CO_2 emissions in transport, particularly those based on quantitative data analysis and the estimation of fuel use under operational conditions. Despite the growing number of studies using operational data, limitations of the existing body of research are still visible, including the fragmented nature of research approaches, the heterogeneity of fuel consumption measurement methods and differences in the scope of data analysis and adopted research assumptions. Further analyses based on operational data from logistics enterprises are needed to better integrate real-world fuel use, emission assessment and the identification of units with the highest contribution to overall fleet consumption. This study responds to this need by focusing on fuel efficiency under fleet operating conditions.

RESEARCH METHODS

Dataset description

The study was based on a heterogeneous set of operational data collected for a fleet of 28 commercial vehicles, consisting of 23 delivery trucks and 5 heavy-duty vehicles. All analysed units met the stringent Euro VI emission standards and were powered by diesel fuel. Vehicle operation took place in international transport under varied road and topographical conditions. The input data were collected between November 2025 and January 2026. The dataset included information from several sources: the telematics system, CAN bus data, fuel level sensors and E100 and Eurowag fuel cards. Due to their highest consistency with the telematics system records, CAN bus parameters were adopted as the primary source of fuel consumption data for further calculations. Data from fuel level sensors and fuel cards were used for supplementary purposes, mainly to verify and compare refuelling-related information. The initial data specification, before cleaning and filtering, is presented in Table 1.

Table 1
Characteristics of the initial dataset before cleaning and filtering

Variable	Value
Number of vehicles	28
Study period	November 2025 – January 2026
Number of refuelling records	1,297
Number of CAN-based records	1,408
Number of tank-level records	1,398
Number of monthly observations	79

Data sources

In order to conduct a comparative assessment of the reliability of individual fuel consumption measurement methods, an analysis was carried out based on two data acquisition systems. The first two methods were based on parameters from the telematics system, whereas the third method relied on settlement data obtained from fuel cards. By basing the analysis on independent on-board, physical and settlement data, it was possible to verify the results against one another, assess their degree of consistency and identify discrepancies resulting from the specific nature of individual data sources. Data from the telematics system included the chronology and location of vehicle refuelling events, as well as parameters used in two separate methods: the system-based method, based on CAN bus records, and the tank-based method, using direct readings from fuel level sensors. In this study, the reference data from the company's telematics system were understood as operational records collected directly from vehicles during real-world fleet operation in the analysed period. These records included vehicle identifiers, refuelling locations, fuel levels before and after refuelling, fuel level differences, fuel consumption, and odometer readings obtained from CAN bus records. The telematics data were not treated as laboratory reference measurements, but as an internal operational benchmark used to assess the consistency of the analysed fuel consumption data sources. In the literature, both CAN-derived parameters and fuel tank level data are used as a basis for analysing real-world fuel consumption. The use of CAN bus parameters to determine fuel consumption under real-world operating conditions is considered justified [32], while fuel level sensor data may serve as an independent analytical basis for assessing changes in the fuel level in a vehicle tank [33]. The third data layer consisted of settlement data obtained from fuel cards. This dataset included the amount of fuel refuelled, the refuelling location, the time of transaction and the fuel price. Settlement records documented individual refuelling events in transactional terms, reflecting the course of fuel purchase operations during the analysed period. Purchase documentation in the form of fuel cards and invoices is also indicated as an important basis for the long-term control of fuel consumption [34]. The adopted research structure enabled the comparison of results from separate recording systems, which made it possible to identify potential discrepancies resulting from the characteristics of individual data sources. Thus, the use of an approach based on several data sources is justified, as it increases the possibility of critically assessing the results and reduces the risk of misinterpreting fuel consumption when relying on a single measurement method [32, 35].

Data preprocessing

Before proceeding with the main analysis, a data verification process was carried out to assess the completeness, consistency and analytical usefulness of the collected empirical material. Observations meeting the criteria of technical and quality correctness were qualified for further calculations. The analysis included data without recording discontinuities, registered vehicle failures or disturbances in the operation of measurement systems. The data preparation stage is important in studies on fuel consumption, as it affects the quality of the input dataset and, consequently, the reliability of further analysis [36]. After the initial verification of source records, unit fuel consumption expressed in L/100 km was calculated and then further checked for outliers. At the next stage of the analysis, the interquartile range (IQR) method was applied, defined as the difference between the third and first quartiles (3). Values falling outside the range determined by the lower (1) and upper (2) bounds were considered potential outliers. The boundary values were determined according to the following relationships:

$$Lower\ Bound = Q_1 - 1.5 \times IQR, \tag{1}$$

$$Upper\ Bound = Q_3 + 1.5 \times IQR, \tag{2}$$

$$IQR = Q_3 - Q_1, \tag{3}$$

where:
Q_1 – first quartile (lower quartile),
Q_3 – third quartile (upper quartile),
IQR – interquartile range.

Additionally, reference ranges of fuel consumption were taken into account for individual vehicle groups. These ranges were based on the enterprise's internal operational benchmarks for comparable vehicle types and gross vehicle weight categories. For delivery trucks up to 3.5 tonnes, the adopted range was 11.5-13 L/100 km, whereas for 40-tonne heavy-duty vehicles it was 24.5-31 L/100 km. The ranges reflected typical fuel consumption values observed in regular fleet operation and were used as practical benchmarks for assessing the plausibility of the results. However, exceeding these ranges did not automatically indicate erroneous data, as higher or lower values could result from real-world operating conditions.

Calculation of fuel consumption and CO_2 emissions

The basis for further analysis was the determination of fuel consumption indicators expressed in L/100 km for the analysed enterprise fleet. Due to the nature of the source data, fuel consumption calculations were adapted to the specificity of each analysed method. The method based on CAN bus data enabled direct readings for individual road sections. Combining this method with odometer data made it possible to calculate fuel consumption for each section according to formula (4). The obtained values were then aggregated to the monthly level (5).

$$FC_{CAN,i} = \frac{V_{CAN,i}}{S_i} \times 100, \tag{4}$$

where:
$FC_{CAN,i}$ – fuel consumption on the i-th section [L/100 km],
$V_{CAN,i}$ – volume of fuel consumed on the i-th section [L],
S_i – distance travelled on the i-th section [km].

$$FC_{CAN,month} = \frac{\sum_{i=1}^{n} V_{CAN,i}}{\sum_{i=1}^{n} S_i} \times 100, \tag{5}$$

where:
$FC_{CAN,month}$ – average monthly fuel consumption [L/100 km],
n – number of road sections recorded in a given month.

In the method based on fuel level sensor data, the amount of fuel consumed was determined on the basis of changes in the fuel level in the tank between consecutive measurement points. These values were then related to the distance read from the odometer, which made it possible to calculate unit fuel consumption for each section according to formula (6). In the next stage, the fuel consumed and the mileage were aggregated to the monthly level according to formula (7).

$$FC_{T,i} = \frac{(L_{after,i-1} - L_{before,i})}{S_i} \times 100, \tag{6}$$

where:
$FC_{T,i}$ – fuel consumption on the i-th section [L/100 km],
$L_{after,i-1}$ – fuel level after the (i-1)-th refuelling [L],
$L_{before,i}$ – fuel level before the i-th refuelling [L].

$$FC_{T,month} = \frac{\sum_{i=1}^{n}(L_{after,i-1} - L_{before,i})}{\sum_{i=1}^{n} S_i} \times 100, \tag{7}$$

where:
$FC_{T,month}$ – average monthly fuel consumption [L/100 km].
Monthly fuel consumption was determined on the basis of data from fuel cards and invoices (9). The total number of litres refuelled during the analysed period was adjusted by the difference in fuel levels in the tank (8), while the distance was adopted based on odometer readings.

$$V_C = V_R + V_S - V_E, \tag{8}$$

where:
V_C – total volume of fuel consumed in the month [L],
V_R – total volume of fuel refuelled (based on fuel cards/invoices) [L],
V_S – fuel level in the tank at the beginning of the month [L],
V_E – fuel level in the tank at the end of the month [L].

$$FC_{C,month} = \frac{V_C}{S_M} \times 100, \tag{9}$$

where:
$FC_{C,month}$ – average monthly fuel consumption [L/100 km],
S_M – total distance travelled in the month [km].
CO_2 emissions were determined at a further stage of the analysis for vehicles showing elevated fuel consumption values. An emission factor of 2.64 kg CO_2 per litre of diesel fuel was used in the calculations [37]. Total emissions for individual vehicles were presented according to equation (10).

$$E_{CO_2} = FC_{CAN,month} \times \frac{S_M}{100} \times 2.64, \tag{10}$$

where:
E_{CO_2} – total monthly CO_2 emissions [kg],
2.64 – CO_2 emission factor [kg/L].
Then, in order to ensure the comparability of results between vehicles with different mileage levels, average CO_2 emissions per 100 km were calculated (11). The conducted analysis made it possible to identify vehicles with unfavourable environmental parameters and thus to define areas requiring the implementation of optimisation measures.

$$E_{CO_{2,100}} = FC_{CAN,month} \times 2.64, \tag{11}$$

where:
$E_{CO_{2,100}}$ – unit CO_2 emissions [kg CO_2/100 km].

Analytical framework

Fuel consumption analysis was carried out according to a defined analytical framework, which included the assessment of the consistency of fuel consumption calculation methods, the identification of vehicles with the largest share in total fuel consumption, the assessment of fuel consumption levels of selected vehicles relative to the average and the estimation of costs associated with above-average fuel consumption. Due to different operating conditions and different ranges of typical fuel consumption, delivery trucks and heavy-duty vehicles were considered as two separate vehicle groups. For each measurement method described above in the Data Sources section, basic descriptive statistics were calculated, including the mean, median, minimum and maximum values, standard deviation and interquartile range. Comparison of these measures made it possible to determine typical fuel consumption levels, the degree of result variability and potential differences between values obtained using individual measurement methods. Consistency between the analysed methods was also assessed. This assessment was based on paired observations, for which differences in fuel consumption were calculated and described using four error measures: bias (Bias) (12), mean absolute error (MAE) (13), root mean square error (RMSE) (14) and symmetric mean absolute percentage error (sMAPE) (15).

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i), \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|, \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}, \tag{14}$$

$$sMAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{2|x_i - y_i|}{|x_i| + |y_i|}, \tag{15}$$

where:
x_i – fuel consumption value obtained from the first compared method for observation i,
y_i – fuel consumption value obtained from the second compared method for observation i,
n – number of observations,
i – index of an individual observation in the analysed dataset.

Pareto analysis was used to identify vehicles with the largest share in total fuel consumption. Based on this analysis, units of the highest operational significance were selected and subjected to further detailed fuel consumption analysis. For the selected vehicles, monthly fuel consumption patterns were also analysed by comparing total monthly fuel consumption with unit fuel consumption expressed in L/100 km. This comparison made it possible to distinguish situations in which high fuel consumption resulted from a greater scope of vehicle operation from cases that could indicate unfavourable operating parameters or lower fuel efficiency. The final part of the analysis involved assessing the fuel consumption of selected vehicles relative to the average level observed in the fleet. For each vehicle and month, the difference between the unit fuel consumption of a given vehicle and the average monthly fuel consumption of the entire fleet was determined (16). Positive deviations were then used to estimate additional fuel consumption and the corresponding costs. In the cost analysis, a diesel fuel price of 1.6 EUR/L was adopted for all months. This value was calculated as the average diesel price recorded in the fuel card transactions included in the analysed dataset. A single average price was used to ensure comparability of cost estimates between vehicles and months and to avoid distortions resulting from country-specific and transaction-specific fuel price fluctuations. The cost of above-average fuel consumption was then calculated according to formula (17). This enabled the technical analysis to be linked with practical economic significance and allowed the identification of vehicles whose fuel consumption had the greatest impact on overall fleet performance.

$$\Delta FC_{i,m} = FC_{i,m} - \overline{FC}_m, \tag{16}$$

$$Excess\ cost = \frac{\Delta FC_{i,m}^{+} \times D_{i,m}}{100} \times P_m, \tag{17}$$

where:
$FC_{i,m}$ – unit fuel consumption of vehicle i in month m [L/100 km],
$\overline{FC}_m$ – average unit fuel consumption of the fleet in month m [L/100 km],

$\Delta FC^{+}_{i,m}$ – positive value of the deviation, considered only when the vehicle fuel consumption was higher than the fleet average,
$D_{i,m}$ – distance travelled by vehicle i in month m [km],
P_m – average fuel price in month m [EUR/L].

RESULTS

Characteristics of the final dataset

Based on the adopted data verification criteria, the final research material was obtained and is characterised in Table 2. The initial dataset included 28 commercial vehicles, consisting of 23 delivery trucks and 5 heavy-duty vehicles. During the data cleaning and verification stage, vehicles with incomplete, inconsistent or erroneous data were excluded from further analysis. As a result, four vehicles were removed from the dataset, including three delivery trucks and one heavy-duty vehicle.
Consequently, the final analysed sample included 24 vehicles, consisting of 20 delivery trucks and 4 heavy-duty vehicles operated between November 2025 and January 2026. Further calculations included 1,126 records from fuel cards; 1,120 records derived from CAN bus data and 1,117 records based on fuel level sensor readings. For the purposes of the comparative analysis, 61 monthly observations were used, as not all vehicles operated throughout the full three-month period. The dataset prepared in this way made it possible to continue the analysis at the section and monthly levels and to compare the results obtained from different measurement sources.

Table 2
Characteristics of the final research dataset

Variable	Value
Number of vehicles	24
Study period	November 2025 – January 2026
Number of refuelling records	1,126
Number of CAN-based records	1,120
Number of tank-level records	1,117
Number of monthly observations	61

Descriptive statistics of fuel consumption

The analysis was conducted on the final research dataset after the data filtering stage, taking into account the three previously described methods of determining fuel consumption. For each vehicle and month of operation, fuel consumption expressed in L/100 km was calculated, and the obtained values served as the basis for determining the basic statistical measures summarised in Table 3 and Table 4.

Table 3
Descriptive statistics of fuel consumption for delivery trucks [L/100 km]

Method	Mean	Median	Min	Max	SD	IQR
CAN	12.57	12.55	10.19	15.18	1.18	1.52
Tank-level	11.26	11.09	8.36	14.03	1.26	1.51
Fuel cards	13.20	13.05	10.23	16.45	1.40	1.64

Table 4
Descriptive statistics of fuel consumption for heavy-duty vehicles [L/100 km]

Method	Mean	Median	Min	Max	SD	IQR
CAN	27.80	28.32	24.91	30.46	2.07	3.58
Tank-level	63.81	68.56	50.75	79.95	10.04	18.51
Fuel cards	27.71	28.12	22.73	31.32	2.59	2.39

For delivery trucks, a high convergence of results was observed across all methods. Average fuel consumption ranged from 11.26 L/100 km to 13.20 L/100 km. Low standard deviation values and similar interquartile range levels for all methods indicate high measurement stability. The obtained values remained close to the reference range, which confirms the overall consistency of the results for this vehicle class. Significant discrepancies were observed in the HDV group for data obtained using the tank-level method. While the CAN and fuel card methods showed similar mean values, the data obtained using the tank-level method clearly deviated from the other methods. The mean value for this method was as high as 63.81 L/100 km, and the maximum values reached nearly 80 L/100 km, which was more than twice the upper limit of the reference range for heavy-duty vehicles. The tank-level method was characterised by a much greater dispersion of results, as confirmed by the high standard deviation of 10.04 L/100 km. For this reason, the results obtained using this method were treated as potentially biased and were subsequently subjected to further verification in the following stages of the analysis.

Method consistency analysis

A key element of the analysis was to identify the fuel consumption calculation method characterised by the highest consistency with reference data from the telematics system. The assessment was carried out on the basis of error measures, including Bias, MAE, sMAPE and RMSE. The indicators were calculated based on differences between unit fuel consumption values expressed in L/100 km. The aggregate results for the entire fleet are presented in Table 5.

Table 5

Consistency indicators of fuel consumption methods compared with telematics data

Method	Bias	MAE	sMAPE [%]	RMSE
CAN	-0.26	0.37	2.33	0.85
Tank-level	3.93	6.47	21.9	14.1
Fuel cards	0.26	1.1	6.93	1.75

The comparison of mean values presented in Figure 1 makes it possible to assess the level of discrepancies between individual methods relative to the adopted reference point.

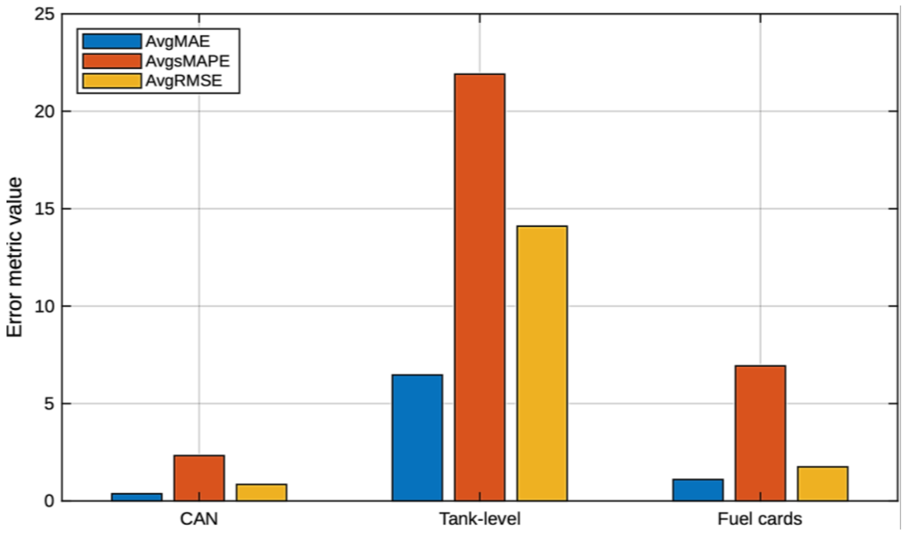

Fig. 1 Average consistency indicators for fuel consumption methods

Alt text: *Figure 1 shows that the CAN bus method achieved the highest consistency with the reference telematics data, as it had the lowest error values among the analysed methods. The fuel card method showed moderate consistency, whereas the tank-level method recorded the largest discrepancies.*

Analysis of the obtained results indicates that the method based on CAN bus data achieved the highest consistency with the reference point. The error values for this method were the lowest among those analysed, indicating only minor deviations from reference data. The negative Bias value reveals a slight tendency to underestimate reported fuel consumption. The fuel card method achieved intermediate results. Its indicator values were higher than for CAN but lower than for the fuel level sensor method, which recorded the largest discrepancies. High indicator values point to considerable measurement variability, particularly reflected in an RMSE value of 14.10 L/100 km. To identify sources of discrepancies more precisely, analysis was extended by dividing the fleet into vehicle groups. In the delivery trucks group, comprising 52 monthly observations, the fuel level sensor method showed higher consistency than at whole-fleet level, reaching an sMAPE value of 12.78%. This result was still higher than for the CAN bus method (where sMAPE was 2.06%) but indicated a much smaller scale of discrepancies than in the heavy-duty vehicle group. In the HDV group, comprising 9 monthly observations, the largest deviations were recorded for the tank-level method. Its sMAPE indicator increased to 74.62%, whereas for CAN it was 3.87%. This means high error values observed in whole-fleet analysis were largely associated with results obtained for heavy-duty vehicles. For this reason, the fuel level sensor method, particularly for HDVs, was rejected as a basis for further calculations. Ultimately, CAN bus data were adopted as a consistent and precise source across all vehicle groups, with sMAPE error not exceeding 3.87%, even in the heavy-duty vehicle group.

Fleet-wide fuel consumption analysis

Fleet-wide fuel consumption analysis made it possible to identify vehicles with the largest share in total fuel consumption. At this stage, CAN bus data were used, as they showed the highest consistency with telematics data. First, a ranking of vehicles was developed according to average monthly fuel consumption. This comparison provided a basis for assessing vehicles with different levels of operation during the analysed period. The results for delivery trucks and heavy-duty vehicles are presented in Figure 2.

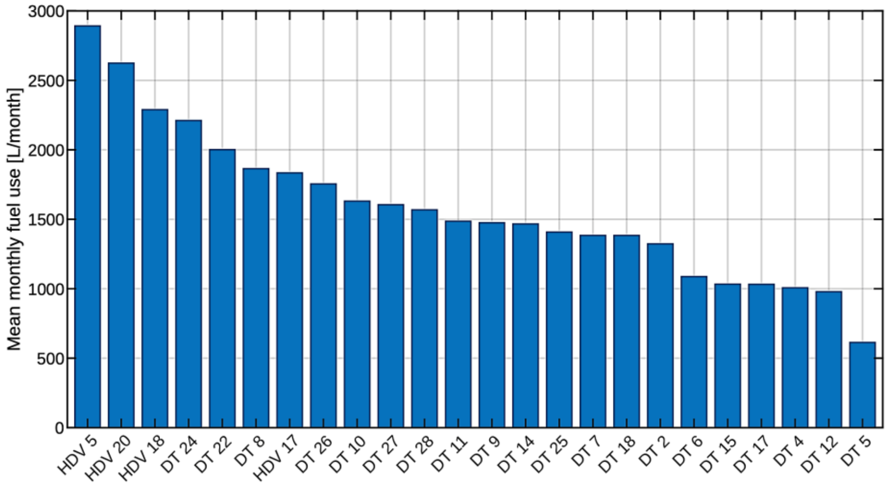

Fig. 2 Ranking of vehicles by mean monthly fuel consumption

Alt text: *Figure 2 shows that HDV 5, HDV 20 and HDV 18 had the highest average monthly fuel consumption. Among the delivery trucks, DT 24, DT 22 and DT 8 recorded the greatest fuel consumption, whereas the other vehicles showed lower values.*

Heavy-duty vehicles numbered 5, 20 and 18 recorded the highest average monthly consumption. Among delivery trucks, the highest values were obtained by DT 24, DT 22 and DT 8. Conversely, the lowest average monthly fuel consumption was noted for DT 12 and DT 5. These results indicate that heavy-duty vehicles generated the highest monthly fuel consumption in the analysed fleet. The ranking of average monthly fuel consumption enables comparison of fuel use between vehicles; however, it does not indicate their cumulative contribution to total fleet fuel consumption. For this reason, the analysis was extended to include Pareto analysis, presented in Figure 3.

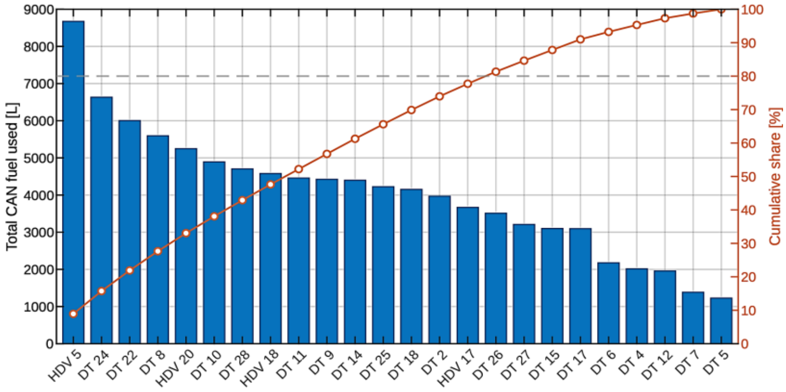

Fig. 3 Pareto chart of total fuel consumption by vehicle based on CAN data [L]

Alt text: *Figure 3 shows that total fuel consumption was concentrated within a selected group of vehicles. Approximately 80% of total fleet fuel consumption was generated by 15 out of 24 vehicles, with HDV 5 having the largest individual share, followed by DT 24 and DT 22.*

Pareto analysis showed that fuel consumption was concentrated within a specific group of vehicles. Approximately 80% of total consumption was generated by 15 out of 24 vehicles, corresponding to about 62.5% of the fleet. The largest share in total fuel consumption was recorded for HDV 5, which accounted for approximately 9% of total fuel consumption. DT 24 and DT 22 had the next highest shares. This demonstrates that the total fuel consumption of the fleet was shaped not only by heavy-duty vehicles but also by delivery trucks. Subsequent stages of the analysis focused on vehicles with the greatest overall impact on fleet fuel consumption. This selection procedure allowed units responsible for the dominant share of fuel consumption in the analysed period to be identified, while limiting further calculations to vehicles of the highest operational significance. For the selected group of vehicles, monthly fuel consumption patterns were classified. Both total monthly fuel consumption, expressed in litres, and unit fuel consumption, expressed in L/100 km, were considered in the analysis. This comparison was intended to determine whether high fuel consumption resulted mainly from intensive vehicle operation or from elevated unit fuel consumption. Results are presented in Table 6.

Table 6

Classification of fleet vehicles based on operational fuel consumption profiles

Vehicle ID	November	December	January
HDV 5	D	A	D
DT 24	B	C	B
DT 22	D	B	B
DT 8	B	B	D
HDV 20	A	-	D
DT 10	B	B	D
DT 28	C	C	B
HDV 18	A	D	-
DT 11	D	A	D
DT 9	D	A	D
DT 14	B	D	A
DT 25	A	A	D
DT 18	B	A	D
DT 2	A	B	C
HDV 17	A	D	-

Legend:

A – high monthly fuel use with normal unit fuel consumption.

B – high monthly fuel use with elevated unit fuel consumption.

C – moderate monthly fuel use with elevated unit fuel consumption.

D – no clear abnormal consumption pattern.

The analysis showed variation in fuel consumption profiles among vehicles with the highest share in total consumption. In the case of HDVs 5, 20, 18 and 17, high fuel consumption resulted mainly from intensive vehicle operation while maintaining typical L/100 km values for this group. In contrast, for selected DTs 24, 22, 28 and 8, high monthly consumption was accompanied by elevated unit fuel consumption values. In the case of DT 28, elevated unit fuel consumption persisted throughout all three months, while its total mileage was lower than that of DT 8. This excludes intensive operation as the main explanation and indicates DT 28 as a unit with a higher diagnostic priority.

CO_2 emissions of selected high-consumption vehicles

Based on Table 6, a group of eight delivery trucks showing elevated unit fuel consumption in at least one month was selected. An assessment of CO_2 emissions was then conducted for the analysed group. Total emissions over the analysed period amounted to 106,497.34 kg CO_2, with the contribution of individual vehicles varying across the group. The highest total emissions were recorded for DT 24, which accounted for 16.44% of the emissions of the analysed group. This vehicle was also characterised by the highest average unit emissions, amounting to 39.44 kg CO_2/100 km. In turn, DTs 22 and 28 accounted for 14.88% and 13.87% of emissions, respectively. In order to compare the environmental efficiency of individual delivery trucks, the deviation of the average unit emissions of each vehicle from the mean value for the entire delivery truck group, amounting to 33.18 kg CO_2/100 km, was also calculated. The results of this comparison are presented in Figure 4.

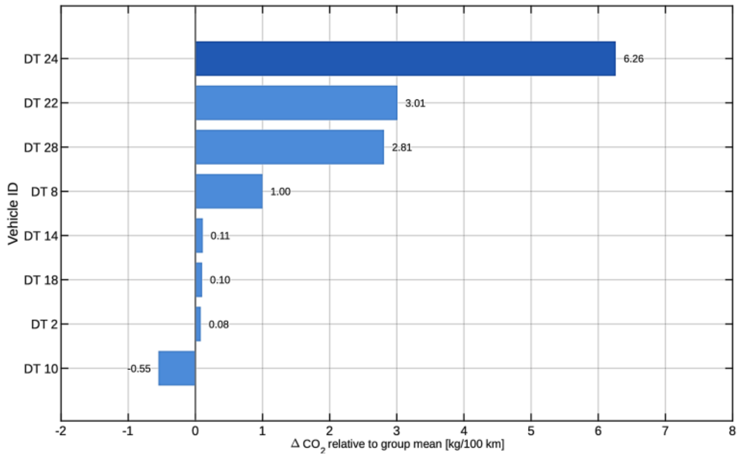

Fig. 4 Deviation of mean CO_2 emissions from the group average

***Alt text:** figure 4 shows that DT 24 had the largest positive deviation in unit CO_2 emissions from the delivery truck group average. DT 22 and DT 28 also exceeded the group average, which indicates that these vehicles had less favourable environmental performance than the other analysed delivery trucks.*

For DT 24, the largest positive deviation was recorded, with average unit emissions exceeding the mean value for the entire group of delivery trucks by 6.26 kg CO_2/100 km. Positive values were also observed for DT 22 and DT 28, amounting to 3.01 kg CO_2/100 km and 2.81 kg CO_2/100 km, respectively. This indicates that these vehicles were characterised by clearly elevated unit emissions relative to the average level observed across the delivery truck group. The lowest deviation from the mean was recorded for DT 10, whose unit emissions were lower than the reference value by 0.55 kg CO_2/100 km.

Economic impact of excess fuel consumption and reduction scenario for selected DTs

Economic assessment was conducted for the three delivery trucks that, in the previous stage, showed the highest positive deviations from the group average. The results are presented in Figure 5.

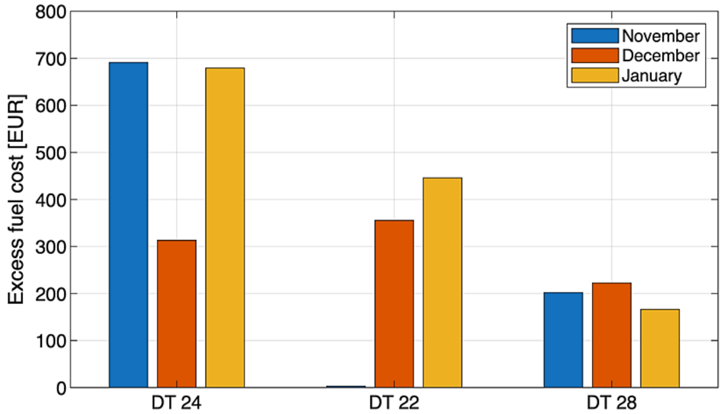

Fig. 5 Estimated monthly excess fuel costs for the three delivery trucks with the highest unit emissions
Alt text: *Figure 5 shows that DT 24 generated the highest excess fuel costs among the three analysed delivery trucks. The excess costs for DT 22 and DT 28 were clearly lower, which indicates that DT 24 had the greatest economic impact and should be prioritised for further diagnostic and optimisation measures.*

The highest costs of excess fuel consumption were recorded for DT 24, for which total costs amounted to EUR 1,683.73. For DT 22, these values were lower by approximately 52%, while for DT 28 they were lower by approximately 65%. Such a clear disproportion indicates the dominant contribution of DT 24 to generating operational losses within the entire group, making it a key target for future optimisation measures. To estimate potential benefits, a scenario analysis was conducted for two variants of reducing the total fuel consumption of DT 24. Assuming an average fuel price in the EU in 2026 of 1.6 EUR/L, a 5% reduction would result in savings of approximately EUR 530.53 and an emission reduction of 875.37 kg CO_2 over the analysed period. In the 10% reduction variant, savings would increase to EUR 1,061.06 and emission reductions to 1,750.74 kg CO_2. The results of this analysis indicate that even a partial improvement in the performance of a single vehicle may bring measurable economic and environmental benefits.

DISCUSSION

The aim of this study was to evaluate fuel consumption in the analysed vehicle fleet based on different data sources and to identify vehicles associated with the greatest economic, environmental and operational burden. The results show that fleet fuel consumption assessment should not be based only on the availability of data, but also on their consistency, completeness and suitability for the purpose of the analysis. This observation is consistent with the broader direction of recent research, which emphasises the importance of real-world operational data in fuel consumption and CO_2 emission analyses [1, 17].

A key finding of the study is that the three analysed data sources had different analytical value. Fuel card and invoice data were useful mainly from an accounting perspective, as they reflected fuel purchases and costs incurred by the enterprise. Such data support cost control, especially in the context of rising fuel prices and their impact on logistics operations [3]. However, they were less suitable for directly reconstructing the actual fuel consumption of a specific vehicle in a given period, because fuel purchased does not always correspond to fuel consumed, particularly in long-distance and international transport. Moreover, the possible use of a fuel card assigned to one vehicle to refuel another may distort vehicle-level interpretation. Therefore, fuel card and invoice data should be treated as a reliable source for cost analysis, but not as a fully sufficient basis for assessing operational fuel efficiency. This is consistent with studies indicating that real-world fuel consumption measurement depends strongly on the type and quality of the data used [32].

The method based on fuel level sensor data provided a more direct insight into changes in the fuel volume in the tank. However, in the analysed fleet this source showed the highest variability, especially among heavy-duty vehicles. This does not mean that fuel level sensors are useless; rather, it indicates that their results require careful interpretation. Fuel level readings may be affected by vehicle inclination, uneven ground, fuel movement inside the tank, partial refuelling and sensor accuracy. These factors are particularly important in international transport, where refuelling often occurs in smaller portions and under different operating conditions. Similar measurement difficulties are discussed in studies concerning fuel level estimation in trucks operating under real conditions [33]. Thus, fuel level sensor data may be valuable as a supplementary diagnostic source, but in this study, they did not provide a sufficiently stable basis for the main comparative assessment.

Compared with the other sources, CAN bus data showed the highest consistency with telematics records and were therefore adopted for further calculations. This result supports the use of in-vehicle and telematics-based data in fleet monitoring, as such systems enable continuous and structured monitoring of vehicle operation and driving-related parameters [8, 19]. At the same time, CAN data should not be interpreted as completely free from limitations. Measurement errors, differences between vehicle models and data processing methods may still influence the results. Nevertheless, in the analysed case, CAN bus data provided the most coherent basis for comparing fuel consumption at both vehicle and monthly levels.

The distinction between total fuel consumption and unit fuel consumption was essential for the interpretation of the results. Total fuel consumption identified vehicles that had the greatest impact on the overall fuel balance and costs of the enterprise. This perspective is important from the managerial point of view, because vehicles consuming the largest amount of fuel directly influence operating costs and fuel demand planning. However, high total consumption does not automatically mean poor fuel efficiency. It may result from higher mileage, more intensive use or longer international routes. For this reason, total consumption alone is insufficient to classify a vehicle as inefficient.

The Pareto analysis showed that total fuel consumption was distributed across a relatively broad group of vehicles. Approximately 80% of total fuel consumption was generated by 15 out of 24 vehicles, which means that fuel use was not concentrated only in a few units. This result has practical significance, as it suggests that optimisation measures should not be based exclusively on one vehicle. At the same time, the highest shares in total fuel consumption were recorded for HDV 5, DT 24, DT 22 and DT 8. This means that these vehicles had the greatest impact on the overall fuel balance of the fleet. However, their high contribution to total fuel consumption should not be interpreted directly as evidence of reduced fuel efficiency, since it may also result from intensive operation, higher mileage or longer routes. Only the comparison of total fuel consumption with unit fuel consumption made it possible to distinguish more accurately between intensively used vehicles and units potentially problematic in terms of fuel efficiency.

The comparison of total and unit fuel consumption made it possible to distinguish between intensively used vehicles and vehicles potentially problematic in terms of fuel efficiency. In the delivery truck group, the adopted reference range of 11.5-13.0 L/100 km provided an operational benchmark for interpretation. The average value for this group fell within the accepted range, which suggests that the fleet did not show a general problem of excessive fuel consumption. However, individual vehicles exceeded this range and therefore required more detailed verification. This result is important because it shows that fleet-level averages may hide vehicle-level deviations. Similar conclusions appear in studies using data-driven methods and anomaly detection to identify vehicles with abnormal fuel consumption patterns [21].

DT 24 was the most important case identified in the study. The vehicle recorded the highest unit fuel consumption in the delivery truck group, and elevated values appeared in consecutive months. This pattern may indicate a recurring operational condition rather than a single incidental measurement. However, the available data do not allow one clear explanation to be assigned. Higher fuel consumption may have resulted from technical condition, driving style, transported load, idling time, route characteristics or weather conditions. Previous studies indicate that fuel consumption is shaped by a combination of driver-related, vehicle-related, road-related and environmental factors [13]. The role of driving behaviour is also confirmed by studies showing its impact on real-driving fuel consumption and emissions [10]. Therefore, DT 24 should not be described as a vehicle with a confirmed technical defect, but rather as a vehicle requiring priority diagnostic verification.

The analysis of refuelling locations indicated that DT 24 operated on international routes covering, among others, France, Italy, Germany, Austria and Spain. This route pattern may suggest exposure to diverse road conditions, including Alpine or Southern European sections. Such sections may increase engine load, particularly when the vehicle is heavily loaded. Similar conclusions are also visible in studies under real driving conditions, where route characteristics and vehicle operating profiles strongly influence fuel and energy demand [20]. Consequently, the elevated consumption of DT 24 may be partly explained by operational conditions. Nevertheless, this does not exclude the possibility of technical or behavioural causes. This uncertainty confirms the need to combine fuel consumption indicators with additional data on route profile, load weight, driver behaviour and service history.

The cases of DT 22 and DT 28 further show that elevated fuel consumption can have different interpretations. DT 28 recorded relatively high but stable unit fuel consumption, which may suggest repeatable operating conditions conducive to increased fuel use. One possible explanation is a regular route profile involving hilly, Alpine or foothill areas. DT 22, in turn, should be interpreted mainly in the context of intensive international operation. Motorway-based and transit-oriented routes may generate high mileage and relatively stable driving conditions, but they do not eliminate factors increasing fuel use, such as higher speed, vehicle load, congestion or adverse weather. These findings confirm that the same numerical indicator may result from different operational mechanisms. Therefore, the interpretation of fuel consumption data should include not only the value of the indicator, but also the context in which the vehicle operated.

Including CO_2 emissions in the analysis extended the interpretation of the results from an economic to an environmental perspective. Vehicles with elevated fuel consumption generate not only higher costs but also a greater emissions footprint. DT 24 was particularly important in this respect, as its average unit emissions amounted to 39.44 kg CO_2/100 km, while the average for the delivery truck group was 33.18 kg CO_2/100 km. This means that the unit emissions of DT 24 were higher than the group average by 6.26 kg CO_2/100 km. This result strengthens the practical importance of identifying vehicles with elevated unit fuel consumption, because fuel efficiency is directly related to emission reduction. The importance of this issue is also confirmed by studies on CO_2 fleet regulation, sustainable heavy-duty transport and emission management in road transport [4, 23].

The scenario analysis showed that a partial reduction in fuel consumption in the vehicle with the greatest deviation could bring measurable economic and environmental benefits. This suggests that targeted actions focused on vehicles with elevated unit fuel consumption and emissions may be useful from both cost and environmental perspectives. However, the results should be interpreted as an estimate of potential savings rather than as a guaranteed effect of corrective measures. The actual scale of benefits would depend on the cause of increased fuel consumption, such as technical condition, driving style, load, route profile or idling time. Therefore, scenario analysis should be treated as a supporting tool for prioritising further verification and identifying where optimisation efforts may be most justified. Driver-oriented actions, such as eco-driving guidance or feedback systems, may also be considered, as previous studies indicate that such interventions can support fuel-efficient operation when properly implemented [12].

The study also has limitations that should be considered when interpreting the results. First, the observation period was relatively short and covered winter months, which may have affected fuel consumption due to lower temperatures, more difficult road conditions and seasonal differences in transport operations. Second, the analysis did not directly include variables such as load weight, driver behaviour, share of urban and motorway driving, idling time, road gradient or detailed maintenance history. These limitations do not undermine the usefulness of the analysis, but they mean that the findings should be treated as a basis for identifying vehicles requiring further verification rather than as a definitive explanation of the causes of elevated fuel consumption.

Overall, the findings indicate that fleet data can support the management of fuel consumption, costs and CO_2 emissions, provided that the data source is appropriate for the analytical objective and the results are interpreted with caution. The greatest practical value comes from combining several perspectives: total consumption, unit consumption, emissions, costs and operating conditions. Such an approach makes it possible to distinguish intensively used vehicles from units that may require technical diagnostics, driver-related interventions or operational changes. The study therefore shows how different fuel consumption data sources can support more targeted and evidence-based fleet management decisions.

CONCLUSION

The findings indicate that a reliable assessment of fleet fuel efficiency requires not only access to operational data but also a critical evaluation of their source. The comparison of data obtained from the CAN bus, fuel level sensors, fuel cards and invoices made it possible to identify CAN bus data as the most consistent source of information relative to telematics data. Consequently, the subsequent analysis of fuel consumption, CO_2 emissions and the costs of excess fuel consumption was based on data providing the highest comparability of results between vehicles. The key conclusion of the study is that the assessment of vehicle efficiency should not be based solely on the total amount of fuel consumed. High monthly fuel consumption may result from both intensive operation and higher mileage, as well as from elevated unit fuel consumption. Only the combined analysis of total fuel consumption, unit fuel consumption, CO_2 emissions and costs made it possible to identify vehicles requiring further verification. In the analysed fleet, particular attention was drawn to DT 24, DT 22 and DT 28, with the least favourable parameters recorded for DT 24. The significance of this result becomes evident when DT 24 is compared with the average level observed for the entire group of delivery trucks. The average fuel consumption in this group was 12.57 L/100 km, corresponding to average emissions of 33.18 kg CO_2/100 km. For DT 24, these values were clearly higher: average fuel consumption amounted to approximately 14.94 L/100 km, while unit emissions reached 39.44 kg CO_2/100 km. This represents an exceedance of the group average by approximately 2.37 L/100 km and 6.26 kg CO_2/100 km. Such a deviation indicates that DT 24 should be treated as a vehicle requiring priority technical and operational diagnostics. The results obtained have important practical implications for fleet management. They show that even a single vehicle with elevated unit fuel consumption may generate noticeable cost-related and environmental consequences, especially when an unfavourable fuel consumption pattern persists over consecutive months. The scenario analysis for DT 24 showed that a 5% reduction in total fuel consumption could result in savings of approximately EUR 530.53 and an emission reduction of 875.37 kg CO_2 over the analysed period. In the 10% reduction variant, potential savings would increase to EUR 1,061.06, while emission reductions would reach 1,750.74 kg CO_2. These findings confirm that selective diagnostics of vehicles deviating from the average may be more operationally justified than implementing uniform measures across the entire fleet. At the same time, the analysis does not allow the causes of elevated fuel consumption to be determined unequivocally. The results should therefore be treated as a basis for selecting vehicles requiring further technical and operational verification rather than as a final diagnosis of fuel inefficiency. Future analyses should include a longer observation period and additional operational variables, such as load weight, route profile, driver behaviour, idling time and vehicle service history. The main value of the study lies in demonstrating that an integrated analysis of fleet data can serve as a practical tool supporting decision-making in a transport enterprise. Combining information on fuel consumption, CO_2 emissions, costs and vehicle operating profiles makes it possible to identify units requiring further control and to determine the potential for reducing costs and environmental impact without the need for immediate vehicle replacement.

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